



## Accuracy assessment of EnMap-Box machine learning algorithms for land use and land cover classification using Landsat imagery

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### Abstract

Land use and land cover (LULC) is essential information for multiple users across multidisciplinary sciences. Currently, free downloads of remote sensing data and public software with novel algorithms are available for LULC classification by scientists and researchers. The study's objectives were (1) to classify and map LULC data for 2022 using random forest (RF) and support vector machine (SVM) classifiers and (2) to assess the thematic accuracy of classified LULC maps with RF and SVM classifiers. The research methodology comprised four significant steps. As a result, the nine LULC classes classified in 2022 using RF and SVM achieve overall accuracy values above 90% and Kappa-hat values above 87%. According to the pairwise Z-test, nine decision tree numbers for RF and 12 combinations of g and C parameters for SVM can classify LULC data for 2022 with insignificant differences in Khat values. In this study, the optimal number of decision trees for LULC classification using RF was 150. Meanwhile, the most suitable parameter for LULC classification by SVM was the Gaussian radial basis function kernel with a g value of 0.01 and a C value of 0.1. However, to apply the EnMap-Box for LULC classification, preparing the training and testing datasets is an important step, and users must collect them carefully. Nevertheless, the research methodology can serve as a guideline for classifying land use and land cover information from Landsat imagery using the EnMap-Box software for urban and land-use planning.

**Keywords:** EnMap-Box software, Landsat data, Machine learning, Random forests, Support vector machine.

### 1. Introduction

Land use and land cover (LULC) data are central to United Nations Agenda 21 issues such as combating deforestation, managing sustainable settlement growth, and protecting the quality and supply of water resources. However, the pace, magnitude, and scale of human alterations to the Earth's land surface are unprecedented in human history [1]. Accurate LULC information can help people understand the relationship between the development of human societies and climate and environmental change [2-4]. Subsequently, LULC is essential information for multiple users across multidisciplinary sciences.

Recently, remote sensing data from many agencies, including GLOVIS, NASA Earth Observation (NEO), USGS Earth Explorer, ESA's Sentinel data, NASA Earth Data, NOAA Class, NOAA Digital Coast, IPPMUS Terra, LANCE, and VITO Vision, can be downloaded via official websites [5]. Meanwhile, numerous open-source remote sensing software packages for digital image analysis, including Sentinel toolbox, QGIS Semi-Automatic Classification Plug-in (SCP), SAGA GIS: System for Automated Geoscientific Analyses, GRASS (Geographic Resources Analysis Support System), PolSARPro, Whitebox GAT, gvSIG, InterImage, ILWIS (Integrated Land and Water Information System), and E-foto OSSIM (Open Source Software Image Map), are available for researchers to extract LULC information [6]. Therefore, many researchers have developed and examined suitable classifiers for LULC classification using remotely sensed data.

The EnMAP-Box (Environmental Mapping and Analysis Program) is a toolbox developed for the processing

and analysis of data acquired by the German spaceborne imaging spectrometer from the EnMAP sensor [7]. The EnMap-Box has been plugged into free and open-source QGIS software. It supports machine learning algorithms for image classification, random forest (RF) and support vector machines (SVM) [8].

The RF is a machine learning algorithm that has become one of the most popular and promising LULC classifiers due to its relatively stable, robust classification accuracy and its effectiveness in handling large, high-dimensional datasets [9-13]. Meanwhile, the SVM is another machine-learning algorithm widely applied in remote sensing for LULC classification [14-18].

However, a systematic examination of LULC classification using RF and SVM in the EnMap-Box with Landsat data across a large area, such as Nakhon Ratchasima province, does not exist. Consequently, RF and SVM classifiers in the EnMap-Box software were selected to assess their capacity to classify LULC for 2022 in Nakhon Ratchasima province using freely downloadable Landsat images. Herein, systematic data input and training and testing datasets will be prepared to classify LULC with RF and SVM and to assess their accuracy. The proposed methodology and the expected output can serve as a guideline for researchers in LULC classification of Landsat images using the EnMap-Box software at no cost. The specific objectives were (1) to classify and map LULC data for 2022 using RF and SVM classifiers, and (2) to assess the thematic accuracy of classified LULC maps with RF and SVM classifiers.

## 2. Materials and methods

### 2.1 Data

The input data for classifying LULC data were (1) four Landsat 8 OLI images, including Path 128/Row 048 (8 January 2022), Path 128/Row 049 (8 January 2022), Path 129/Row 048 (7 January 2022), and Path 129/Row 049 (7 January 2022) and (2) SRTM DEM from the USGS website (<https://earthexplorer.usgs.gov/>).

### 2.2 Methods

The workflow of the method, with four significant steps, is displayed in Figure 1.

