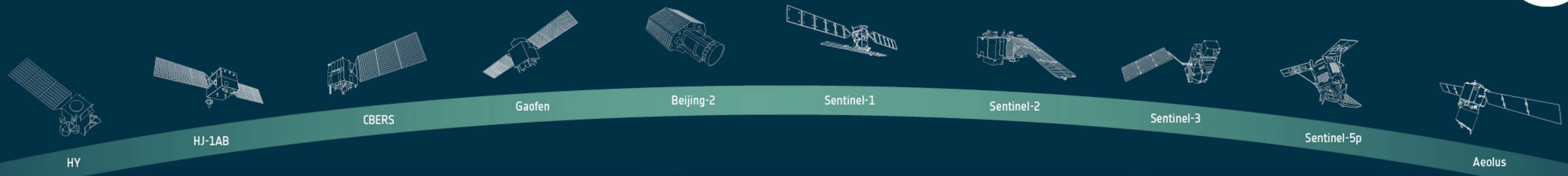


2022 DRAGON 5 SYMPOSIUM

MID-TERM RESULTS REPORTING

17-21 OCTOBER 2022

PROJECT ID. 59313

GRASSLAND DEGRADATION DETECTION AND ASSESSMENT BY REMOTE SENSING

Dragon 5 Mid-term Results Project

20/OCT

ID. 53913

PROJECT TITLE: GRASSLAND DEGRADATION DETECTION AND ASSESSMENT BY REMOTE SENSING

PRINCIPAL INVESTIGATORS: ZHIHAI GAO, ALAN GRAINGER

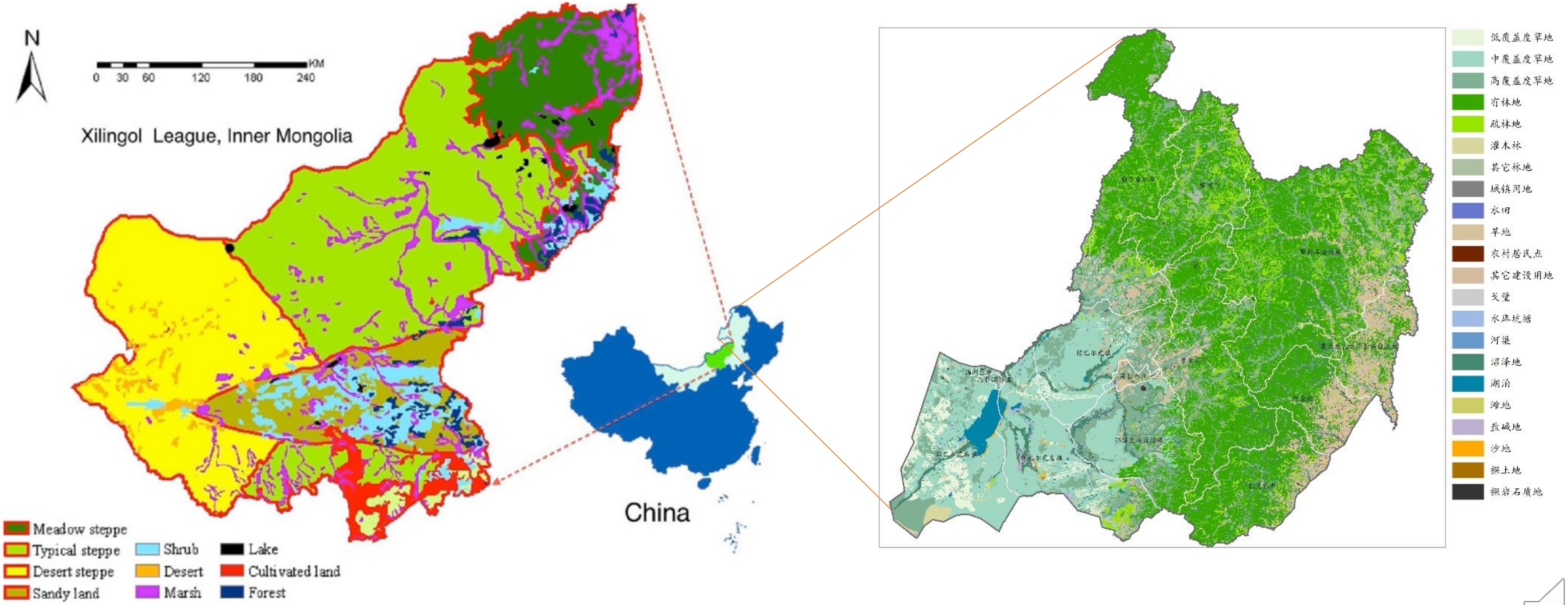
CO-AUTHORS: XIAOSONG LI, BIN SUN, HANWEN CUI, JUNTING YANG, CHAOCHAO CHEN

PRESENTED BY: XIAOSONG LI

Objectives

- To develop new methodologies for estimating grassland parameters related to degradation, such as vegetation structure, soil etc., based on multi-source ESA and Chinese EO data;
- To establish a robust grassland degradation assessment model through fusing EO-based variables, biophysical models and field observations.

Study area


N
0 30 60 120 180 240 KM
Xilingol League, Inner Mongolia
China
Meadow steppe
Typical steppe
Desert steppe
Sandy land
Shrub
Desert
Marsh
Lake
Cultivated land
Forest
低覆盖度草地
中覆盖度草地
高覆盖度草地
有林地
疏林地
灌木林
其它林地
城镇用地
水田
旱地
农村居民点
其它建设用地
戈壁
水库坑塘
河渠
沼泽地
湖泊
滩地
盐碱地
沙地
裸土地
裸岩石质地

EO Data Delivery

Data access (list all missions and issues if any). NB. in the tables please insert cumulative figures (since July 2020) for no. of scenes of high bit rate data (e.g. S1 100 scenes). If data delivery is low bit rate by ftp, insert "ftp"

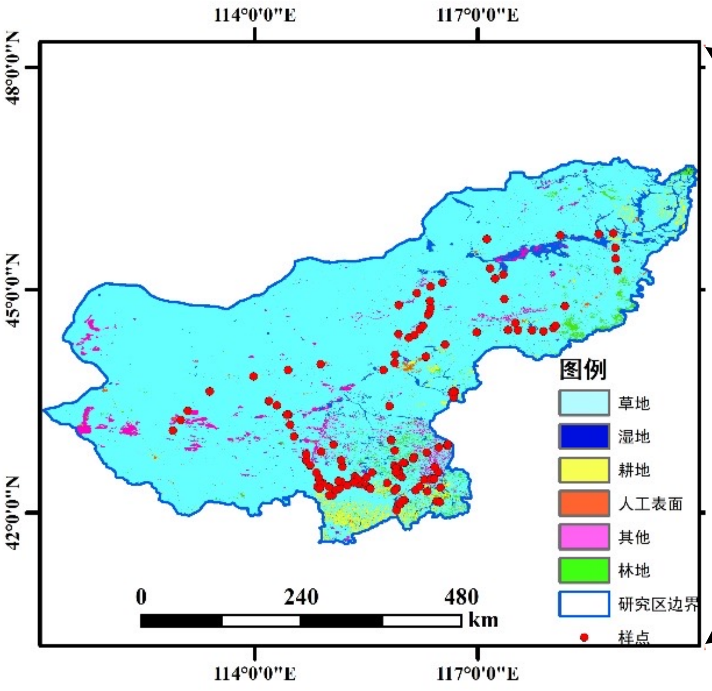
ESA Third Party Missions	No. Scenes
1.	
2.	
3.	
4.	
5.	
6.	
Total:	
Issues:	

ESA Third Party Missions	No. Scenes
1.Sentinel-2	128
2.Sentinel-1	85
3.	
4.	
5.	
6.	
Total:	213
Issues: All the data from GEE.	

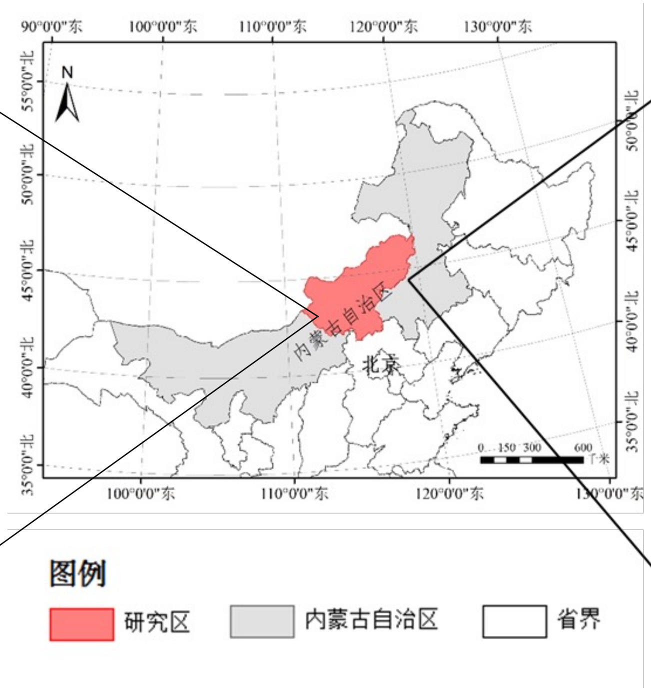
Chinese EO data	No. Scenes
1.GF-6	55
2.GF-2	30
3.	
4.	
5.	
6.	
Total:	85
Issues:	

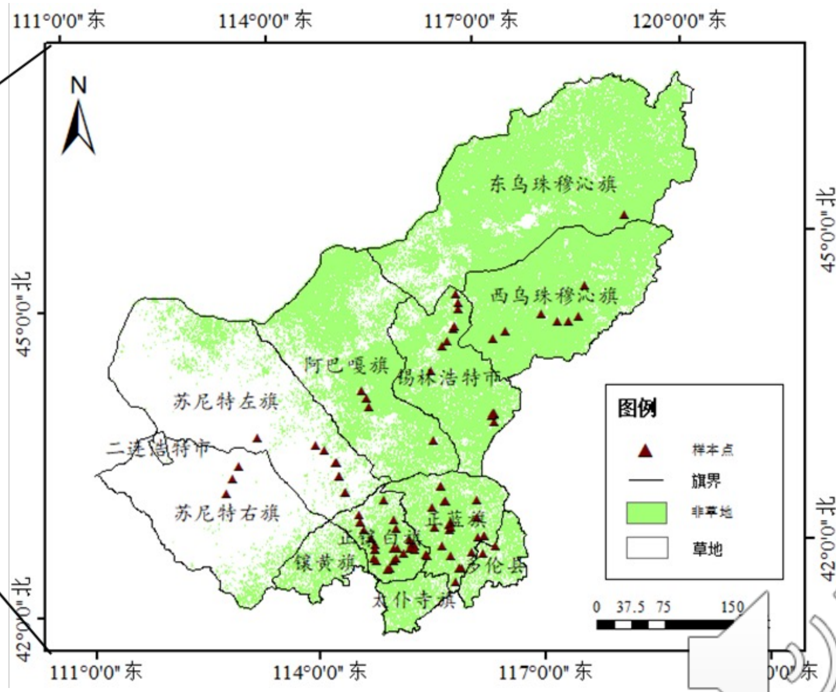
In-situ data measurements

- Collect time:2019
- Sample size:30m*30m
- Vegetation, FVC(shrub and herbaceous respectively), AGB
- Soil, soil organic carbon(SOC) and soil total nitrogen(STN) in topsoil(0-20cm)



Soil samples(n=140)



