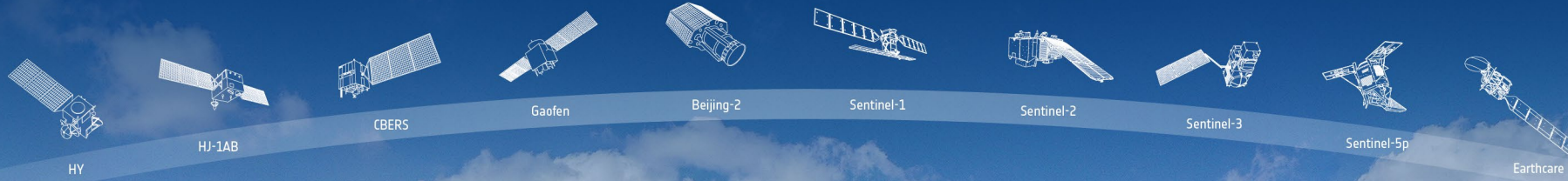




中国科学技术交流中心
China Science and Technology Exchange Center



→ THE EUROPEAN SPACE AGENCY



2025 DRAGON 6 SYMPOSIUM

14-18 JULY 2025

PROJECT ID. 95393

PROJECT Title: Use of Earth Observation for Urban Security: addressing heat risk and geological hazards



2025 Dragon 6 Symposium: Project Overview



TUESDAY, 15/JULY/2025 14:45 - 15:30

ID. 95393

PROJECT TITLE: USE OF EARTH OBSERVATION FOR URBAN SECURITY: ADDRESSING HEAT RISK AND GEOLOGICAL HAZARDS

PRINCIPAL INVESTIGATORS: CONSTANTINOS CARTALIS (NKU), HUILI GONG (CNU)

CO-AUTHORS: LIN ZHU, KONSTANTINOS PHILIPPOPOULOS, MINGLIANG GAO, ILIAS AGATHANGELIDIS, BEIBEI CHEN, CHAOFAN ZHOU, LIN GUO, ANASTASIOS POLYDOROS

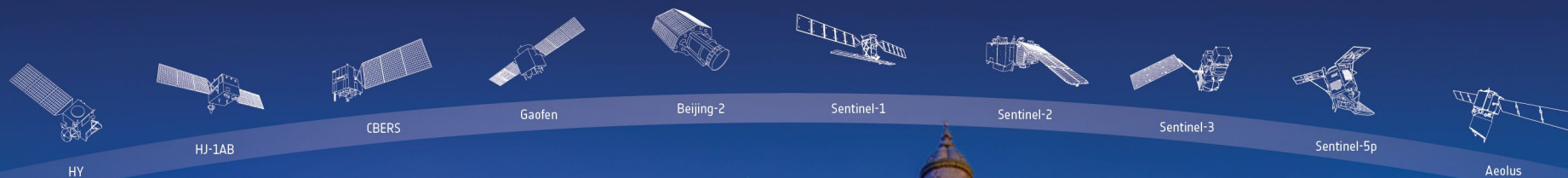
PRESENTED BY: CONSTANTINOS CARTALIS (HEAT RISK), LIN ZHU (GEOLOGICAL HAZARDS)



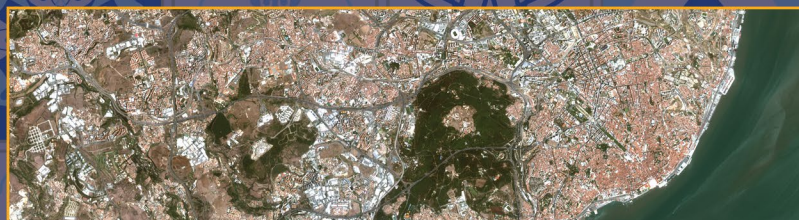
The project primarily focuses on using Earth Observation to address two distinct themes of **urban security**:

Theme 1: urban heat risk

Theme 2: geological hazards that are associated with land subsidence



Theme 1: Urban Heat Risk



Dragon 6 - Project objectives for Theme 1



Development of a machine learning-based framework for:

- **predicting the urban thermal environment**

Advanced downscaling methods and machine learning techniques to unravel the temporal dimension of remotely sensed satellite data and quantify the dynamics of thermal risk

- **Impact of green parks (size, location)**

Assessment of factors such as park size, shape, and type. The methodology involves satellite imagery analysis, park selection criteria, surface temperature data computation, and the evaluation of extreme events on PCI.

- **Impact of ventilation pathways**

Machine learning techniques will be employed, allowing for a comprehensive study of wind-sensitive planning

Main areas of application: Athens, Greece, and Beijing, China.



Climate indicators assessment

- Identifying and selecting the most relevant urban climate indicators to assess changes in the thermal environment
- To capture not just general warming trends, but specifically changes in the intensity, frequency, and persistence of extreme heat conditions

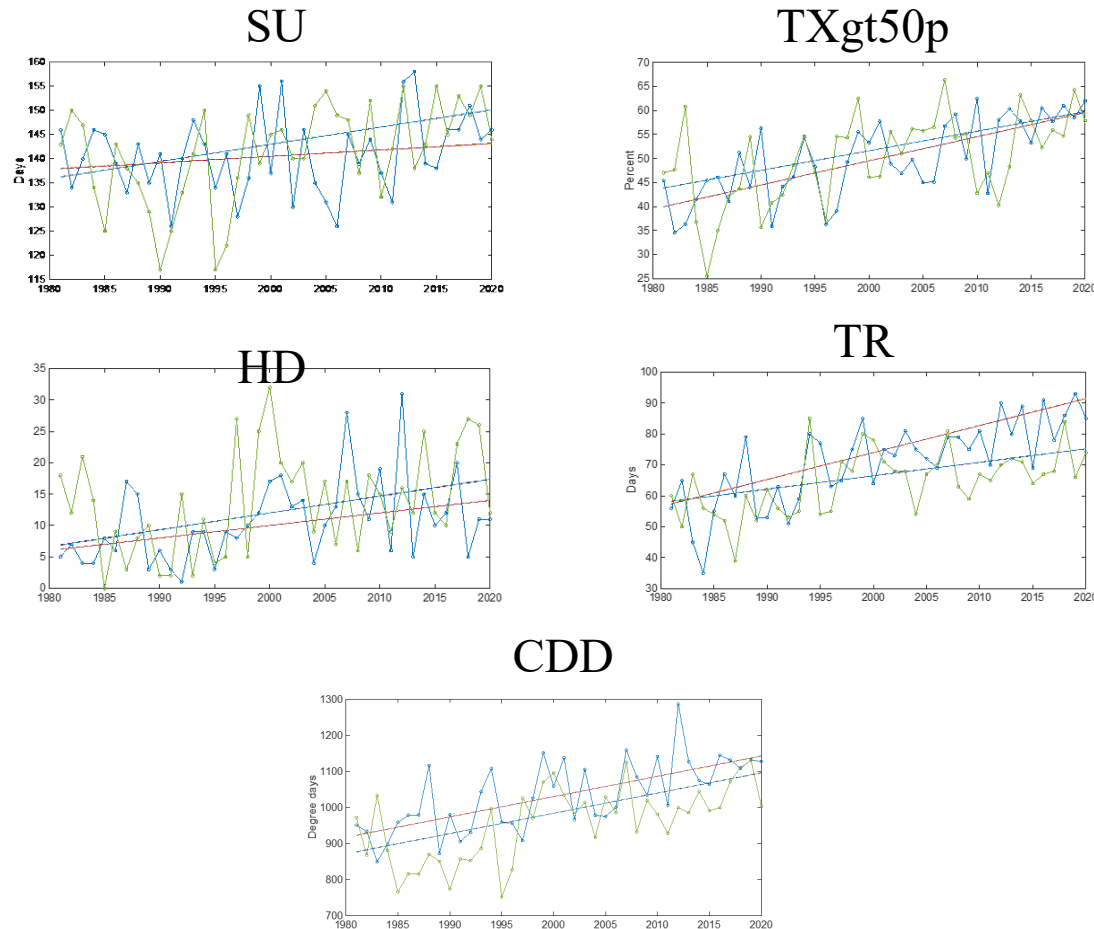
Urban Climate Indicator	Description
Summer days (SU)	Annual count of days when daily maximum temperature > 25°C
Fraction of days with above average temperature (TXgt50p)	Percentage of days when daily maximum temperature > 50th percentile
Hot days (HD)	Annual count of days when daily maximum temperature > 35 °C
Tropical nights (TR)	Annual count of days when daily minimum temperature > 20 °C
Cooling degree days (CDD):	Measure of the energy demand needed to cool a building

This analysis was applied to two case study cities, Athens, Greece and Beijing, China, providing a basis for comparative assessment under differing climatic and urban conditions.

Dragon 6 - Urban thermal environment



Climate indicators assessment



Sen-slope estimator and statistical significance

	Athens		Beijing	
	Slope	Statistical significance	Slope	Statistical significance
SU	0.13	-	0.36	**
TXgt50p	0.50	**	0.40	**
HD	0.20	**	0.27	*
TR	0.87	**	0.44	**
CDD	5.63	**	5.60	**

Mann–Kendall non-parametric test

Sen's slope estimator

These findings point to a consistent intensification of heat-related conditions in both urban areas over the past four decades.



