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Performance Assessment of Maximum Likelihood, Random Forest and Support Vector Machines Classifier for Urban Land Use Classification: A Case Study of Dhaka Metropolitan City, Bangladesh

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ABSTRACT

Segmentation of remotely sensed satellite images is obligatory for multifarious earth observation studies, including land use and land cover (LULC) analysis. It is also inherent in environment, ecosystem, and urban development in analytical perspectives and complex inputs for modeling urban planning and disaster management. Assessment of LULC pattern uses different segmentation methods for assigning specific given classes to pixels of bands containing an image of natural color composite to define land use land cover classes such as water body, vegetation, bare soil, and built-up areas. The process of assigning classes to pixels varies from one to another, and thus, different accuracy levels are obtained. The accuracy of frequently used methods for LULC classification was assessed in this study, where the Dhaka metropolitan area has been taken as a sample to observe the LULC. The classification was conducted by using three methods where the Support vector machines classification (SVMC) produced the best accuracy results of 83.2% overall accuracy and overall kappa coefficient value of 0.74 than both random forest classification (RFC) and maximum likelihood classification (MLC) methods with 86.34% and 83% spatial similarity rate respectively. Besides, RFC and MLC are roughly equivalent in kappa and overall accuracy values, though MLC revealed less capability at classifying vegetation. However, MLC showed a high spatial similarity with RFC and dissimilarity with SVMC. This study on segmentation methods in classifying LULC will help users make an informed choice in selecting the best method for relevant studies.

Keywords: Urban Land Use Classification, Dhaka Metropolitan City, Maximum Likelihood Classification, Random Forest, Support Vector Machines

1. Introduction

Land use and land cover (LULC) are the fundamental terms used to define urbanization, its expansion, and changes in environmental components such as vegetation cover and water bodies. LULC maps are critical in urban and regional planning for land management and monitoring and assessment in land use, land use policy, urban planning, agricultural planning, and ecosystem services (DeFries et al., 2004; Guidici & Clark, 2017). Additionally, this technology serves various advantageous functions, such as reducing survey time, ensuring the availability of updated maps, being more cost-effective, and extracting spectral information (Mondal et al., 2012).

Dhaka is one of the world's fastest-growing cities (*Dhaka, Bangladesh Metro Area Population 1950–2021*, n.d.; UN, 2014). A rapid increase in population density results in rapid urbanization, leading to constant changes and major landscape transformations (Ishtiaque et al., 2014). The environmental repercussions of Dhaka's rapid and uncontrolled expansion have significantly impacted natural ecosystems and land (Dewan et al., 2012; Dewan & Yamaguchi, 2009). These impacts result in a high rate of unplanned urbanization, urban development, and decline of water bodies and vegetation, contributing to the city's rapid land-use changes (Rai et al., 2017). Thus, monitoring LULC is crucial for planning and management (Islam & Ahmed, 2011). The most significant way to produce LULC maps is to classify remotely sensed images (Alshari & Gawali, 2021; Santosa, 2016).

Digital classification methods have been in use for land use segmentation since 1972 from satellite data (Hall et al., 1995; Lu & Weng, 2007; Townshend, 1992). The quality of the digital classification method used to generate a valid LULC map is just as critical as the information supplied in the segmentation. Without high accuracy, the product cannot be used reliably, limiting its applicability; additionally, increased accuracy in land cover classification is critical for obtaining more reliable results in research or practical applications such as development work, particularly in the case of urban planning (Fenstermaker, 1994). So the comparative study on different digital classification methods is mandatory based on their accuracy for applying the appropriate one. However, the digital images are generally classified using the reflectance collected by remote sensing systems, but sometimes in the composite landscape's images, there are many mixed pixels exists which might lead the difficulty in the segmentation process. LULC classification of densely urbanized areas is quite challenging with low or medium spatial resolution due to mixed pixels and the spectral confusions among different classes (Jeon & Landgrebe, 1990). In these mixed pixel cases, almost all classifiers have difficulty differentiating class types, resulting in incorrect classification in various cases. Yet, some classifiers performed better in this problem than others regarding classification accuracy.

