ESA–MOST Dragon Cooperation

中国科技部-欧洲空间局“龙计划”合作

2017 DRAGON 4 SYMPOSIUM

2017年“龙计划”四期学术研讨会

ID：32396

Land degradation surveillance of drylands in China

LI：Prof. Gao Zhihai and Prof. Gabriel del Barrio

26–30 June 2017 | Copenhagen, Denmark

2017年6月26-30日，丹麦 哥本哈根

ADVANCED REMOTE SENSING METHODS FOR LAND DEGRADATION ASSESSMENT BY COUPLING VEGETATION PRODUCTIVITY AND CLIMATE IN DRYLANDS

Zhihai Gao*, Bin Sun, Maria E. Sanjuán, Jaime Martinez-Valderrama, Gabriel del Barrio, Li Xiaosong, Juan Puigdefábregas, Wang Bengyu

Outline

Project's partners

Principal Investigators

Prof. Gao Zhihai

Institute of Forest Resource Information Techniques (IFRIT), Chinese Academy of Forestry (CAF), China

Prof. Gabriel del Barrio

Arid Zone Research Station (EEZA), Scientific Research Council (CSIC), Spain

Dr. Li Xiaosong （RADI, CAS）

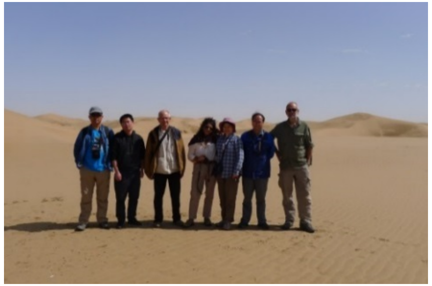
Dr. Sun Bin（IFRIT, CAF, China）

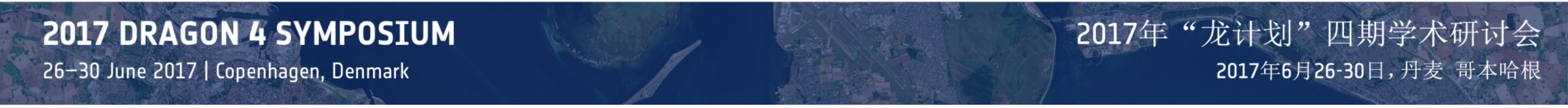
Dr. Jaime Martinez-Valderrama（EEZA, CSIC, Spain）

Dr. Wang Bengyu（IFRIT, CAF, China）

Maria E. Sanjuán（EEZA, CSIC, Spain）

Prof. Juan Puigdefabregas（EEZA, CSIC, Spain）



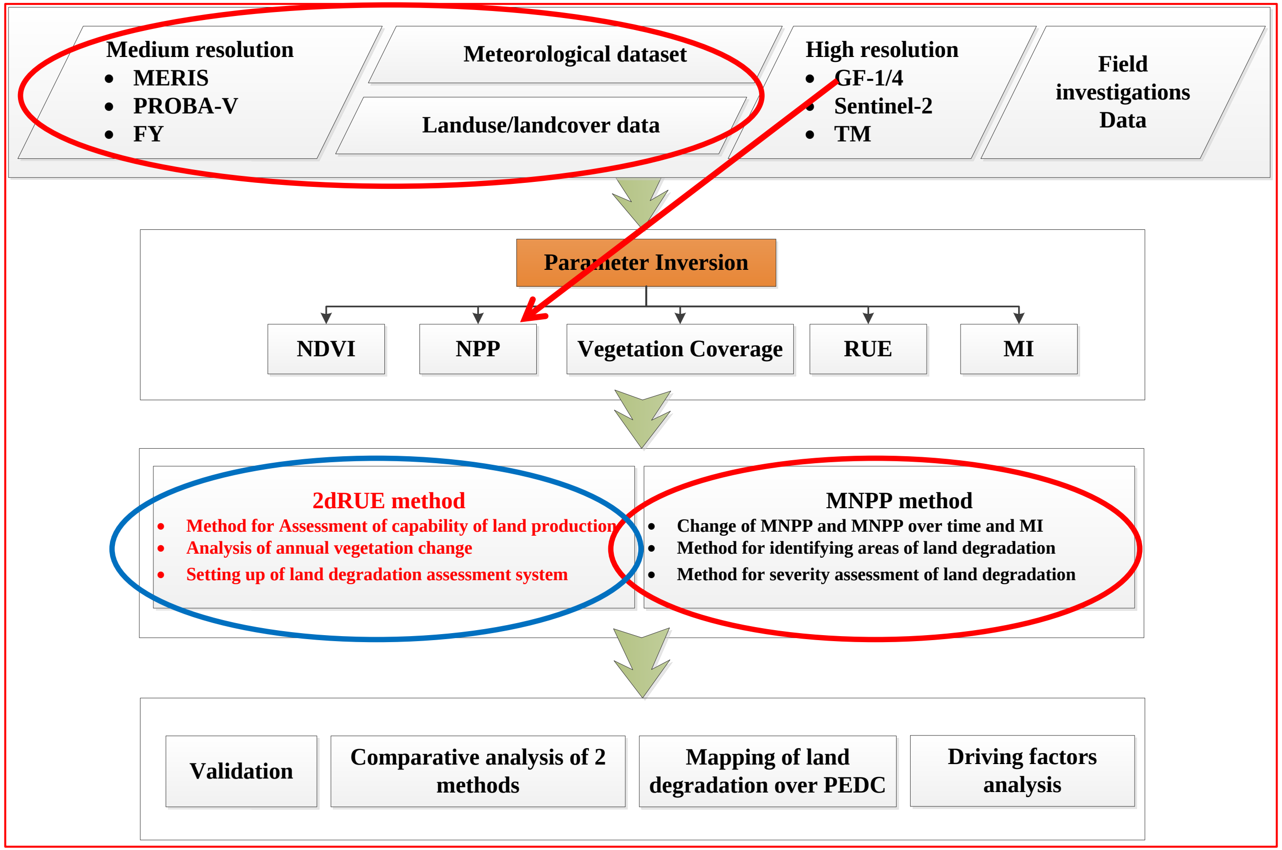


Project objectives

Detecting land degradation in dry lands at a regional scale.

Objectives:

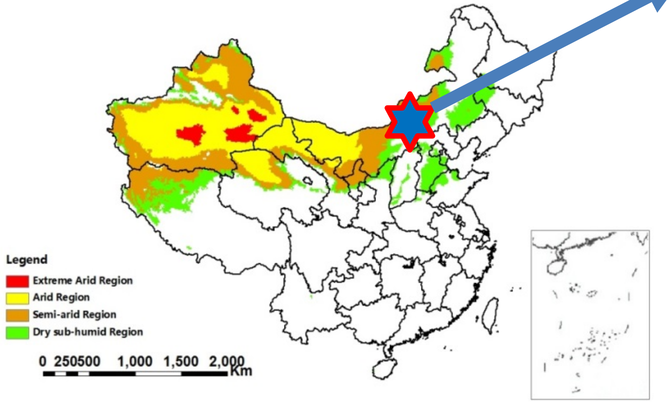
1. To enhance, benchmark and validate two novel approaches to land degradation surveillance by remote sensing: a two-dimensional implementation of Rain Use Efficiency (2dRUE), and a Moisture-responded Net Primary Productivity (MNPP).
2. To use the said approaches to map land degradation in a study area defined by the Potential Extent of Desertification in China. This is a delimitation of UNCCD-affected areas in terms of drylands within China.



