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Monitoring and evaluating land use changes using remote sensing techniques and satellite images (case study: Bam plain)

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ABSTRACT

One way to effectively manage geographical space, natural resources, and the environment is through the use of land use maps. Understanding the quantitative and qualitative characteristics of changes in land use is crucial for environmental planning, land use, and sustainable development. The study aims to assess the potential of Landsat satellite data in identifying, detecting, and monitoring changes in land use. This involves using various digital processing techniques on satellite images to produce maps. The focus is on evaluating both the quantitative and qualitative changes in land use in the Bam Plain in Kerman province. To conduct research using Landsat satellite images from 2003 to 2018, a land use map for the year 2018 was prepared using the maximum likelihood algorithm, neural network, and support vector machine. The accuracy of the algorithms for this year was then discussed. The evaluation of the classification results shows that maximum likelihood classification has an overall accuracy of 95% and a kappa coefficient of 94%, which is higher than the accuracy of 93% and kappa of 91% for neural network classification, as well as the accuracy of 88% and kappa of 85% for support vector machine classification. Then, Using the maximum likelihood algorithm, which had high accuracy, the map of other years was also prepared. then the map of changes for each period was also obtained, which showed the changes in land use during the 5-year periods of 2003-2008, 2008-2013, and 2013-2018. although these maps revealed fluctuations in land area over the mentioned periods, during the last 15 years (2003-2018) significant changes were observed in the extent of barren and Salty lands in the study area. In 2003, these lands covered approximately 6811.91 Km^2, which accounted for about 38.52% of the study area. This area expanded to 6877.17 Km^2 in 2018, covering approximately 38.91% of the study area. During this period, agricultural lands and pastures diminished due to overuse. The results of this research assist managers and decision-makers in making more informed decisions regarding changes in land use, as well as the control, protection, and sustainable use of land.

Highlights

- The potential of Landsat satellite data in identifying, detecting, and monitoring changes in land use was investigated.
- The focus is on evaluating the quantitative and qualitative changes in land use in the Bam Plain in Kerman province.
- land use maps were prepared using the maximum likelihood algorithm, neural network, and support vector machine.
- The result of land use change detection showed significant changes in the extent of barren and Salty lands.
- During this period, agricultural lands and pastures diminished due to overuse.

1. Introduction

Understanding changes in land use and analyzing its patterns is essential for managing and evaluating natural resources. The monitoring of changes in land use over time is achieved through remote sensing, which offers shorter time intervals, lower costs, and greater accuracy (Lausch & Herzog, 2002). Land use has always been one of the most

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important factors through which humans have influenced their environment. Historically, the most significant change in land use that human has made has been the destruction of forests and their conversion to agricultural lands and settlements (Galdavai et al., 2013). Effective land management requires accurate and current information in the form of a map. Considering the widespread and unregulated changes in land use, including the depletion of natural resources in recent years, it is essential to analyze the evolving patterns of land use over time using satellite images. On the other hand, Satellite data is repeatable, up-to-date, and covers a wide area, making it increasingly utilized. In recent years, the efficiency of satellite data and geographic systems capabilities have drawn researchers' attention to studying land use changes. Monitoring land use changes is essential for ecology, deforestation, sustainable resource management, urbanization, and modeling climate change impacts (Galdavi et al., 2024). With recent advances in remote sensing and satellite technology, the latest geographic information is now more accessible and affordable for users. As a result, the use of remote sensing has become more common due to reduced costs and time compared to ground mapping. For several decades, the integration of remote sensing and geographic information system technology has been utilized to observe, monitor, and the dynamics of land use and land cover change (Longley et al., 2010).

Today, the investigation of land use changes, including Urban changes, is related to the conversion of forest, range, agricultural, and orchard lands into residential areas and urban facilities through the process of revealing changes using multi-temporal remote sensing images (Galdavi et al., 2013; Galdavi et al., 2015 and Shayesteh et al., 2018), which increases the speed Checking and accuracy of the results replace expensive, time-consuming and often less accurate methods. Remote sensing, along with geographic information systems (GIS), is a valuable tool for monitoring changes in land coverage on both regional and global scales in developing countries. RS and GIS are superior and efficient technologies for studying environmental changes and managing resources. Today, remote sensing images are considered the most up-to-date information for studying land cover and land use (Galdavi et al., 2013). The use of images is crucial for creating accurate land use maps due to providing up-to-date information, a variety of shapes, digitality, and the possibility of processing. Remote sensing techniques can display and present land cover classes by classification processes. Land use plans affect certain changes that have specific consequences for the structure and function of the ecosystem in the landscape pattern (Zhang & Li, 2022).

Numerous studies have been conducted in the field of monitoring land use and land cover changes using satellite data such as Landsat, Spot, and IRS. Among these studies, Singh (1989) compared the techniques of image difference, image ratio, normalized vegetation index difference, and post-classification comparison. The result showed the image difference method had the highest accuracy, while the comparison method after classification had the lowest accuracy in monitoring forest changes in the northeastern region of India. Gao et al. (2006) utilized Landsat TM and ETM+ satellite images to identify land use changes in Northeast China in 1995, 1990, and 2000. The analysis revealed an increase in urban areas, water bodies, and forests. Agricultural lands predominantly transitioned into urban areas, water bodies, and forests, while forest and grassland areas converted to agricultural lands.

