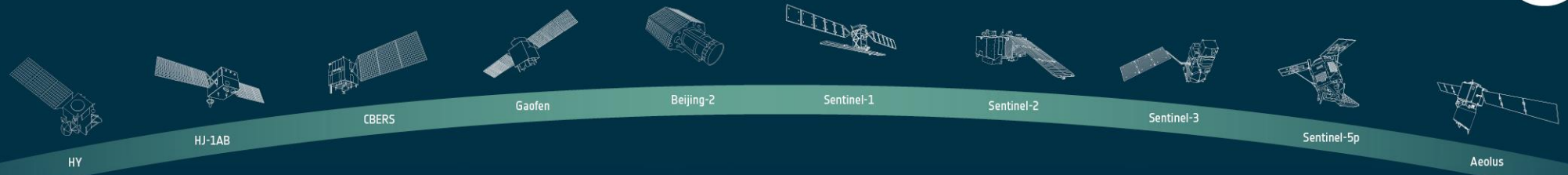

2022 DRAGON 5 SYMPOSIUM

MID-TERM RESULTS REPORTING

17-21 OCTOBER 2022

PROJECT ID. 59197
UTILIZING SINO-EUROPEAN EARTH OBSERVATION DATA TOWARDS AGRO-ECOSYSTEM HEALTH DIAGNOSIS AND SUSTAINABLE AGRICULTURE

MONDAY, 17/OCTOBER/2022

ID. 59197

PROJECT TITLE: UTILIZING SINO-EUROPEAN EARTH OBSERVATION DATA TOWARDS AGRO-ECOSYSTEM HEALTH DIAGNOSIS AND SUSTAINABLE AGRICULTURE

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PRESENTED BY: CARSTEN MONTZKA

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Carsten Montzka


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Jordan Bates


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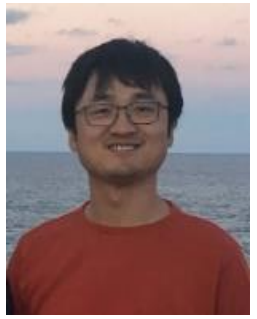

Renmin Yang


Liang Liang


Shuguo Wang


Yuquan Qu


Rahul Raj


Wenqin Huang


Shirin Moradi


Qianjie Wang


Jin Shi


Siyi Qiu

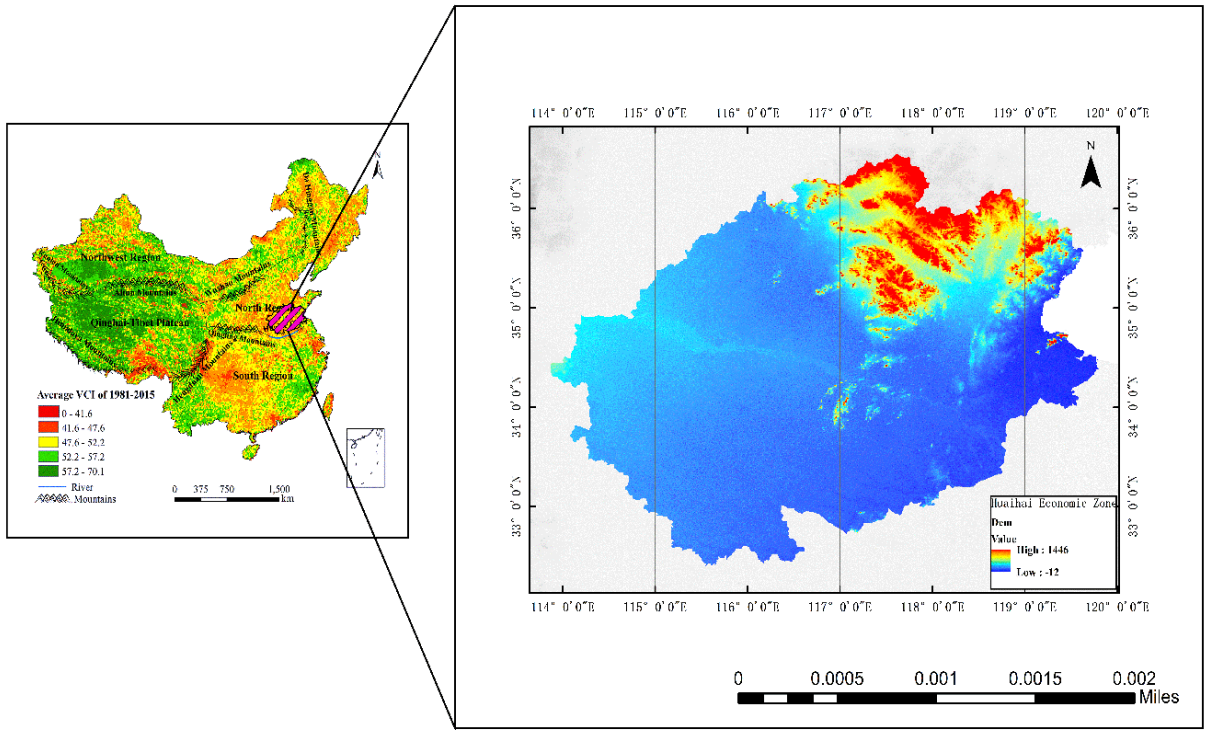

Yanyan Shi


Visakh Sivaprasad

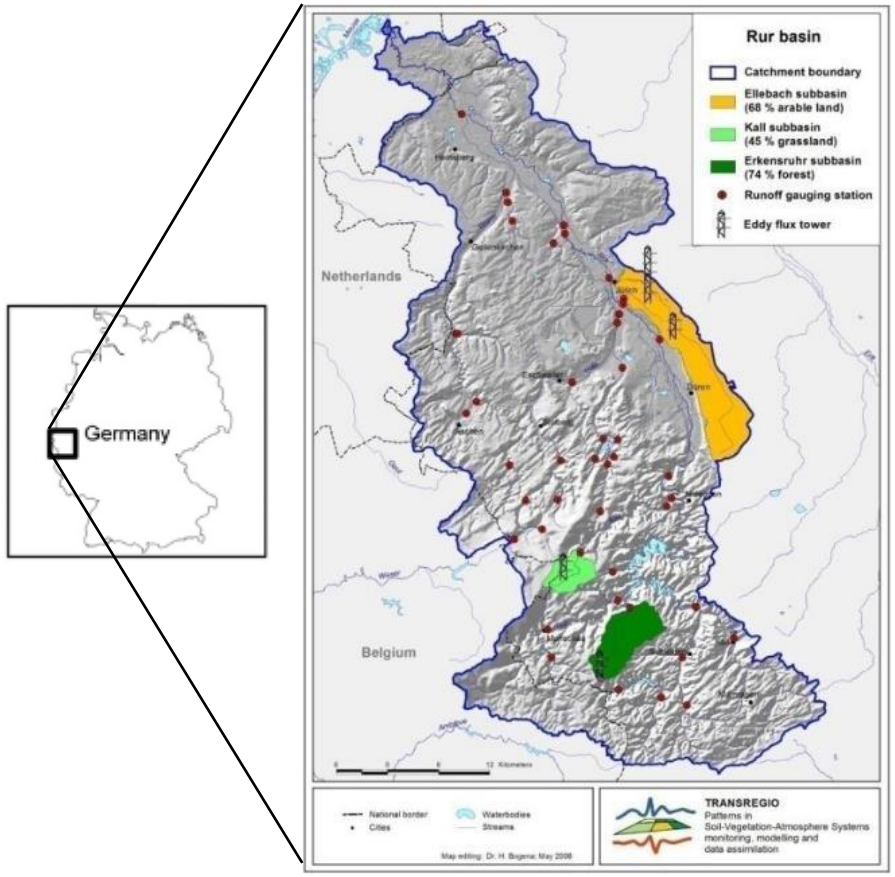
Central aims:

- to monitor essential variables in agriculture based on various in situ and remote observations
- to investigate agricultural processes and to carry out a full agro-ecosystem health diagnosis by data assimilation
- to conserve, protect, and improve the efficiency of the use of natural resources to facilitate sustainable agricultural development
- to prepare for agricultural applications of future missions like ROSE-L, CHIME, CIMR, and LSTM.

Research Areas



The Huaihai Economic Zone, China



The Rur Catchment, Germany

Towards agroecosystem carbon budgets

Carbon farming as ecosystem service

"Agriculture is the ONE sector that has the ability to transform from a net emitter of CO2 to a net sequesterer of CO2 —there is no other human managed realm with this potential".

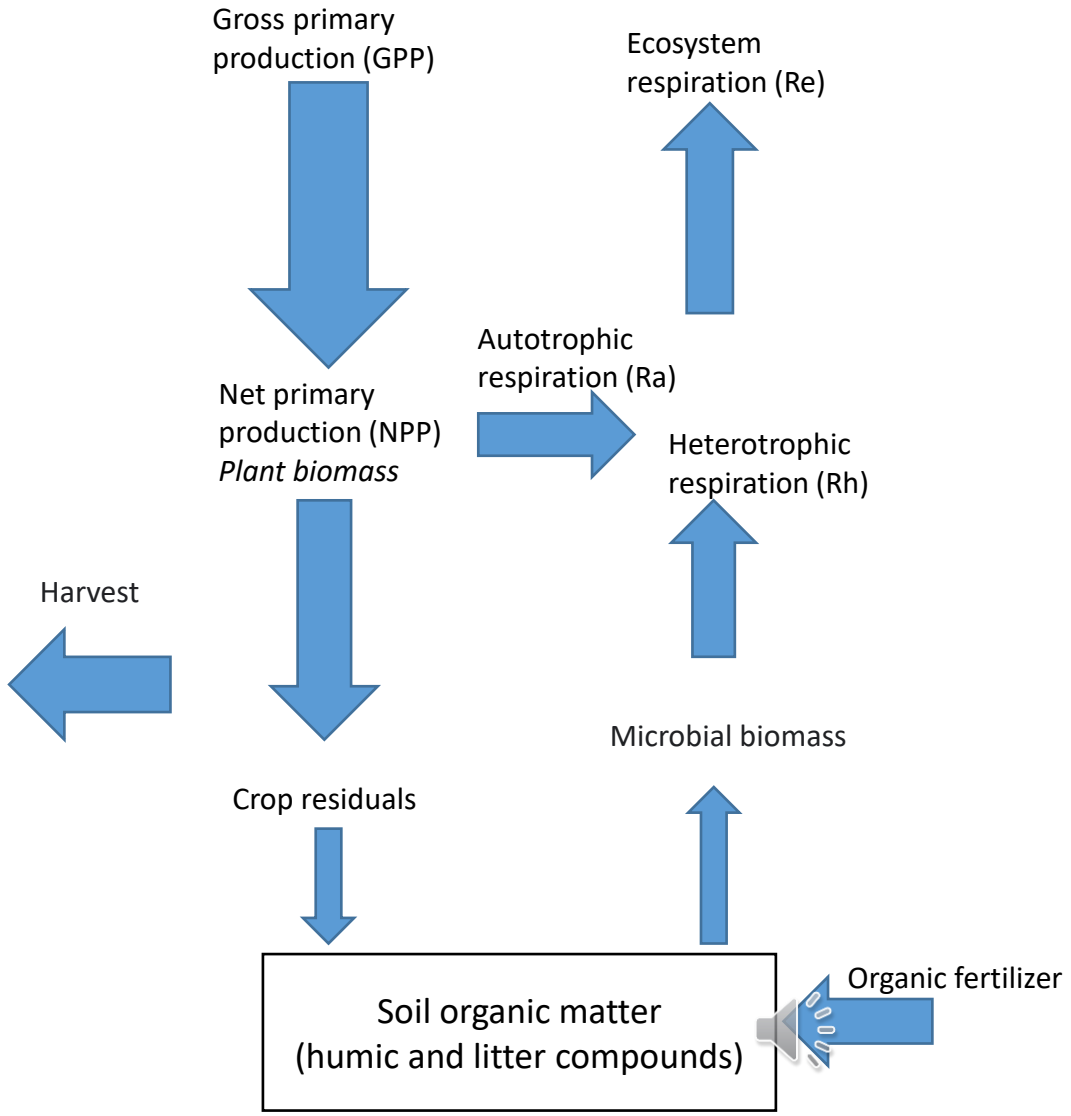
Contribution of agroecosystem:

- 10–14% of global anthropogenic greenhouse gas emissions
- store soil carbon up to 1 GT year^{-1}, offset around 10% of the annual GHG emissions of 8–10 GT year^{-1}

Carbon budget for crops:

- Net ecosystem carbon budget (NECB) = net ecosystem production (NEP) + carbon gain (e.g., due to organic fertiliser, seeds, root vegetables) + carbon loss in the biomass at harvest or during fire.

=> Multivariate agricultural monitoring



(https://www.carboncycle.org/carbon-farming/)

Multivariate agricultural monitoring

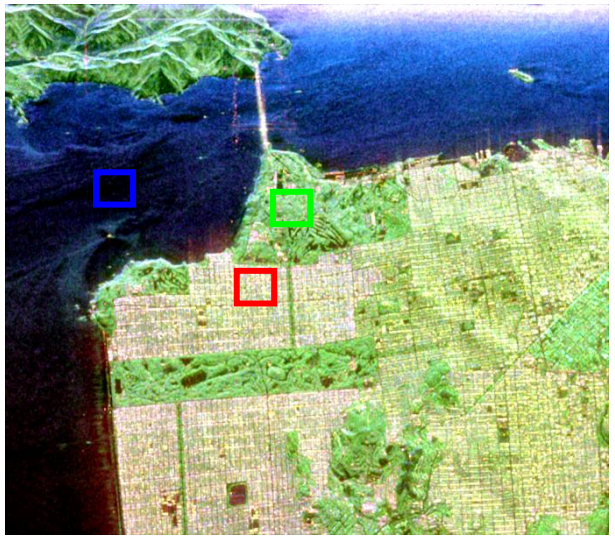
Towards agroecosystem carbon budget monitoring several intermediate steps are necessary:

1. Crop identification by SAR polarimetry
2. LAI estimation by a hybrid inversion strategy
3. Soil moisture estimation by C-band SAR
4. Agricultural water stress monitoring by MSG-SEVIRI
5. Monitoring drought evolution based on vegetation indices
6. Monitoring Net Primary Productivity (NPP)
7. Estimation of vegetation carbon sinks (NEP)

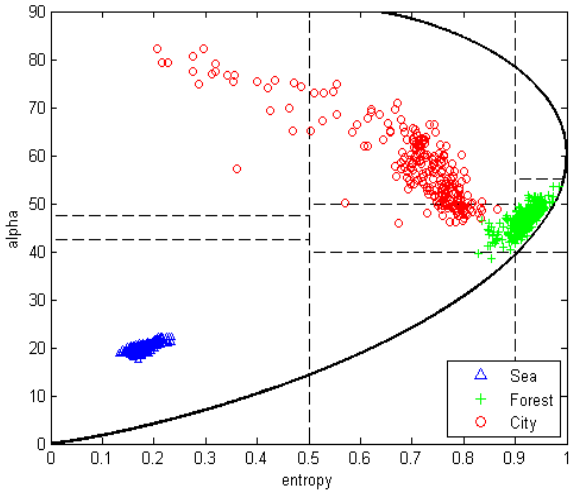
Presented in the following (each topic 2 slides)

1. Crop identification by SAR polarimetry

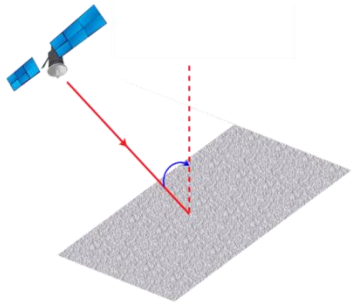
(a) Intensity image



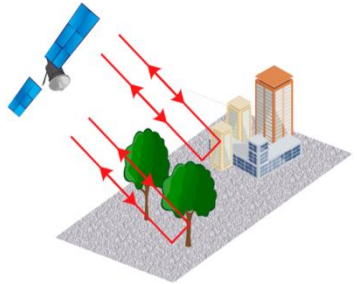
(b) PauliRGB Pseudocolor image



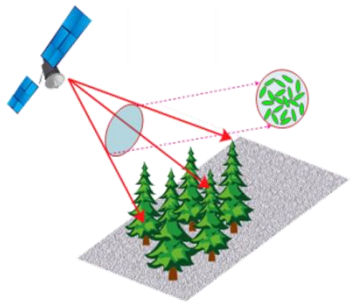
(c) H/α plane



Odd-bounce scattering



Double-bounce scatter

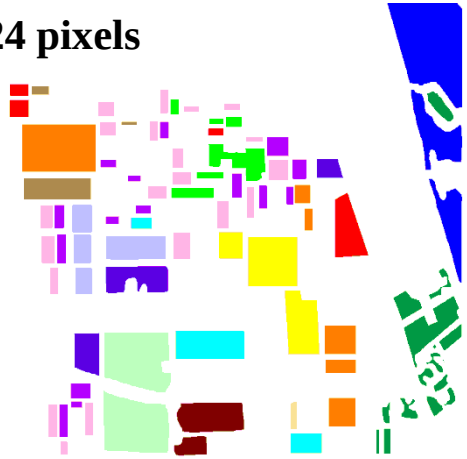


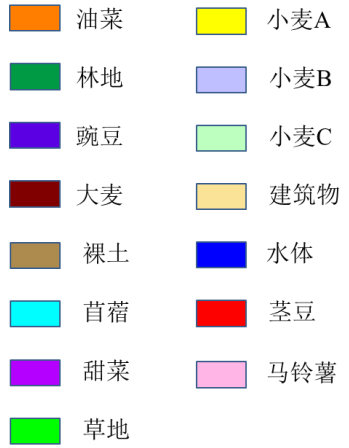
Volume scatter

1. Crop identification by SAR polarimetry

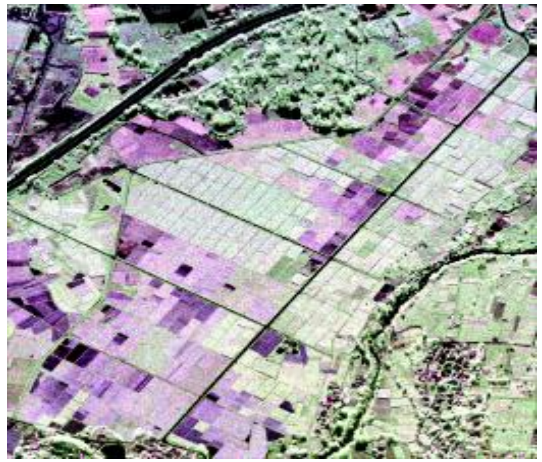
Flevoland (AIRSAR,1989)

750 × 1024 pixels



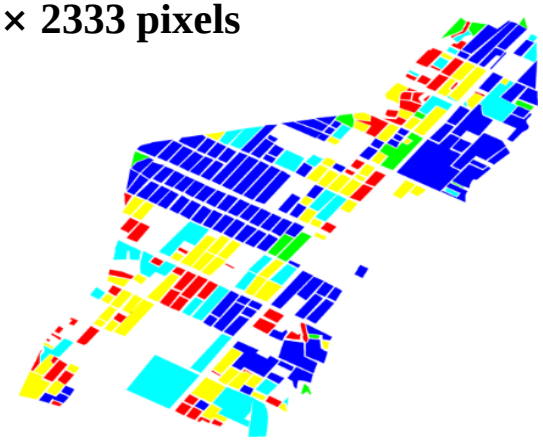


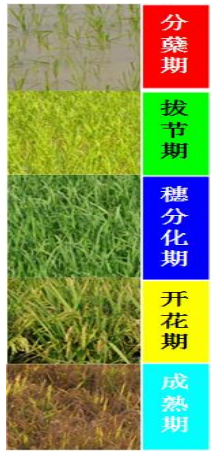
Classification results (Flevoland)



Lingshui County, Hainan (CETC38，2012)