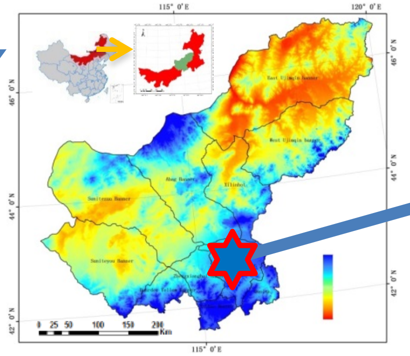
Flowchart of technique route for Project

Test site and data acquisition

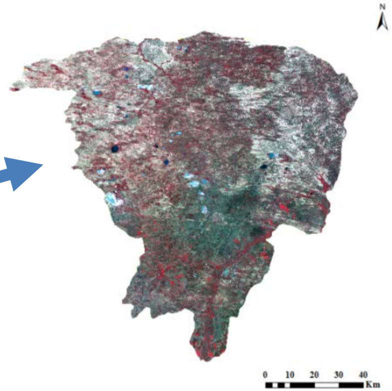
Test sites



Scope of the general potential extent of desertification in China（1981-2010）



DEM of Xilin Gol League
(Resolution:30m)



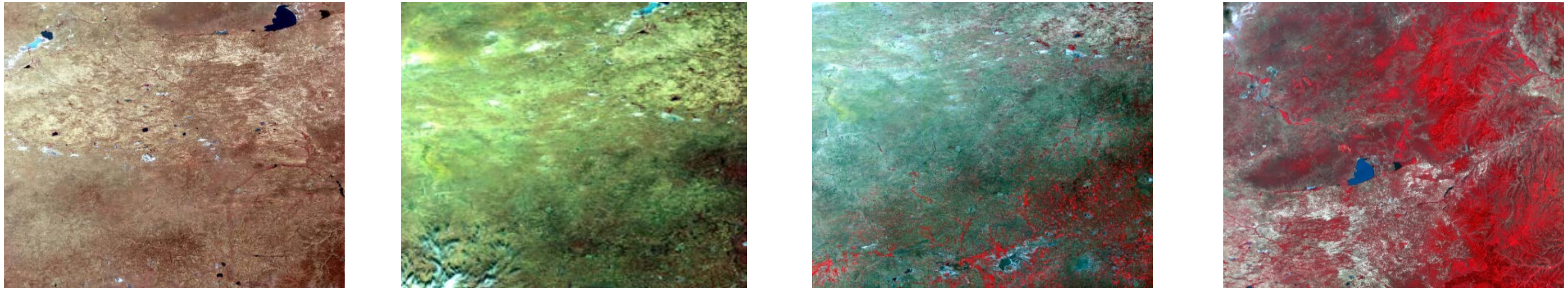
Zhenglan Banner(GF-1)

Test sites and data acquisition

Remote sensing data acquisition

DATA	SCENE	TIME	COVERAGE
10-Day composite NDVI From Envisat-Meris	358	2002/04-2012/03	China
GF-1	51	2014	Zhenglan Banner, Xilin Gol League

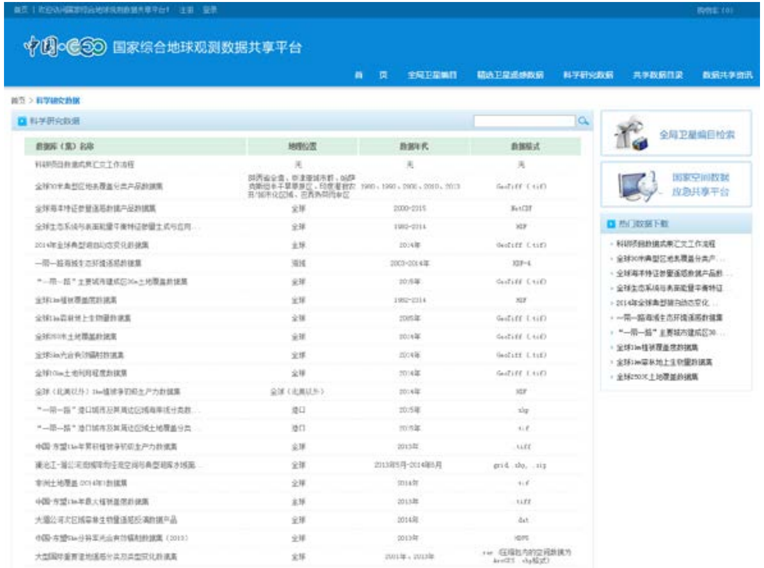
GF image



National Integrated Earth Observation Data Sharing Platform

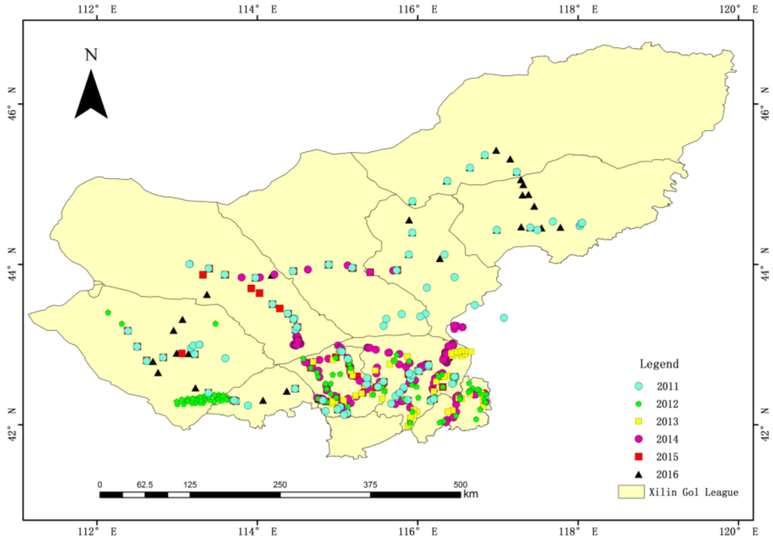
国家综合地球观测数据共享平台 (China GEO)

http://www.chinageoss.org/dsp/home/index.jsp



Field Campaigns

- **Time:**2011-2016
- **Sites:** **Xilingol League, Inner Mongolia**
- **Contents:** **Types of landform， Vegetation patterns， Vegetation fraction， Biomass， Soil organic matter(SOM)， In-situ spectra measurement, etc.**
- **Number of sampling: 524**
- **Size of samples:** **30m×30m**



Sampling positions(2011-2016)

Joint Research progress

NPP Estimation Using GF-1 Data in Semi Steppe Area

Identification of Land Degradation based on MERIS data

NPP estimation

Background

- Net primary productivity (NPP) is an important ecological indicator to evaluate ecosystem, it plays an important role in the global carbon balance and evaluation;
- The vegetation in Arid and semi arid areas is sparse, the surface conditions are relatively complex, grassland is the main land cover use. But the existing data is coarse resolution and influenced by soil background greatly, making it different to achieve high precision result;
- With the development of high resolution remote sensing technology. It provide an adequate technical support for the NPP high precision estimation in arid and semiarid regions.

CASA model

$$NPP(x,t)=APAR(x,t)\times\varepsilon(x,t)$$

$$\varepsilon(x,t) = T_{\varepsilon1}(x,t)\times T_{\varepsilon2}(x,t)\times W_{\varepsilon}(x,t)\times\varepsilon_{max}$$

Based on landuse/landcover

$$APAR(x,t)=0.5\times SOL(x,t)\times FAPAR(x,t)$$

$$FAPAR_{NDVI}(x,t)=\frac{(FAPAR_{max}-FAPAR_{min})\times(NDVI(x,t)-NDVI_{i,min})}{(NDVI_{i,max}-NDVI_{i,min})}+FAPAR_{min}$$

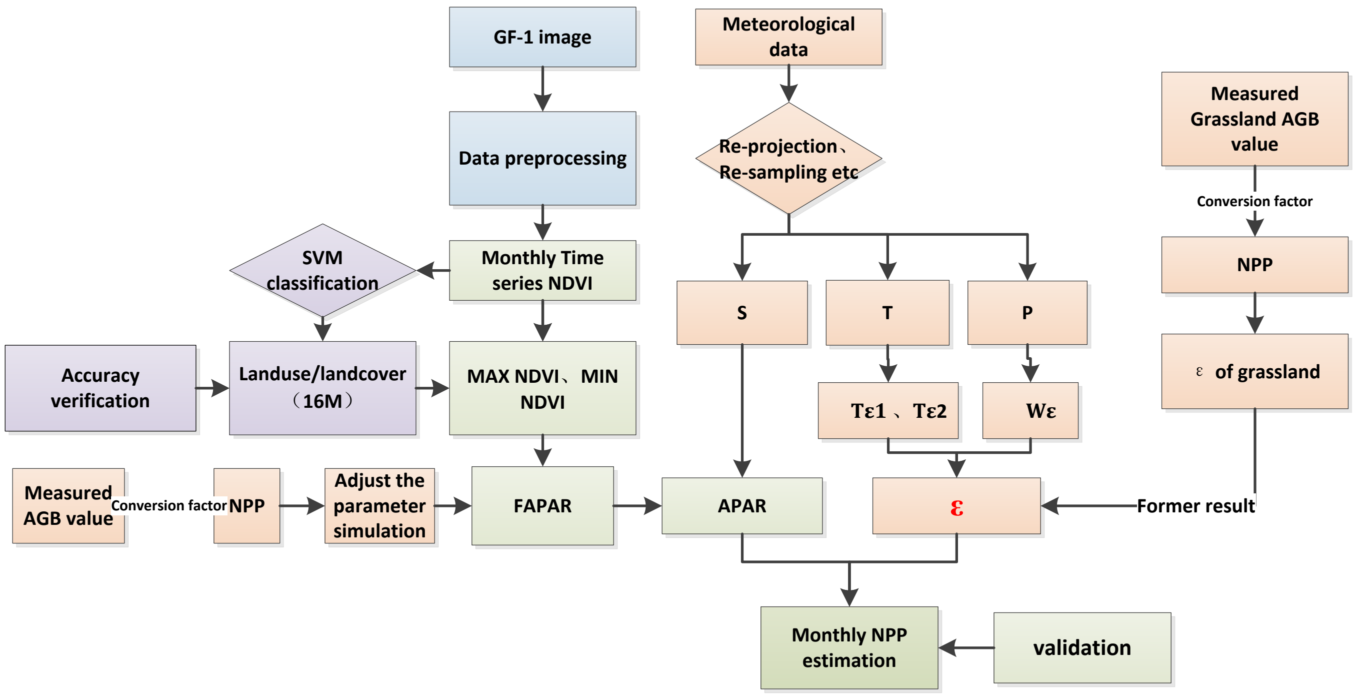
$$FPAR_{SR}(x,t)=\frac{(FPAR_{max}-FPAR_{min})\times(SR(x,t)-SR_{i,min})}{(SR_{i,max}-SR_{i,min})}+FPAR_{min}$$