Among all classification methods, maximum likelihood classification (MLC) is one of the most common, popular, and widely used classification methods for segmenting major classes (Huang et al., 2002). MLC classification is based on the parametric application in identifying the chosen classes in a normal distribution (Kavzoglu & Reis, 2008). This classification method is widely used for its simple and easy steps in the application as well as its efficiency. In recent years, machine learning-based algorithms have given great recognition and remarkable performance in remote sensing-based applications compared to traditional techniques (Gislason et al., 2006; Kavzoglu et al., 2018; Thanh Noi & Kappas, 2018). There are several machine learning-based algorithms are currently in use, e.g., random forest (RF), support vector machines (SVMs), artificial neural network (ANN), K-means clustering, and principal component analysis (PCA). Among them, RF and SVMs are two non-parametric segmentation techniques which are comparatively less complex yet highly efficient and well-known developed popular classifier methods (Mansaray et al., 2020). Random forest classification (RFC) is widely applied for its capability of accurate classification (Abdi, 2020). This algorithm propagates more than one decision tree during the segmentation process to increase the accuracy of resulting thematic maps. Support vector machines (SVMs) is another popular and widely used machine learning algorithm based on statistical theory; it is used for classification and regression problems (Vapnik, 1995). SVMs are a group of supervised classification algorithms that are the latest in remote sensing applications. The accuracy produced in segmentation by SVMs might show differences upon using a kernel function and its parameters (Kavzoglu & Colkesen, 2009). The SVM method has been used widely for pattern recognitions. Many researchers have found that a higher degree of closeness can be obtained by SVMs application regarding other segmentation techniques (Foody & Mathur, 2004; Naguib et al., 2009; Oommen et al., 2008; Pal & Mather, 2005).

This study defines how well the classifiers are interpreted with mixed pixel problems and provides overall high and specific class accuracy. Spatial similarity and areal accuracy assessment have also been performed from these classification techniques to show how the classifiers interpret among them, and the segmentation classes vary in different classifications. This study may lead future research to more accurate land use segmentation methods for more reliable information, especially in urbanized areas like Dhaka Metropolitan City.

2. Material and Methods

2.1. Study area

Dhaka is the capital of Bangladesh and a rapidly advancing mega-city of the world (BBS, 1998). Therefore, such rapid urbanization in Dhaka significantly impacts land use land cover changes. This study was conducted in the Dhaka Metropolitan City (DMC) area, Bangladesh, which lies between 23˚40'00" and 23˚55'00"N latitudes, and 90˚20'00" and 90˚31'00"E longitude (Figure 1).

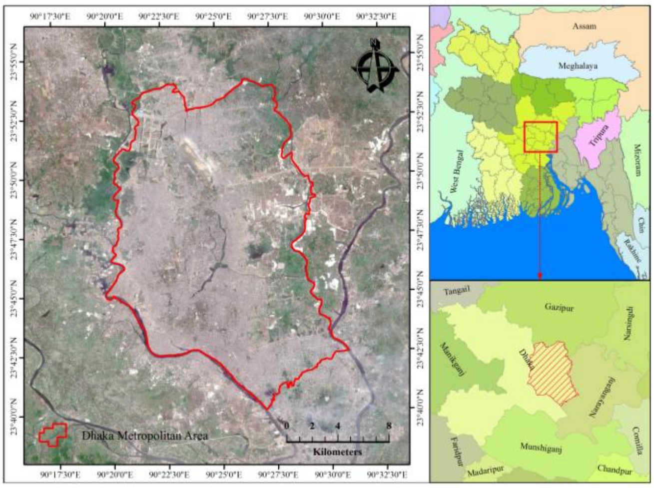

Figure 1. Study Area Map of Dhaka Metropolitan City

2.2. Data Source

Sentinel-2 satellite image bands had been selected for the classification of land use by Maximum Likelihood Classification (MLC), Random Forest Classification (RFC) and Support Vector Machines Classification (SVMC) algorithms. The date of satellite imagery with a spatial resolution of 10m had been acquired on 31st January 2021, available from the earth explorer website of the United States Geographical Survey (USGS). The satellite images had no radiometric and geometrical distortions; hence a minor geometric and atmospheric correction was applied by processing the images in ENVI for improving the quality.

