Land cover/land use mapping and change detection in Mongolian plateau using remote sensing data

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Impact of Climate Change on Region Specific Systems

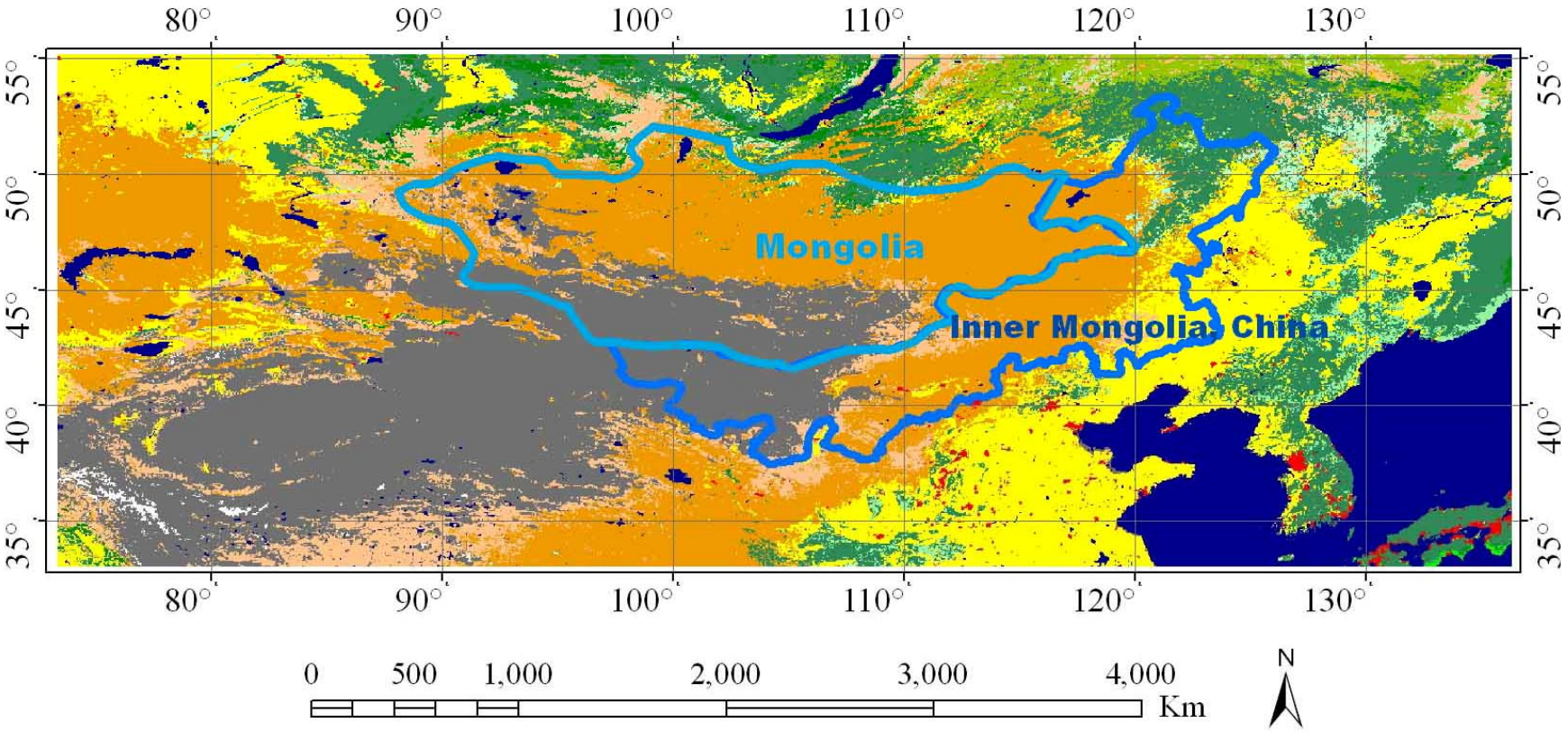
November 6, 2009, Hokkaido University

Contents

1. Background information

1. Background information

Mongolian Plateau is covering the country of Mongolia in the north, the Inner Mongolia Autonomous Region of China in the south, and also covering the neighborhood region.



1. Background information

Land degradation is one of the major environmental problems. Numerous scientists have suggested that desertification in Mongolian plateau is caused by human activities, for example,

Population increases: mainly in Inner Mongolia

Over-reclamation: mainly in Inner Mongolia

Collection of fuel wood: mainly in Inner Mongolia

Over-grazing: both in Inner Mongolia and Mongolia

Mining: both in Inner Mongolia and Mongolia




So, our objectives are (1) using remote sensing data to obtain a better understanding of land cover of the Mongolian plateau and (2) analyze the land cover change in this region.

2. Introduction

2. Introduction

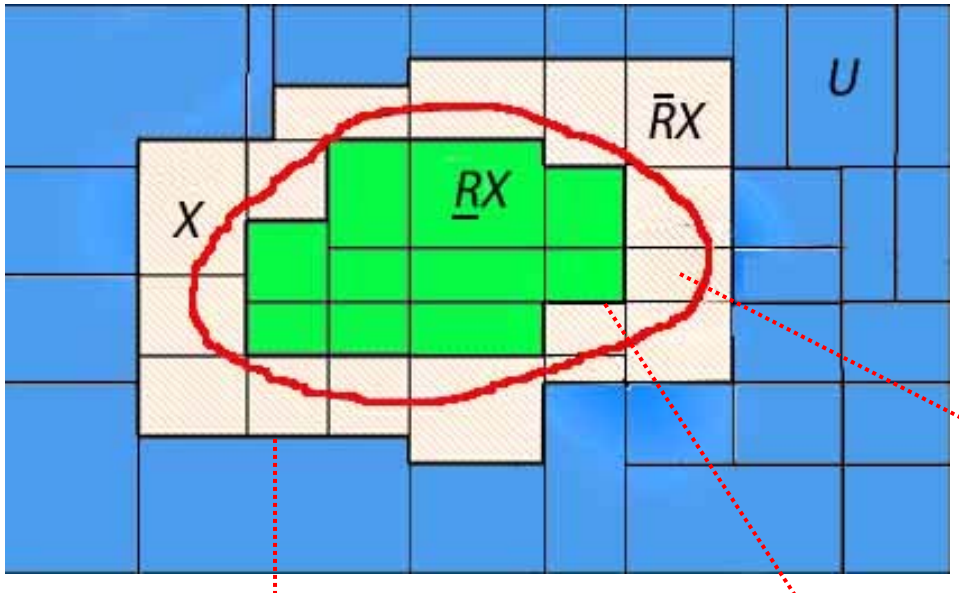
For accurate extract the land cover information from remote sensing data, we developed some algorithms for land cover classification.

Here, we briefly describe the following algorithms:

1. Rough set: data preprocessing
2. Wavelet fusion: fusion different spatial resolution data
3. SOM Neural network: land cover classification
4. Subspace method: land cover classification

2. Introduction – Rough sets

We developed rough set methods for training data filtering to improve the accuracy of land cover classification.



U : a non-empty finite set of objects

R : subset of attributes

Boundary set

Upper approximation set

Lower approximation set

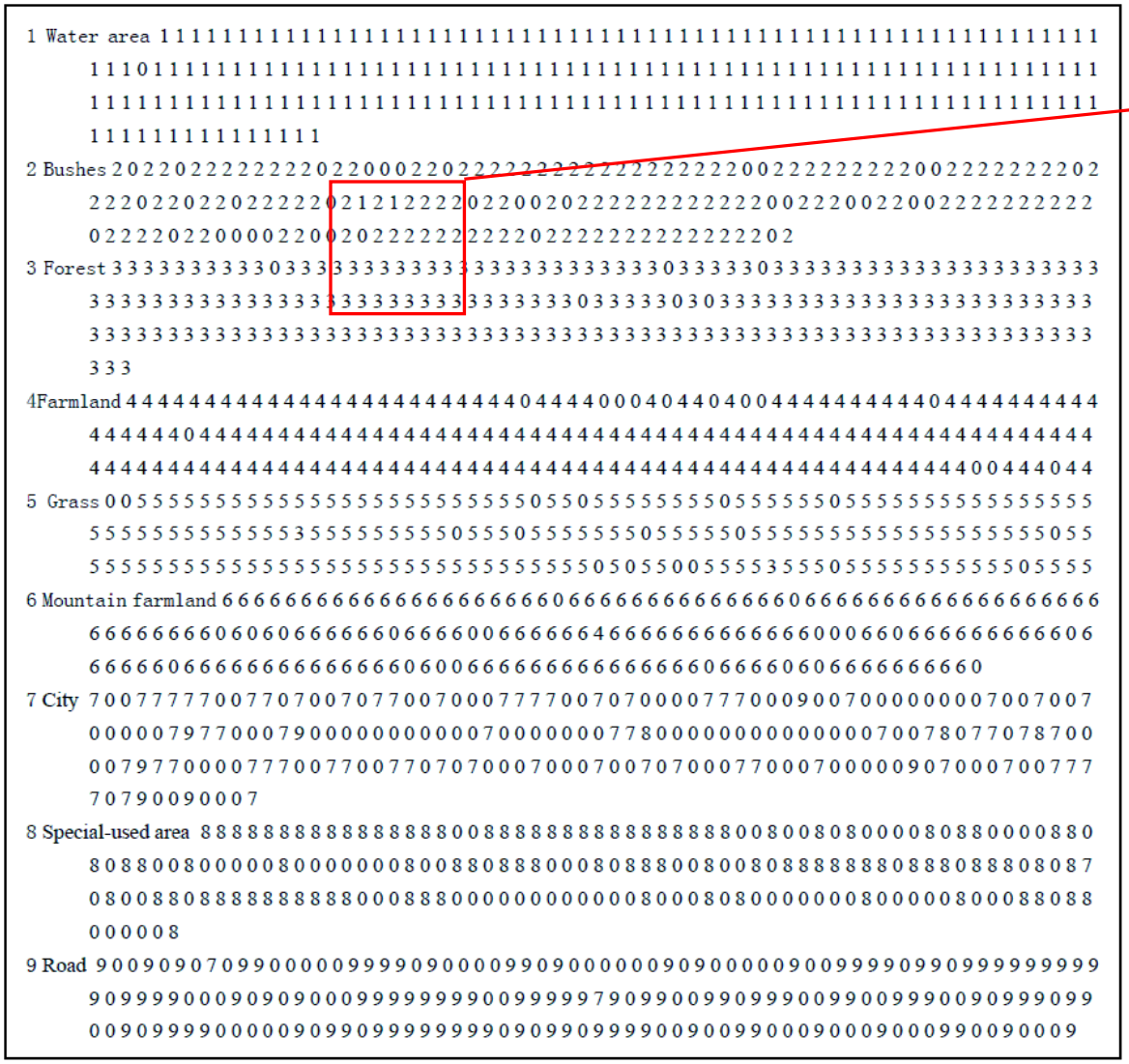
Boundary set of X is defined as: $BN(X) = \overline{R}X - \underline{R}X$

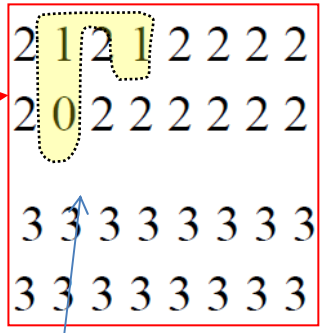
Lower approximation set is a subset of X. X is a subset of upper approximation set.