$$FPAR(x,t)=\beta FPAR_{NDVI}+(1-\beta)FPAR_{SR}$$ (Los,1994)

$$T_{\varepsilon1}(x,t) = 0.8 + 0.02\times T_{opt}(x) - 0.0005\times[T_{opt}(x)]^2$$

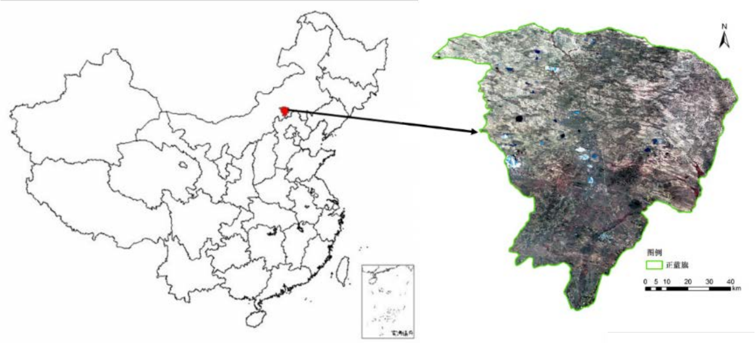
$$W_{\varepsilon}(x,t) = 0.5 + 0.5\times E(x,t)/E_p(x,t)$$

$$T_{\varepsilon2}(x,t) = 1.184/\{1+exp[0.2\times(T_{opt}(x)-10-T(x,t))]\}\times 1/\{1+exp[0.3\times(-T_{opt}(x)-10+T(x,t))]\}$$



Flowchart of technique route

Test site and data



- Image type: GF-1
- Spatial resolution : 16m
- Imaging time: 2014.01-07
- Total scenes: 51

Month	scene	Quality
1	6	NO Cloud，Good
2	2	NO Cloud，Good
3	3	NO Cloud，Good
4	5	NO Cloud，Good
5	1	NO Cloud，Good
6	4	Small cloud，No effect
7	5	NO Cloud，Good
8	3	Small cloud，No effect
9	4	NO Cloud，Good
10	8	NO Cloud，Good
11	5	NO Cloud，Good
12	5	NO Cloud，Good

Meteorological data:China’s high-resolution meteorological dataset, monthly rainfall, temperature and solar radiation data. Resolution： 0.1° ×0.1°

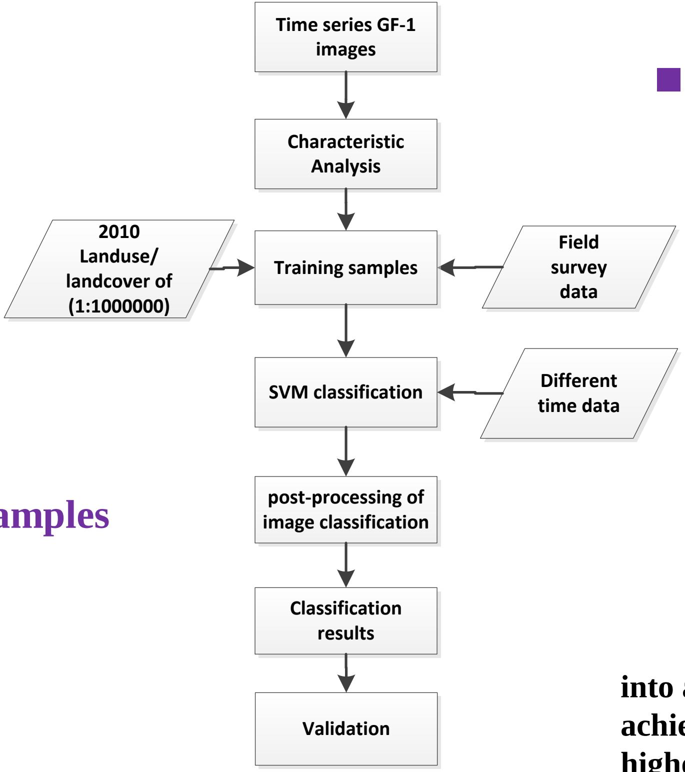
Land Cover Classification Based on GF - 1 Time Series Data

■ Classification system

According to the land cover classification system used in the 2010 National 30m Land Cover Map published by the Chinese Academy of Sciences, and considering the actual characteristics of the study area, it is divided into 12 categories

■ Training and validation samples

Samples:307
Training samples:154
Validation samples:153



Flow chart for land cover classification

■ Classification method

(1) Feature analysis method (Jefries-Matusita (J-M) method)

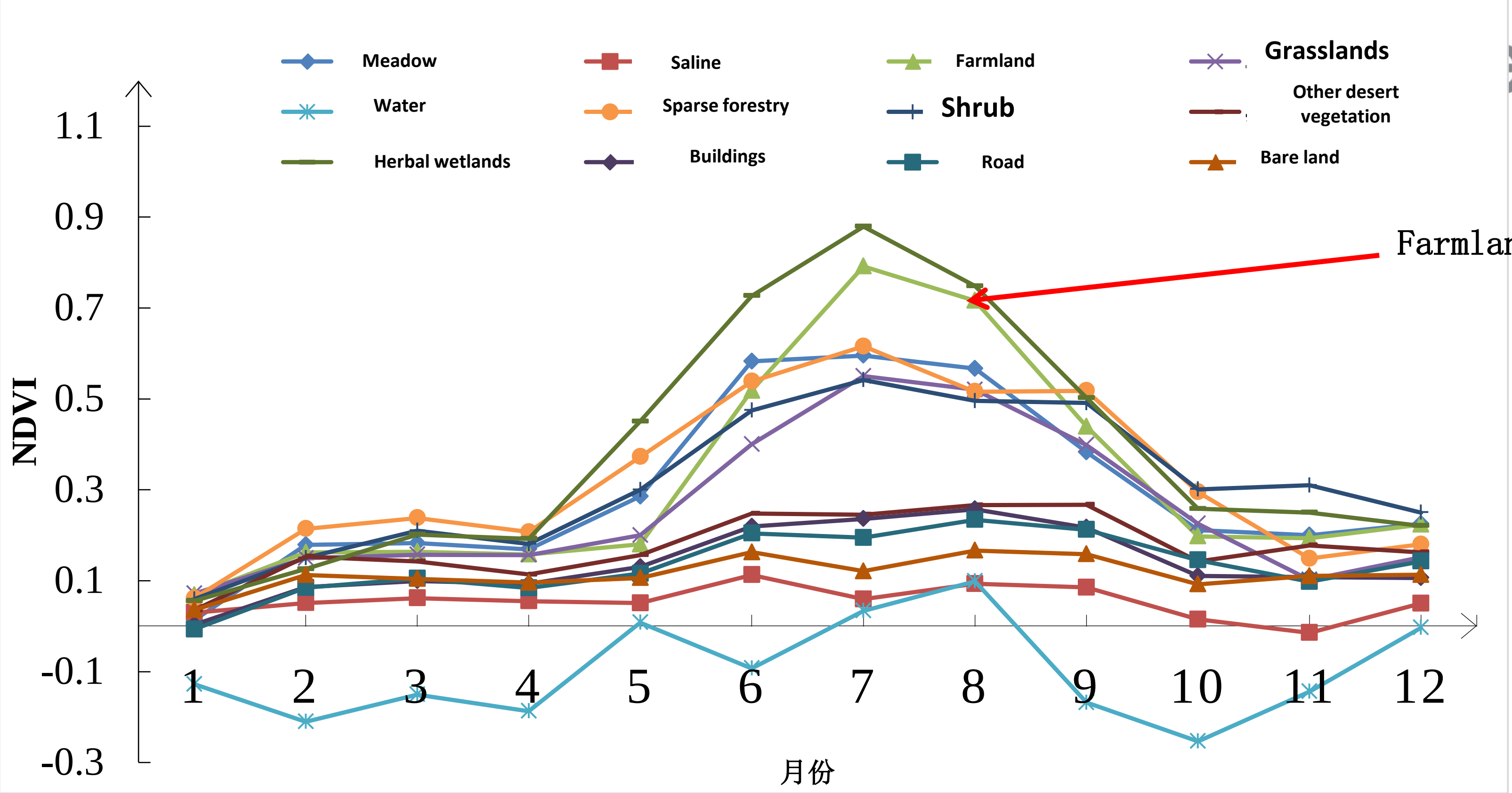
Determine the separability between categories