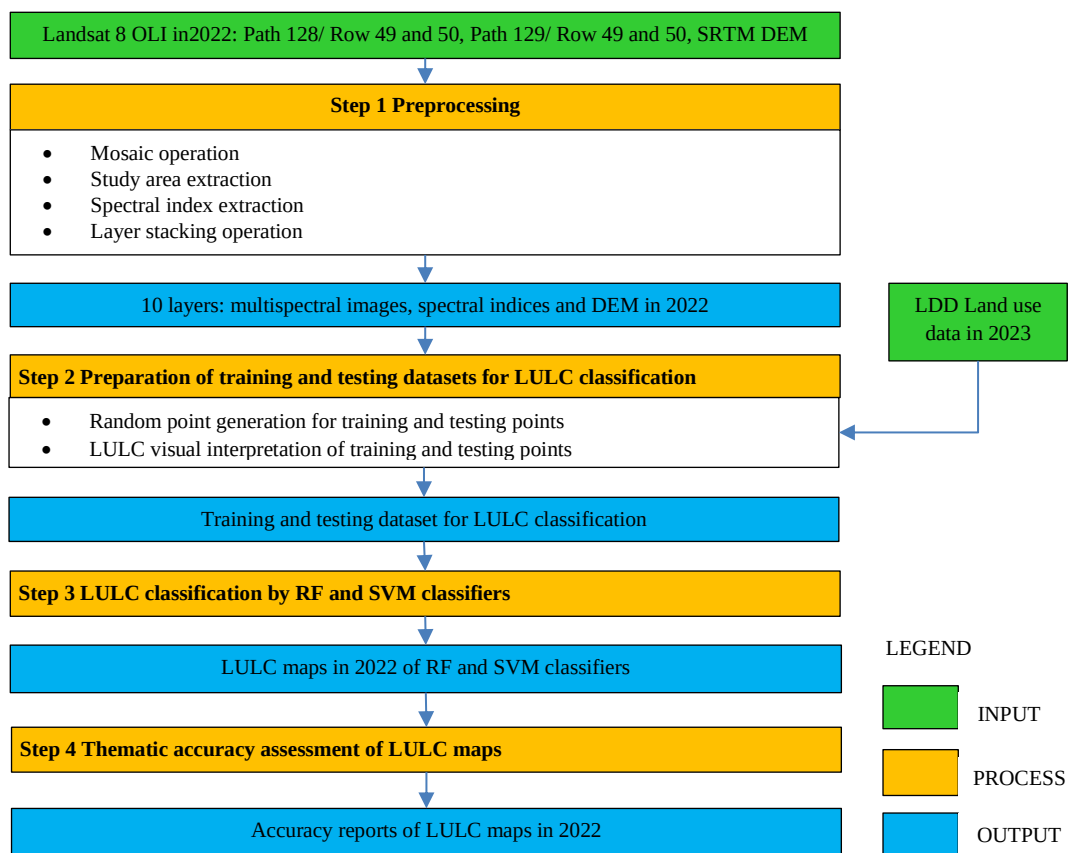


**Figure 1** The workflow of the research methodology

Step 1 Preprocessing. The four collected Landsat 8 OLI scenes in 2022 with WGS 1984 UTM Zone 48N were first mosaicked, and the extracted data were used over the study area. Later, it was applied to calculate spectral indices, including the normalized difference vegetation index (NDVI), the modified normalized difference wetness index (MNDWI), and the normalized difference built-up index (NDBI).

NDVI quantifies vegetation by measuring the difference between NIR and Red bands, which vegetation strongly reflects, and red light, which vegetation absorbs [19]:

$$NDVI = \frac{NIR-RED}{NIR+RED} \quad (1)$$

MNDWI uses the Green and SWIR-1 bands to enhance open-water features. It also diminishes built-up area features that are often correlated with open water in other indices [20]:

$$MNDWI = \frac{GREEN-SWIR-1}{GREEN+SWIR-1} \quad (2)$$

NDBI uses the NIR and SWIR-1 bands to emphasize manufactured built-up areas. It is a ratio based on mitigating the effects of terrain illumination differences as well as atmospheric effects [21]:

$$NDBI = \frac{SWIR-1-NIR}{SWIR-1+NIR} \quad (3)$$

After that, multispectral bands, spectral indices, and DEM data were combined using a layer stacking operation as follows: Blue, Green, Red, NIR, SWIR-1, SWIR-2, NDVI, MNDWI, NDBI, and SRTM DEM.

Step 2 Preparation of training and testing datasets for LULC classification. Random sampling points for LULC classification and accuracy assessment were generated using the random point function with distances of 500, 750, 1,000, 1,500, 2,000, and 2,500 m over the study area in ESRI ArcMap. Subsequently, the sampling points were split into two datasets: training and testing, with odd and even ID numbers, respectively (see Table 1). The suitable random sampling points for the training and testing datasets were justified based on the number and spatial distribution of sampling points, as shown in Figure 2, with a sampling distance of 1,000 m.

**Table 1** Examination results for training and testing dataset preparation

| No | Distance (m) | No. of sampling points | No. of training and testing points | Remark                                                      |
|----|--------------|------------------------|------------------------------------|-------------------------------------------------------------|
| 1  | 500          | 5,000                  | 2,500, 2,500                       | The number of points is rather high                         |
| 2  | 750          | 5,000                  | 2,500, 2,500                       | The number of points is rather high                         |
| 3  | 1,000        | 3,754                  | 1877, 1877                         | Suitable number of points with sampling distance of 1,000 m |
| 4  | 1,500        | 1,669                  | 835, 834                           | The number of points is rather small                        |
| 5  | 2,000        | 939                    | 470, 469                           | The number of points is small                               |
| 6  | 2,500        | 601                    | 301, 300                           | The number of points is small                               |

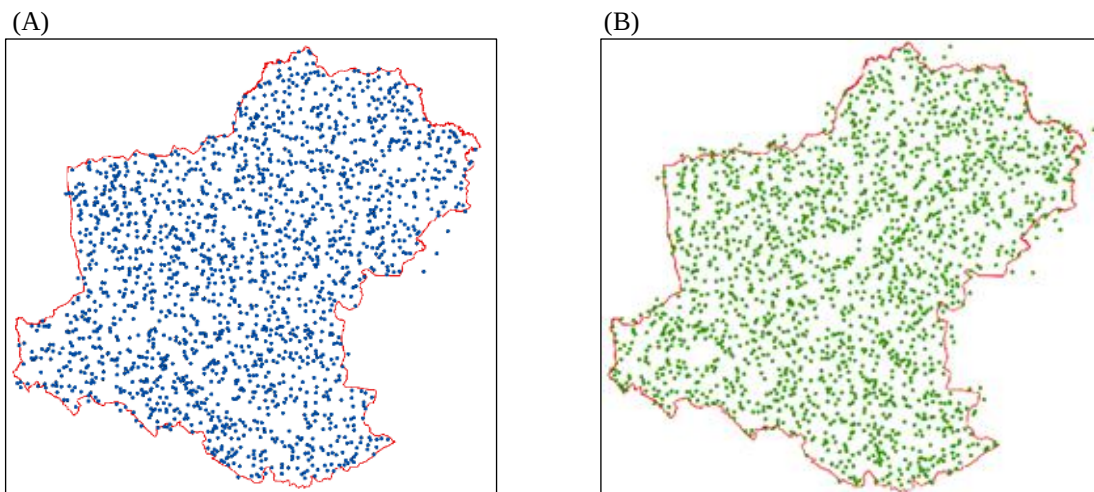


**Figure 2** Spatial distribution of training and testing datasets over the study area: (a) training dataset and (b) testing dataset

After that, each sampling point in both datasets was assigned a LULC type by visual interpretation on-screen in ArcMap software based on Landsat imagery, supplemented by 2023 land-use data from the Land Development Department and very high-resolution ArcGIS imagery. Herein, seven identified LULC types, including (1) urban and built-up areas, (2) paddy fields, (3) field crops, (4) perennial trees and orchards, (5) forest land, (6) water body, and (7) miscellaneous land, were identified, as summarized in Table 2.

**Table 2** Number of training and testing points of each LULC type for LULC classification and accuracy assessment

| Land use and land cover type | Number of points |                 |
|------------------------------|------------------|-----------------|
|                              | Training dataset | Testing dataset |
| Urban and built-up area      | 155              | 167             |
| Paddy fields                 | 584              | 589             |
| Field crops                  | 654              | 608             |
| Perennial trees and orchards | 50               | 96              |
| Forest land                  | 335              | 328             |
| Water body                   | 63               | 59              |
| Miscellaneous land           | 36               | 30              |
| Total                        | 1,877            | 1,877           |

Step 3 LULC classification by RF and SVM classifiers. For LULC classification using the RF classifier, nine decision-tree values (100, 150, 200, 250, 300, 350, 400, 450, and 500) with the Gini coefficient impurity index were applied to classify LULC data for 2022 using the training dataset. The number of decision trees and features plays a significant role in LULC classification [22-24]. Meanwhile, nine combinations of gamma (g) and regularization (C) parameters for the Gaussian radial basis function (RBF) kernel of the SVM classifier were used to classify the LULC data for 2022 using the same training dataset. The performance of the SVM varies with the choice of kernel function and its parameter [25-29]. The pre-assigned RF and SVM configurations for LULC classification using the EnMap-Box software (Version 2.2.1) are presented in Table 3.

