



RESEARCH ARTICLE

Comparison of SVM and k-NN Algorithms for the Detection and Mapping of Slow-Moving Landslides

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Abstract

In this paper, the performances of k-NN and SVM classifiers and Pleiades-1 data for the detection and mapping of slow-moving landslides, in Kutlugün in Maçka district of Turkey, are evaluated. In the results, the SVM method had higher producer accuracy (85.9%), user accuracy (89.4%) and kappa index (0.82) compared to the k-NN algorithm that had producer accuracy (83.1%), user accuracy (86.0%) and kappa index (0.80). A total of 128 slow-moving landslides were detected using the k-NN algorithm, while a total of 134 landslides were detected using the SVM algorithm. For the first time, this paper attempts to compare and evaluate the performance of two supervised classifiers (k-NN and SVM) for the detection and mapping of slow-moving landslides using Pleiades-1 data. The adopted approaches combine object-based image analysis with k-NN and SVM supervised learning algorithms, and were able to detect 95% of the landslides present in the study area, using a very high-resolution Pleiades-1 image. The results obtained in this study have added to the growing number of applications of object-based image analysis (OBIA) for semi-automated landslide mapping using very high-resolution optical data.

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1. INTRODUCTION

Landslides play a key role in the evolution of landscapes and represent a serious geological hazard, mostly in mountainous regions of the world (Novellino *et al.*, 2024; Sassa *et al.*, 2015). The expansion of urban settlements into mountainous terrains exposes people to the hazards and risks associated with landslides. Landslides have caused destruction to thousands of lives and damage to infrastructure and properties annually (Holbling *et al.*, 2012). Mapping for landslide susceptibility and hazard assessment is an important requirement for land-use planning. This is particularly useful to avoid expanding urban settlements into landslide-prone areas, thus mitigating future economic and human losses. The occurrence of future landslides is contingent on the understanding of past landslide activities. Therefore, landslide mapping is an important step in hazard assessment (Guzzetti *et al.*, 2012).

Pleiades-1 is the satellite system of the French Italian Optical and Radar Federated Earth Observation program designed for land and coastal applications. It includes Pleiades-1A which was launched in December 2011, and Pleiades-1B launched in December 2012. Pleiades-1A and 1B share the same orbital plane as SPOT-6 and 7, giving daily revisits over any point on the Earth. It is a system with a wide swath (20 km), high spatial resolution (70 cm in panchromatic mode, resampled to 50 cm, and 2.8 m in multispectral mode, resampled to 2 m), temporal resolution (24 h), and multispectral (panchromatic and 4 spectral bands) capabilities. The Pleiades-1 optical data have been utilised in a wide range of studies, including land cover mapping (Inglada, 2016), forestry (Guyon and Bréda, 2016), crop monitoring (Todoroff and Kemp, 2016), preparation of digital terrain models (Delvit and Michel, 2016), and extraction of urban green space information (Zylshal *et al.*, 2016). Pleiades stereo imagery was used to estimate variations in height during earthquakes (Zhou *et al.*, 2015). Particularly, in landslide studies, the practicality of Pleiades-1 has been tested with high potential of application (Lacroix *et al.*, 2015; Zizioli *et al.*, 2014; Stumpf *et al.*, 2014). However, because Pleiades-1 belongs to the new generation of satellite imagery, there is still a paucity of studies related to their application and more research is imperative to evaluate their usefulness in landslide detection and mapping.

Several studies have been carried out to determine the optimal classification algorithms for land use/cover studies by comparing the performance of the various classification algorithms. For example, in land use/cover classification studies conducted in (Ghosh and Joshi, 2014; Adam *et al.*, 2014), the results produced by SVM and RF algorithms were similar. In another study conducted in Khatami *et al.* (2016), SVM, k-NN, and RF algorithms produced better results compared to other supervised classifiers. A study that focused on the effects of the classifier selection, reference sample size, reference class distribution, and scene heterogeneity in per-pixel classification using Landsat images is reported in Heydari and Mountrakis (2018). The results of the study show that SVM and k-NN were the best classification techniques, compared to Naïve Bayes (NB), Bootstrap-aggregation ensemble of decision trees (BagTE) and deep neural network (DNN) approaches.