2.3. Training Sample Classification

Sentinel 2 satellite image bands were interpreted by their spatial and spectral values to develop training sites. Natural color composite (RGB = 4,3,2) was used for digitizing polygons around each training site for similar land cover. Then unique identifiers were assigned to each known land cover type for segmentation (Ahmed & Ahmed, 2012). DMC is already a crowded area, and most of the area is used for human and industrial settlement. Still, for growing residential and industrial facilities requirements, the expansion for settlement areas is simultaneously increasing. New areas formerly where water bodies or vegetation cover areas are undergoing development to expand the settlement. Considering the facts mentioned earlier and previous research (Ahmed et al., 2013), four different classes were taken to train the sample for MLC, RFC, and SVMC method (Table 1).

Table 1. Description of different land cover class

Class Name	Description
Water Body	Lake, open water, ponds, canals, river, seasonal/permanent wetlands, depressed areas and swamps
Vegetation	Natural vegetation, trees, parks, gardens and grassland, playgrounds, vegetated lands, cultivation lands, and crop fields
Bare Soil	Construction sites, fallow land, sand filling lands, developed land, excavation areas, bare soils and open space
Built-up Area	All infrastructural built-ups such as commercial, residential, mixed-use and industrial areas, settlements, road networks, pavements, and man-made structures

2.3 Maximum Likelihood Classification Method (MLC)

The MLC was used to pinpoint the defined class distribution when the maximum for a given statistic (Scott & Symons, 1971). This segmentation method had been used widely and frequently in remote sensing, where a pixel was designated to the corresponding class by the classifier (Rosenfeld & Banerjee, 1992). If there had been a predefined class, in that case, the class posterior probability would be described as,

$$P(k|x) = \frac{P(k)P(k|x)}{\sum_{i=1}^{m} P(i)P(k|i)} \qquad (1)$$

Where P(k) was expressed as the anterior probability of class k and P(k|x) was evaluated as the conditional probability of observing x from class k (probability density function). The likelihood function P(k|x) for normal distributions was given as,

$$L_k(x) = \frac{1}{(2\pi)^{\frac{n}{2}}|\sum k|^{\frac{1}{2}}} \exp(-\frac{1}{2}\left(x-\mu_k\right)^T \sum\nolimits_k^{-1} (x-\mu_k)\Big) \qquad (2)$$

Where $x = (x_1, x_2 \ldots x_n)^T$ corresponds to the vector of a pixel with n number of bands; $L_k(x)$ signifies the likelihood membership function of x belonging to class k and $\mu_k = (\mu_{k}1, \mu_{k}2 \ldots \mu_{k}n)^T$ was denoted as the mean of the k^{th} class;

$$K^{th}\ class; \sum k = \begin{pmatrix} \sigma_{11} & \sigma_{12} & \cdot & \cdot & \sigma_{1n} \\ \sigma_{21} & \sigma_{22} & \cdot & \cdot & \sigma_{2n} \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ \sigma_{n1} & \sigma_{n2} & \cdot & \cdot & \sigma_{nn} \end{pmatrix} \qquad (3)$$

2.4. Random Forest Classification (RFC)

The RFC was applying decision trees as the primary classifier and generating a collective learning model by integrating multiple decision trees (Breiman, 2001). Random forest showed better performance than other classifiers because of being robust against overfitting, easy to parameterize and speed (Kavzoglu, 2017). The primary objective of this classifier was to generate numerous decision trees using a bootstrapped sampling method. The training data was applied to generate tree models in the decision forest was randomly selected from the training set. Approximately 70% of the randomly sampled data was applied to develop the decision tree structure and the rest was used to test the validity of the generated decision tree model. The label of an uncertain class was determined by assessing the majority voting principle of each tree model in the decision forest (Pranckevičius & Marcinkevičius, 2017).