2220 × 2333 pixels

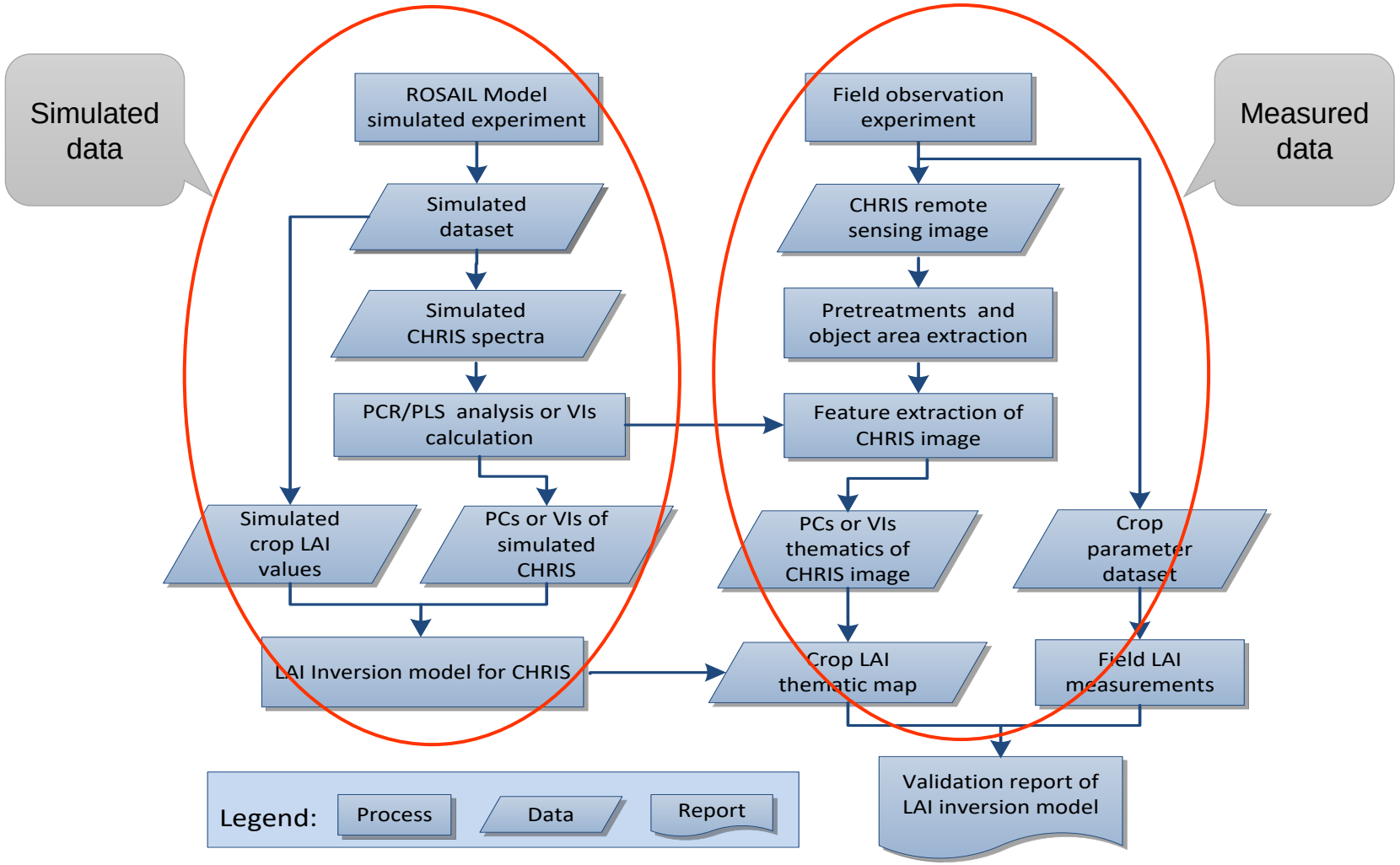




Classification results (Lingshui County)

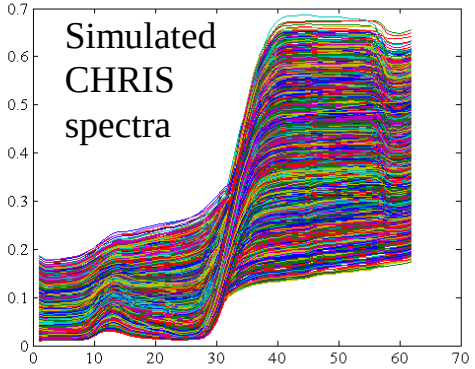
Liu wensong, yangjie, zhao jinqi, et al. A Dual-Domain Super-Resolution Image Fusion Method With SIRV and GALCA Model for PolSAR and Panchromatic Images, *IEEE Transactions on Geoscience and Remote Sensing*, 2022, 60: 5218814.

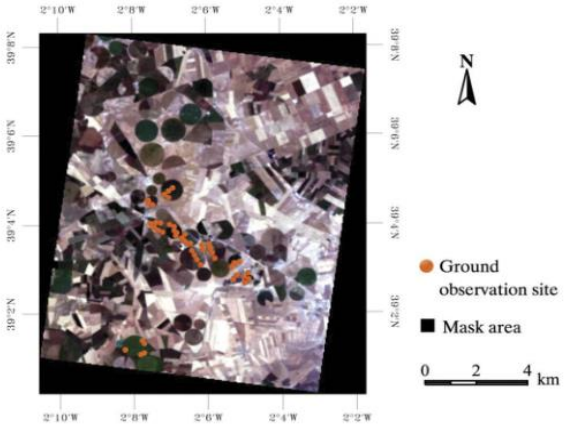
2. LAI estimation by a hybrid inversion strategy



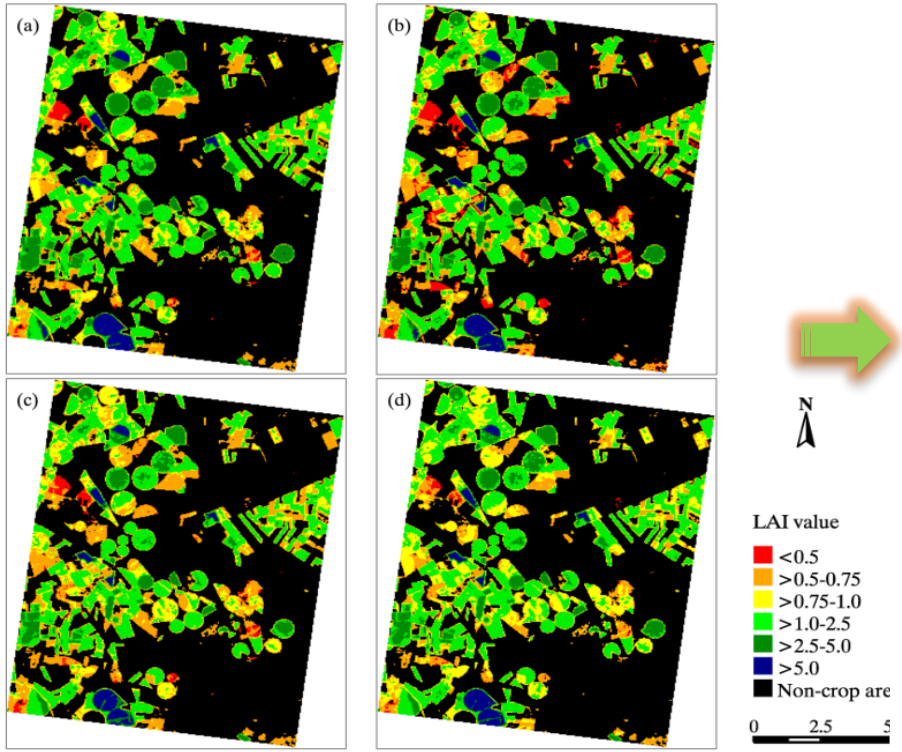
Flow chart of vegetation LAI remote sensing estimation based on integrated inversion strategy

2. LAI estimation by a hybrid inversion strategy

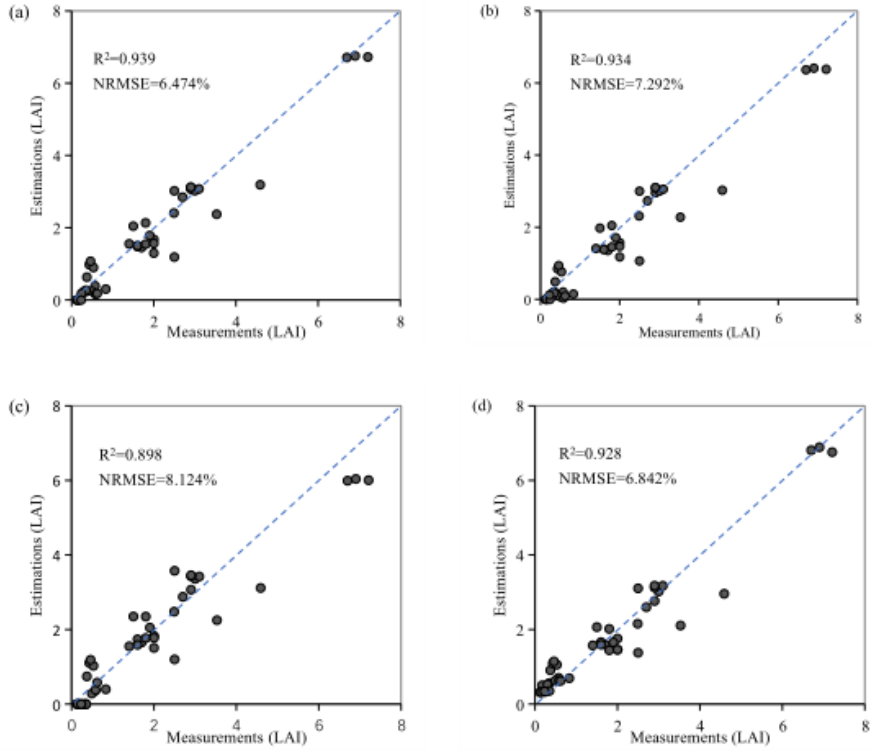




CHRIS image of study area



Spatial distribution map of the crop LAI predicted from the CHRIS remote sensing image and various RFR models in Sentinel-3 Experiment: (a) Specific2_PLS_RFR, (b) Specific1_PLS_RFR, (c) Generic_PLS_RFR , (d) Specific2 _OSAVI_RFR.



Ground-measured LAI versus the LAI estimated from the RFR inversion model in the Sentinel-3 Experiment: (a) Specific2_PLS_RFR, (b) Specific1_PLS_RFR, (c) Generic1_PLS_RFR, and (d) Specific2 _OSAVI_RFR.