Climate indicators assessment – Compound events

Evaluation of the climate in Beijing, China, and Athens, Greece in terms of droughts and heatwaves, focusing on their compound effects (CDHWs)

Compound Drought and HeatWave events

Heatwaves and droughts are identified using extreme indices

- Excess Heat Factor (EHF) for heatwaves
- 3-month SPI for meteorological drought

Definition of events

- ERA5-Land data (1991-2022)
- $\text{EHF} > 0\text{ }^{\circ}\text{C}$ and $\text{SPI} \leq -1.3$ (moderate and extreme drought conditions)

Total mean CDHW events
Beijing: 53.2 - Athens: 51.8

Increased sensitivity of CDHW to the urban fabric

Beijing Urban Grid point(LCZ4):66 events

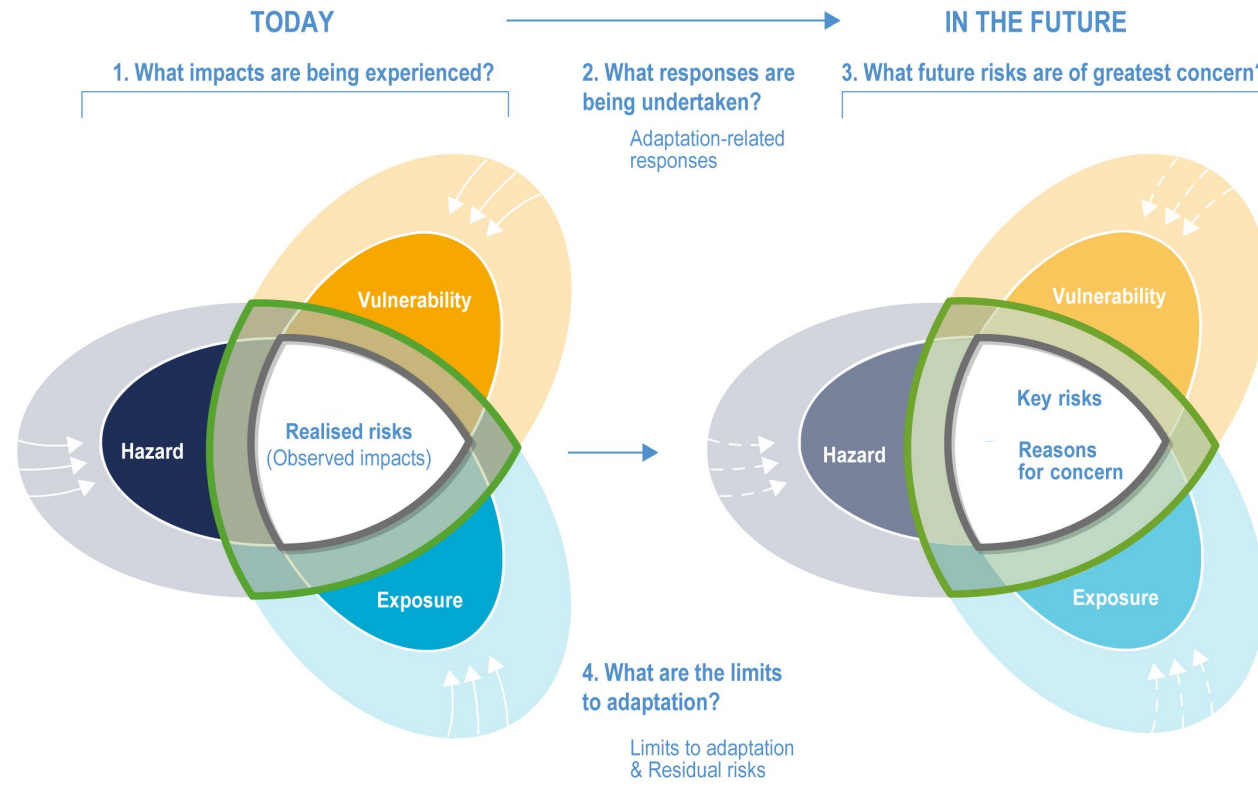
Beijing Urban Grid point(LCZ4):84 events

Beijing Rural Grid Point (LCZA):45 events

Athens Urban Grid point (LCZ6):75 events

Athens Rural Grid Point (LCZA): 44 events

Exploitation of the IPCC risk framework



(Source: AR6 IPCC)

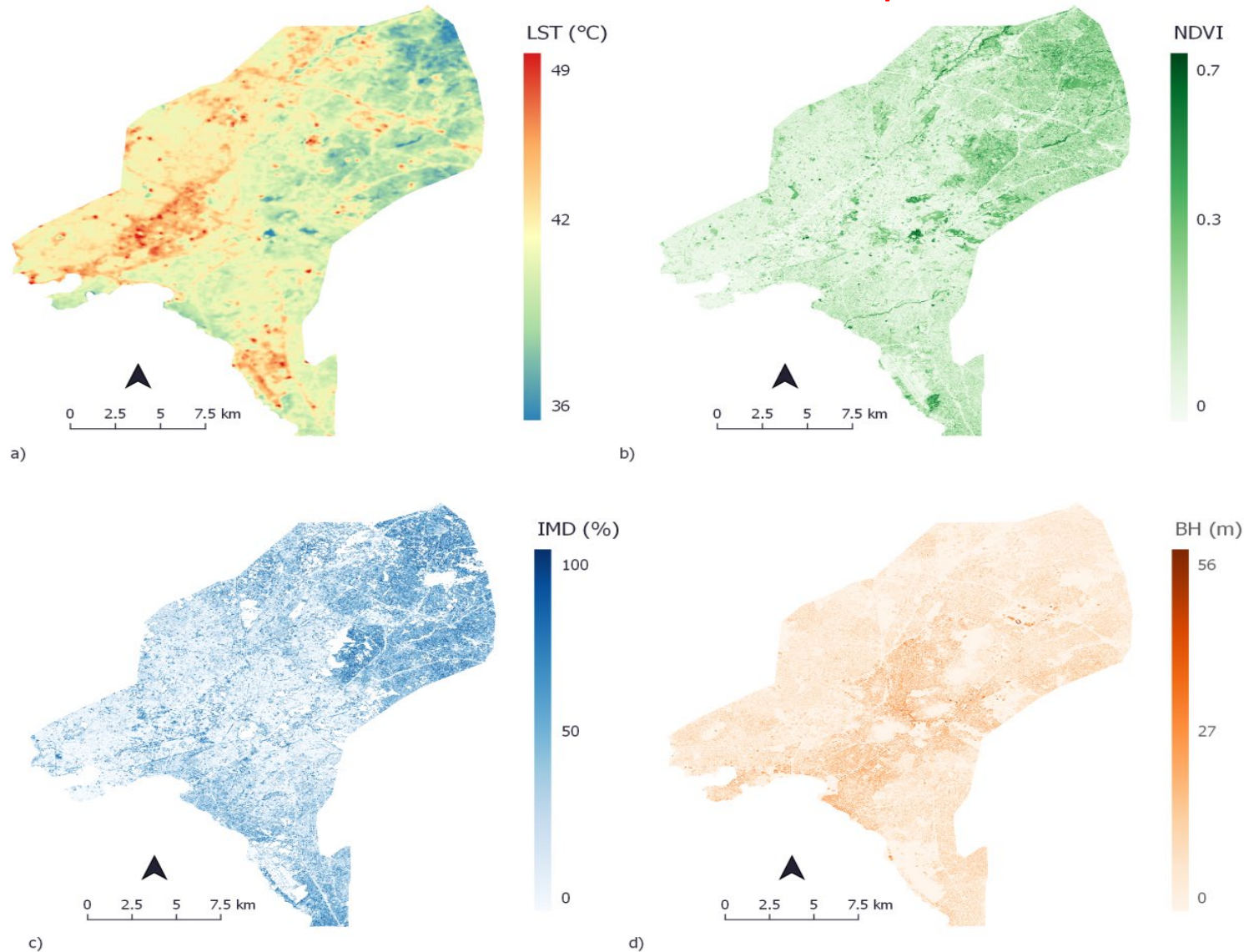


Innovation of the approach: use of climatic and non-climatic factors

Hazard	Climatic factors	
	Extreme temperatures	Summer days - SU
		Tropical nights - TR
		Hot days - HD
		Annual maximum temperature - TXX
Exposure Vulnerability	Non-climatic factors	
	Geophysical parameters	Downscaled Land Surface Temperature (LST)
		NDVI
		Impervious density fraction (IMD)
		Building Height (BH)
	Demographics	Land Use
		Population Density