A set ***X*** is said to be *Rough* if its boundary region is non-empty.

2. Introduction – Rough sets

We select Landsat TM scene (2003, Beijing) for experiment, and chose 9 land cover types for classification. Below is the entire 9 class training data after Rough set processing.





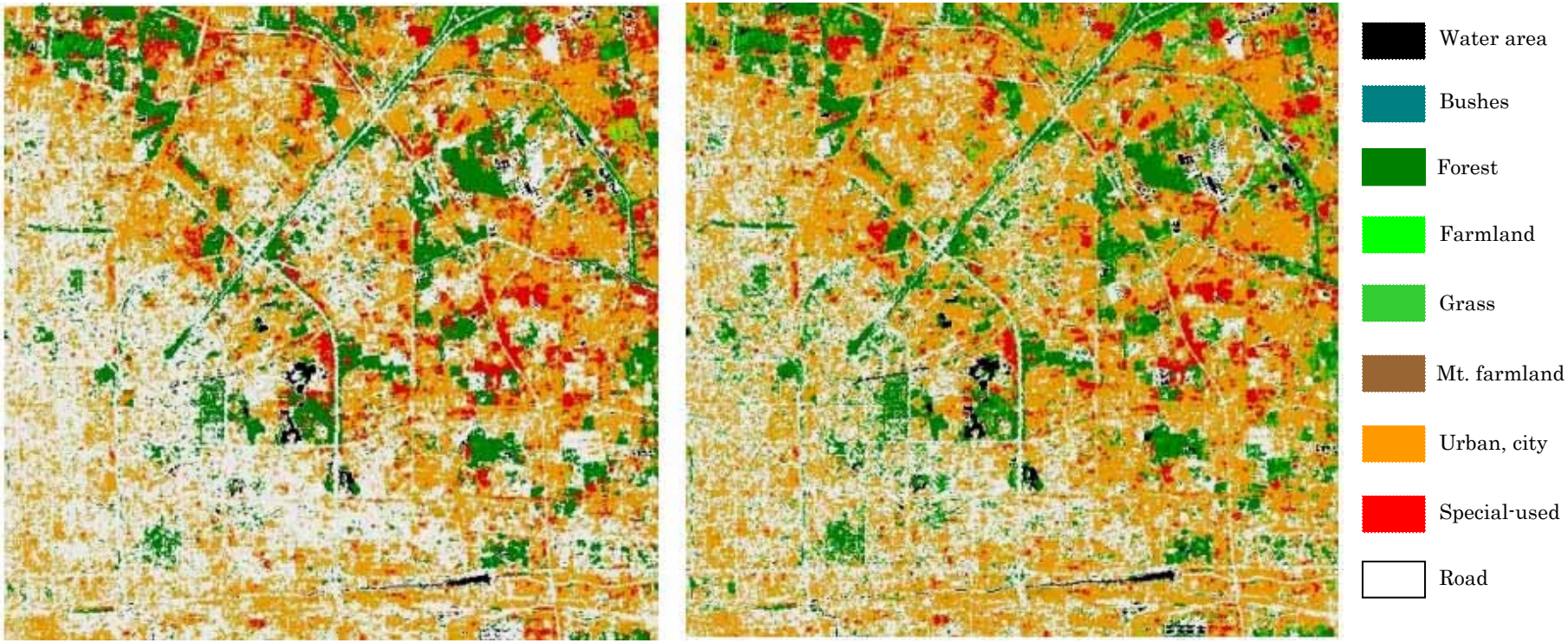
These 3 pixel were removed from class 2

After rough sets processing, all the ambiguous training samples were removed from the training data set.

(Hasi Bagan et al, Science in China, 2004)

2. Introduction – Rough sets

We adopt the *BP* (Back propagation) neural network for land cover classification.



Without rough set

With rough set

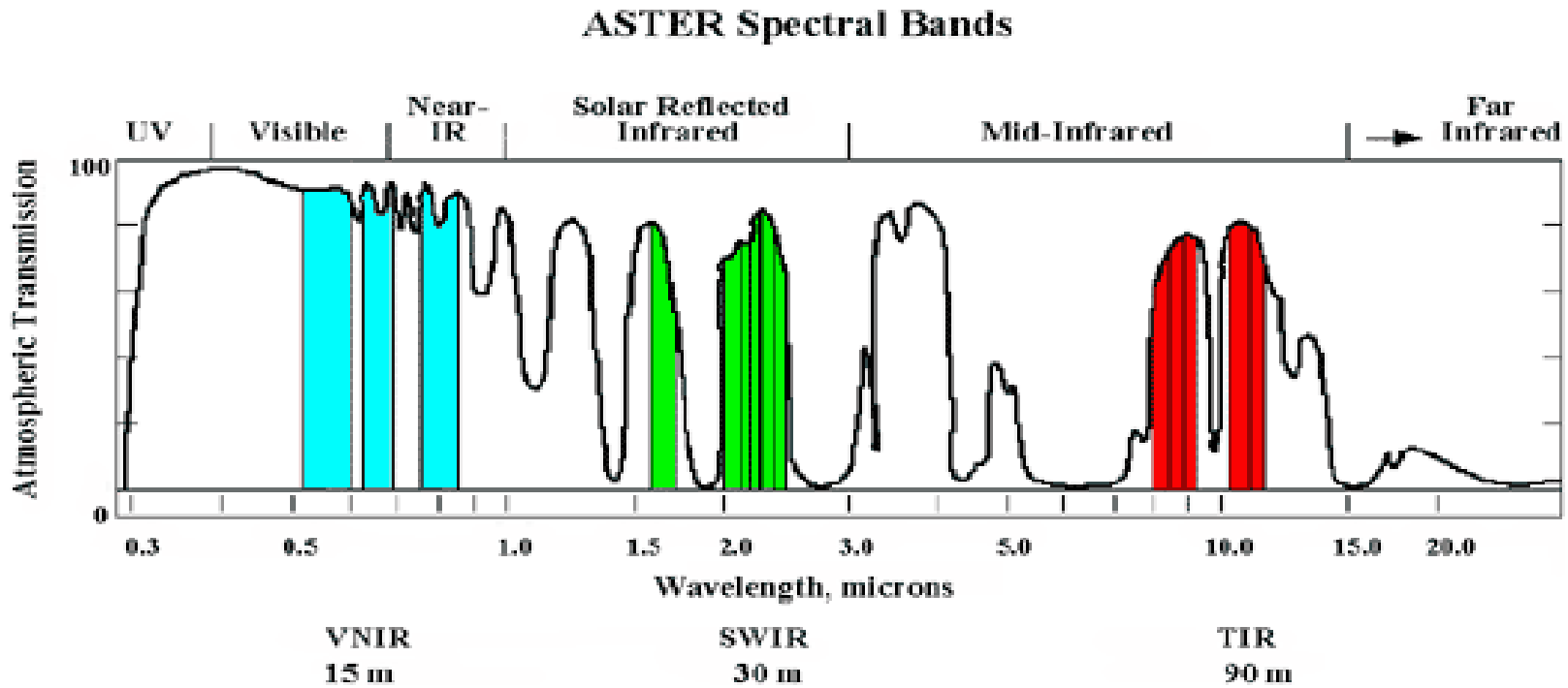
When directly use BP, the accuracy was only 87%. But, the accuracy was increased up to 93% when using rough set for training data preprocessing.

2. Introduction – Wavelet fusion

ASTER consists of 3 subsystems that are VNIR, SWIR, and TIR. ASTER is useful for land cover classification because it has 14 spectral bands.

The limitation is that the spatial resolution of VNIR, SWIR, and TIR is different. It should be converted to same spatial resolution so that we can easy use the full 14 bands for land cover classification.

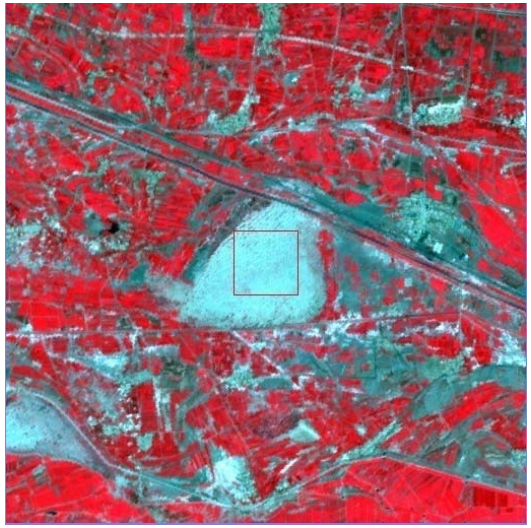
For this purpose, we developed wavelet fusion method for ASTER data.



(*Source: from ERSDAC*)

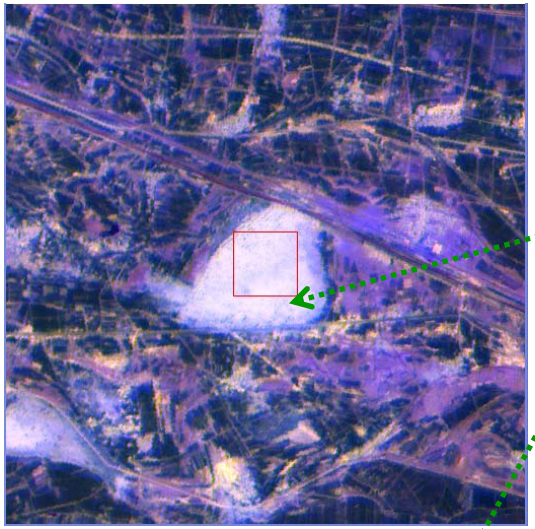
2. Introduction – Wavelet fusion

Comparison of before-fusion image and the after-fusion image



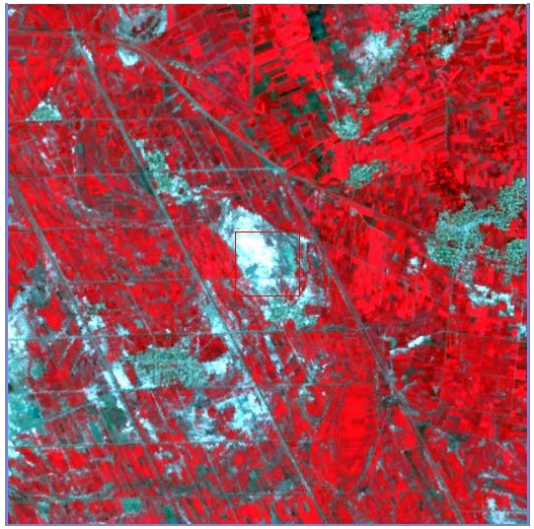
Before fusion (RGB = 3,2,1)

Sand

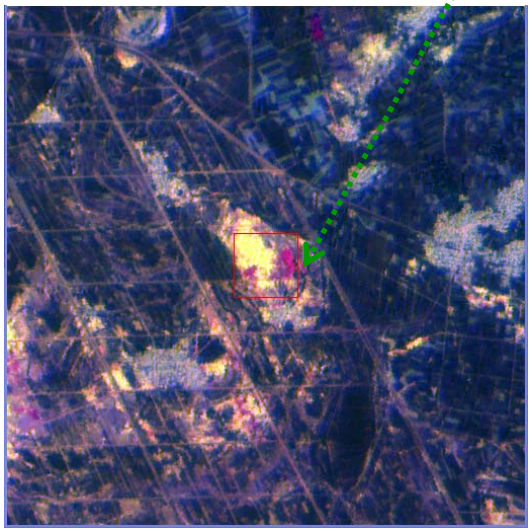


After fusion (RGB = 2,7,14)

After fusion, we can easily distinguish saline and sand by visual image interpretation.



