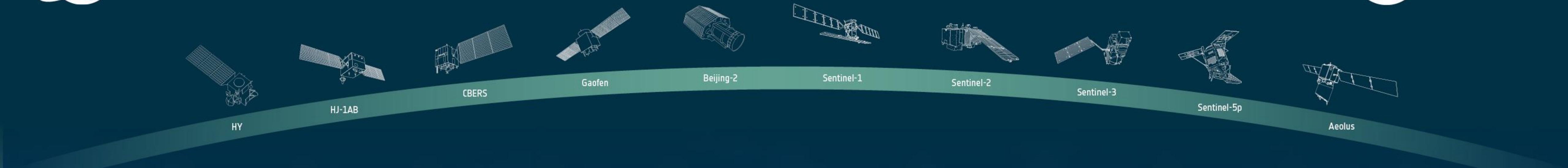


2022 DRAGON 5 SYMPOSIUM

MID-TERM RESULTS REPORTING

17-21 OCTOBER 2022

PROJECT ID: 58815

PROJECT TITLE: IMPACTS OF FUTURE CLIMATE CHANGE ON WATER QUALITY AND ECOSYSTEM IN THE MIDDLE AND LOWER REACHES OF THE YANGTZE RIVER

Water conflicts during continuous and intensifying drought in humid areas

Jianzhong Lu*, Liang Zheng, Xiaoling Chen
State Key Laboratory of Information Engineering in Surveying, Mapping and Remote Sensing, Wuhan University, Wuhan 430079, China

Herve Yesou
ICUBE SERTIT, University Strasbourg, France

Juliane Huth
Earth Observation Center of the German Aerospace Center, DLR, Wessling, Germany

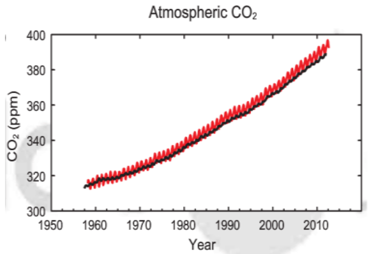
*Email: lujzhong@whu.edu.cn,

October 17-21, 2022

Outlines

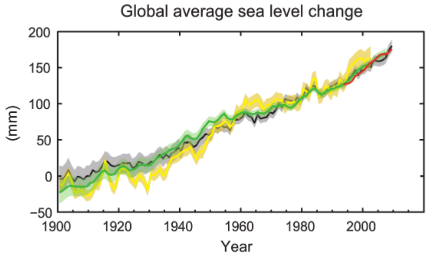
- Background
- Research and results
  - Variation of Vegetation Greenness
  - Influencing factors of greenness change
  - Greening intensifies water conflict
- Conclusion

Background



Increased co_2 concentration

GHG emission

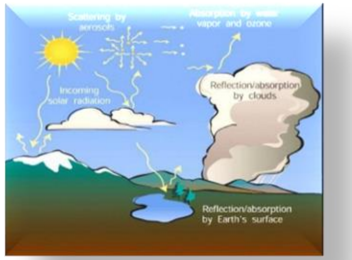


Climate warming

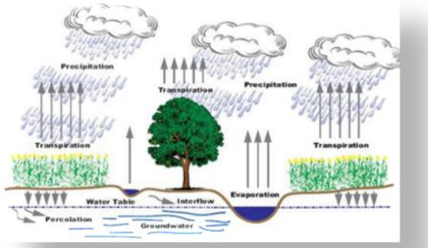
Ecosystem degradation

Global change

Carbon cycle



Radiation balance



Water Circulation

Terrestrial ecosystem

Vegetation

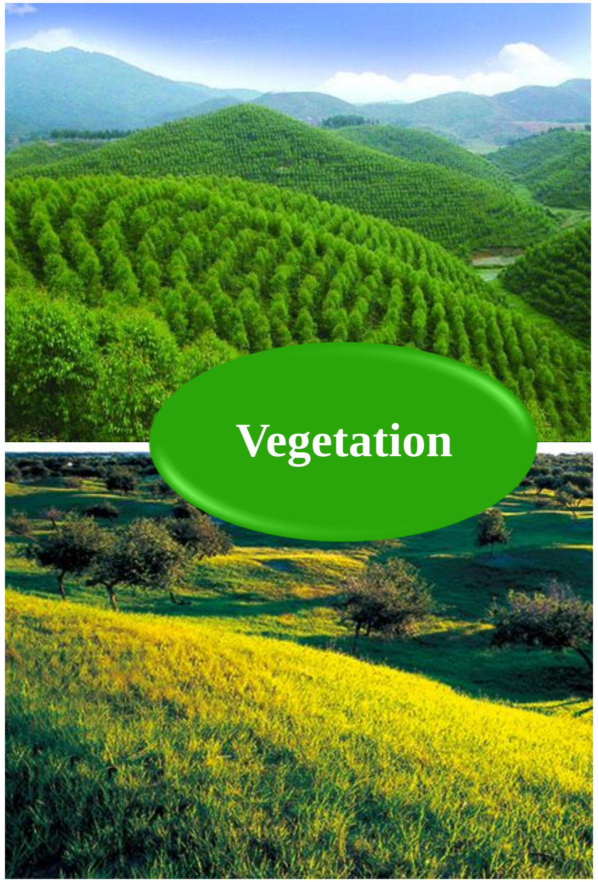
- **An important part of terrestrial ecosystems**
- **An important factor of global environmental change**

Background

- **Indicators describing land surface vegetation coverage**
- **Reflects the change of land surface ecological environment quality**

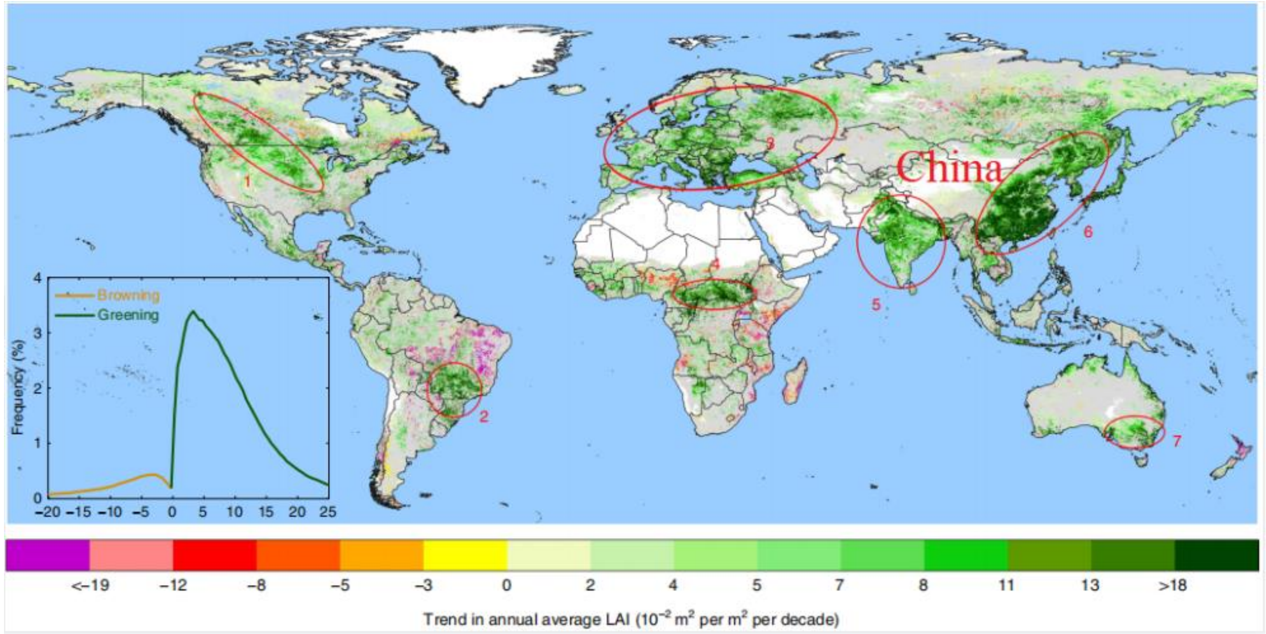
Leaf Area Index (LAI)
Normalized Differential Vegetation Index (NDVI)
Enhanced Vegetation Index (EVI)
Photochemical Reflectance Index (PRI)
Sun/Solar-induced Chlorophyll Fluorescence (SIF)
……

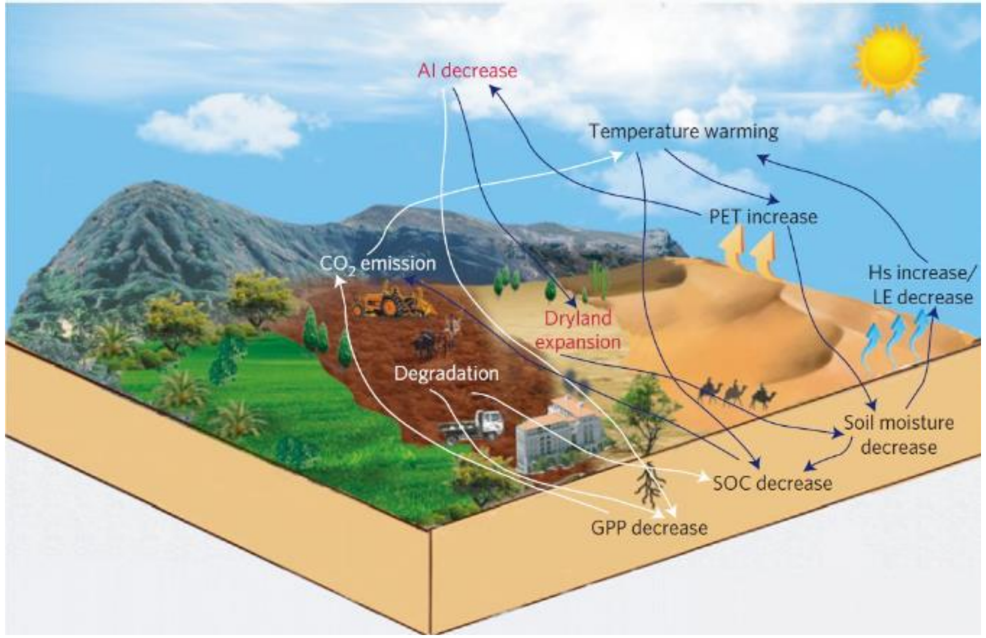
Vegetation greenness is an index used to describe the land surface vegetation coverage, which directly reflects the change of inland surface vegetation in a certain spatial and temporal range, and indirectly reflects the change of land surface ecological environment quality.