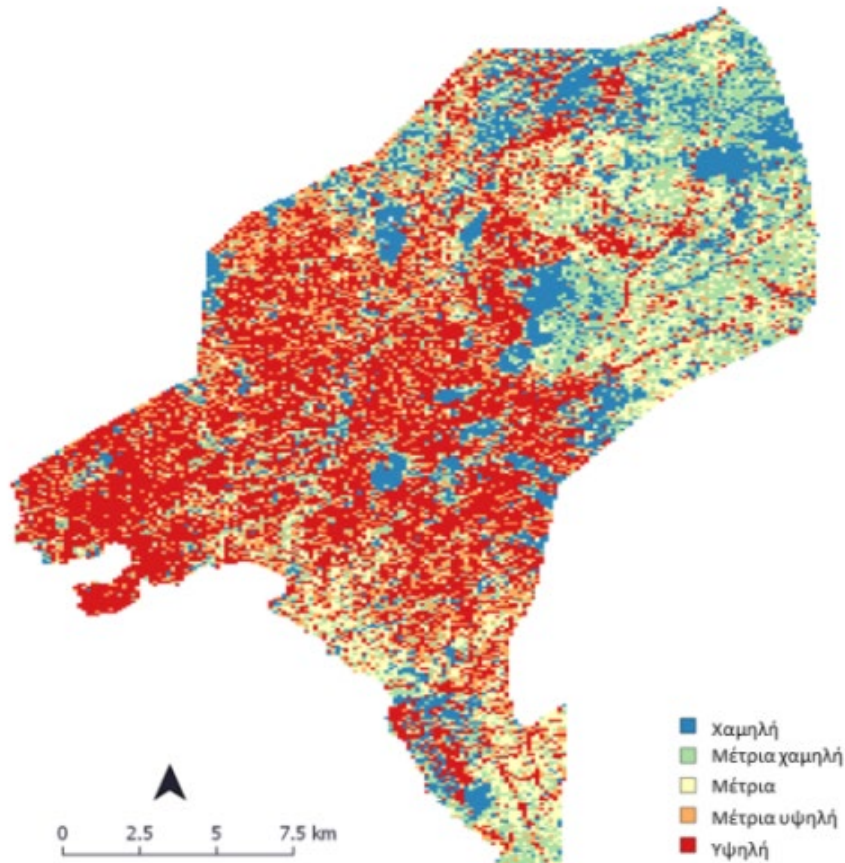


Urban Heat Risk – Exposure and Vulnerability Assessment





Urban Heat Risk – Synthesis of Exposure and Vulnerability



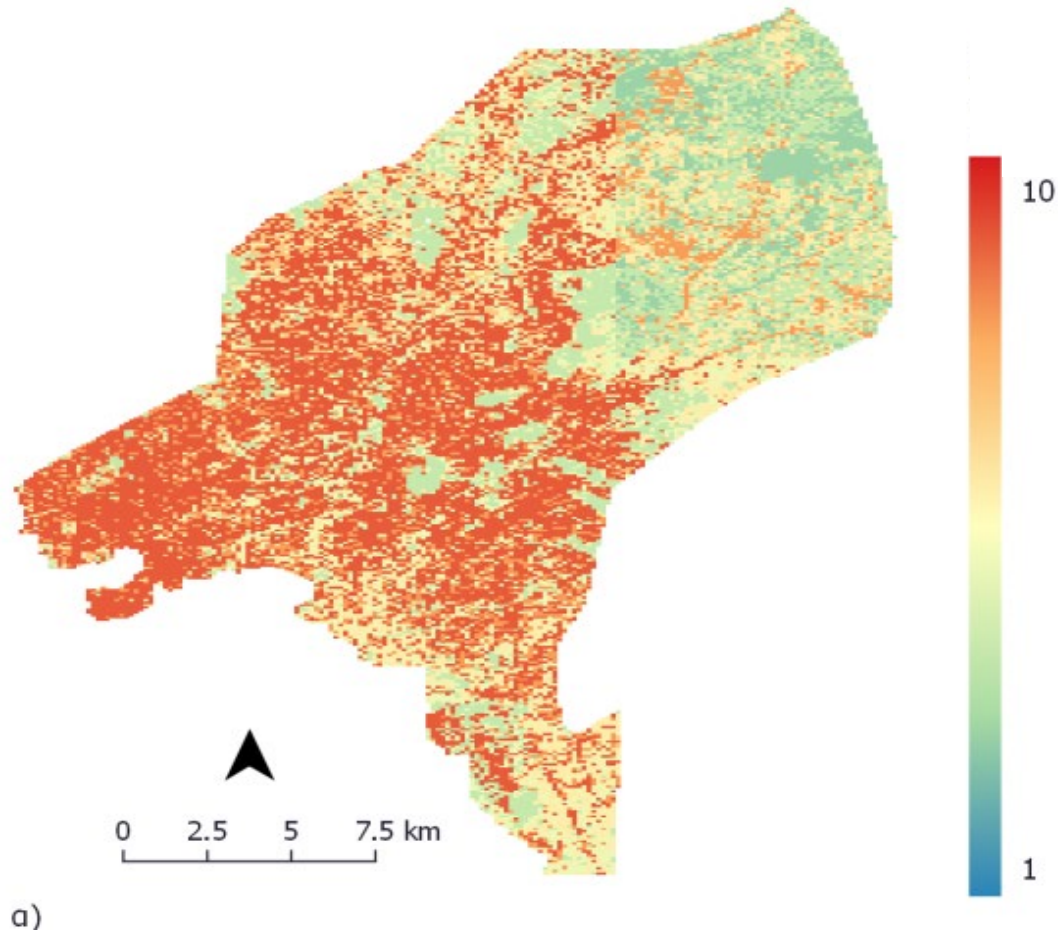
Class	LST (°C)	NDVI	IMD (%)	BH (m)	Land cover
1	41.47	0.30	2.1	0.7	Urban fabric: 28%, Industrial zones.: 20%, Urban Green: 52%
2	41.22	0.24	35.8	3.81	Urban fabric: 57%, Industrial zones. : 33%, Urban Green: 10%
3	41.43	0.16	64.8	5.97	Urban fabric: 71%, Industrial zones.: 23%, Urban Green: 6%
4	42.39	0.13	75.3	5.1	Urban fabric: 62%, Industrial zones.: 33%, Urban Green: 5%
5	42.68	0.06	96.5	6.8	Urban fabric: 59%, Industrial zones.: 37%, Urban Green: 4%

Dragon 6 - Urban thermal environment



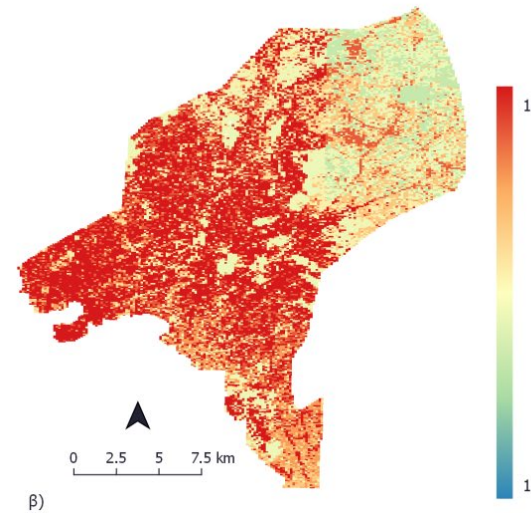
Urban Heat Risk Assessment

1981-2010

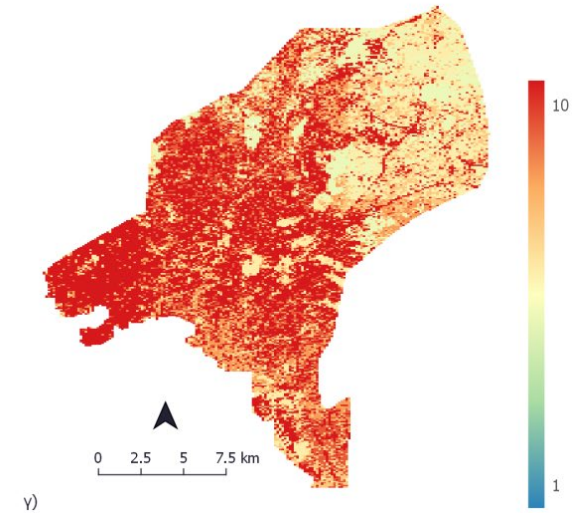


2046-2065

RCP 4.5



RCP 8.5



- Observations indicate that green infrastructure-based heat mitigation strategies can offset the burden of urban overheating.
- Urban parks form distinct, cool “oasis” patches within the urban fabric.
- The park cooling effect typically extends beyond park boundaries, as cooler air is advected into its built-up periphery.
- Park cooling influence: **Park Cool Island (PCI)**



Dragon 6 - Park Cool Island (PCI) magnitude and Park categories

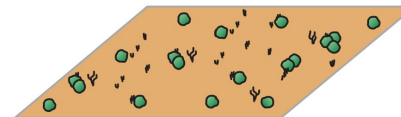
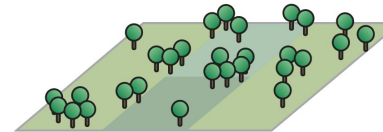
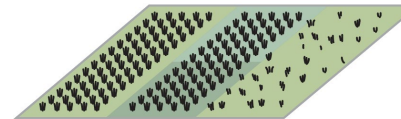
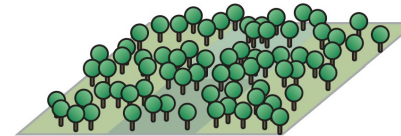


$$PCI = T_{\text{urban}} - T_{\text{park}} \text{ (Cao et al. 2010)}$$

T_{urban} : the mean urban LST within a 500-meter buffer zone from the park border

T_{park} : the mean LST inside the park

1. Dense trees (LCZ A)
2. Grass (LCZ D)
3. Trees & grass (LCZ B)
-
4. Shrubs & soil (LCZ C, F)
5. Multi-use parks (LCZ 9)





Geospatial data

- Urban area extents from the Natural Earth Urban Areas database
- Combined with population data from Oak Ridge National Laboratory (LandScan) (~1 km spatial resolution)
- Park boundaries from the open crowd-sourced OpenStreetMap (OSM) platform.

Park selection criteria

1. Minimum area of 1 hectare ($100 \times 100 \text{ m}^2$)
2. The average Normalized Difference Vegetation Index (NDVI) inside the park should exceed the mean NDVI of all parks in a given city minus half the standard deviation.
3. No other parkland or extended urban greenery should exist in the vicinity of the park, via the Global Artificial Impervious Areas (GAIA) dataset and visual inspection.



- **Thermal Risk Maps:**

Finalize high-resolution thermal risk maps for both cities using advanced downscaling and machine learning techniques to capture the temporal dynamics of satellite-derived surface temperature.

- **Urban Green:**

Assess the impact of park size, shape, type, and location on the Park Cool Island (PCI) effect under extreme heat, using high resolution SDGSAT-1 and downscaled Sentinel-3 imagery.

- **Ventilation Pathways:**

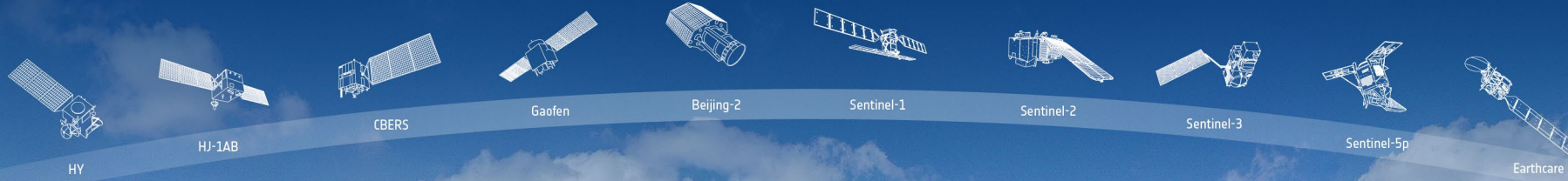
Evaluate urban ventilation corridors using machine learning to support wind-sensitive urban planning.



中国科学技术交流中心
China Science and Technology Exchange Center



→ THE EUROPEAN SPACE AGENCY



Theme 2: Geological hazards that are associated with land subsidence





- Monitoring and mitigating urban geological hazards (predominantly regional land subsidence)

Remote sensing, geophysical exploration, hydrogeology, ...

- Identifying the differential evolution patterns of urban groundwater levels

InSAR, ground-penetrating radar (GPR), and multi-field numerical analysis, ...

