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Development of a 1-km landcover dataset of China using AVHRR data

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Abstract

This paper describes the development of a 1-km landcover dataset of China by using monthly NDVI data spanning April 1992 through March 1993. The method used combined unsupervised and supervised classification of NDVI data from AVHRR. It is composed of five steps: (a) unsupervised clustering of monthly AVHRR NDVI maximum value composites is performed using the ISOCLASS algorithm; (b) preliminary identification is carried out with the addition of digital elevation models, eco-region data and a collection of other landcover/vegetation reference data to identify the clusters with single landcover classes; (c) re-clustering is performed of clusters with size greater than a given threshold value and containing two or more disparate landcover classes; (d) cluster combining is performed to combine all clusters with a single landcover class in one cluster, and all other clusters into one mixed cluster; and (e) supervised classification is used to carry out post-classification of the mixed cluster generated in the previous step by using the maximum likelihood algorithm and the identified single landcover classes of the previous step as training data. The classification is based on extensive use of computer-assisted image processing and tools, as well as the skills of the human interpreter to take the final decisions regarding the relationship between spectral classes defined using unsupervised methods and landscape characteristics that are used to define landcover classes. © 1999 Elsevier Science B.V. All rights reserved.

Keywords: landcover; dataset; China; AVHRR; Normalised Difference Vegetation Index (NDVI)

1. Introduction

Landcover/landuse is one of the main factors that have a great impact on the natural environment and the social and economic activities of human beings. Multi-temporal, multi-resolution landcover/use datasets at different scales (local, regional, national, continental, global, etc.) are very useful for scientific research in various disciplines and management of natural resources and environment. China is a developing country with complex terrestrial landcover. Thus, it is necessary to pay enough attention to landcover monitoring and landuse planning, so as to protect natural environment and ecosystem effectively. Many programs have been initiated and/or finished to extract landcover/landuse information for small important areas (e.g., urban areas) at local

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or regional scale by using high-resolution satellite data such as Landsat Thematic Mapper (TM), SPOT etc. But there is little research involving large areas, like the whole of China, by using coarse-resolution (e.g., 1 km) satellite data.

The National Oceanic and Atmospheric Administration (NOAA) Advanced Very High Resolution Radiometer (AVHRR) sensor has been in operation since 1982 and collects daily coverage of the earth at a nominal 1 km pixel resolution. AVHRR data and the Normalized Difference Vegetation Index (NDVI) calculations and other interpretations derived from them are very important for monitoring regional, continental and global landcover conditions.

Efforts have been made by many scientists all over the world to map landcover using AVHRR and NDVI. For example, the International Geosphere-Biosphere Programme-Data and Information System (IGBP-DIS) began the 1 km landcover project in 1990 and a global 1 km landcover dataset was created on a continent-by-continent basis. The classification approach used is based on unsupervised classification of NDVI time series with ancillary datasets, such as digital elevation models (Loveland et al., 1991; Brown et al., 1993). Related activities have also been initiated in Asian and Oceanic countries. The Asian Association on Remote Sensing (AARS) established the Working Group on 1 km Landcover Database of Asia in October 1993. The Working Group consists of 44 members from 27 Asian and Oceanic countries, and aims to produce a landcover dataset of Asia and Oceania using 1 km AVHRR data. The development of a 1 km landcover dataset for the whole of China is an important objective of the Working Group.

2. Data acquisition and processing

The satellite data used in this study are the 10-day composite NDVI datasets produced by the Global Land 1 km AVHRR Dataset Program at USGS EROS Data Center. The data were collected between April 1992 and March 1993. Monthly values were derived from the 10-day composites. The use of monthly values rather than 10-day composite values represents a compromise between temporal frequency and the need for cloud-free data (Moody and Strahler, 1994). It also provides a means to reduce data volume, while maintaining annual phenological information. The recomposing of the NDVI data was performed for the whole of Asia from top-left at the Barents Sea (90°N, 25°E) to down-right at the Coral Sea (15°S, 165°W). The data for China cover the area from top-left at (53°31′N, 73°5′E) to down-right at (18°N, 135°5′E), which includes all land area of China, except some islands.

After screening the 12 monthly NDVI images, the data for November 1992 and March 1993 were discarded from the analysis. Thus, 10 monthly datasets including that from April 1992 to October 1992 and from December 1992 to February 1993 were used to carry out the landcover classification of China. Statistics for the data used in the study area are shown in Table 1. The data are shown with values in the range of 0 to 255, transformed from the original data with values in the range of -1 to 1.