Fan et al. (2008) used TM 1998 and ETM^+ 2003 images to investigate land use and land cover changes in the Pearl River Delta. They employed the maximum likelihood classification method, and the temporal and spatial changes in land use and land cover from 1998 to 2003 were revealed using the post-classification method. Jabbar and Zhou (2011) used remote sensing techniques and geographic information systems to identify ecological changes in Basra province, located in the south of Iraq, from 1990 to 2003. They found that processes such as desertification, salinity, urbanization, destruction of vegetation, and destruction of wetlands were the main factors contributing to the ecological degradation of the region. Hussain et al. (2013) used pixel-based algorithms and object-oriented methods to detect changes in a high-spatial-resolution images. They concluded that the object-oriented method has higher potential for change detection. Galdavi et al. (2013) detected urban changes by integrating multi-temporal remote sensing data over a 19-year period in the Gorgan region of Golestan province in northern Iran. The findings revealed a predominant conversion of agricultural lands into residential areas. Arulbalaji and Gurugnanam (2014) utilized remote sensing data to observe land use changes in the Salem area of South India. They noted that the most significant changes took place in the central part of the study area. These changes were attributed to the socio-economic development of the region, which has implications for water and mineral resources.

Madurapроma et al. (2015) identified land use changes in the Pipsten Creek 4 basin in North Dakota by using remotely sensed data and a supervised classification method from 1976 to 2011. They stated that the remotely sensed data digitized land cover changes and could be considered as a necessary input in land management policies.

Ramezani et al. (2018) conducted a study on land use changes in Esfrain (North Khorasan) over a period of four decades using Landsat images. They employed the supervised classification method and post-classification comparison to analyze the changes. The study achieved a kappa coefficient of approximately 87% and an overall accuracy of 90%. The findings indicated significant changes in irrigated lands and residential areas during the study period. Arekhi (2014) documented the land use changes in the Abdanan region over a 25-year period. The findings indicated a decrease in average and good range coverage between 1985 and 2010, suggesting a trend of degradation in the region due to the replacement of these ranges with poor ranges and barren lands. In a study, Yousefi et al. (2011) monitored land use changes in Marivan City using Landsat images from TM and ETM sensors for 16 years with the reclassification method. The results showed that the most changes are related to agricultural and forest lands. These changes include reducing the forest and agricultural lands and increasing residential areas during the studied period of this region.

Shaisteh et al. (2018) detected the changes in Kurdkovi city in Golestan province from 1987 to 2015. They created land use maps for 1987, 2000, and 2015 using Landsat satellite time series images. Subsequently, they identified changes in the city using the post-classification method. The results indicated that 333 hectares approximately were added to the urban areas during the study period. The study also found that agricultural and forest areas contributed the most to the increase in urban lands, with 306 hectares and 27 hectares of land conversion, respectively. Galdavi et al. (2024) identified and monitored forest land changes in 20 years in the Gorgan region of Golestan province. For this purpose, land use maps were prepared in two 10-year periods using satellite images, and the changes revealed by the post-classification method. The results showed a decrease in the extent of forest lands in the studied period, and the main reason was the development of residential areas and agricultural lands in the region.

A review of past research showed that using remote sensing data is most useful and highly effective for identifying land use changes over time. Therefore, in the current research, using remote sensing (RS) and geographic information system (GIS) data, land use changes and their trend in Bam Plain have been studied.

2. Materials and methods

2.1. The study area

The city of Bam is located in the Kerman province and has a population of over 300,000 people. Bam experiences a dry desert climate. The main occupations of the residents are agriculture and horticulture. Water for drinking and agriculture is mainly sourced from underground water Aqueducts and wells. Bam Plain is a closed rectangular plain located at approximately 58°21' east longitude and 29°6' north latitude. It is situated in the southwest-northeast direction, about 207 Km southeast of the capital of Kerman province. Bam Plain is located on the edge of the Lut desert, which is considered one of the dry areas of the country. In these plain, deep and semi-deep wells are very popular due to the existence of many agricultural lands. The study area is a part of the Lut desert catchment area with a hot desert climate. Its height above mean sea level is 960 meters, and its area is 9921 Km^2, of which 4357 Km^2 includes plains.

2.2. Data

The research utilized Landsat satellite images and 1:25000 topographic maps. The images have been requested from the USGS website and received at the L1T correction level. The specifications of the images used can be found in Table 1. Since the study area is located in two frames two images were received for each year. These images were then mosaiced after necessary corrections and clipped using the area's border.

Table 1. Specifications of satellite images used in the research

	Date of Images	Pass and row number	Satellite	Sensor	Resolution (m)
1	2003	159-40	LANDSAT_5	TM	30
		158-40	LANDSAT_5		
2	2008	159-40	LANDSAT_7	ETM	30
		158-40	LANDSAT_7		
3	2013	159-40	LANDSAT_8	OLI	30
		158-40	LANDSAT_8		
4	2018	159-40	LANDSAT_8	OLI	
		158-40	LANDSAT_8		

After preparing satellite images for the study area, ENVI 5.1 was used during different stages of image processing. Also, the Maximum Likelihood Classifier (MLC), neural network, and support vector machine methods were used to investigate land use changes and evolutions.