- Revealing land subsidence responses driven by the natural-social dual water cycle

Natural and anthropogenic drivers

- Providing optimal schemes for urban land subsidence regulation

Regulation threshold

Opening Statement



中国科学技术交流中心
China Science and Technology Exchange Center

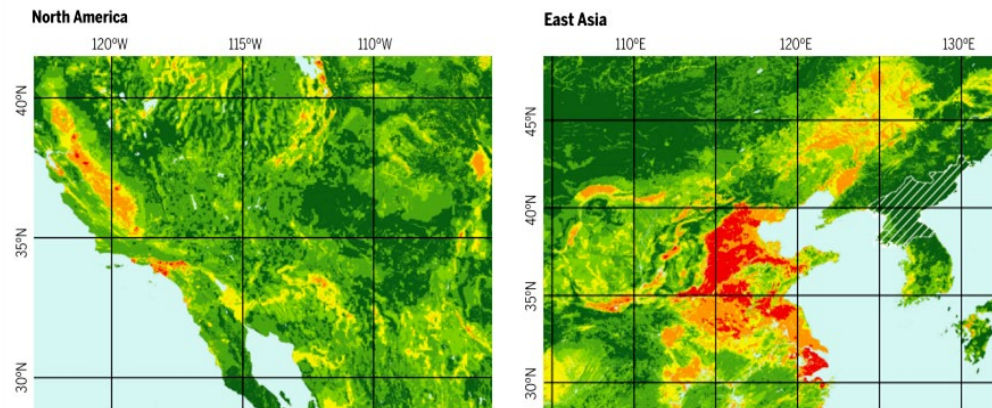
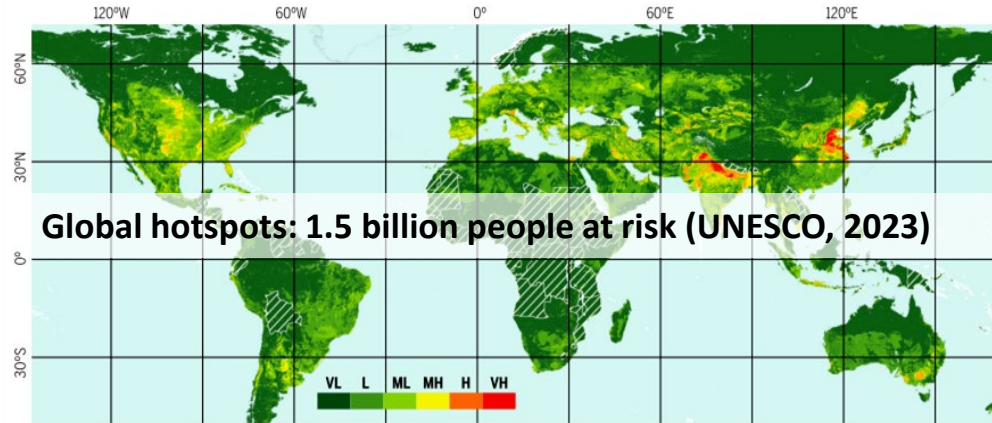


→ THE EUROPEAN SPACE AGENCY

Urban areas host 56% of the global population, but geological hazards threaten their security.

Potential global subsidence

The color scale indicates the probability intervals classified from very low (VL) to very high (VH), for every 30-arcsec resolution pixel (1 km by 1 km at the Equator). The white hatched polygons indicate countries where groundwater data is unavailable, and the potential subsidence only includes information on the susceptibility. See maps of other regions in supplementary materials.



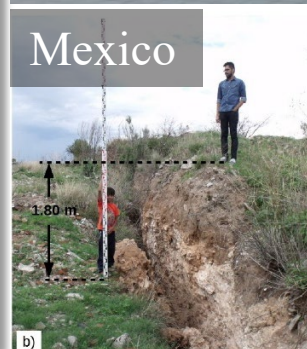
Tokyo



San Joaquin Valley, CA



Mexico



Australia



Jakarta



From Tokyo's sinking neighborhoods to Mexico City's fissured infrastructure, land subsidence alone causes \$13 billion annual losses.

Introduction

Hydrological Processes

Mechanical Response

Fracture Evolution

Key Geological Hazards Urban Security



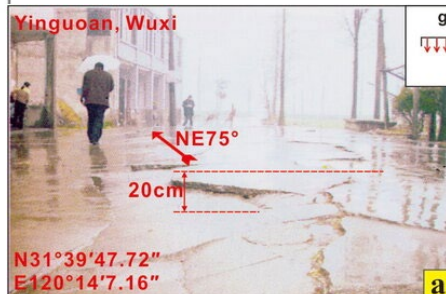
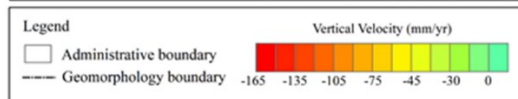
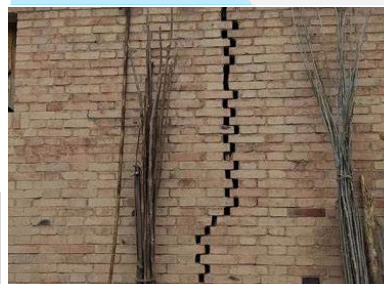
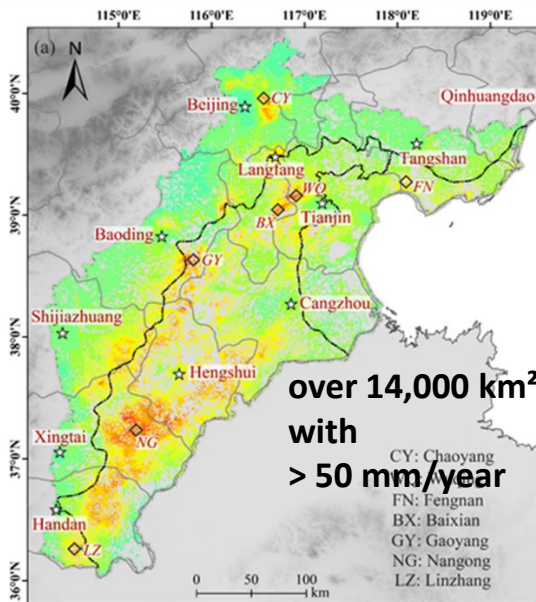
中国科学技术交流中心
China Science and Technology Exchange Center



→ THE EUROPEAN SPACE AGENCY

Land Subsidence: 16% cities in China with subsidence rate $> 10\text{mm/year}$, 7% population, Global Mean Sea Level rising

Earth Fissures: Correlate with 30% higher building damage rates (USGS study)



The North China Plain (NCP) stands out with:

- ❁ A groundwater depression cone of $20,000\text{ km}^2$
Overexploitation of groundwater: 2014~2020: $2.86\text{ billion m}^3/\text{year}$
- ❁ Over $14,000\text{ km}^2$ with $> 50\text{ mm/year}$ subsidence
- ❁ Cumulative displacements exceeding 1.5 m in parts
- ❁ South-to-North Water Diversion Project
Operate in Dec. 2014, cumulative water volume over 70 billion m^3
- ❁ Subway networks and high speed railway networks
- ❁ Important agricultural production region



Introduction

Hydrological Processes

Mechanical Response

Fracture Evolution

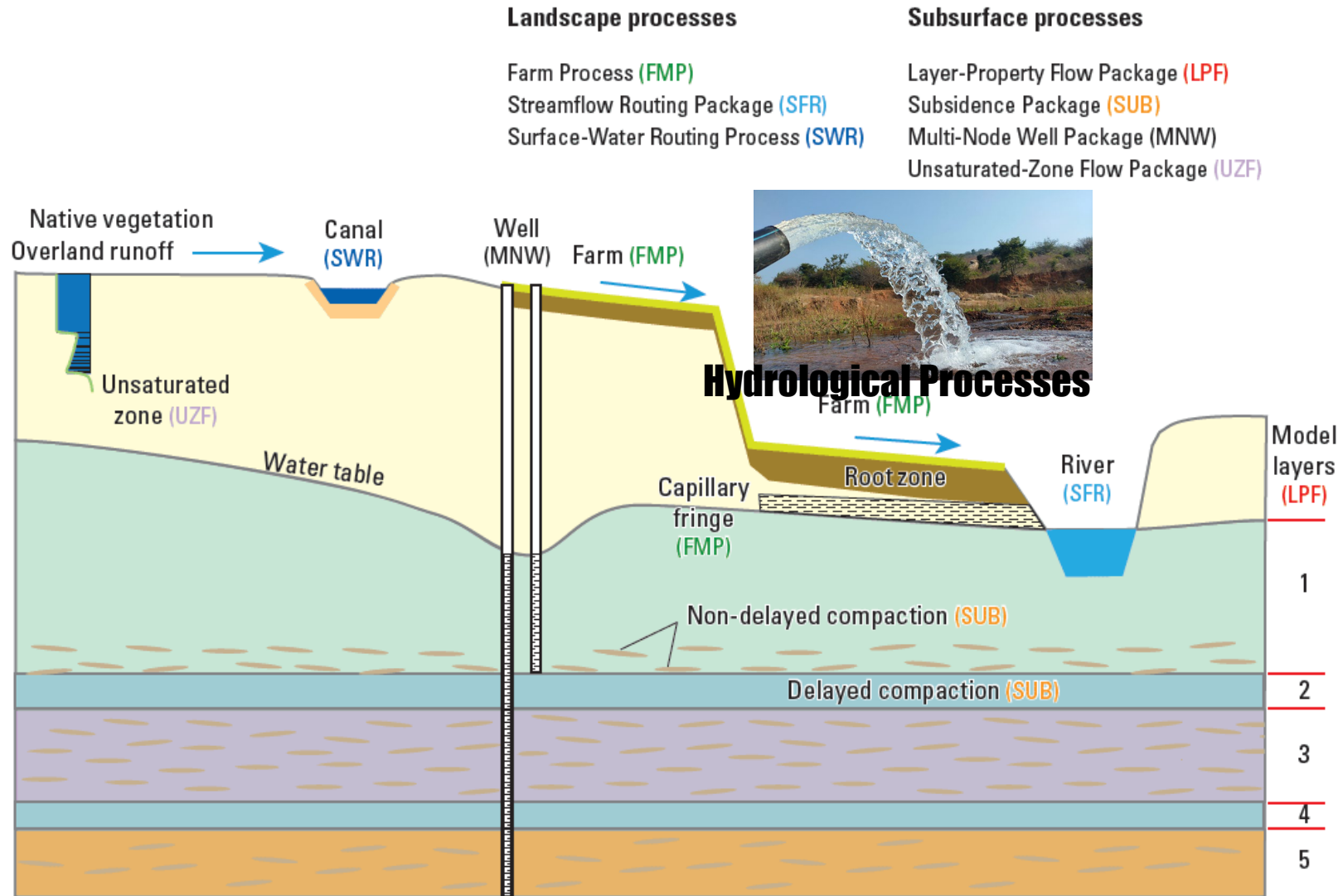
Process of Aquifer Consolidation Caused by Pumping