While numerous studies have been conducted to evaluate the performance of the various algorithms in land use/cover classification, no study that compares the performances of the different classifiers using Pleiades-1 imagery for landslides investigation has been reported in the literature. It is, therefore, important to conduct a study to compare and evaluate the performance of these classifiers for the detection and mapping of slow-moving landslides in Kutlugün, North-eastern Turkey, using Pleiades-1 data. In this paper, the performances of k-NN and SVM classifiers and Pleiades-1 data for the detection and mapping of slow-moving landslides are evaluated. The k-NN algorithm is a standard method that has been employed by professionals in practice, while the SVM classifier is a modern technique for scientific studies.

2. MATERIALS AND METHODS

2.1 The Study Area

The study area is about 25 km², located in Kutlugün in the Maçka district of Turkey (Figure 1). The area experiences a temperate climate in the summer and a rainy season usually starting from September and ending around April. The topography consists of hillsides, mountains, valleys and stream channels. The hydrology of this area is regulated by the activities of the Değirmendere River Basin, which is surrounded by high mountains with a maximum elevation of 3080 m. The geology of the Kutlugün slow-moving landslide area consists of weathered andesite-basalt and pyroclastic rocks, with clays developing due to the weathering of the rocks (Yalçinkaya and Bayrak, 2005). Road construction, quarrying and tunnelling through the high mountainous terrain are the main anthropogenic activities in the study area. The type of landslide movement in the study area is translational, and the movement amounts to several centimetres per month (Yalçinkaya and Bayrak 2005).