Available conventional data and maps for this study include: (a) Landuse map of China (1:1,000,000), edited by the Editorial Committee for the 1:1,000,000 Landuse Map of China (Editor-in-Chief: Wu Chuanjun), published by Science Press,

Table 1
Statistics of monthly NDVI images of China[a]

Statistics	Band 1	Band 2	Band 3	Band 4	Band 5	Band 6	Band 7	Band 8	Band 9	Band 10
Minimum	0	1	1	1	1	1	1	1	1	1
Maximum	255	194	189	194	195	189	195	194	194	192
Mean	151	99	100	103	108	113	113	114	109	105
Median	175	116	116	121	122	129	128	136	128	122
Std. Dev.	77.2	49.7	50.0	49.3	53.0	55.8	58.3	58.2	54.9	53.4
Corr. Eigenval.	9.581	0.219	0.091	0.027	0.024	0.017	0.014	0.010	0.010	0.006
Cov. Eigenval.	30593.0	724.8	279.4	87.8	75.5	51.4	46.4	31.7	28.6	15.6

[a] Band 1: April 1992; Band 2: May 1992; Band 3: June 1992; Band 4: July 1992; Band 5: August 1992; Band 6: September 1992; Band 7: October 1992; Band 8: December 1992; Band 9: January 1993; Band 10: February 1993.

Beijing, 1990; (b) Resources and environment data of China (1:4,000,000), produced by the State Key Laboratory of Resources and Environment Information Systems of the Institute of Geography, at the Chinese Academy of Sciences, Beijing (November 1996). The data include 17 specific datasets: national boundaries, provincial boundaries, county boundaries, canals, desertification, geomorphology, glaciers, landslide development, railway system, rivers, main road system, soils, wetlands, topography, vegetation, and surface waters; (c) GTOPO30: Global 30 ArcSecond Elevation Dataset that USGS offers to the public through the Internet; and (d) Ground truth data acquired by the AARS Global 4-min Landcover Dataset Program.

The image analysis and classification, and geographic information processing were carried out using the ER Mapper and CITYSTAR software tools. ER Mapper is a geographic image processing software produced by the Earth Resources Mapping Pty. Ltd., which can display and enhance raster data, display and edit vector data, and link them with data from geographic and land information systems, database management systems or virtually any other sources (Earth Resources Mapping Pty. Ltd., 1995). CITYSTAR is an integrated RS, GIS and GPS multimedia system, developed by the Institute of Remote Sensing and GIS, Peking University.

3. Methodology of landcover classification

The method used in this study combines unsupervised classification and supervised classification of NDVI data (Chen, 1998). It is composed of five steps as shown in Fig. 1. The LCWG/AARS Landcover Classification System was used to develop the landcover classification in China (Tateishi and Wen, 1996). The classification is based on the use of computer-assisted image processing and tools, as well as the skills of the human interpreter to take the final decisions regarding the relationship between spectral classes (defined using unsupervised methods) and landscape characteristics that are used to define landcover classes.

3.1. Unsupervised classification

The initial segmentation of the 10-month NDVI composites into seasonal greenness classes is performed using unsupervised clustering. This classification method is preferred for studies in which the location and characteristics of specific classes are unknown. Unsupervised classification uses clustering to identify *natural* groupings of pixels with similar NDVI properties. In this case, the clusters correspond to annual sequences of green-up, peak, and senescence. Clustering algorithms used for the unsupervised classification of remotely sensed data generally vary according to the efficiency with which the clustering takes place. Different criteria of efficiency lead to different approaches (Haralick and Fu, 1983). The specific clustering algorithm used is ISOCLASS (ER Mapper, Earth Resources Mapping Pty. Ltd., 1995). It calculates class means that are evenly distributed in the data space and then iteratively clusters the remaining pixels using minimum distance techniques. Each iteration recalculates means and reclassifies pixels with respect to the new means. This process continues until the number of pixels in each class changes by less than the selected pixel change threshold or the maximum number of iterations is reached.

3.2. Preliminary identification of greenness clusters

The purpose of this step is to provide a general understanding of the characteristics of each cluster (or seasonal greenness class) and to determine which clusters include a single landcover class within their spatial distribution. Clusters with a single landcover class may be also used as training data for the final supervised classification. Preliminary identification involves inspecting the spatial patterns and spectral or multitemporal statistics of each class, comparing each class to reference data, and taking decisions concerning landcover types. This step includes two primary tasks. One is the generation of statistics and graphics for each of the *n* clusters, describing their relationship to the available ancillary data. The other is the interpretation of the summaries, graphs, and reference data to determine the general landcover class or classes associated with each seasonal greenness cluster and to identify the clusters that represent single landcover classes.