Background

- Under the influence of climate change (climate warming, precipitation increasing) and human activities (forestry protection projects, green food projects, CO_2 fertilization), vegetation greening in China is significant
- In arid and semi-arid areas, the increase of vegetation greenness may lead to water demand conflicts





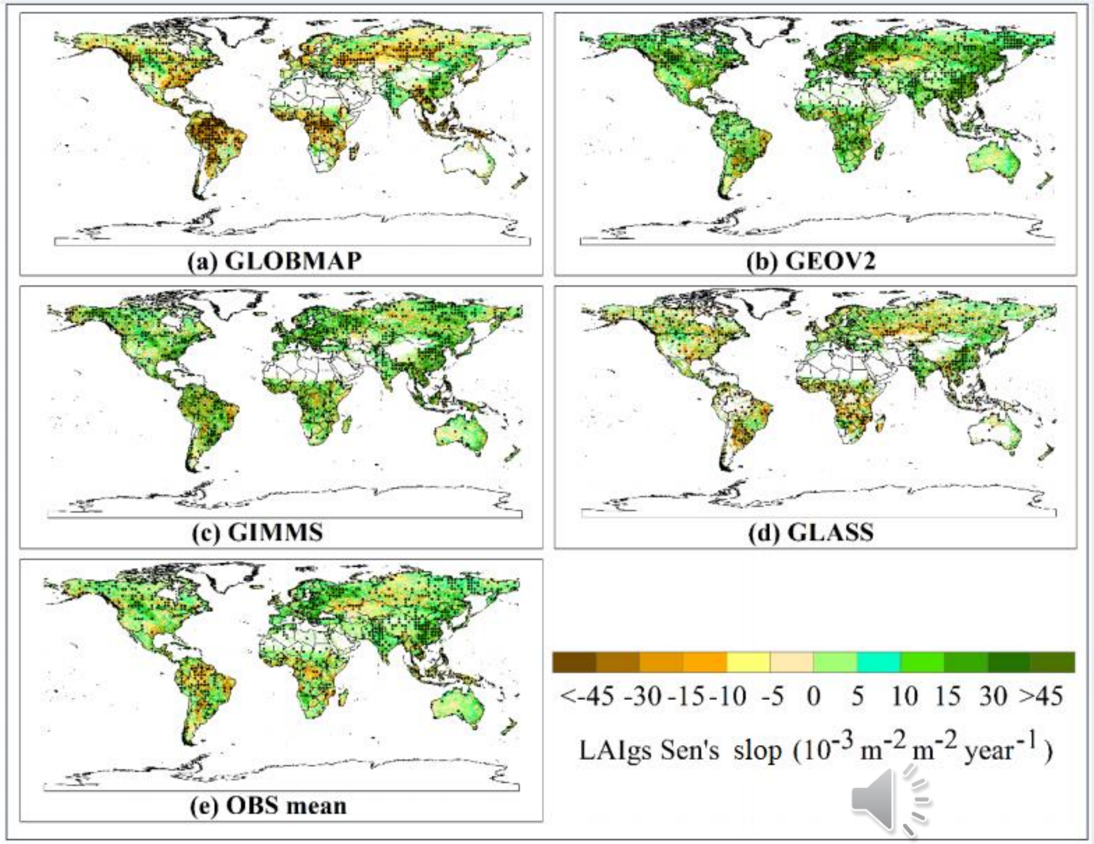
What is the impact of greening on water yield in humid areas?

Variation of Vegetation Greenness

- **LAI of the growing season observed by four groups of satellites from 2000 to 2014 was used to characterize vegetation greenness, and the Spatio-temporal variation pattern of greenness was analyzed on a global scale**

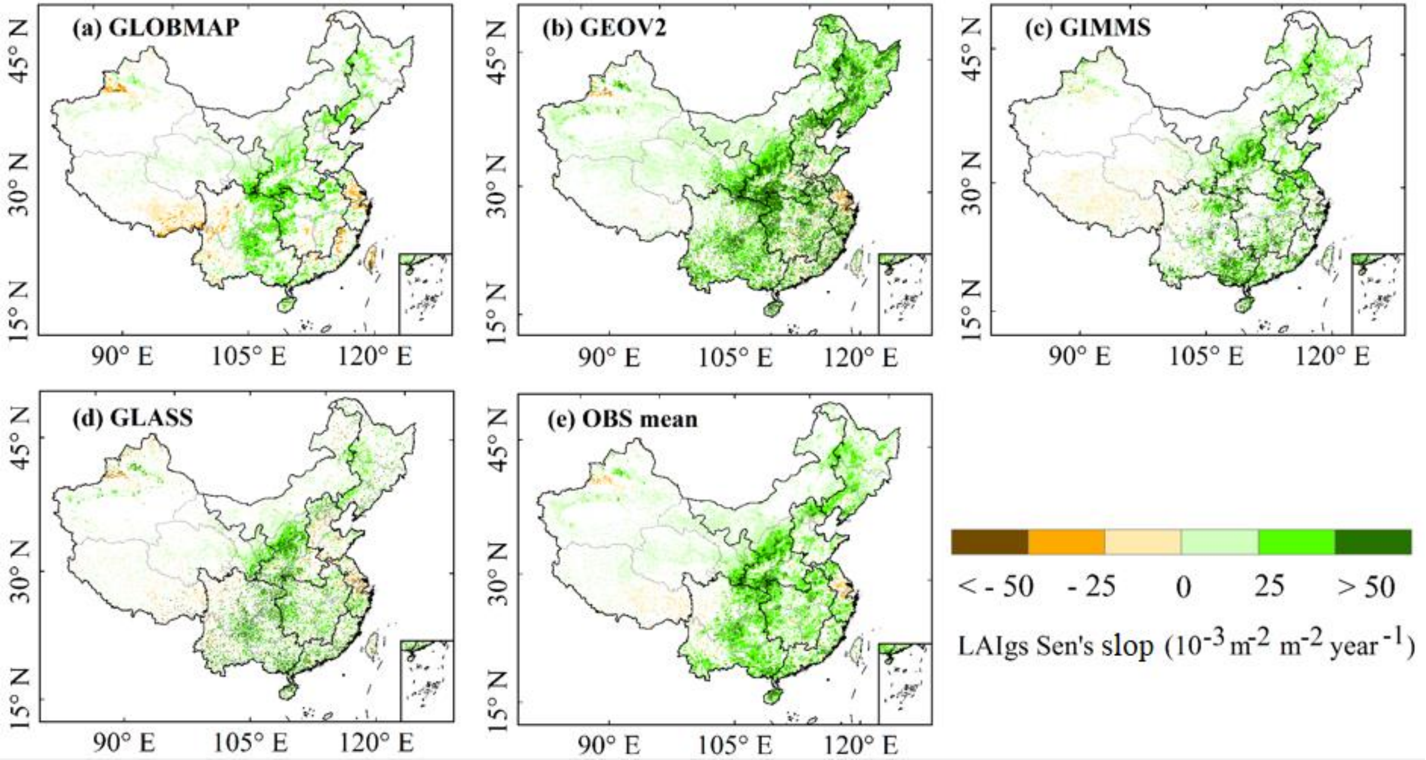
Dataset	Spatial Resolution	Temporal Resolution	Validation (Root Mean Square Error)
GLOBMAP LAI	8 km	15 days	0.81 [48]
GEOV2 LAI	(1/12)°	10 days	0.74 [49], [50]
GIMMS LAI3g	(1/12)°	15 days	0.68 [51]
GLASS LAI	1 km	8 days	0.64 [52]

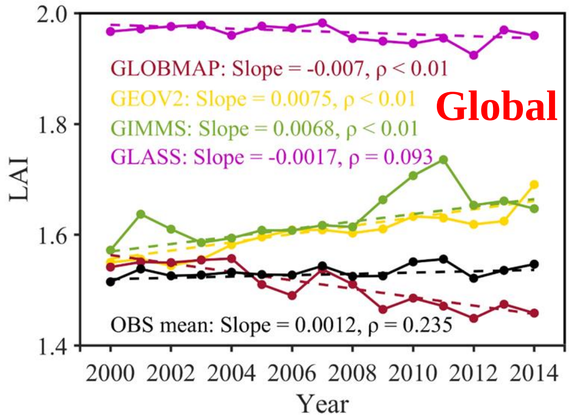
- The greenness of most vegetation regions in the world (northern hemisphere) showed a significant increasing trend, and the greening trend in China was the fastest
- The areas where vegetation browned were eastern South America, Central Africa, and Central Asia
- Most of the vegetation in the southern hemisphere is turning brown

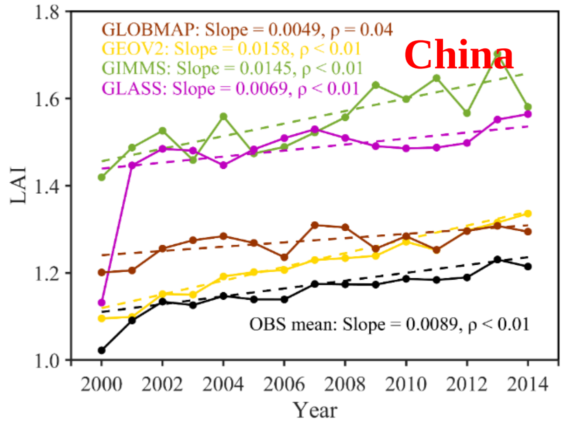


Variation of Vegetation Greenness

- **Different satellite products showed significant greening in China, but different LAI products had great uncertainties**
- **There was a trend of global vegetation greening from 2000 to 2014, and the trend of regional vegetation greening in China was more significant**



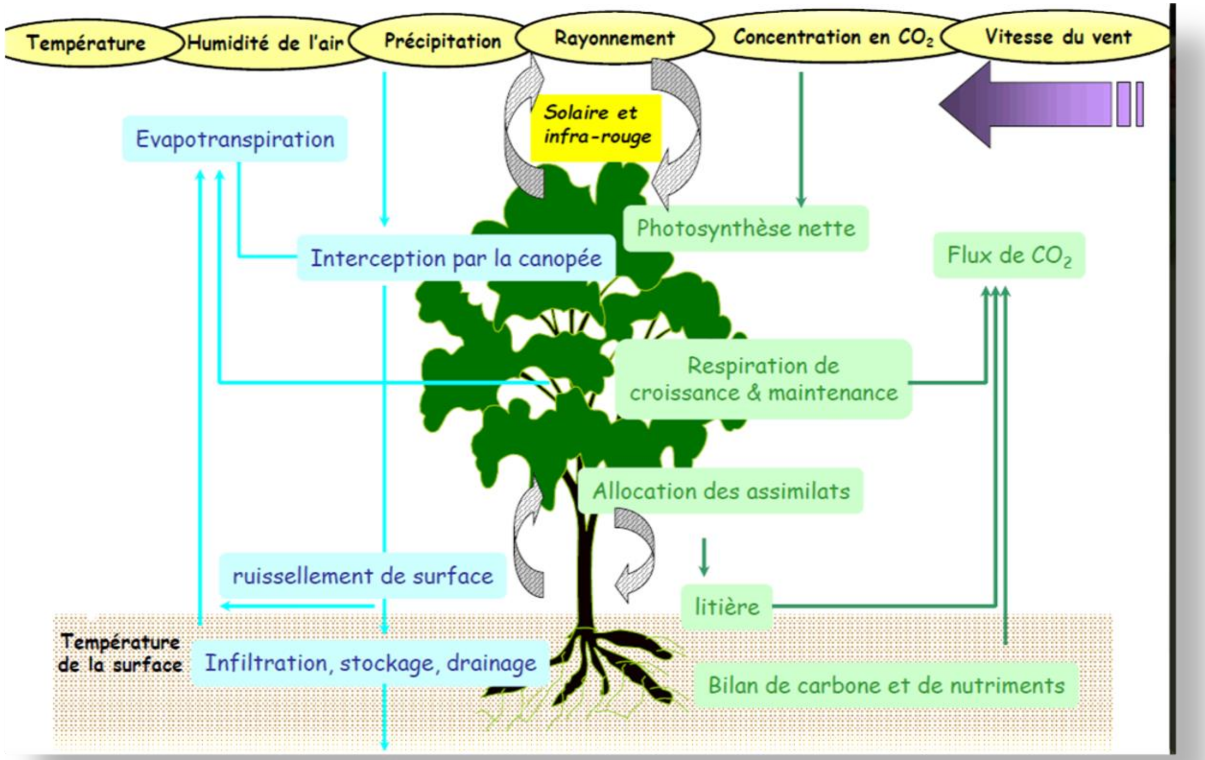




Variation of Vegetation Greenness

Dynamic Global Vegetation Models, DGVMs

- The global vegetation model is a key technology to study the interaction between vegetation greenness and the environment. However, LAI results of the single dynamic vegetation model have great uncertainties and all have their own regional adaptability.