Saline



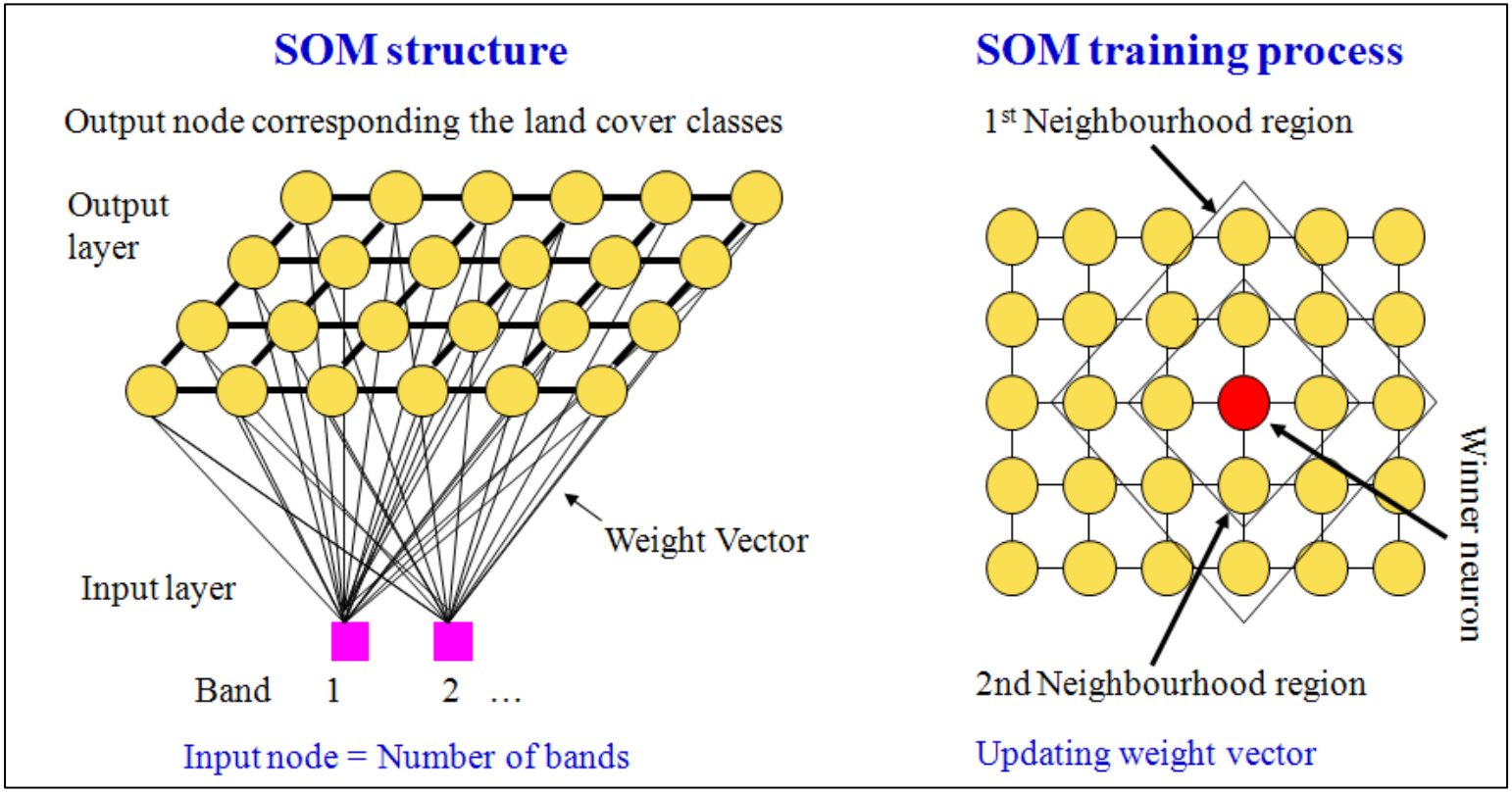
Because, After fusion, the possible color composite images are increased from 1 (C_3^3) to 728 (C_{14}^3).

2. Introduction – SOM neural network

The SOM method have two layers, an input layer and an output layer. The input layer nodes are all connected to those of the output layer

SOM can convert high-dimensional data into a low-dimensional map. The neuron in the output layer are arranged by topological order in the input space.

SOM structure and training process.



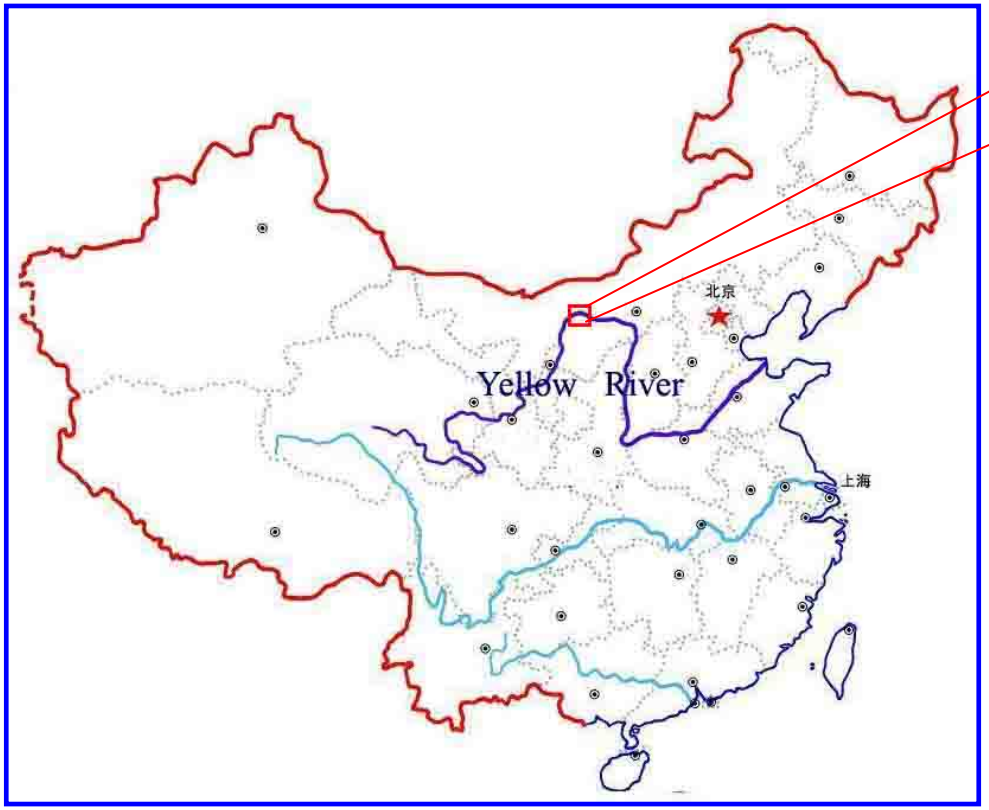
(*Hasi Bagan et al, Int. J. Remote. Sens., 2005*)

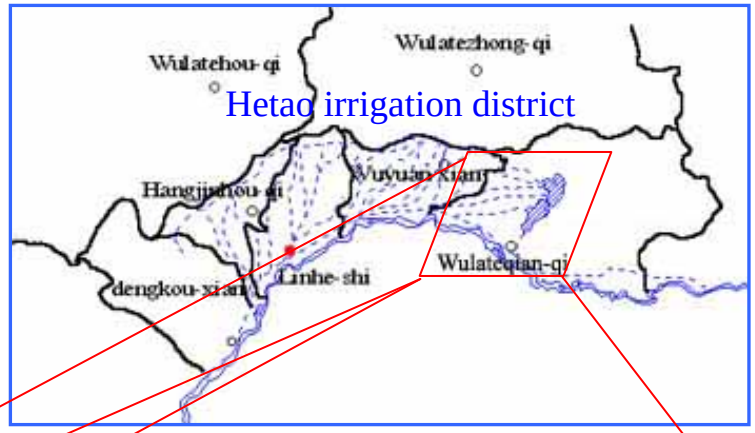
2. Introduction – SOM neural network

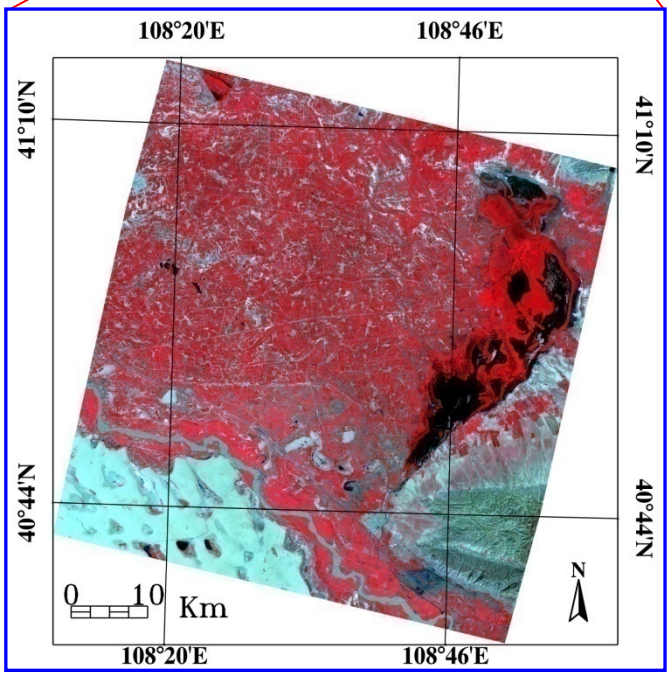
We use the wavelet fused ASTER data for SOM classification experiment.