2.5 Support vector machines Classification (SVMC)

As a non-parametric segmentation method, SVMs were implemented to solve segmentation problems in data sets where patterns within the variables were unknown. SVMs was formulated from statistical learning where mathematical algorithms were formulated to classify data that were linear and have two different classes. It was generalized to determine nonlinear data and multiclass data (Vapnik, 1995). This segmentation included the training and testing data sets. Each training set of data had a distinct target value and several attributes. The main function of the SVMC was predicting the target values of the given test data. A training data pairs(x_i, y_i), i=1,...,i where $x_i \in R^n$ and $y \in \{1,-1\}^i$ were required to solve the main equation (Boser et al., 1992; Cortes & Vapnik, 1995).

$$\underbrace{min}_{W,b,\xi} \frac{1}{2} w^T w + C \sum\nolimits_{i=1}^{i} \xi_i \qquad (4)$$

$$\text{Subject to } y_i(W^T \phi(X_i) + b) \geq 1 - \xi_i, \xi_i \geq 0 \qquad (5)$$

In a high dimension space, training vector x_i was used in the function ϕ, where SVMs required (finds) a linear hyperplane with a separated maximum margin. Here the parameter of the error was C > 0. The kernel function was,

$$k(x_i, x_j) \equiv \phi(x_i)^T \phi(x_j) \qquad (6)$$

2.6 Accuracy assessment

There were several popular methods for the accuracy assessment. Error matrix was considered one of the widespread techniques for calculating thematic map accuracy (Foody, 2002). It was measured by acquiring a sample from a certain class of a classified map, and then the actual class was validated from the field (Congalton, 1991). Producer's, user's and overall accuracies were calculated where overall accuracy was acquired for each class and was asserted as producer's and user's accuracy. The producer's accuracy was enumerated by dividing the number of valid sampling points in one class by the entire points and taken from the reference data. For the enumeration of user's accuracy, classified units valid in a class are divided by the total number of units already classified in that specific class (Mondal et al., 2012).

2.6.1 Kappa coefficient

Kappa coefficient (κ) was demonstrated as the discrete multivariate technique applied for enumerating the accuracy of maps acquired from remote sensing techniques and error matrices (Congalton et al., 1983). The equation of Kappa statistic was,

$$\kappa = \frac{(TS \times TCS) - \sum(N_c \times N_r)}{(TS^2) - \sum(N_c \times N_r)} \qquad (7)$$

Where, TS was the total sample and TCS was the total corrected sample. Nc and Nr represent the column total and row total respectively. A Kappa coefficient (κ) up to 1 means perfect agreement, whereas a value near to zero signifies that the agreement is poor (Landis & Koch, 1977).

3. Result and Discussion

3.1. Classification Accuracy

Error matrix has been calculated after the classification of the raw satellite image. Total 107 random sampling points have been taken to assess accuracy from all three of these classifications. The user and producer accuracy of three land use classification methods—Maximum Likelihood Classification (MLC), Random Forest Classification (RFC), and Support Vector Machines Classification (SVMC)—for Dhaka Metropolitan City are compared in Table 2. For water bodies, all three methods exhibit the same producer accuracy of 87.5%, but user accuracy differs, with RFC performing better at 63.64%, followed by SVMC at 58.33%, and MLC at 46.67%. In vegetation classification, MLC and SVMC both achieve 100% user accuracy, meaning all classified vegetation pixels were correct. However, SVMC has a higher producer accuracy of 62.5%, compared to MLC, which stands at 43.75%. RFC shows a more balanced performance, reaching 100% user accuracy and 75% producer accuracy. For bare soil classification, SVMC attains the highest user accuracy at 81.82%, while MLC follows at 77.14% and RFC at 75.76%. Producer accuracy for MLC and SVMC is identical, both reaching 81.82%, whereas RFC's producer accuracy value appears incorrect and needs verification. In built-up areas, SVMC provides the most accurate classification, with a user accuracy of 86.54% and a producer accuracy of 90%. MLC follows closely, achieving 88% for both user and producer accuracy, while RFC shows slightly lower accuracy, with 80.4% for user accuracy and 82% for producer accuracy. Overall, SVMC outperforms the other methods, correctly classifying 89 points, whereas both MLC and RFC classify 85 points accurately.

The comparison of kappa statistics and overall accuracy of three land use classification methods are shown that SVMC demonstrates the highest classification performance, achieving an overall accuracy of 83.2% and a kappa coefficient of 0.74, indicating a strong level of agreement between the classified results and reference data (Table 3). In contrast, both RFC and MLC produce identical results, with an overall accuracy of 79.44% and a kappa coefficient of 0.69, reflecting a slightly lower agreement compared to SVMC.