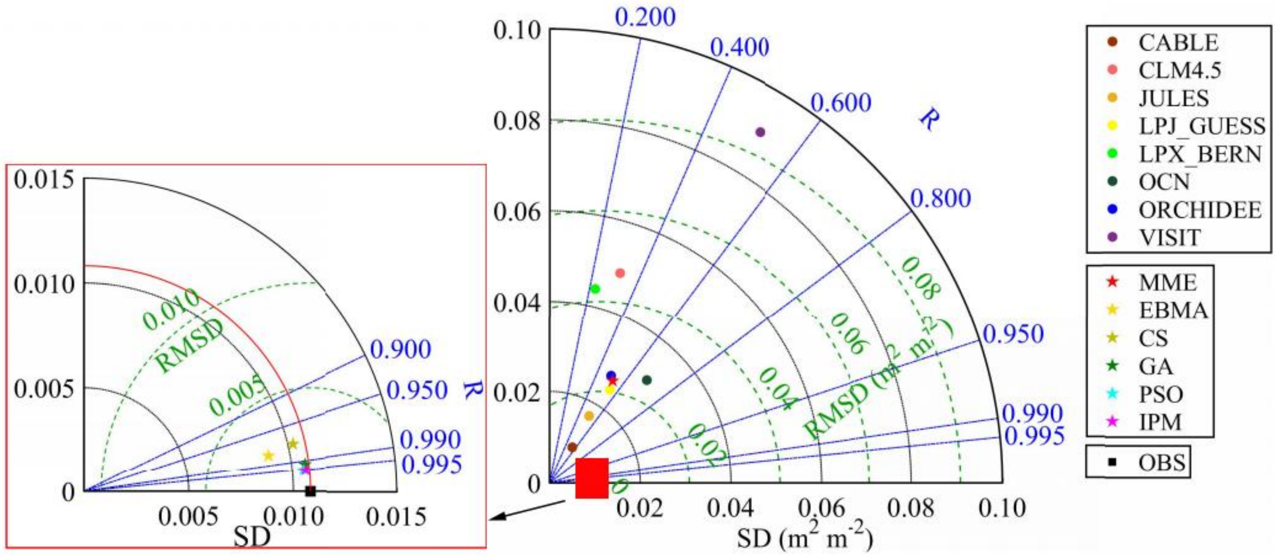
Variation of Vegetation Greenness

Dynamic Global Vegetation Models optimization

- Multi-model ensemble mean (MME)
- Ensemble Bayesian model averaging (EBMA)
- Genetic Algorithm (GA)
- Particle Swarm Optimization (PSO)
- Cuckoo Search (CS)
- Interior-point Method (IPM)

Model	Driving Datasets			Important Process included in models							Spatial resolution (Lon × Lat)
	Land cover change	Climate variability	CO_2 fertilization	Land use change						Carbon-nitrogen interactions	
				DFRAA	WHFD	SC	CH	PF	FSS		
CABLE	Y	Y	Y	Y	Y	N	Y	N	N	Y	0.5° × 0.5°
CLM4.5	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	1.25° × 0.9°
JULES	Y	Y	Y	Y	N	N	N	N	N	N	1.85° × 1.25°
LPJ_GUESS	Y	Y	Y	Y	N	N	Y	N	Y	N	0.5° × 0.5°
LPX_BERN	Y	Y	Y	Y	N	N	Y	N	Y	Y	1° × 1°
OCN	Y	Y	Y	Y	Y	N	Y	N	N	Y	1° × 1.2°
ORCHIDEE	Y	Y	Y	Y	N	N	Y	N	N	N	0.5° × 0.5°
VISIT	Y	Y	Y	Y	Y	Y	Y	N	Y	N	0.5° × 0.5°

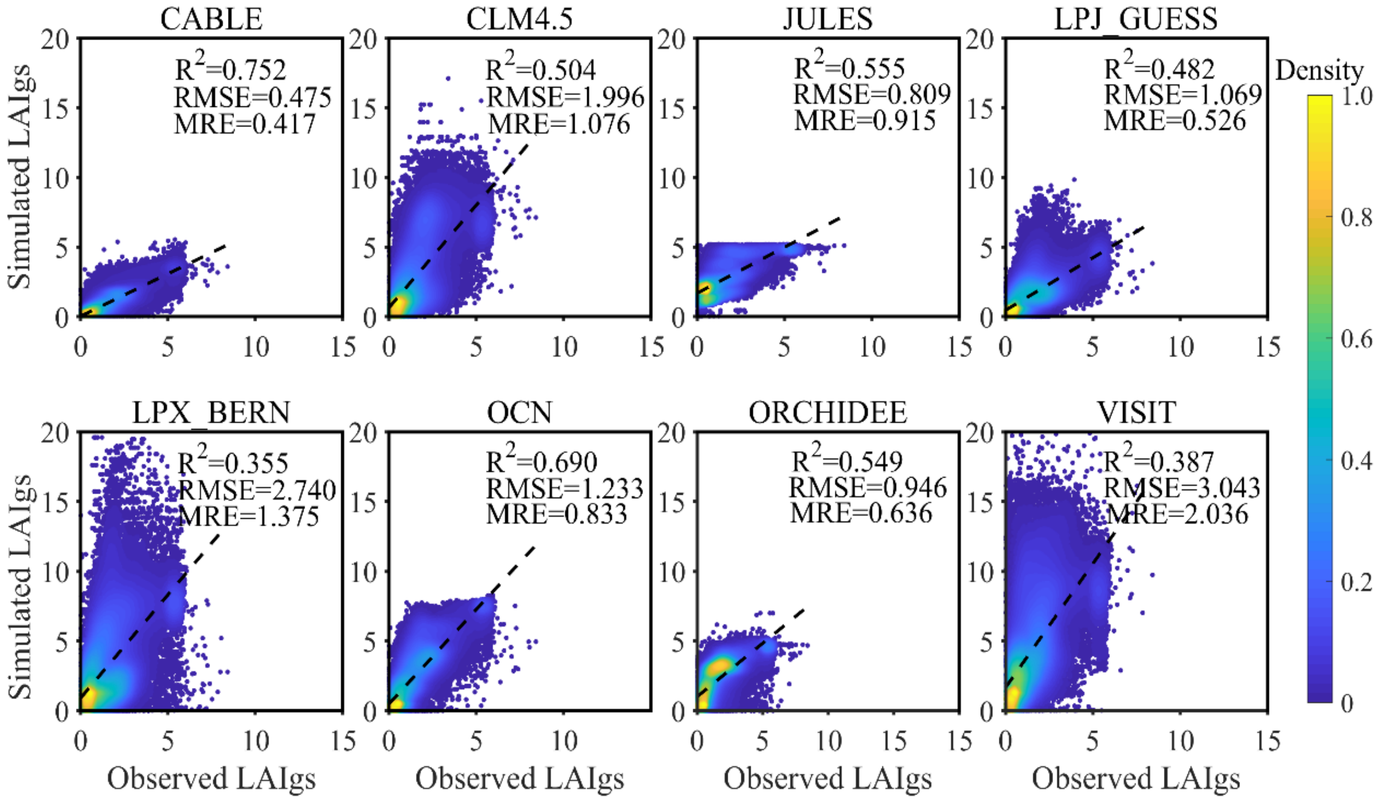
DFRAA = Deforestation and Forest Regrowth after Abandonment of Agriculture, WHFD = Wood Harvest and Forest Degradation, SC = Shifting Cultivation, CH = Cropland Harvest, PF = Peat Fires, FSS = Fire Simulation and/or Suppression, CO_2 = Carbon Dioxide.

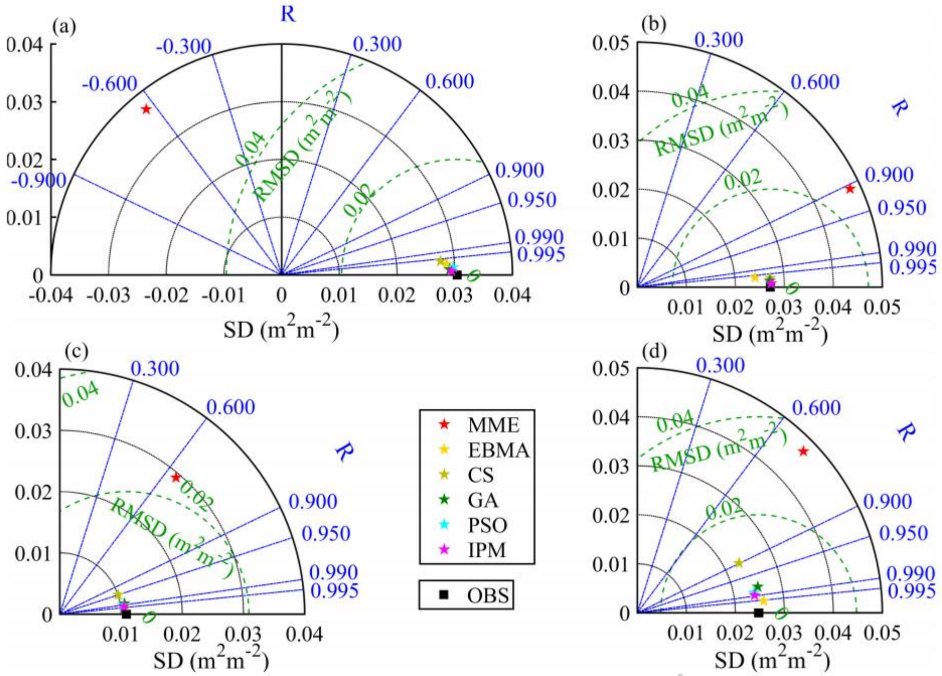


Among the six model ensemble methods, except the MME ensemble model, the performance of the other five optimized ensemble models is significantly better than that of the single dynamic global vegetation model.