3.3. Reprocessing of mixed classes

The purpose of this step is to refine large clusters containing two or more disparate landcover classes.

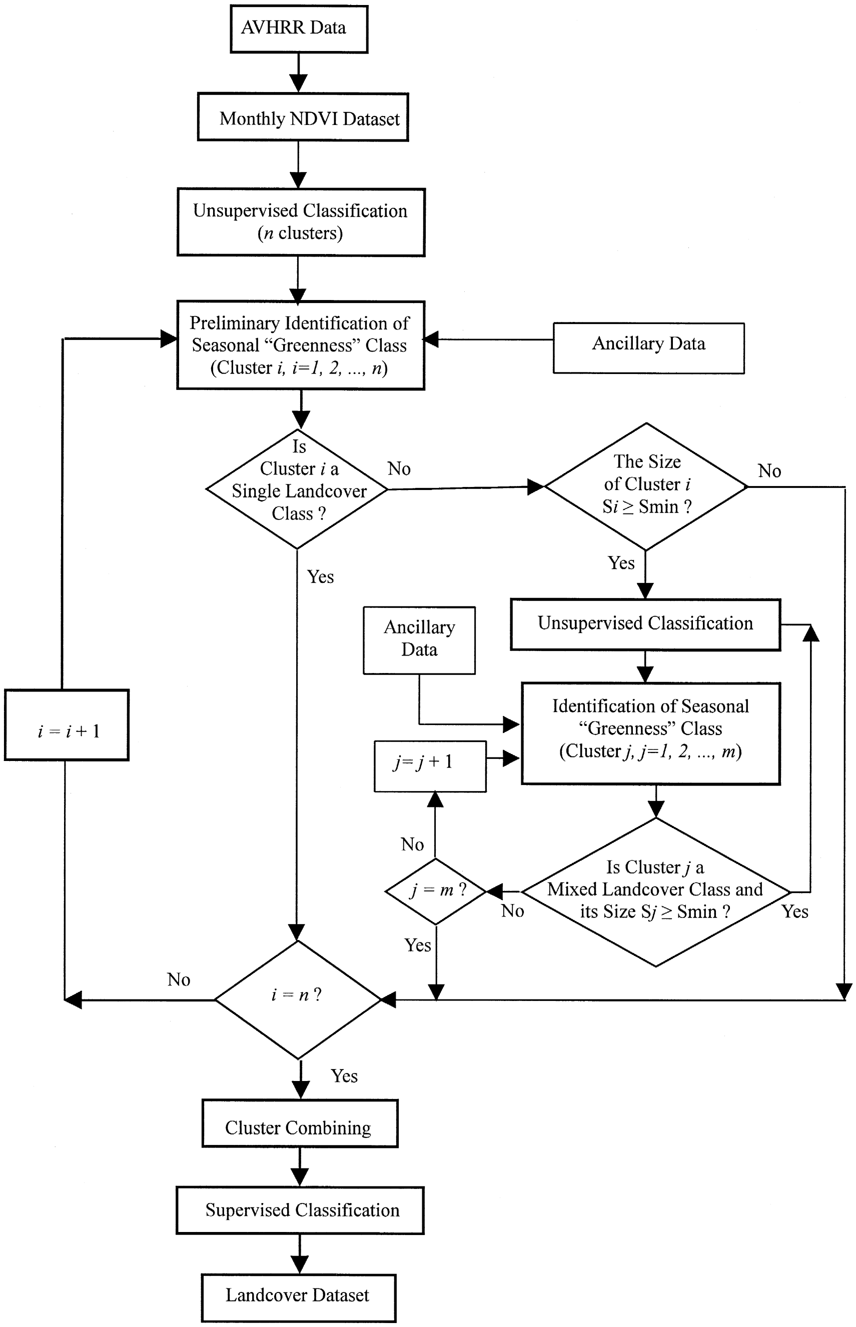

Fig. 1. Flowchart of landcover dataset development.

For the clusters with two or more landcover classes, a threshold value of the cluster size, S_{min}, is used to decide whether the cluster will be re-clustered or not. The decision rule is: If the size of cluster i (S_i) is equal to or greater than S_{min} (i.e., $S_i \geq S_{min}$), then this cluster should be re-clustered by the unsupervised algorithm.

