Land use and landscape pattern changes of Weihai, China based on object-oriented SVM classification from Landsat MSS/TM/OLI images

Qingying Lin\textsuperscript{a,b,c}, Jinyun Guo\textsuperscript{a,d}, Jinfeng Yan\textsuperscript{a} and Wang Heng\textsuperscript{a}

\textsuperscript{a}College of Geodesy and Geomatics, Shandong University of Science and Technology, Qingdao, China; \textsuperscript{b}Institute of Cartography and Geographic Information System, Chinese Academy of Surveying and Mapping, Beijing, China; \textsuperscript{c}Geographic Information Branch, Jinan, China; \textsuperscript{d}State Key Laboratory of Mining Disaster Prevention and Control. Cofounded by Shandong Province and Ministry of Science & Technology, Shandong University of Science and Technology, Qingdao, China; \textsuperscript{e}Laboratory of Digital Earth Science, Center for Earth Observation and Digital Earth, University of Chinese Academy of Sciences, Beijing, China.

ABSTRACT

Weihai’s urban development model is representative of coastal cities in China. Landsat MSS/TM/OLI images were used to extract the land use types of Weihai from 1985–2015 using the object-oriented support vector machine (SVM) classification method. The landscape pattern indexes were calculated based on the classification results of land use. The temporal and spatial characteristics of land use and landscape pattern were analyzed by considering Weihai’s economic development. The overall kappa (OK) coefficients were greater than 83% and the overall accuracy (OA) values were greater than 85%. Over 80% of both producer’s accuracy (PA) and user’s accuracy (UA) values of different land use types were greater than 85%. Changes in land use and landscape patterns were closely related to the local economic development. The areas of cultivated land and woodland continued to decrease. The expansion of construction land came mainly from the cultivated land and woodland as with as very little from waters. Under the combined effect of economic development and human activities, the landscape pattern of Weihai as a whole has been decentralized. The internal structure is relatively complex and the fragmentation of land use is increasing. The development model of Weihai is the expansion-aggregation-expansion.

Introduction

With the dramatic growth in population and the relatively less available land resources since the 20th century, the land use has gradually been attracting the attention of many countries. Land use, a major determinant of global changes, is an indispensable part of human development as a result of the interactions of humans, nature and other complex factors (Bai, Chen, & Wang, 2015; Du et al., 2019; Long, Chen, Wang, & Zhao, 2011). It is of great significance to realize the sustainable land use and help people to assess and forecast land use by studying long-term land use (Almeida et al., 2016; Chang, Guo, & Wang, 2011; Feng et al., 2010). The spatial landscape pattern can reflect the results of various ecological processes at different scales, and it is also an important manifestation of landscape heterogeneity that is a combination of natural and human factors (Li et al., 2014; Wu, 2000). Analysis on landscape patterns and their changes is important for monitoring and evaluating the ecological effects caused by urbanization, land use change and industrial change. Land use changes have a significant impact on the changing landscape patterns (Peng, Wang, Zhang, Ye, & Wu, 2006), which conversely reflect the changes of land use (Jia, Yan, Yu, & Cao, 2016; Yang, Chen, & Zheng, 2015). City’s development and changes can be thoroughly studied by analyzing land use and landscape pattern changes in recent years (Liu, Zhang, Yang, Qiu, & Wang, 2016; Smiraglia, Ceccarelli, Bajocco, Perini, & Salvati, 2015; Yu et al., 2017).

Landsat satellite images achieve earth observations from space, which promotes the remote sensing technique as the main means of land use monitoring (Li et al., 2014). The object-oriented classification method and the support vector machine (SVM) classification method are the most commonly used methods for remote sensing image classification (Han & Feng, 2013; Yang, He, & Du, 2011). The object-oriented classification method uses object features, such as the shape, texture, topology and other characteristics so that the results can achieve a high accuracy (Gao, Fei, & Han, 2014; Lackner & Conway, 2014). Compared with other methods, the SVM classification method requires less a prior intervention and provides stable classification results with high efficiency (Tsang, Kwok, & Cheung, 2005; Xiao, 2000).
Zhao, Hu, Liu, & Li, 2010; Chang & Lin, 2011; PasolPasolli, Melgani, Tuia, Pacifici, & Emery, 2014). There is seldom any research that uses the object-oriented SVM classification method for remote sensing image processing in the study of land use and landscape pattern changes.

Weihai located in the Shandong Peninsula, at the junction of the Bohai Sea and the East China Sea, is China’s maritime transport hub and the northern foreign trade export channel. In recent years, with the rapid economic development, the land use in Weihai has become more diversified. The rationality of land use has become the relevant concern, and it also determines whether the city can develop healthily and permanently. The dynamic changes of land use, the geomorphological features of the beach, and the landscape pattern indexes were calculated based on the results of the land use types. The local economic development, land use changes, changes of landscape pattern, and the development pattern of Weihai were analyzed.

**Study area and data sets**

**Study area**

Weihai (121°11’~122°42’E, 36°41’~37°35’N) is a representative city of the blue economy area of Shandong Peninsula in China (see Figure 1). Weihai’s land use types can be divided into the cultivated, woodland, water, construction and aquaculture. Since the city establishment in 1987, the economic development of Weihai has grown rapidly. The preferable geographical location, good policies and increasing investment opportunities make it appealing for tourists and potential homeowners. At present, Weihai is one China’s famous coastal tourist city and national new urbanization comprehensive pilot area with a resident population of 2.8 million, an annual economic aggregate of about 300 billion RMB and an urbanization rate of about 60%.

**Data sets**

Landsat images were downloaded from the United States Geological Survey (USGS) (http://glovis.usgs.gov/) and divided into seven periods from 1985 to 2015 at 5-year interval. The images used were the MSS in 1985, the TM in 1990, 1995, 2000, 2005 and 2010, and the OLI in 2015. The image information is listed in Table 1.

Google Earth is one virtual global tool developed by Google. It puts satellite images, aerial imageries and geographic information system (GIS) into a three-dimensional model of the Earth. Its resolution is generally 30 m, but the resolution for large cities, special buildings and other special regions can reach up to 1 m or 0.5 m. Google Earth has often been used to verify classification accuracy (Sun, Leinenkugel, Guo, Huang, & Kuenzer, 2014; Yu et al., 2017).