3.2 Areal statistics of MLC, RFC and SVMC

The areal distribution of different land use types classified using Maximum Likelihood Classification (MLC), Random Forest Classification (RFC), and Support Vector Machines (SVM) for Dhaka Metropolitan City is presented in Table 4 and Figure 2. In the case of water bodies, SVM classifies the highest area at 36 km^2, covering 11.76% of the total area, while MLC follows with 35 km^2 (11.44%) and RFC with 34 km^2 (11.11%). For vegetation, RFC identifies the largest area, classifying 33 km^2 (10.78%), closely followed by SVM at 32 km^2 (10.46%), whereas MLC estimates a much smaller vegetation cover of 21 km^2 (6.86%). In bare soil classification, MLC assigns the highest area at 89 km^2 (29.08%), while RFC and SVM classify 78 km^2 (25.49%) and 75 km^2 (24.51%), respectively. Among all land use categories, built-up areas dominate, with MLC and RFC both classifying 161 km^2 (52.61%), whereas SVM slightly exceeds them with 163 km^2 (53.27%). While SVM allocates the highest percentage to water bodies and built-up areas, RFC identifies the most vegetation cover, and MLC estimates the most extensive bare soil area. These variations highlight that the SVM tends to classify more urbanized regions, RFC provides a more balanced distribution of vegetation, and MLC attributes a larger portion of the landscape to bare soil.

3.3 Spatial Similarity Analysis

The spatial similarities among the MLC, RFC, and SVM classification methods are compared in terms of matched and unmatched areas (Figure 3). In the comparison between SVMC and MLC, the matched area is 254 km^2, comprising 83% of the total area, while the unmatched area is 52 km^2, or 17%. When comparing SVMC to RFC, the matched area increases slightly to 264.2 km^2, representing 86.34%, while the unmatched area is 41.8 km^2 (13.66%). Lastly, the comparison between RFC and MLC shows the largest matched area of 270.5 km^2, or 88.4%, and the smallest unmatched area of 35.5 km^2, which makes up 11.6%. In terms of spatial similarity, RFC and MLC have the highest overlap with 270.5 km² matched or 88.4%. SVMC and MLC yield the smallest match at 254 km² (83%), while SVMC and RFC show a slightly better overlap than SVMC and MLC (Table 5).

Table 2. User and producer accuracy of different land use classification methods of Dhaka Metropolitan City

Maximum Likelihood Classification (MLC)					
Type	Reference Total	Classified Total	Number of Correct Points	User Accuracy (%)	Producer Accuracy (%)
Water Body	15	8	7	46.67	87.5
Vegetation	7	16	7	100	43.75
Bare Soil	35	33	27	77.14	81.82
Built-up Areas	50	50	44	88	88
Total	107	107	85		
Random Forest Classification (RFC)					
Water Body	11	8	7	63.64	87.5
Vegetation	12	16	12	100	75
Bare Soil	33	33	25	75.76	7576
Built-up Areas	51	50	41	80.4	82
Total	107	107	85		
Support Vector Machines Classification (SVMC)					
Water Body	12	8	7	58.33	87.5
Vegetation	10	16	10	100	62.5
Bare Soil	33	33	27	81.82	81.82
Built-up Areas	52	50	45	86.54	90
Total	107	107	89		

Table 3: Kappa statistics and overall accuracy for MLC, RFC and SVMC

Classification Method	Overall accuracy (%)	Kappa Coefficient (κ)
SVM	83.2	0.74
RFC	79.44	0.69
MLC	79.44	0.69

Table 4: Areal statistics of MLC, RFC and SVM

Type	MLC		RFC		SVMs	
	Area (km²)	%	Area (km²)	%	Area (km²)	%
Water Body	35	11.44	34	11.11	36	11.76
Vegetation	21	6.86	33	10.78	32	10.46
Bare Soil	89	29.08	78	25.49	75	24.51
Built-up Areas	161	52.61	161	52.61	163	53.27
Total	306	100	306	100	306	100

Table 5. Spatial similarities among MLC, RFC and SVMC

Spatial Similarity	SVMC vs. MLC		SVMC vs. RFC		RFC vs. MLC	
	Area (km^2)	%	Area (km^2)	%	Area (km^2)	%
Matched	254	83	264.2	86.34	270.5	88.4
Unmatched	52	17	41.8	13.66	35.5	11.6
Total	306	100	306	100	306	100

