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Supplementary Materials: Spatial Patterns and Driving Forces of Greenhouse Land Change in Shouguang City, China

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1. Method

1.1. Image Pre-Processing

In the feature extraction step, preprocessed images were subject to a Kauth-Thomas transformation (also called a 'tasselled cap transformation'), computation of normalized difference vegetation index (NDVI), a Karhunen-Loeve transformation, and a minimum noise fraction (MNF) rotation.

Kauth-Thomas transformation is a linear transformation that rotates coordinate space. After rotation, coordinate axes point in the direction most closely related to ground features. Thus, Kauth-Thomas transformation is able to identify the features of vegetation and soil in multispectral space. Three sub-images representing brightness, greenness, and moisture were separately generated after transformation.

The NDVI denotes reflectivity of vegetation in near-infrared and red bands. This index is the optimal indicator for vegetation growth status and coverage, as it can eliminate the impact of altitude angle, satellite observation angle, terrain, and radiation change induced by cloud shadows or other atmospheric conditions. The formula used to calculate NDVI is as follows:

$$NDVI = \frac{NIR - R}{NIR + R} \tag{1}$$

In this expression, NIR denotes band 4 (near-infrared) in Enhanced hematic mapper (ETM) images, while R denotes band 3 (red).

The Karhunen-Loeve transformation is based on statistical properties and can be used to generate a new multispectral image by performing linear combinations using transformation matrices. This transformation can achieve data compression, noise separation, and image enhancement, although the amount of information contained in the principal components of new bands will gradually decrease. Results show that the first principal component contained the largest amount of information, accounting for 86.78% of the total, while the amount of information in the second principal component accounted for 12.21%. Over 98% of the information was contained in these two components, while the remaining component was almost entirely made up of noise.

MNF rotation was used to determine the dimensionality of image data (i.e., the number of bands), to eliminate noise, and reduce the computational work of subsequent processing. This rotation is essentially a double-cascaded principal component analysis (PCA) transformation, as the elements of vectors obtained have no correlation with each other. A large amount of information will be contained in the first component; as the number of bands increases, image quality gradually deteriorates, and image data subsequent to MNF rotation are ranked in descending order on the basis of their signal-to-noise ratios. MNF rotation is usually used for the removal of noise, feature extraction, the detection of changes, and to reduce data dimensionality. In this study, we obtained seven bands following MNF rotation; the first four of these were selected for subsequent processing as they contained 99.99% of information.

1.2. Mathematical Description of a Support Vector Machine (SVM)

Assuming samples are (x_i, y_i) (where x_i is the input space of potential observations, and y_i is the possible decision space) the general form of linear discriminant function is $g(x) = w \cdot x + b$. Thus, the following constraint is applied:

$$\left.\begin{cases} y_i\left[\left(w \cdot x_i\right) + b\right] \geq 1 - \xi_i \\ \xi_i \geq 0 \end{cases}\right\} \left(i = 1, \cdots, l\right) \tag{2}$$

Based on this expression, we need to find the minimum from the following:

$$\Phi\left(w, \xi\right) = \frac{1}{2}\left(w \cdot w\right) + C\left(\sum_{i=1}^{n} \xi_i\right) \tag{3}$$

In this expression, $\xi_i \geq 0$ is a relaxation term. According to duality theory, this problem can be converted into an extremum problem of the quadratic function. The following additional constraint is applied:

$$\begin{cases} \sum_{i=1}^{l} y_i \alpha_i \\ 0 \leq \alpha_i \leq C \end{cases} \qquad (i = 1, \cdots, l) \tag{4}$$

In this expression, $\alpha_i > 0$ is the Lagrange coefficient, and $C > 0$ is a specified constant. Building on this, we need to find the maximum in the following:

$$W\left(\alpha\right) = \sum_{i=1}^{l} \alpha_i - \frac{1}{2} \sum_{i,j=1}^{l} \alpha_i \alpha_j y_i y_j \left(x_i \cdot x_j\right) \tag{5}$$

After solving the problem above (in 5), the following optimal discriminant function can be used for classification:

$$f\left(x\right) = \operatorname{sgn}\left(\sum_{i=1}^{l} \alpha_i y_i \left(x_i \cdot x\right) + b\right) \tag{6}$$

1.3. Training Sample Selection

Using the characteristics of remote sensing (RS) images, the seven types of ground features discussed in the main text were selected with reference to maps and the present land use characteristics of the study area. Samples were selected according to the characteristics of different ground features. Thus, in false color composite images (bands 4, 3, and 2), land use for greenhouses land was a pink color, with a relatively regular shape, while other arable land was bright red, forest was dark brown, grassland was dark red, areas of water were sky blue, dark blue, white, or black, and construction land had an off-white color and non-uniform tone (Figure S1). Samples selected should encompass the ground characteristics of different spectral features, in order to ensure a comprehensive sampling approach.