This image was acquired on Aug. 2003, located in Hetao irrigation district, Inner Mongolia

Location of the study area.



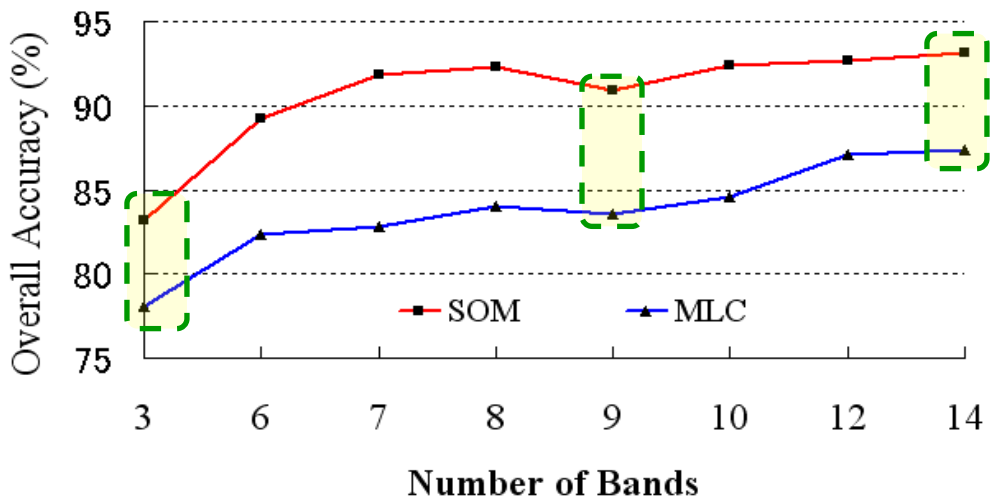




2. Introduction – SOM neural network

Blue: VNIR band; *Green: SWIR* band; *Red: TIR* band

Number of bands	Band combination
3	1 2 3
6	1 2 3 4 5 8
7	1 2 3 4 5 8 13
8	1 2 3 4 5 8 10 13
9	1 2 3 4 5 6 7 8 9
10	1 2 3 4 5 6 7 8 9 13
12	1 2 3 4 5 6 7 8 9 10 12 14
14	1 2 3 4 5 6 7 8 9 10 11 12 13 14



We designed 9 land cover types and adopt the SOM and MLC methods for land cover classification.

Classification accuracy increases as the number of bands increases in both SOM and MLC classification methods.

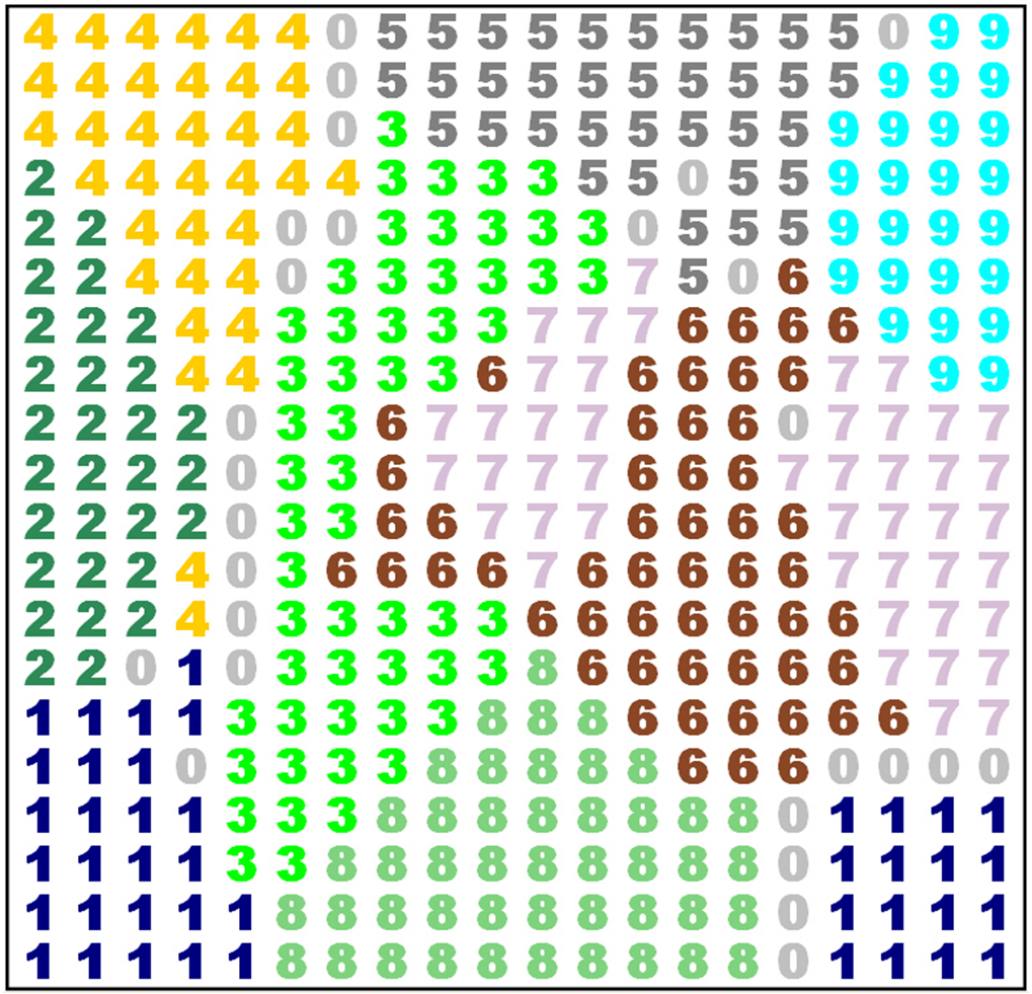
When we use TIR bands, the accuracy is higher than that of only use both VNIR and SWIR bands.

SOM: self-organizing map neural network; ***MLC***: maximum likelihood classifier

2. Introduction – SOM neural network

This map shows the SOM training results when using full 14 bands ASTER data. After SOM training, all training data are clustered into output layer (2D map).

1.Water; 2.Reed; 3.Grasslands; 4.Cropland 5.Desert; 6.Urban; 7.Open area; 8.Tidal flat; 9.Saline soil



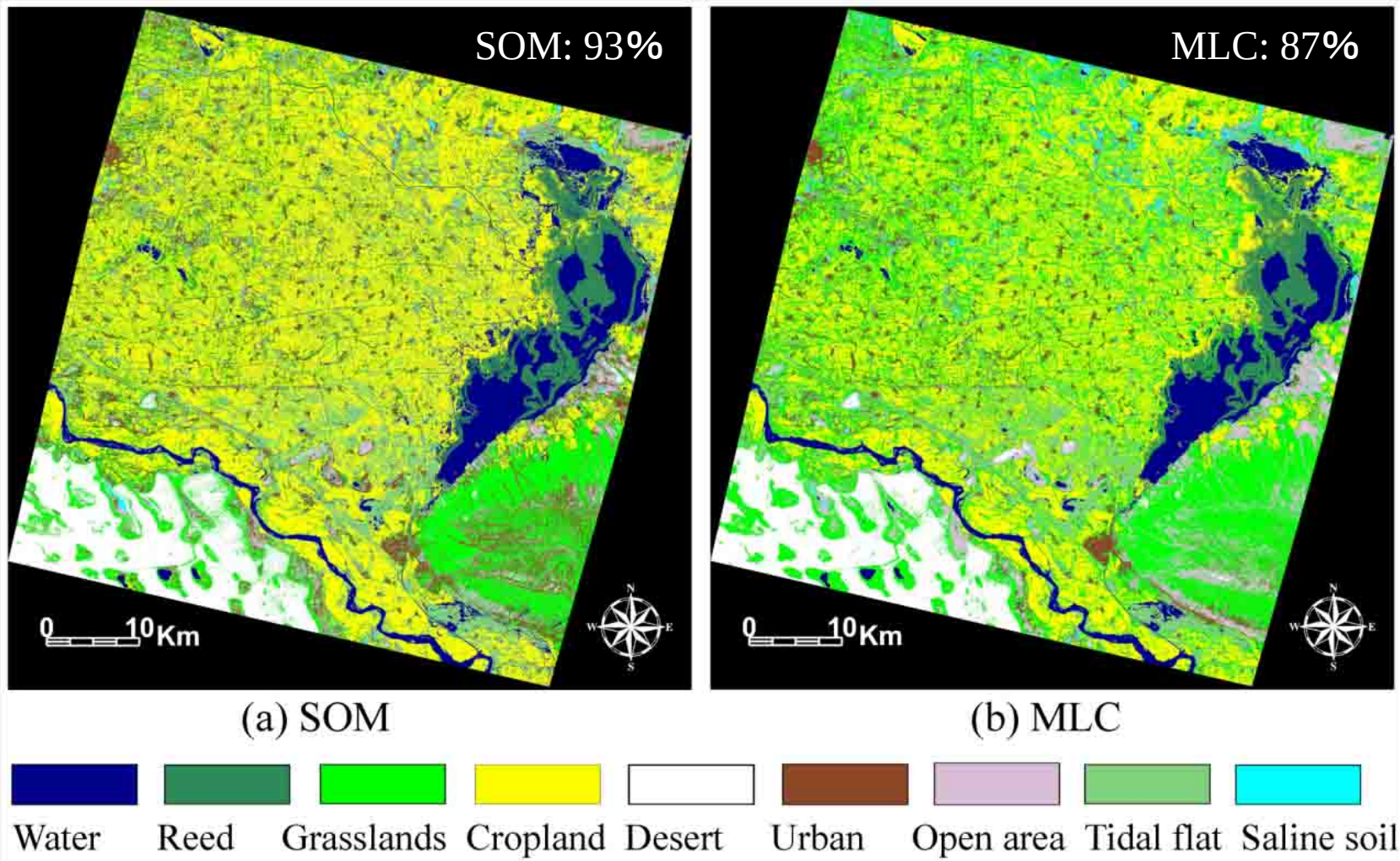
Each class was clustered into own topology region.

River and lake waters were clustered into two parts because the water component are different.

6 (urban) and 7 (open) classes are somewhat mixed with each other, because it's difficult to separate them in this region.

2. Introduction – SOM neural network

Classification results with ASTER 14-band data: (a) SOM, and (b) MLC method.