$$J_{ij} = \sqrt{\int_x [\sqrt{p(X/w_i)} - \sqrt{p(X/w_j)}]^2 dx}$$

(2) Support Vector Machine (SVM)

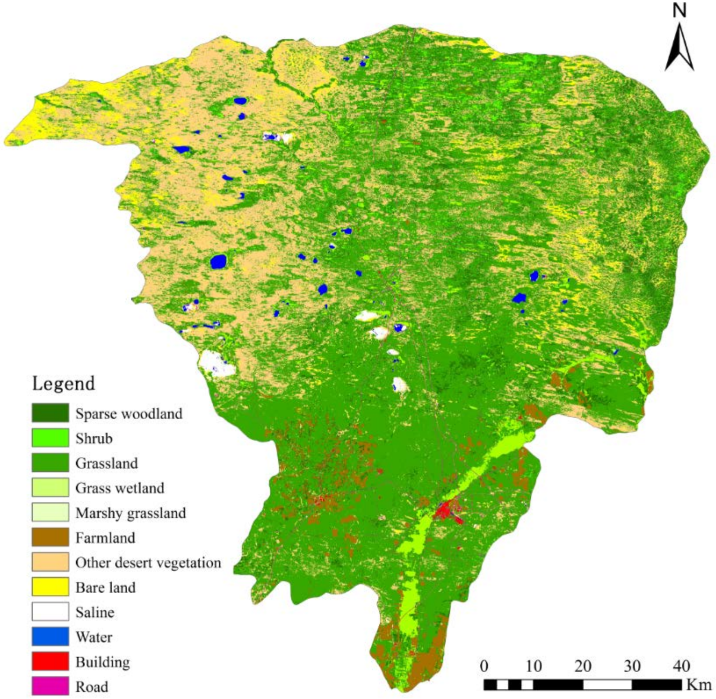
$$f(x) = w \cdot x + b$$

SVM method can turn the linear problem into a nonlinear problem and solve it well, can achieve better generalization ability and get a higher classification accuracy.



Time series variation of NDVI in different landuse types

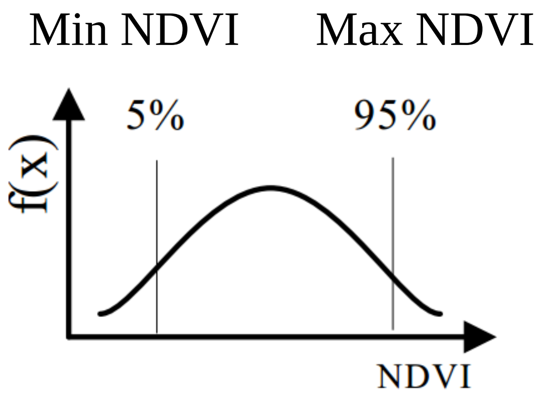
Classification result evaluation using spectral characteristics combined with NDVI time series data



Classification results using spectral characteristics combined with NDVI time series data

Types	Mapping accuracy%	User accuracy%
Sparse forestry	70.11	75.58
Buildingland	58.7	66.31
Grasslands	88.25	85.66
Meadow	77.73	83.56
Herbal wetlands	78.96	82.51
Road	47.25	59.61
Shrub	67.84	70.10
Farmland	94.38	85.59
Water	100	100
Other desert vegetation	75.21	65.79
Bare land	93.56	89.24
Saline	84.25	86.77
Total accuracy	83.37	Kappa factor 0.79

Determination of NDVI maxima and minimum of regional scale



The maximum and minimum value of NDVI data

Types	Pixel number	NDVI maximum	NDVI minimum	SR maximum	SR minimum
Herbal wetlands	1225220	0.871	0.122	14.5	1.28
Saline	243183	0.232	0.122	1.6	1.28
Water	207173	0.539	0.122	3.34	1.28
Meadow	6604	0.898	0.122	18.6	1.28
Grasslands	20984653	0.519	0.122	3.16	1.28
Farmland	1054292	0.892	0.122	17.52	1.28
Sparse forestry	3237832	0.654	0.122	4.78	1.28
Bushwood	663674	0.755	0.122	7.16	1.28
Bareland	1765047	0.253	0.122	1.68	1.28
Other desert vegetation	10553015	0.388	0.122	2.27	1.28
Building	50567	0.420	0.122	2.45	1.28
Road	178911	0.414	0.122	2.41	1.28

■ Estimation of the ε_{max} of grassland and optimization of Parameter β

$$NPP(x) = \sum_{t=1}^{m}\left(\left[\left(\beta\begin{pmatrix} FPAR_{NDVI}(i,t) \\ -\ FPAR_{SR}(i,t)\end{pmatrix} + FPAR_{SR}(i,t)\right)\cdot 0.5\cdot SOL(i,t) \cdot \begin{pmatrix} T_{\varepsilon 1}(i,t)\times T_{\varepsilon 2}(i,t) \\ \times W_{\varepsilon}(i,t)\times \varepsilon_{max}\end{pmatrix}\right]\right)$$

Set the result of the known parameter to **W** and **Y**

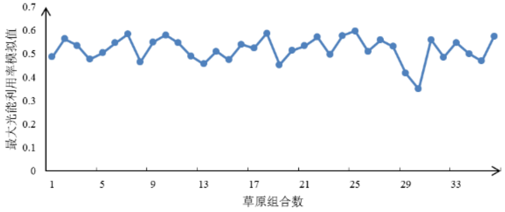
$$\boxed{NPP(x) = W\beta\varepsilon_{max} + Y\varepsilon_{max}}$$

Two combinations could calculate ε_{max} and β

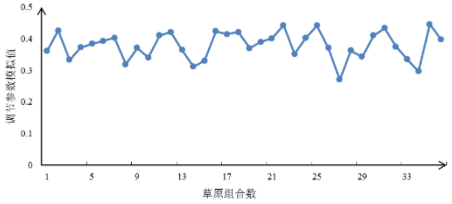
Herbal wetlands： 4 points， 6 combinations

Meadow： 3 points， 3 combinations

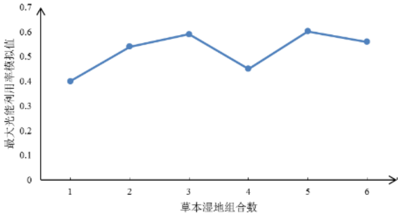
Grassland： 9 points， 36 combinations



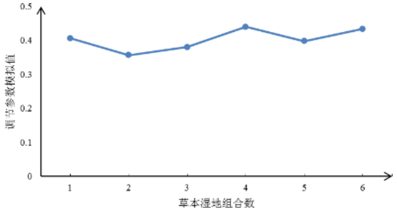
Distribution of steppe largest light energy utilization efficiency



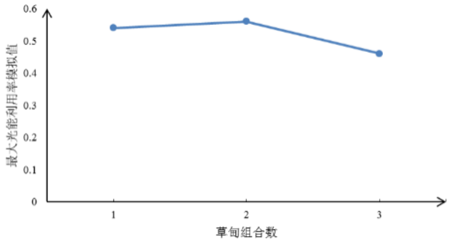
Distribution of steppe simulation parameter value