Variation of Vegetation Greenness

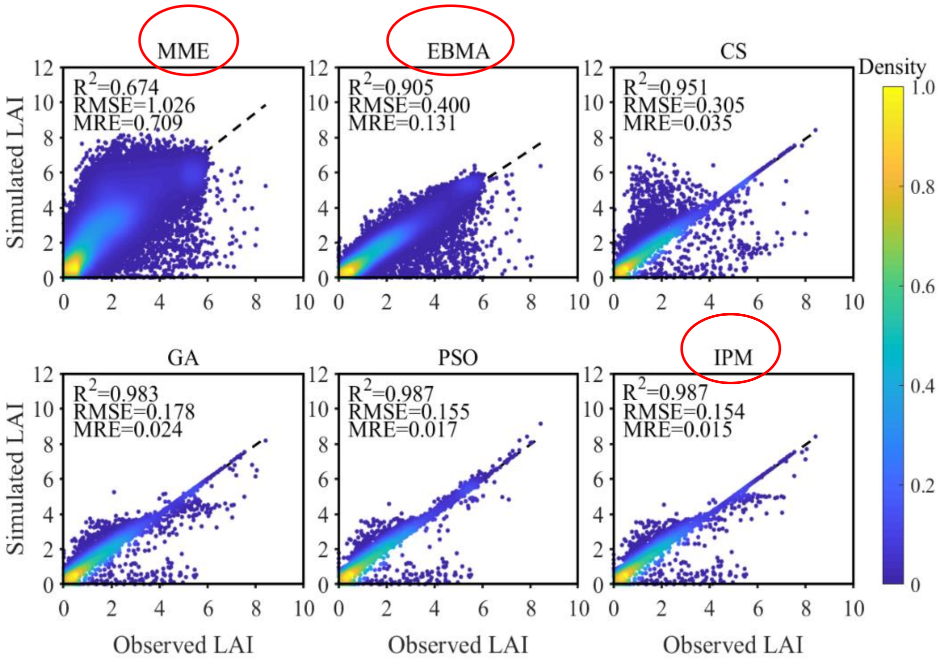
- The global vegetation dynamics model (DGVM) has great differences in simulating global LAIgs temporal and spatial changes and its accuracy needs to be improved

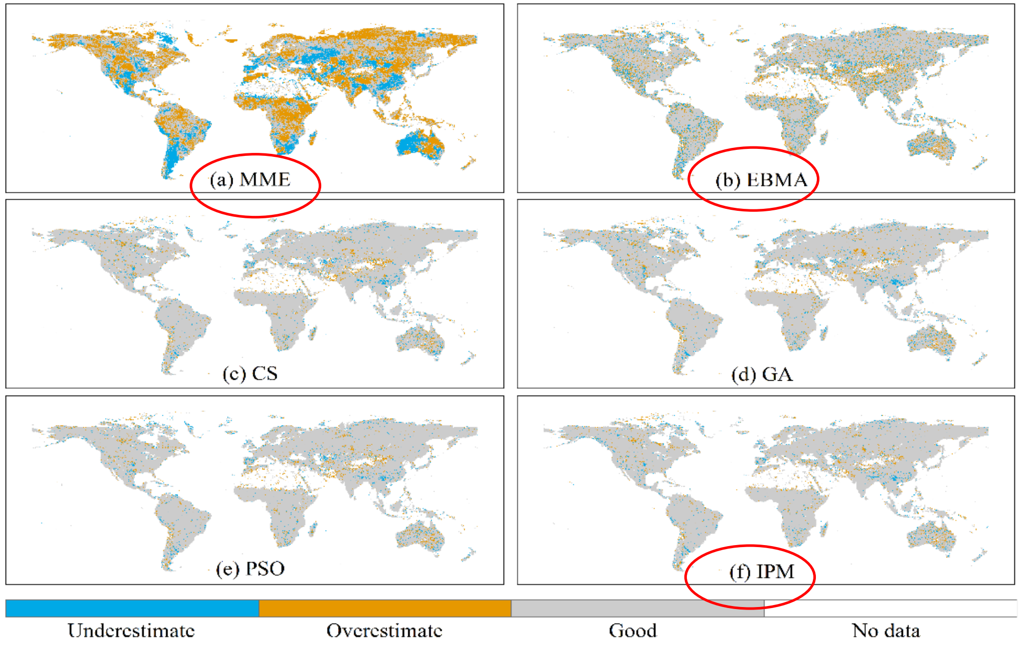




Variation of Vegetation Greenness

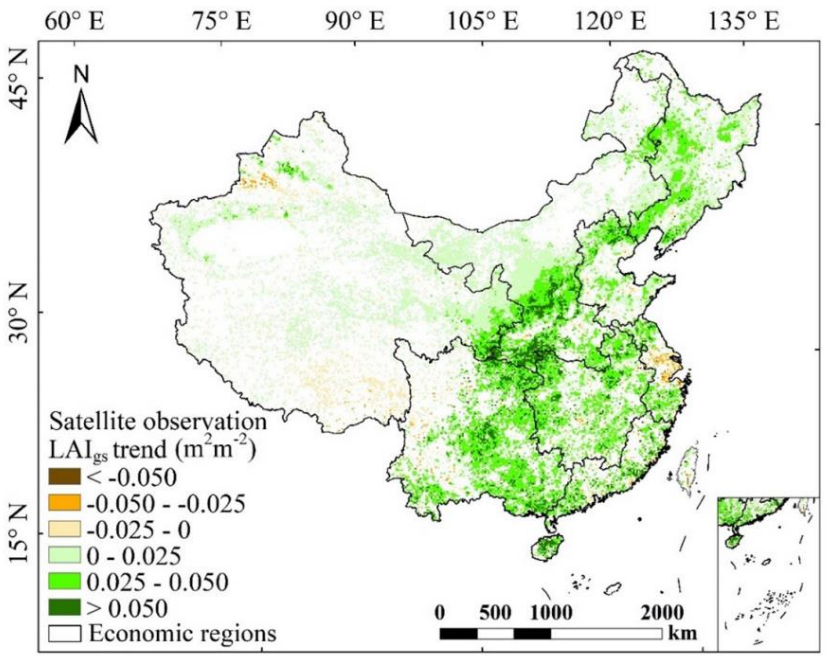
- In terms of simulating LAIgs change, the performance of the MME integration model was significantly better than that of the single dynamic global vegetation model
- Compared with MME and EBMA, the root mean square error of the IPM ensemble model with the best performance is reduced by 85.09% and 61.75%, respectively
- According to the ensemble optimization results based on the IPM method, the area of LAIgs optimal change trend accounts for 91.62% of the global vegetation area, which is 1.2 times that of the MME (EBMA) ensemble model.

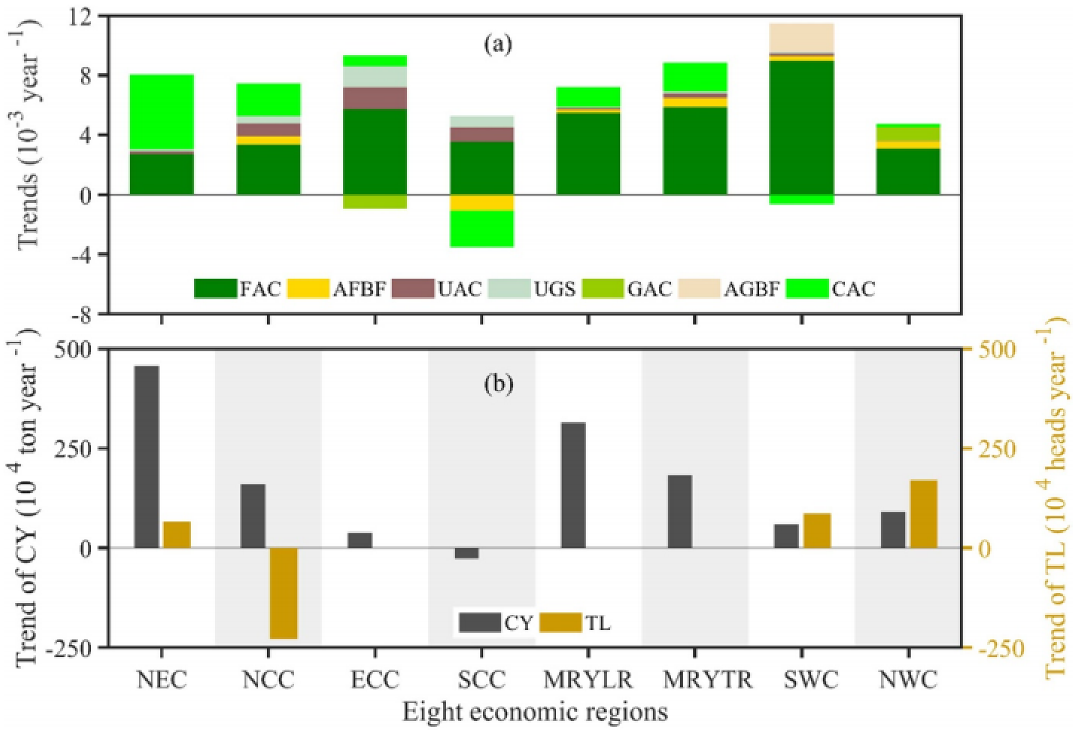




Influencing factors of greenness change

Land use change





- Take China as an example, where the vegetation is significantly green and the land use changes dramatically
- To quantitatively evaluate the impacts of major land use change factors (including agricultural improvement, afforestation, urbanization, forest, and grassland biological hazards, fire, and overgrazing) on vegetation greenness change in China from 2000 to 2014
- The global vegetation dynamics model (DGVM) optimized by the Interior Point Algorithm (IPM) ensemble was used to quantitatively analyze the impact of land use on greenness.

Influencing factors of greenness change

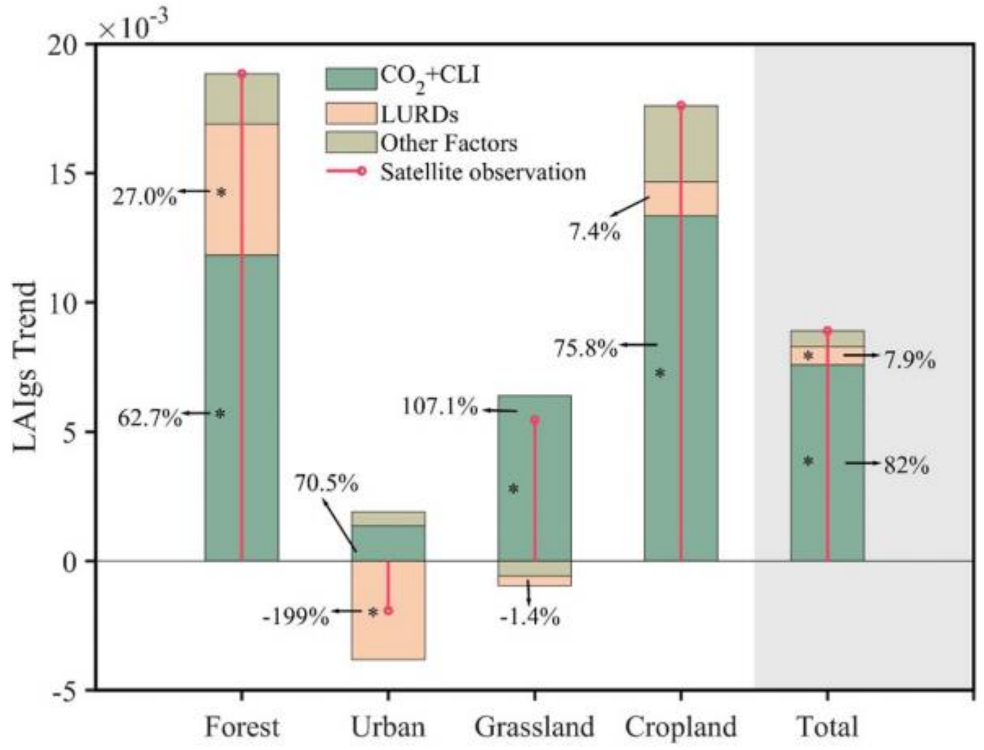
- Based on scenario simulation and BMA evidence, the impacts of land use change factors on regional vegetation greenness in China were illustrated

Resources and environmental statistics variables	PIP	PM
Forest area change	0.998	0.477
Urban area change	0.997	−0.753
Area change of forest biodisasters and fire disasters	0.848	−0.237
Urban green space	0.316	0.111
Area change of grassland biodisasters and fire disasters	0.273	−0.035
Crop yield	0.225	0.025
Total livestock	0.183	−0.012
Grassland area change	0.179	0.011
Cropland area change	0.165	0.002

Notes: PIP indicates posterior inclusion probability. PM indicates a posterior mean.