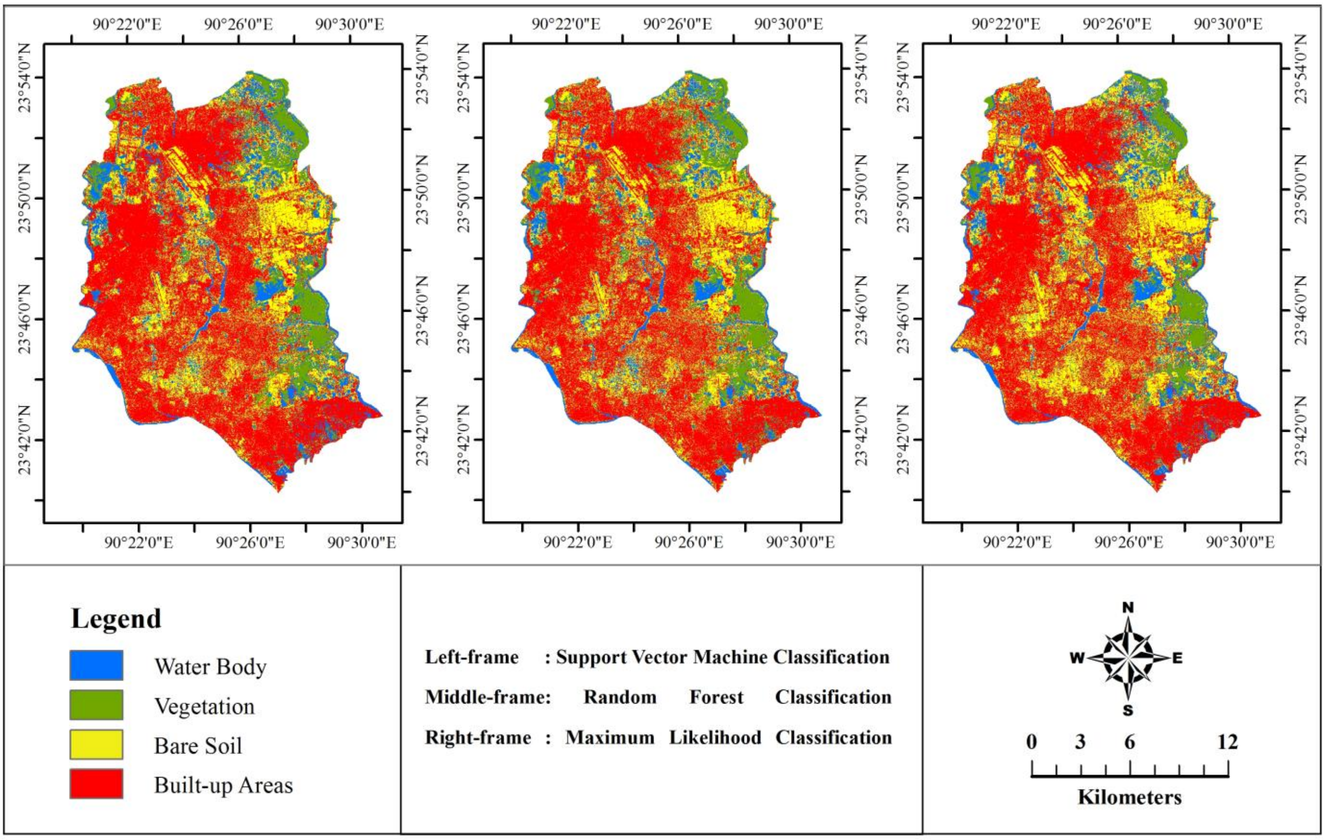

Figure 2. Land use and land cover map of Dhaka Metropolitan City

Figure 3 shows the map of spatial similarity in the area of Dhaka metropolitan city computed by MLC, RFC and SVMC technique.

The comparison of three land use classification methods—Maximum Likelihood Classification (MLC), Random Forest Classification (RFC), and Support Vector Machines Classification (SVMC)—reveals distinct differences in performance. Among these, SVMC consistently demonstrates superior classification accuracy and Kappa coefficient, indicating its robustness in land use classification. Spatial similarity assessments further reinforce these findings, with SVMC achieving the highest matched area compared to MLC and RFC.