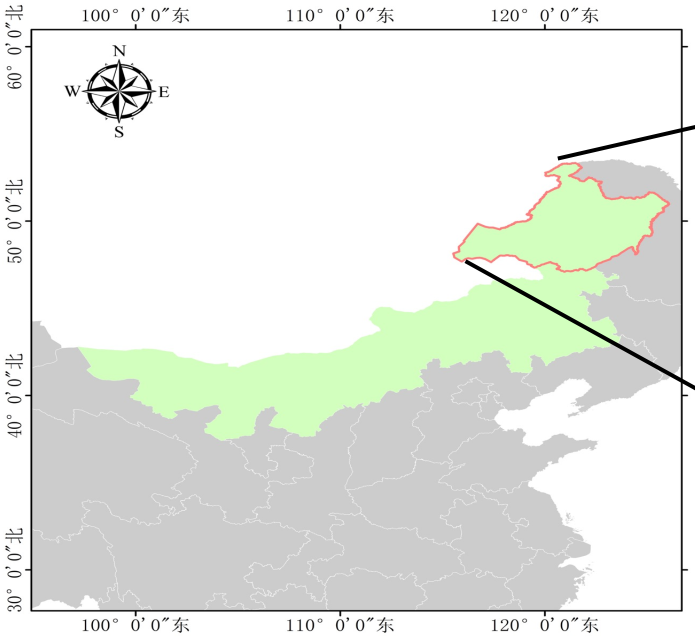


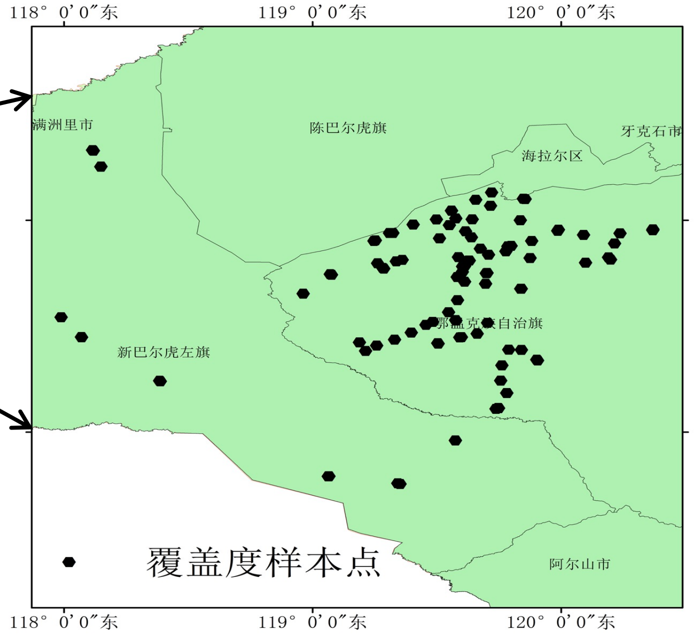
Vegetation samples(n=89)

In-situ data measurements

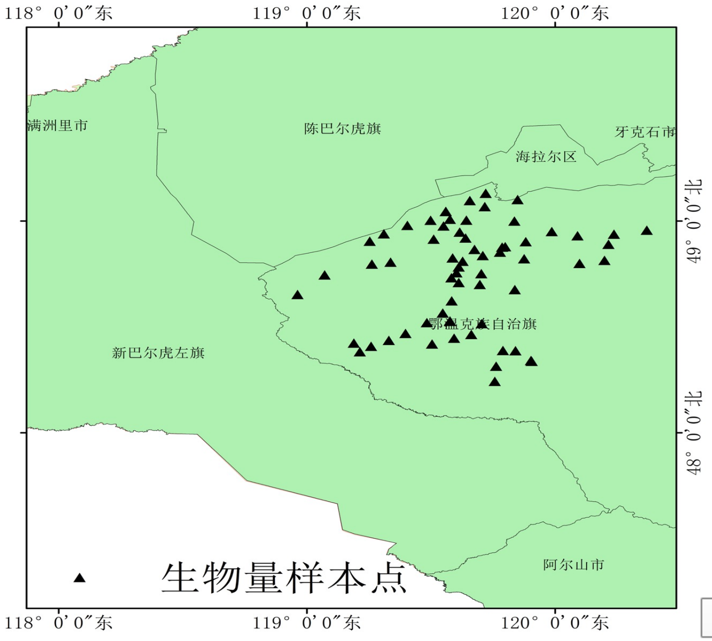
Hulunbuir Grassland

- Collect time:2019~2022
- Sample size:30m*30m
- Vegetation, FVC(shrub and herbaceous respectively), AGB





FVC samples(n=101)



AGB samples(n=64)

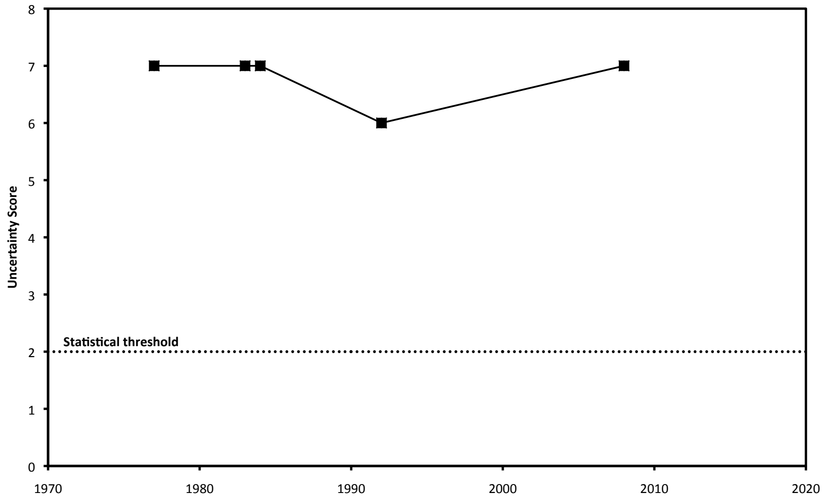
State of the Art:

The extent and rate of change of desertification, of which grassland degradation is a major component, have been persistently uncertain:

1. The Third Edition of the World Atlas of Desertification (2018) included no maps of the actual distribution of desertification based on satellite data.
2. Methods proposed in recent studies for using 'Big Data' to monitor Land Degradation Neutrality only lead to small reductions in uncertainty.

Measuring desertification at planetary scale is challenging because of its:

1. **High variability**. The high areal and temporal variability of soil degradation and vegetation degradation often demand sensors with high to very high spatial and temporal resolution for accurate measurement.
2. **Complexity**. Changes in multiple attributes of soil degradation and vegetation degradation must be measured and then combined to map the overall change in this complex phenomena.



Persistence of Uncertainty in Estimates of Global Extent of Desertification Using the Uncertainty Assessment Framework (Grainger, 2022)

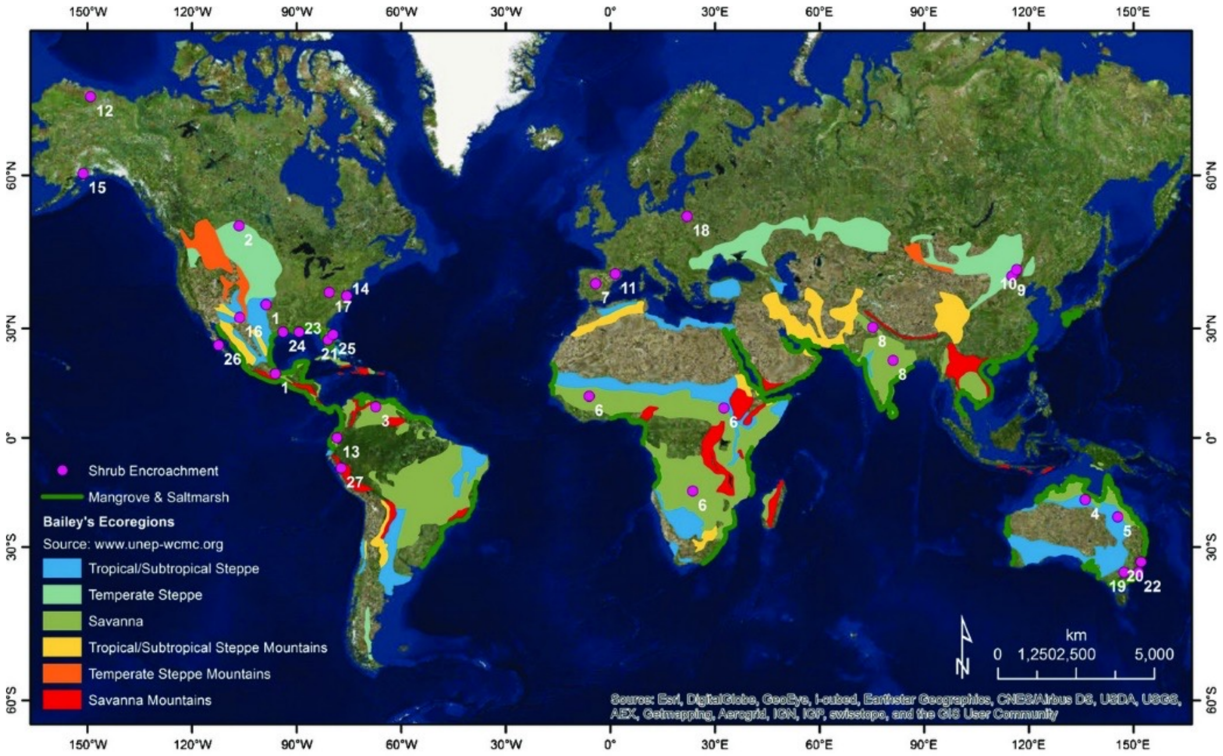
Seven Rules for Planetary Measurement

- **Seven Rules for Planetary Measurement**
- 1. Define a phenomenon clearly and appropriately.
- 2. Specify the minimum number of attributes to measure
- 3. Disaggregate measurement of a phenomenon
- 4. Minimize spatial systematic errors: use sensors whose spatial resolution matches the areal variability of a phenomenon and whose spectral resolution matches its most distinctive property.
- 5. Minimize temporal systematic errors: choose a monitoring frequency consistent with the turnover time of a phenomenon.
- 6. Minimize systematic and random errors associated with the method used to classify satellite images.
- 7. Minimize systematic and random errors associated with the algorithm used to combine estimates of various attributes of a phenomenon.

Planetary Measurement of Desertification	
Seven Rules	Applied to Desertification
Definitions	Use UNCCD definition
Specification	Include all 7 attributes
Disaggregation	By land use, aridity and salinization type
Minimize spatial systematic errors	
Vegetation area and density	Very high resolution
Water erosion	Very high resolution
Salinization, alkalinization, waterlogging	Medium to high resolution
Wind erosion, soil compaction	New methods required
Minimize temporal systematic errors	≤ 2 year monitoring frequency
Minimize classification errors	Automated methods still awaited
Minimize combination errors	Algorithms still awaited

Shrub encroachment monitoring with S1&S2

- A recent trend towards semi-arid and mesic grassland conversion to shrub dominance is global in scale and common to all vegetated continents
- Over 5 million hectares of the inner Mongolian grassland has been encroached by *Caragana microphylla*.
- Large scale monitoring is a challenge, since the herbaceous and shrub is difficult to identify in the spectral at the medium resolution.



1 Van Auken (2009)
2 Bai *et al.* (2009)
3 Silva *et al.* (2001)
4 Book and Bowman (2006)
5 Fensham *et al.* (2005)
6 Sankaran *et al.* (2008)
7 Maestre *et al.* (2009)
8 Misra (1983)
9 Peng *et al.* (2013)
10 Zhang *et al.* (2006)
11 Montané *et al.* (2010)
12 Tape *et al.* (2006)
13 Mason and Bart (2013)
14 Young *et al.* (2007)
15 Berg *et al.* (2009)
16 Gibbens *et al.* (2005)
17 Stine *et al.* (2011)
18 Kotowski and Piórkowski (2005)
19 Colloff *et al.* (2014), Bren (1992)
20 Johnson *et al.* (2003)
21 Duever (2005), Knickerbocker *et al.* (2009)
22 Saintilan and Williams (1999)
23 Giri *et al.* (2011)
24 Bianchi *et al.* (2013)
25 Cavanaugh *et al.* (2014)
26 López-Medellín *et al.* (2011)
27 Saintilan *et al.* (2014)