Bayesian model averaging (BMA) evidence
PIP represents the posterior inclusion probability. If the PIP value is greater than 0.99, the explanatory variables show a decisive influence on PM and represent the posterior mean value.
If **PM** is positive, it means that the increase of explanatory variable value has a positive impact on vegetation greenness

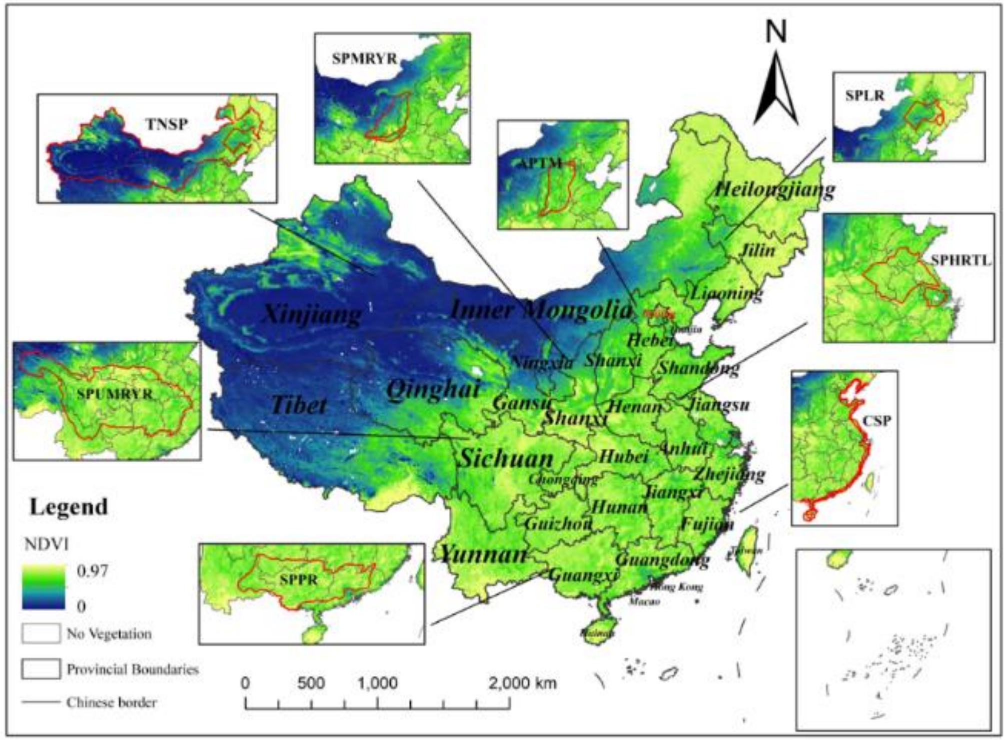
Scenario	LAI	LUCC	T	P
S1	●	●	●	●
S2	○	○	●	●



- Scenario I (S1): The atmospheric CO_2 concentration, climate, and lUCC change with time, and this scene reflect the vegetation change in the "real" scene.
- Scenario II (S2): Atmospheric CO_2 concentration and climate change with time, while LULCC does not change with time. This scenario reflects that vegetation is influenced by both atmospheric CO_2 concentration and climate

- Forests: Afforestation in the concentrated distribution area contributed **27%** to the greening of the vegetation in the area
- Urbanization: the browning impact caused by urbanization was approximately **three** times the greening effects of both climate change and CO2 fertilization on the urban area

Forestry projects and climate change



Eight Large Forestry projects in China

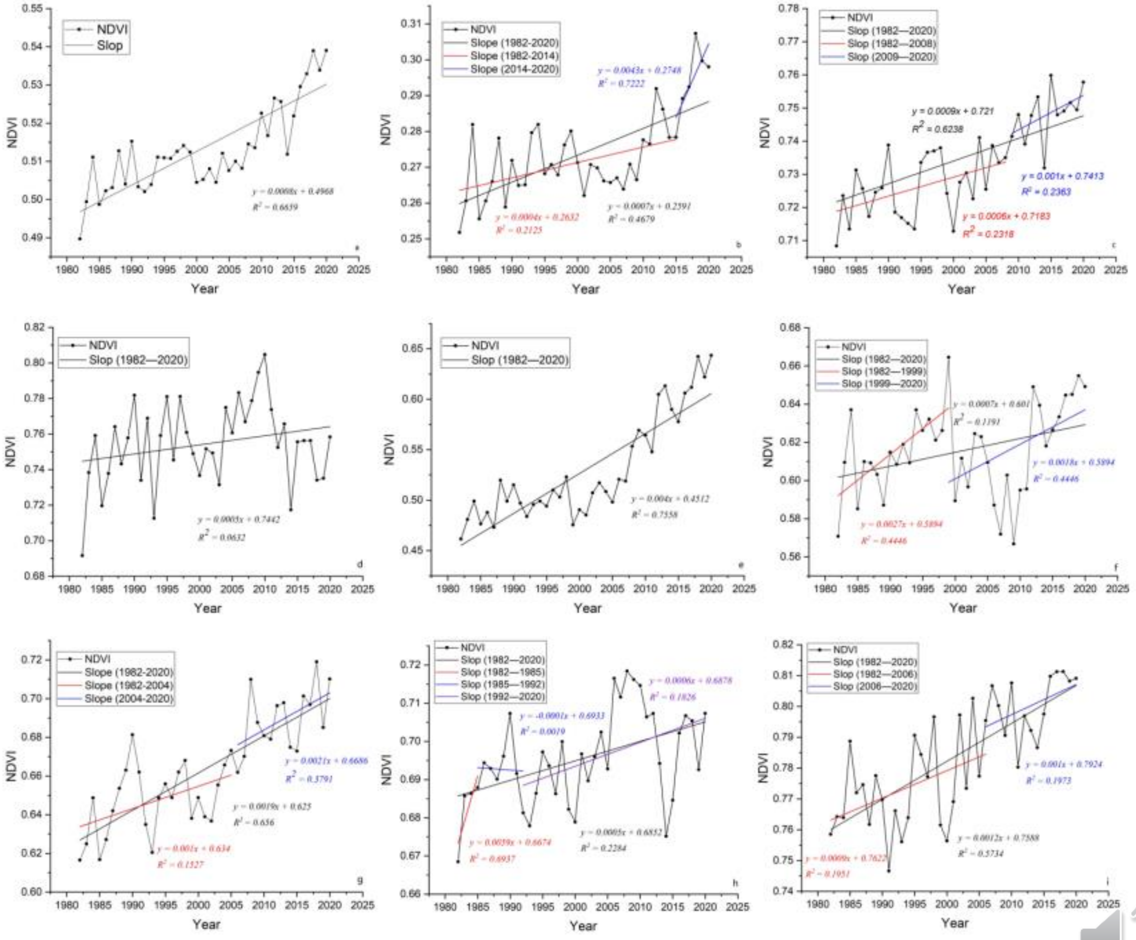


Figure 3. Annual average NDVI changes from 1982 to 2020: (a) China, (b) TNSP, (c) SPUMRYR, (d) SPHRTL, (e) SPMRYR, (f) SPLR, (g) APTM, (h) CSP, and (i) SPPR.

Influencing factors of greenness change

➢ The relative contribution of forestry projects and climate change to vegetation restoration (degradation)

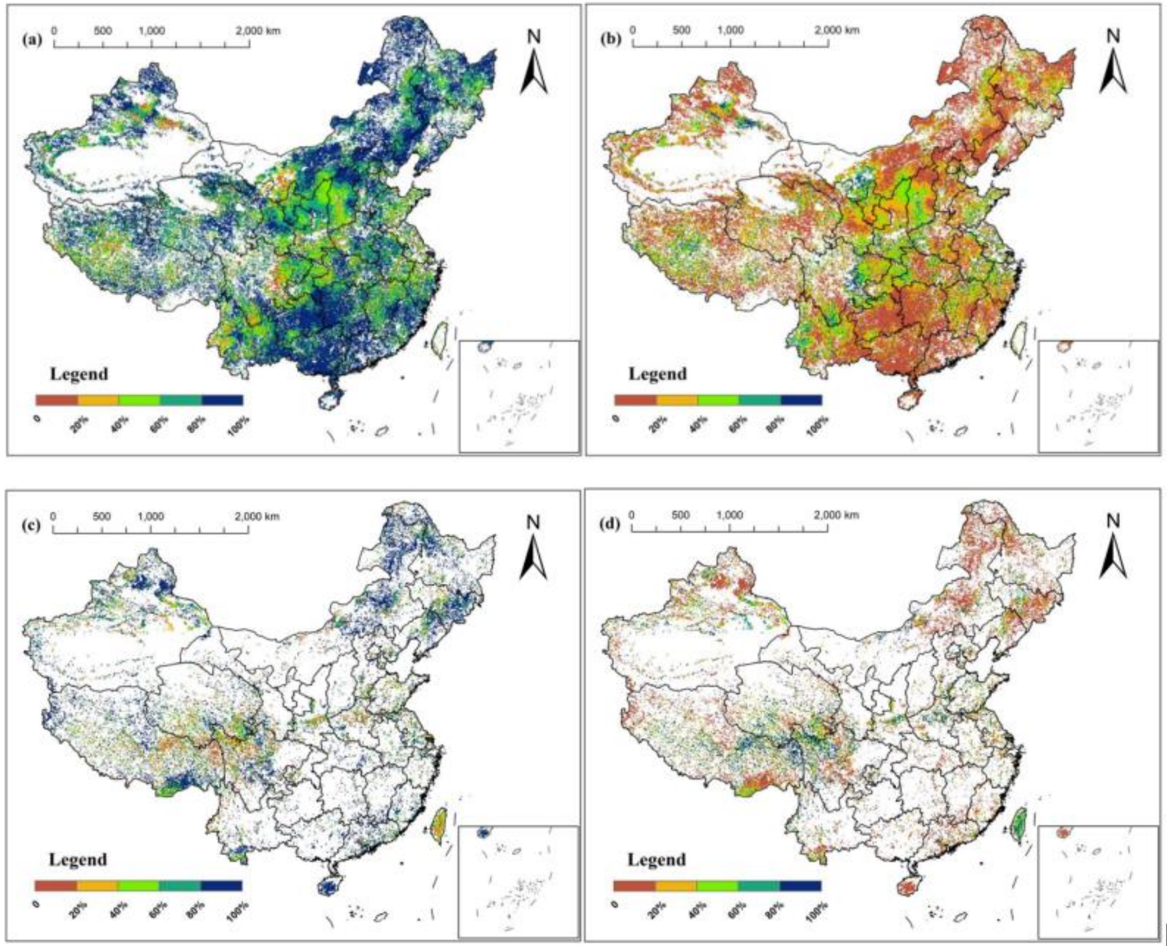
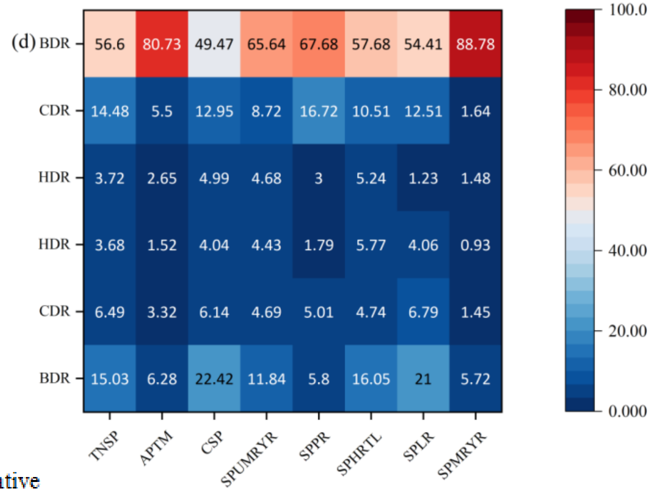
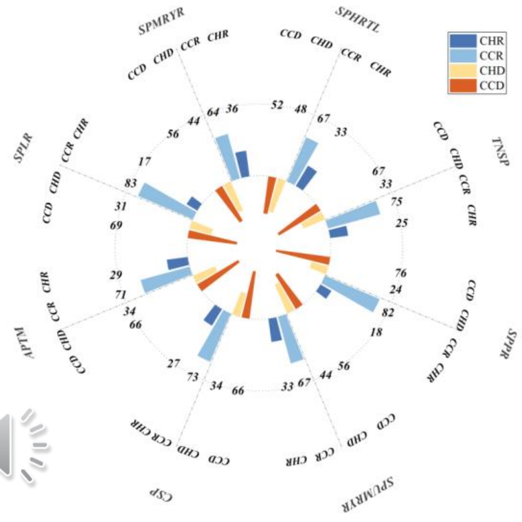