**Table 3** Pre-assigned parameters of RF and SVM classifiers for LULC classification under EnMap-Box software

| RF parameterization |                      |                       | SVM parameterization |      |      |                        |
|---------------------|----------------------|-----------------------|----------------------|------|------|------------------------|
| No                  | Decision tree number | RF configuration file | No                   | g    | C    | SVM configuration file |
| 1                   | 100                  | RF-T100.svm           | 1                    | 0.01 | 0.01 | SVMg001c001.svc        |
| 2                   | 150                  | RF-T150.svm           | 2                    | 0.01 | 0.1  | SVMg001c01.svc         |
| 3                   | 200                  | RF-T200.svm           | 3                    | 0.01 | 1    | SVMg001c1.svc          |
| 4                   | 250                  | RF-T250.svm           | 4                    | 0.01 | 10   | SVMg001c10.svc         |
| 5                   | 300                  | RF-T300.svm           | 5                    | 0.1  | 0.01 | SVMg01c001.svc         |
| 6                   | 350                  | RF-T350.svm           | 6                    | 0.1  | 0.1  | SVMg01c01.svc          |
| 7                   | 400                  | RF-T400.svm           | 7                    | 0.1  | 1    | SVMg01c1.svc           |
| 8                   | 450                  | RF-T450.svm           | 8                    | 0.1  | 10   | SVMg01c10.svc          |
| 9                   | 500                  | RF-T500.svm           | 9                    | 1    | 0.01 | SVMg1c001.svc          |
|                     |                      |                       | 10                   | 1    | 0.1  | SVMg1c01.svc           |
|                     |                      |                       | 11                   | 1    | 1    | SVMg1c1.svc            |
|                     |                      |                       | 12                   | 1    | 10   | SVMg1c10.svc           |

Step 4 Thematic accuracy assessment of LULC maps. The classified LULC points for 2022, generated with RF and SVM classifiers, were assessed for thematic accuracy using the random testing dataset as a confusion matrix, including overall accuracy (OA), producer's accuracy (PA), user's accuracy (UA), and Kappa hat coefficient of agreement (Khat).

In addition, the pairwise Z-test was applied to examine the significant difference in the derived Khat values among the classified maps from SVM and RF classifiers based on their confusion matrices [30]:

$$Z = \frac{|Khat_1 - Khat_2|}{\sqrt{\widehat{var}(Khat_1) + \widehat{var}(Khat_2)}} \quad (4)$$

and the variance of the Kappa hat coefficient is calculated by:

$$\widehat{var}(Khat) = \frac{1}{n} \left\{ \frac{\theta_1(1-\theta_1)}{(1-\theta_2)^2} + \frac{2(1-\theta_1)(2\theta_1\theta_2-\theta_3)}{(1-\theta_2)^3} + \frac{(1-\theta_1)^2(\theta_4-4\theta_2^2)}{(1-\theta_2)^4} \right\} \quad (5)$$

$$\text{When:} \quad \theta_1 = \frac{1}{n} \sum_{i=1}^k n_{ii} \quad (6)$$

$$\theta_2 = \frac{1}{n^2} \sum_{i=1}^k n_{i+} n_{+i} \quad (7)$$

$$\theta_3 = \frac{1}{n^2} \sum_{i=1}^k n_{ii} (n_{i+} + n_{+i}) \quad (8)$$

$$\theta_4 = \frac{1}{n^3} \sum_{i=1}^k \sum_{j=1}^k n_{ij} (n_{j+} + n_{+i})^2 \quad (9)$$

Where  $Z$  is standardized and normally distributed,  $k$  is the number of rows (land use and land cover classes) in the error matrix,  $n_{ii}$  is the number of observations in row  $i$  and column  $i$ ,  $n_{i+}$  is the marginal total for row  $i$ ,  $n_{+i}$  is the marginal total for column  $i$ , and  $n$  is the total number of observations. Herein, given the null hypothesis  $H_0: (Khat_1 - Khat_2) = 0$ , and the alternative  $H_1: (Khat_1 - Khat_2) \neq 0$ ,  $H_0$  is rejected if  $Z \geq Z\alpha/2$ .

### 3. Results

#### 3.1 LULC classification by RF and SVM

The spatial distributions of LULC classifications for 2022 by RF and SVM classifiers with pre-assigned parameters, based on the same 1,877 training dataset, are displayed in Figures 3 and 4, respectively. The proportional LULC type areas of both classifiers with different parameters are displayed in Figure 5.