Urban environments pose significant challenges in classification due to the mixed-pixel problem, where a single pixel represents multiple land use types. Composite pixels impact the effective utilization of remotely sensed data in urban land use/cover classification (Cracknell, 1998; Fisher, 1997). In the present study, conducted in a densely built-up urban area, distinguishing land cover features was particularly challenging due to their spectral similarity. The classification accuracy improved by approximately 4% when using SVMC, primarily due to its ability to handle mixed-pixel problems more effectively than RFC and MLC (Varma et al., 2016). Unlike MLC, which assumes that each pixel belongs to a single land use class, SVMC constructs an optimal hyperplane in a high-dimensional feature space, enhancing its ability to classify overlapping land use types accurately. RFC, although a robust ensemble method, is susceptible to class imbalance and overfitting, particularly in dense urban settings with intricate land cover patterns (Shi & Yang, 2015). MLC, being a probabilistic model, often misclassifies complex land cover types due to its reliance on prior statistical distributions, making it less effective in heterogeneous urban landscapes (Mustapha et al., 2010).

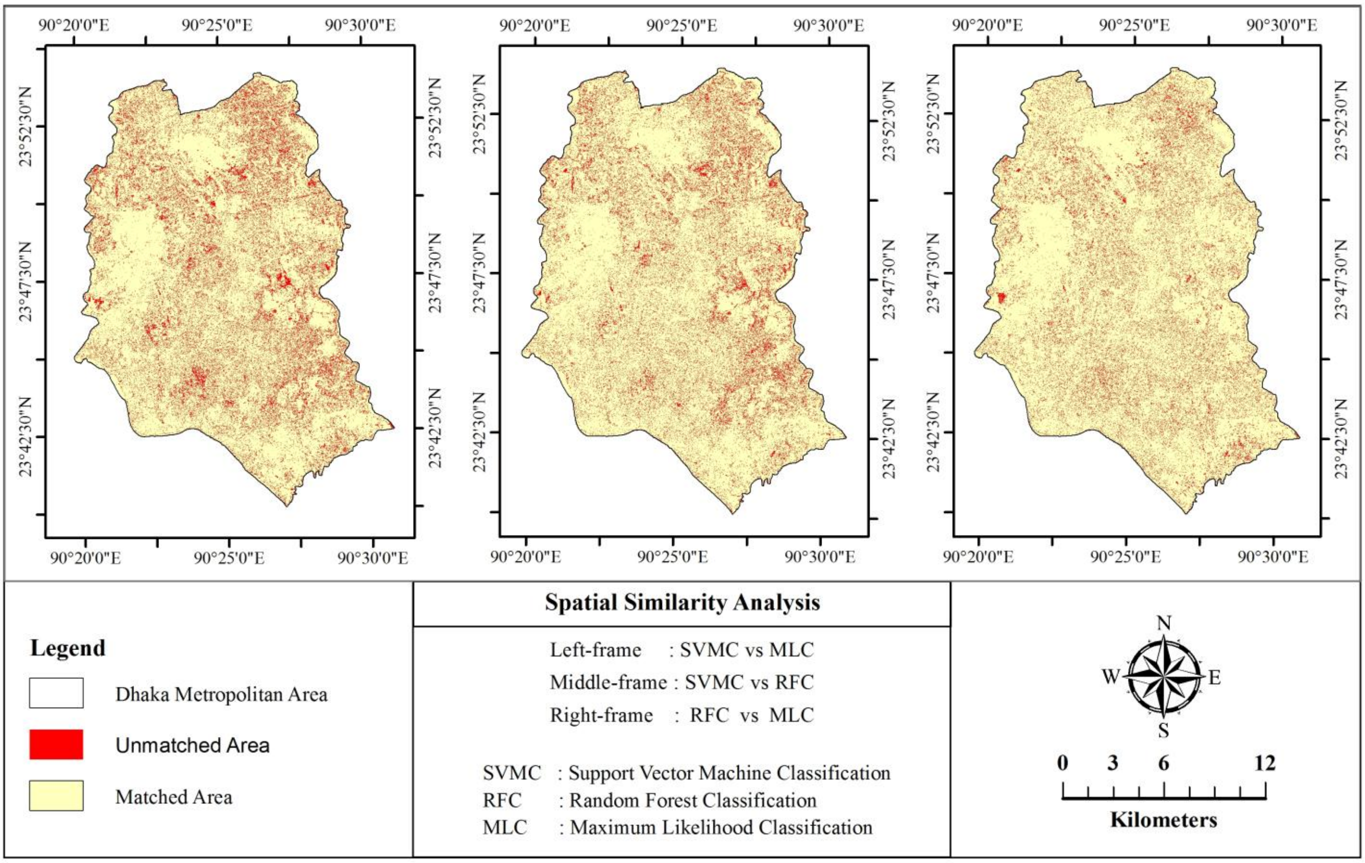

Figure 3. Spatial similarity map of Dhaka Metropolitan City

SVMC's capability to manage mixed pixels makes it a suitable choice for urban land use mapping, particularly in a complex environment like Dhaka Metropolitan City. The city's dense built-up areas lead to frequent mixed pixels, requiring a classification model that can differentiate subtle spectral variations. SVMC, by considering both local and global spatial contexts, enhances classification accuracy, making it a valuable tool for urban planning, infrastructure development, and environmental monitoring.

The error matrix analysis highlights that all classifiers faced challenges in distinguishing built-up areas from bare soil. However, SVMC exhibited superior performance in correctly classifying built-up areas, with fewer misclassified pixels compared to RFC and MLC. Despite this, all classifiers accurately classified water bodies due to their distinct spectral characteristics (Table 2). Interestingly, RFC performed better in classifying vegetation compared to SVMC and MLC due to its efficient handling of mixed numerical and categorical features (Wright & König, 2019), though its accuracy declined in classifying bare soil. Areal statistics indicate that while SVMC performed better overall, MLC occasionally surpassed RFC, particularly in identifying bare soil more accurately (Table 4). Previous studies also support these findings, showing that SVMC outperforms both RFC and MLC in terms of overall accuracy and Kappa coefficient (Huang et al., 2002; Kranjcic et al., 2019; Pal & Mather, 2005; Szuster et al.Analysis