Figure 7. Relative contribution of climate change (a) and human activities (b) to vegetation improvement during 1982-2020; Relative contribution of climate change (c) and human activities (d) to vegetation degradation during 1982-2020.

Table 1. six scenarios were established to identify driving forces for forest dynamics.

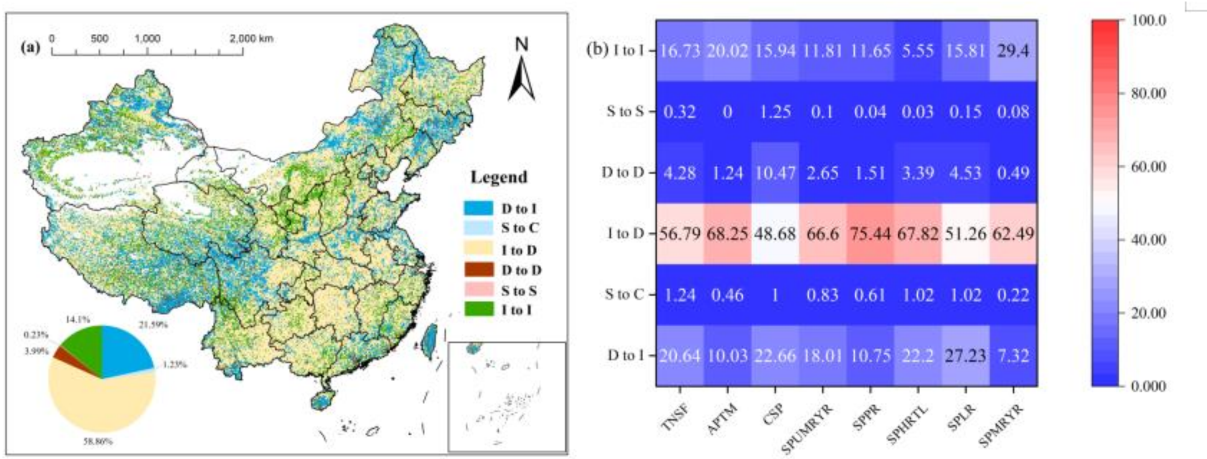
Forest Status	Scenario	S_{ONDVI}	S_{PNDVI}	S_{RNDVI}	Dominant Driving Force	Relative contribution of climate change	Relative contribution of human activities
Forest restoration	1	>0	>0	<0	Climate-dominated vegetation restoration (CDR)	100	0
	2	>0	<0	>0	Human-dominated vegetation restoration (HDR)	0	100
	3	>0	>0	>0	Both dominated vegetation restoration (BDR)	$\frac{S_{PNDVI}}{S_{PNDVI}+S_{RNDVI}}$	$\frac{S_{RNDVI}}{S_{PNDVI}+S_{RNDVI}}$
Forest degradation	4	<0	>0	<0	Human-dominated vegetation degradation (HDD)	0	100
	5	<0	<0	>0	Climate-dominated vegetation degradation (CDD)	100	0
	6	<0	<0	<0	Both dominated the vegetation degradation (BDD)	$\frac{S_{PNDVI}}{S_{PNDVI}+S_{RNDVI}}$	$\frac{S_{RNDVI}}{S_{PNDVI}+S_{RNDVI}}$

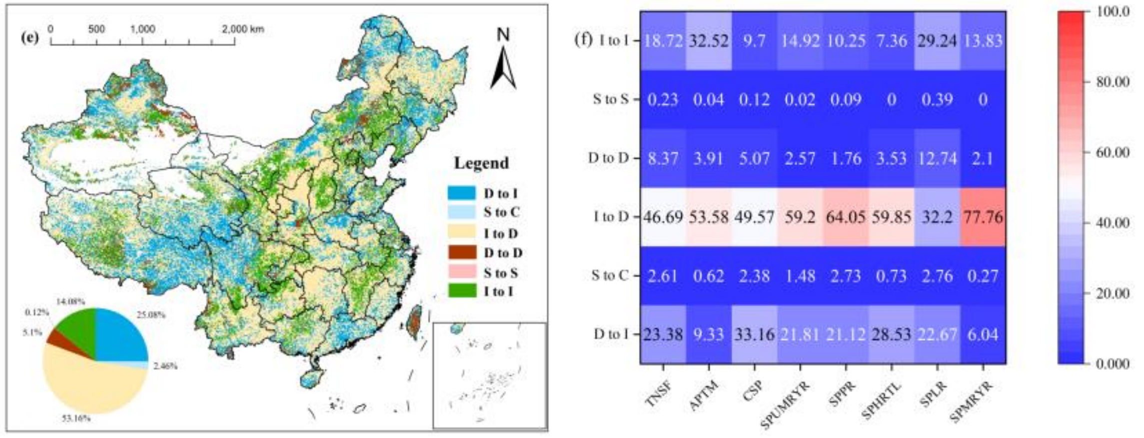


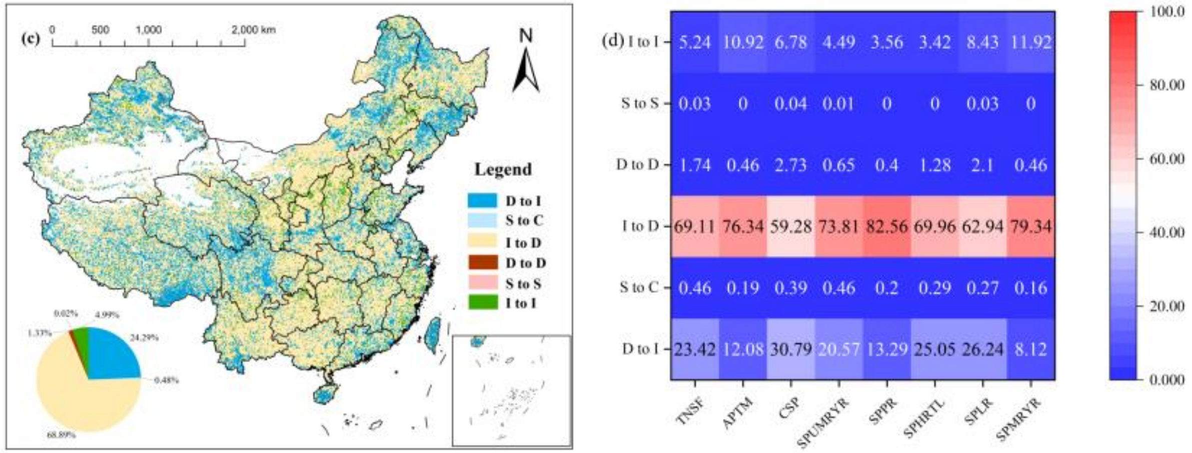


Influencing factors of greenness change

➢ Future changes in vegetation greening, climate change and forestry projects







- The risk of future vegetation degradation was high, and NDVI continued to increase in only **14%** of the regions.
- The **anti-persistent** of climate change contribution is high, in the future, **69%** will change from increase to decrease.
- The forestry project contribution changes are more complex. In the future, **53%** will change from increase to decrease, and **25%** has changed from decrease to increase.

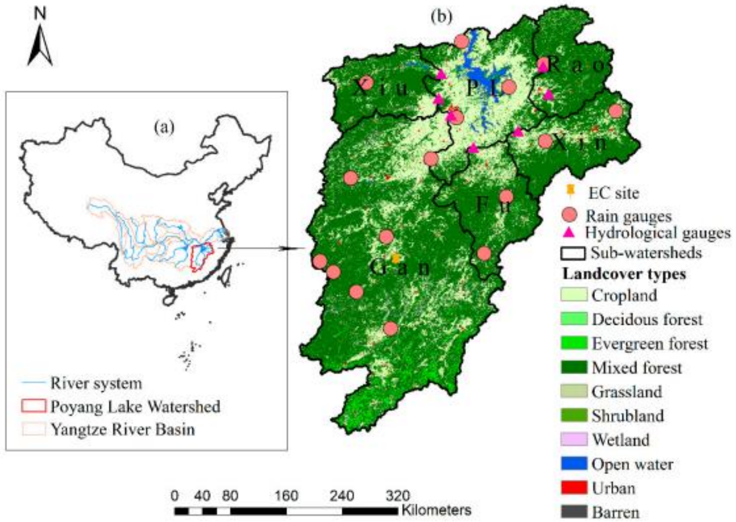
Greening intensifies water conflict under a drought background

- Identifying Droughts with Differing Intensity

2009: Moderate drought with a long duration

2011: Extreme drought with a short duration

2013: Moderate drought with a short duration



Poyang Lake watershed

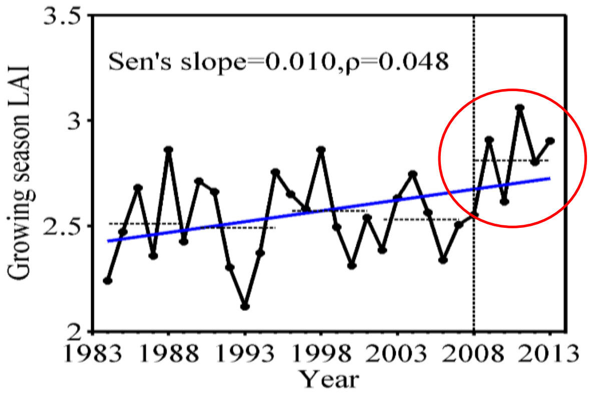


Table S1. Drought classification based on the SPEI.