**Data processing methods**

Figure 2 shows the data processing flow. First, the image pre-processing was performed with no atmospheric correction due to cloudless remote sensing images (Taubenbock et al., 2012). The geometric correction accuracy was within one pixel, the adopted projection method was the Universal Transverse Mercator (UTM) projection, and the coordinate

![Figure 1. Geographical location of Weihai.](image)
system was WGS-84. The resampling method was the bilinear method with a resolution of 30 m.

In order to highlight the various characteristics of land covers, many vegetation indexes are widely used (Kasimu, Tateishi, & Hoan, 2009; Wei, Liu, Song, & Chen, 2008). In this study, we used the normalized difference vegetation index (NDVI) (Townshend & Justice, 1986), soil-adjusted vegetation index (SAVI) (Baret and Guyot, 1991) and normalized difference water index (NDWI) (McFeeters, 1996).

### Image segmentation

Multi-scale segmentation is one critical step in the object-oriented classification. The multi-scale segmentation of remote sensing images is carried out using the classification grid evolution algorithm (Manjunath & Chellappa, 1991) with eCognition software (Nussbaum & Menz, 2008). The main task of segmentation process is to set parameters, such as the weight of each band, the division size, the shape factor and the compactness factor. In order to make full use of band information, the weight of each band was set to 1. The division size is based on the maximum standard deviation with the uniformity criterion of the weighted image layer. While

---

**Table 1. Landsat images information for MSS, TM and OLI.**

| Year | Type | Resolution (m) | Time     | Number of bands |
|------|------|----------------|----------|-----------------|
| 1985 | MSS  | 80             | Oct. 1985| 4               |
| 1990 | TM   | 30             | Oct. 1990| 7               |
| 1995 | TM   | 30             | May 1995 | 7               |
| 2000 | TM   | 30             | Oct. 2000| 7               |
| 2005 | TM   | 30             | Oct. 2005| 7               |
| 2010 | TM   | 30             | Sep. 2010| 7               |
| 2015 | OLI  | 30             | Sep. 2015| 9               |

---

![Figure 2. Flow of data processing.](image-url)
selecting the division parameters, it is necessary to ensure that each image object contains only one kind of object, and that the division size of image object is appropriate, neither general nor broken. The division size of MSS and TM images were set to 10–15 by testing, and the scale factor of OLI was set to 35. The shape factor is closely related to the color factor (Esch et al., 2010), and the sum of these two parameters is equal to 1. In order to make full use of spectral information while segmenting, we gave the shape factor a smaller weight. The compactness factor and the smoothness factor both belong to the shape factor. The smoothness mainly considers the edge of the shape, and the compactness considers the whole shape. Through many tests, the shape factor ranged from 0.1 to 0.3 and the compactness factor ranged from 0.5 to 0.7.

Object-based SVM classification

SVM is a machine learning method (Vapnik, 1995), and it has been widely used in the image classification field (Xiao et al., 2010; Yu et al., 2017). SVM projects data into one high dimensional space, then constructs the optimal hyperplane in the high dimensional space, and finally, classifies different data in one optimal plane (Brown, Lewis, & Gunn, 2000; Foody & Mathur, 2004).

Object-oriented SVM classification takes the image object as the smallest unit. Then, SVM classifies the image by considering the spectral and spatial information. In this article, the object and pixel-based integration remote sensing imagery classification system (OPICS), developed by the Chinese Academy of Sciences, was used to classify the remote sensing images. OPICS uses the SVM classifier constructed by the Gaussian radial basis kernel function. The kernel width, γ, and the penalty parameter, C, in the kernel function are the two necessary parameters (Devos, Ruckebusch, Durand, Duponchel, & Huvenne, 2009; Liu, Huang, Gong, & Wang, 2015) that have a direct impact on the accuracy of classification results. When the remote sensing images are processed for classification, the result will be better on the condition that C is 100 and γ is the reciprocal of the number of bands (Sun, Guo, Li, Lu, & Du, 2011). The number of MSS image bands that participated in the classification was 6, so γ was 1/6 and C was 100. The number of the TM/OLI image bands participating in the classification was 9, so γ was 1/9 and C was 100.

Classification post-processing

There are some uncontrollable factors during classifying since Landsat images are the mid-resolution and the resolution of MSS images is 80 m. It is necessary to make some reasonable adjustments about the results once classification is completed. The post-processing was done with ArcGIS 10.2 software, and includes the manual modification and logical analysis. The manual modification corrects the obvious errors in classification results compared to the remote sensing images and Google Earth images. The logical operation was directed mainly at the classification results of construction land. With the continuous economic development and population increase, the construction area is theoretically increasing. If a region was the construction land in a previous year, then the area will still be the construction land in the next year. If a region is not presently the construction land, and then the same region is not the construction land in the previous year.

Results and discussion

According to the land use situation of Weihai and the V-I-S model (Ridd, 1995), the land use of Weihai was divided into five types, that is, cultivated land, construction land, woodland, waters and aquaculture land (Bauer, Doyle, & Heinert, 2002). The Landsat images were processed according to Figure 2. The classification results are shown in Figure 3.

Accuracy of classification results

There were 200 verification points that were randomly selected from the categories of each period classification result, so the total verification points of each period image is 1,000. We used Google Earth images and original remote sensing images as references for verification (Sun et al., 2014; Yu et al., 2017). The classification results were analyzed with the overall kappa (OK), overall accuracy (OA), user’s accuracy (UA) and producer’s accuracy (PA) (Felbier et al., 2014; Sun et al., 2011; Yang et al., 2011). The results are shown in Figure 4.

In Figure 4(a), the OKs are equal to or greater than 83% and the OAs are equal to or greater than 85%. In Figure 4(b), most of the UAs and PAs in different periods are greater than 80%. The results show that the accuracy of the object-oriented SVM classification method is high, which provides a good basis for the analysis on land use and landscape pattern.