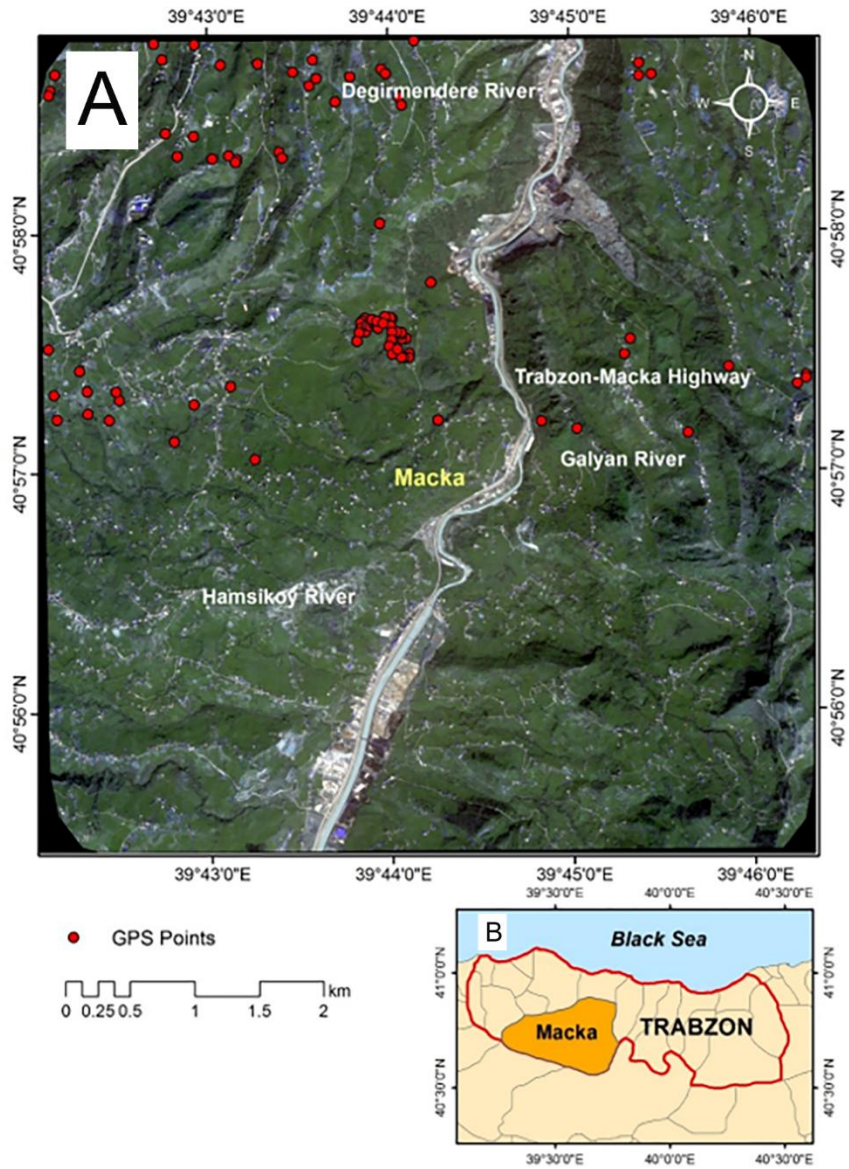


Figure 1. (A) Pleiades-1 image of the study area showing GPS points; (B) Map of Turkey showing the location of the study area

2.2 Data Collection

The data employed for the study, along with the acquisition parameters, are given in Table 1.

Table 1. Data used for the study

Data	Date/time of acquisition (dd/mm/yyyy)	Mean Across/ Mean along-track viewing angle	Mean Across/ Mean along-track incidence angle	Solar azimuth/ elevation	Spectral bands	Resolution
Pleiade s-1 (Mono)	21-10-2017 08:30:15.8	15.66/ -12.24	-19.79/ 9.97	168.92/ 37.70	PAN: 0.47-0.83 µm (black and white); MS bands: Blue = 0.43-0.55 µm; Green = 0.50-0.62 µm; Red = 0.59-0.71 µm; Near Infrared = 0.74-0.94 µm	PAN = 0.7 m MS = 2.8 m
Pleiade s-1 (Mono)	03-04-2018 08:18:20.9	-4.47/ 2.08	5.26/ -1.20	152.73/ 51.66		
RTK-GPS 1	24-10-2017 25-01-2018					
RTK-GPS 2	25-03-2018					
RTK-GPS 3						

2.3 Methodology

The workflow is based on the object-based supervised classification (OBIA) technique with the following steps: data pre-processing, image segmentation, the selection of training and testing samples, detection of landslide objects and accuracy assessment. The performance of two classifiers: non-parametric k-Nearest Neighbors (k-NN) and Support Vector Machine (SVM) is evaluated using Pleiades imagery, to detect and map small and slow-moving landslides in the Kutlugün study area. The object-based supervised classification approach is implemented in the ENVI 5.1 image processing software.

2.3.1 Data pre-processing

The Pleiades-1A image acquired on 3 April 2018 was used. Radiometric calibration and atmospheric correction were performed using ENVI to obtain the surface reflectance data of the acquired Pleiades-1 imagery. The georeferenced Pleiades-1 imagery was orthorectified using the ASTER GDEM. The high-spatial-resolution multispectral Pleiades-1 imagery was enhanced by combining 0.7 m resolution panchromatic and 2.8 m resolution multispectral data with the ENVI PCA Pan-Sharpener module. ASTER GDEM was also used to calculate the topographic parameters (slope and elevation) of landslides in the study area.

2.3.2 Image segmentation

The object-based image analysis (OBIA) approaches rely on good segmentation algorithms. Image segmentation is a process that involves separating the image into objects or regions using the homogeneity of the pixel values. In the detection and mapping of small landslides, image segmentation is performed to create objects or segments that completely delineate the boundary of the landslide features.

In this paper, the edge-based segmentation algorithm was implemented in ENVI 5.1 to extract small landslide features from the Pleiades-1 image. Using this algorithm, the optimal level of small landslide details and the average segment size are influenced by three parameters, namely - scale level, the merge level and the number of selected bands applied in the delineation and merging step. The number of

segments is controlled by the scale level, while several smaller segments are combined into a larger one using the merge level. The optimal scale (25 on a scale from 0 to 100) and merge level (75 on a scale from 0 to 100) that best delineated the small landslide objects were selected. The 4 bands, namely Red, Blue, Green, and NIR, were used as input bands in the segmentation process to produce homogenous segmentation results for accurate separation of the landslide objects from other surrounding features.