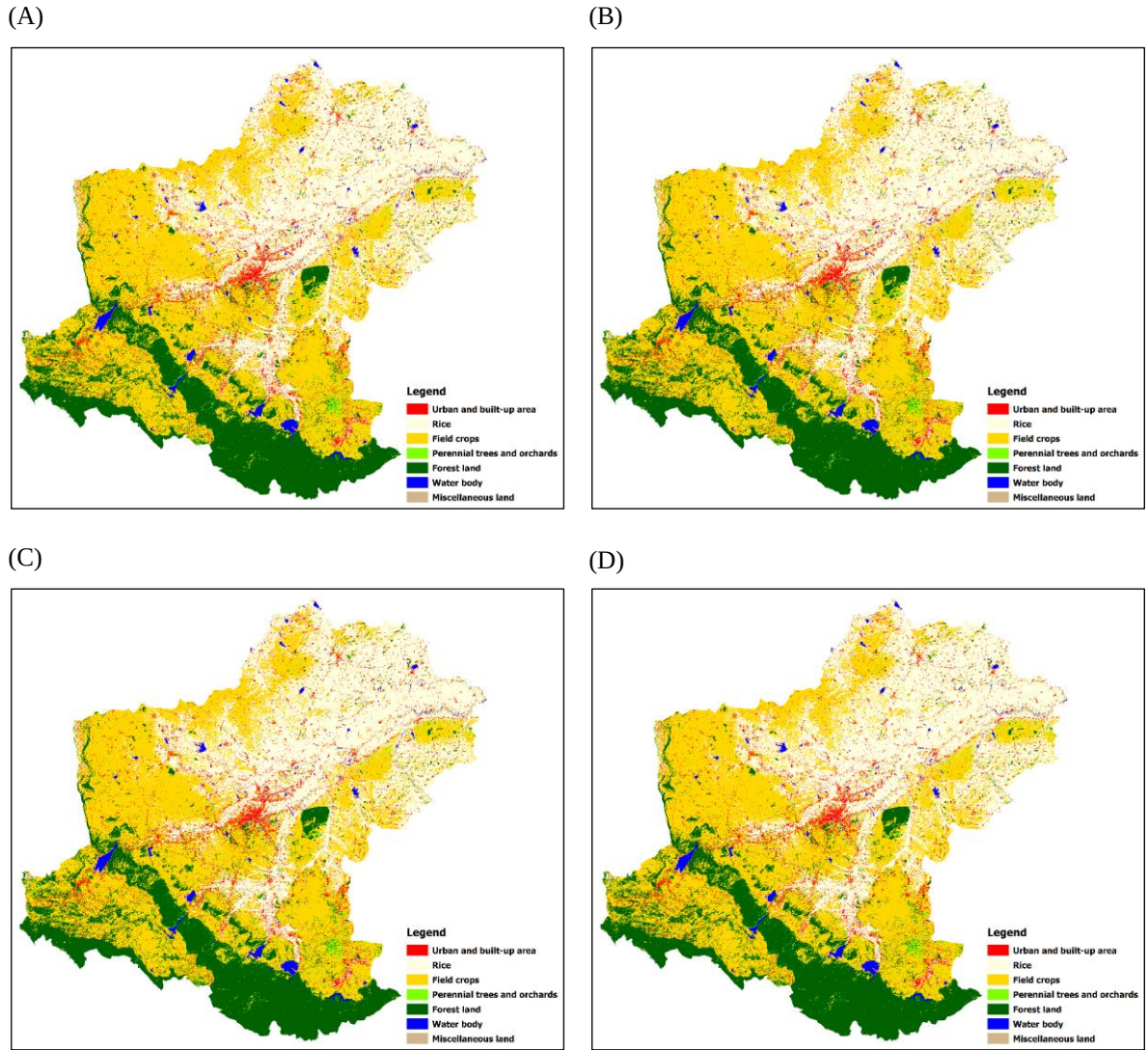


**Figure 3** Spatial distribution of classified LULC maps in 2022 by RF classifier with nine different parameters: (A) 100 trees, (B) 150 trees, (C) 200 trees, (D) 250 trees, (E) 300 trees, (F) 350 trees, (G) 400 trees, (H) 450 trees, and (I) 500 trees

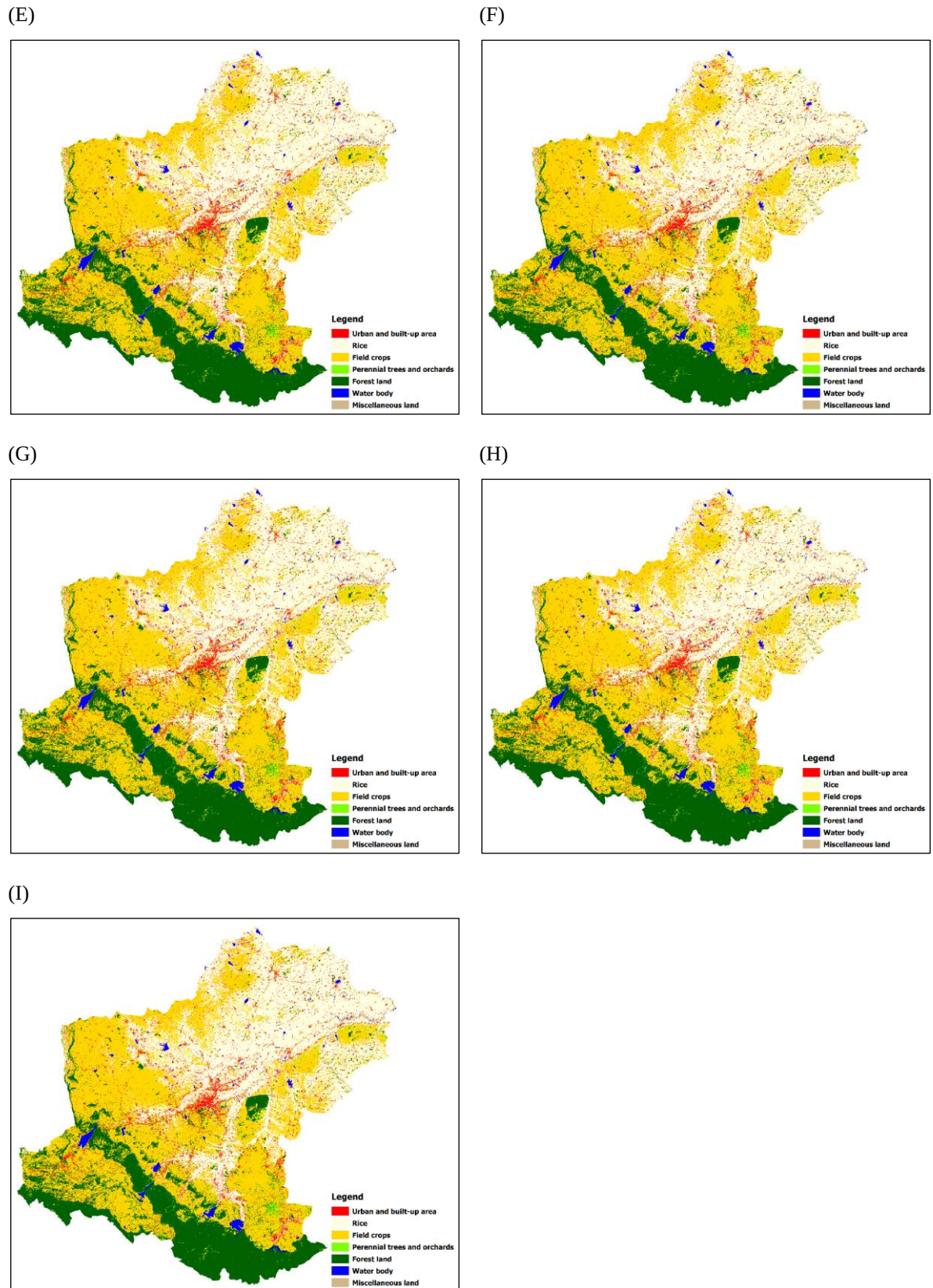


**Figure 3** Spatial distribution of classified LULC maps in 2022 by RF classifier with nine different parameters: (A) 100 trees, (B) 150 trees, (C) 200 trees, (D) 250 trees, (E) 300 trees, (F) 350 trees, (G) 400 trees, (H) 450 trees, and (I) 500 trees (Cont.)