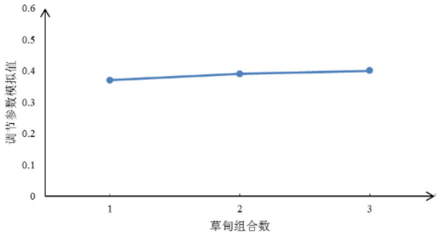
Distribution of Herbal wetlands
largest light energy utilization efficiency



Distribution of Herbal wetlands
parameter value



Distribution of meadow
largest light energy utilization efficiency

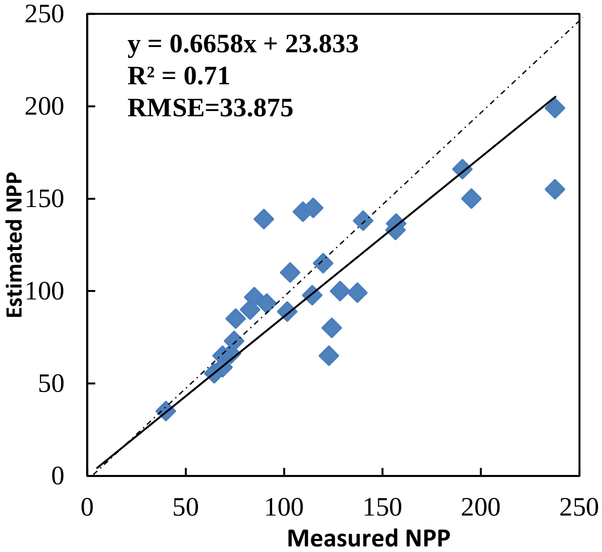


Distribution of meadow simulation parameter value

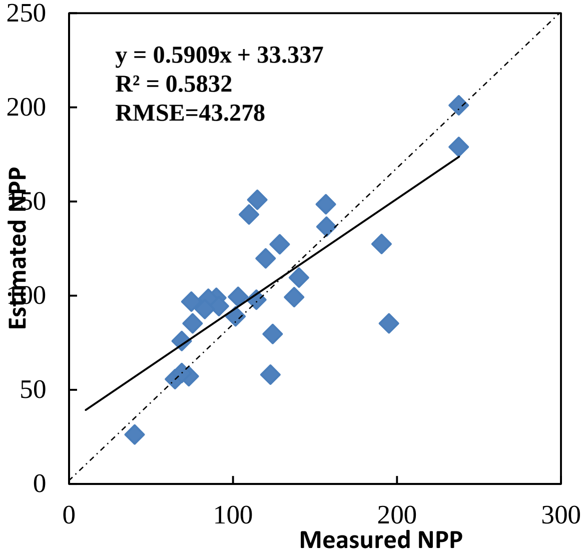
The largest light use efficiency of Variout land cover types in Zhenglan Banner

Vegetation types	Simulation value（mean）
Sparse forest	0.9075
Bushwood	0.7147
Grasslands	0.518
Farmland	0.604
Meadow	0.52
Herbal wetlands	0.523
Other desert vegetation	0.389
Others	0.389

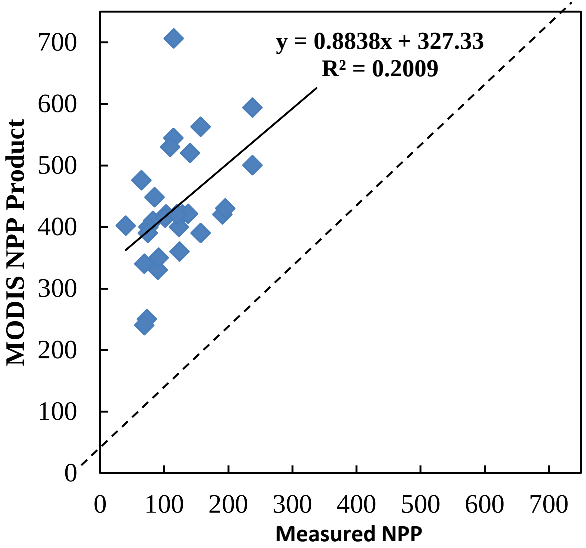
Validation



NPP validation (After parameter optimization)

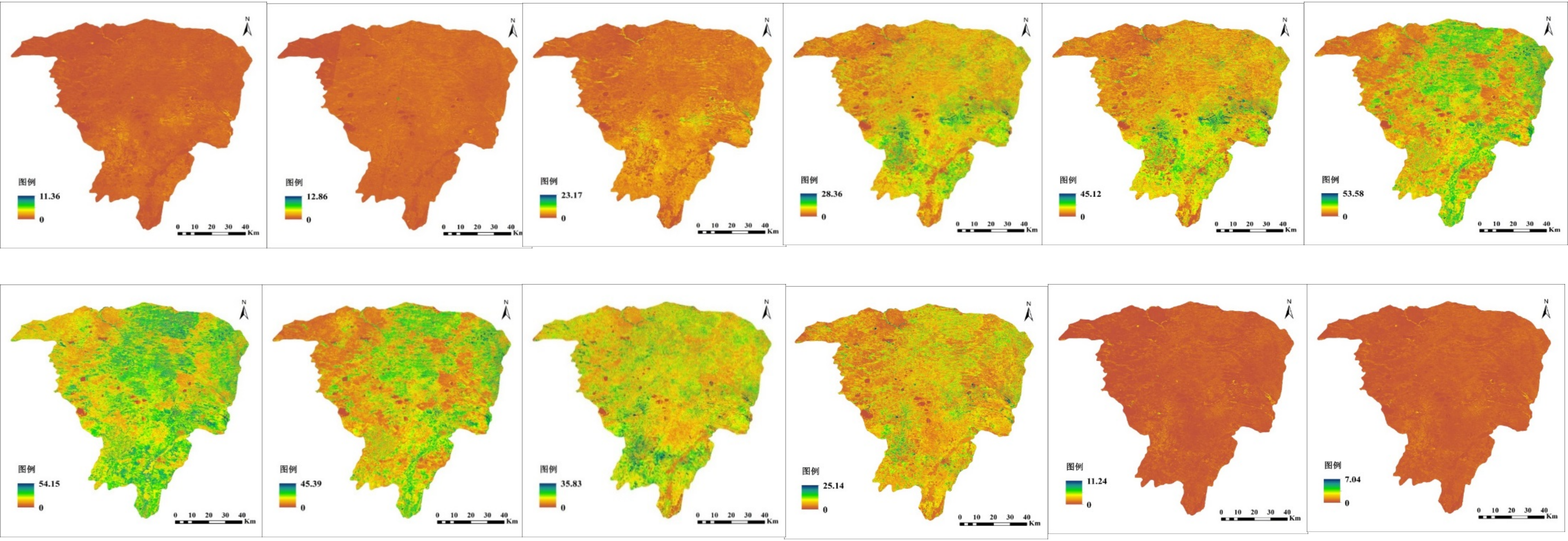


NPP validation (Before parameter optimization)

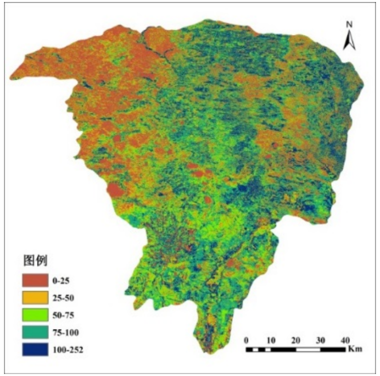


correlation coefficient between measured data and MODIS product

Distributions of monthly NPP in Zhenglan Banner



■ 2014 NPP spatial distribution of Zhenglan Banner

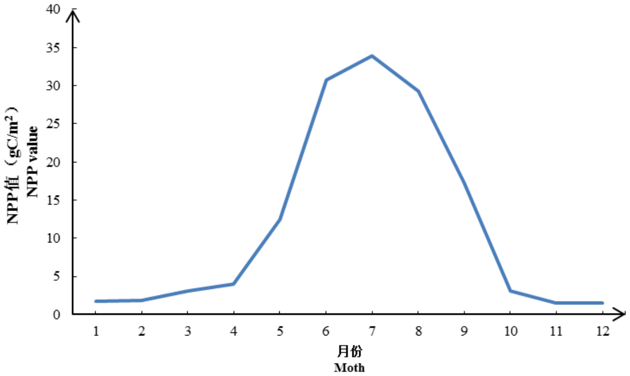


NPP distribution of Zhenglan Banner

- AVERAGE NPP is 140.28gC/m^2·a；
- High-value areas are mainly distributed in sparse woodland and shrub areas, most of the grassland is at a moderate level；
- In whole, the NPP production in the south is high, and the low NPP area is mainly concentrated in the desert vegetation and bare land type, mainly distributed in the northwest region of Zhenglan Banner.