Land use analysis

Land use type, land use dynamics and land use transfer matrices (Feng et al., 2010; Yang, Zheng, Zhang, & Liu, 2013) were used to analyze land use changes in this study. The formula for land use dynamics is:

\[ K = \frac{U_b - U_a}{U_a} \times \frac{1}{T_{ab}} \times 100\% \]  

(1)

where \( K \) is the land use dynamics of a land use type in a study period; \( U_a \) is the area of a certain land use type at the beginning of the study period; \( U_b \) is the
area of a land use type at the end of the study period; and $T_{ab}$ is the study period in year.

The land use dynamics can be used to analyze the dynamic change of land use type, which sufficiently reflects the degree of regional land use changes. The land use transfer matrix assesses the area of a land use type converted to other types, as well as types for a certain period.

**Land use types analysis**

Land use patterns in different periods are generally different, and these land types reflect the pattern and speed of economic development in the region to a certain extent (Li et al., 2017; Wang & Li, 2007; Zhou & Wang, 2016). The correlation coefficient can be calculated between different land use types and different economic development indexes (Lacerda et al., 2016; Xie, 2004) by analyzing Figures 5(a) and 6, and the results are shown in Figure 7(a).

Figure 5(a,b) show the area and percentage of different land-use types, respectively. Figure 5(c,d) are respectively the area changes of different land use types and the dynamics of land use types. Figure 5 indicates that the cultivated land is the main type of land use in Weihai, with more than 3,000 km$^2$. Its area changed little from 1985 to 2000, but decreased faster each year from 2000 to 2015.
Figure 6 shows the economic development indexes for different periods. Figure 7 emphasizes the elevation of land use and landscape patterns with the economic development. Figures 6 and 7(a) suggest that Weihai’s economic development has shown an increasing trend. The correlation between cultivated land and economic development is relatively large with the correlation coefficients of 0.75 or more. The correlation between the economic aggregate and traffic mileage is very large, reaching more than 0.9. Therefore, it can be concluded that the regional economic development accelerated the use of cultivated land, resulting in a gradual reduction of the cultivated land area.

The construction land area exhibits an increasing trend. The growth rate reaches a maximum in 2000, after which the growth rate gradually decreases, but yet remains positive. The construction land area increased from 61 km² in 1985 to 799 km² in 2015, which means it increased 12 times during the past 30 years. As one can see from Figure 7(a), the construction land has a strong relationship with the regional economic development since the correlation coefficients are relatively large. Relative to other economic indicators, the correlation between construction land and economic aggregate is the smallest based on its coefficient. Due to China’s reform and opening up, the policy of Shandong Peninsula Blue Economic Zone as well as the China’s attention to marine economic development and rational use of those resources (Wang, 2013), Weihai’s economic development is growing rapidly. The increase of non-agricultural population, traffic mileage and enterprise’s quantity results in the increased construction land area.
Woodland is the second major land type, occupying about 20% of the total area. Woodland area is gradually declining. The area and rate of woodland reduction before 2000 were increasing, and the area and rate of reduction after 2000 were decreasing as indicated in Figure 5(c,d). This is because the national protecting forest policy saw success and people improved their awareness of environmental protection since 2000. It can also be seen from Figure 7(a) that the woodland area is closely related to the local economic development, especially with the non-agricultural population and enterprise quantity, since the correlation coefficients are greater than 0.9.

As we can see from Figure 5(a,b), the water area and aquaculture area are relatively small compared to the other land types. Water area was always around 300 km² but it declined a little from 2005 to 2015. Aquaculture area did not vary much before 2000; instead, it experienced an increase after 2000. Figure 7(a) also shows that the aquaculture land has a strong correlation with the economic aggregate and traffic mileage because the traffic development allows aquaculture products to be transported outwards, in turn promoting the use of aquaculture land.

**Land use transfer matrix analysis**

The land use transfer matrix shows the land transfer among different land use types from 1985 to 2015. Table 2 emphasizes that the changed cultivated land was transformed into the construction land and woodland. Before 2005, most of the reduced arable land was converted to forest, and part of it was converted to construction land. After 2005, this phenomenon reversed. The situation of woodland is similar to that of cultivated land. This phenomenon

---

*Figure 6. Economic development indexes.*

*Figure 7. Relevance of land use and landscape patterns with economic development.*
Table 2. Transfer matrix of land use change in different periods.

| Years        | Type          | Cultivated Land | Construction land | Woodland | Waters | Aquaculture Land |
|--------------|---------------|-----------------|-------------------|----------|--------|------------------|
| 1985 ~ 1990  | Cultivated land | 3,258.00        | 29.42             | 154.91   | 1.35   | 0.00             |
|              | Construction land | 0.00     | 61.65             | 0.00     | 0.00   | 0.00             |
|              | Woodland       | 192.29         | 2.76              | 1,108.54 | 0.00   | 0.00             |
|              | Waters         | 0.00           | 0.00              | 0.00     | 342.55 | 5.71             |
|              | Aquaculture Land | 0.00     | 0.00              | 0.00     | 3.59   | 178.98           |
| 1990 ~ 1995  | Cultivated land | 3,226.41        | 95.00             | 128.89   | 0.00   | 0.00             |
|              | Construction land | 0.00     | 98.84             | 0.00     | 0.00   | 0.00             |
|              | Woodland       | 195.31         | 7.89              | 1,060.25 | 0.00   | 0.00             |
|              | Waters         | 0.00           | 0.00              | 0.00     | 337.72 | 9.77             |
|              | Aquaculture Land | 0.00     | 0.00              | 0.00     | 1.42   | 183.27           |
| 1995 ~ 2000  | Cultivated land | 3,263.31        | 81.96             | 74.45    | 0.00   | 0.00             |
|              | Construction land | 0.00     | 201.73            | 0.00     | 0.00   | 0.00             |
|              | Woodland       | 169.00         | 35.43             | 979.85   | 2.15   | 4.86             |
|              | Waters         | 0.15           | 0.00              | 0.00     | 324.62 | 14.36            |
|              | Aquaculture Land | 0.00     | 0.00              | 0.00     | 42.97  | 150.06           |
| 2000 ~ 2005  | Cultivated land | 3,178.46        | 116.82            | 119.54   | 19.64  | 0.00             |
|              | Construction land | 0.00     | 319.12            | 0.00     | 0.00   | 0.00             |
|              | Woodland       | 187.12         | 18.10             | 846.85   | 0.00   | 2.23             |
|              | Waters         | 2.35           | 0.00              | 0.00     | 316.07 | 51.33            |
|              | Aquaculture Land | 0.00     | 0.00              | 0.00     | 28.53  | 140.76           |
| 2005 ~ 2010  | Cultivated land | 3,147.31        | 122.78            | 97.72    | 0.13   | 0.00             |
|              | Construction land | 0.00     | 454.04            | 0.00     | 0.00   | 0.00             |
|              | Woodland       | 67.70          | 35.70             | 860.25   | 2.74   | 0.00             |
|              | Waters         | 5.22           | 0.00              | 7.27     | 326.48 | 25.27            |
|              | Aquaculture Land | 0.00     | 0.00              | 0.64     | 3.94   | 189.74           |
| 2010 ~ 2015  | Cultivated land | 3,047.43        | 116.39            | 56.37    | 0.03   | 0.00             |
|              | Construction land | 0.00     | 612.52            | 0.00     | 0.00   | 0.00             |
|              | Woodland       | 75.46          | 68.08             | 822.34   | 0.00   | 0.00             |
|              | Waters         | 1.46           | 2.45              | 0.00     | 294.27 | 35.11            |
|              | Aquaculture Land | 0.00     | 0.00              | 0.00     | 8.82   | 206.19           |