Woody plant encroachment of grasslands

Data collection and pre-processing

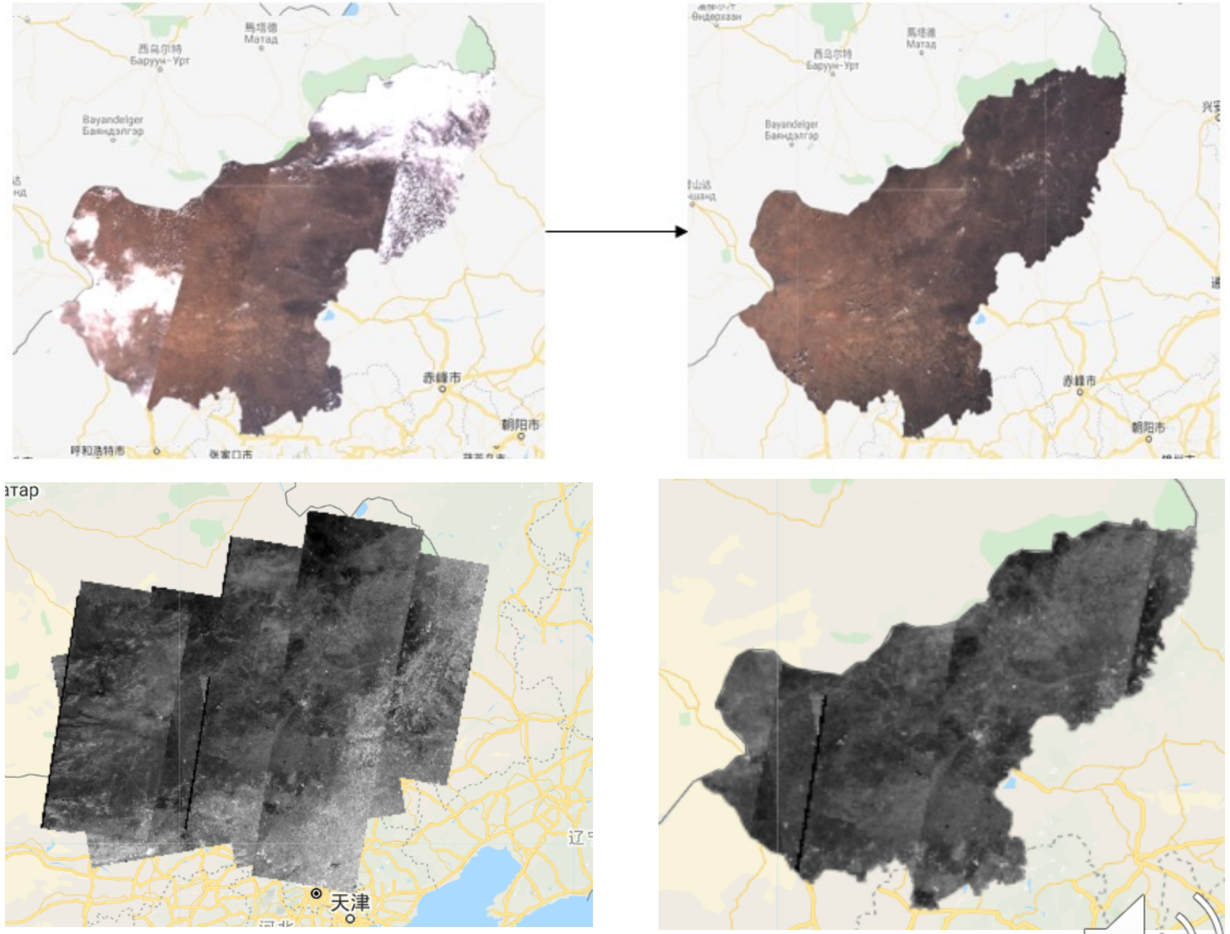
EO data(GEE platform)

Sentinel-1: “COPERNICUS/S1_GRD”

- Spatial filter(mean)
- Time series composition（monthly）

Sentinel-2 L1C: “COPERNICUS/S2”

- Cloud detection
- Vegetation indices
- Maximum NDVI composition(monthly)

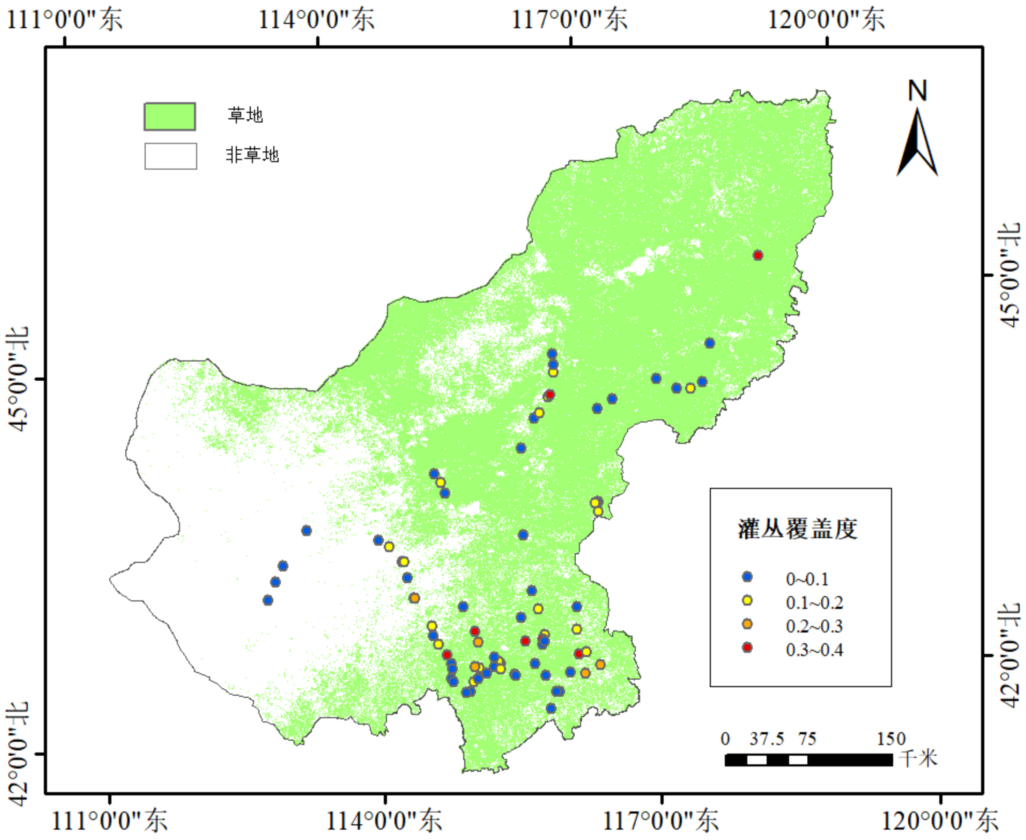


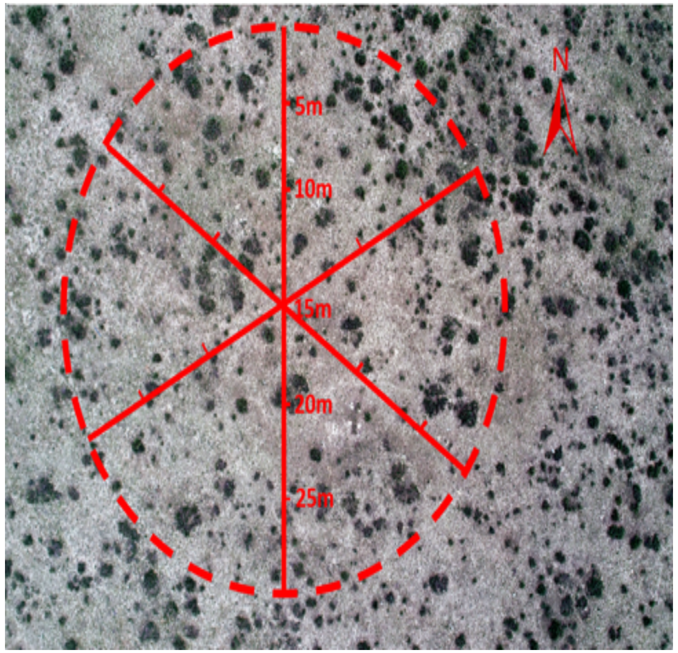
Predictor variables

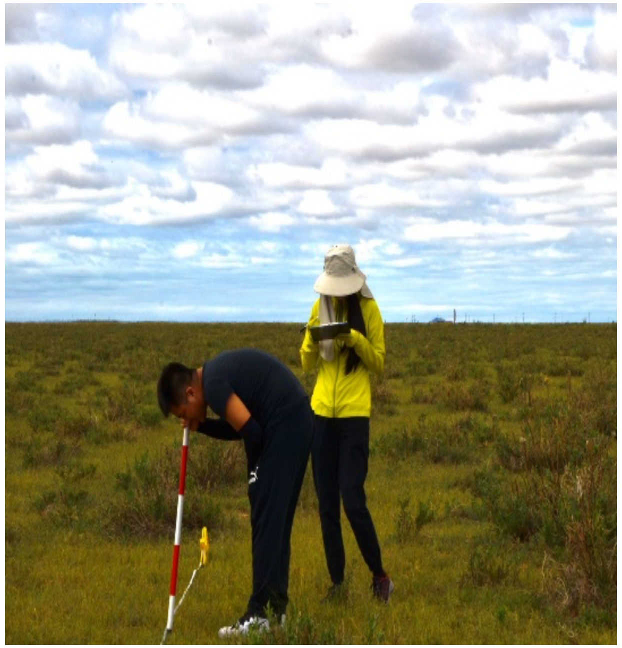
Type	Name	Formula
SAR	VH	mean
	VV	mean
Traditional VIs	NDVI	$\frac{B8-B4}{B8+B4}$
	EVI	$2.5\ \left(\frac{B8-B4}{B8+6B4-7.5B2+1}\right)$
	SAVI	$1.5\ \left(\frac{B8-B4}{B8+B4+0.5}\right)$
Red-edge	NDRE	$\frac{B6-B5}{B6+B5}$
	NDRE2	$\frac{B6-B5}{B6+B5-2B1}$
	MSR	$\frac{B6-B1}{B6+B1}$
	MTCI	$\frac{B6-B5}{B5-B4}$
	REP	$705+35\frac{0.5(B4+B7)-B5}{B6-B5}$
	CI	$\frac{B7}{B5}-1$
	IREcI	$\frac{B7-B4}{B5/B6}$
	MCARI2	$\frac{B6}{B5}((B6-B5)-0.2(B6-B3))$
Canopy water content	NDWI	$\frac{B11-B8A}{B11+B8A}$
	MSI	$\frac{B11}{B7}$
	NDII	$\frac{B11-B8}{B11+B8}$

Data collection and pre-processing

Field data







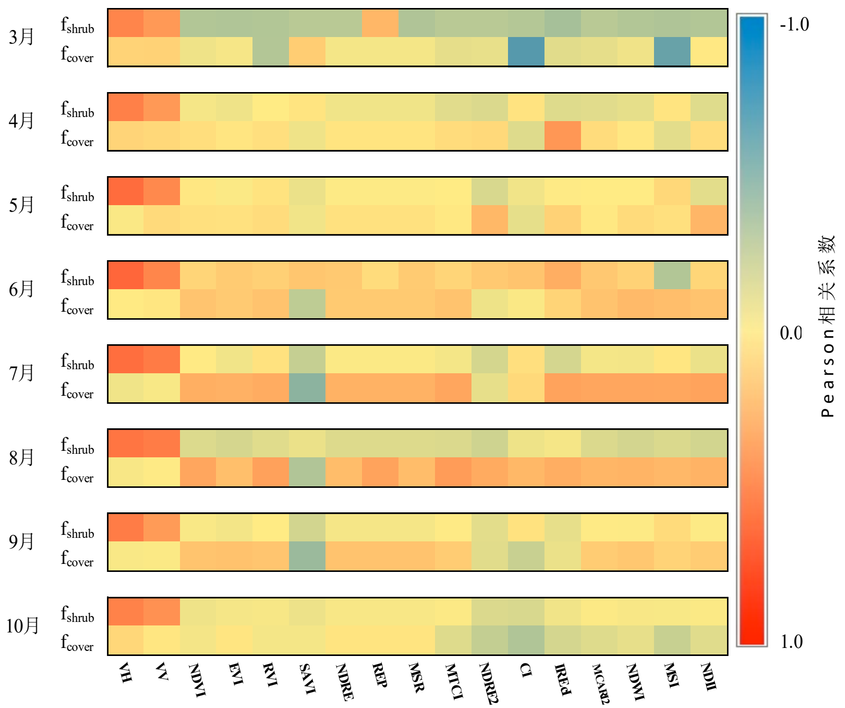
Potential of S1&S2 for differentiating shrub and herbaceous

- S2 is significantly related to the total grassland vegetation coverage, but not sensitive to the shrub coverage.
- SAR data have a strong sensitivity to shrub coverage (VH polarization is better than VV polarization), among which the correlation between VH polarization data and shrub coverage in June can reach 0.64.