2.3. Pre-processing of satellite images

The quality of the satellite data was assessed for geometric and radiometric errors, such as striations, non-overlapping scan lines, repeated pixels, and atmospheric errors like cloud patches. Pre-processing involves correcting these distortions and errors to extract primary information and prepare the data for further processing (Akbari et al., 2016). In this research, to check the geometric condition of the images, the layers of Roads and Rivers were extracted from 1:25000 topographic maps and placed on the satellite images. Also, there are different methods for atmospheric correction, and in this research, the Dark Subtract method was achieved using ENVI software. In this method, a constant value is subtracted from the total value of pixels in a band. The turbidity reduction method assumes that the non-zero values for clean and deep water in the near-infrared band are caused by atmospheric path radiance (Lp). In this case, the constant value Lp is subtracted from all the values of the surface pixels (Akbari et al., 2016).

2.4. Classification of satellite images

Land use classification methods were used to process the images. Classification methods are divided into two categories: Supervised classification and Unsupervised Classification. Supervised methods need basic information such as the number of classes, their characteristics, and also several known examples of each class. In contrast to the unsupervised methods, most of them are automatic methods that do not need known samples and decide on their classification based on the values of the pixels themselves (Fatemi and Rezaei, 2016). The classification algorithms used in this research are of the supervised type, which includes maximum likelihood, neural network, and support vector machine.

The maximum likelihood algorithm for classification is based on variance and covariance. This method assumes that all training areas have a normal distribution. To ensure representative samples, it is important to use as many samples as possible to cover a wide range of spectral characteristics. In maximum likelihood classification, the pixel is assigned to the class with the highest probability of belonging to that class (Akbari et al., 2016).

Support vector machine (SVM) is a binary classifier. In the case of two classes, the SVM method tries to create a hyperplane that maximizes the distance of each class to the hyperplane. Point data that is closer to the hyperplane are used to measure this distance. Therefore, these point data are called support vectors. In general, SVM is a binary and linear classifier which, by developing it and using kernel functions, is also used as a multi-class and non-linear classifier. In this research, the RBF kernel (Radial Basis Function) was used due to its widespread use in land use change studies with data from different satellites and also its better performance than other kernels. RBF kernel was determined from the formula (Eq. 1):

$$k(xi, xj) = \exp(-\gamma \, \| xi, xj \| 2), \quad \gamma > 0 \tag{1}$$

In this formula; xi and xj are sets of training data and γ is a parameter defined by the user as kernel assumption. γ is the inverse of the number of spectral bands of the sensor (Akbari et al., 2016).

The first step in supervised classification is determining the type and number of classes. This classification is based on prior knowledge and used as training examples in data classification. The study area includes agricultural lands, rangelands, barren lands, built lands, and water areas. These classes are defined based on visits to the area, differences in satellite image reflections, and past similar studies. For each type of land cover and land use, any number of training samples can be defined with an ID, but in general, there should be a suitable number of cells for each type of land use for statistical analysis. An important rule is that the number of cells of each training sample or all training samples of a land use class should not be less than ten times the number of bands (Salman Mahiny and Kamyab, 2010). The land use map for the year 2018 was produced after determining training points using maximum likelihood methods, the neural network, and vector machine support. Then, the accuracy of the mentioned methods was evaluated for choosing the best algorithm. After that, the maps of other years were also determined with the best algorithm.

2.5. Evaluation of classification accuracy

Evaluation of classification results is one of the important steps of classification, which shows the level of correctness in classification. According to most well-known researchers, no classification can be relied upon until its accuracy has been evaluated, except when sampling pixels as a pattern of spectral or informative classes, evaluating the spectral reflectance of the classes, and distinguishing Their adaptability can also be done at the same time. The accuracy of the classification indicates the level of confidence in the extracted map, and it should be at least 85 in the land use maps obtained from remote sensing images (Akbari et al., 2016). Error evaluation and estimation of classification accuracy are usually based on statistical parameters that are extracted from the error matrix, one of the most common methods of expressing the classification accuracy is to prepare the classification error matrix. The error matrix compares the relationship between known reference data (ground truths) and the relevant results of an automatic classification class by class. Based on the error matrix, several parameters are extracted to express accuracy and error, which include total accuracy, producer accuracy, user accuracy, and kappa coefficient. Based on the accuracy of the manufacturer and the user, two errors of omission and commission can also be obtained. From the point of view of theory, total accuracy probabilities cannot be a good criterion for evaluating classification results. Because the role of chance is significant in this index. The overall accuracy is obtained from the sum of the elements of the main diameter of the error matrix divided by the total number of pixels according to the following relationship (Akbari et al., 2016).