■ Analysis of NPP Change in the Year of 2014

- **NPP growth is the largest in July, starting from April, NPP began to increase rapidly, began to decline in September, less accumulated in October.**
- **Average growth rate of NPP in July was 33.86gC/m^2,**
- **The high values of NPP mainly appear in grassland (grassland, herbal wetland, meadow, etc.) and sparse forest land。**



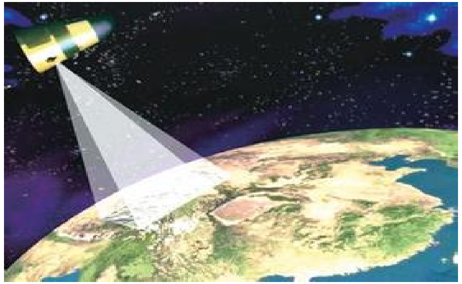
Monthly NPP change trend in a year

Conclusion and Discussion

- **GF-1 data have high spatial and high temporal resolution characteristics, it is useful to distinguish land cover types in semi-arid areas based on NDVI time series data， the accuracy was 83.37% and Kappa coefficient was 0.79.**
- **The maximum light energy utilization rate and FAPAR parameters of grassland were simulated and optimized. Compared with the measured data, the result was R^2 with 0.71, it showed that NPP estimation by GF-1 data based on the new parameters in semi-arid area is feasible.**

Identification of Land Degradation based on MERIS data

by MNPP



The scope of Land degradation/desertification may be extended during this century, which threatens the safety of grain production in China （Wang et al. 2008）.

With the development of remote sensing technology, Long time series remote sensing data have been widely used in Land degradation/desertification Assessment and Monitoring （Bai et al,2008;Gabriel et al 2010）.

1.Introduction

Acronyms

NPP	**Net Primary Production.**
MNPP	**Moisture-responded Net Primary Productivity**
CASA	**Carnegie-Ames-Stanford Approach**
MI	**Moisture Index**

1.1 Concept of Land degradation

Land degradation is a process that land productive capacity continues to decline significantly or even lose completely under the influence of natural forces and human activities.

- land degradation in China is severe, especially in Northern part of China.

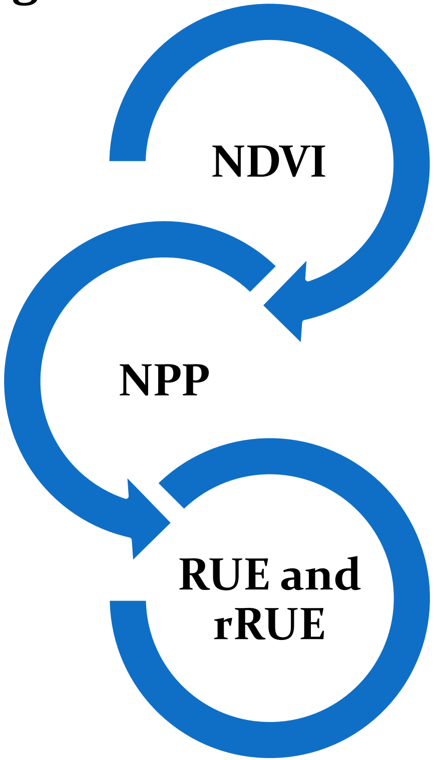
■ Land degradation assessment

- ➢ **GLASOD, ASSOD, RUSSIA**
- ➢ **GLADA, GLADIS**
- ➢ **RESTREND**
- ➢ **rRUE**

◆ Vegetation degradation is sheltered to a certain extent by vegetation variation caused by climatic fluctuation

◆ Areas of degraded lands can not be identified accurately by simple trend analysis of vegetation parameters, e.g. NDVI, NPP etc.

■ Land degradation assessment indicator



2.Materials

2.1 Data

- **Remote sensing data**

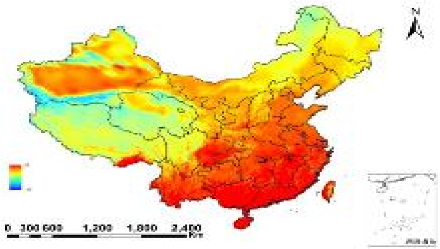
  2003-2011 MERIS NDVI data. Resolution： 4km×4km

- **Meteorological data**

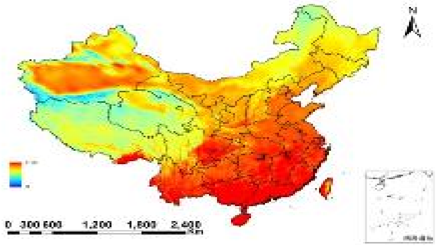
  China’s high-resolution meteorological dataset, monthly rainfall, temperature and solar radiation data. Resolution： 0.1° ×0.1°

- **Land use and cover data(2000, 2010)**

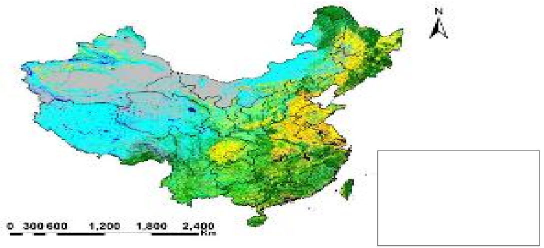
  Environmental & Ecological Science Data Center for West China



Temperature(2003)



Precipitation(2003)



Land cover data

2.2 Annual NPP estimation

Improved CASA model :

$$NPP(x,t)=APAR(x,t)\times \varepsilon(x,t)$$

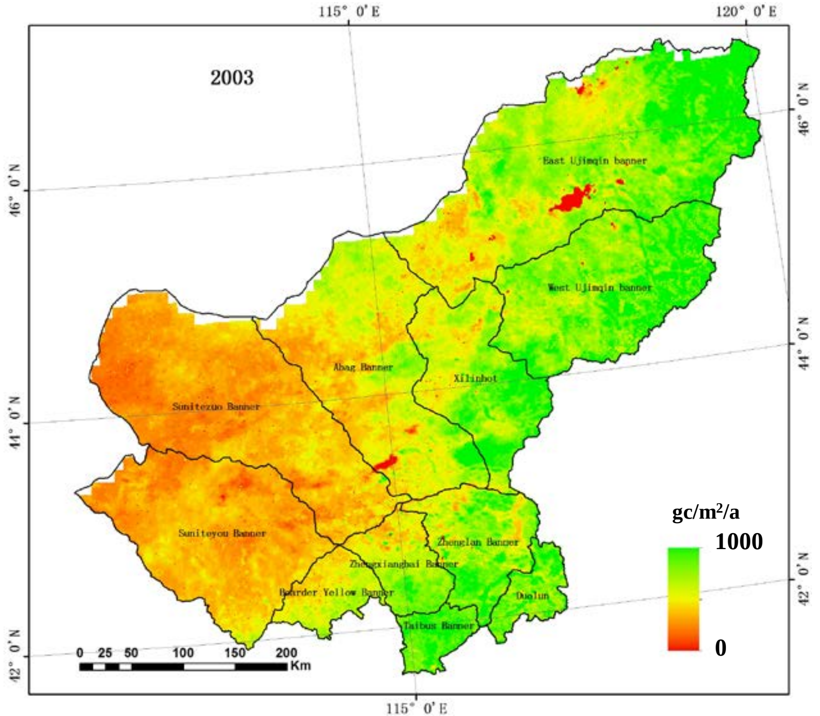
$$APAR(x,t)=SOL(x,t)\times FPAR(x,t)\times 0.5$$

$$\varepsilon(x,t)=T_{\varepsilon 1}(x,t)\times T_{\varepsilon 2}(x,t)\times W_{\varepsilon}(x,t)\times \varepsilon_{max}$$

Max of solar energy use efficiency for different land cover types in the study area (gC/MJ) (Zhu et al.,2007)

Land cover type	Forest	Shrub	Open forest	Grass	Water	City	Unuse. land	Farmland
ε_{max}	0.638	0.429	0.475	0.542	0.542	0.542	0.542	0.542