（a）灌木覆盖度为4%的灌丛化草地实地照片及对应高分影像

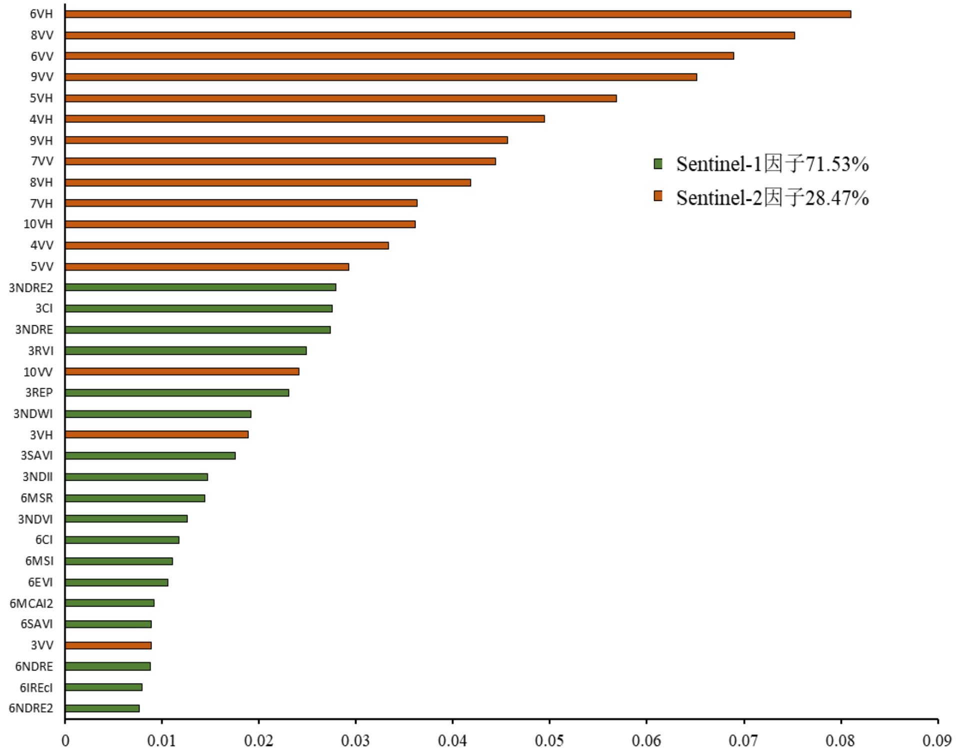
（b）灌木覆盖度为22%的灌丛化草地实地及对应高分影像

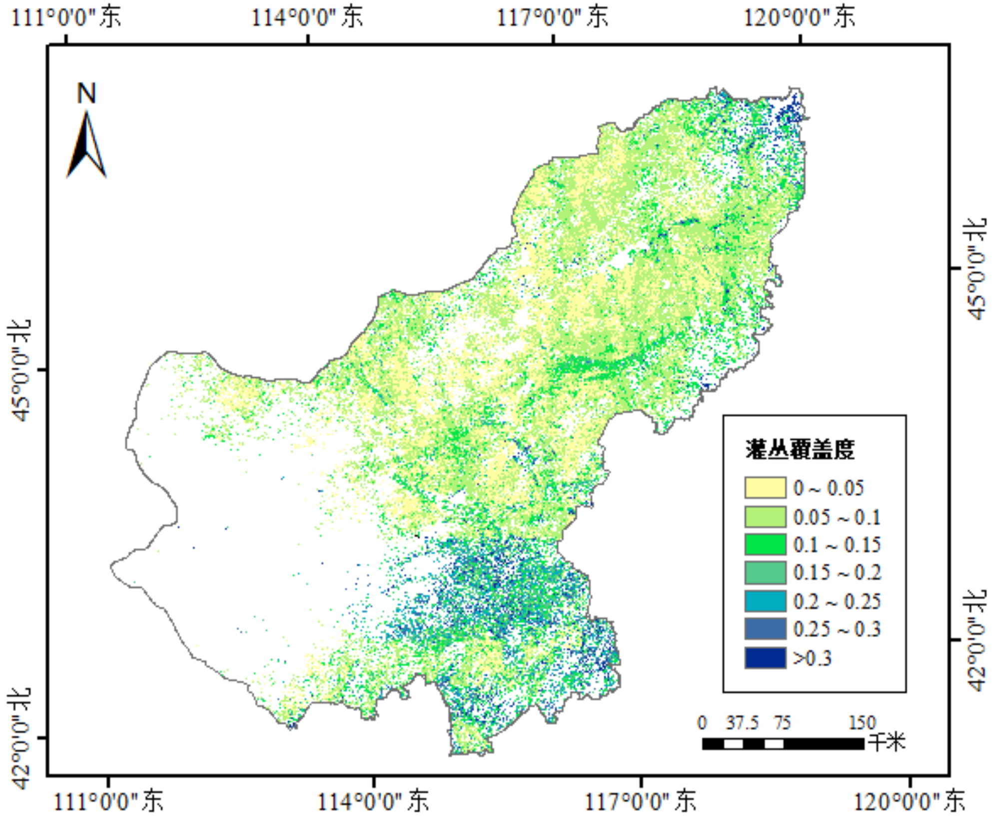
（c）灌木覆盖度为50%的灌丛化草地实地照片及对应高分影像



Estimation of shrub coverage with RF model and S1&S2 predictors

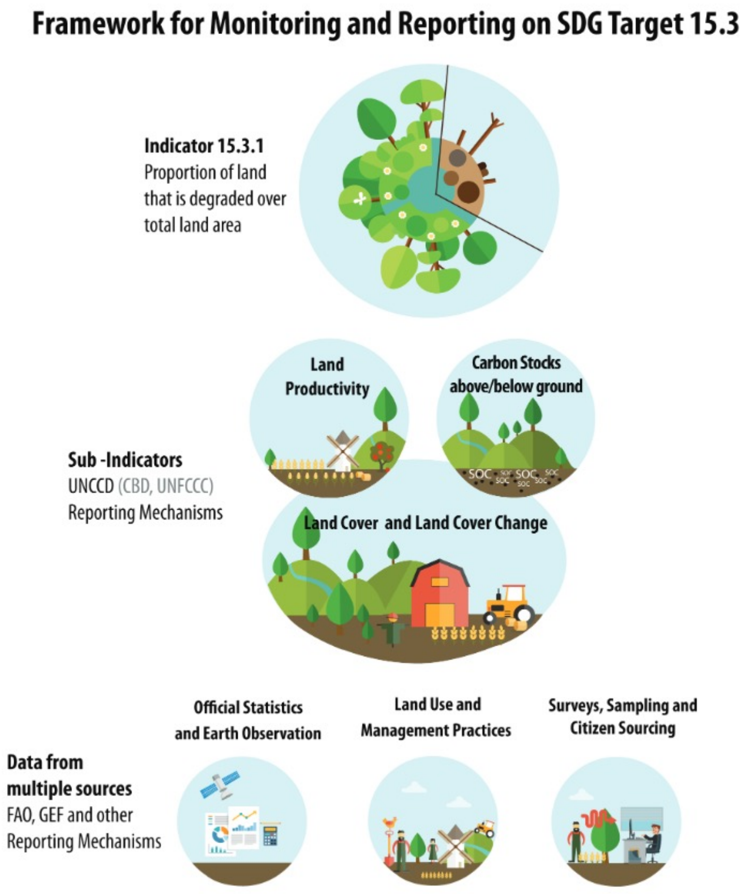
The random forest model based on the combination of optical and radar data can achieve a high accuracy estimation of grassland shrub coverage ($R^2 = 0.76$, RMSE = 0.05), in which the contribution of sentinel-1 radar data is 71.54%, and that of sentinel-2 optical data is 28.47%.





Digital soil mapping(SOC, STN) driven by S2 variables

- Soil properties is the key indicators of grassland degradation.
- Lack of high resolution products, existed product, spatial resolution is lower, limited samples and low accuracy in degraded grassland area.
- EO-based method with machine learning has the potential.



Data used

EO data

Time: June to September, 2019

Pre-process: Maximum NDVI composition

- Sentinel-2 band reflectance
- NDVI, DFI, CI, IRECI

Ancillary data

Topographic: elevation, slope, aspect, TWI

Climate: Average precipitation, temperature

Soil properties

Sample size： 30m * 30m

Depth: 0-20cm

Content: SOM and STN

Sample number: 140

Model employed

RF

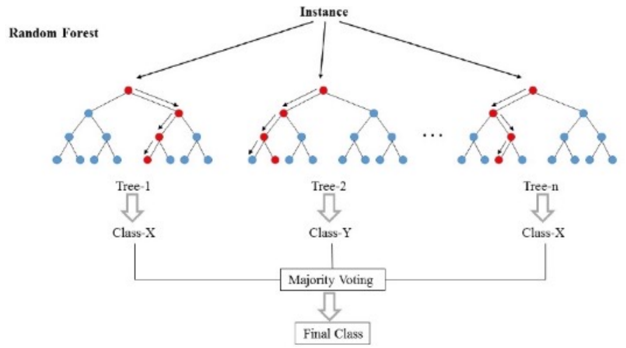
A ensemble learning method based on decision trees ,could tackle the complex non-linear relationship model , and assess the variable importance.

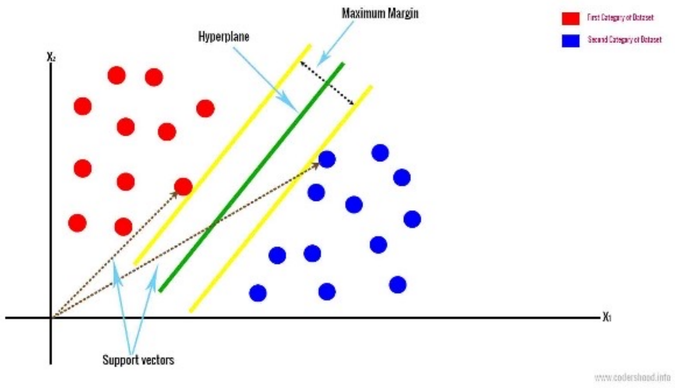
SVM

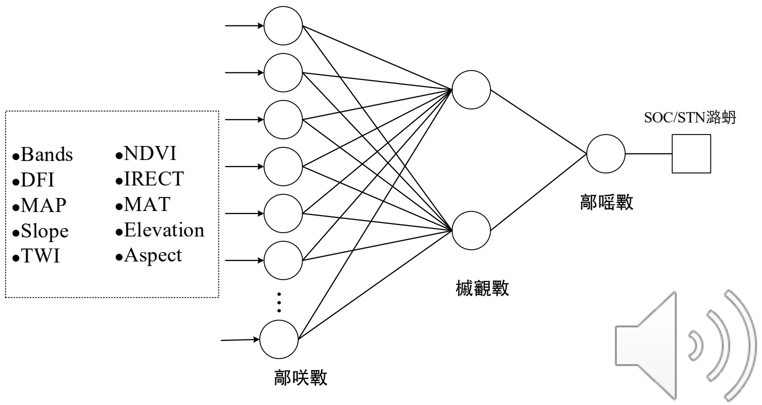
A machine learning method based on the principle of structural risk minimization .

MLP

A multilayer perceptron (MLP) is a class of feedforward artificial neural network.