2.3.3 Selection of training and testing samples

The key aspect of a classification system is that it should be able to accommodate numerous variables, such as imagery type, classifications needed, feature importance, and training data quality. It is important in the classification process to not only consider the object of interest, which is a landslide in this study, but also to classify as many surrounding objects as possible. This approach is useful in understanding the variations in spectral, textural and spatial values of surrounding objects. In the Kutlugün study area, the main land use/cover types are green tea, hazelnut, deciduous, coniferous, pasture, soil, rock, water, agriculture, and urban (Kavzoglu *et al.*, 2015). In this study, training and sample data were generated from the four main classes covering all the land cover, namely: landslide, road, building, and vegetation.

In supervised classification, known samples (training samples) are utilised to construct a model for the classification of unknown (testing) samples. The selected training samples were spread throughout the image and efforts were targeted at ensuring a uniform number of training samples with spectral homogeneity based on careful visual inspection. The training samples distributed fairly over the entire study area were randomly selected. For an accurate assessment of the classification results, separate training and testing sample sets were selected for the four main land use/cover classes. In order to acquire the training sample data, the ArcGIS 10.3 toolbox was used to create 100 polygons for each land cover class (Table 2). The effectiveness of the two classification methods was assessed by selecting random testing sample sets for every land cover class, as shown in Table 2.

Table 2. Training and testing samples for the individual class

Land Cover	Training	Testing
Landslide	100	107
Road	100	161
Building	100	132
Vegetation	100	135

2.3.4 Classification algorithms

2.3.4.1 Support Vector Machine (SVM)

Support Vector Machine (SVM) belongs to a family of boundary classifiers that have been applied in remote sensing applications (Mountrakis *et al.*, 2011). One main goal of the SVM algorithm is to determine an optimal decision boundary (or hyperplane) and to segregate the dataset into a pre-defined number of classes (Vapnik, 1999). SVM seeks to determine the widest margin between two classes in feature space. To maximize the margin between the classes, SVM needs to divide the classes with a decision surface. The surface is referred to as the optimal hyperplane. The critical elements of the training set are the support vectors and they are the points closest to the hyperplane. The SVM approach involves different classes that are linearly separable and based on a non-linear transformation of the covariates. As is common with imagery datasets with inherent problems of class overlap, the assumption of linear separability becomes invalid. To produce higher-order and non-linear solutions using SVM algorithms, slack-variable kernels such as radial basis functions are introduced. SVM produces robust classification under class-imbalance and variable cross-correlation with the appropriate choice of features, kernels and parameters (Statnikov *et al.*, 2008). SVM may be employed independently for variable selection, though the internal measures of variable importance are not included (Archibald and Fann, 2007).

The main peculiar features of SVM are robustness to noise and non-linear decision boundaries. Their probabilistic outcome is easily implementable, and they have an inherent capacity to affect high-

dimensional classification problems (Ballabio and Sterlacchini, 2012). SVM algorithms have been extensively applied in landslide susceptibility mapping (Lee *et al.*, 2017; Heleno *et al.*, 2016; Ballabio and Sterlacchini, 2012), due to their capability to utilise data with unknown statistical distributions and small training samples.

2.3.4.2 k-Nearest Neighbors (k-NN)

The k-NN algorithm is a non-parametric technique that has been applied in statistical applications since the early 1970's (Franco-Lopez *et al.*, 2001). Being a non-parametric method, no assumptions are required on the underlying data distribution. It is referred to as a lazy algorithm because it does not apply the training data points to perform any generalization. The principle of k-NN is based on the use of calibration dataset to find a group of k samples that are nearest to unknown samples (e.g., based on distance functions). The technique computes the Euclidean distance from each image segment to every defined training sample. The distance is measured in an n-dimensional space, where n represents the number of attributes for the individual training sample. The class of unknown samples is determined from these k samples by computing the average of the response variables (i.e., the class attributes of the k-NN) (Akbulut *et al.*, 2017). The k is a tuning parameter and plays an important role in the performance of the k-NN algorithm (Qian *et al.*, 2015). k-NN classifier is very suitable for experimenting because it only requires one parameter (k) to be optimized. k-NN algorithms have been employed in landslide detection and mapping (Cheng *et al.*, 2013; Li *et al.*, 2013).