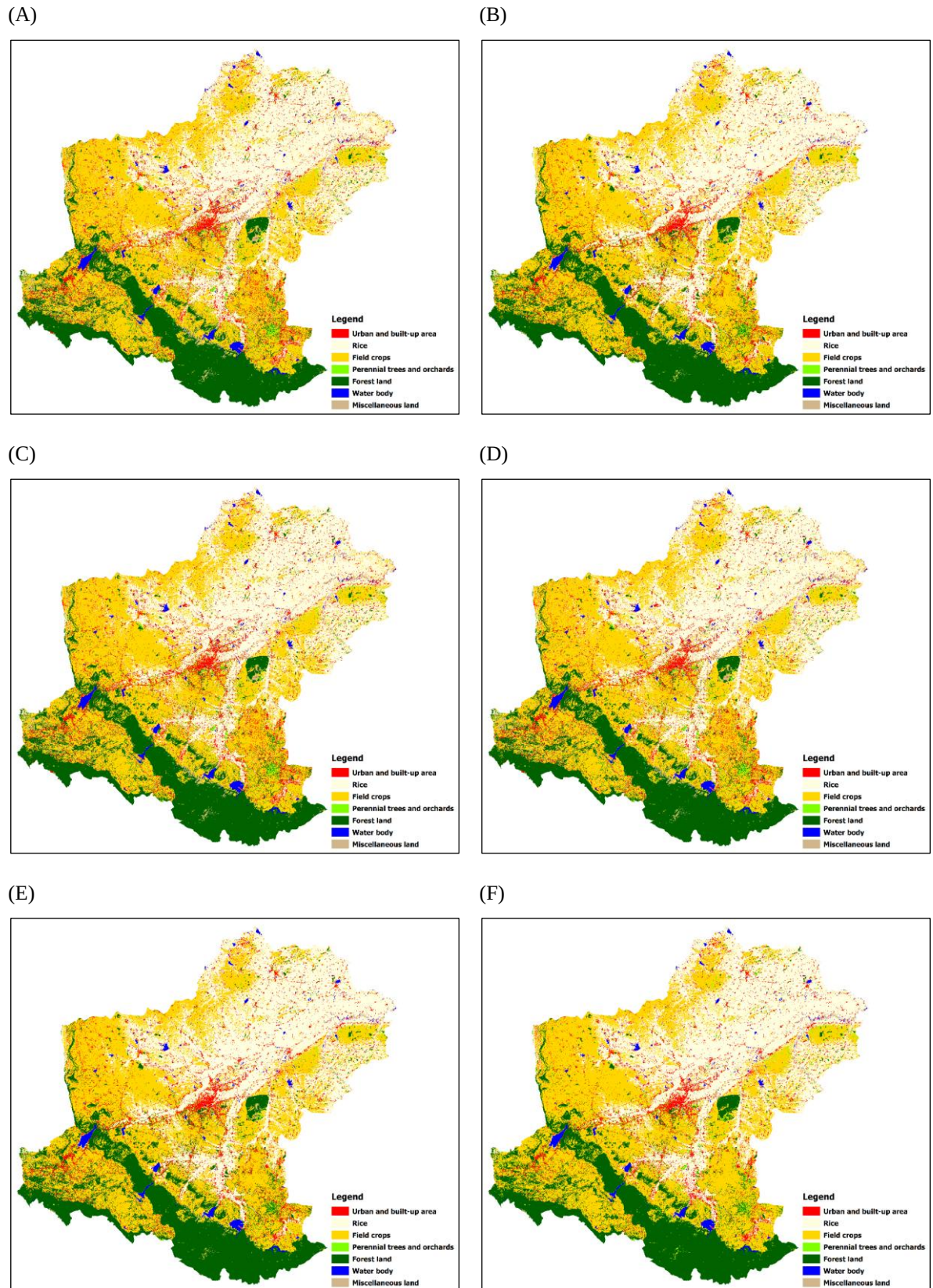


**Figure 4** Spatial distribution of classified LULC maps for 2022 by SVM with 12 different parameters: (A) SVM-g001c001, (B) SVM-g001c01, (C) SVM-g001c1, (D) SVM-g001c10, (E) SVM-g01c001, (F) SVM-g01c01, (G) SVM-g01c1, (H) SVM-g01c10, (I) SVM-g1c001, (J) SVM-g1c01, (K) SVM-g1c1, and (L) SVM-g1c10