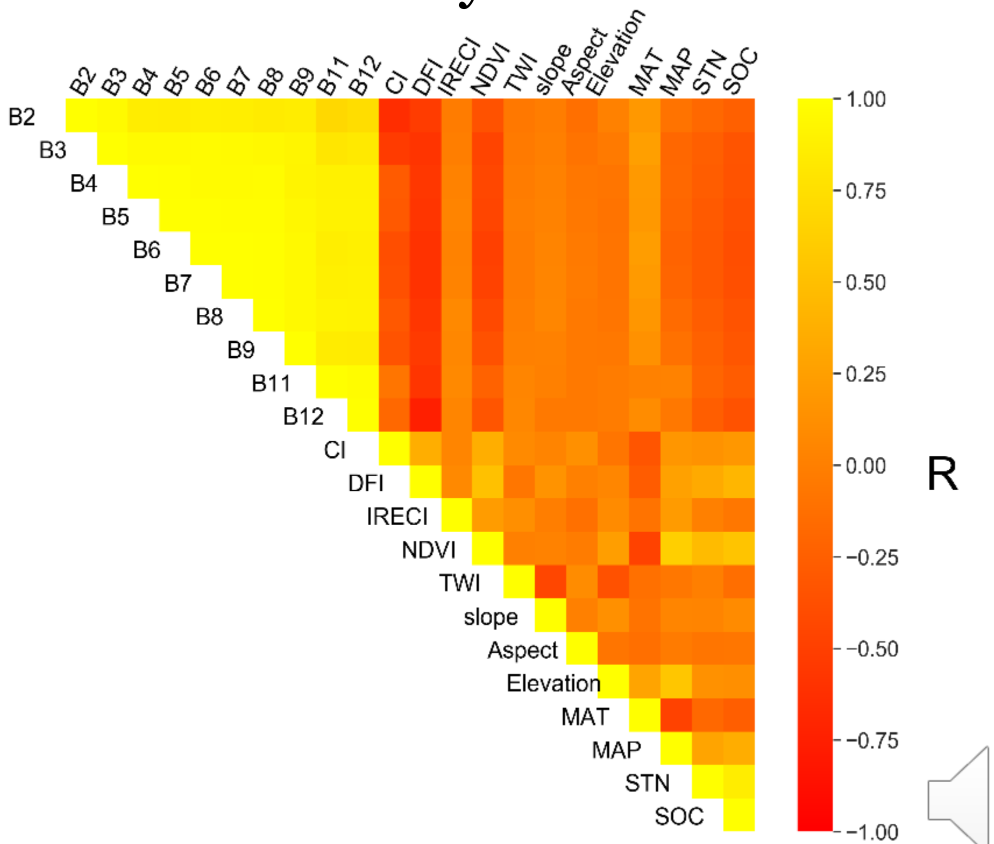


Relationship between predictor variables and SOC/STN

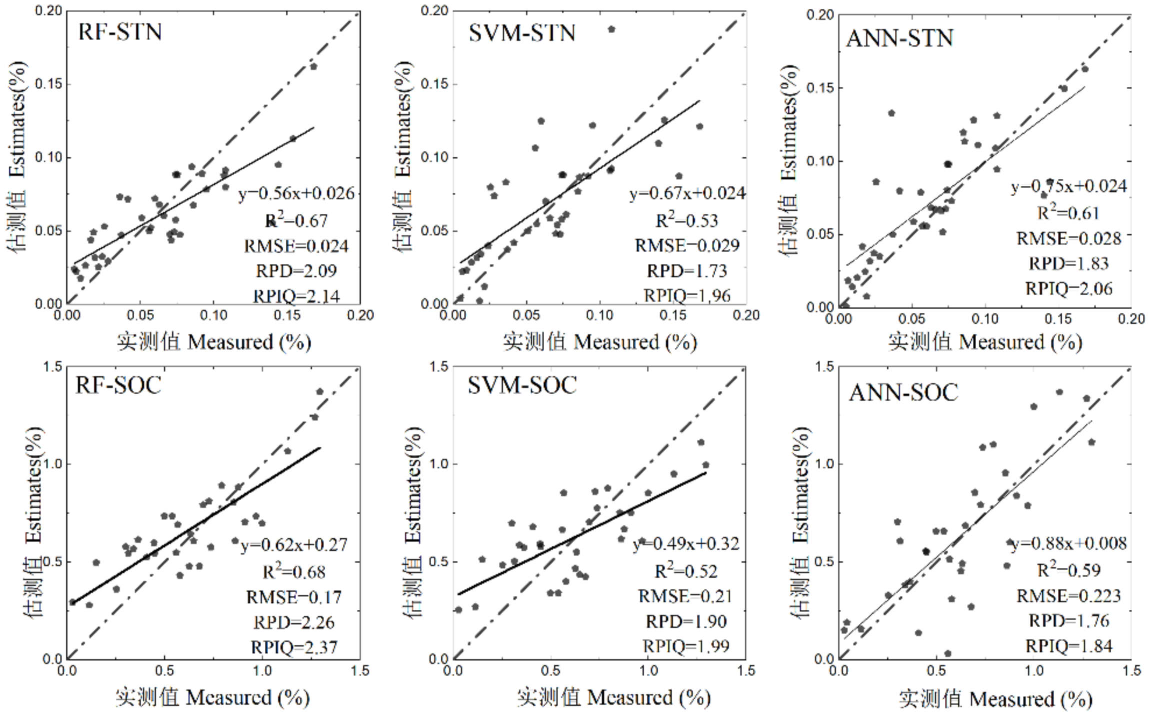
Predictor selection

Theme	Name	Source	Resolution
Vegetation indices	NDVI DFI CI IRECI	Sentinel-2	10-60m
Climate factors	MAT MAP	ERA5 CHIRPS	0.25° 0.25°
Topographic factors	Elevation Slope Aspect TWI	SRTM90_V4	90 m
S2 band reflectance	Reflectance	Sentinel-2	10-60m

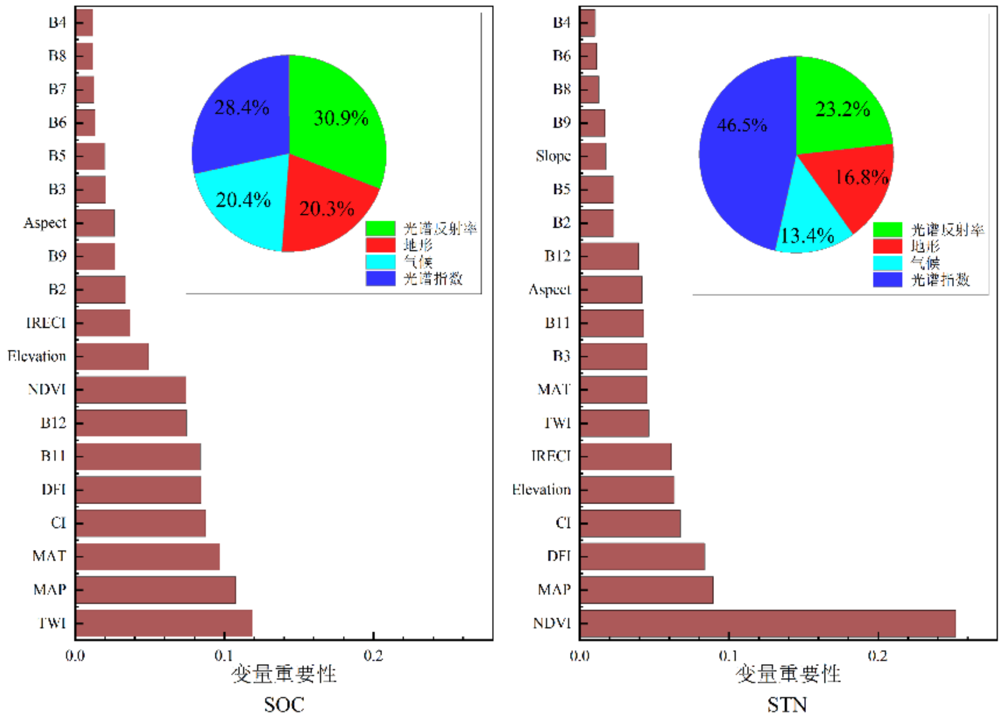
Correlation analysis



Performance between different models(ANN/SVM/RF)