The S_{min} value is determined subjectively based mainly on actual conditions. For example, it can be 1% or 5% of the total size of all clusters.

Generally, this is an iterative process in which the initial criteria are tested, refined, and finally used to permanently modify the original class. This results in a number of new seasonal greenness classes, that through the following steps, become the final landcover classes.

3.4. Cluster combining

The cluster combining is performed to combine those clusters with the same landcover class, and combine all other clusters with $S_i < S_{min}$ into one mixed cluster. The former are directly used in the final landcover regions, while the latter are re-classified in next step.

3.5. Supervised classification

A maximum likelihood algorithm was chosen to perform the supervised classification, due to its successful use in prior research (Chen, 1997; Chen and Hu, 1999).

The maximum likelihood decision rule assigns each pixel having pattern measurements or features X to the class c, whose units are most probable or likely to have given rise to the feature vector X (Swain and Davis, 1978; Foody et al., 1992). It assumes that the training data statistics for each class in each band are normally distributed, i.e., Gaussian (Blaisdell, 1993). In other words, training data with bi- or tri-modal histograms in a single band are not ideal. The decision rule applied to the unknown measurement vector X is (Swain and Davis, 1978; Schalkoff, 1992):

Decide X is in class c if, and only if,

$$p_c \geq p_i \tag{1}$$

where $i = 1, 2, 3, \ldots, m$ possible classes, and

$$p_c = -\frac{1}{2}\left\{\log_e\left[\det(V_c)\right] + (X - M_c)^T V_C^{-1}(X - M_c)\right\} \tag{2}$$

with M_c the mean vector and $\det(V_c)$ the determinant of the covariance matrix V_c. Therefore, to classify the measurement vector X of an unknown pixel into a class, the maximum likelihood decision rule computes the value p_c for each class. Then, it assigns the pixel to the class that has the maximum value.

This assumes that each class has an equal probability of occurring in the terrain. However, in most remote sensing applications, there is a high probability of encountering some classes more often than others. Thus, we would expect more pixels to be classified as some class simply because it is more prevalent in the terrain. It is possible to include this valuable a priori information (prior knowledge) in the classification decision. We can do this by weighting each class c by its appropriate a priori probability, a_c. The equation then becomes:

Decide X is in class c if, and only if,

$$p_c(a_c) \geq p_i(a_i) \tag{3}$$

where $i = 1, 2, 3, \ldots, m$ possible classes, and

$$p_c(a_c) = \log_e(a_c) - \frac{1}{2}\left\{\log_e\left[\det(V_c)\right] + (X - M_c)^T V_C^{-1}(X - M_c)\right\} \tag{4}$$

This algorithm was used to carry out post-classification of the mixed cluster generated in the previous step. The classes with single landcover classes, identified and combined in previous steps, are used as training data.

Following the generation of the landcover classification in this step, the remaining steps in the dataset generation are as follows.

(1) Generate final attributes of the landcover dataset and sort out relative data such as landcover classification system, file listing, ground truth data, and any additional sources used in dataset production and/or useful for reference.

(2) Produce landcover map with legend and administrative boundaries.

(3) Translate the landcover classifications into other global landcover classification schemes in order to produce multiple thematic datasets to meet the requirements of the scientific community and management agencies.

4. Results and discussion

4.1. Landcover classification system

Certain classification schemes have been developed that can readily incorporate landuse and/or landcover data obtained by interpreting remotely sensed data, e.g., US Geological Survey Landuse/Landcover Classification System, US Fish and Wildlife Service Wetland Classification System, NOAA CoastWatch Landcover Classification System (Jensen, 1996) and the LCWG/AARS Landcover Classification System (Tateishi and Wen, 1996). The LCWG/AARS Landcover Classification System was used in this study (see Appendix A).

4.2. Landcover classification

The ISOCLASS algorithm was used to perform unsupervised clustering with 10-month composites AVHRR NDVI data for April 1992 through February 1993 (except November 1992). In order to ensure that there will be enough clusters with single landcover classes after the unsupervised clustering, the maximum number of clusters which is an input parameter of this algorithm must be set high. In this case, it was selected as 100.

Based on the clustering result (Fig. 2), statistics (the size of each clusters, mean values and the standard deviation of the 10-month NDVI) and graphics for each of the 100 clusters were calculated and visualised. As an example, Table 2 shows the size of each cluster and Fig. 3 shows the mean values of the 10-month NDVI for 9 of the 100 clusters.