Spatial similarity analysis reveals that 86.34% of classified areas were matched between SVMC and RFC, while 83% matched between SVMC and MLC. SVMC and RFC share higher similarity because both rely on pixel-wise spectral classification, ignoring spatial and contextual information (Fauvel et al., 2013; Ghamisi et al., 2018). Unlike MLC, which assumes a prior data distribution, SVMC minimizes classification errors using probabilistic outputs and structural risk minimization (Zhang et al., 2015). RFC and MLC showed comparable performance in terms of gross accuracy and Kappa coefficient (Table 3), with spatial similarity analysis indicating an 88.4% match between them. This could be due to RFC's use of large homogeneous training datasets and extensive decision trees (Breiman, 2001; Jin, 2012). MLC's reliance on Bayesian classification metrics helps reduce misclassification for distinct land cover types (Sisodia et al., 2014).

Future research should focus on optimizing SVMC for urban land use and land cover (LULC) classification, particularly in rapidly changing metropolitan areas. Given its efficiency in handling mixed pixels, SVMC could be integrated with advanced spatial-contextual techniques to improve classification accuracy. Expanding its application in densely populated urban landscapes will enhance urban planning, climate resilience strategies, and sustainable development initiatives.

4. Conclusions

Classification method comparison reveals that the Maximum Likelihood classification yielded minimal outcomes. The Support Vector Machines performed better than Random Forest and Maximum Likelihood classification, as shown by visual interpretation of the classified map and the classification accuracy percentage. Results of segmentation from these techniques have been validated by ground-truthing using GPS (Global Positioning System). The degree of accuracy has also been evaluated through different validated parameters. The degree of accuracy is comparatively better in the SVMC method than RFC and MLC methods. The areal difference obtained between RFC and SVMC methods is comparatively less, while MLC and the rest are comparatively high. The spatial similarity is obtained more rather than dissimilarity in all cases. Still, because of superior accuracy in the SVMC method, it is considered more appropriate than the RFC and MLC method for preparing land use land cover maps of Dhaka metropolitan city.

4. Conflict of Interests

The authors of this article declare that they have no conflicts of interest.

5. Acknowledgment

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