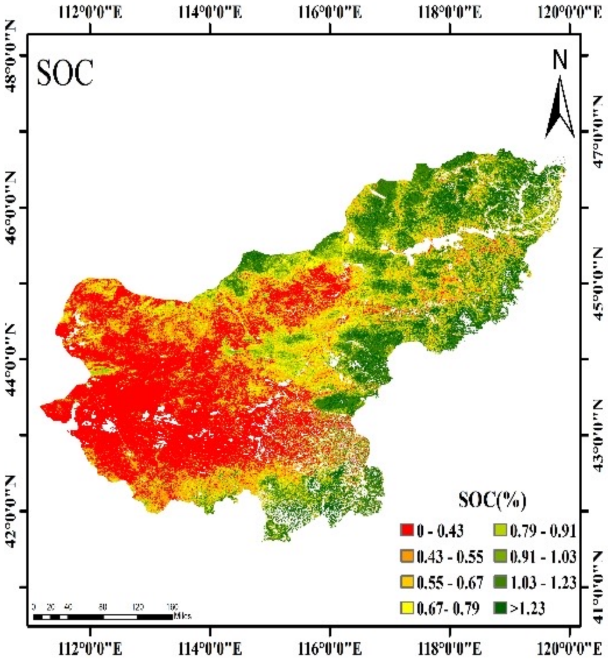


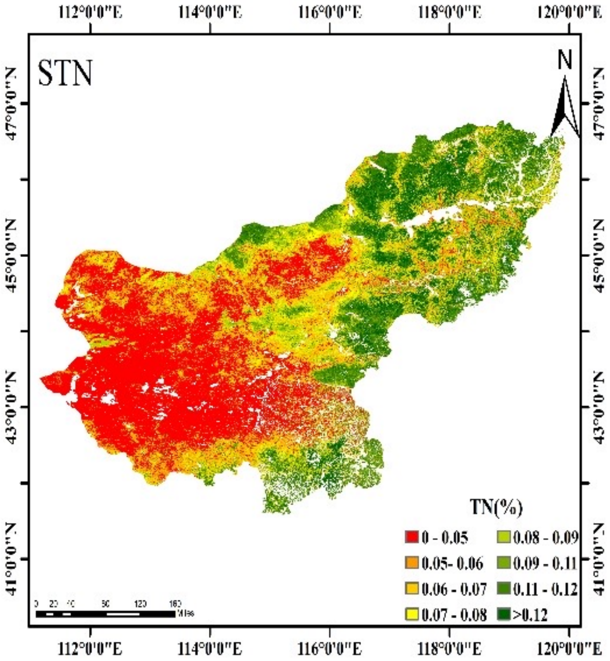
Validation accuracy

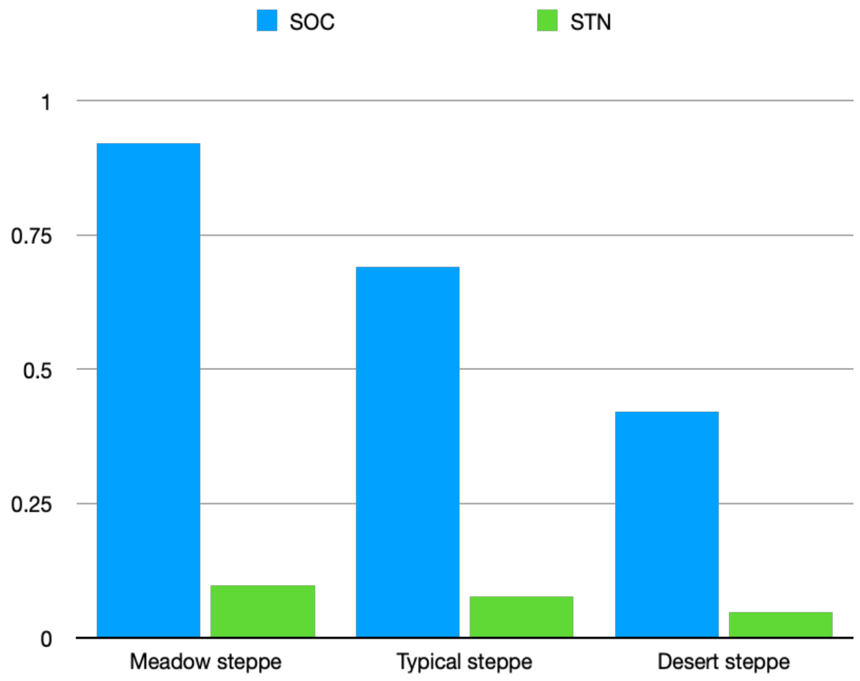


Variable importance

Spatial distribution map of SOC and STN with RF

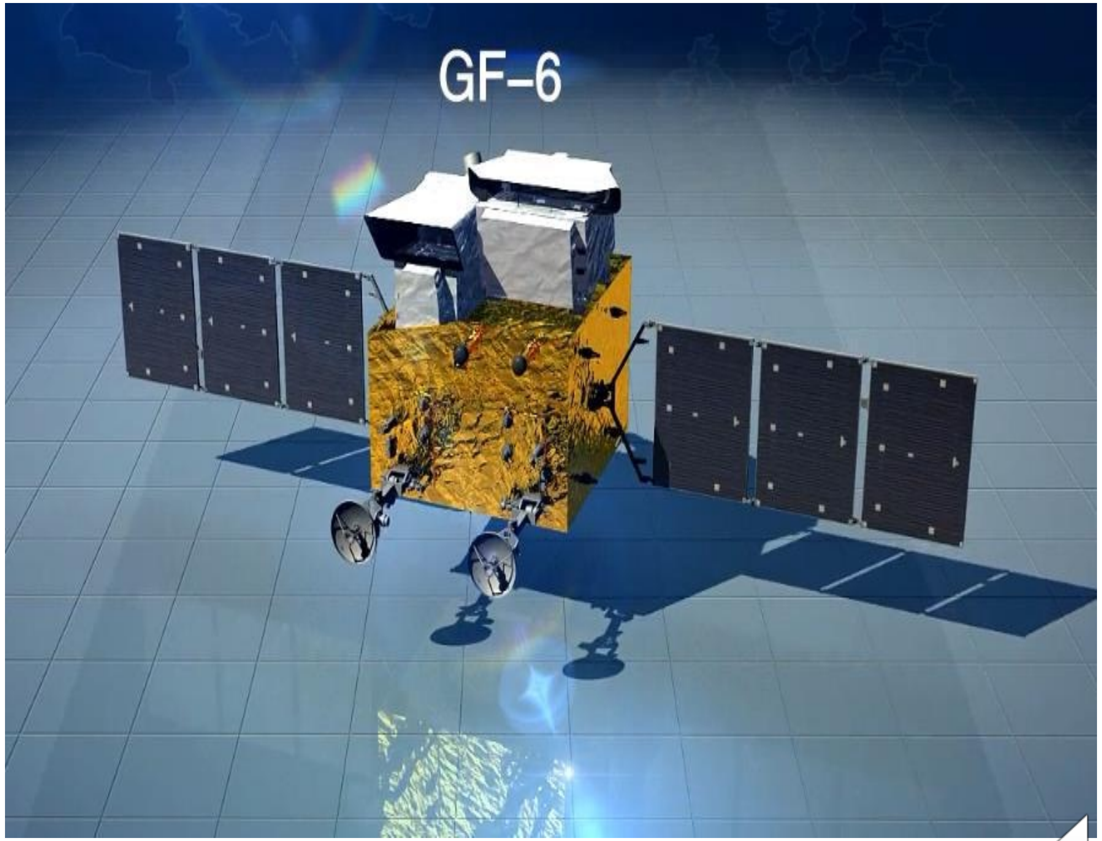






GF-6 based grassland vegetation coverage and biomass estimation

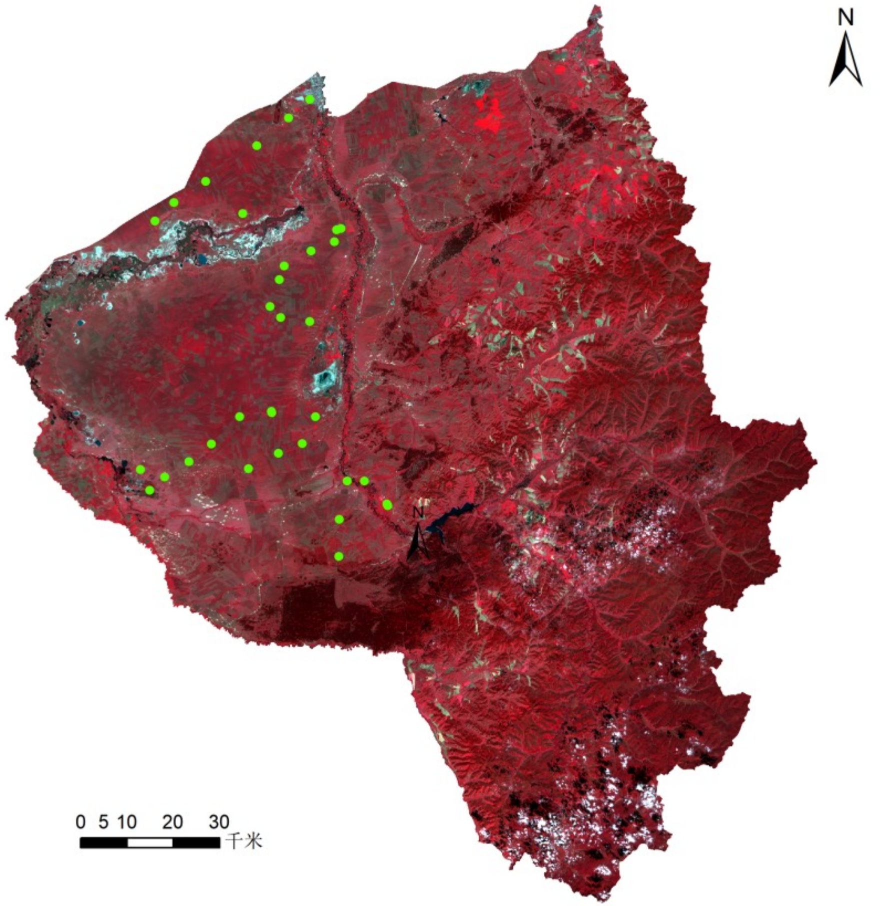
- GF-6 data is added with "red edge" band with a spatial resolution of 16 m, and a swath width of 800 km.
- To explore the grassland monitoring capability of GF-6 WFV sensor, a remote sensing estimation model of grassland vegetation coverage and biomass was established



Data collection and pre-processing

Image data： GF- 6 WFV

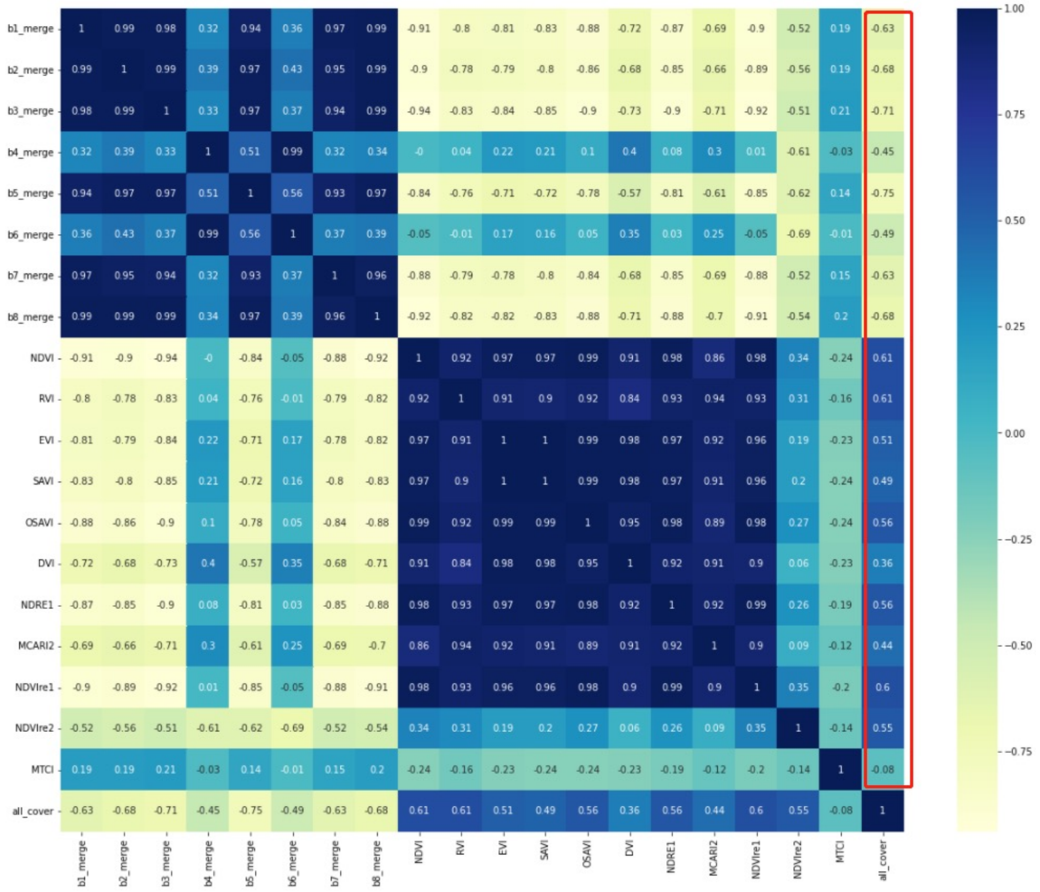
- Radiation calibration
- atmospheric correction
- geometric correction
- clipping



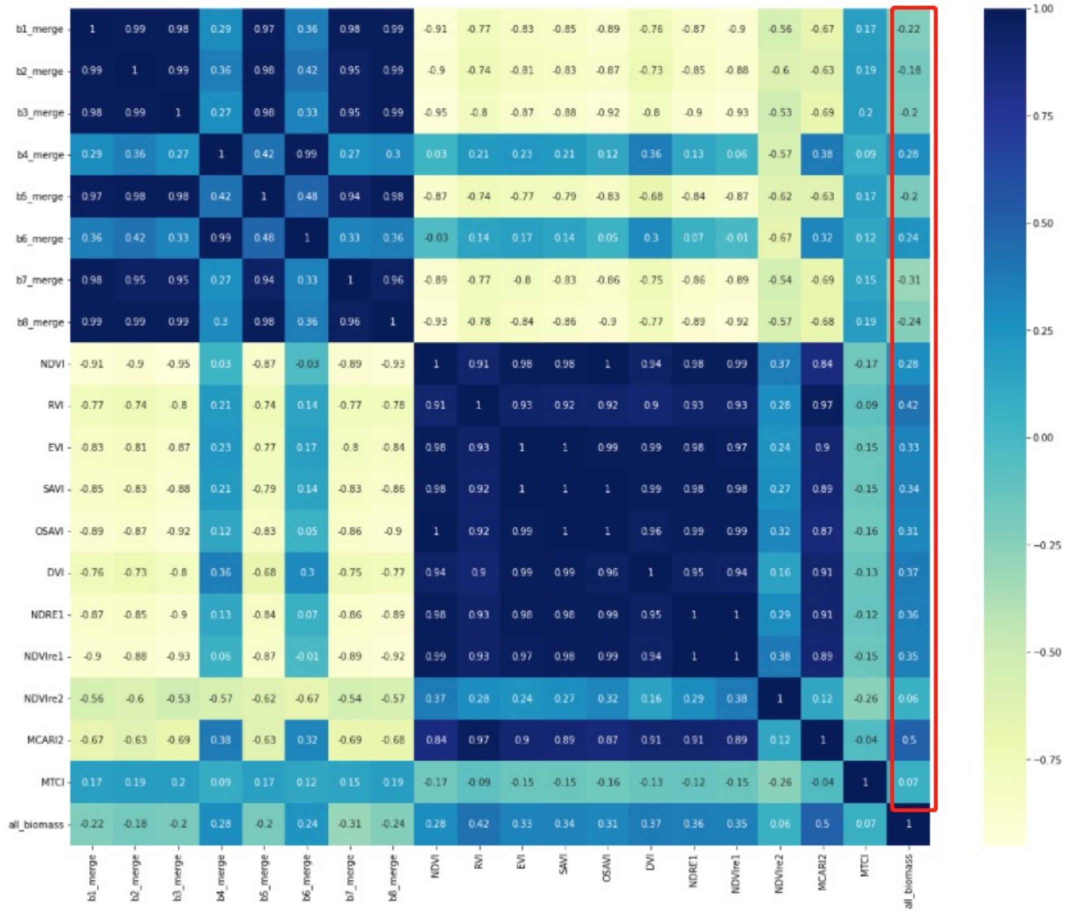
Predictor variables

Type	Name	
Original band	B1-B8	
vegetation index	NDVI	= (B4 - B3) / (B4 + B3)
	EVI	= (2.5 * ((B4 - B6) / (B4 + 6 * B6 - 7.5 * B6 + 1))))
	RVI	= (B4 / B6)
	SAVI	= (B4 - B3)*(1+0.5)/(B4 + B3+0.5)
	OSAVI	= (B4 - B3)/(data_nir+data_red+0.16)
	DVI	= (B4 - B3)
Red edge vegetation index	NDRE	= (B6 - B5) / (B6 + B5)
	MCARI2	=((B6 - B5)-0.2*(B6 - B5))*(B6/B5)
	MTCI	=(B6 - B5)/(B5-B3)
	NDVIre1	= (B4 - B5) / (B4 + B5)
	NDVIre2	= (B4 - B6) / (B4 + B6)

Dragon 5 Mid-term Results Reporting



Person Correlation Analysis Chart of Prediction Factors and Grassland Vegetation Coverage