In this regard:

$$OA = \frac{1}{N} \sum P_{ii} \tag{2}$$

- OA overall accuracy
- N number of test pixels
- ΣPii sum of elements of the main diameter of the error matrix

Due to the defects in the overall accuracy, the kappa index is often used in executive works where the comparison of classification accuracy is considered. Because the kappa index focuses on the incorrectly classified pixels, the kappa index is calculated from the following relationship (Bonyad & Hajyghaderi, 2008).

$$Kappa = \frac{\mathrm{po} - \mathrm{pc}}{1 - \mathrm{pc}} \tag{3}$$

That in the above formula:

po – correctly observed

pc – expected agreement

The producer's accuracy is the probability that a pixel in the classified image is in the same class on the ground, and the user's accuracy is the probability that a certain class on the ground is in the same class on the classified image. They are calculated through the following formula (Bonyad & Hajyghaderi, 2008).

$$\mathrm{PA} = \frac{ta}{ga} * 100 \tag{4}$$

$$\mathrm{UA} = \frac{ta}{n_1} * 100 \tag{5}$$

that in the above formulas:

PA – Class A accuracy percentage for manufacturer's accuracy

ta - number of correct pixels classified as class a

ga - the number of classes a pixel in ground reality

UA – Class an accuracy percentage for user accuracy

n1 - the number of pixels of class a as a result of the classification based on the two mentioned accuracies, the two errors assigned 1 and omitted 2 are defined as follows (Fatemi and Rezaei, 2016).

Ce = 1- UA

Oe = 1- PA

The assigned error (Ce), which is calculated based on the accuracy of the user, is equivalent to the percentage of pixels that do not belong to the desired class, but the classifier considers them to be part of that particular class. The omitted error (Oe) is related to the percentage of pixels that belong to the desired class in the ground reality and are classified as other classes.

2.6. Change Detection

The change detection process is determining the changes in a subject or a phenomenon in a certain period (Coppin et al., 2004). In this study, after ensuring the acceptable accuracy of the maps and extracting the land use maps produced with the best algorithm in the desired years from the method of comparison after classification to prepare the matrix of land use changes for the period of 2003- 2008, 2008-2013, and 2013-2018 have been used. In this method, based on equation (7), the intensity of changes was determined by comparing the changes in the type of land use between the images of two different times. The result of this method is an image that shows the changes in land use between two dates (Singh, 1989). In this method, the area and percentage of the classes from the total will be determined in each year, and the amount of their changes in the investigated period.

$$DN = x(t1) * 10 + x(t2) \quad (7)$$

3. Results and discussion

In this research, 4 satellite images have been used at different times for detecting Changes in Land use and Land cover types in Bam Plain. The results of investigating the radiometric quality and geometric control of the images showed that the images had good quality. Also, the images overlayed with the vector layers of roads and rivers for investigating the geometry which showed they are spatially located in the correct place. After that, maximum likelihood supervised classification (MLC), neural network, and support vector machine were used to prepare land use maps. For this purpose, according to the existing Land uses in the region, training samples were prepared for 5 classes, including agricultural lands, urban lands, range lands, Salty lands, and bare lands, and based on the land use maps were extracted. Then, the accuracy of land use maps was assessed. For this purpose, land use maps and ground samples were analyzed in ENVI 5.1 software and the results of the error matrix for 2018 for all three algorithms of the neural network, maximum likelihood, and support vector machine was indicated in Tables 2 and 3. According to the result, the land use maps prepared by the all three algorithms have had high accuracy, however, the maximum likelihood algorithm has higher accuracy and precision than other algorithms (Table 3). This result is consistent with the findings of several researchers, including Akbari et al. (2016), Alizadeh et al. (2015), Morgan et al. (2015), and Madhura and Venkatachalam (2015). By comparing the accuracy of different supervised classification methods, the mentioned researchers stated that the maximum likelihood method has a suitable accuracy.

Table 2. Accuracy assessment of classification for Land use map 2018

Methods	Total accuracy (%)	kappa coefficient
Maximum likelihood	95.65	94.44
Neural network	93.11	91.25
Support vector machine	88.76	85.57

Table 3. Statistical characteristics of producer and user accuracy for OLI image for 2018

Methods	Maximum likelihood		Support vector mac		Neural network	
Accuracy Classes	Producer (%)	User (%)	Producer (%)	User (%)	Producer (%)	User (%)
Agriculture	94.55	94.55	92.73	94.44	94.55	92.86
Bare	98.78	96.43	100.00	95.35	90.24	96.10
Range	98.78	98.31	93.55	90.63	93.55	100.00
Salty lands	93.55	100.00	95.24	75.47	95.24	100.00
Urban	91.43	86.49	40.00	73.68	94.29	73.33