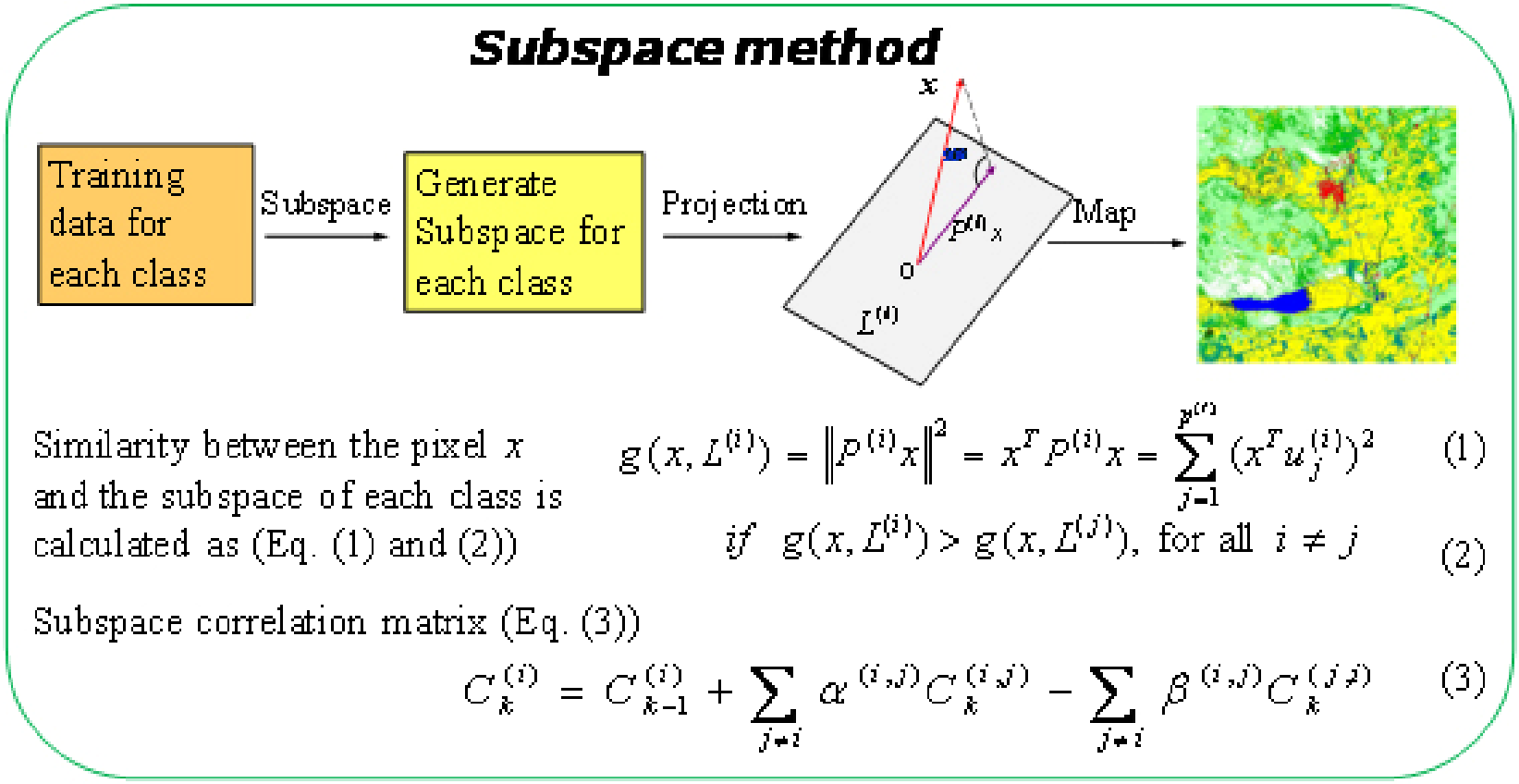
So, SOM +wavelet fusion can improve the accuracy of ASTER data classification.

(*Hasi Bagan et al, PERS, 2008*)

2. Introduction – Subspace method

Subspace methods also project high-dimensional data onto a low-dimensional feature space, but it differs from SOM that the different classes are represented in their own low-dimensional space.

Procedure of subspace method



Similarity between the pixel x and the subspace of each class is calculated as (Eq. (1) and (2))

$$g(x, L^{(i)}) = \left\| p^{(i)} x \right\|^2 = x^T p^{(i)} x = \sum_{j=1}^{p^{(i)}} (x^T u_j^{(i)})^2 \qquad (1)$$

$$\text{if} \quad g(x, L^{(i)}) > g(x, L^{(j)}), \text{ for all } i \neq j \qquad (2)$$

Subspace correlation matrix (Eq. (3))

$$C_k^{(i)} = C_{k-1}^{(i)} + \sum_{j \neq i} \alpha^{(i,j)} C_k^{(i,j)} - \sum_{j \neq i} \beta^{(i,j)} C_k^{(j,j)} \qquad (3)$$

(*Hasi Bagan et al, IEEE GRSL., 2008*)

2. Introduction – Subspace method

The advantages of subspace method are:

- Only need to set 3 parameters, and these optimal values can easily be determined by an automatic procedure.
- The computational speed is faster than that of the SVM method and near to that of the MLC method.
- The results indicate that the subspace method could be a promising tool for land cover classification.

3. Case Study: Land cover/land use change

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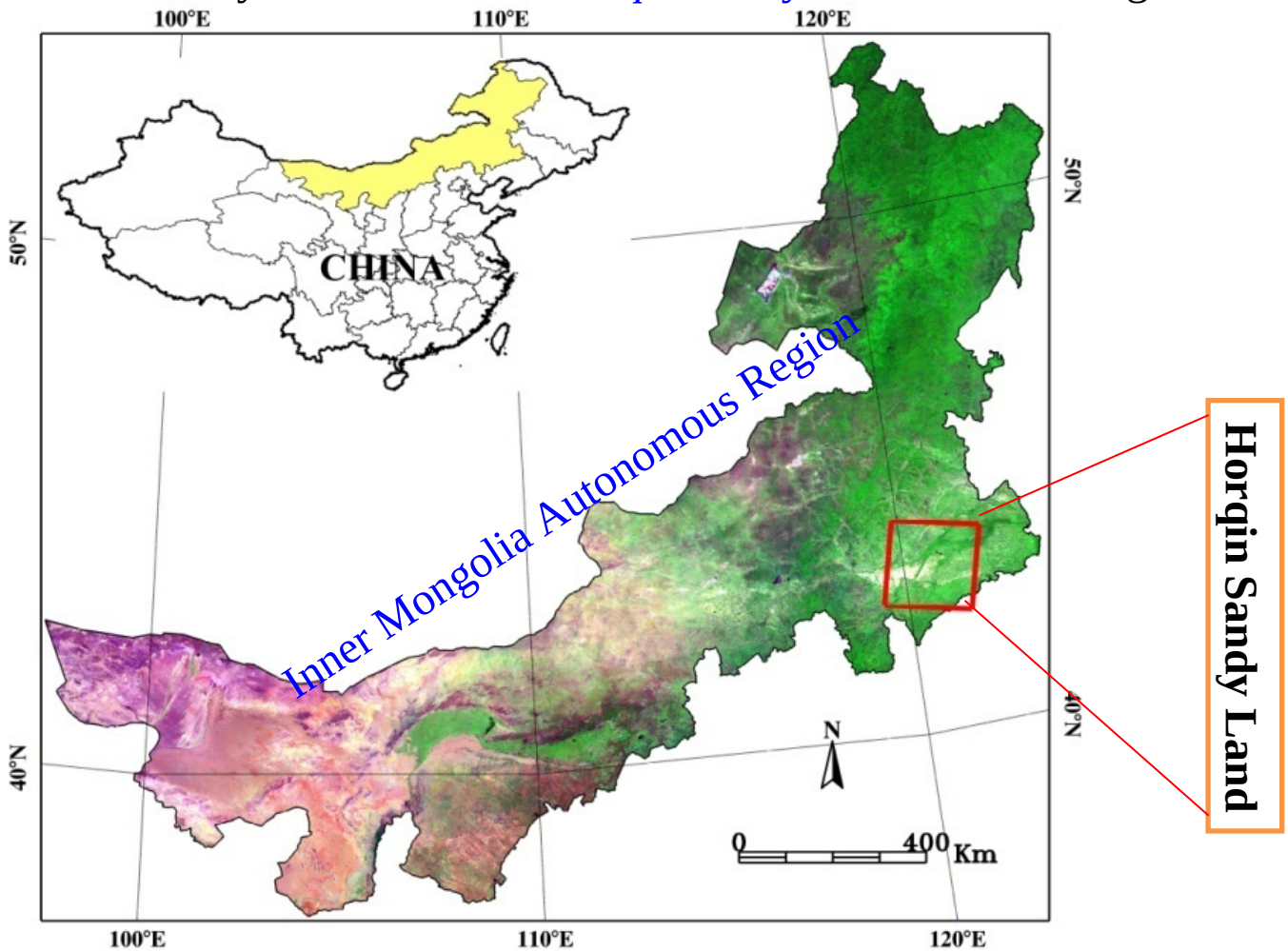
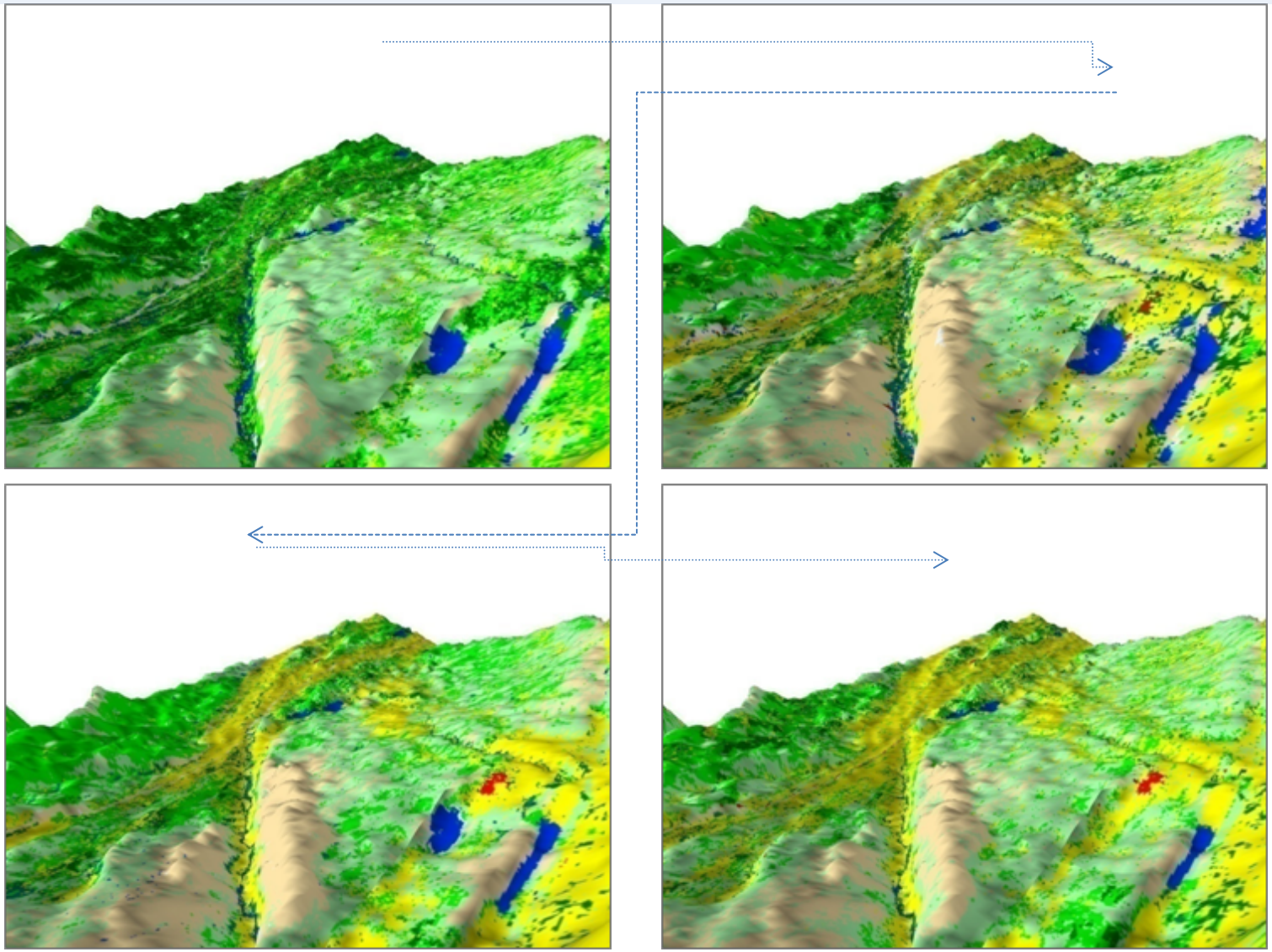
Location of the study area located in Horqin Sandy Land, Inner Mongolia.