NPP distribution

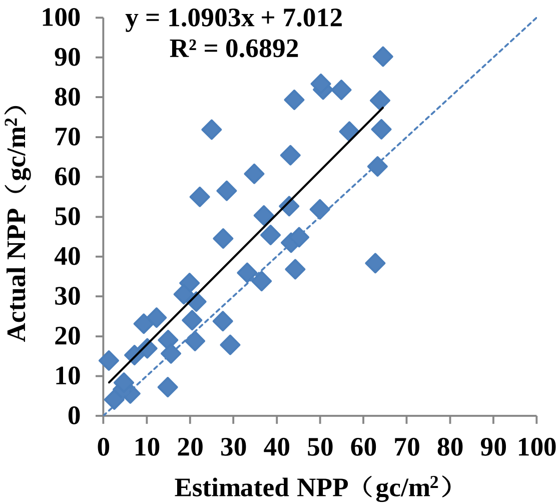


Annual NPP distribution in Xilin Gol League, Inner Mongolia during 2003-2011

Landcover type: Grassland

N=45

Time: Aug, 2011



NPP Validation

2.3 MI estimation (Thornthwaite method）

$$MI = \frac{P}{PE} \qquad PE = E_0 * CF \qquad E_0 = 16 * \left(10\frac{T}{I}\right)^a \qquad I = \sum_{i=1}^{12}\left(\frac{T}{5}\right)^{1.514}$$

$$a = \left(0.675 * I^3 - 77.1 * I^2 + 17920 * I + 492390\right) * 10^{-6}$$

Where *P* is monthly precipitation, *PE* is modified potential evapotranspiration, E_0 is monthly evapotranspiration in centimeters, *T* is average monthly temperature in ℃, *CF* is coefficients varying among places, and *I* is the total heat of 12 months.

The formula is adapted to temperatures between 0℃ and 26.5℃. If the temperature is below 0℃, E_0=0, and if the temperature is above 26.5℃, E_0 will be calculated using following formula：

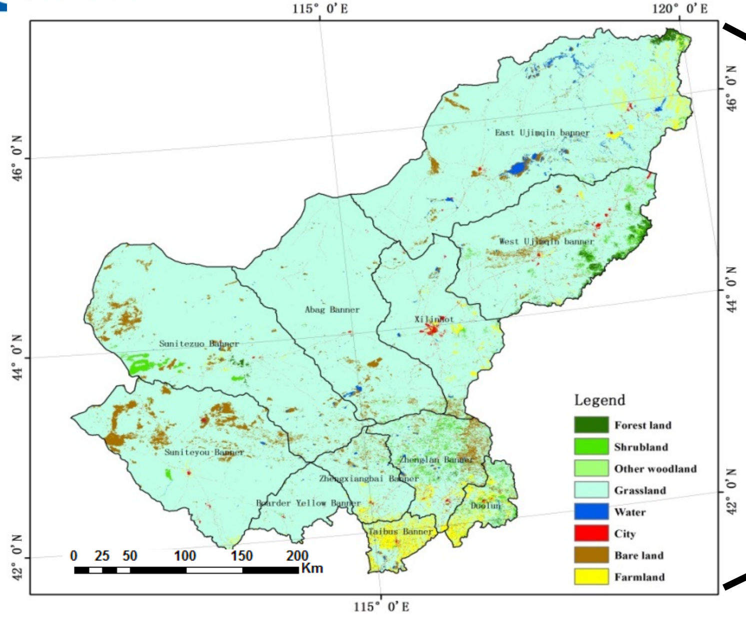
$$E_0 = -0.43T^2 + 32.24T - 415.8$$

Identification of Land Degradation based on MERIS data

By 2dRUE

By MNPP

Study area



Land use/cover of Xilin Gol League (2010)

Grassland

Desert

- Xilin Gol League is located in middle eastern part of Inner Mongolia Autonomous Region, China, and mainly covered by grasslands and sandylands.
- Land degradation is much severe, and attributes to overgrazing and climate change in study area.

3.Methods

2003-2011 MERIS NDVI dataset | 2003-2011 meteorological dataset | Landuse data

Annual NPP | **Annual MI** | **Annual MNPP**

Trend of annual NPP | **Correlation Analyses of annual MNPP with MI** | **Trend of annual MNPP**

Identification of Land Degradation

Figure for study route

3.Methods

MNPP estimation

To coupling NPP and climate factors, a new vegetation indictor—MNPP was defined, which is the NPP divided by MI:

$$MNPP = \frac{NPP}{MI * 100}$$

Normally MNPP has a significant negative correlation with MI for a healthy ecosystem.

Pearson's correlation coefficient:

$$r_{xy} = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2 \times \sum_{i=1}^{n}(y_i - \bar{y})^2}}$$

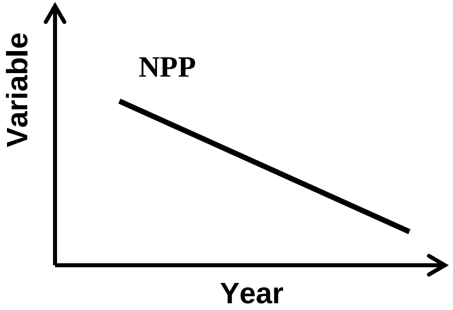
Trend of annual NPP

Trend of annual MNPP

Correlation Analyses of annual MNPP and MI

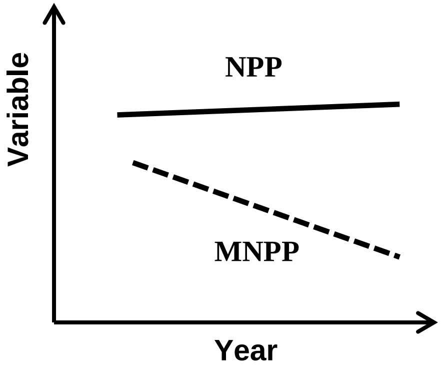
Patterns of vegetation change on degraded lands

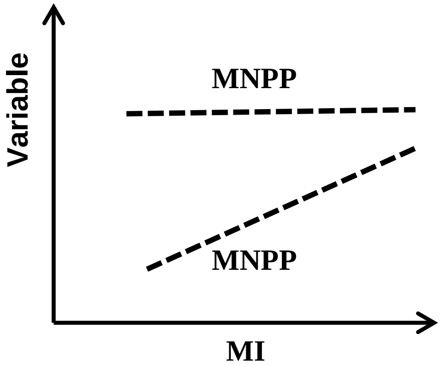
A



Degradation(A): Annual NPP decreases with year significantly.

B





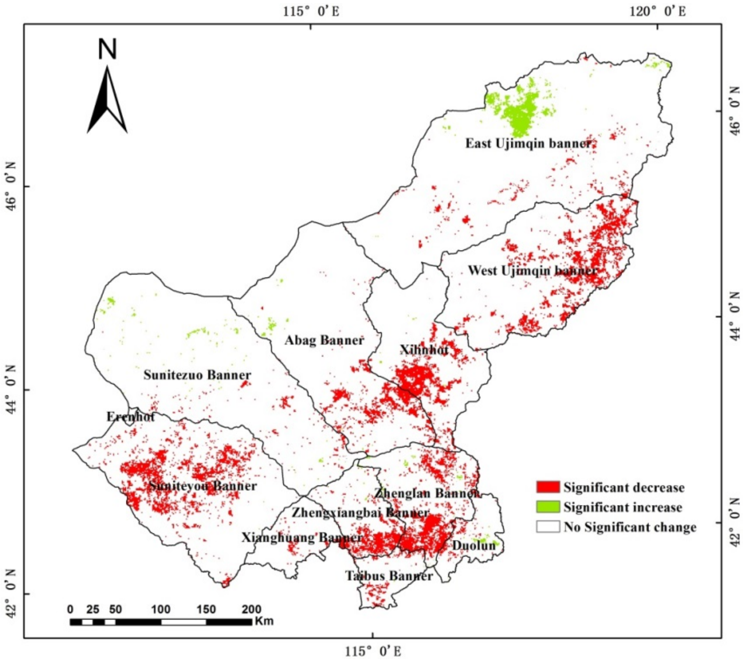
Degradation(B) : Annual NPP changes with year insignificantly and MNPP decreases with year significantly; MNPP correlates with MI insignificantly, or increases with MI significantly.