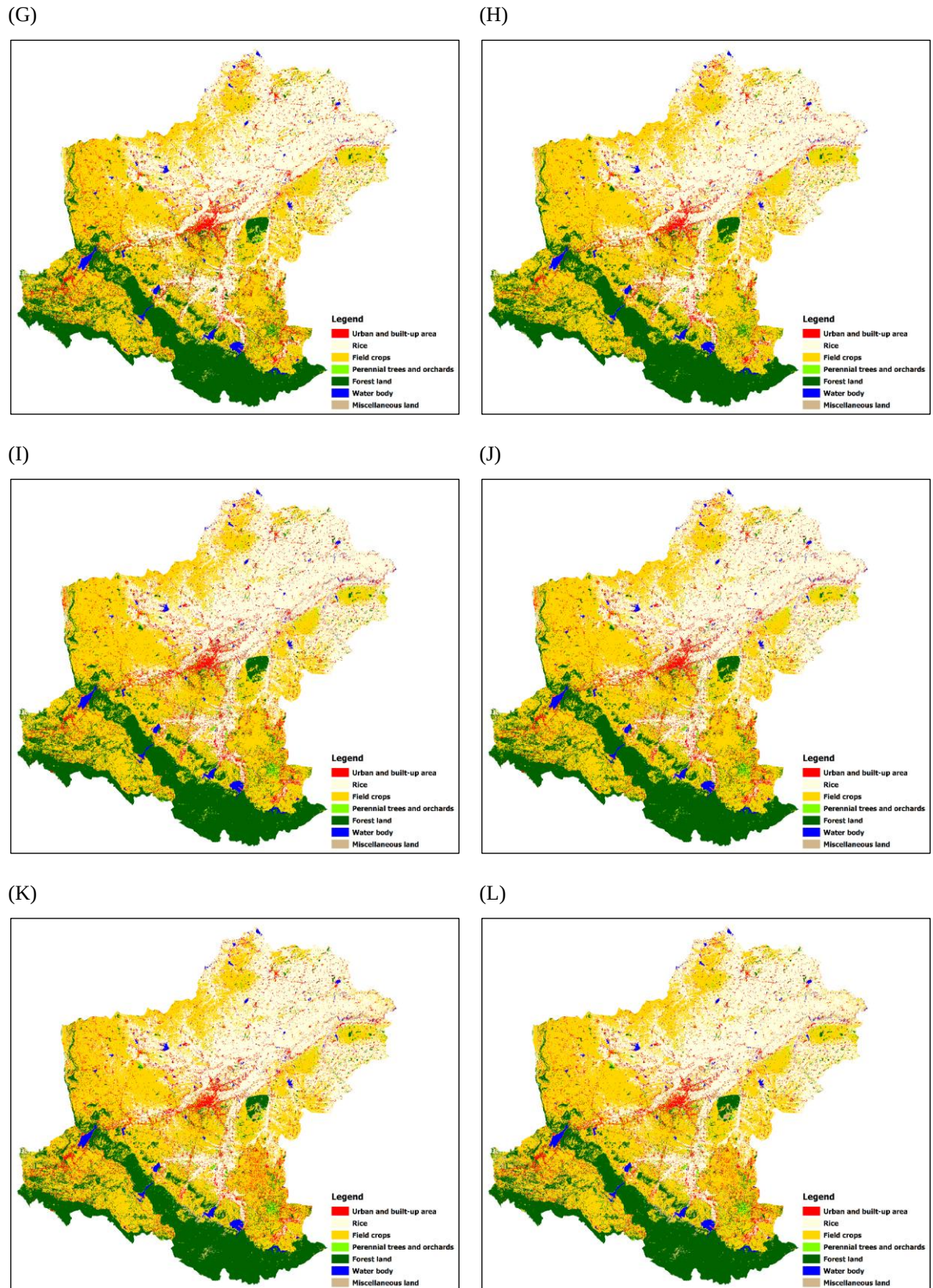
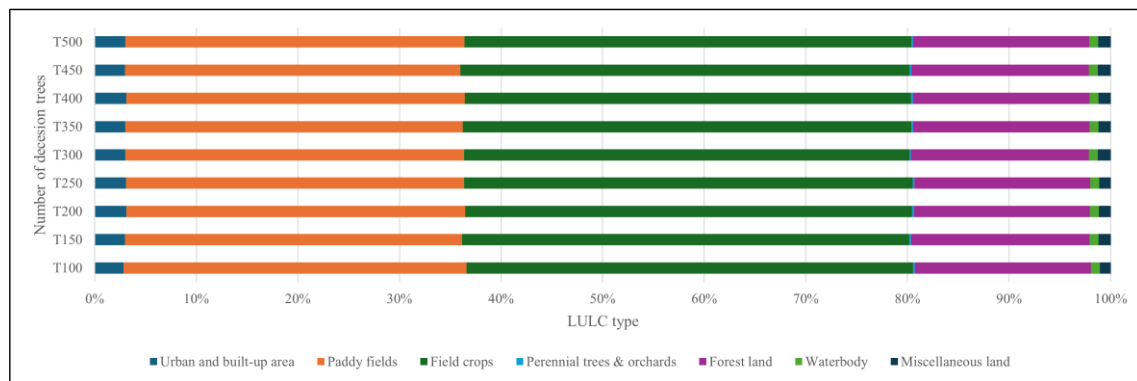


**Figure 4** Spatial distribution of classified LULC maps for 2022 by SVM with 12 different parameters: (A) SVM-g001c001, (B) SVM-g001c01, (C) SVM-g001c1, (D) SVM-g001c10, (E) SVM-g01c001, (F) SVM-g01c01, (G) SVM-g01c1, (H) SVM-g01c10, (I) SVM-g1c001, (J) SVM-g1c01, (K) SVM-g1c1, and (L) SVM-g1c10 (Cont.)

(A)



(B)

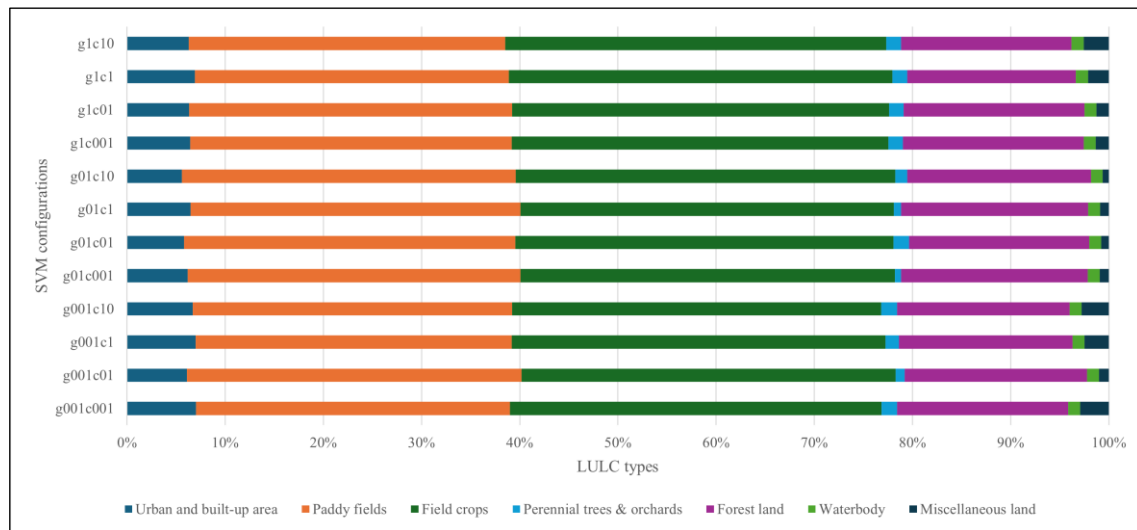


**Figure 5** Proportional LULC type areas in LULC maps: (A) RF classifier and (B) SVM classifier

### 3.2 Thematic accuracy of LULC maps by RF and SVM

The results of the thematic accuracy assessment of LULC maps for 2022 for the RF and SVM classifiers, based on the same 1,877 testing dataset, are reported in Tables 4 and 5, respectively. Meanwhile, the results of the pairwise Z-test based on the confusion matrices of nine classified LULC maps by RF and 12 classified maps by SVM are reported in Tables 6 and 7, respectively.

**Table 4** Thematic accuracy assessment of LULC maps 2022 from RF classifier

| No | Number of trees | OA (%) | Khat (%) | Average PA (%) | Average UA (%) | Rank |
|----|-----------------|--------|----------|----------------|----------------|------|
| 1  | 100             | 91.10  | 88.11    | 79.99          | 91.20          | 5    |
| 2  | 150             | 91.42  | 88.54    | 80.92          | 91.81          | 1    |
| 3  | 200             | 91.05  | 88.04    | 81.14          | 91.65          | 6    |
| 4  | 250             | 91.37  | 88.46    | 81.18          | 92.02          | 2    |
| 5  | 300             | 91.26  | 88.33    | 81.13          | 91.74          | 3    |
| 6  | 350             | 91.00  | 87.96    | 80.50          | 91.66          | 8    |
| 7  | 400             | 90.94  | 87.89    | 79.86          | 91.68          | 9    |
| 8  | 450             | 91.05  | 88.03    | 80.52          | 91.98          | 7    |
| 9  | 500             | 91.26  | 88.32    | 80.73          | 91.94          | 4    |