Referring to these results, the statistic characteristics of monthly NDVI images, and the available conventional data (landuse map of China, resources and environment data of China, GTOPO30, ground truth data, etc.), the clustering result was comprehensively analysed and the clusters with single landcover classes were identified. For the clusters with mixed landcover classes and size more than 1.0% of the total pixels, unsupervised clustering was carried out again. The identified clusters with single landcover were combined. The remaining clusters were combined into one mixed cluster.

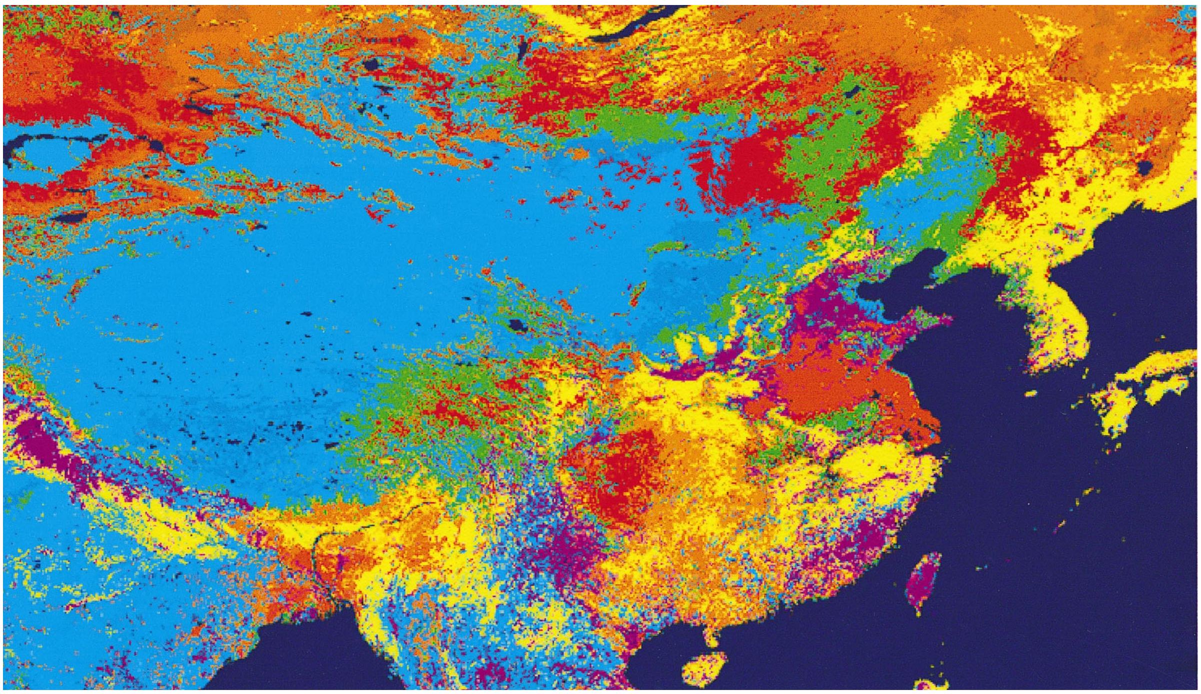

Fig. 2. Clustering result of the 10-month NDVI of China.