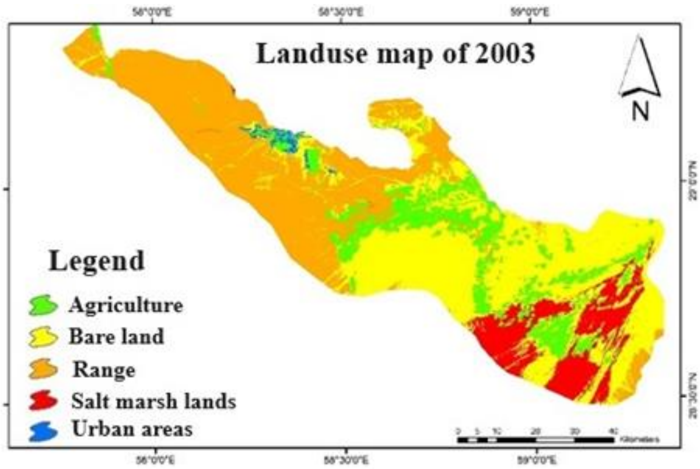

Figure 1. Land use map of 2003

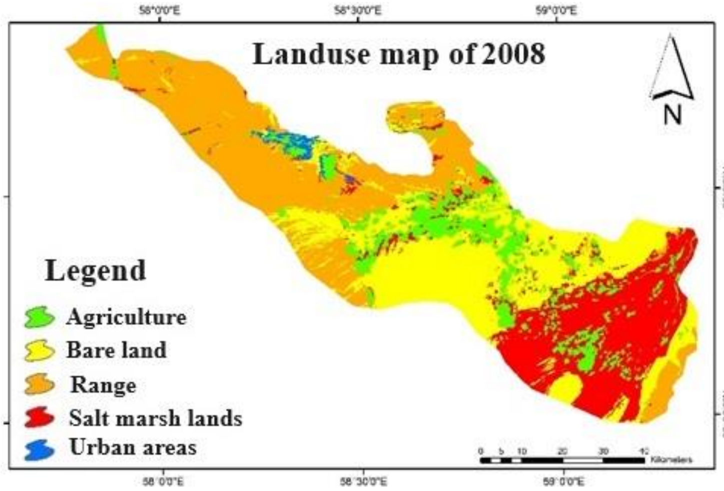

Figure 2. Land use map of 2008

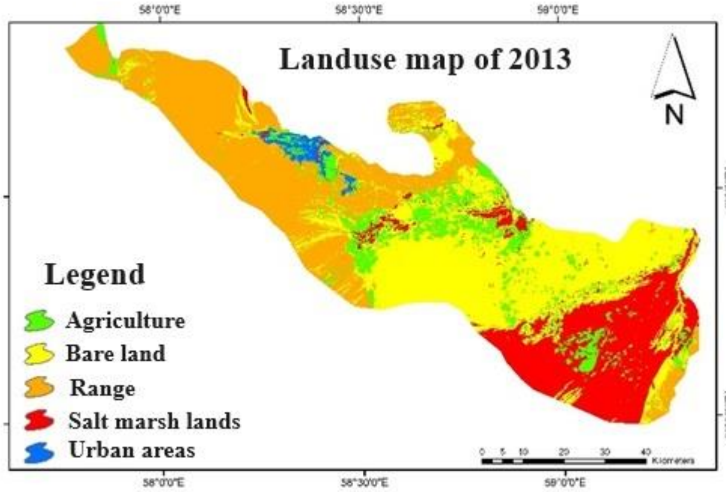

Figure 3. Land use map of 2013

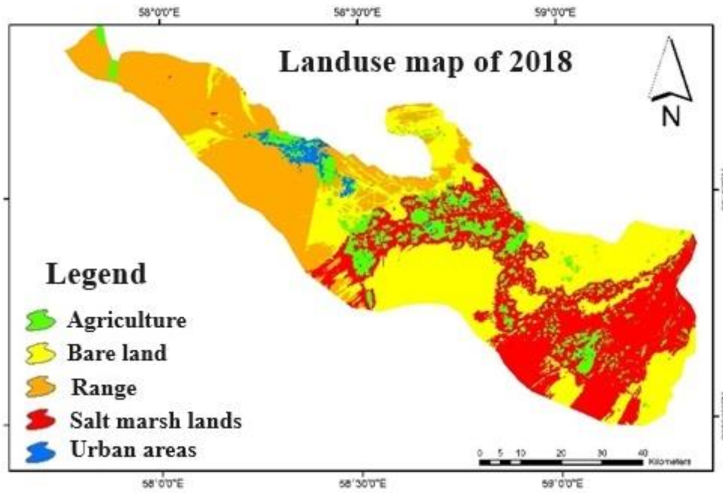

Figure 4. Land use map of 2018

The producer's and user's accuracy for all types of land use in images classified by the investigated algorithms - except urban in the neural network and support vector machine algorithm - were estimated above 80%, which is an acceptable level. After choosing the best algorithm, land use maps for other studied years were also prepared and their accuracy was evaluated. The accuracy of these maps was more than 80%, which is very accurate when compared with studies such as Lefsky and Cohen (2003). They have stated that overall accuracy and kappa coefficients greater than 0.7 are very good and less than 0.4 are poor. Figures 1 to 4 show the land use maps of the studied years.

After preparing the land cover/use map of three time periods, the area of five classes of land cover/use was obtained (Table 4). The results show a decrease in range and agricultural lands and an increase in bare and Salty lands. In 2003, the total of bare and Salty lands was 50%, and in 2018, these lands reached nearly 63%. After preparing the land cover/use map of three time periods, the area of five classes of land cover/use was obtained (Table 4). The results show a decrease in pasture and agricultural lands and an increase in barren and saline lands. In 2003, the total of barren and saline lands was 50%, and in 2018, these lands reached nearly 63%. On the other hand, range and agricultural lands have been reduced, which is the result of the indiscriminate destruction of them and their transformation into bare and Salty lands.