We evaluated the changes of land cover by using Landsat archive images from 1976-2007. The SOM neural network method and the subspace method were used for land cover classification.

3. Case Study: Land cover/land use change



Water Tree Crop Sandy Sparse Grass Urban Bare Wetland

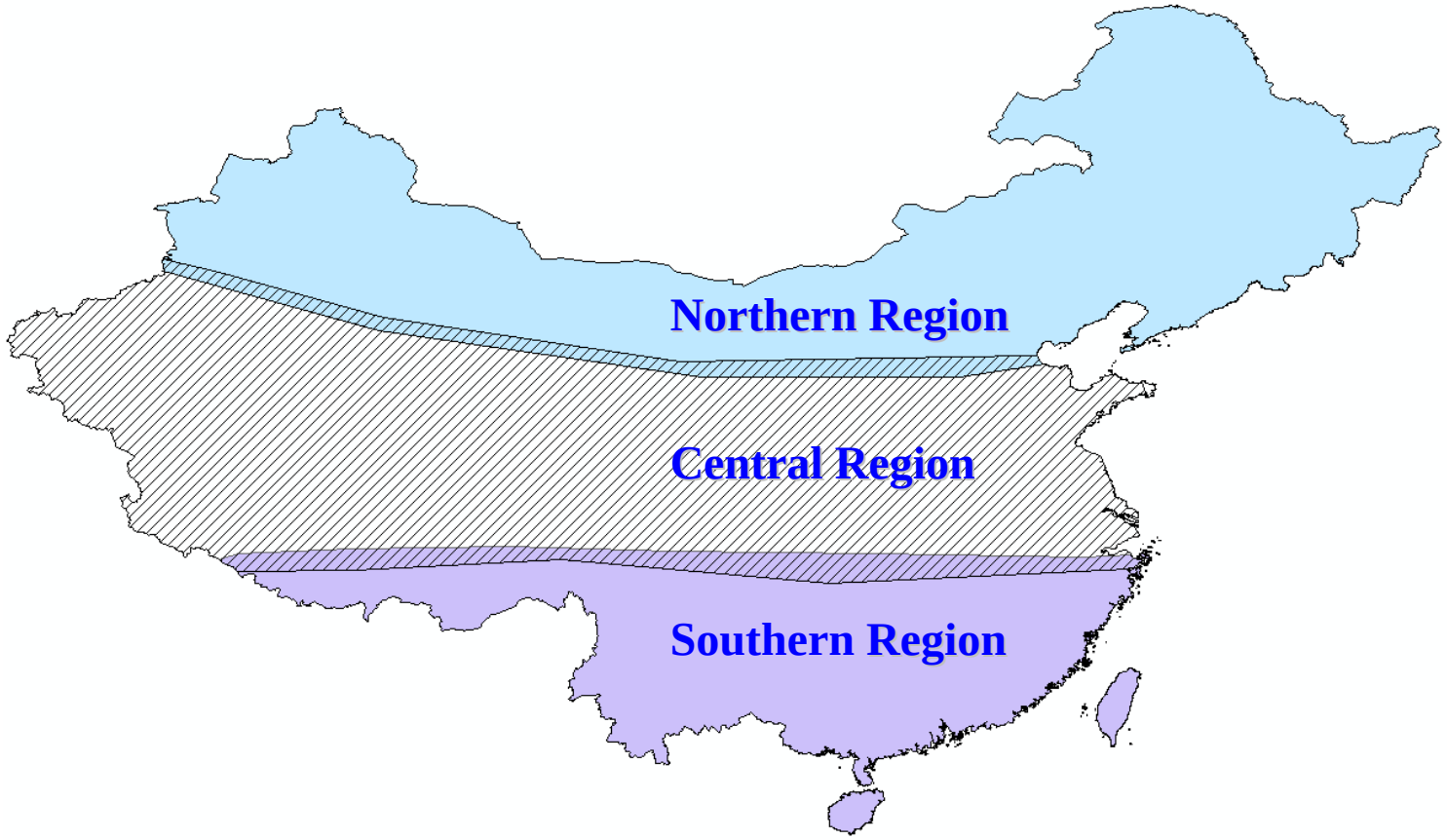
The major changes observed is the conversion of grassland and woodland to cropland. Moreover, lakes and rivers disappeared rapidly in the three decades.

4. Land cover classification in China

4. Land cover classification in China

We divided China into three regions based on the climatic and agricultural cultivation conditions.

Each region has some overlapping areas with its neighborhood regions to avoid the borderline problem.



4. Land cover classification in China

We adopt MODIS Enhanced Vegetation Index (EVI) data for classification. MODIS data is suitable for environmental monitoring in a large scale due to its unique combination of spectral, temporal and spatial resolutions.

MODIS EVI is defined as:

$$\textbf{MODIS EVI} = 2.5 \times \frac{NIR - \mathrm{Red}}{NIR + 6 \times \mathrm{Red} - 7.5 \times Blue + 1}$$

Compared to NDVI, EVI shows better dynamic range, less saturation.

4. Land cover classification in China

MODIS data:

1. EVI : time-series 16-day composite 500-m EVI data of 17 dimensions from March 6 to December 2 in 2003
2. RGB: **Red**, near infrared (**NIR**), and **Blue** reflectance data from MOD13A1 on July 2003 were used for record the location of ground reference data sites.

Ancillary data:

1. TM/ETM, ASTER data were used for selecting ground reference data by visual image interpratation .
2. NLCD-2000 GIS data: The China National land cover/land use dataset were used to confirm the ground reference data.
3. Statistical data: County-level agricultural census data in year 2000 were used as another reference data to evaluate the cropland area extend.

Classification method:

SOM method is implemented for time-series data analysis.

4. Land cover classification in China

9 Land-cover types:

1. Water, 2. Woodland, 3. Grassland, 4. Dry farmland, 5. Sandy land, 6. Paddy rice, 7. Wetland, 8. Urban/bare soil, 9. Snow/Ice.

Collection of ground reference data:

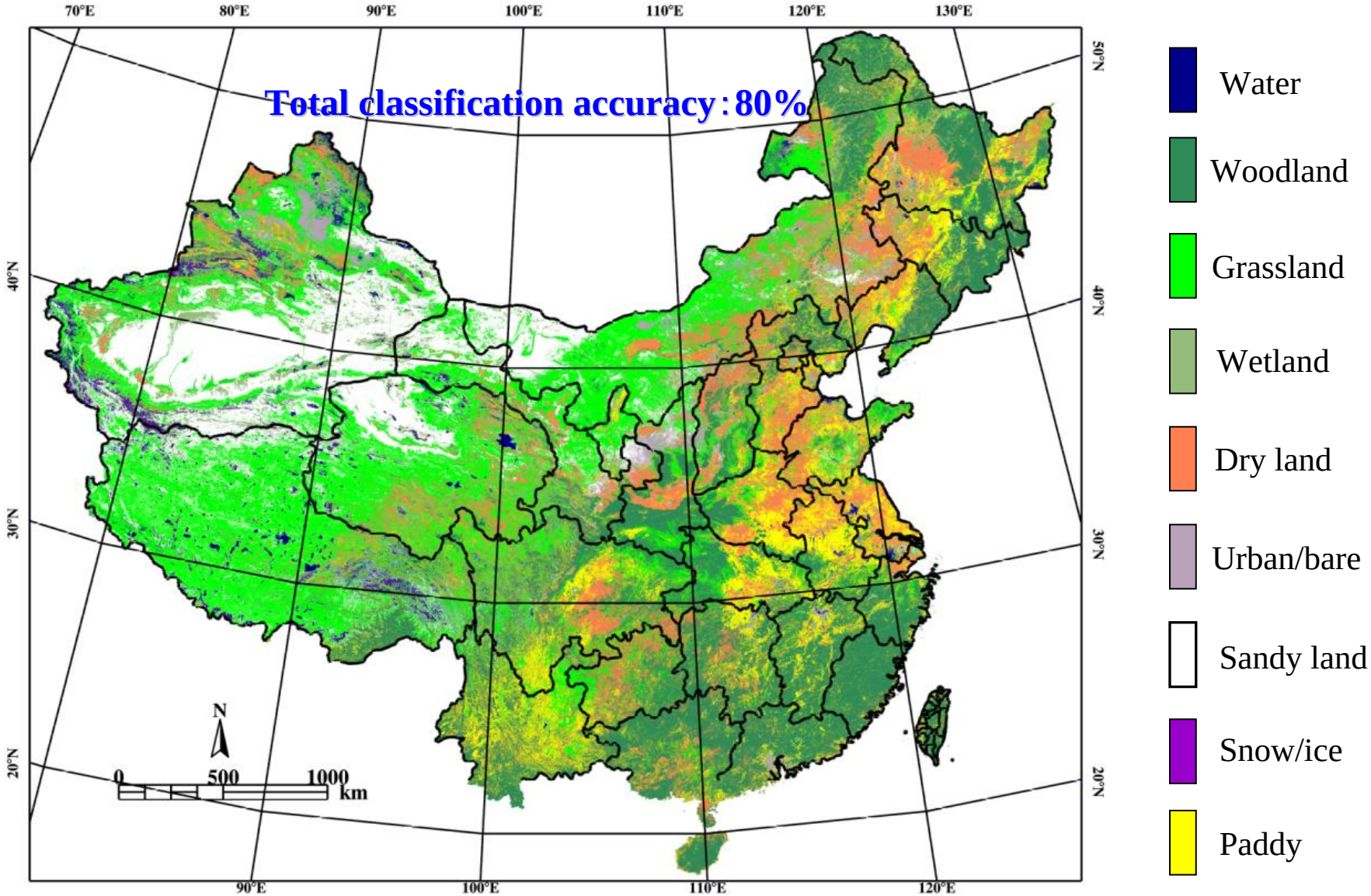
First, visual interpretation of ASTER, TM/ETM and MODIS RGB composite color image to select ground reference pixels (sites) for each land cover types.