shows that people have increased their awareness of using and protecting cultivated land and woodland, resulting in a positive effect.

The main sources of increased construction land are woodland and cultivated land. From 1985 to 2015, the construction land increased by 732 km², of which 562 km² was converted from cultivated land, and 168 km² from woodland, with a little from waters. As determined from Figures 5 to 7 and Table 2, the increase in non-agricultural population led to an increase in construction land, such as residential areas and corporate industries, which promoted economic development and increased economic aggregates. The increase in construction land has led to a decrease in woodland and cultivated land.

The mutual change is what drove the changes of these two land types. However, there is still a portion of waters that have turned into cultivated land, woodland, and construction land. The aquaculture area has led to an increase in construction land, such as residential areas and corporate industries, which promoted economic development and increased economic aggregates. The increase in construction land has led to a decrease in woodland and cultivated land.

The landscape pattern analysis

Researchers commonly study the landscape pattern changes by analyzing the landscape index calculated from the land use classification (Li et al., 2014; Wu, 2000, 2004; Yang, Zheng, & Chen, 2014). Fragstats, one landscape analysis software, was used to calculate the landscape index. We studied the landscape pattern changes of Weihai from 1985 to 2015 for two aspects which are land use level and landscape level. In the analysis of land use level, the landscape indexes selected are the patch density (PD), the largest patch index (LPI), the edge density (ED), the landscape shape index (LSI), and the mean Euclidean nearest neighbor distance (ENN_MN). In the landscape level analysis, the landscape indexes selected are PD, LSI, ENN_MN and division (Feng et al., 2010; Jia et al., 2016; Peng et al., 2006; Yu et al., 2017).

Analysis of landscape patterns at the level of land use types

The greater the LPI is, the greater the impact of land type on the landscape is. Table 3 states the LPI of cultivated land is always greater than 60%, which is similar to the percentage of cultivated land. The cultivated land’s impact on the entire landscape pattern is greatest. The ENN_MN represents the degree of patch agglomeration. The ENN_MN in waters and aquaculture land shows a yearly decreasing trend, indicating that they have become more concentrated. This suggests that people’s protection of water areas is improving and the aquaculture industry is becoming more scalable.

These three indicators PD, ED and LSI are measures of landscape fragmentation and internal structural complexity. The ED and LSI of construction land both show a yearly increasing trend. The trend
Table 3. Landscape indexes at land use type level in different periods.

| Year | Type          | PD     | LPI    | ED     | LSI     | ENN_MN  |
|------|---------------|--------|--------|--------|---------|---------|
| 1985 | Cultivated land | 0.1346 | 62.7304 | 26.9114 | 66.4667 | 150.0568 |
|      | Construction land | 0.1475 | 0.0458 | 1.3526 | 34.8590 | 366.4432 |
|      | Woodland      | 0.4587 | 2.0703 | 23.5029 | 86.6363 | 203.6973 |
|      | Waters        | 0.2934 | 1.2079 | 8.2281 | 56.2566 | 439.1239 |
|      | Aquaculture land | 0.3050 | 0.0978 | 3.8834 | 50.2296 | 481.5085 |
| 1990 | Cultivated land | 0.4506 | 61.8497 | 38.8764 | 92.5625 | 110.7007 |
|      | Construction land | 0.3539 | 0.1417 | 3.6135 | 53.8810 | 284.8659 |
|      | Woodland      | 1.5094 | 1.4080 | 35.0811 | 132.4342 | 148.7494 |
|      | Waters        | 0.4863 | 0.7261 | 4.9417 | 52.9600 | 310.0114 |
|      | Aquaculture land | 0.6672 | 1.1996 | 6.1879 | 59.2146 | 405.2277 |
| 1995 | Cultivated land | 0.6208 | 61.1698 | 31.3910 | 74.0285 | 108.9370 |
|      | Construction land | 0.5154 | 0.4117 | 6.9100 | 72.2816 | 239.6977 |
|      | Woodland      | 1.2592 | 1.7327 | 25.5115 | 104.0598 | 185.2631 |
|      | Waters        | 1.0073 | 0.6835 | 8.3064 | 78.0408 | 286.7394 |
|      | Aquaculture land | 0.6518 | 1.1421 | 5.4375 | 53.6949 | 339.7335 |
| 2000 | Cultivated land | 0.4627 | 60.2838 | 38.4699 | 88.6897 | 107.4604 |
|      | Construction land | 0.5275 | 0.6601 | 7.5734 | 75.0460 | 233.3136 |
|      | Woodland      | 1.5487 | 0.9156 | 31.5710 | 137.0836 | 162.2997 |
|      | Waters        | 0.9926 | 0.6752 | 7.5744 | 78.5963 | 266.3789 |
|      | Aquaculture land | 0.6021 | 1.1470 | 5.7038 | 55.7505 | 346.8859 |
| 2005 | Cultivated land | 0.4645 | 61.0687 | 27.8769 | 63.6545 | 113.2904 |
|      | Construction land | 0.5431 | 1.0178 | 9.2864 | 78.9921 | 226.4612 |
|      | Woodland      | 0.8252 | 1.1010 | 17.4702 | 86.7781 | 225.3814 |
|      | Waters        | 1.2000 | 0.3433 | 8.8642 | 81.7562 | 269.6437 |
|      | Aquaculture land | 0.4752 | 1.2904 | 4.3014 | 43.1547 | 238.3449 |
| 2010 | Cultivated land | 0.7478 | 58.7355 | 36.4457 | 84.4898 | 104.1594 |
|      | Construction land | 1.2712 | 1.2332 | 20.5452 | 121.7683 | 184.5285 |
|      | Woodland      | 1.0454 | 1.1278 | 36.6836 | 89.4676 | 246.8691 |
|      | Waters        | 1.8971 | 0.2490 | 11.5947 | 103.4329 | 207.3663 |
|      | Aquaculture land | 0.5538 | 0.5004 | 5.4919 | 58.3314 | 253.7953 |
| 2015 | Cultivated land | 0.8641 | 49.3392 | 77.1690 | 90.6891 | 90.2399 |
|      | Construction land | 3.9418 | 2.1136 | 37.3510 | 176.3333 | 128.2914 |
|      | Woodland      | 6.4321 | 1.2653 | 52.3313 | 213.6108 | 105.5055 |
|      | Waters        | 6.0229 | 0.2423 | 28.1283 | 207.3663 | 131.2557 |
|      | Aquaculture land | 1.8318 | 0.3812 | 10.0778 | 108.8801 | 211.2280 |