**Table 5** Thematic accuracy assessment of LULC maps for 2022 from SVM classifier

| No | SVM configuration | OA (%) | Khat (%) | Average PA (%) | Average UA (%) | Rank |
|----|-------------------|--------|----------|----------------|----------------|------|
| 1  | SVMg001c001.svc   | 90.78  | 87.71    | 80.61          | 84.74          | 8    |
| 2  | SVMg001c01.svc    | 91.53  | 88.66    | 78.68          | 89.34          | 1    |
| 3  | SVMg001c1.svc     | 90.78  | 87.71    | 80.42          | 84.9           | 9    |
| 4  | SVMg001c10.svc    | 91.10  | 88.13    | 80.83          | 86.12          | 4    |
| 5  | SVMg01c001.svc    | 91.42  | 88.51    | 77.84          | 91.61          | 2    |
| 6  | SVMg01c01.svc     | 90.46  | 87.25    | 77.36          | 91.61          | 10   |
| 7  | SVMg01c1.svc      | 91.1   | 88.09    | 77.68          | 89.4           | 5    |
| 8  | SVMg01c10.svc     | 91.41  | 87.17    | 77.02          | 90.06          | 3    |
| 9  | SVMg1c001.svc     | 90.36  | 87.12    | 78.36          | 87.18          | 11   |
| 10 | SVMg1c01.svc      | 90.36  | 87.12    | 78.36          | 87.18          | 12   |
| 11 | SVMg1c1.svc       | 90.78  | 87.72    | 81.5           | 85.49          | 7    |
| 12 | SVMg1c10.svc      | 90.84  | 87.77    | 80.47          | 85.31          | 6    |

**Table 6** The paired Z-test results of the confusion matrices for nine tree numbers of the RF classifier

| Z-Value |         |         |         |         |         |         |         |        |
|---------|---------|---------|---------|---------|---------|---------|---------|--------|
| RF-150T | 0.3529  |         |         |         |         |         |         |        |
| RF-200T | 0.0504  | 0.4031  |         |         |         |         |         |        |
| RF-250T | 0.2931  | 0.0598  | 0.3433  |         |         |         |         |        |
| RF-300T | 0.1785  | 0.1743  | 0.2288  | 0.1145  |         |         |         |        |
| RF-350T | 0.1162  | 0.4688  | 0.0657  | 0.4090  | 0.2945  |         |         |        |
| RF-400T | 0.1759  | 0.5286  | 0.1254  | 0.4688  | 0.3543  | 0.0597  |         |        |
| RF-450T | 0.0612  | 0.4137  | 0.0107  | 0.3539  | 0.2395  | 0.0550  | 0.1147  |        |
| RF-500T | 0.1720  | 0.1808  | 0.2222  | 0.1210  | 0.0065  | 0.2879  | 0.3477  | 0.2329 |
| RF-100T | RF-150T | RF-200T | RF-250T | RF-300T | RF-350T | RF-400T | RF-450T |        |

Note: Critical values at different confidence levels of 80%, 90%, 95%, and 100% are 1.28, 1.65, 1.96 and 2.58, respectively.

**Table 7** The paired Z-test results of the confusion matrices for 12 combinations of g and C parameters of the SVM classifier

| Z-Value |         |        |        |        |         |        |        |        |        |        |        |
|---------|---------|--------|--------|--------|---------|--------|--------|--------|--------|--------|--------|
| SVMg00  |         |        |        |        |         |        |        |        |        |        |        |
| 1c01    | 0.7757  |        |        |        |         |        |        |        |        |        |        |
| SVMg00  |         |        |        |        |         |        |        |        |        |        |        |
| 1c1     | 0.0045  | 0.7803 |        |        |         |        |        |        |        |        |        |
| SVMg00  |         |        |        |        |         |        |        |        |        |        |        |
| 1c10    | 0.3409  | 0.4347 | 0.3455 |        |         |        |        |        |        |        |        |
| SVMg01c |         |        |        |        |         |        |        |        |        |        |        |
| 001     | 0.6485  | 0.1272 | 0.6531 | 0.3075 |         |        |        |        |        |        |        |
| SVMg01c |         |        |        |        |         |        |        |        |        |        |        |
| 01      | 0.3731  | 1.1485 | 0.3686 | 0.7138 | 1.0213  |        |        |        |        |        |        |
| SVMg01c |         |        |        |        |         |        |        |        |        |        |        |
| 1       | 0.3081  | 0.4680 | 0.3127 | 0.0330 | 0.3407  | 0.6812 |        |        |        |        |        |
| SVMg01c |         |        |        |        |         |        |        |        |        |        |        |
| 10      | 0.4359  | 1.2111 | 0.4313 | 0.7765 | 1.0839  | 0.0628 | 0.7439 |        |        |        |        |
| SVMg1c0 |         |        |        |        |         |        |        |        |        |        |        |
| 01      | 0.4747  | 1.2496 | 0.4702 | 0.8152 | 1.1225  | 0.1018 | 0.7827 | 0.0390 |        |        |        |
| SVMg1c0 |         |        |        |        |         |        |        |        |        |        |        |
| 1       | 0.4747  | 1.2496 | 0.4702 | 0.8152 | 1.1225  | 0.1018 | 0.7827 | 0.0390 | 0.0000 |        |        |
| SVMg1c1 | 0.0070  | 0.7684 | 0.0115 | 0.3337 | 0.6412  | 0.3799 | 0.3010 | 0.4427 | 0.4815 | 0.4815 |        |
| SVMg1c1 |         |        |        |        |         |        |        |        |        |        |        |
| 0       | 0.0444  | 0.7311 | 0.0489 | 0.2964 | 0.6039  | 0.5850 | 0.2636 | 0.4801 | 0.5189 | 0.5189 | 0.0374 |
|         | SVMg001 | SVMg00 | SVMg00 | SVMg00 | SVMg01c | SVMg01 | SVMg0  | SVMg01 | SVMg1c | SVMg1  | SVMg   |
|         | c001    | 1c01   | 1c1    | 1c10   | 001     | c01    | 1c1    | c10    | 001    | c01    | 1c1    |

Note: Critical values at different confidence levels of 80%, 90%, 95%, and 100% are 1.28, 1.65, 1.96 and 2.58, respectively.

## 4. Discussion

### 4.1 LULC classification by RF and SVM

As a result, in Figures 3–5, the percentages of each LULC type for 2022 from the nine decision tree outputs of the RF classifier are quite similar. These findings confirm that the number of decision trees and features is vital in LULC classification using the RF [22–24]. In contrast, the percentages of each LULC type for 2022, based on the 12 combination parameters of the SVM classifier, are slightly different. These findings confirm that when using the SVM, the combination of parameters (g and C) and features is vital for LULC classification [25–29].