Second, compare each reference site on the image corresponding on the NLCD-2000 GIS data. If these pixel locations coincide with the center of NLCD-2000 GIS data, they were defined as ground reference data; otherwise, we removed the pixels from ground reference datasets.

Finally, The ground reference data is randomly divided into training and testing sets.

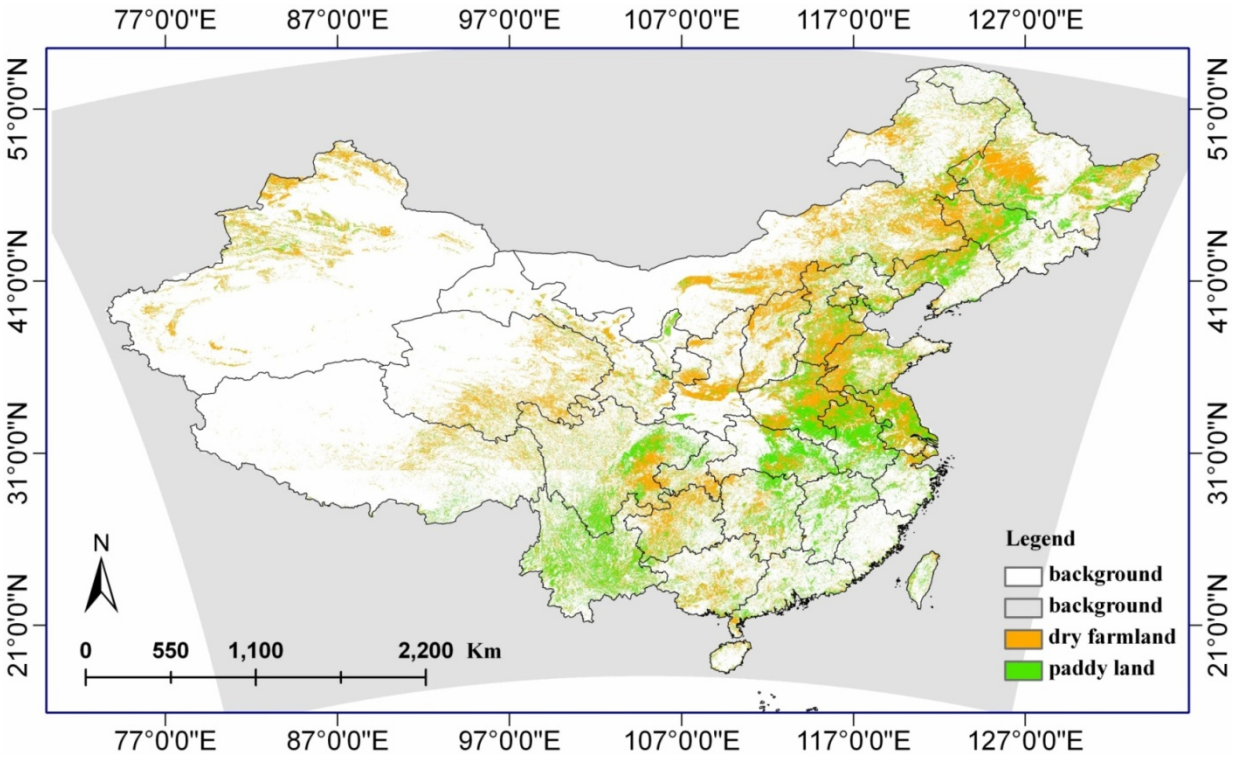
4. Land cover classification in China

Land cover classification map of China from MODIS EVI by SOM.



4. Land cover classification in China

To analyze the spatial distribution of the cropland areas in China, we extracted the cropland areas from the classification map and present it in bellow.



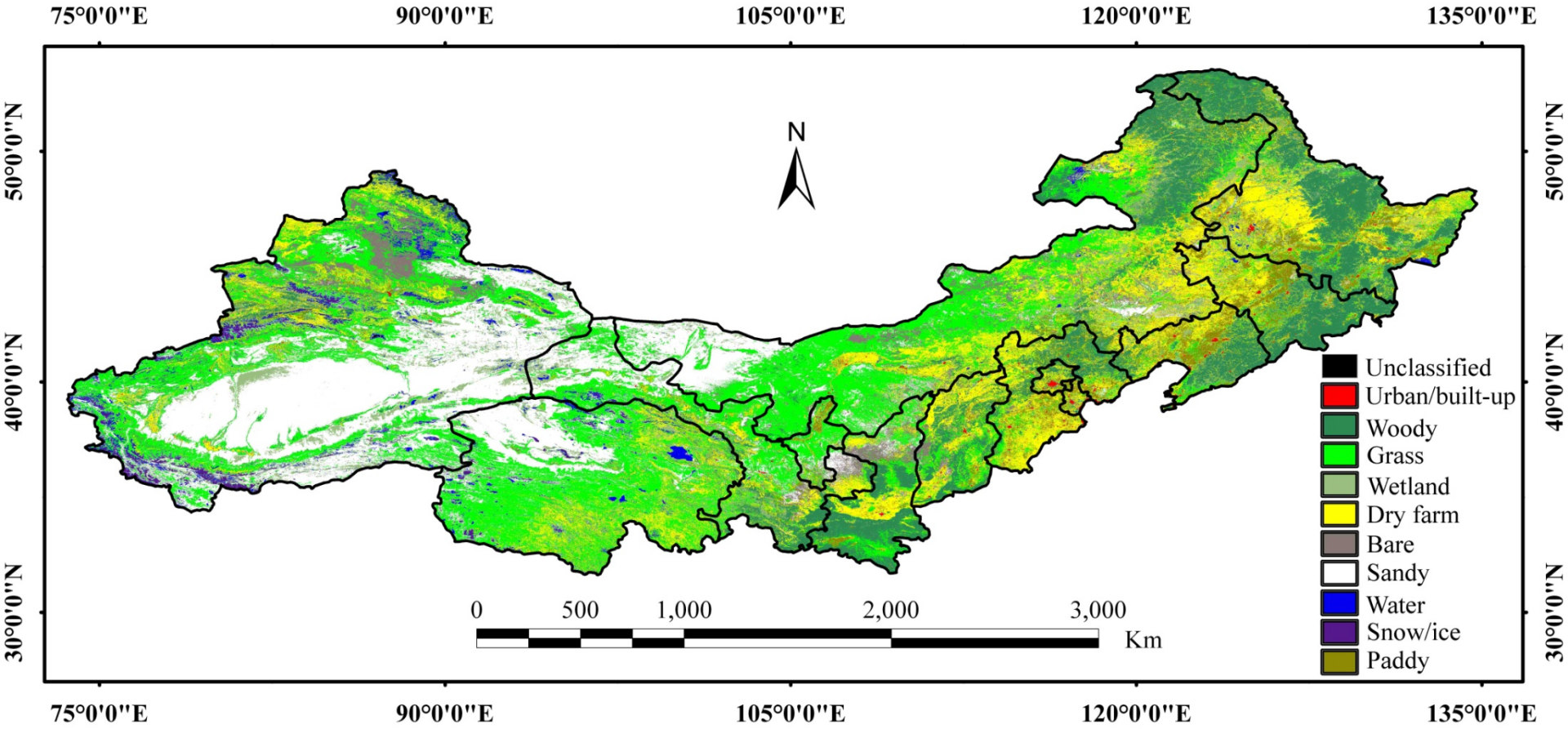
As can be seen, the North and Southeastern regions appeared to lose croplands.

While the northeastern and northwestern regions show large expansion in croplands.

Most of the lost cropland had good quality with high productivity, but most gained cropland was poor quality land with less suitability for crop production.

4. Land cover classification in China

Following map is land cover map in north China. Here, the urban/build-up areas were separated from the urban/bare category by using NLCD-2000 GIS data, because separate the urban/built-up areas from bare areas is difficult at 500 m spatial resolution.

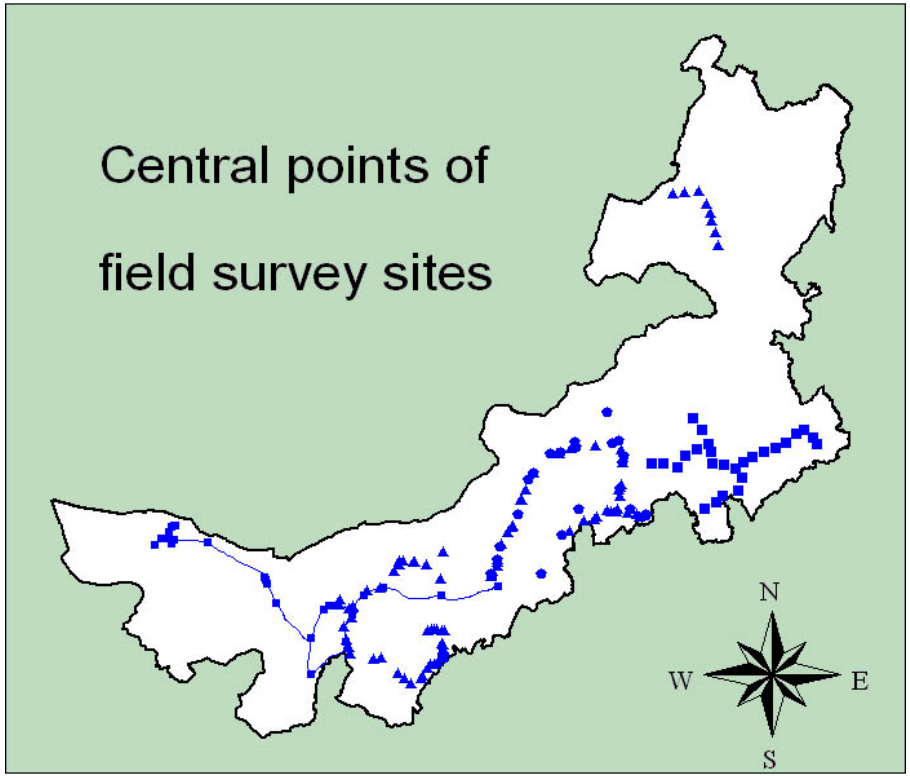


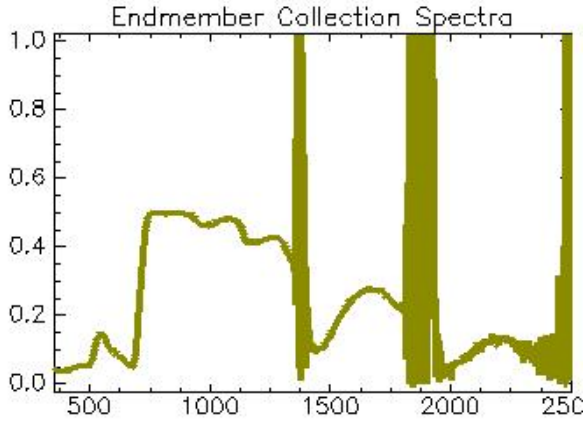
4. Land cover classification in China

To focus on land degradation and desertification in Inner Mongolia, we designed 13 land-cover types for land cover classification.