Table 4. Area of land uses for the years 2003, 2008, 2013, and 2018

Type of land use	The area of land use in the map of 2003		The area of land use in the map of 2008	
	Area (Km^2)	**Area (%)**	**Area (Km^2)**	**Area (%)**
Agriculture	661.3606	13.20	660.6602	12.432
Bare Lands	1987.5751	39.67	1515.885	30.266
Range	1811.7372	36.16	1743.775	34.816
Salty lands	515.2188	10.28	1084.828	21.659
Urban areas	33.7453	0.673	41.3296	0.825
Type of land use	**The area of land use in the map of 2013**		**The area of land use in the map of 2018**	
	Area (Km^2)	**Area (%)**	**Area (Km^2)**	**Area (%)**
Agriculture	553.0828	11.04	532.3891	10.62
Bare Lands	1795.5394	35.84	1698.828	33.91
Range	1584.4821	31.36	1268.6685	25.32
Salty lands	1007.2589	20.10	1441.1678	28.77
Urban areas	70.1349	1.40	69.4448	1.38

Finally, maps of land use changes in the periods of 2003-2008, 2008-2013, and 2013-2018 were prepared (Figures 5 to 7). According to the results, in the period from 2003 to 2018, range lands decreased and Salty lands and bare lands increased, which indicates the general trend of destruction in the region by replacing range and agriculture with Salty lands and bare lands. Most conversions have been related to agriculture to saline lands due to excessive use of agricultural lands over time, these lands have been destroyed and turned into saline lands and no longer can be used for agriculture. Likewise, the bare lands of the region have also turned into Salty lands over time, in 2018 nearly 29% of the region is salty lands, which cannot be cultivated or converted to other uses. Table 5 shows the rate of conversion of each user to another user.