Analysis of landscape patterns at landscape level

Figure 7(b) shows the correlation between landscape pattern indexes and economic development. Figure 8 shows the landscape indexes at the landscape level. From Figures 7(b) and 8(a), we can see that the PD is increasing as a whole, and PDs have a strong correlation with the local economic development. With the development of the economy and the influence of human activities, the land use is increasingly more diversified. The patch density also becomes larger, and the overall landscape pattern is more fragmented.

The correlation coefficients of both LSI and division with economic development are relatively small. It can be found that the correlation between LSI and company’s quantity is relatively large, and the correlation between division and the economic aggregate is relatively large. The change of LSI was variable, but it became stable after 2010. This indicates that with the increase of enterprises, the spatial distribution of their factory buildings is disorderly, which has caused the complex and changeable internal structure of the landscape. Division is an indicator of the degree of landscape dispersion. The change of division shows a decreasing trend first and then increasing. With the development of the regional economy, these factors, such as non-agricultural population, number of enterprises and transportation development, have led to the overall landscape pattern exhibiting a trend of dispersal after gathering. The trend of ENN_MN is decrease, increase and then decrease. Its correlation coefficients with various economic factors are similar. Under the combined effects of economic factors and human factors, the internal structure of the landscape pattern presents a trend of aggregation, decentralization and re-aggregation. The land use is also increasingly planned and rational.

Construction land, also known as the impervious surface, is an important part of urban land features and also an indicator of urban development. It also demonstrates that with the development of the economy, especially the increase of the number of the non-agricultural population and enterprises, the annual construction land increases and the landscape internal structure becomes more complex. The PD, ED and LSI in cultivated land and woodland varied before 2005, but they have the same trend of change. After 2005, they continually increased. By analyzing the transfer matrix of land use, we can see that there are many mutual transformations between these two, and a larger part of them was converted into construction land. It also shows that under the influence of human activities, the internal landscape structure complexity is growing.
provides the scientific reference significance for the future planning and development of the city (Dougherty, Dymond, Goetz, Jantz, & Goulet, 2004; Linden & Hostert, 2009; Taherzadeh, Shafri, Mansor, & Ashurov, 2012). In this article, the three landscape pattern indexes of architectural land are selected to study the development of the city, that is, PD, LPI and ENN_MN. The results are shown in Figure 9.

As shown in Figure 3, there are only some scattered areas of construction land in 1985. From 1985 to 2005, the construction land increased on the basis of the original land year by year. After 2005, besides the designated construction sites, new construction sites began to emerge and continue expansion. PD and LPI show an increasing trend, but LPI began to decrease from 2010 to 2015, indicating that the number of construction land patches gradually increased and the area of original industrial sites continued to expand. After 2010, the growth of enterprises slowed down, so construction lands could no longer expand significantly. Increasing patches can reduce ENN_MN and then increase ENN_MN. ENN_MN shows a trend of decrease, increase and decrease, indicating that the construction land experienced a process of expansion.

Figure 8. Landscape indexes at the landscape level.

Figure 9. Landscape indexes of construction land.
gathering and re-expansion. It also notes that the development of Weihai has experienced the expansion, aggregation and re-expansion procedure.

Conclusions

Landsat MSS/TM/OLI images of Weihai from 1985 to 2015 were processed to extract the land use types of different periods with the object-oriented SVM method. The land use classification results were used to calculate the landscape pattern indexes for different periods. We calculated the correlation indexes between land use and landscape patterns with the regional economic development. The changes of land use landscape were analyzed by considering local economic development.

We randomly selected 1,000 verification points for each classification to verify the classification results. The results show that the OKs are greater than 83% and the OAs are greater than 85%. Over 80% of the values of both PA and UA for different land use types are greater than 85% in the different periods. This result shows that the object-oriented SVM classification method has the high accuracy, which can be used to classify remote sensing images. This result provides a good basis for the analysis of land use types and landscape pattern in Weihai.