中国科学技术交流中心
China Science and Technology Exchange Center



→ THE EUROPEAN SPACE AGENCY



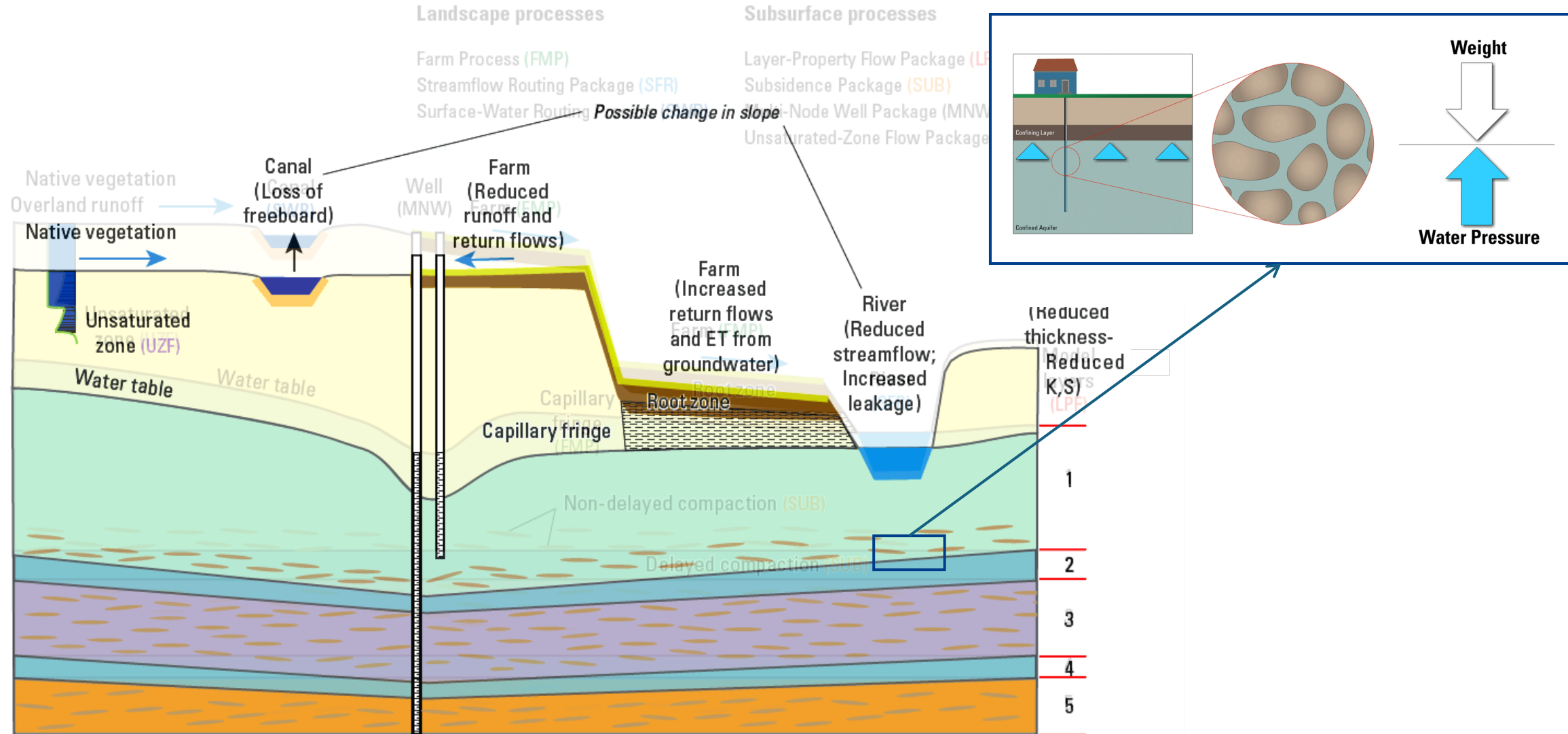
Process of Aquifer Consolidation Caused by Pumping



中国科学技术交流中心
China Science and Technology Exchange Center



→ THE EUROPEAN SPACE AGENCY



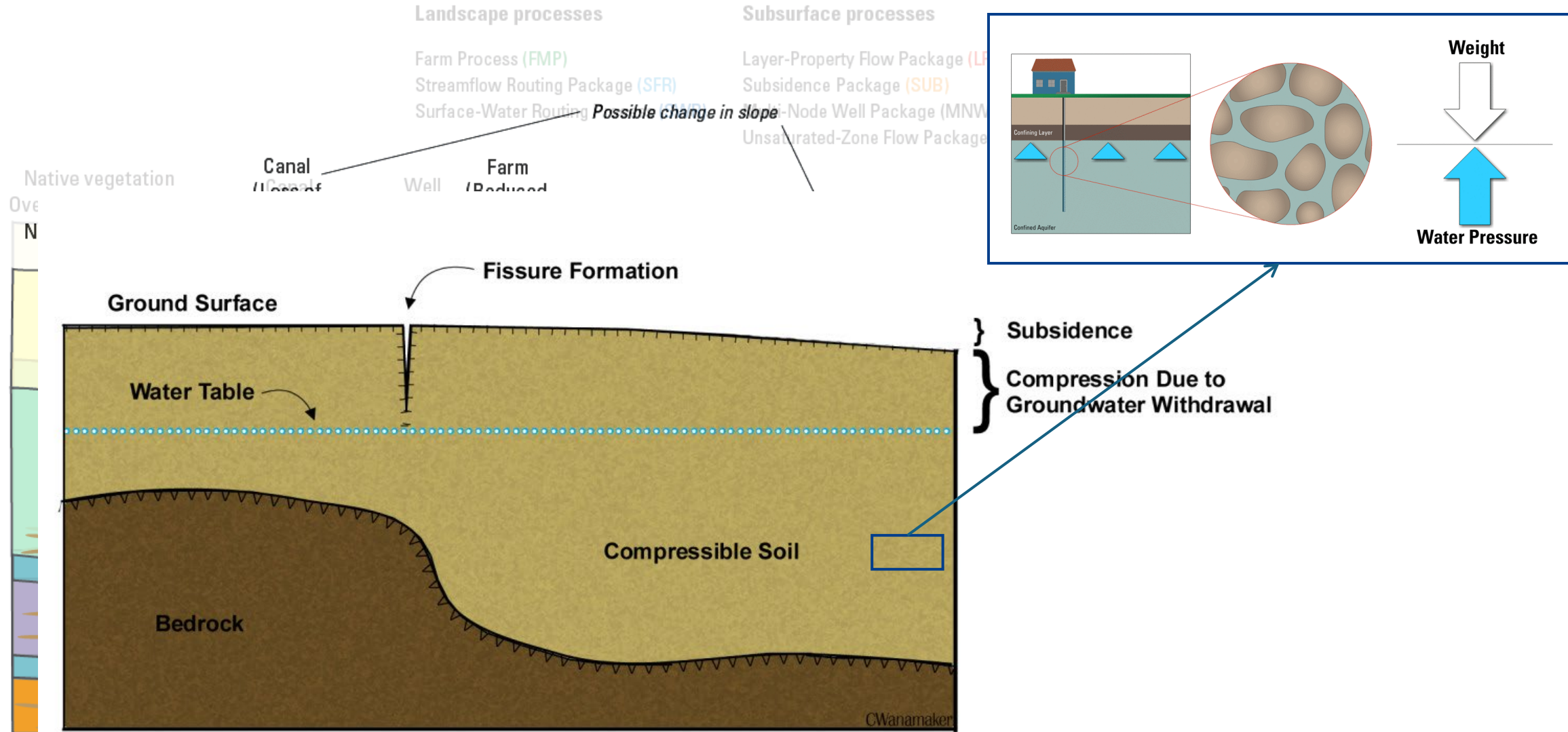
Induced Land Subsidence and Earth Fissure Hazards