Data: A 16-day composite EVI time-series data for 2003 (from March 22 to September 30 in 2003, 14 dimensions) used for land cover mapping

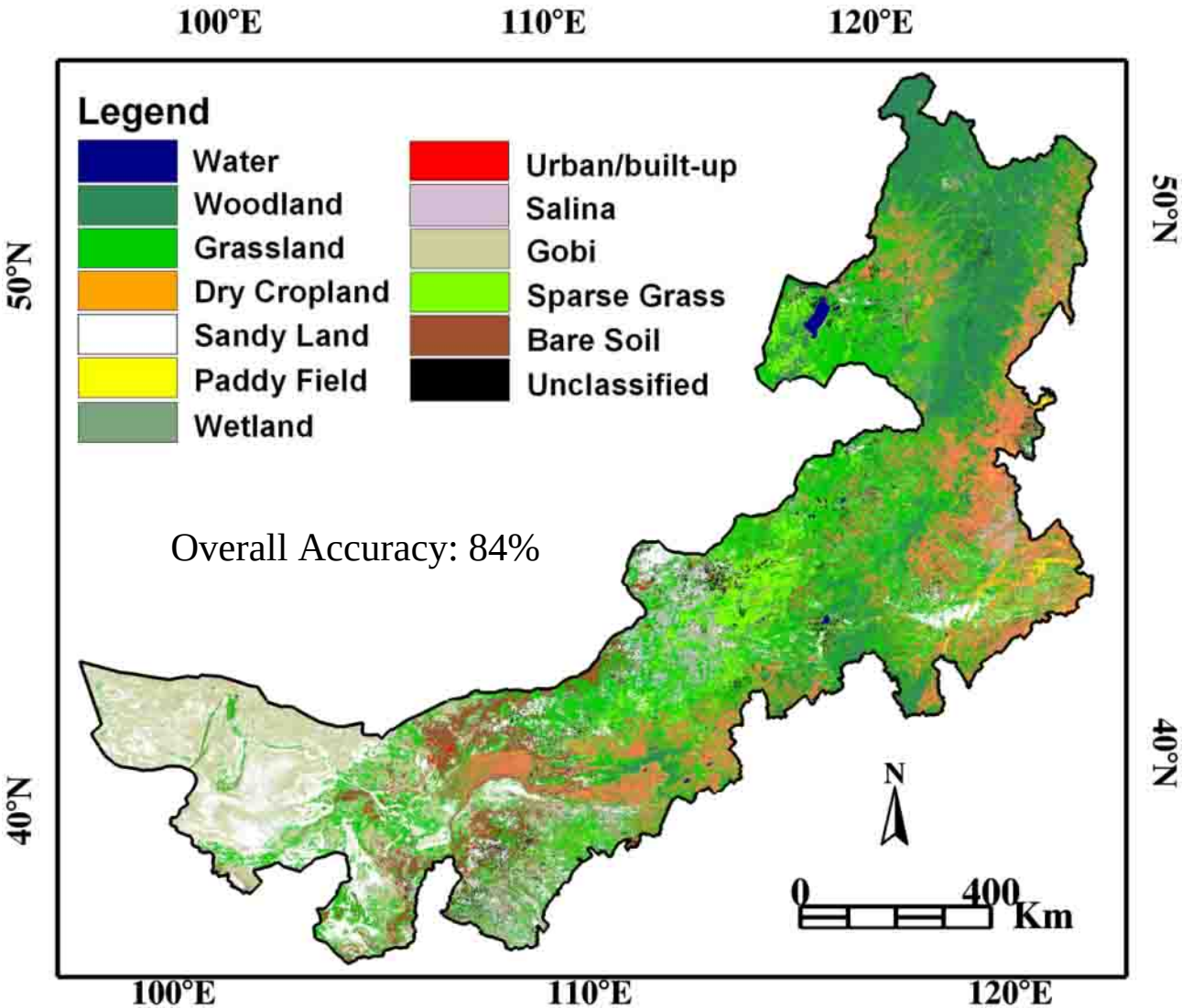
Ancillary data: ASTER, TM/ETM, SPOT, GIS data, aerial photographs, and field survey data were used as the ground truth.





4. Land cover classification in China

Land cover classification map of Inner Mongolia.



These results demonstrate that:

1)SOM could work well for the MODIS EVI time-series data

2)MODIS EVI time-series data can produce accurate land cover classification map from region to country level

3)SOM+MODIS EVI only request limited ancillary data and little labor-input.

(*Hasi Bagan et al, J. Appl. Remote. Sens., 2007*)

5. Land cover classification in Mongolia

5. Land cover classification in Mongolia

Data:

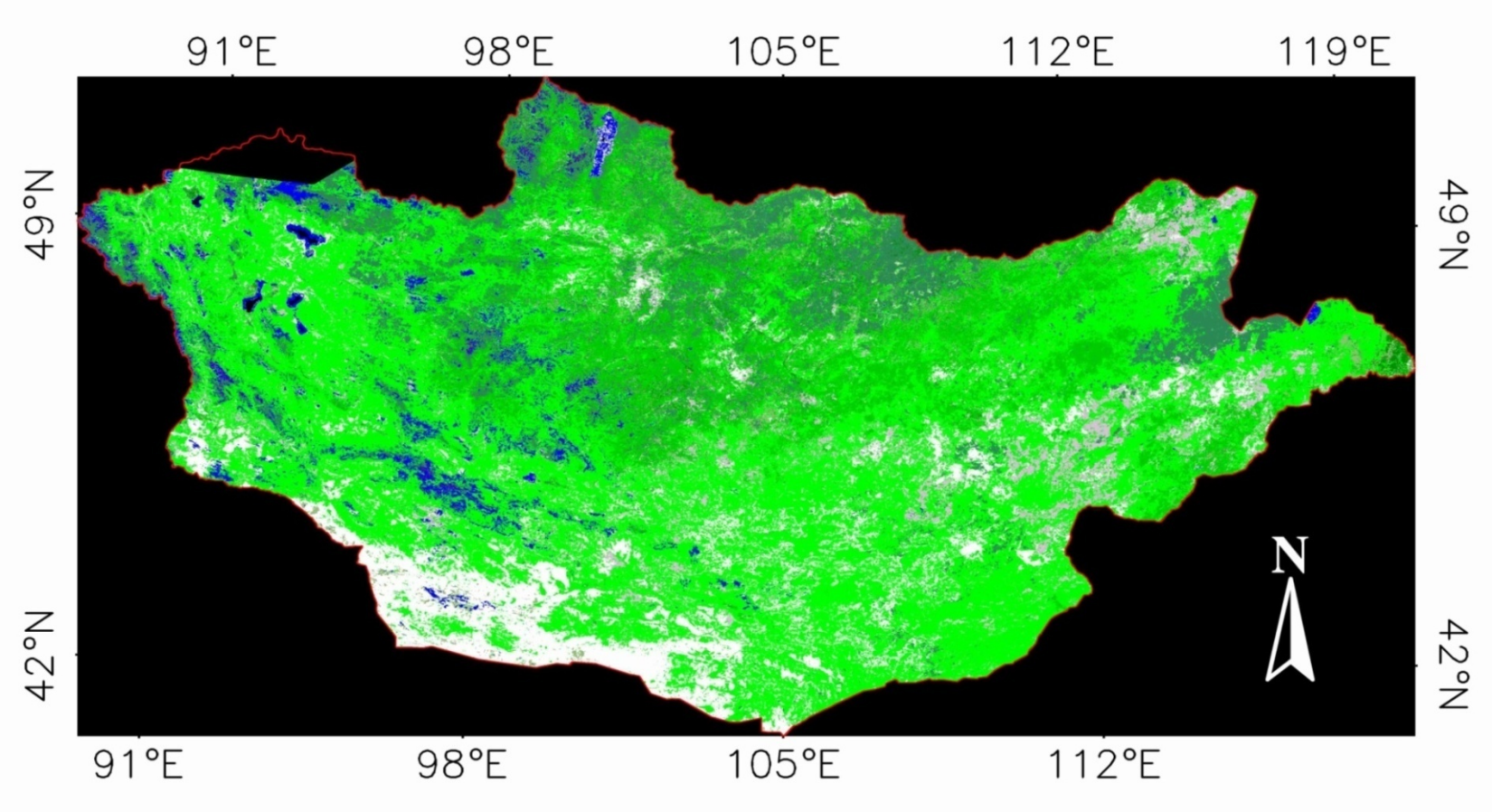
A 16-day composite EVI time-series data for 2003 (March 22 to September 30 in 2003, 14 dimensions) used for land cover mapping

Ancillary data:

Only fine resolution satellite images (ASTER, TM/ETM) used for selecting ground reference data by visual image interpretation.

5. Land cover classification in Mongolia

The image below shows land cover classification map of Mongolia. Some grassland and woodland pixels are incorrectly classified as water region.



The classification error is due to the fact that 1) lack of good ground reference datasets; 2) selected time period is maybe out of growing season of vegetation.

5. Land cover classification in Mongolia

To improve an accuracy of land cover map in Mongolia, we need to increase our scientific knowledge and experience, for example:

1.Conduct field survey in Mongolia

2.Collect ancillary GIS datasets (e.g., water, transportation)

3.Collect statistics datasets and related maps

4.Choice some typical landscape and geographic region to conduct land cover classification based on fine spatial resolution images (ASTER, ALOS, and Landsat TM).

5.Then, select suitable period of time-series MODIS data to mapping entire Mongolia.

6. Conclusions and future work

6. Conclusions and future work

1. SOM method is suitable for classification of MODIS EVI time-series data,
2. SOM+MODIS required limited ancillary data and little labor-input, so it can be used to produce an accurate land cover classification map in country scale.
3. Subspace method is useful for classification of medium resolution data, such as ASTER, TM, *et al*.
4. Land cover and land use change analysis in Horqin Sandy Land indicated heavily environmental problems in this region.
5. We have produced an accurate land cover map in China. However, the result of land-cover analysis in Mongolia is prone to some classification errors due to lack of field survey data and other ancillary data.
6. Future work is to improve classification accuracy in Mongolia and analyze impacts of land cover changes. We also plan to use remote sensing data to extract most suitable region for build solar energy plant.

Thank you very much for your attention

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