In the past 30 years, the land use of Weihai has changed immensely. The areas of cultivated land and woodland continue to decrease. Cultivated land converted to woodland, and vice versa, and the conversion in the later period became less. The speed of reduction decreased, indicating that they were well protected. The reduction of cultivated land and woodland is mainly related to the regional economic development. The reduction of cultivated land is mainly related to the economic aggregates and traffic development. The diminished woodland can be correlated with an increase of non-agricultural population and enterprises. The construction land in 2015 increased 12 times compared to that in 1985. The expansion of construction land mainly comes from the cultivated land and woodland. The construction land is closely related to the economic development, and the combined effects of various economic factors have led to the increase in the construction land. The water area changed relatively little and was always around 300 km². However, the economic development still leads to the reduction of water at a certain degree. The traffic development resulted in increasing aquaculture land mainly in coastal waters since the aquaculture products were exported outward after 2005.

Cultivated land is the main landscape type in Weihai. The internal structure of cultivated land and woodland is becoming more complex. The water area is becoming more concentrated and the aquaculture land is becoming more large-scale. The construction land experienced expansion, gathering and re-expansion, which shows that the development of Weihai has undergone the process of expansion-aggregation-expansion. This economic development, especially the increase of economic aggregates and number of enterprises, has decentralized the landscape pattern of Weihai as a whole. The internal structure is relatively complex and the fragmentation of land use is increasing.

We analyzed the changes in Weihai’s land use and landscape pattern by combining the local economic development with the remote sensing technique. The results show that remote sensing plays an important role in studying urban development. Although Weihai enjoys the rapid economic development, the land use still has unreasonable phenomena. The destruction of forest land and cultivated land is serious, and the planning of construction land is insufficient. This study provides a scientific basis for the sustainable development of Weihai and has the important guiding significance for the rational use of land, environmental protection and new urbanization construction.

The analysis of land use and landscape pattern has an important guiding significance for the sustainable development of a city. The research method of this article has certain scientific guiding significance for the city’s research in this field. For other regions, land use types need to be analyzed firstly, and then the Object-SVM Classification method will train land use samples which obtained from the segmentation results and classify remote sensing image. After that the land use and landscape correlation indexes will be calculated based on the classification results of remote sensing images, and the land use status and landscape pattern changes will be analyzed by the calculated data. The results of analysis could be used to plan and adjust the urban development of a region. The research method of this article also has some limitations, and it is difficult to operate. How to simplify the operation process is the direction of our next research and efforts.

Acknowledgments

We thank the anonymous reviewers for their helpful comments. We are very grateful to USGS for providing Landsat images. This study was supported by the National Natural Science Foundation of China (Grant Nos. 41774001 and 41374009), the High-resolution Remote Sensing Mapping Application Demonstration System and the SDUST Research Fund (Grant No. 2014TDJH101).

Author contributions

Jinyun Guo and Qingying Lin conceived and designed the experiments; Qingying Lin and Heng Wang performed the experiments; Qingying Lin, Jinfeng Yan and Jinyun Guo worked on the interpretation of results and the final version of this contribution.
Disclosure statement

No potential conflict of interest was reported by the authors.

Funding

This work was supported by the National Natural Science Foundation of China [41374009,41777601]; High-resolution Remote Sensing Mapping Application Demonstration System and the SDUST Research Fund [2014TD]H101.

References

Almeida, C.A.D., Coutinho, A.C., Esquerdo, J.C.D.M., Adami, M., Venturieri, A., Diniz, C.G., . . . Gomes, A.R. (2016). High spatial resolution land use and land cover mapping of the Brazilian Legal Amazon in 2008 using Landsat-5/TM and MODIS data. Acta Amazonica, 46(3), 291–302. doi:10.1590/1809-4392201505504

Bai, X.Y., Chen, X.H., & Wang, Z.L. (2015). A study on land use information extraction based on object-oriented classification technology and temporal-spatial variation. Remote Sensing Technology and Application, 30(4), 798–809. doi:10.11873/j.issn.1004-0323.2015.4.0798

Baret, F., & Guyot, G. (1991). Potentials and limits of vegetation indices for LAI and PAR assessment. Remote Sensing of Environment, 35(2–3), 161–173. doi:10.1016/0034-4257(91)90009-U

Bauer, M.E., Doyle, J.K., & Heinert, N.J. (2016). A study on land use information extraction based on object-oriented classification technology and temporal-spatial variation. Remote Sensing Technology and Application, 30(4), 798–809. doi:10.11873/j.issn.1004-0323.2015.4.0798

Bai, X.Y., Chen, X.H., & Wang, Z.L. (2015). A study on land use information extraction based on object-oriented classification technology and temporal-spatial variation. Remote Sensing Technology and Application, 30(4), 798–809. doi:10.11873/j.issn.1004-0323.2015.4.0798

Bauer, M.E., Doyle, J.K., & Heinert, N.J. (2002). Impervious surface mapping using satellite remote sensing. Geoscience and Remote Sensing Symposium 2002 (IGARSS), 4, 2334–2336. doi:10.1109/IGARSS.2002.1026536

Brown, M., Lewis, H.G., & Gunn, S.R. (2000). Linear spectral mixture models and support vector machines for remote sensing. IEEE Transactions on Geoscience & Remote Sensing, 38(5), 2346–2360. doi:10.1109/36.868891

Chang, C.C., & Lin, C.J. (2011). LIBSVM: A library for support vector machines. ACM Transactions on Intelligent Systems and Technology, 2(3), 1–39. doi:10.1145/1961189.1961199

Chang, X., Guo, J., & Wang, X. (2011). Detecting the amount of eroded and deposited sand using DhSAR. Terrestrial, Atmospheric and Oceanic Sciences, 22(2), 187–194. doi:10.3339/TAC.2010.08.13.02(TibXS)

Devos, O., Ruckebusch, C., Durand, A., Duponchel, L., & Huyvenne, J.P. (2009). Support vector machines (SVM) in near infrared (NIR) spectroscopy: Focus on parameters optimization and model interpretation. Chemometrics and Intelligent Laboratory Systems, 96(1), 27–33. doi:10.1016/j.chemolab.2008.11.005