中国科学技术交流中心
China Science and Technology Exchange Center



→ THE EUROPEAN SPACE AGENCY



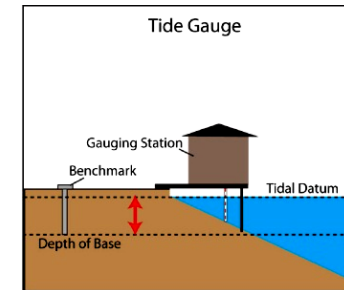
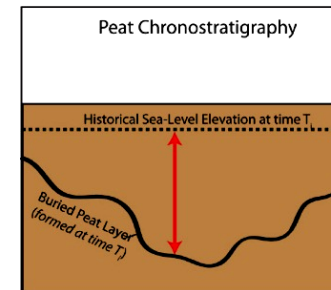
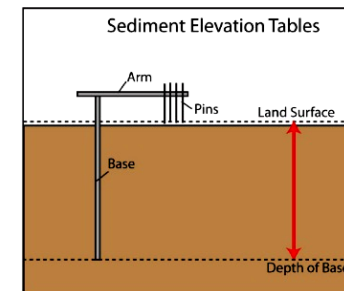
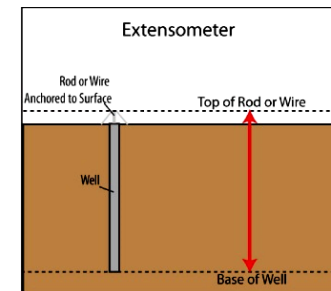
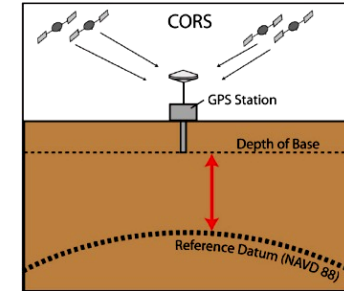
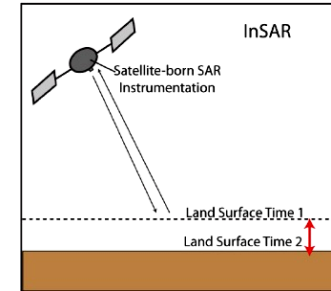
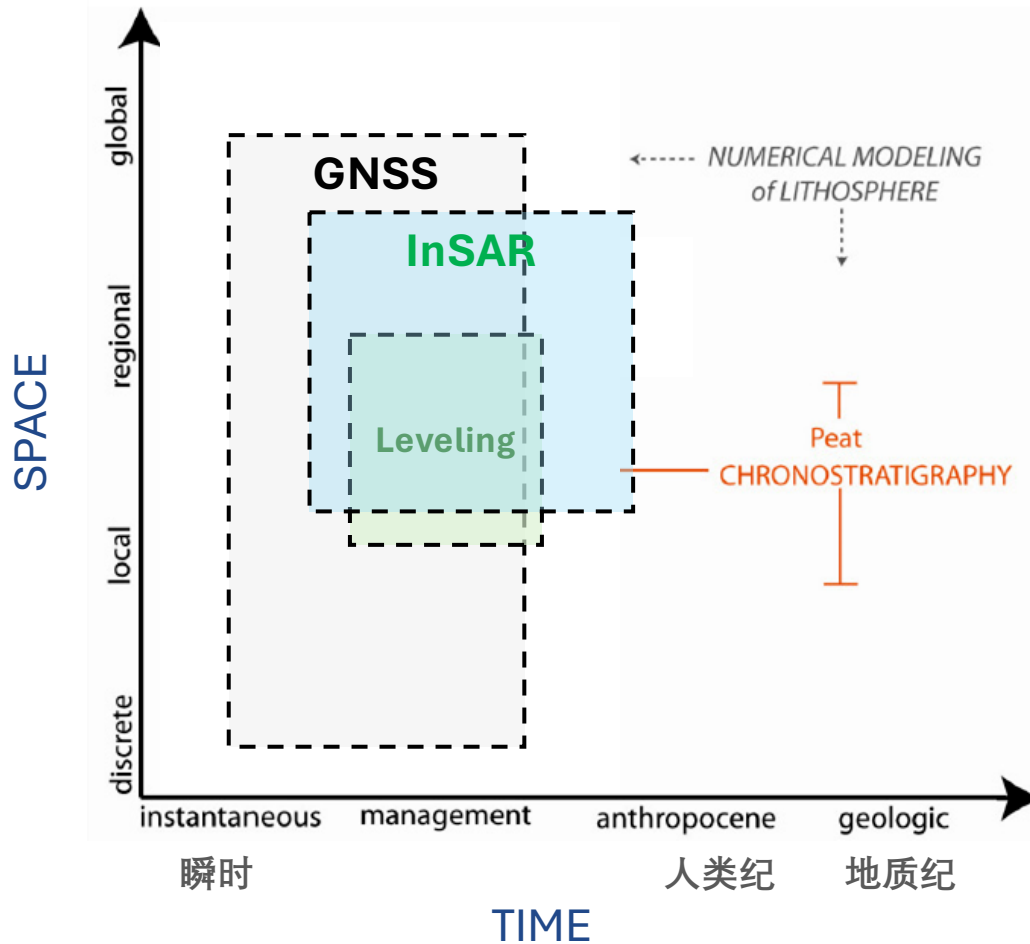
Monitoring Techniques for Land Subsidence in Urban Area



中国科学技术交流中心
China Science and Technology Exchange Center



→ THE EUROPEAN SPACE AGENCY



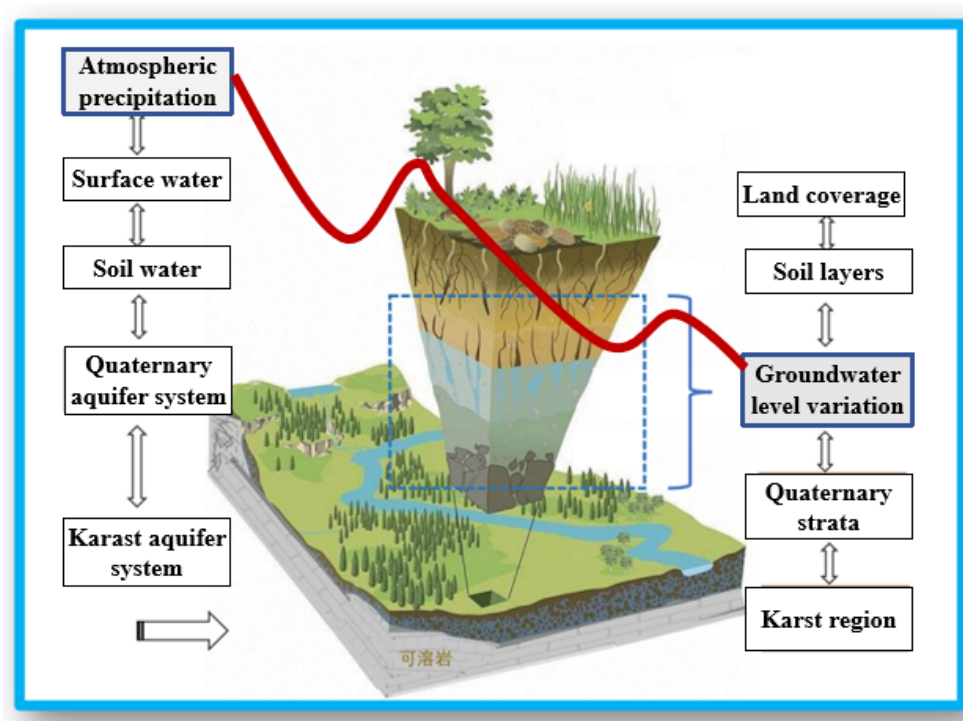
Space – time characterization of various techniques available to monitor land subsidence in sedimentary basins

Reconstructing the Complex Hydrological Cycle System

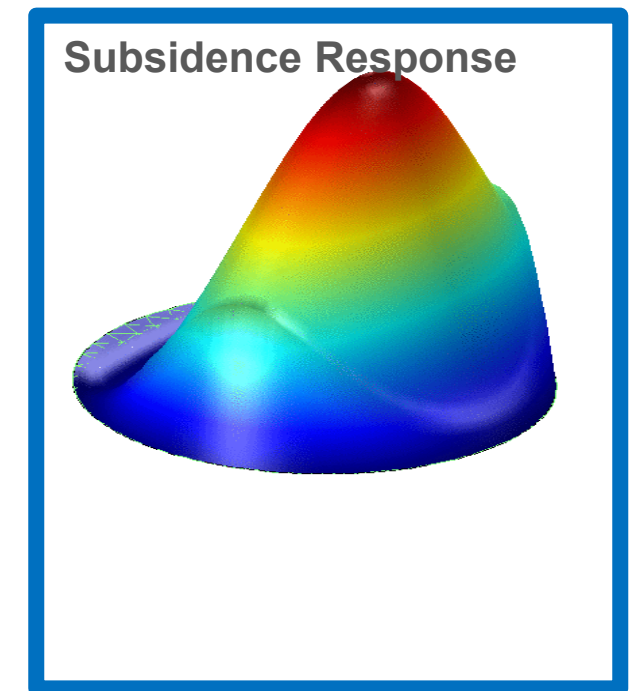
The essence of settlement is the imbalance of the water-soil system.

the "Natural-Social" Dual Water Cycle Framework (NSDWCF): three key chains

- Hydrological processes chain: Water balance models *CASE STUDY1*
- Mechanical response chain: Physics-informed neural networks (PINNs) *CASE STUDY2*
- Fracture evolution chain: Peridynamics (PD) *CASE STUDY3*



Linear or nonlinear
Transfer function



Relationship between regional water cycle and land subsidence- **Threshold** of subsidence control

Water balance models for hydrological processes

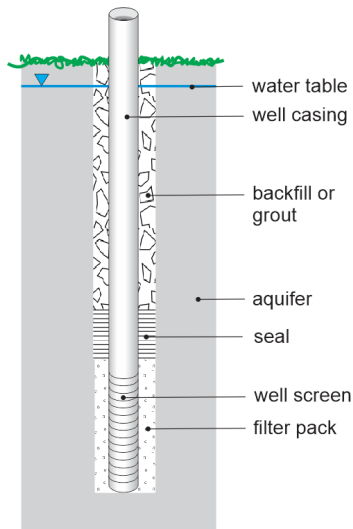


中国科学技术交流中心
China Science and Technology Exchange Center

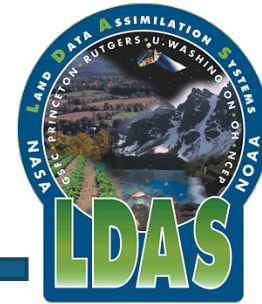
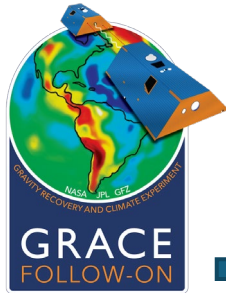