Table 2
Size of each cluster calculated by the ISOCLASS algorithm

Cluster No.	Size (Cells)	Percentage (%)
1	5520	0.018
2	7344	0.023
3	207 856	0.661
4	66 944	0.213
5	8624	0.027
6	7088	0.022
7	10 288	0.033
8	5552	0.018
9	5008	0.016
10	15 048	0.048
11	11 808	0.038
12	15 392	0.049
13	16 144	0.051
14	12 944	0.041
15	14 112	0.045
16	12 672	0.040
17	14 064	0.045
18	4416	0.014
19	7072	0.022
20	14 176	0.045
21	14 976	0.048
22	12 960	0.041
23	22 320	0.071
24	14 784	0.047
25	19 632	0.062
26	12 256	0.039
27	289 280	0.921
28	1 025 648	3.264
29	1 415 840	4.506
30	1 120 032	3.564
31	539 312	1.716
32	1 205 680	3.837
33	1 087 120	3.460
34	310 448	0.988
35	619 152	1.970
36	363 104	1.156
37	771 680	2.456
38	692 768	2.205
39	298 752	0.951
40	720 720	2.294
41	246 960	0.786
42	596 688	1.899
43	635 216	2.022
44	602 960	1.919
45	488 768	1.555
46	550 928	1.753
47	474 592	1.510
48	701 104	2.231
49	570 352	1.815
50	674 976	2.148
51	438 000	1.394
52	321 456	1.023
53	137 680	0.438
54	169 408	0.539
55	22 496	0.072
56	419 728	1.336
57	14 400	0.046
58	13 184	0.042
59	16 160	0.051
60	39 008	0.124
61	15 1664	0.483
62	16 800	0.053
63	115 120	0.366
64	53 104	0.169
65	21 504	0.068
66	145 664	0.464
67	311 184	0.990
68	235 053	0.748
69	278 016	0.885
70	611 008	1.944
71	371 552	1.182
72	456 384	1.452
73	319 568	1.017
74	494 512	1.574
75	521 312	1.659
76	309 184	0.984
77	183 120	0.583
78	288 448	0.918
79	88 400	0.281
80	94 048	0.299
81	234 976	0.748
82	247 472	0.788
83	189 568	0.603
84	234 560	0.746
85	93 712	0.298
86	6560	0.021
87	6000	0.019
88	9680	0.031
89	8144	0.026
90	11 216	0.034
91	157 280	0.500
92	90 240	0.287
93	189 344	0.603
94	262 736	0.836
95	50 400	0.160
96	80 784	0.257
97	112 688	0.359
98	204 864	0.652
99	116 176	0.370
100	187 312	0.596
Total	31 422 573	100

By using the combined clusters with single land-cover classes as training data, the maximum likeli-

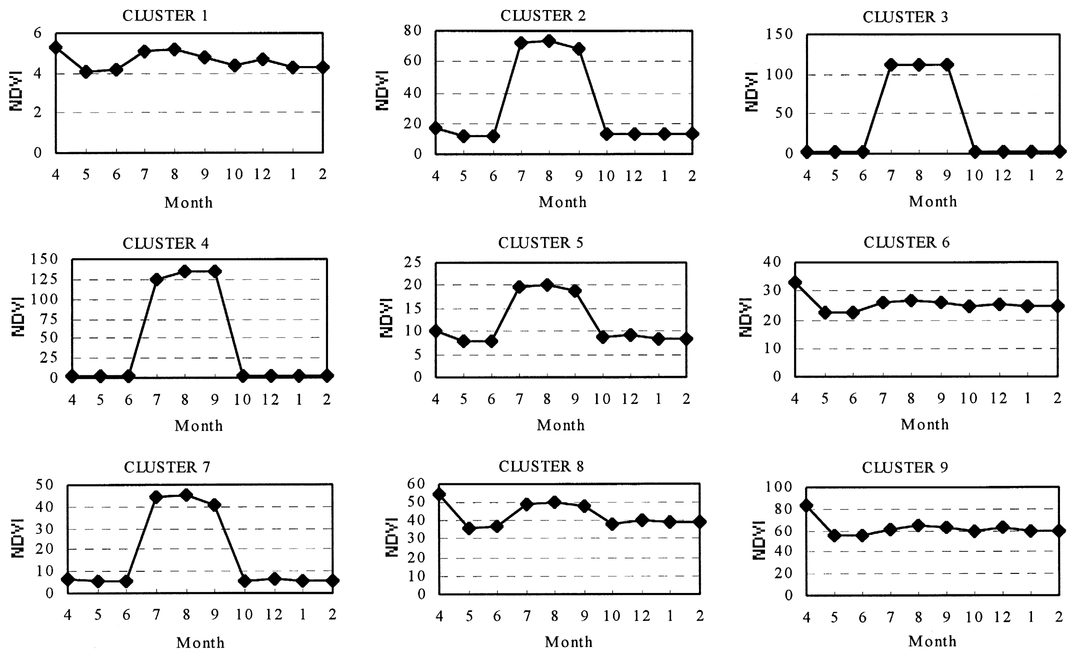

Fig. 3. Mean values of the 10-month NDVI of China for the first nine clusters.

hood algorithm was used to separate the mixed cluster.

4.3. Landcover dataset and map

Finally, the landcover dataset of China was generated with 11 classes that are described in Table 3. Fig. 4 shows a landcover map of China with legend.

4.4. Accuracy assessment

Vegetated surfaces change seasonally based on the composition of the vegetation present. Past investigations have demonstrated that classes developed from multitemporal NDVI data represent characteristic patterns of seasonality and correspond to relative patterns of productivity (Loveland et al., 1991; Brown et al., 1993). Thus, it is reasonable to use monthly NDVI data through the year to identify seasonal greenness (Chen, 1998). However, experience has shown that at least 60% of the seasonal greenness classes represent multiple landcover types (Brown et al., 1993; Running et al., 1995). This is the result of spectral similarities between some natural and agricultural landcover types. These problems can usually be solved by developing criteria based on the relationship between the confused seasonal greenness classes and selected ancillary datasets.