Dougherty, M., Dymond, R.L., Goetz, S.J., Jantz, C.A., & Goulet, N. (2004). Evaluation of impervious surface estimates in a rapidly urbanizing watershed. Photogrammetric Engineering and Remote Sensing, 70(11), 1275–1284. doi:10.14358/pers.70.11.1275

Du, W., Liu, X., Guo, J., Shen, Y., Li, W., & Chang, X. (2019). Analysis of the melting glaciers in Southeast Tibet by ALOS-PALSAR data. Terrestrial, Atmospheric and Oceanic Sciences, 30(1), 1–13. doi:10.3319/TAO.2018.07.09.03

Esch, T., Thieli, M., Schenk, A., Roth, A., Muller, A., & Dech, S. (2010). Delineation of urban footprints from TerraSAR-X data by analyzing speckle characteristics and intensity information. IEEE Transactions on Geoscience & Remote Sensing, 48(2), 905–916. doi:10.1109/TGRS.2009.2037144

Felbier, A., Esch, T., Heldens, W., Marconcini, M., Zeidler, J., Roth, A., . . . Taubenböck, H. (2014). The global urban footprint - processing status and cross comparison to existing human settlement products. Geoscience and Remote Sensing Symposium (IGARSS), 4816–4819. doi:10.1109/IGARSS.2014.6947572

Feng, Y.X., Luo, G.P., Zhou, D.C., Han, Q.F., Lu, H., Xu, W.Q., . . . Li, Y.Z. (2010). Effects of land use change on landscape pattern of a typical arid watershed in the recent 50 years: A case study on Manas RiverWatershed in Xinjiang. Acta Ecologica Sinica, 30(16), 4295–4305.

Foody, G.M., & Mathur, A. (2004). A relative evaluation of multiclass image classification by support vector machines. IEEE Transactions on Geoscience & Remote Sensing, 42(6), 1335–1343. doi:10.1109/TGRS.2004.827257

Gao, X.W., Fei, X.Y., & Han, B. (2014). Land use change and object-oriented driving force of Lianyungang coastal zone. Marine Science, 38(4), 81–87. doi:10.11759/ hyks20121116001

Han, Y.W., & Feng, S.C. (2013). A study on dynamic land use monitoring based on object-oriented classification technique. Bulletin of Surveying and Mapping, (62), 170–173.

Jia, W.C., Jia, X.Y., Li, F.Y., & Wang, J.L. (2009). Dynamic changes of land use fractal characteristic in Weihai, China. Progress in Geography, 28(2), 193–198.

Jia, Y., Yan, L., Yu, F., & Cao, L.L. (2016). Land use change and landscape pattern of typical semi-arid and arid watershed of western China: A case study on Shiyang River Basin. Remote Sensing Information, 31(5), 66–73.

Kasimu, A., Tateishi, R., & Hoan, N.T. (2009). Global urban characterization using population density, DMSP and MODIS data. 2009 Joint Urban Remote Sensing Event, 1–7. doi:10.1109/URS.2009.5137544

Lacerda, M.P.C., Dematté, J.A.M., Sato, M.V., Fongaro, C. T., Gallo, B.C., & Souza, A.B. (2016). Tropical texture determination by proximal sensing using a regional spectral library and its relationship with soil classification. Remote Sensing, 8, 701. doi:10.3390/rs8090701

Lackner, M., & Conway, T.M. (2014). Determining land-use information from land cover through an object-oriented classification of IKONOS imagery. Canadian Journal of Remote Sensing, 34(2), 77–92. doi:10.5589/m08-016

Li, C.X., Wu, K.N., Liu, P.J., Song, W., Gao, X.Y., & Wu, J.H. (2017). Study on land use change and socioeconomic driving forces - taking Beijing-Tianjin-Hebei region as an example. Jiangsu Agricultural Sciences, 45(12), 279–283.

Li, X., Ding, J.L., Wang, G., Zhang, Y.J., Zhang, Z., & Yan, X.Y. (2014). Change of LUCc and characteristic of landscape pattern in a typical oasis in Turkmengistan. Journal of Desert Research, 34(1), 260–267. doi:10.7522/j.issn.1000-694X.2013.00307

Linden, V.D., & Hostert, P. (2009). The influence of urban structures on impervious surface maps from airborne hyperspectral data. Remote Sensing of Environment, 113 (11), 2298–2305. doi:10.1016/j.rse.2009.06.004

Liu, C., Huang, H., Gong, P., & Wang, X. (2015). Joint use of ICESat/GLAS and Landsat data in land cover classification: A case study in Henan Province, China. IEEE Journal of Selected Topics in Applied Earth Observations & Remote Sensing, 8(2), 511–522. doi:10.1109/JSTARS.2014.2327032

Liu, X.R., Zhang, L., Yang, L., Qiu, Y., & Wang, J. (2016). The effects of ecological cropland-conversion on
landscape pattern change and its topography driving in loess hilly region. Research of Soil and Water Conservation, 23(1), 103–109.

Long, L., Chen, L., Wang, X., & Zhao, J. (2011). Use of Landsat TM/ETM+ data to analyze urban heat island and its relationship with land use/cover change. International Conference on Remote Sensing, Environment and Transportation Engineering, 922–927. doi:10.1109/RSETE.2011.5964429

Manjunath, B.S., & Chellappa, R. (1991). Unsupervised texture segmentation using Markov random field models. IEEE Transactions on Pattern Analysis & Machine Intelligence, 13(5), 478–482. doi:10.1109/34.134046

McFeeters, S.K. (1996). The use of the normalized difference water index (NDWI) in the delineation of open water features. International Journal of Remote Sensing, 17(7), 1425–1432. doi:10.1080/01431169608948714

Nussbaun, S., & Menz, G. (2008). eCognition image analysis software, (pp. 29–39). Berlin: Springer Netherlands.