→ THE EUROPEAN SPACE AGENCY

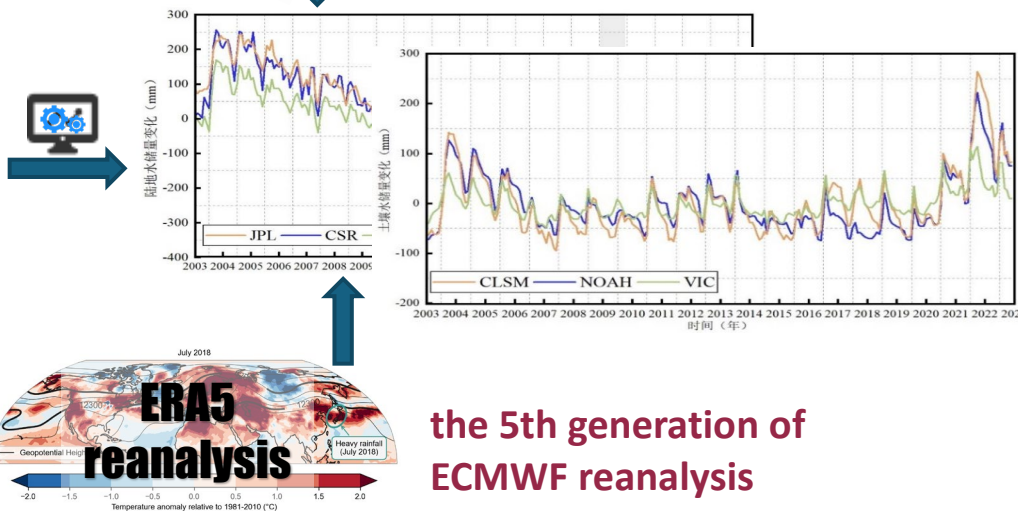
Gravity Recovery and Climate Experiment



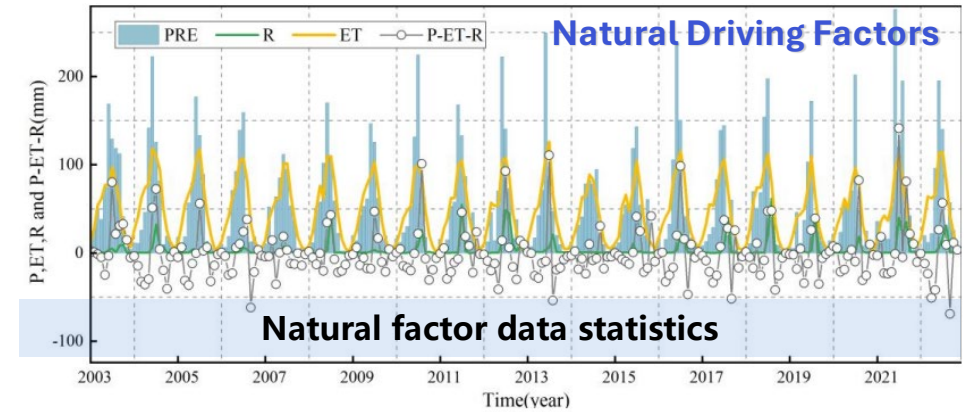
in-situ wells Monitoring



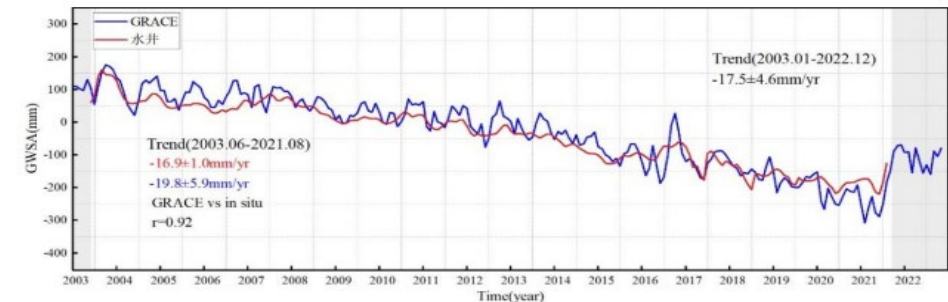
the Global Land Data Assimilation System



the 5th generation of ECMWF reanalysis



Natural factor data statistics



Time series of Ground Water Storage Anomaly obtained based on GRACE and measured water well data

The ERA-5 reanalysis dataset, GRACE satellite gravity data, in-situ well and GLDAS hydrological model were combined to obtain the temporal characteristics of key water cycle elements including precipitation, runoff, evaporation, and groundwater extraction in recent twenty years.

Water balance models for hydrological processes

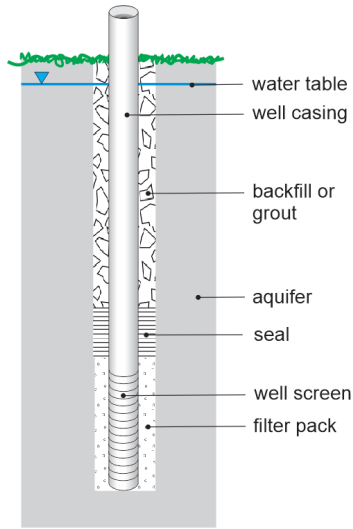


中国科学技术交流中心
China Science and Technology Exchange Center

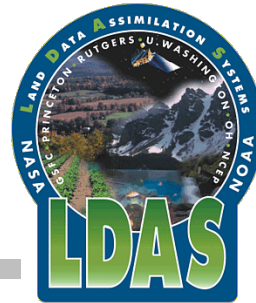
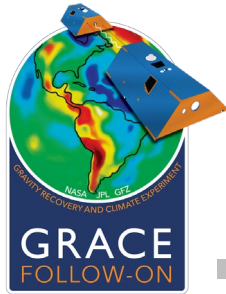


→ THE EUROPEAN SPACE AGENCY

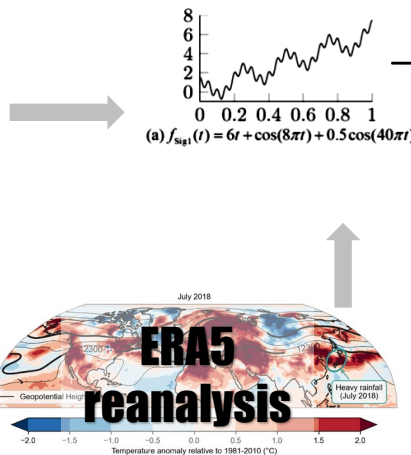
Gravity Recovery and Climate Experiment



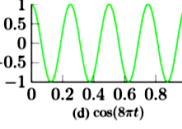
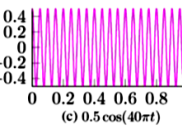
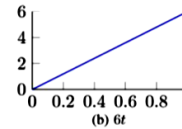
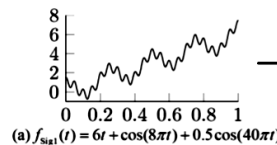
in-situ wells Monitoring



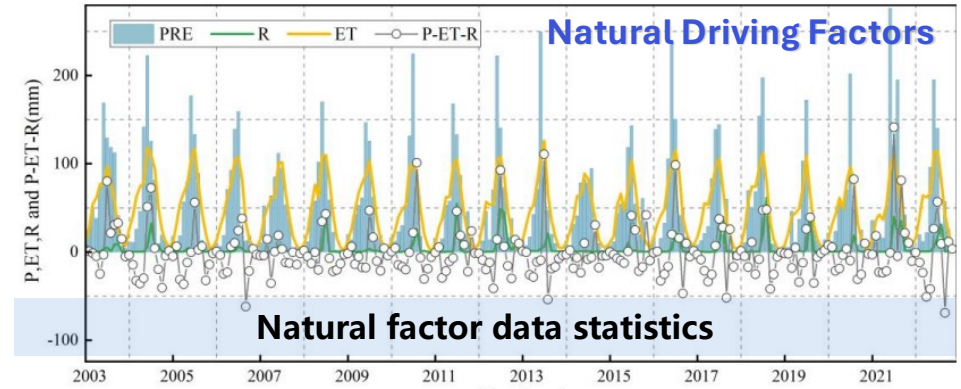
the Global Land Data Assimilation System



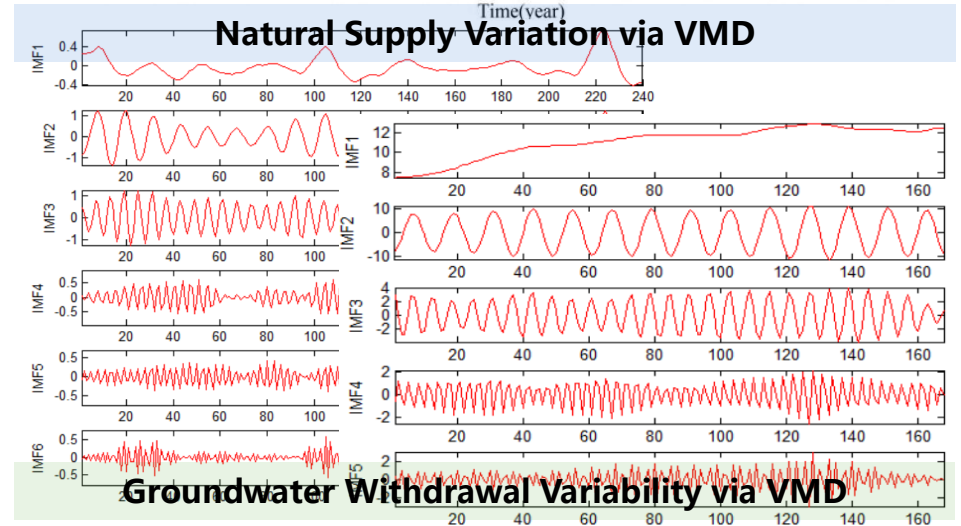
the 5th generation of ECMWF reanalysis



VMD



Natural factor data statistics



Groundwater Withdrawal Variability via VMD

- ▶ Temporal dissection of groundwater storage, natural recharge, and extraction volumes
- ▶ Segregating seasonal variations from long-term trends
- ▶ Quantifying the precise contributions of various driving forces to groundwater dynamics

Variational Mode Decomposition (VMD)

Water balance models for hydrological processes

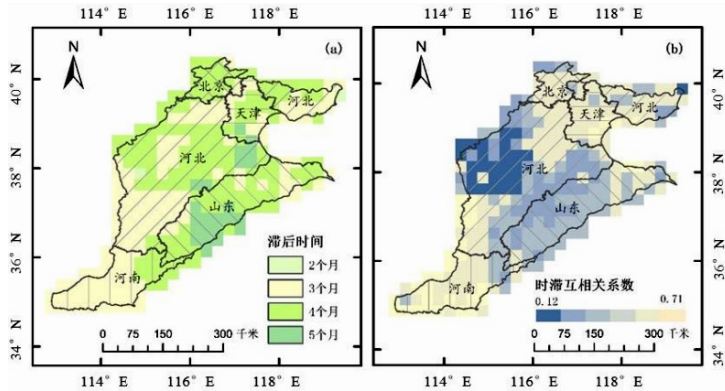


中国科学技术交流中心
China Science and Technology Exchange Center

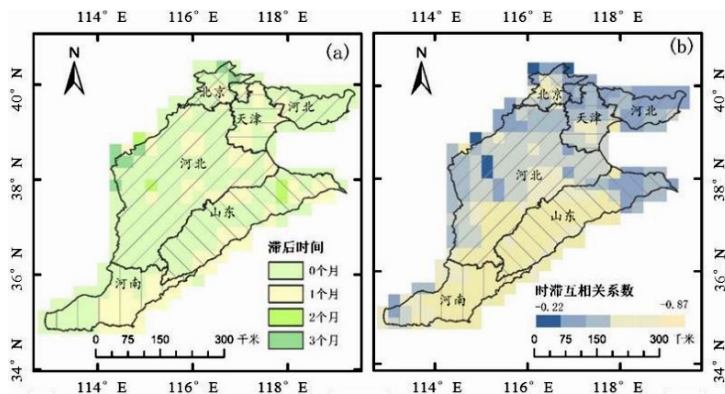


→ THE EUROPEAN SPACE AGENCY

Time-lagged response mechanisms and quantitative attribution mechanisms of long-term groundwater storage trends driven by new water cycle dynamics.