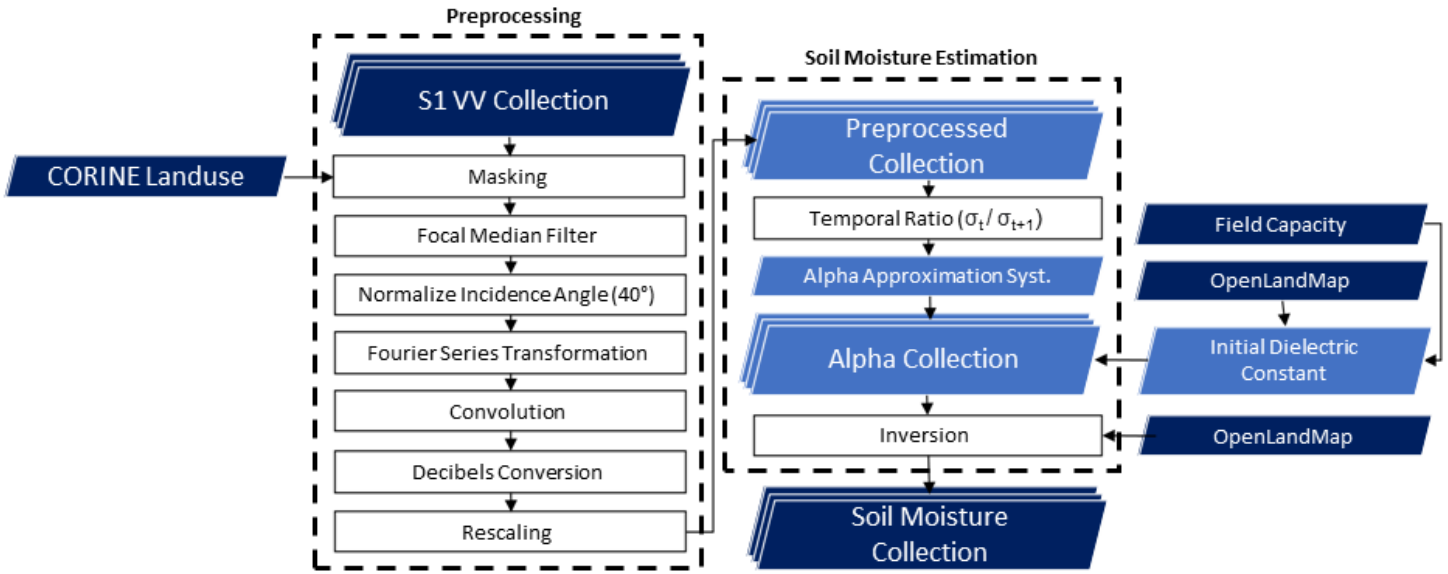
Liang Liang*, Di Geng, Juan Yan, et al. Estimating Crop LAI Using Spectral Feature Extraction and the Hybrid Inversion Method[J]. *Remote Sensing*, 2020, 12（21): 3534(1-27).

3. Soil moisture estimation by C-band SAR

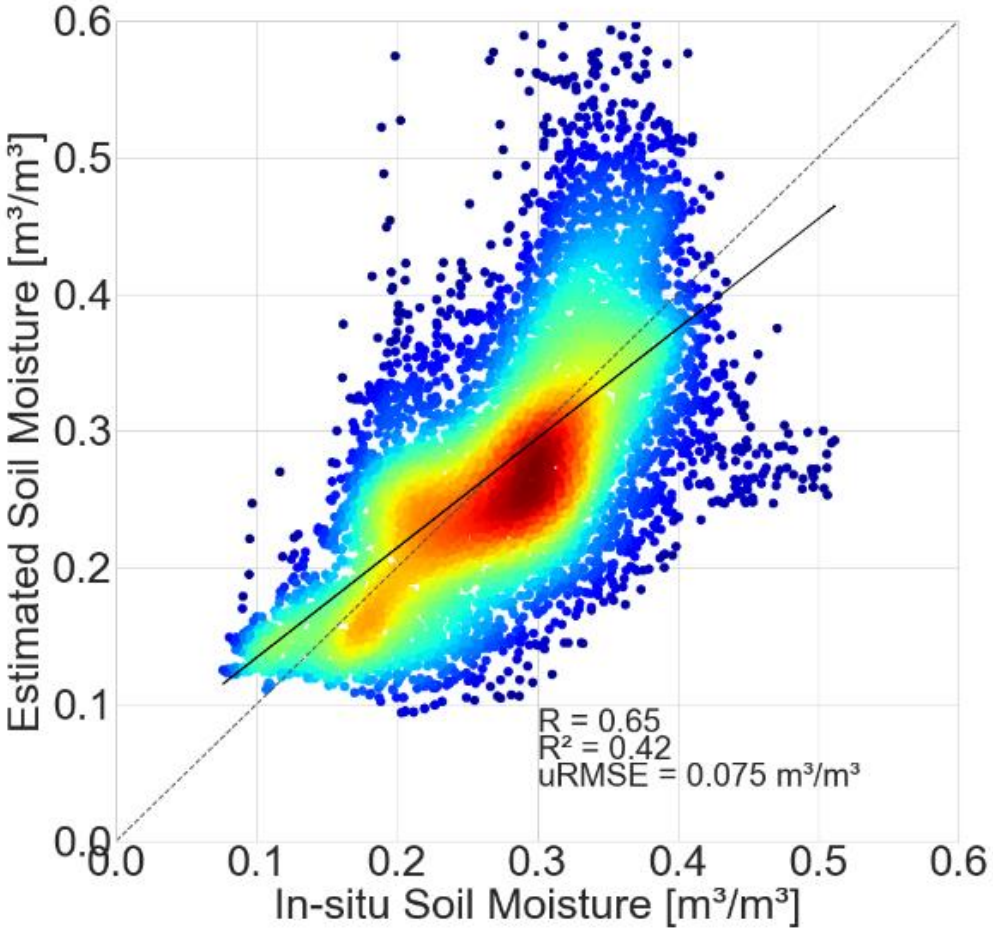
Basic principle: Between two consecutive SAR observations, change in backscattering signal is caused by a change in dielectric constant and incidence angle, as other surface parameters do not change considerably within these short time interval

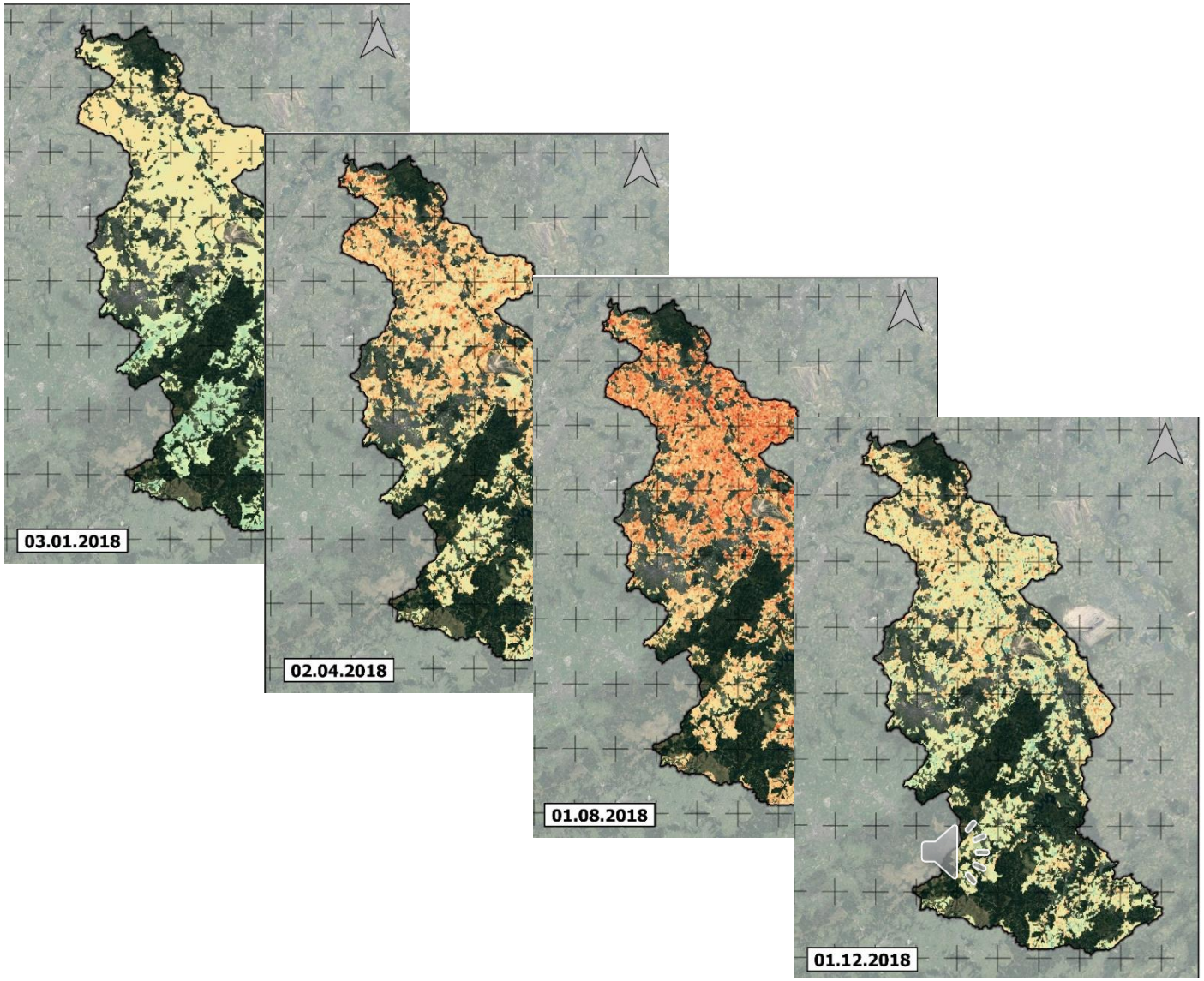
Workflow can be divided into two sections:

- Pre-processing of Sentinel-1 SAR
- Soil moisture estimation



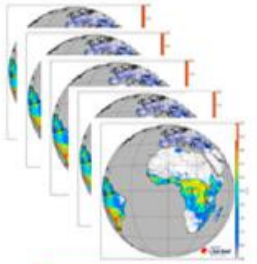
3. Soil moisture estimation by C-band SAR





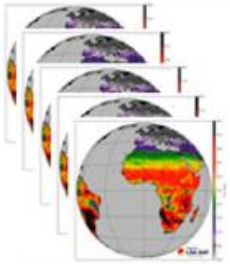
4. Agricultural water stress monitoring by MSG-SEVIRI

Input data on the FTP



SEVIRI-ET_a

Country borders



SEVIRI-ET_0

Docker technology

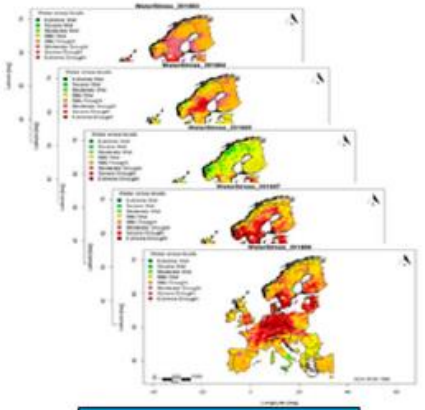
R:

- GDAL
- Raster, sp, prettymapr libraries

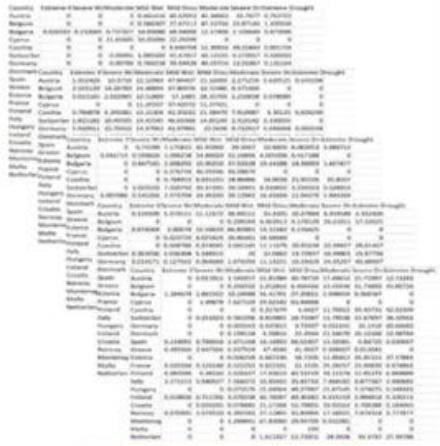
Model

- Read, pre-process and re-project time series of SEVIRI data (ET_a and ET_0)
- Calculate monthly ET_a and ET_0 data from daily inputs
- Calculate monthly ESI data
- Calculate long-term mean and standard deviation
- Calculate monthly ESI anomalies
- Classify monthly anomalies and generate water stress maps and reports