2.3.5 Supervised classification process and tuning parameter

When applying SVM and k-NN algorithms, the tuned parameters is important in obtaining high accuracy results. The tuning steps and tuned parameters are different for each classifier. In this paper, a series of values for the tuning process was tested for each classifier, to determine the optimal parameters to produce the highest overall classification accuracy. The best parameters applied to produce the classified results were employed to compare the performance of the classifiers. In ENVI 5.1 image processing software, the parameter adopted for the k-NN classifier is - number of neighbors: 1.

The four types of kernels for the SVM classifier in ENVI 5.1 are: linear, polynomial, radial basis function (RBF), and sigmoid. The RBF is the commonly used kernel and performs well in land cover classification studies (Shi and Yang, 2015). The best prediction accuracy was realised with the RBF kernel, and the following processing parameters were adopted after several tests - degree of kernel polynomial: 1, bias in kernel function: 1, gamma in kernel function: 0.03, penalty parameter: 100. In the processing scheme, 95% was set as the classification confidence threshold, implying that features with less than 95% confidences in each class were set to unclassified.

2.3.6 Accuracy assessment

There are many metrics reported in the literature for assessing the accuracy of classification performance. In this study, accuracy assessment was implemented based on user accuracy (UA), producer accuracy (PA), and the kappa index. The results of the supervised object-based classification were also compared with the landslide inventory map of the study area. The landslide inventory map was derived from ground truth data acquired using RTK-GPS field survey of 95 known points within the landslide study area.

3. RESULTS

3.1 Results of landslide detection using the two classifiers

The summary of the final classification results and the accuracy assessment of the k-NN and SVM classifiers are presented in Tables 3 and 4. The results show that SVM performs better than the k-NN classifier. The preparation of an accurate landslide inventory is a complex process, requiring techniques that are capable of detecting and reducing errors. The SVM algorithm performs better for small landslide detection as it operates based on the concept of optimization and error reduction. In the landslide detection, the SVM method had higher producer accuracy (85.9%), user accuracy (90.4%) and kappa index (0.82) in

contrast to the k-NN algorithm that had lower producer accuracy (83.1%), user accuracy (86.0%) and kappa index (0.80). The performance of the SVM classifier was also better than that of the k-NN algorithm when detecting buildings. But the k-NN classifier outperformed the SVM method in the classification of roads. The low performance of the SVM classifier can be attributed to the use of large training samples, which were spectrally homogenous. It is known that the SVM classifier produces high classification results with small training samples (Tzotsos, 2006).

Table 3. Accuracy of the k-NN classifier for four classes

Class	Producer Accuracy (%)	User Accuracy (%)	Kappa Index
Landslide	83.1	86.0	0.80
Road	69.7	74.2	0.70
Building	70.6	75.4	0.72
Vegetation	81.4	86.0	0.82

Table 4. Accuracy of the SVM classifier for four classes

Class	Producer Accuracy (%)	User Accuracy (%)	Kappa Index
Landslide	85.9	89.4	0.82
Road	59.5	64.8	0.62
Building	80.3	85.7	0.80
Vegetation	82.9	89.4	0.80

Figure 2 shows the results of landslide mapping of the training and testing samples using k-NN and SVM models. These two algorithms are efficient and of high accuracy. The map shows the detected landslides in brown, roads in purple, buildings in yellow and vegetation in green. A total of 128 small landslides were detected in the study area using the k-NN algorithm (Figure 3), while a total of 134 landslides were detected using the SVM algorithm (Figure 4).