To correctly perform classification accuracy assessment, it is necessary to compare two sources of information: (1) the remote-sensing-derived classification map and (2) what we will call reference test

Table 3
Derived landcover dataset of China

Value	Landcover class
0	Sea
14	Evergreen Forest or shrubland
70	Deciduous Forest or shrubland
120	Mixed forest or shrubland
132	Natural grassland/pasture
140	Grass crops
170	Wetland
180	Little vegetation
191	Bare ground
200	Perennial snow or ice
222	Inland water

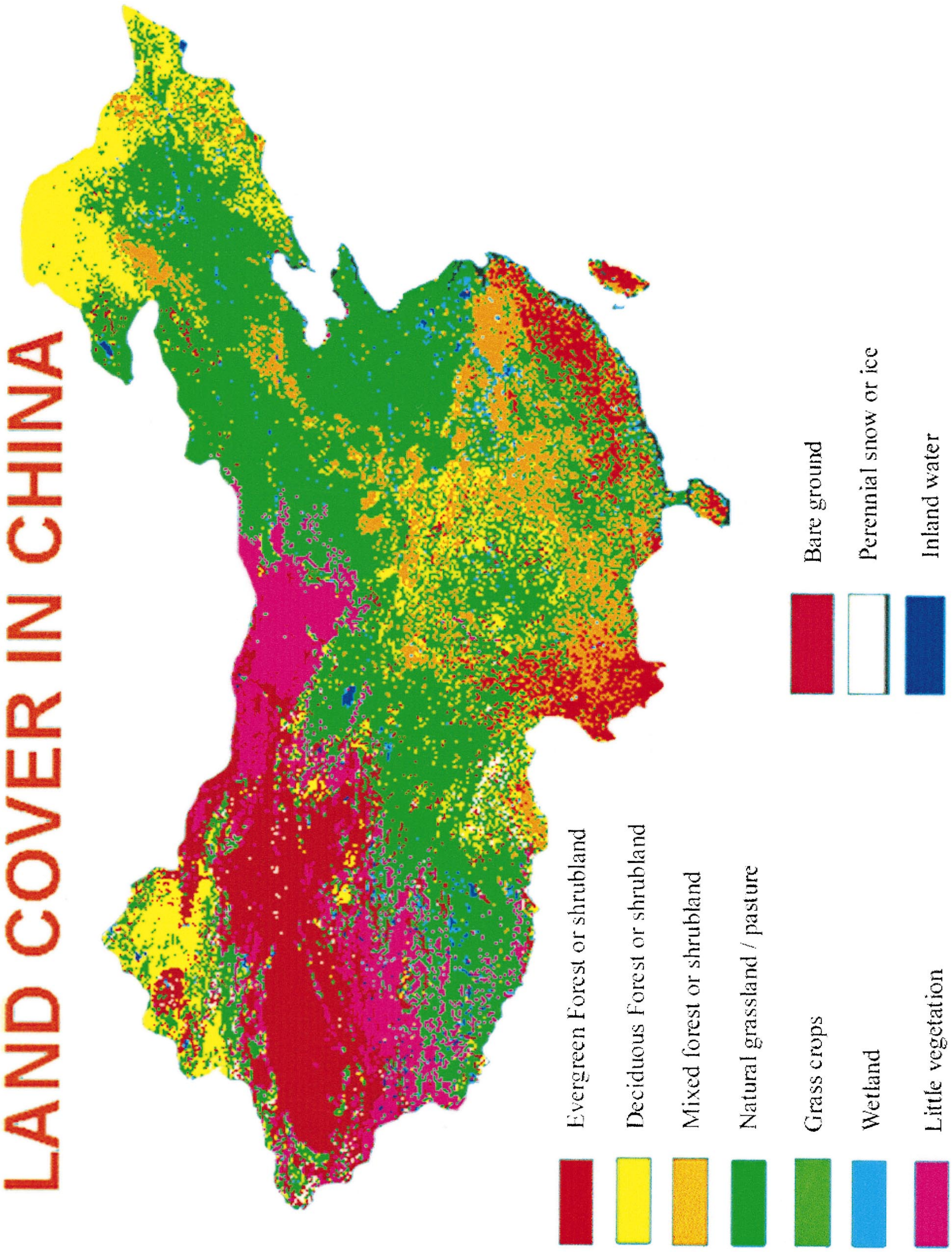

Fig. 4. Landcover in China.

information (which may in fact contain errors). The relationship between these two sets of information is commonly summarised in an error matrix.