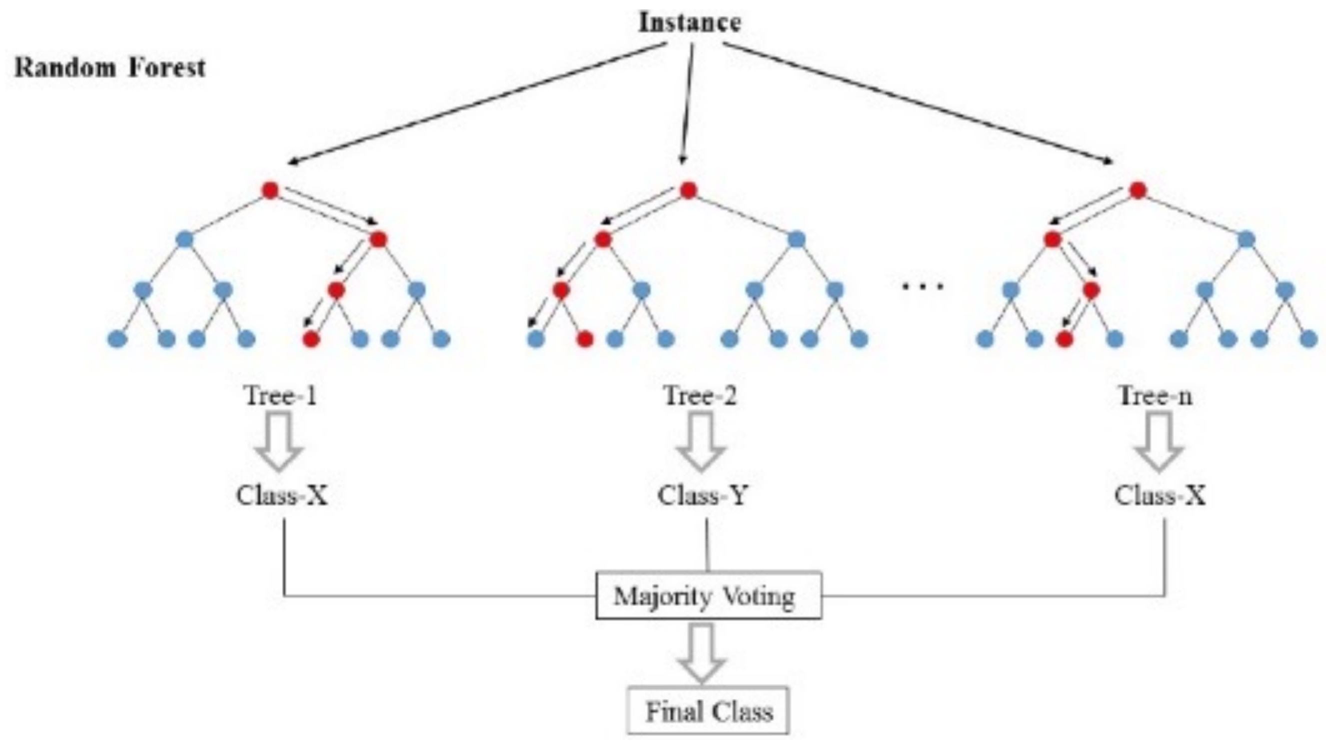


Person Correlation Analysis Chart of Prediction Factors and Grassland biomass

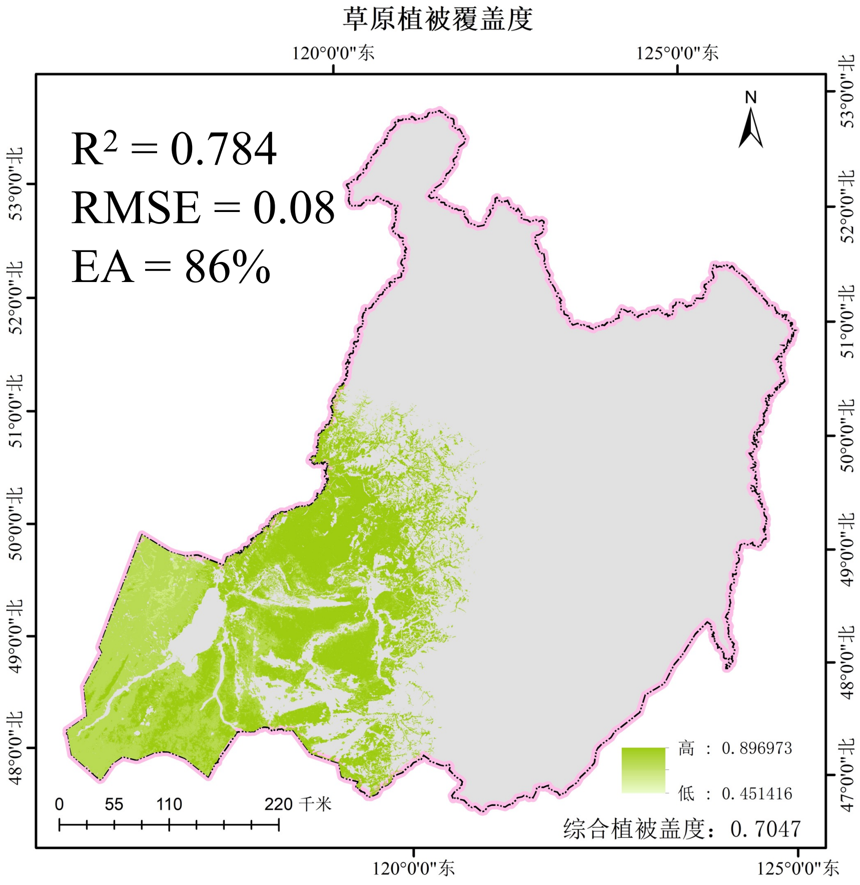
Model employed

Random Forest

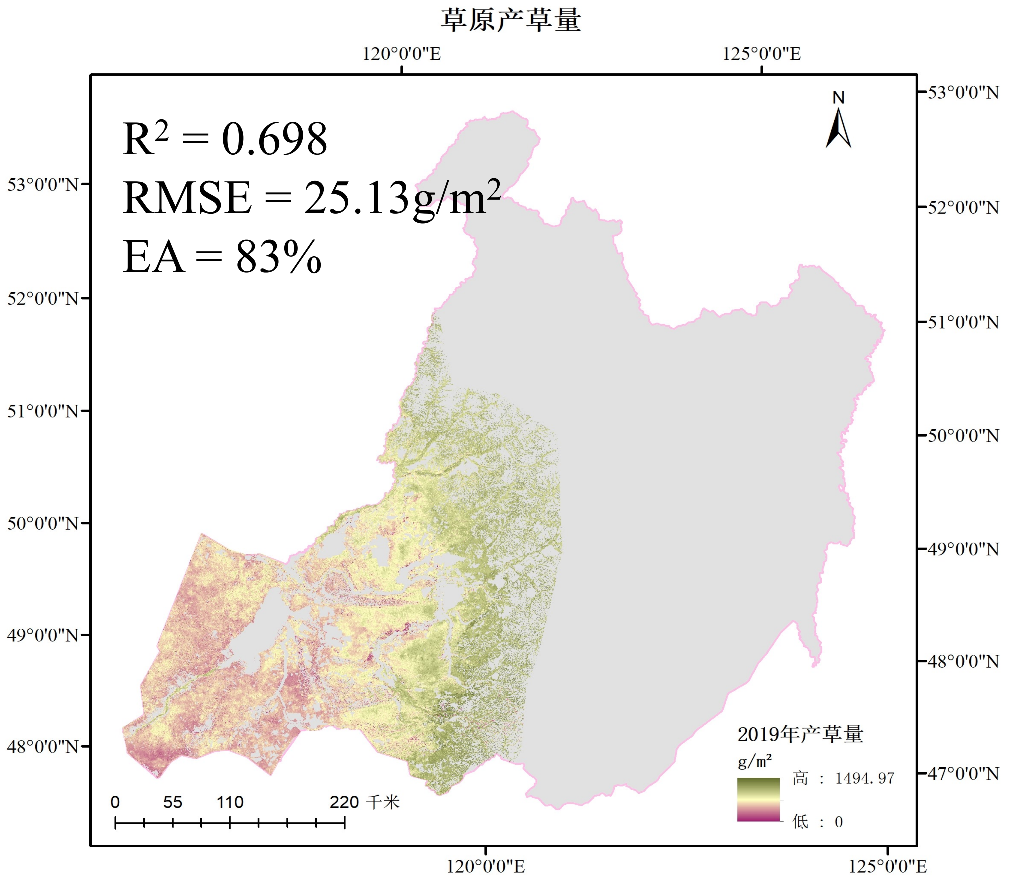
A ensemble learning method based on decision trees ,could tackle the complex non-linear relationship model , and assess the variable importance.



Estimated results



Estimation Results of Grassland Vegetation Coverage with 16m Resolution



Estimation Results of Grassland biomass with 16m Resolution

Global grassland degradation mapping

- Grassland degradation has been increasing in recent years, but there are few comprehensive diagnostic analyses.
- Common methods suitable at the local scale is a challenge for evaluation on a global scale.
- Developments in Earth observation technology have increased potential to serve these issues

Field survey of grassland degradatio

Data and methods

Data type	EO Data		Meteorological data	Land use/land cover data
Datasets	Global vegetation net primary productivity (NPP) products	Medium to high resolution remote sensing data	ERA5 global meteorological reanalysis dataset	ESA GlobCover dataset
Introduction to the data	Yearly 2000-2020 500m	GF-1/2 etc.	Daily temperature and precipitation products 2000-2020 0.1°	2015 300m

EO data、Meteorological data
、Land use/land cover data
、Ground data and other auxiliary data

Data entry

Construction of indicators for monitoring grassland degradation dynamics

Grassland degradation detection and evaluation techniques

- **NPP dataset estimation**
- **MI dataset construction**
- **MNPP dataset construction**
- **Land cover dataset**

- **Sen+Mann-Kendall**
- **Identification of grassland degradation changes**
- **Grassland Degradation Landscape Assessment**
- **Driving force analysis**