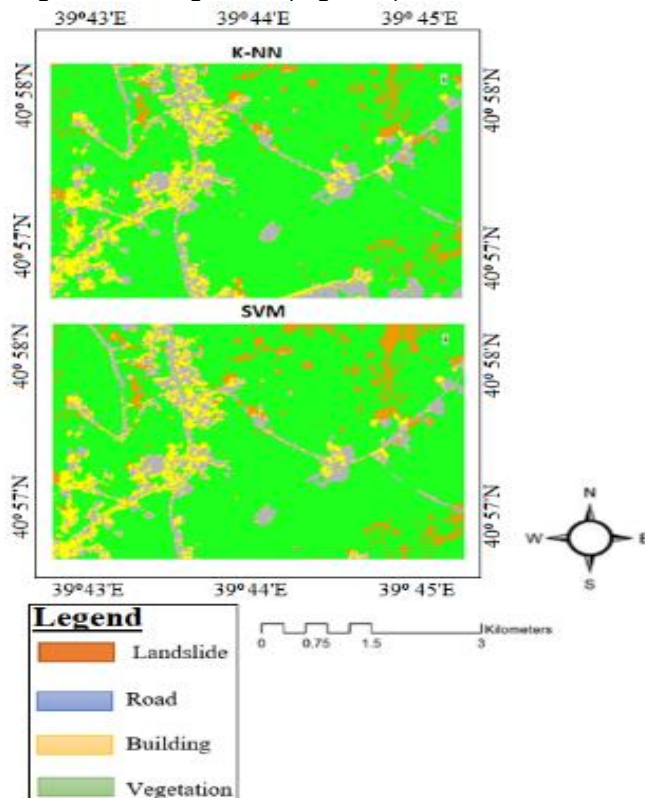


Figure 2. Training and testing samples for the separation of the landslide from other surrounding objects

The inventory map of the Kutlugün study area consists of coordinates of 95 points acquired using RTK-GPS periodic field observations. The accuracy of the detected landslides was realised by using ArcMap 10.3 to compare the observed GPS points with the polygons obtained from the semi-automated OBIA-derived landslides. The results of the point-to-polygon comparison are given in Figures 3 and 4. The accuracy using the k-NN algorithm was 80.4%, while that of the SVM algorithm was 83.75%.