SPEI values	Flood/Drought category
≥0.5	Wet
-0.49 -- 0.49	Near normal
-0.99 --0.50	Mild drought
-1.49 --1.00	Moderate drought
-1.99 --1.50	Severe drought
≤-2.0	Extreme drought

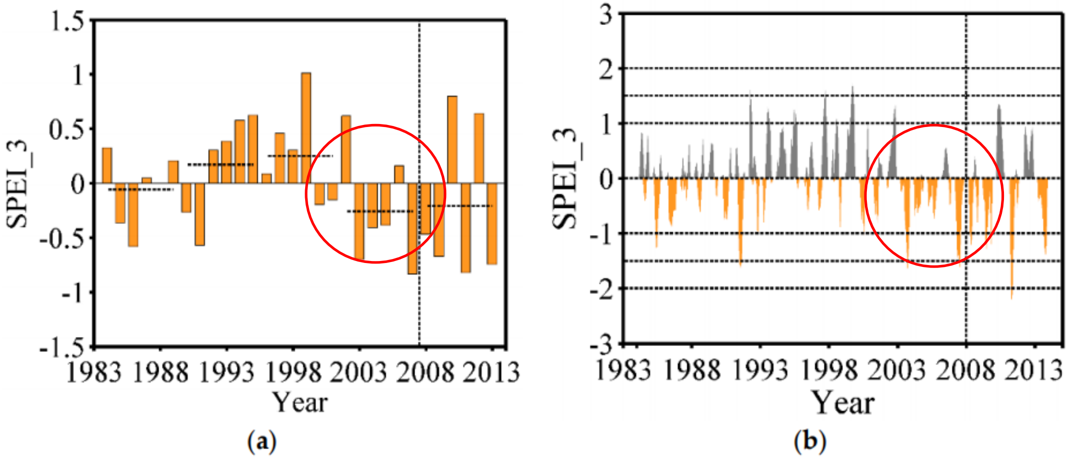
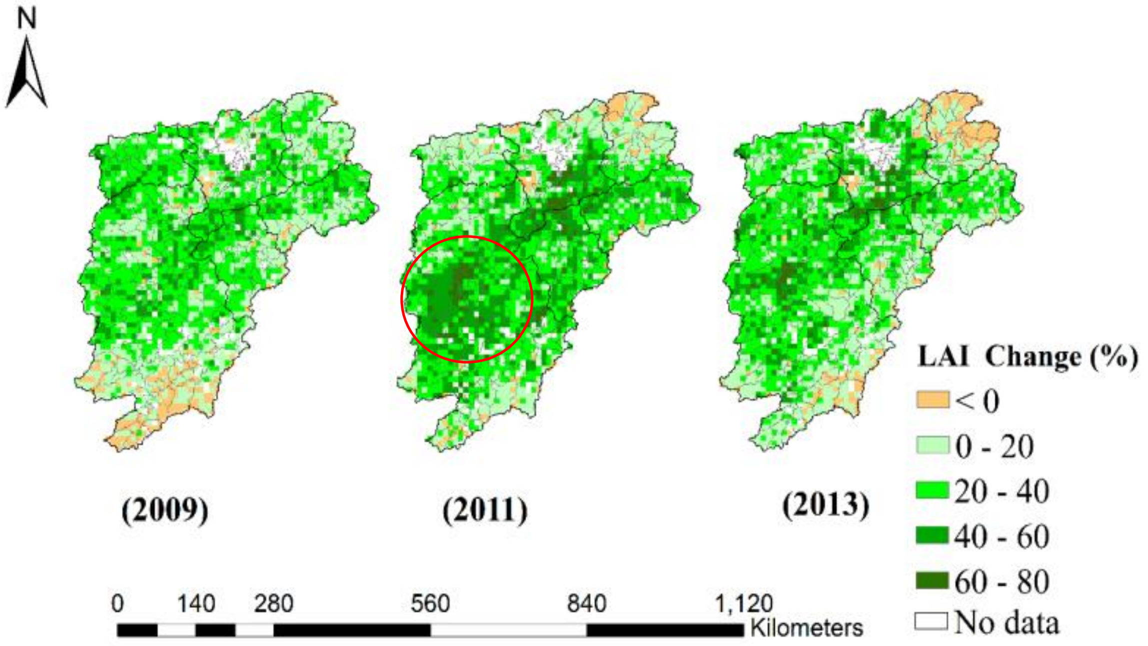
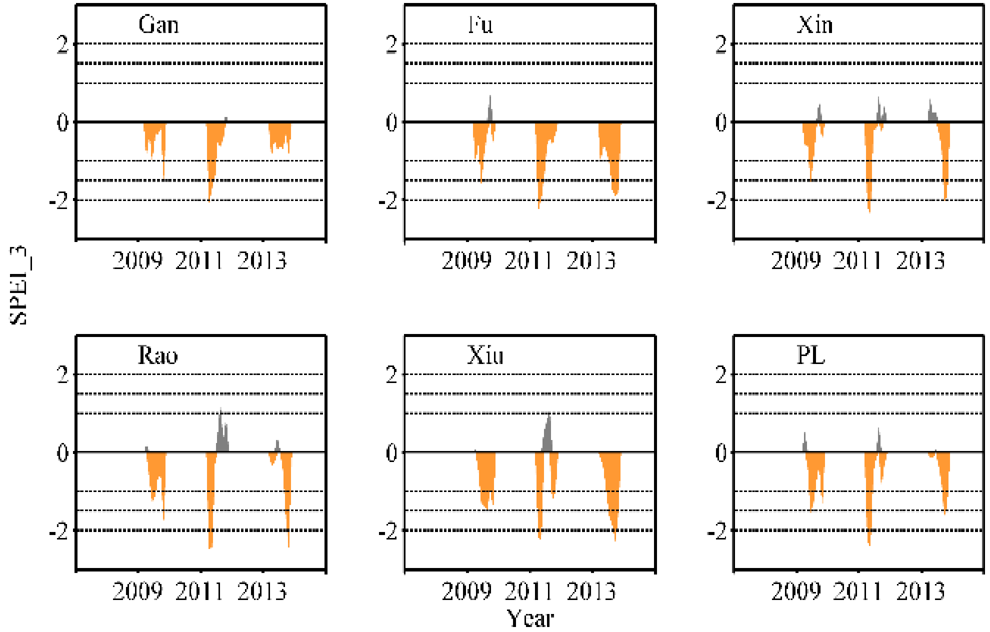


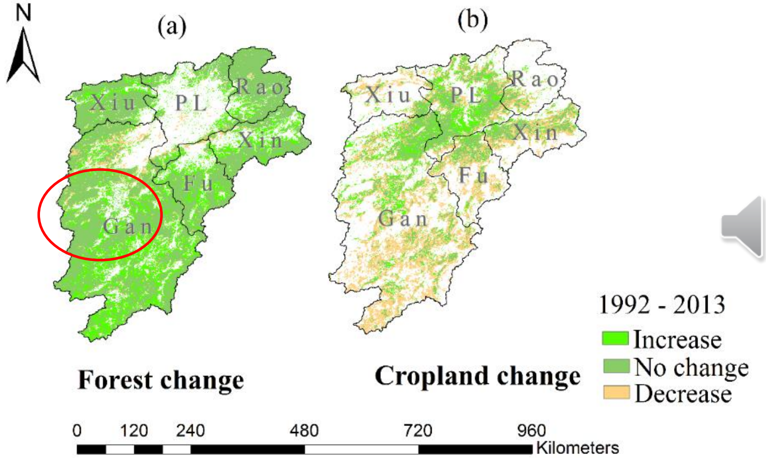
Figure 2. (**a**) Mean growing season Standardized Precipitation Evapotranspiration Index at a three-month time scale (SPEI_3) over the Poyang Lake watershed during the period 1984 to 2013. The horizontal dashed lines indicate the mean growing-season SPEI_3 in the five periods of 1984–1989, 1990–1995, 1996–2001, 2002–2007, and 2008–2013, respectively; (**b**) Area-averaged SPEI_3 in the Poyang Lake watershed during the growing seasons of 1984–2013.

Greening intensifies water conflict

Response of greenness to drought events







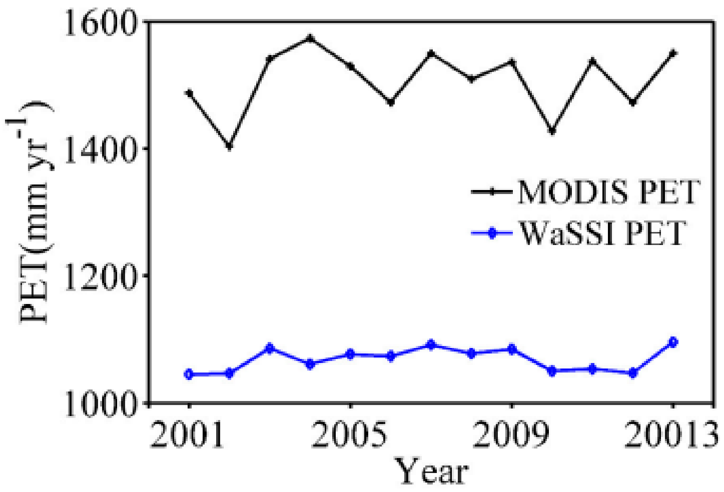
- Although Poyang Lake Basin has experienced droughts of different intensities in recent years, the vegetation greenness of the basin has shown a broad increasing trend since 1983