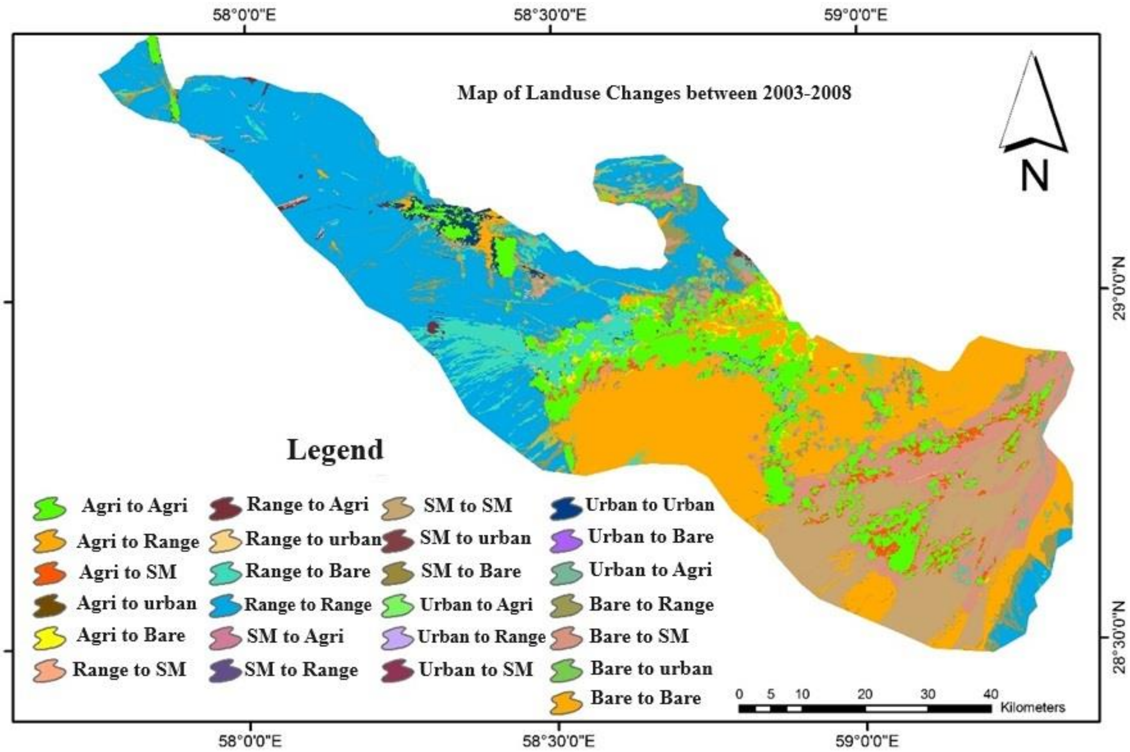

Figure 5. Map of Land use changes between 2003-2008

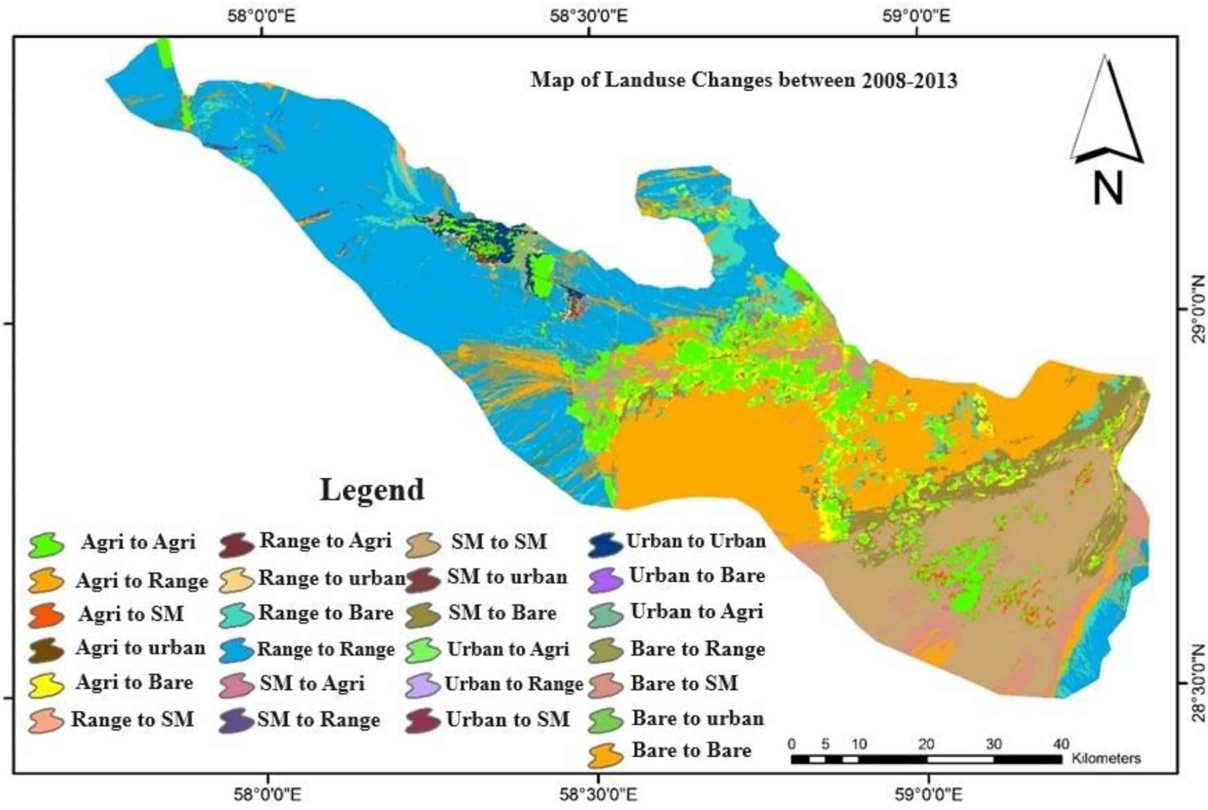

Figure 6. Map of Land use changes between 2008-2013

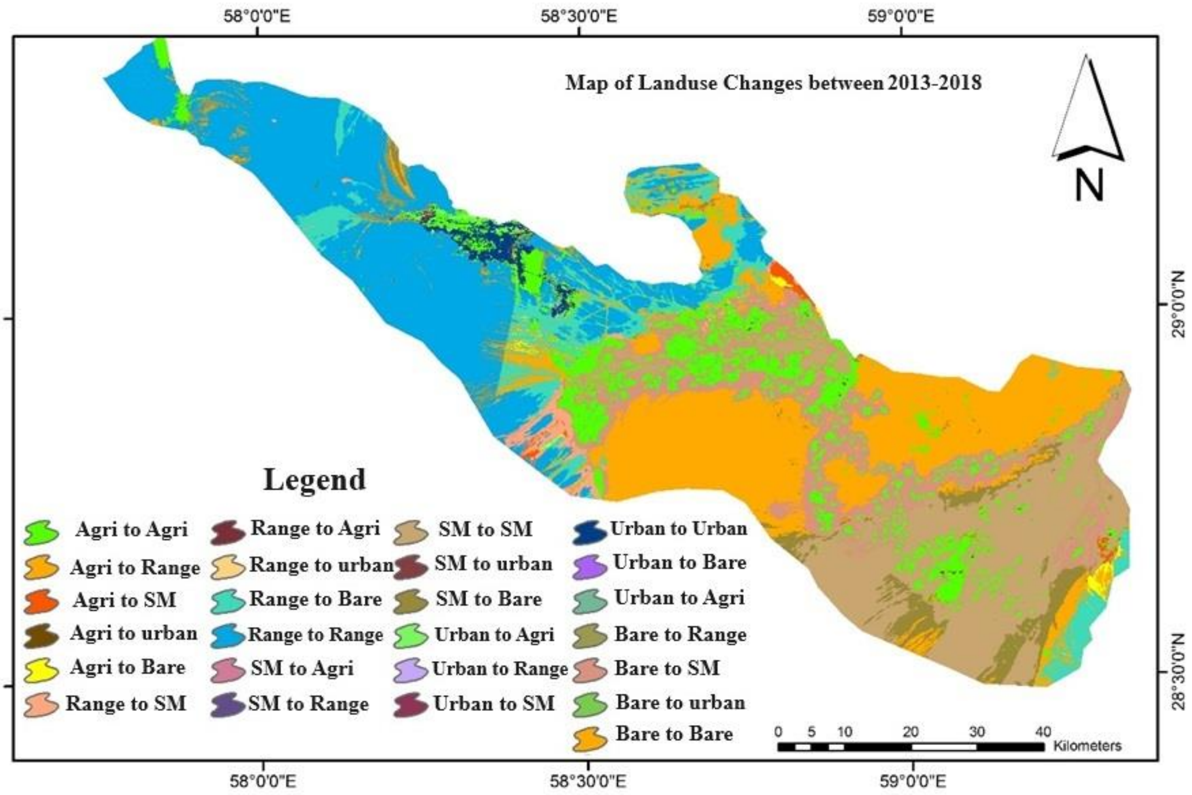

Figure 7. Map of Land use changes between 2013-2018

Land use changes predominantly involve agricultural and range land, which are decreasing in trend. Conversely, changes in bare, saline, and urban areas are increasing. Over the 15-year study period, 131 square kilometers of agricultural land changed, with the most significant changes occurring in the initial period. Overall, the majority of agricultural land changes involve the transformation of these lands into barren and salty lands. In the initial period, the majority of land use change occurred in range land, with 5% of its total area transforming into bare land. Subsequently, more range land became bare, resulting in a total change of nearly 17% over three periods. The investigation suggests that the changes in range and agricultural lands are due to irresponsible land use practices in the region. The majority of bare lands have been transformed into salty lands, with approximately 23% of the bare lands of the region now being salty.

Table 5. The results of land use change detection in the studied time periods

	Abbreviation signs in Figures 5-7	Land use changes between 2003-2008		Land use changes between 2008-2013		Land use changes between 2013-2018	
		Area ($Km^{2)}$	Area (%)	Area ($Km^{2)}$	Area (%)	Area ($Km^{2)}$	Area (%)
Agriculture to Agriculture	Agri to Agri	519.5165	10.37	417.2871	8.33	495.9823	9.89
Agriculture to Bare	Agri to Bare	36.3884	0.72	157.7443	3.149	20.789	0.41
Agriculture to Range	Agri to Range	5.7236	0.114	11.6768	0.23	11.8249	0.23
Agriculture to Salty lands	Agri to SM	95.8575	1.913	28.9984	0.57	23.3024	0.46
Agriculture to urban	Agri to urban	3.8518	0.076	7.0084	0.139	1.1842	0.023
Bare to Agriculture	Bare to Agri	78.3657	1.56	50.2944	1.0041	14.5967	0.29
Bare to Bare	Bare to Bare	1218.7605	24.333	1114.8652	22.258	1176.3436	23.47
Bare to Range	Bare to Range	224.3512	4.47	133.8194	2.671	68.1544	1.36
Bare to Salty lands	Bare to SM	461.7773	9.219	206.602	4.124	529.6474	10.57
Bare to urban	Bare to urban	3.618	0.072	10.3219	0.206	6.7973	0.135
Range to Agriculture	Range to Agri	24.2581	0.484	52.9098	1.0563	3.2844	0.065
Range to Bare	Range to Bare	255.7302	5.105	248.3279	4.957	332.584	6.63