Information in the error matrix may be evaluated using (1) simple descriptive statistics and/or (2) discrete multivariate analytical statistical techniques. By using the simple descriptive statistics technique, *overall accuracy* is computed by dividing the total correctly classified pixels (sum of the major diagonal) by the total number of pixels in the matrix. *KAPPA analysis* is a discrete multivariate technique of use in accuracy assessment (Congalton and Mead, 1983; Jensen, 1996). *KAPPA* analysis yields a K_{hat} statistic (an estimate of *KAPPA*) that is a measure of agreement or accuracy (Rosenfield and Fitzpartrick-Lins, 1986; Congalton, 1991). The K_{hat} statistic is computed as

$$K_{\mathrm{hat}} = \frac{N \sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r} (x_{i+} \times x_{+i})}{N^2 - \sum_{i=1}^{r} (x_{i+} \times x_{+i})} \tag{5}$$

where r is the number of rows in the matrix, x_{ii} is the number of observations in row i and column i, x_{i+} and x_{+i} are the marginal totals for row i and column i, respectively, and N is the total number of observations.

A training dataset produced by combining ground truth data and the data collected randomly from the landuse map of China and the resources and environment data of China, was used to assess the accuracy of the landcover classification. The error matrix of the classification was analysed by using the training dataset. The calculated overall accuracy was 91.3%, while K was equal to 89.4%.

Based on the accuracy assessment, most landcover classes were successfully classified. The classes with disparate seasonal greenness characteristics, like those with vegetation and without vegetation, are easily separated. However, the classes with similar seasonal greenness characteristics such as natural grassland/pasture and gross crops, bare ground and perennial snow or ice, are difficult to separate. The accuracy limitation of this landcover classification has mainly resulted from the use of limited channels of satellite data, i.e., NDVI only, and ancillary data.

5. Conclusions

A landcover dataset for the whole of China is very useful for many applications, especially in global change research, land resources development and management, natural disaster monitoring and damage evaluation, and can support decision making for sustainable development. While the 1-km landcover dataset of China produced in this study is currently the best available, the accuracy of the dataset and the details of landcover classification were limited because the classification was performed by using only NDVI and limited ancillary data.

To refine this product, it will be necessary to improve this derived landcover dataset by using more ancillary data, such as DTM, more ground truth data, field survey results, data derived from higher resolution satellite data (e.g., Landsat TM, SPOT, etc.), and other landcover/landuse maps. Also it would be better to attempt this procedure using all five channels of AVHRR information as much as possible rather than only NDVI derived from channel 1 and channel 2. This will also make it be possible to produce a landcover dataset with landcover classes as many as those described in the LCWG/AARS Landcover Classification System. In addition, the authors suggest the development of an integrated database to assess the results and integrate the datasets in a GIS so that they can be conveniently used by various users.

Appendix A. The LCWG / AARS landcover classification system

Value	**Landcover Class**
10	**Vegetation**
12	*Forest or shrubland*
14	Evergreen
16	Forest
18	Broadleaf
20	Natural
22	Tree crops
23	Oil palm
24	Coconut
33	Other

36	Needleleaf
42	Shrubland
44	Natural
46	Shrub crops
47	Tea
57	Other
60	Forest and shrubland
70	Deciduous
72	Forest
74	Broadleaf
76	Natural
78	Tree crops
79	Rubber
87	Other
90	Needleleaf
92	Shrubland
94	Natural
96	Shrub crops
97	Cotton
107	Other
110	Forest and shrubland
120	Mixed forest or shrubland
130	*Grassland*
132	Natural grassland/pasture
140	Grass crops
141	Paddy
142	Wheat
143	Sugarcane
144	Corn
146	Wheat and rice
157	Other
160	*Mixed vegetation*
170	*Wetland*
172	Mangrove
174	Swamp
180	*Little vegetation*
182	Tundra
184	Other
190	**Non-vegetation**
191	*Bare ground*
192	Rock
193	Stones or gravel
194	Sand
195	Clay
200	*Perennial snow or ice*
210	*Built-up area*
220	*Water*
222	Inland water
224	Water with seasonal change
226	Tidal flat

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