Contingency table for land degradation/restoration

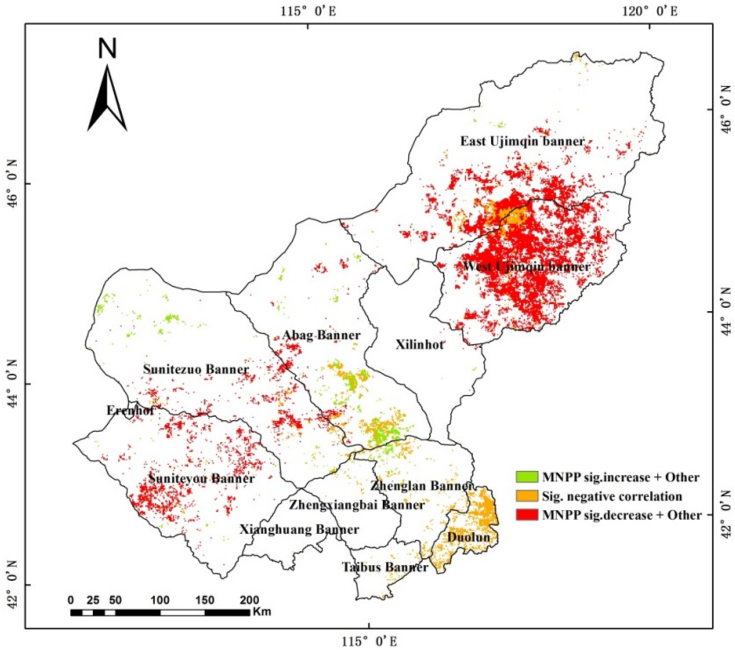
Indicators & Trend			**NPP**		
			Sig.↓	No Sig.	Sig.↑
MNPP	Sig.↑	Sig.(MI)↓	Deg.	Flu.	Res.
		Others	Deg.	Res.	Res.
	Insig.		Deg.	Flu.	Res.
	Sig.↓	Sig. (MI)↓	Deg.	Flu.	Res.
		Others	Deg.	Deg.	Res.

* Sig. and Insig. present for significance and insignificance to time at 0.10 level separately; Sig.(MI) presents for significance to MI at 0.10 level.

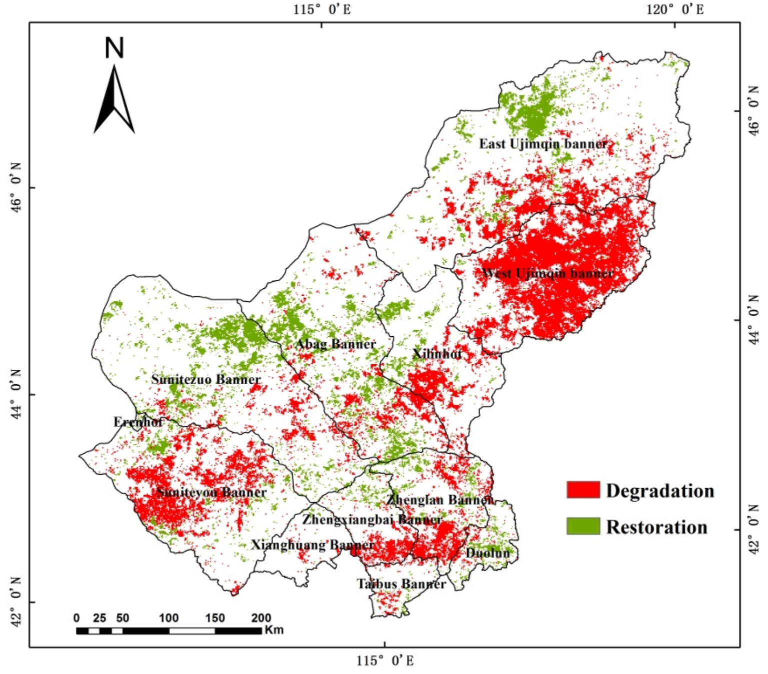
4.Results and Analysis



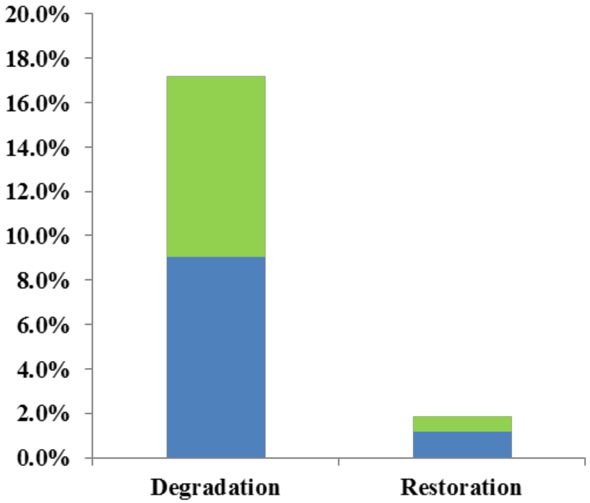
Trend of NPP change in Xilin Gol League during 2003-2011



Degraded and restored lands in insignificant change areas of NPP in Xilin Gol League during 2003-2011



Distribution of land degradation and restoration in Xilin Gol League during 2003-2011



Histogram of land degradation and restoration in Xilin Gol League during 2003-2011

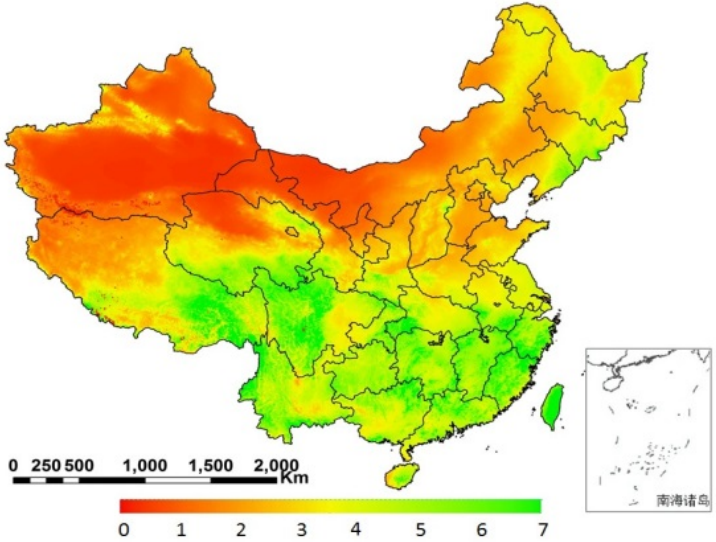
5.Conclusion and Discussion

- In this study, a new approach for land degradation assessment was preliminary promoted based on NPP and MNPP changes. The applicability of the method should be further studied in the future.
- Results of land degradation and restoration assessment showed that 17.2% and 8.1% lands suffered from land degradation and restoration respectively in Xilin Gol legue during 2003 to 2011. The ecological engineering projects were implemented in the study area have achieved significantly, especially in Otindag sandylands.

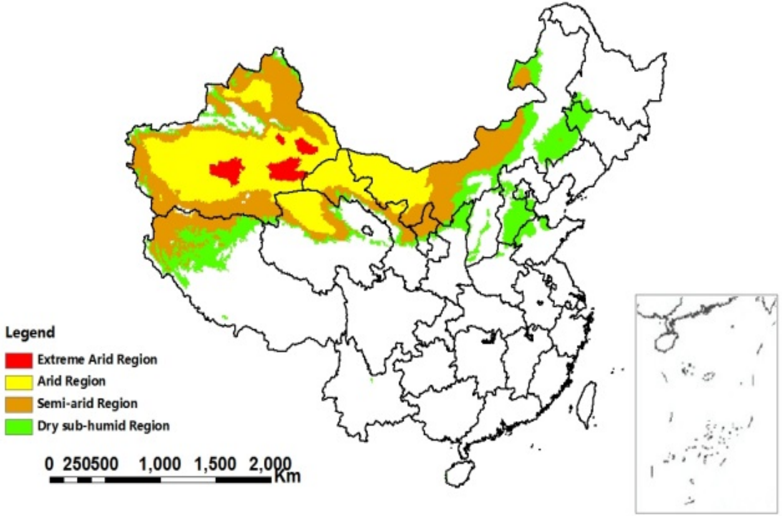
Work plan in future

Dragon 4(ID:32396_2): Advanced remote sensing methods for land degradation assessment by coupling vegetation productivity and climate in drylands

- Collect time series high-resolution remote sensing data in typical area.
- To enhance, benchmark and validate two novel approaches to land degradation surveillance by remote sensing: 2dRUE method and MNPP.
- To use the said approaches to map land degradation in a study area defined by the PEDC.



30-year average MI spatial distribution in China（1981-2010)



Scope of the general PEDC（1981-2010）

Thank you for your attention!