Next, using selected samples, we analyzed the separability of the new image synthesized after MNF rotation, Kauth-Thomas transformation, computation of NDVI, and extraction of textural features. Separability between any two types of ground features was calculated, with ensuing values ranging between 0 and 2. Although values larger than 1.8 indicate that corresponding ground feature types are easily distinguished from each other, when values are equal to, or smaller than, 1.8, reclassification following merger of the two feature types is recommended. Our calculation results show that the separability between any two types always exceeded the 1.8 value threshold in 2000, 2010, and 2015. Thus, classification was performed in this study with the SVM algorithm.

1.4. Classification Accuracy

Classification accuracy is the ratio between the number of correct classifications and total sample size. Thus, this statistic represents the probability of consistency between a classification result and actual type for every random sample. The Kappa coefficient is used to evaluate the degree of agreement between actual type and the classification result; this coefficient is able to quantitatively determine alterations in quantity, location, and comprehensive information (i.e., lost spatial information) during the course of landscape change, thereby revealing spatial variations.

Table S1. Properties of downloaded ETM images.

	Landsat 7 ETM images
Acquisition date	16 April 2000 25 April 2010 3 May 2015
Available number of bands	8
Spatial resolution (in m)	30 m (panchromatic band 15 m/thermal infrared band 60 m)
Spectral resolution (in μm)	Blue: (0.45–0.52) Green: (0.52–0.60) Red: (0.63–0.69) NIR: (0.76–0.90)

Notes: ETM data comprise eight bands. Of these, bands 1–5 and 7 are multispectral (i.e., their spatial resolution is 30 m), band 6 is thermal infrared (i.e., spatial resolution is 120 m), and band 8 is panchromatic (spatial resolution is 15 m).

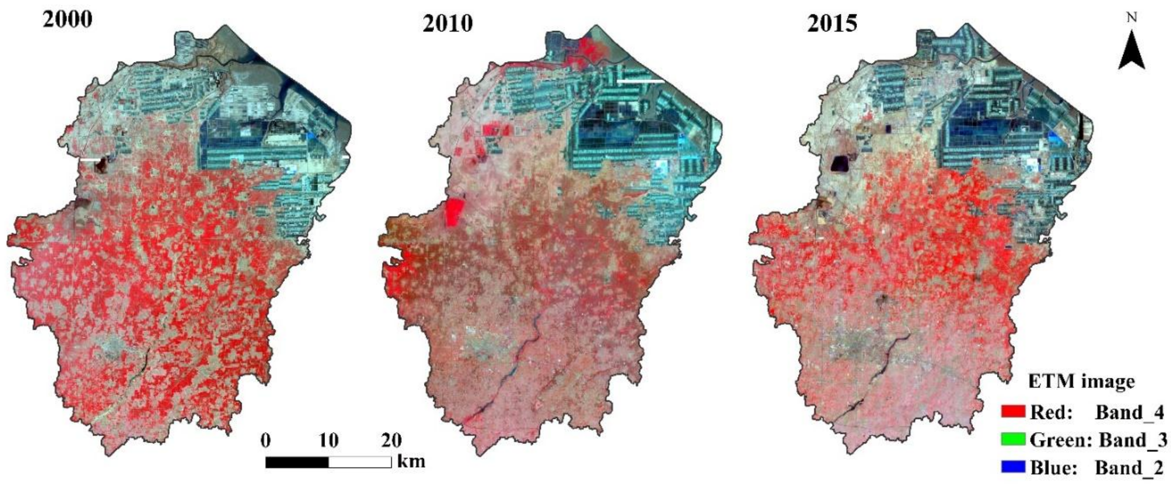

Figure S1. False color (i.e., bands 4, 3, and 2) composite image maps of Shouguang in 2000, 2010, and 2015.