Range to Range	Range to Range	1512.7309	30.203	1428.619	28.522	1187.8403	23.70
Range to Salty lands	Range to SM	17.7987	0.355	6.7718	0.135	59.4998	1.18
Range to urban	Range to urban	0.7944	0.0158	7.2862	0.145	1.2736	0.025
Salty lands to Agriculture	SM to Agri	0.0695	0.0013	30.8569	0.616	4.5639	0.091
Salty lands to Bare	SM to Bare	4.855	0.0969	273.9336	5.469	168.9238	3.37
Salty lands to Range	SM to Range	0.9023	0.0180	9.6894	0.193	0.6725	0.0134
Salty lands to Salty lands	SM to SM	509.3736	10.170	764.7601	15.26	828.7074	16.53
Salty lands to urban	SM to urban	0.0148	0.00029	5.5517	0.110	4.3913	0.087
Urban to Agriculture	Urban to Agri	0.4504	0.0089	1.383	0.0276	13.9618	0.278
Urban to Bare	Urban to Bare	0.1504	0.0030	0.0303	0.00060	0.1875	0.0037
Urban to Range	Urban to Range	0.0674	0.00134	0.0052	0.00010	0.1764	0.0035
Urban to Salty lands	Urban to SM	0.021	0.00041	0.0068	0.00013	0.0108	0.00021
Urban to Urban	Urban to Urban	33.0506	0.659	39.9201	0.7970	55.7984	1.113

4. Conclusion

In this research, satellite images of Landsat 5, 7, and 8 were used in the study area between 2003 and 2018 to investigate land use changes in the Bam Plain. First, the pre-processing of satellite images, including geometric, radiometric, and atmospheric corrections was achieved. Then land use maps were prepared in four time periods 2003, 2008, 2013, and 2018. For this purpose, 5 classes including agriculture, range, urban, salty land, and bare were considered. So, supervised classification methods of maximum likelihood, neural network, and support vector machine were used to extract land use Maps in 2018. The results of calculating the total accuracy, kappa coefficient, producer, and user accuracy of the prepared land use maps showed that the maximum likelihood method (MLC) has a good accuracy for determining land use in the region. Therefore, the maps of other considered years were also extracted by the maximum likelihood method and then the change maps were prepared for three periods 2003-2008, 2008-2013, and 2013-2018. The most changes are related to agricultural and range lands in this area. The trend of changes in agriculture and range is decreasing, and the trend of changes in bare, saline, and urban lands is increasing. Over the 15-year study period, 131 Km^2 of agricultural lands have been changed in use. The most change of range land was to bare land and the most change of bare land was to salty land.

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