In addition, the three dominant LULC types from RF and SVM—field crops, paddy fields and forest land—are similar. These findings are consistent with the 2023 land-use data from LDD [31].

### 4.2 Thematic accuracy of LULC maps by RF and SVM

As a result, in Table 4, the nine RF-classified LULC maps have OA values above 91% and Khat values above 88%. The average PA values of each LULC type are higher than 80%, and the average UA values of each LULC

type are higher than 92%. A Khat value of more than 80% indicates strong agreement or accuracy between the classified and reference maps [32-33]. Also, the overall accuracy of more than 85% of the LULC map is considered acceptable for LULC classification [34]. Besides, the highest OA and Khat values for the LULC map for 2022 are consistent with those reported in a previous study by Pinyoyang [35], who applied RF in the EnMAP-Box software to classify 12 LULC types in 2019 from a Landsat 8-OLI image. The OA and Khat values for the LULC data in 2019 were 91.37% and 88.26%, respectively.

In the meantime, the 12 classified maps from 2022 using the SVM can achieve OA values above 90% and Khat values above 87%. The average PA values of each LULC type are higher than 77%, and the average UA values of each LULC type are higher than 85% (see details in Table 5). As with RF, a Khat value of more than 80% indicates strong agreement or accuracy between the classified and reference maps [32-33]. The overall accuracy of more than 85% for the LULC maps from 2022 is acceptable [34]. Also, the highest OA and Khat values for the LULC map for 2022 are marginally higher than those reported in the previous study by Kulsoontornrat [36], who applied the SVM algorithm in the EnMAP-Box software to classify 10 LULC types in 2019 from Landsat 8-OLI. The OA and Khat values for the 2019 LULC data were 89.59% and 85.85%, respectively.

Moreover, by considering OA, average PA, average UA, and Khat values across the nine LULC classes identified by RF, the most suitable parameter for LULC classification in 2022 from Landsat 8 OLI data, spectral indices, and elevation is 150 decision trees. It delivered the OA value of 91.42%, Khat value of 88.54%, average PA value of 80.92% and average UA of 91.81%. Meanwhile, the most suitable parameter for LULC classification in 2022, using the same data, is the Gaussian RBF kernel with a  $g$  value of 0.01 and a  $C$  value of 0.1. It delivered an OA value of 91.53%, Khat value of 88.66%, average PA value of 78.68% and average UA value of 89.34%. According to the confusion matrices for thematic accuracy assessment of RF and SVM, the significant omission and commission errors in perennial trees and orchards mostly come from forest land. This is because the signature of mature perennial trees, such as rubber trees or eucalyptus, on satellite images is similar to that of forest land.

Furthermore, according to the pairwise Z-test based on confusion matrices of nine classified LULC maps by the RF and 12 classified maps by the SVM, as shown in Tables 6 and 7, both classifiers with pre-assigned parameters can classify 2022 LULC data. There were no significant differences in Khat values since all Z statistic values were lower than the critical values at all confidence levels. These findings indicate that variations in the number of decision trees of the RF classifier and in the gamma ( $g$ ) and regularization ( $C$ ) parameters of the RBF kernel of the SVM classifier marginally affect accuracy.

Additionally, the pairwise Z-test based on confusion matrices of classified LULC maps for the most suitable parameters of the RF and SVM classifiers shows insignificant differences in Khat values, as the Z statistic is lower than the critical value at all confidence levels (Table 8). This finding indicates that both classifiers can be used to classify LULC maps because they produce approximately equal classifications [30].

**Table 8** Pairwise Z-Test between the most suitable parameters of RF and SVM for LULC classification in 2022

| Pair-wise  | Khat     | Variance | Z-Statistic | Confidential level of critical value |      |      |      |
|------------|----------|----------|-------------|--------------------------------------|------|------|------|
|            |          |          |             | 80%                                  | 90%  | 95%  | 100% |
| RF-150T    | 0.885372 | 0.000073 | 0.101902    | 1.28                                 | 1.65 | 1.96 | 2.58 |
| SVMg001c01 | 0.886600 | 0.000072 |             |                                      |      |      |      |

## 5. Conclusions

This study examines the performance of RF and SVM classifiers in the EnMAP-Box software for LULC classification. As a result, the optimal number of decision trees for RF in classifying LULC data for 2022, based on Landsat-8-OLI data, derived spectral indices, and elevation, was 150. The classified map delivers an overall accuracy of 91.42%, a Kappa coefficient of agreement of 88.54%, an average producer's accuracy of 80.92%, and an average user's accuracy of 91.81%. Meanwhile, the suitable configuration of SVM for classifying LULC data for 2022 based on Landsat-8-OLI data, derived spectral indices, and elevation data, was a Gaussian RBF kernel with a  $g$  value of 0.01 and a  $C$  value of 0.1. The classified map produces an overall accuracy of 91.53%, a Kappa coefficient of agreement of 88.66%, an average producer's accuracy of 78.68%, and an average user's accuracy of 89.34%. These findings can serve as guidelines for LULC classification using RF and SVM in the EnMAP-Box software. Both classifiers achieved overall accuracies above 85% and Kappa coefficients above 80%, which are considered acceptable to the researchers. Thus, researchers can apply the free EnMAP-Box software and downloadable Landsat data to classify land use and land cover at no cost. This cost-effective approach differs from previous studies, which often rely on expensive commercial software.

Nevertheless, preparing the dataset of training and testing sample points is an important step, and users must collect them carefully. The training dataset is applied to parameterize the RF and SVM classifiers for LULC classification, whereas the testing dataset is used to assess accuracy using a confusion matrix. The evaluation metrics include overall accuracy, producer's accuracy, user's accuracy, and the Kappa hat coefficient, which are used here to evaluate classifier performance. We recommend identifying LULC types by visual interpretation on-

screen using auxiliary data, such as land-use data and very high-resolution ArcGIS imagery, within ArcGIS software. Nevertheless, the research methodology can serve as a guideline for classifying land use and land cover information from Landsat imagery using the EnMap-Box software for urban and land use planning. For future studies, a freely downloadable high-resolution image, such as a Sentinel-2A image, should be examined for land use and land cover classification. Additionally, the framework of research methodology should be examined to validate the results in another area.

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## 7. Author Contributions

Conceptualization, S.O., S.D., P.P., S.K., and T.S.; methodology, S.O. and T.S.; software, S.O., S.K., and T.S.; validation, S.O., S.D., and P.P.; formal analysis, S.O., and T.S.; investigation, S.O., S.D., P.P., S.K., and T.S.; resources, S.K., and T.S.; data curation, S.K., and T.S.; writing – original draft preparation, S.K., and T.S.; and writing – review and editing, S.O., S.D., and P.P.; visualization, S.O., S.K., and T.S.; supervision, S.O.; project administration, S.O., and funding acquisition, SO.

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