Pasolli, E., Melgani, F., Tuia, D., Pacifici, F., & Emery, W.J. (2014). SVM active learning approach for image classification using spatial information. IEEE Transactions on Geoscience & Remote Sensing, 52(4), 2217–2233. doi:10.1109/TGRS.2013.2258676

Peng, J., Wang, Y.L., Zhang, Y., Ye, M.T., & Wu, J.S. (2006). Research on the influence of land use classification on landscape metrics. Acta Geographica Sinica, 61(2), 157–168. doi:10.11211/jxb200602005

Ridd, M.K. (1995). Exploring a V-I-S (Vegetation -Impermeable Surface-Soil) model for urban ecosystem analysis through remote sensing: Comparative anatomy for cities. International Journal of Remote Sensing, 16(12), 2165–2185. doi:10.1080/01431169508954549

Sai, L.L., Wang, T., Chen, K., Qu, Y.H., & He, F.H. (2016). Analysis on land use and land cover change (2000-2010) and prediction using Markov chain model in Weihai city in China. Journal of Ludong University (Natural Science Edition), 32(2), 162–167.

Smiraglia, D., Ceccarelli, T., Bajocco, S., Perini, L., & Salvati, L. (2015). Unraveling landscape complexity: Land use/land cover changes and landscape pattern dynamics (1954-2008) in contrasting peri-urban and agro-forest regions of northern Italy. Environmental Management, 56(4), 1–17. doi:10.1007/s00267-015-0533-x

Sun, Z.C., Guo, H.D., Li, X.W., Lu, L.L., & Du, X.P. (2011). Estimating urban impervious surfaces from Landsat-5 TM imagery using multilayer perceptron neural network and support vector machine. Journal of Applied Remote Sensing, 5(1), 053501. doi:10.1117/1.3539767

Sun, Z.C., Leinenkugel, P., Guo, H.D., Huang, C., & Kuenzer, C. (2014). Extracting the rubber distribution from Landsat remote sensing imagery using the C5.0 decision tree method. Journal of Applied Remote Sensing, 11(2), 026011. doi:10.1117/1.JRS.11.026011

Taherzadeh, E., Shafri, H.Z.M., Mansor, S., & Ashurov, R. (2012). A comparison of hyperspectral data and worldview-2 images to detect impervious surfaces. Hyperspectral Image and Signal Processing: Evolution in Remote Sensing (WHIPERS), 1–4. doi:10.1109/WHIPERS.2012.6874305

Taubenbock, H., Esch, T., Felbier, A., Wiesner, M., Roth, A., & Deich, S. (2012). Monitoring urbanization in megacities from space. Remote Sensing of Environment, 117, 162–176. doi:10.1016/j.rse.2011.09.015

Townshend, J.R.G., & Justice, C.O. (1986). Analysis of the dynamics of African vegetation using the normalized difference vegetation index. International Journal of Remote Sensing, 7(11), 44–49. doi:10.1080/01431168608948946

Tsang, I.W., Kwok, J.T., & Cheung, P.M. (2005). Core vector machines: Fast SVM training on very large data sets. Journal of Machine Learning Research, 6(1), 363–392.

Vapnik, V.N. (1995). The nature of statistical learning theory. IEEE Transactions on Neural Networks, 8(6), 988–999. doi:10.1109/TNN.1997.641482

Wang, F.M., & Li, Z.D. (2007). Study on local government behavior in regional economic development - take Shandong Jiaodong Peninsula manufacturing base construction as an example. Industrial Technology and Economy, 26(9), 2–6.

Wang, Y. (2013). Study on the development of urban circular economy in the construction of blue economic zone in Shandong Peninsula (Master’s Dissertation). Shandong Normal University.

Wei, Y., Liu, Z.M., Song, Y.Y., & Chen, Y. (2008). Spectral mixture analysis of impervious surface in Changchun, China based on normalized image. International Workshop on Education Technology and Training 2008 and 2008 International Workshop on Geoscience and Remote Sensing. ETT and GRS. IEEE, 1, 815–818. doi:10.1109/ETTandGRS.2008.248

Wu, J.G. (2000). Landscape ecology. Beijing: Higher Education Press.

Wu, J.G. (2004). Effects of changing scale on landscape pattern analysis: Scaling relations. Landscape Ecology, 19(2), 125–138. doi:10.1023/B:LAND.0000021711.40074.ee

Xiao, A., Zhao, W.J., Hu, D.Y., Liu, L.G., & Li, J.C. (2010). Remote sensing information extraction base on object-oriented and support vector machines. Science of Surveying and Mapping, 35(5), 154–157.

Xie, M.W. (2004). The relation of covariance, correlation coefficient and correlation. Journal of Application of Statistics and Management, 23(3), 33–36.

Yang, J.C., Li, G.X., Gong, L.X., Wang, N., & Zhang, B. (2012). Status and causes of beach erosion in Weihai, Shandong Province. Periodical of Ocean University of China, 42(12), 97–106.

Yang, X., Chen, R., & Zheng, X.Q. (2015). Simulating land use change by integrating ANN-CA model and landscape pattern indices. Geomatics Natural Hazards & Risk, 7(3), 1–15. doi:10.1080/19475705.2014.1001797

Yang, X., Zheng, X.Q., & Chen, R. (2014). A land use change model: Integrating landscape pattern indexes and Markov-CA. Ecological Modelling, 283(7), 1–7. doi:10.1016/j.ecolmodel.2014.03.011

Yang, Y., He, C., & Du, S. (2011). Improving the support vector machine-based method to map urban land of China using DMSP/OLS and SPOT VGT data. Geoscience and Remote Sensing Symposium (IGARSS), 2141–2144. doi:10.1109/IGARSS.2011.6049589

Yang, Y.T., Zheng, D., Zhang, X.Q., & Liu, Y. (2013). The spatial coupling of land use changes and its environmental effects on Hotan Oasis during 1980-2010. Acta Geographica Sinica, 68(6), 813–824.

Yu, S.S., Sun, Z.C., Guo, H.D., Zhao, X.W., Sun, L., & Wu, M.F. (2017). Monitoring and analyzing the spatial dynamics and patterns of megacities along the Maritime Silk Road. Journal of Remote Sensing, 21(2), 111–121. doi:10.11834/jrs.20176031

Zhou, N., & Wang, Y.P. (2016). Weihai statistical year book (pp. 9–12). Weihai: Weihai Bureau of Statistics.