Outputs on VLab platform



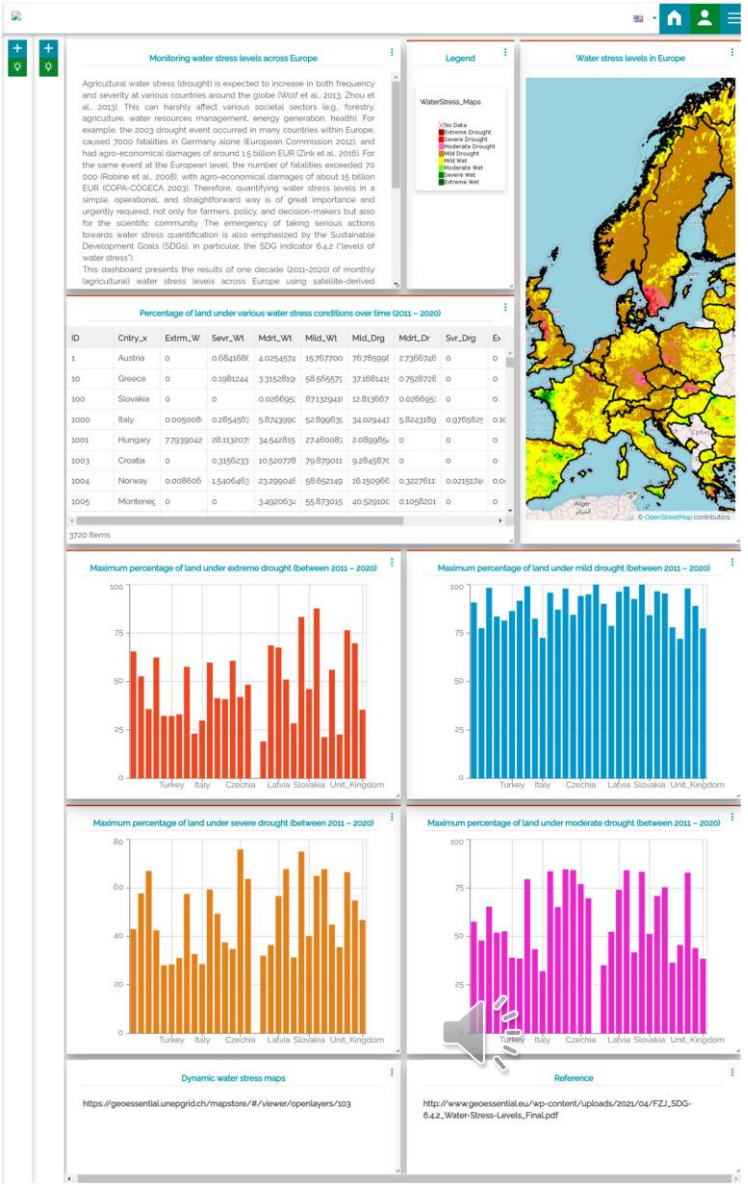
Water stress maps



Water stress reports

4. Agricultural water stress monitoring by MSG-SEVIRI

- Daily time series of actual and potential evapotranspiration by SEVIRI
- Reports for policy information and decision support
- Monthly agricultural water stress maps for Europe
- Processed in VLAB on AWS, stored in GeoServer, documented in GeoNetwork, and made available through MapStore



Bagher Bayat, Carsten Montzka, Alexander Graf, Gregory Giuliani, Mattia Santoro & Harry Vereecken (2022) One decade (2011–2020) of European agricultural water stress monitoring by MSG-SEVIRI: workflow implementation on the Virtual Earth Laboratory (VLab) platform, International Journal of Digital Earth, 15:1, 730-747, DOI:10.1080/17538947.2022.2061617

5. Monitoring drought evolution based on vegetation indices

Analysis of drought occurrence frequency and change trend in China using long time series VCI, TVDI index products and meteorological data

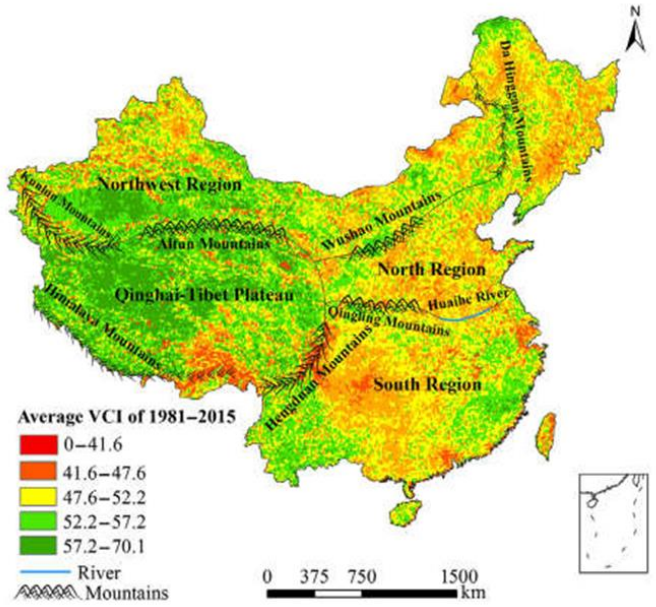


Fig. 1. Overview of the study area. The background is the average vegetation condition index (VCI) value from 1981 to 2015.

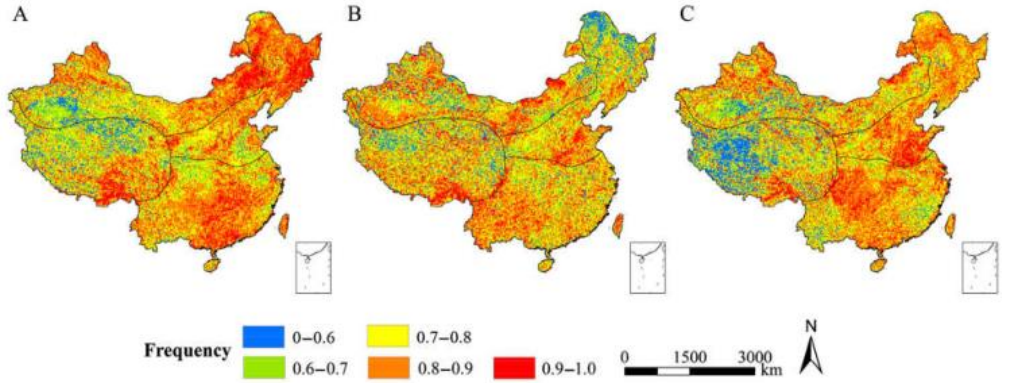


Fig. 2. Spatial distribution of the total drought occurrence frequencies in China for (A) spring, (B) summer, and (C) autumn.

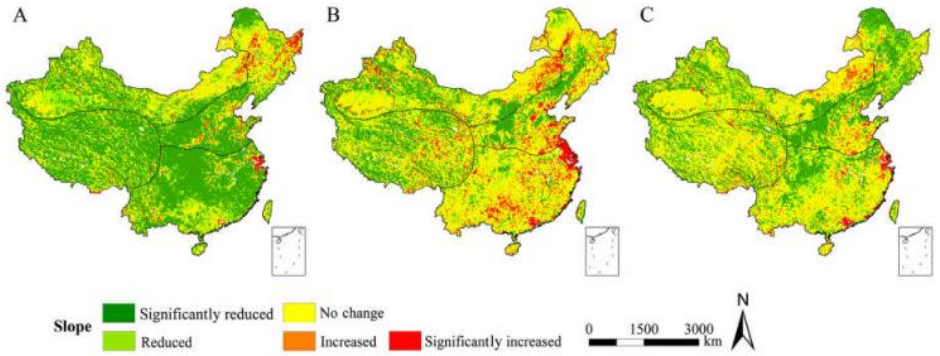
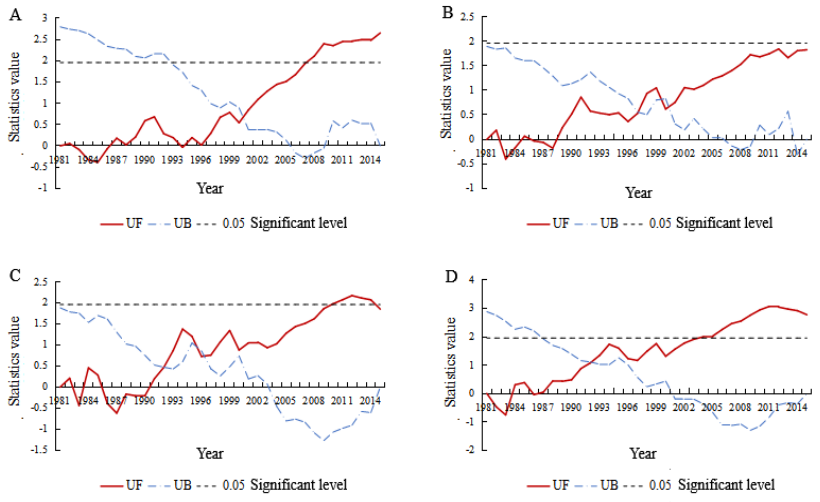
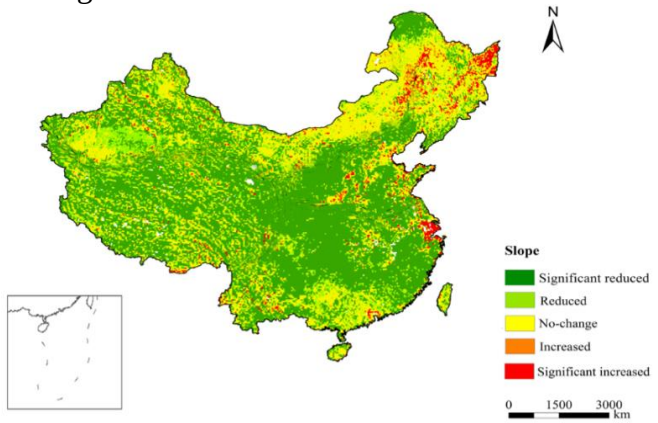


Fig. 4. Vegetation condition index trends from 1981 to 2015 in China for the (A) spring, (B) summer, and (C) autumn.