Evaluation system construction

Global grassland degradation

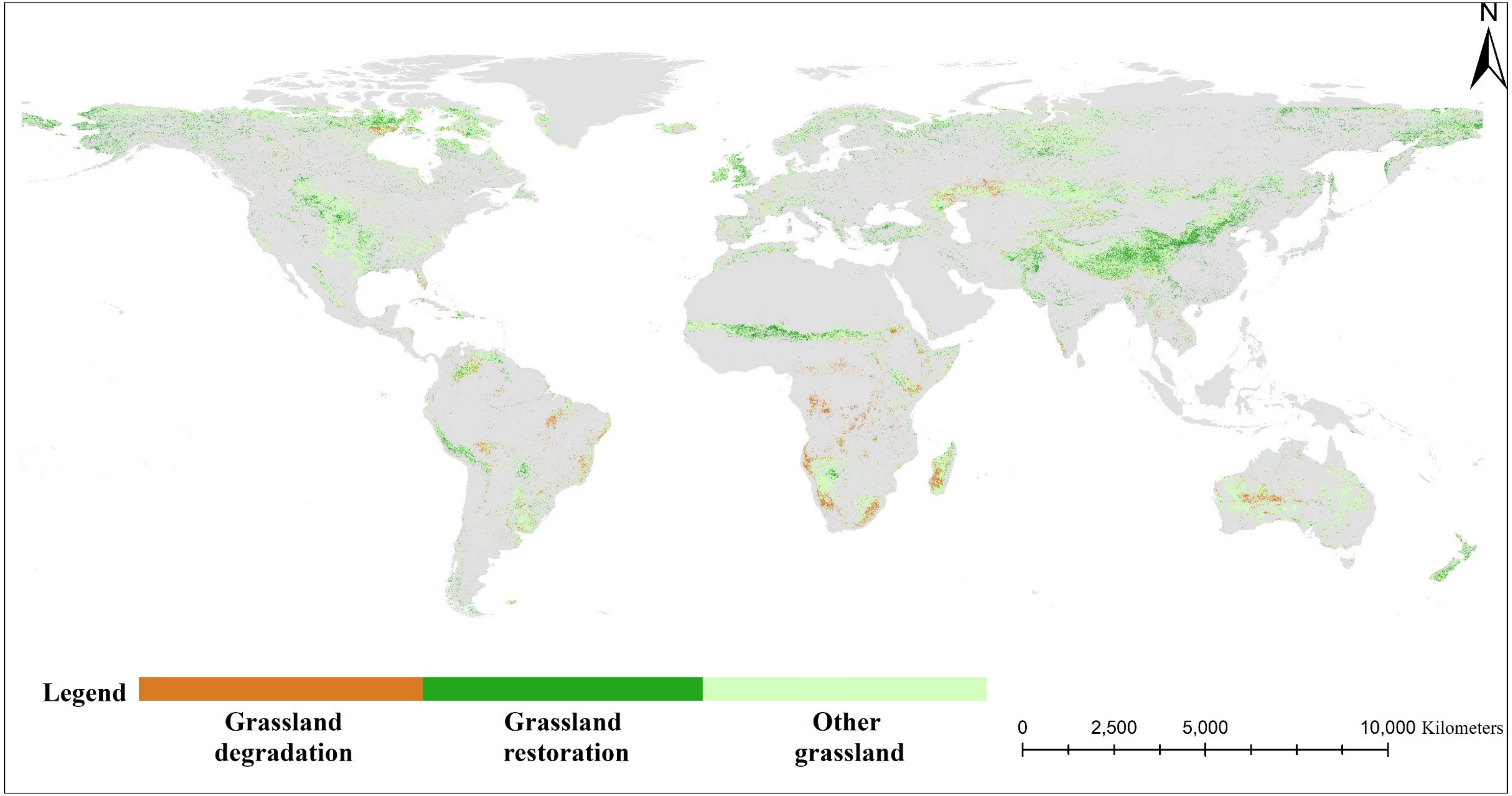
nal conclusions

Methods for detecting changes in grassland degradation

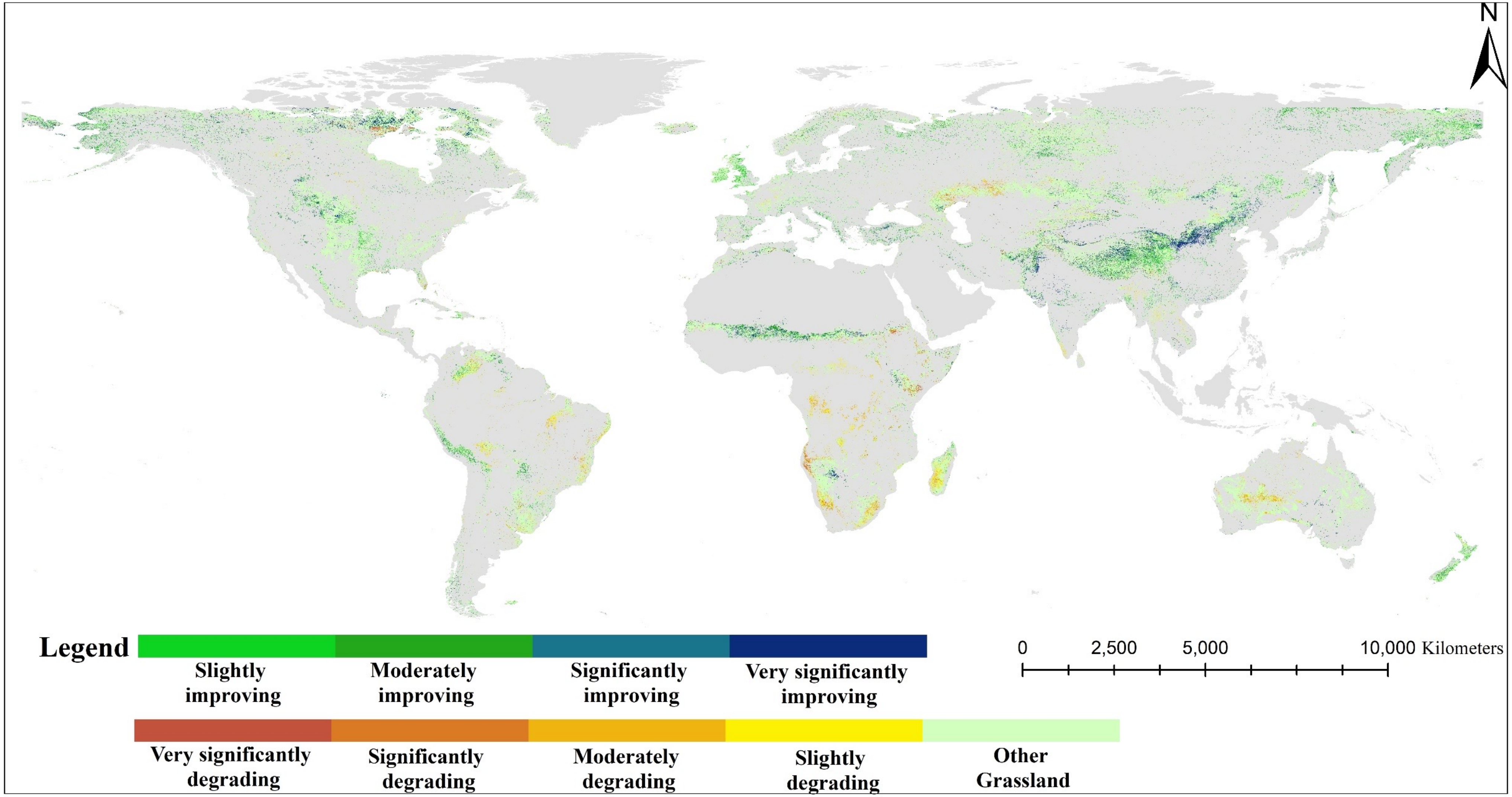
- ✓ **Preliminary analysis of the global extent：** NPP、Sen+Mann-Kendall trend test
- ✓ **Final test results:** MNPP、MI、Correlation analysis

Categories	Degrees	Change rates（%）
Degrading	Very significantly degrading	<-30.0
	Significantly degrading	-30.0~-20.0
	Moderately degrading	-20.0~-10.0
	Slightly degrading	-10.0~0
Improving	Slightly improving	0~10.0
	Moderately improving	10.0~20.0
	Significantly improving	20.0~30.0
	Very significantly improving	>30.0

Global Extent of Grassland Degradation and Improvement

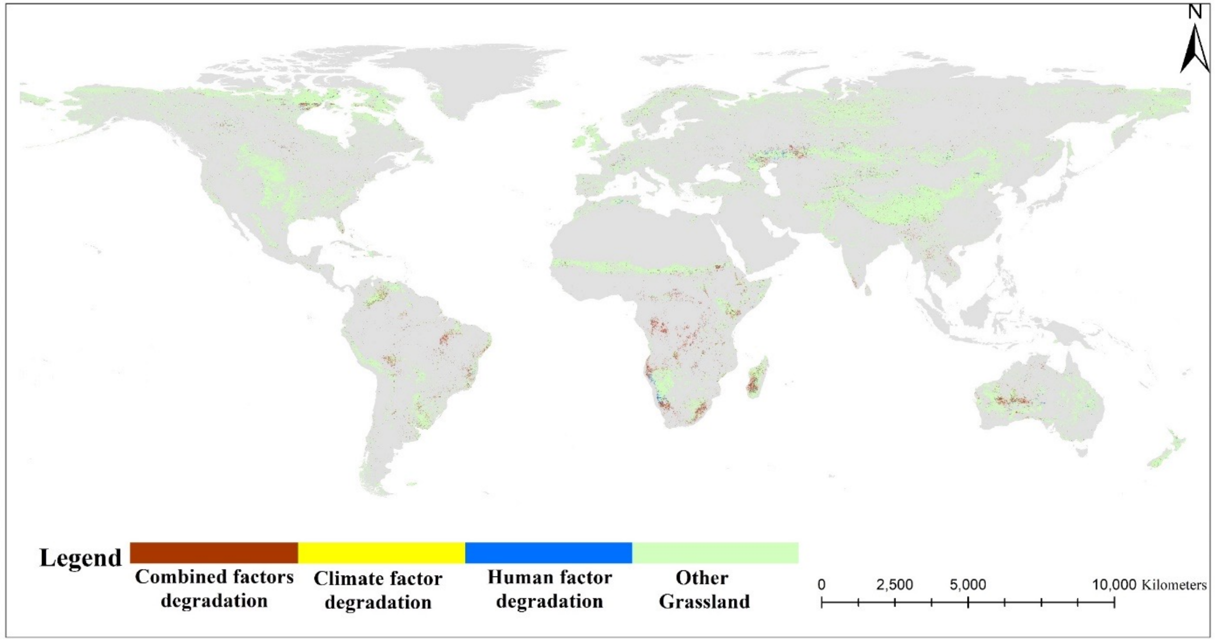


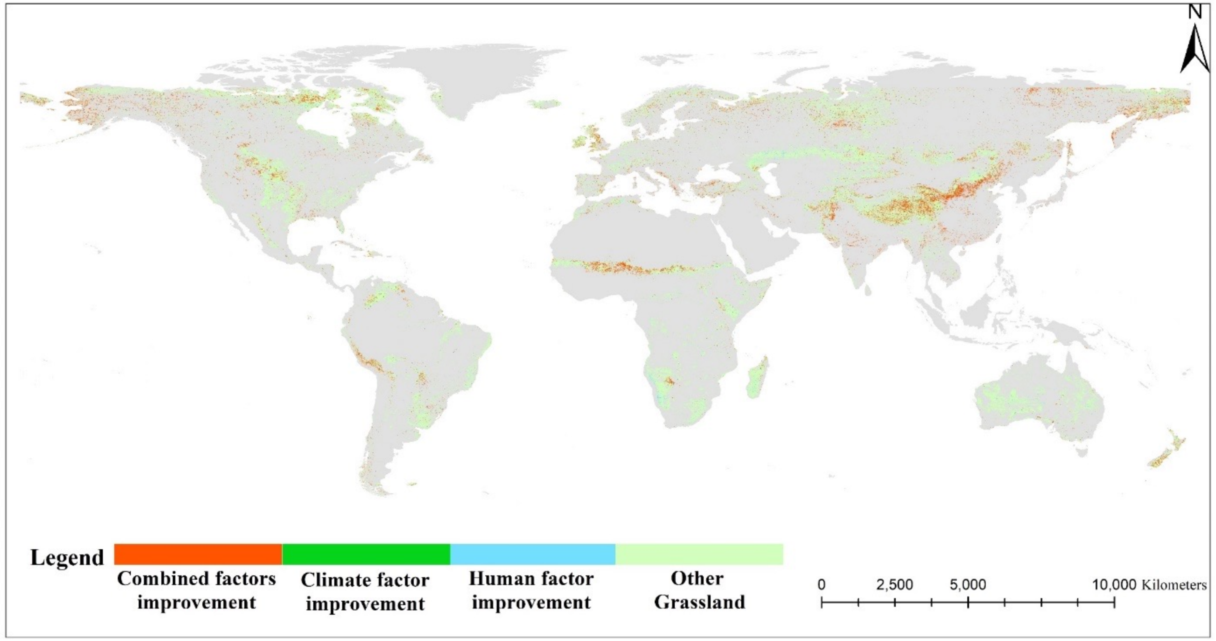
Global Grassland Degradation and Improvement Degree



Global Mechanisms Driving Grassland Degradation and Improvement

This image shows the global spatial distribution of driving mechanisms of grassland degradation (left) and improvement (right)





- ✓ **Combined factors**: combined influence of climatic and human factors
- ✓ **Climatic and human factors**: a single role
- ✓ Most grassland degradation and improvement globally is influenced by combined factors, with a single factor having minimal scope

5.Schedule and plan for the following year

- Analyse the relationships between vegetation and soil parameters and field truth degradation status;
- Classify the types of grassland use based on the time series S1,S2 & Chinese GF data;
- Determine the baseline of grassland degradation through remote sensing-based variables and biophysical model simulation.

6.Contribution of partners

- Alan, theoretical indicator framework of grassland degradation assessment driven by EO;
- Bin Sun, global grassland degradation mapping;
- Junting Yang, soil properties mapping with S2 by employing different machine learning methods;
- Jing Shao, monitoring of shrub encroachment into grassland with S1&S2;
- Hanwen Cui, grassland coverage and AGB monitoring with GF-6.

Chinese Young scientists contributions in Dragon 5

Name	Institution	Poster title	Contribution
Junting Yang	AIRCAS	Master student	Soil parameters monitoring with S2 data
Jing Shao	AIRCAS	Master student	Shrub encroachment mapping with S2 & S1 data
Hanwen Cui	AIRCAS	Master student	Grassland vegetation parameters mapping with GF-6 data