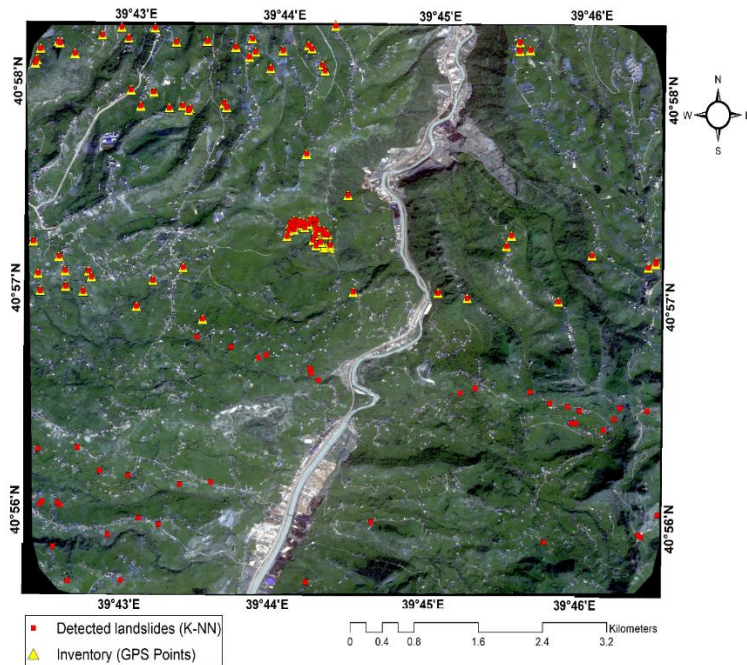


Figure 3. Detected landslides using the k-NN algorithm

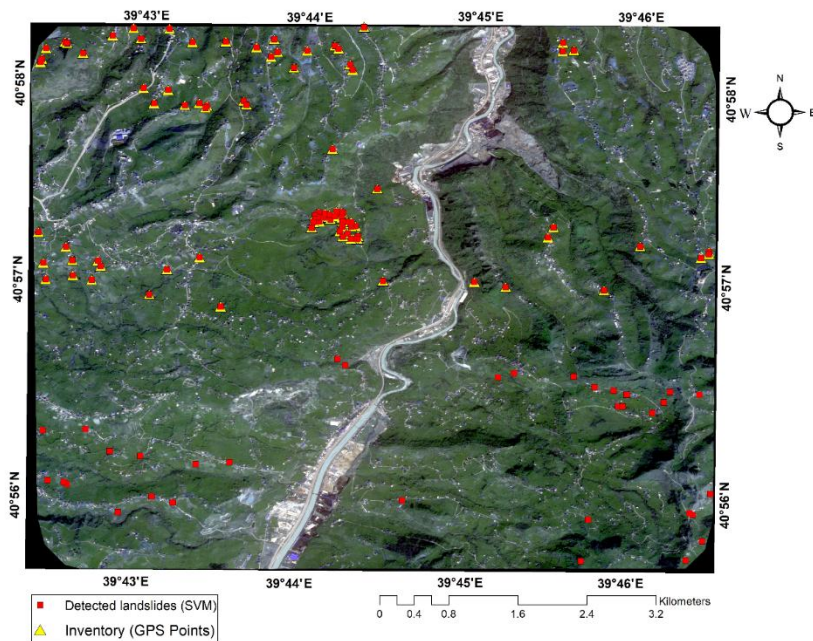


Figure 4. Detected landslides using the SVM algorithm

4. DISCUSSION

Some of the important requirements for supervised landslide detection include – selection of input layers and landslide attribute parameters, selection of a classifier, and the fine-tuning of parameters of the selected classifier (Chen *et al.*, 2014). The main input layers in this paper were the Pleiades-1 image and ASTER

GDEM. The ASTER GDEM was acquired on 17 October 2015, before the acquisition of the Pleiades-1 image on 3 April 2018, so it did not represent surface changes that occurred during the landslide mapping period. However, it assisted the classifier decision by providing unique geomorphic features such as slope, elevation, and aspect to each segmented object. The topographic information assisted in reducing the ambiguity presented by objects with similar spectral characteristics.

In this paper, the performances of two supervised classifiers (k-NN and SVM) were assessed on a Pleiades-1 image for four land cover classes, namely, landslides, roads, buildings, and vegetation. The results show that the SVM algorithm performs better for small landslide detection compared to the k-NN approach. The performance of the SVM classifier was also better for the detection of buildings, while the k-NN algorithm performed better in the classification of roads.

For the first time this paper attempts to compare and evaluate the performance of two supervised classifiers (k-NN and SVM) for the detection and mapping of small and slow-moving landslides using Pleiades-1 data. The adopted approaches combine object-based image analysis with k-NN and SVM supervised learning algorithms and were able to detect 95% of the small landslides present in the study area, using the VHR Pleiades-1 image. The results obtained in this study have added to the growing number of applications of object-based image analysis (OBIA) for semi-automated landslide mapping using VHR optical data.

5. CONCLUSION

Landslide inventory maps are vital tools that provide essential information for studies and investigations related to landslide susceptibility, hazard, and risk assessments. They also aid the engineers, planners and government agencies in various decision-making processes and policies. Developing an efficient technique to detect and map landslides is a challenging task. The main goal of this paper was to formulate techniques to produce landslide inventory maps semi-automatically. The main step to achieve this goal involves the evaluation of the performance of two well-known classifiers (k-NN and SVM) for supervised landslide detection using Pleiades-1 image.

The overall evaluations of the two classifiers show that using supervised classification at the object level with Pleiades-1 image is possible and can be improved. The results of this study show that both k-NN and SVM are suitable classifiers for object classification using Pleiades-1 data, with SVM producing better results compared to the k-NN classifier. Although the k-NN approach provides less accurate results compared to the SVM method in this paper, this does not imply that k-NN is an inefficient classification method. It is suggested in Maillard and Clausi (2006) that the wisest classification decision is not dependent on selecting the 'best' classifier, since the classifiers that are considered to be less accurate may produce valuable information. Thus, all classifiers can be best for certain situations, taking cognizance of the fact that a specific classification metric is better suited to a specific situation.

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