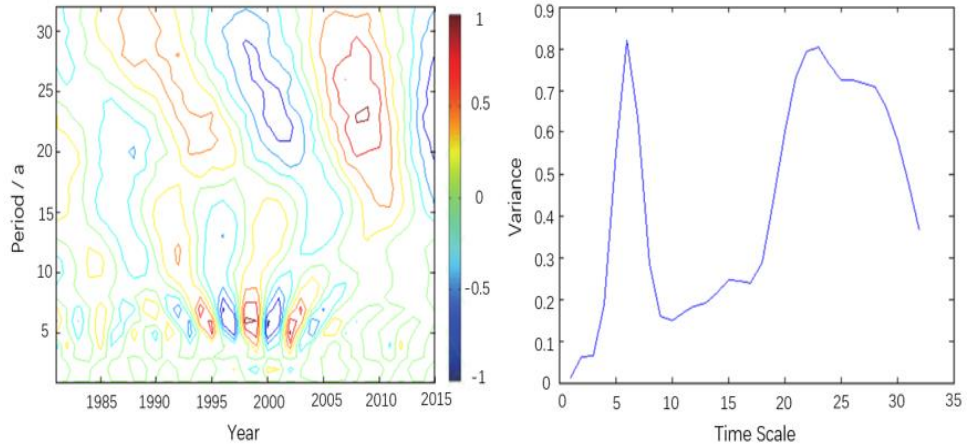
5. Monitoring drought evolution based on vegetation indices



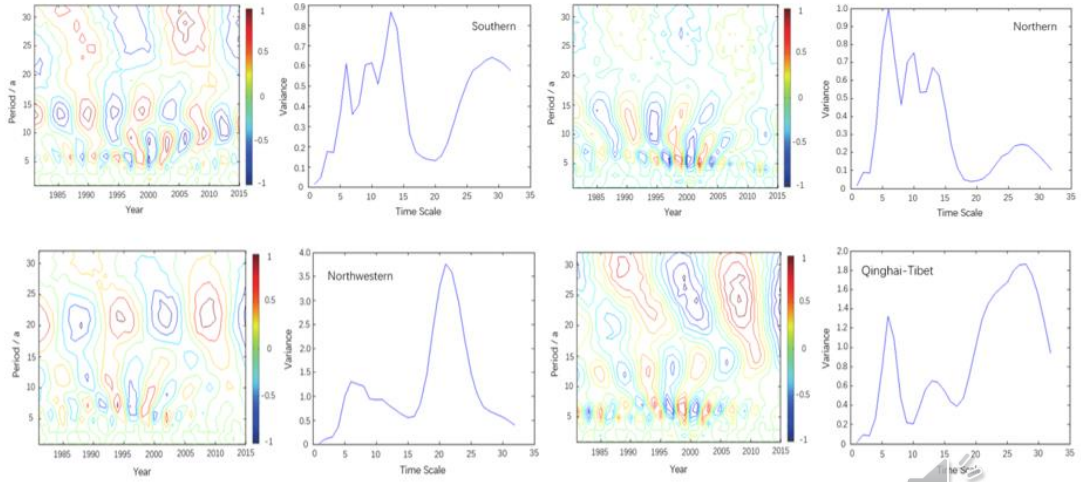
Mann-Kendall mutation analysis results of VCI time series for various regions of China



Slope trend of the average VCI in spring from 1981-2015 in China



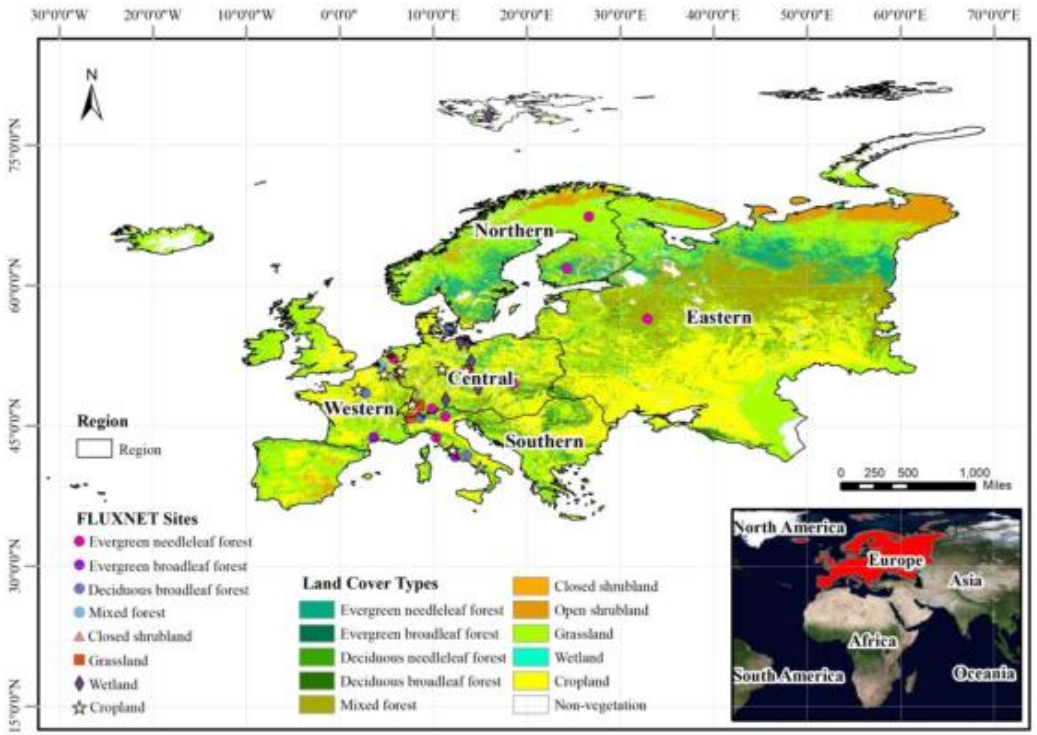
Wavelet time series analysis of spring VCI in China, 1981-2015.



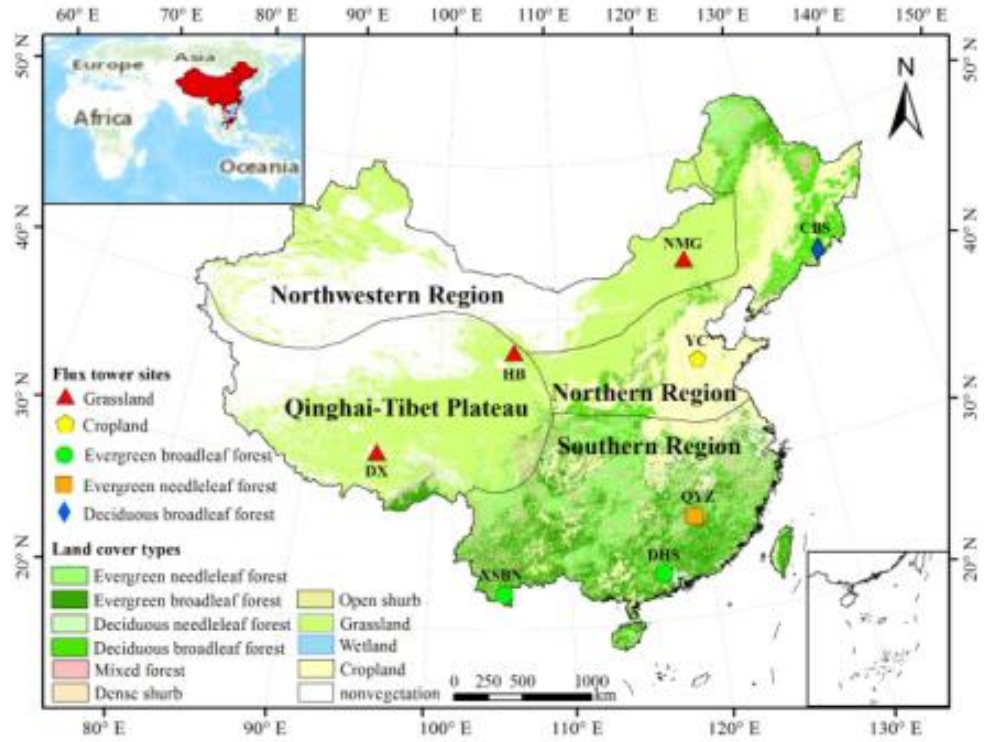
Spring VCI wavelet time series analysis maps for the southern (A), northern (B), northwestern (C) and Qinghai-Tibet (D) regions of China.

Liang, Liang*, Siyi Qiu, Juan Yan, et al. VCI-Based Analysis on Spatiotemporal Variations of Spring Drought in China. *International Journal of Environmental Research and Public Health*, 2021; 18(15):7967.