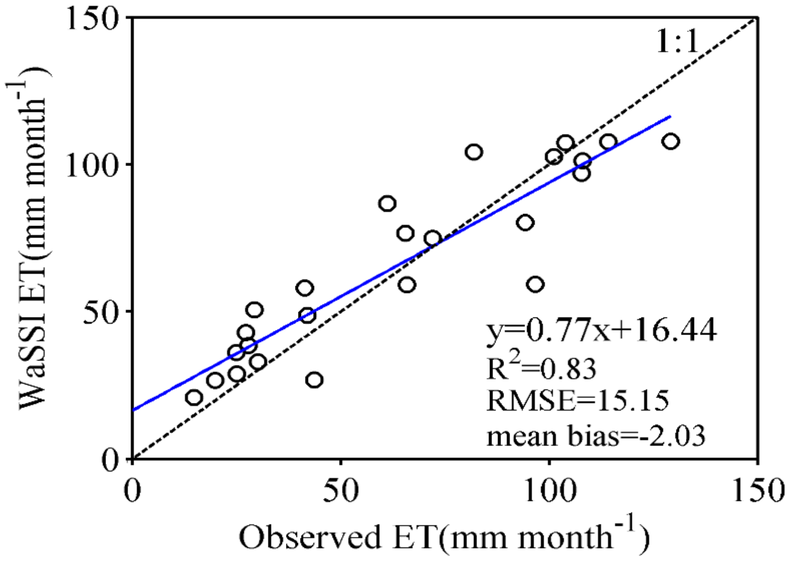
Greening intensifies water conflict

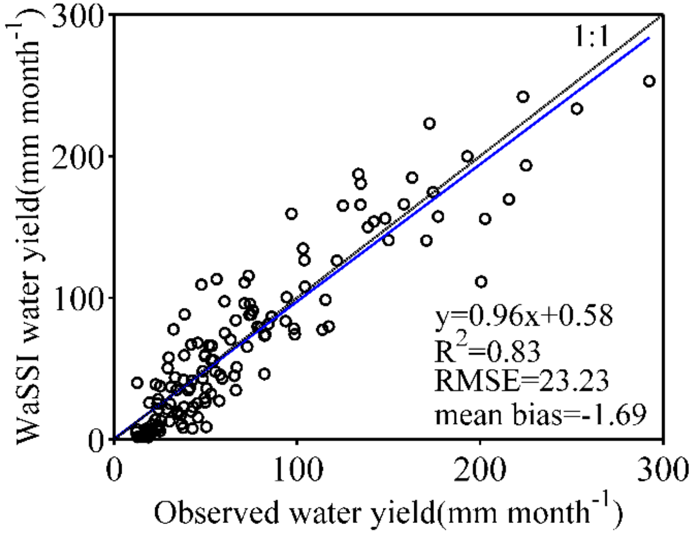
Water Supply Stress Index (WASSI)

- Modifying the WaSSI Model

Compared with MODIS PET products, the original Wassi model underestimated the PET value







ET:

$R^2 = 0.83$

RMSE = 15.15

Water yield:

$R^2 = 0.83$

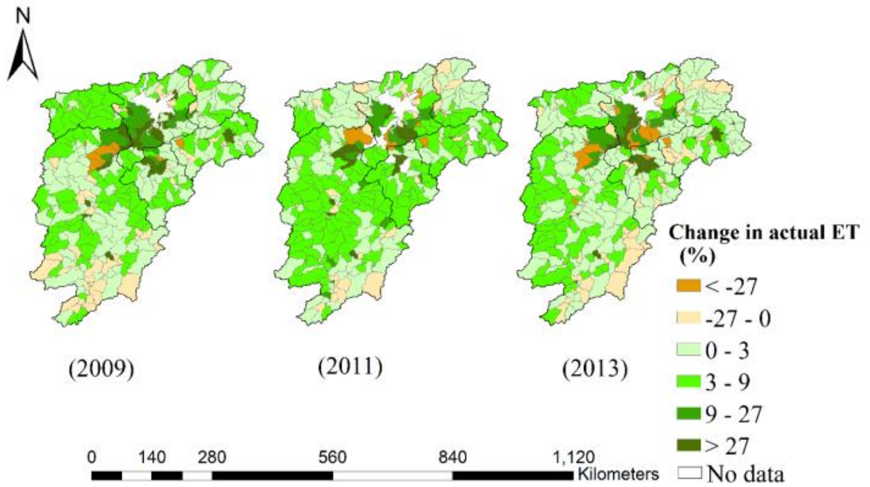
RMSE = 23.23

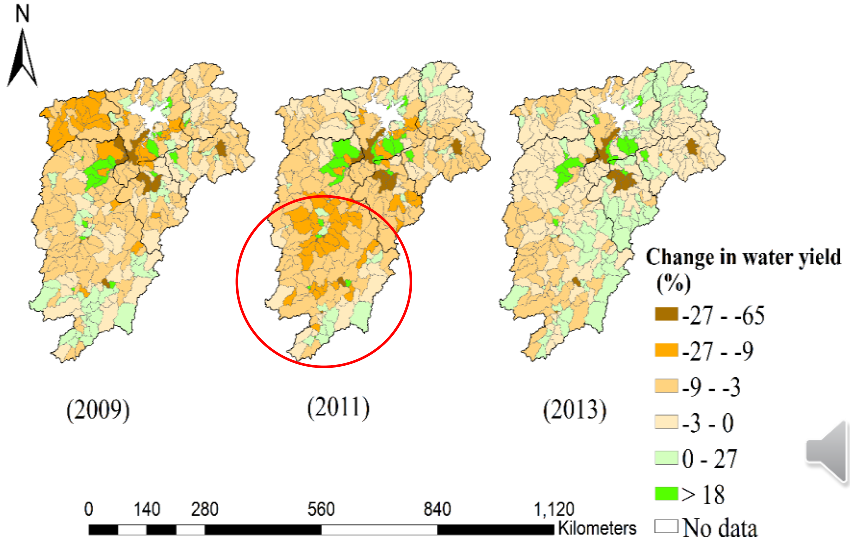
Greening intensifies water conflict

Effect of greening on water yield under drought conditions

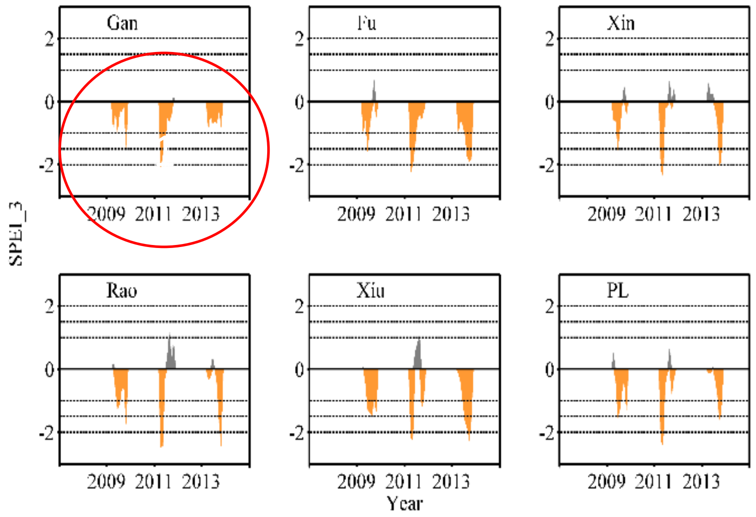
Watershed	2009		2011		2013	
	LAI Change (%)	Difference in Water Yield (%)	LAI Change (%)	Difference in Water Yield (%)	LAI Change (%)	Difference in Water Yield (%)
Gan	19.3	−2.0	32.0	−4.9	24.9	−1.3
Fu	22.7	−7.9	34.2	−10.9	20.0	−5.0
Xin	21.0	−4.3	27.9	−3.6	20.4	−2.8
Rao	16.5	−0.7	9.5	−1.5	3.0	−0.2
Xiu	29.2	−10.1	19.2	−2.9	24.1	−2.1
Poyang Lake area	25.9	−8.5	29.8	−4.4	31.1	−2.0
Entire watershed	21.3	−5.6	28.5	−4.7	22.9	−2.2

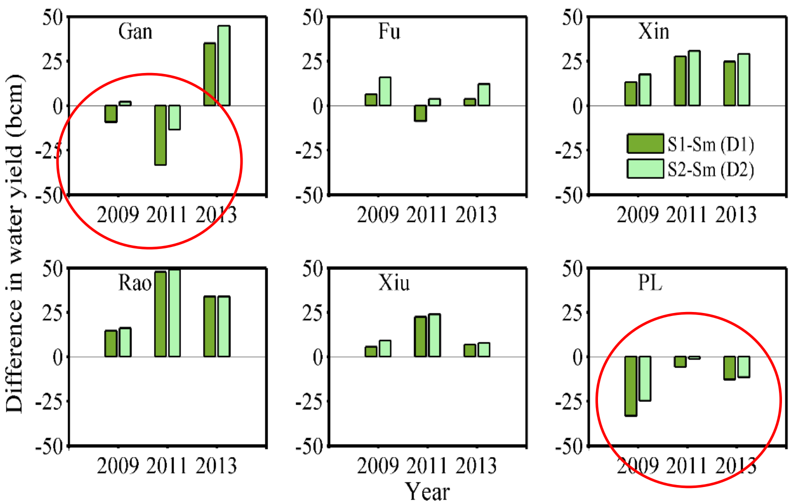
- A 20% to 80% increase in vegetation greenness typically results in a 3% to 27% reduction in water yield under drought conditions
- The increase of vegetation greenness can lead to the reduction of water yield by 2-3 times under persistent high-intensity drought than under short-term moderate drought



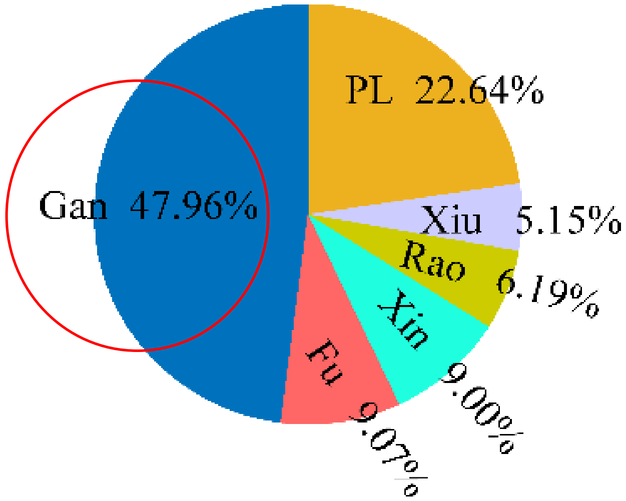


Greening intensifies water conflict





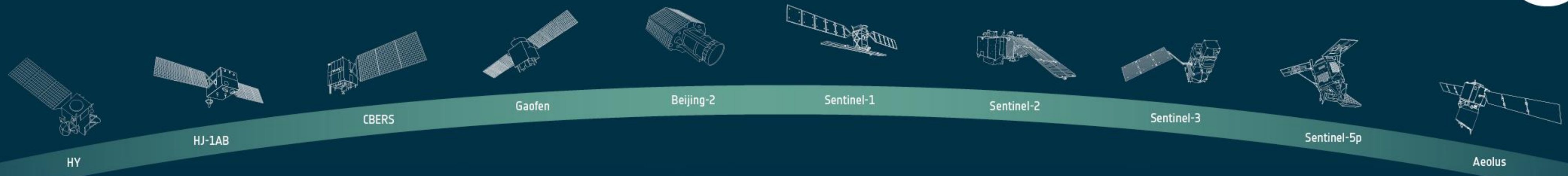
➢ Under the condition of continuous drought, vegetation greenness increases obviously, and water demand also increases, which aggravates the contradiction between ecological water demand and human water storage



The percentage of human living and production water demand in the six regions of Poyang Lake Basin in the total water demand of the whole basin

Result

- A multi-model ensemble optimization framework was constructed to evaluate the performance of multiple optimization algorithms in optimizing and integrating multi-dynamic global vegetation models
- Taking China as a typical area of greenness change, the driving factors of vegetation greenness change were quantitatively analyzed
- The effects of vegetation greening on the water supply of the ecosystem under drought conditions in humid regions were discussed, and the conflict between ecological water demand and human water demand was revealed



Thanks for your attentions

Jianzhong Lu
lujzhong@whu.edu.cn