6. Monitoring Net Primary Productivity (NPP)

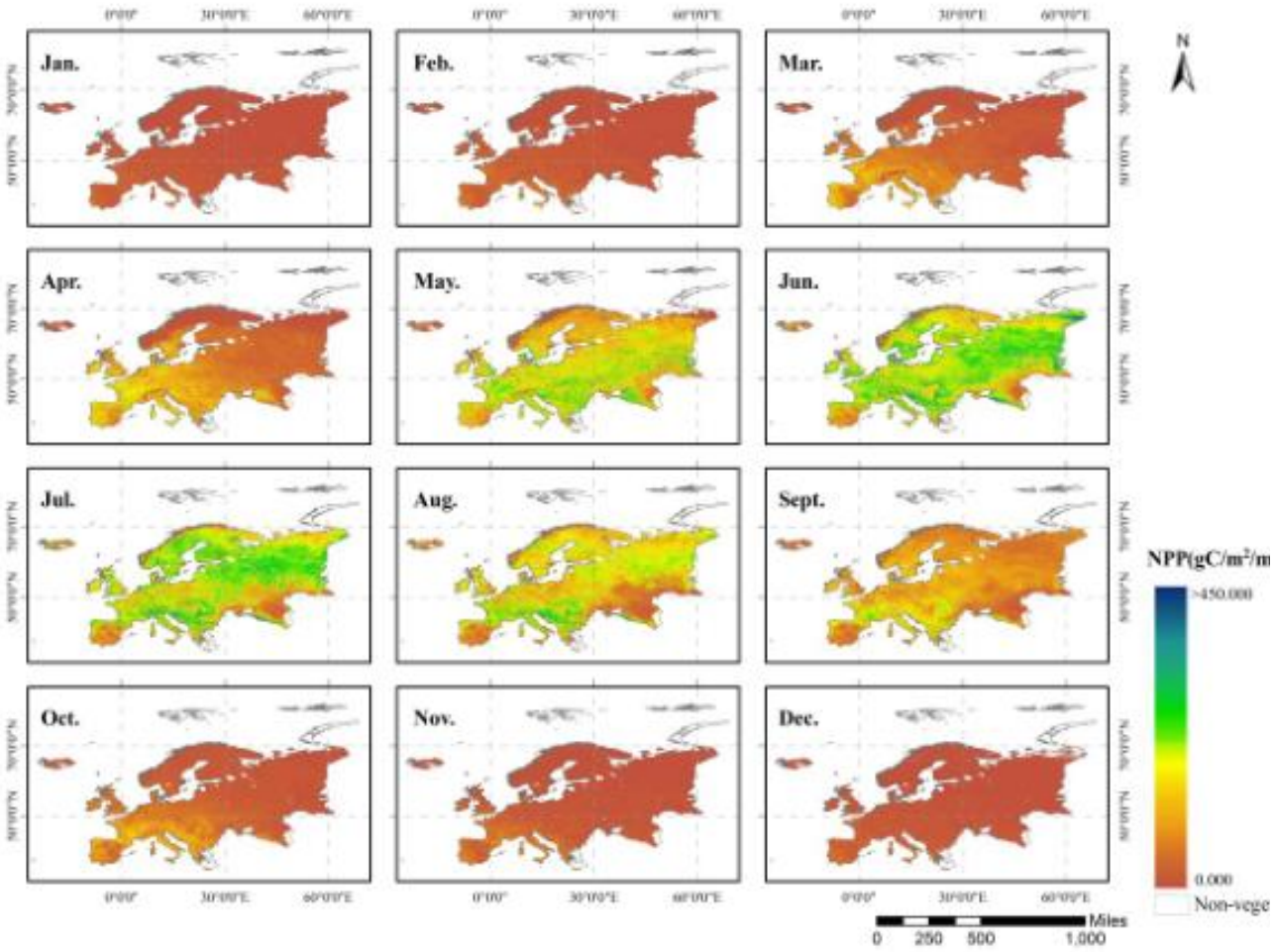


Types of Land Cover and Distribution of Flux Stations of Study Area

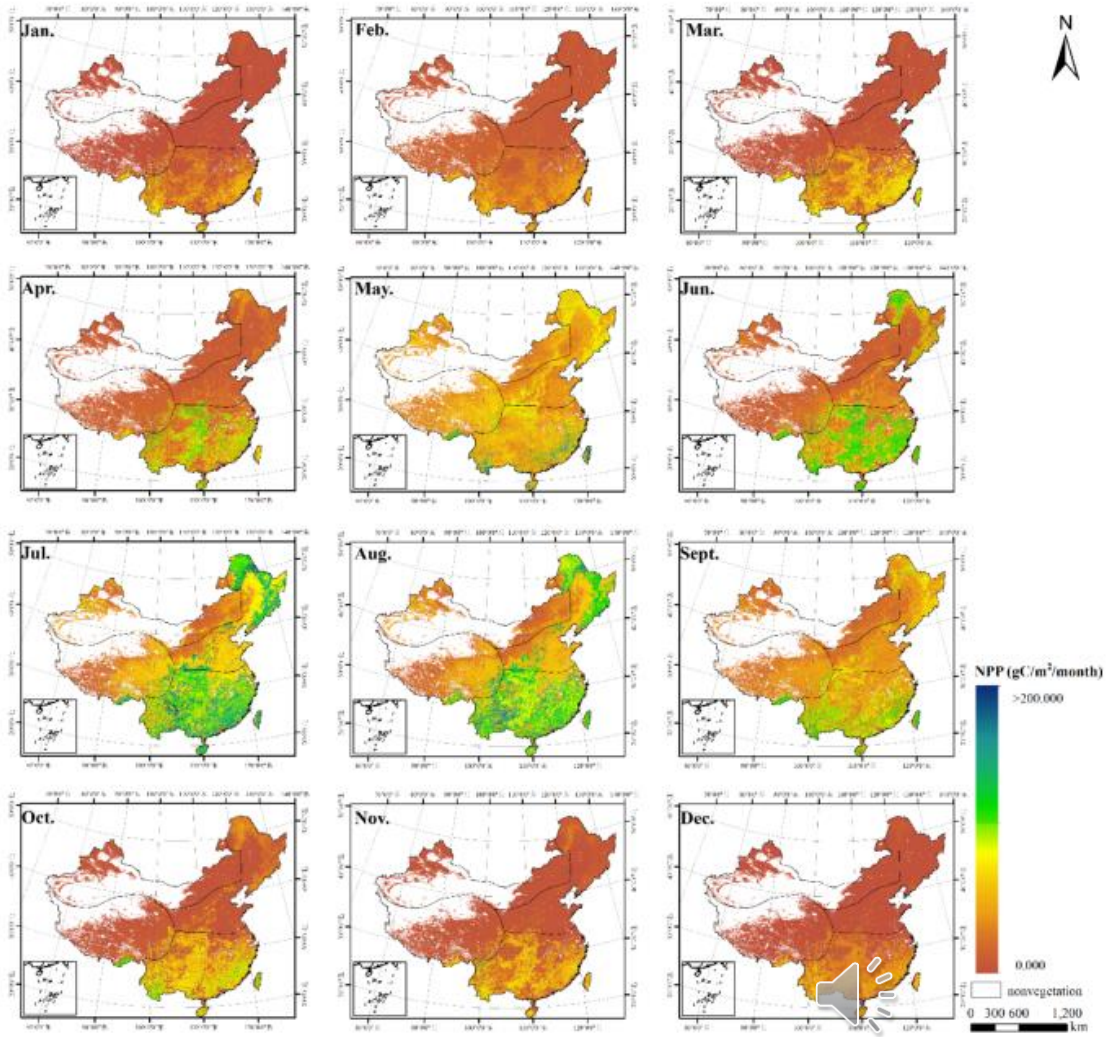


Land cover types, the locations of the eight flux tower sites and the distribution of the four geographical regions.

6. Monitoring Net Primary Productivity (NPP)

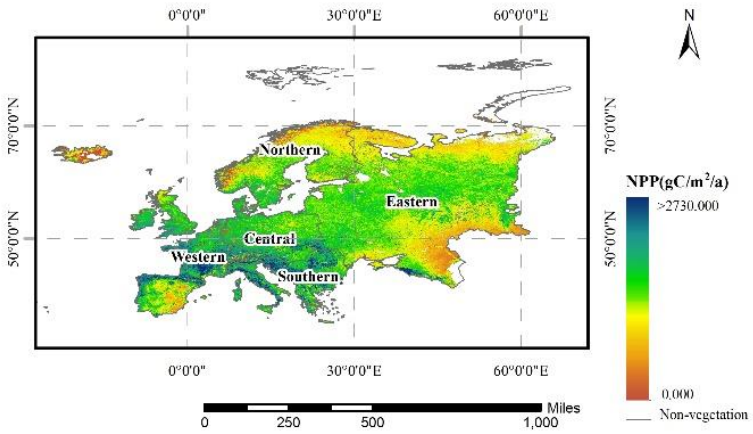


Spatiotemporal distribution of Monthly NPP in Europe Based on Optimized Model.

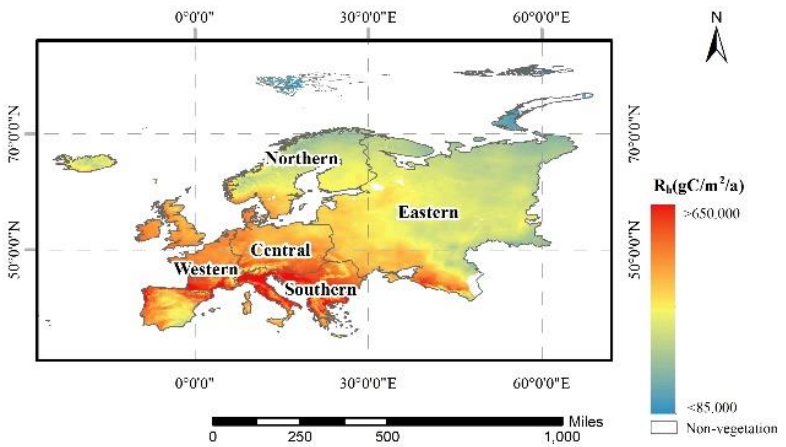


Spatial pattern of monthly NPP estimated over China by the improved CASA model.

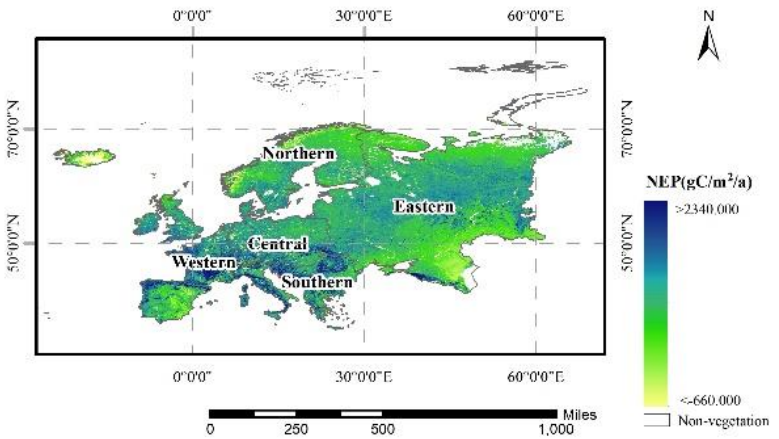
7. Estimation of vegetation carbon sinks (NEP)



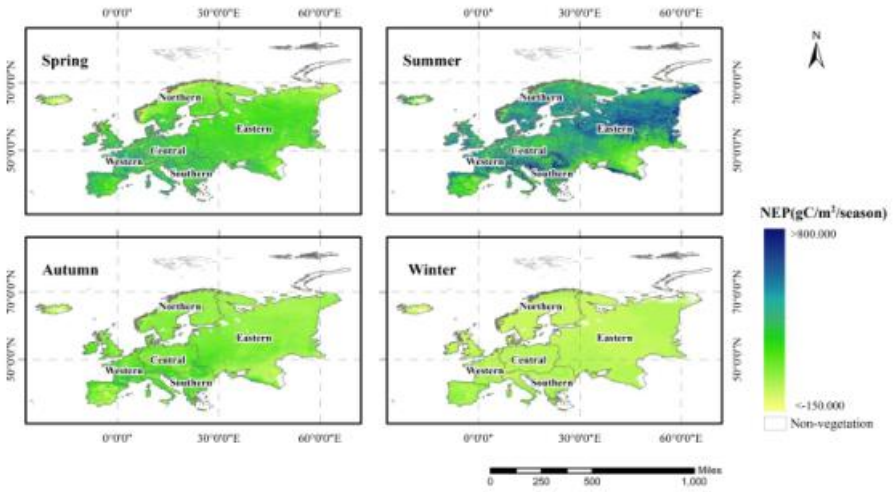
Annual NPP of Europe



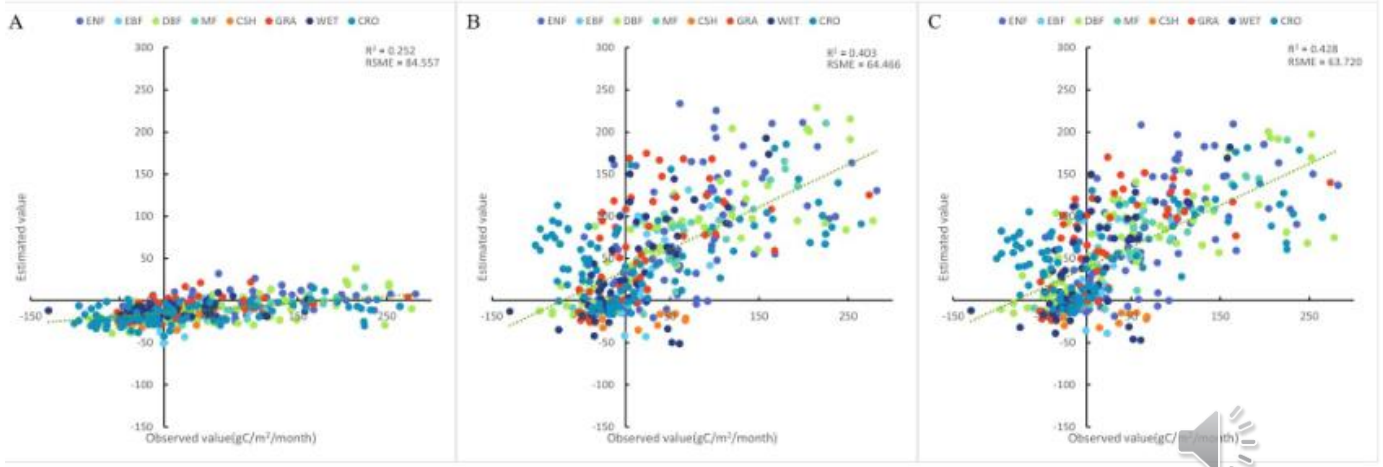
Annual Rh of Europe



Annual NEP of Europe



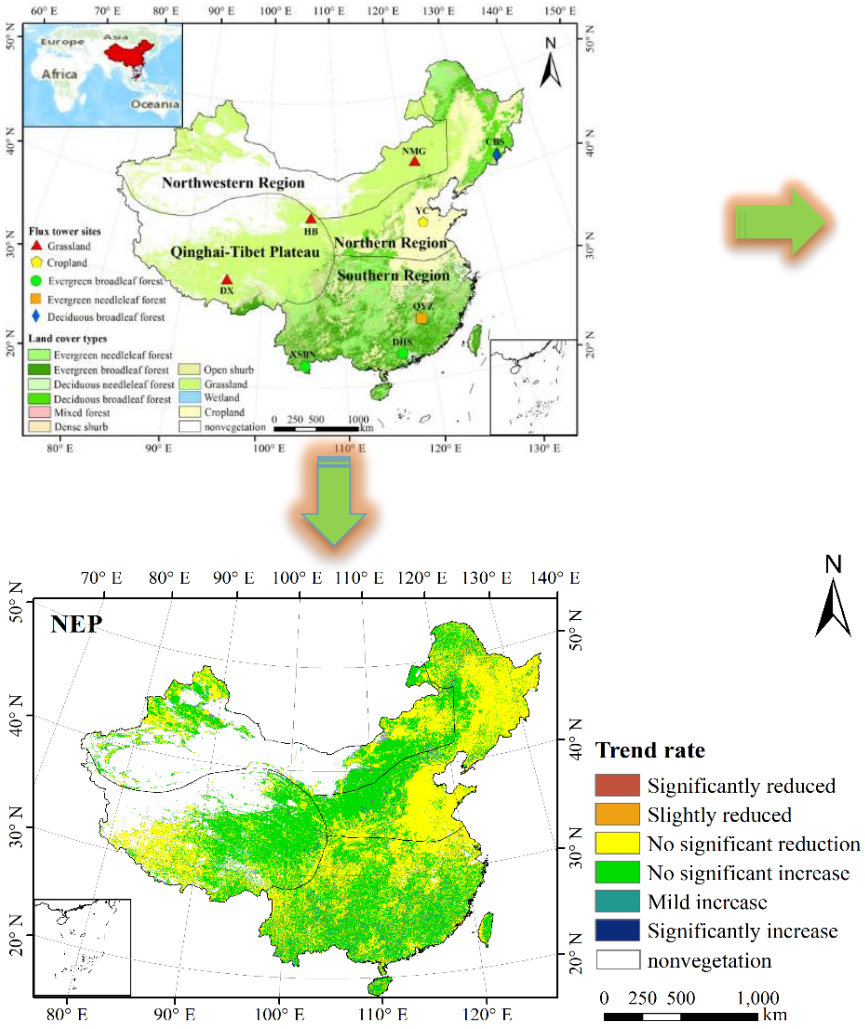
Spatiotemporal Distribution of Seasonal NEP in Europe during 2014.



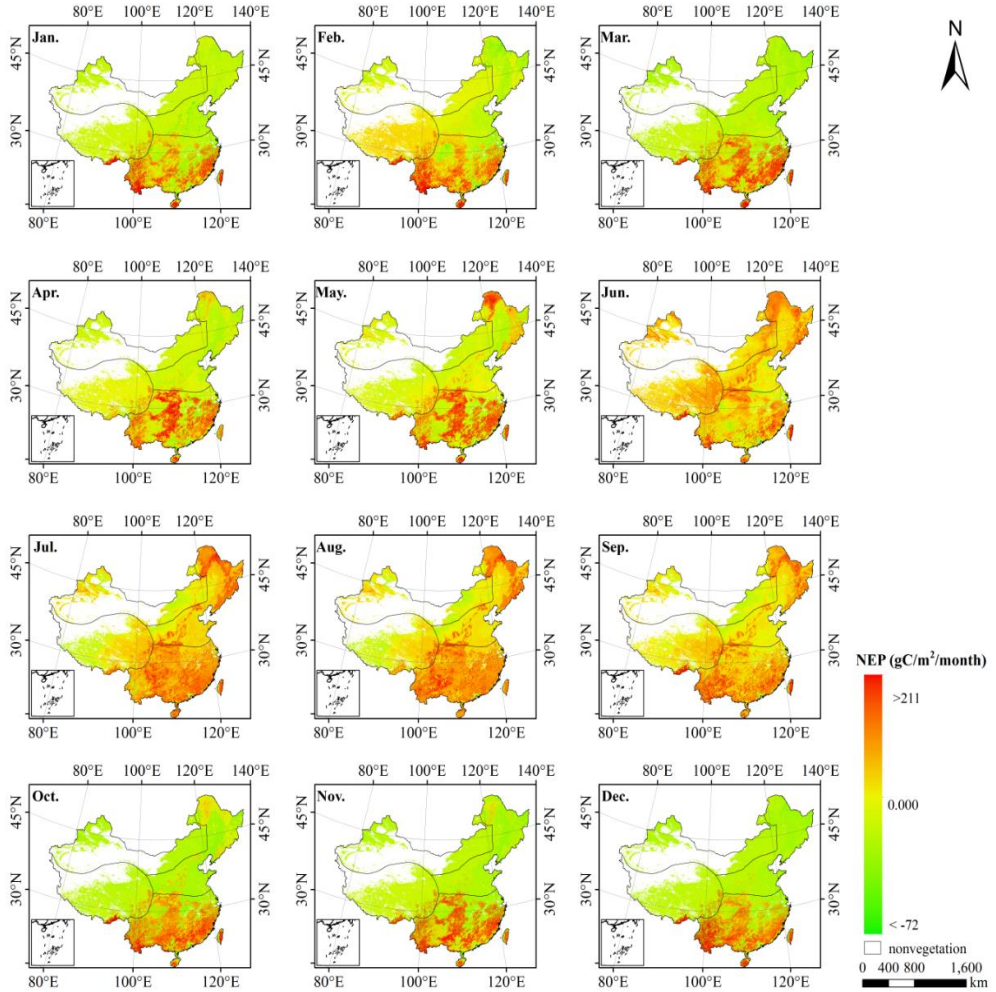
omparison of NEP Observations and Estimates. （A. Verifications results of original model; B. Verification results with ptimized ε_{max}; C. Verification results with optimized ε_{max} and T_{opt}）

Siyi Qiu, Liang Liang*, Di Geng, et al. Estimation of European Terrestrial Ecosystem NEP Based on Improved CASA Model. *IEEE J-STAR*, 2022, Submitting.

7. Estimation of vegetation carbon sinks (NEP)



Spatial distribution of summer NEP trends in China from 2001 to 2016



Monthly average estimation results of NEP of terrestrial ecosystem vegetation in China

Liang Liang*, Di Geng, Juan Yan, et al. Remote Sensing Estimation and Spatiotemporal Pattern Analysis of Terrestrial Net Ecosystem Productivity in China. Remote Sensing, 2022, 14(9), 1992.

European Young scientists contributions in Dragon 5

Name	Institution	Poster title	Contribution
David Mengen	Research Center Jülich	Soil Moisture Remote Sensing using Sentinel-1 time series	Estimating soil moisture by the alpha approximation approach for multiple incidence angles in the Google Earth Engine

Chinese Young scientists contributions in Dragon 5

Name	Institution	Poster title	Contribution
Siyi Qiu	Jiangsu Normal University	Remote Sensing Estimation of NEP in Europe and Improvement of CASA Model	The Carnegie Ames Stanford approach (CASA) model was optimized by the maximum light use efficiency and the optimal temperature, and the NEP value of the European terrestrial ecosystem was estimated by coupling the soil respiration model.
Yanyan Shi	Jiangsu Normal University	Assessment of Classification Accuracy of Four Global Land Cover Data in Nine Urban Agglomerations	A conference paper has been published, and various ground object sample points have been collected by visual interpretation on Google Earth.
Jin Shi	Jiangsu Normal University	A remote sensing extraction method for garlic distribution in PiZhou City Using GEE cloud platform	To obtain accuracy of classification by obtaining characteristic information of garlic. Through this, we can improve the efficiency of garlic extraction by remote sensing.
Qianjie Wang	Jiangsu Normal University	Insights into Spatiotemporal Variations of Net Primary Productivity of Terrestrial Vegetation in Africa During 1981-2018	Data products such as spatial and temporal distribution patterns and dynamic changes of global NPP can be obtained to determine the main factors affecting global NPP.

Thank you!

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