Time delayed response between climate change and groundwater storage



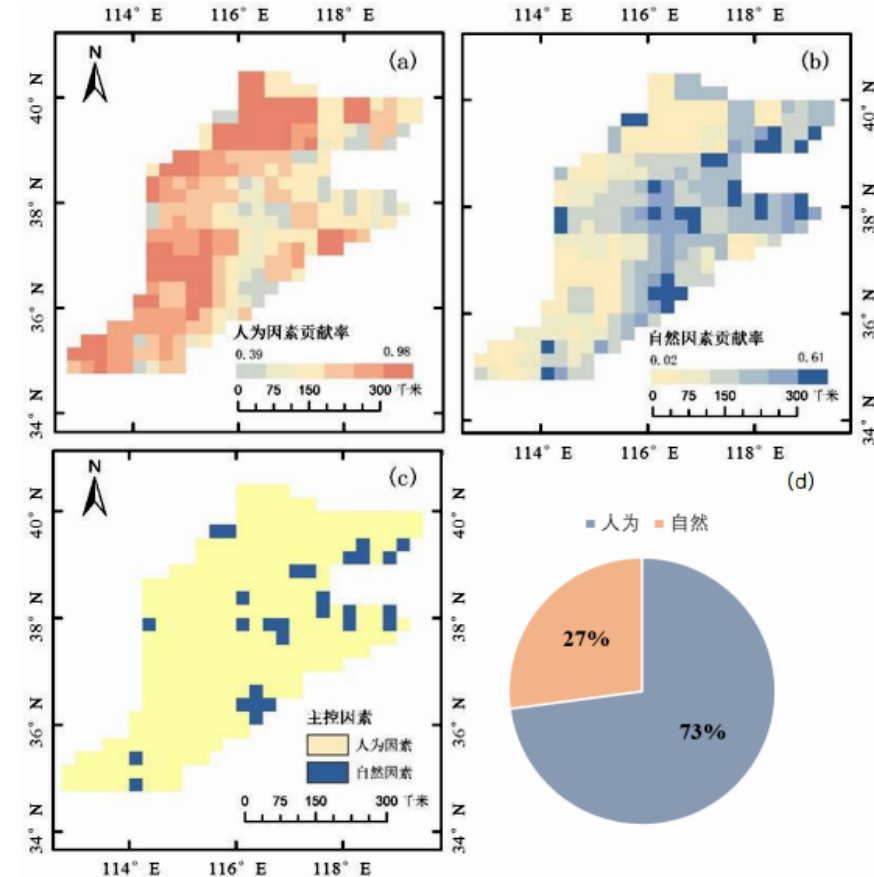
Time delayed response between groundwater mining output and groundwater storage

Spatiotemporal heterogeneity in natural recharge: nonlinear aquifer responses to climate fluctuations.

V.S.

Immediate anthropogenic regulation: direct human dominance over groundwater dynamics.

Within the "Natural-Social" Dual Water Cycle Framework (NSDWCF), GWS dynamics exhibit distinct new features: **seasonal fluctuations superimposed on long-term depletion trends, with anthropogenic factors governing both short-term (seasonal) variability and long-term decline.**



Quantitative Attribution of Groundwater Reserve Trend Factors via Random Forest

Physics-Informed Neural Networks (PINNs)

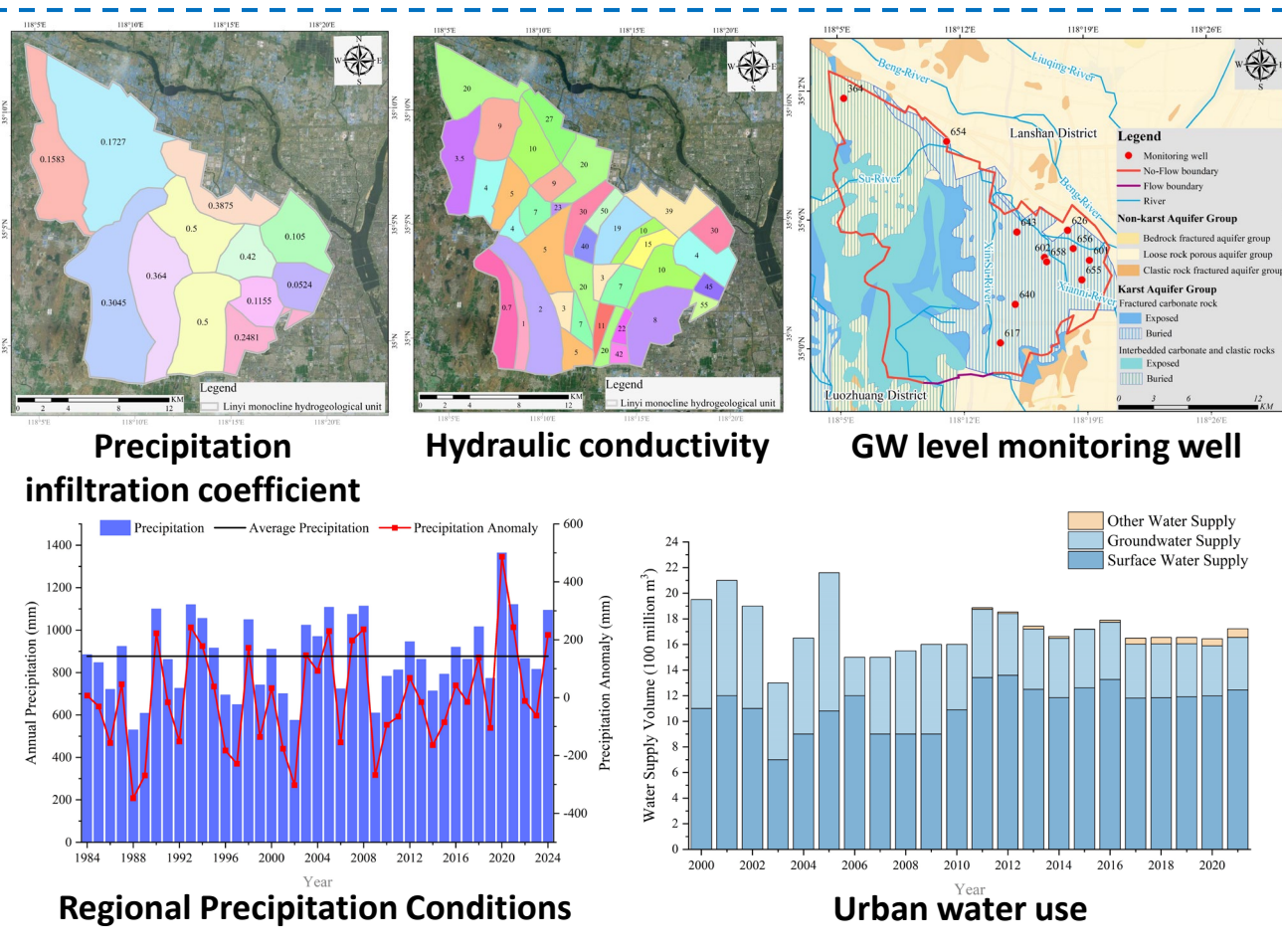


中国科学技术交流中心
China Science and Technology Exchange Center

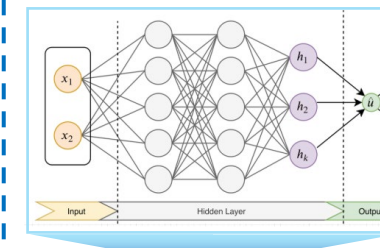


→ THE EUROPEAN SPACE AGENCY

PINNs (proposed by Raissi et al. 2019), combines the generalization capability of neural networks with physical laws, guiding the neural network's learning process by encoding constraint conditions from physical equations.



"Natural-Social" Dual Water Cycle Framework (NSDWCF)



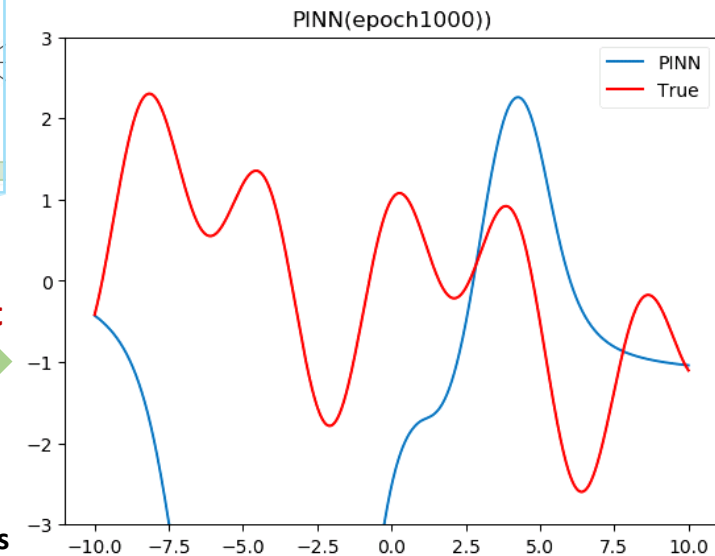
Black box



Partial Differential Equations

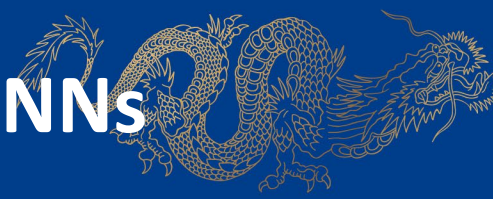
$$\begin{cases} S_s \frac{\partial h}{\partial t} = \frac{\partial}{\partial x} \left(K_x \frac{\partial h}{\partial x} \right) + \frac{\partial}{\partial y} \left(K_y \frac{\partial h}{\partial y} \right) + W \\ h|_{t=0} = h_0 \\ K \frac{\partial h}{\partial n} \Big|_{s_2} = q(x, y, t) \end{cases}$$

Governing Equation for 2-D Unsteady GW Flow



The proposed framework embeds the 2-D unsteady GW flow equation into PINNs' loss function, enabling coupled modeling that balances physical consistency (via Darcy's law constraints) and nonlinear fitting (via neural network layers).

Groundwater level simulation via PINNs



中国科学技术交流中心
China Science and Technology Exchange Center

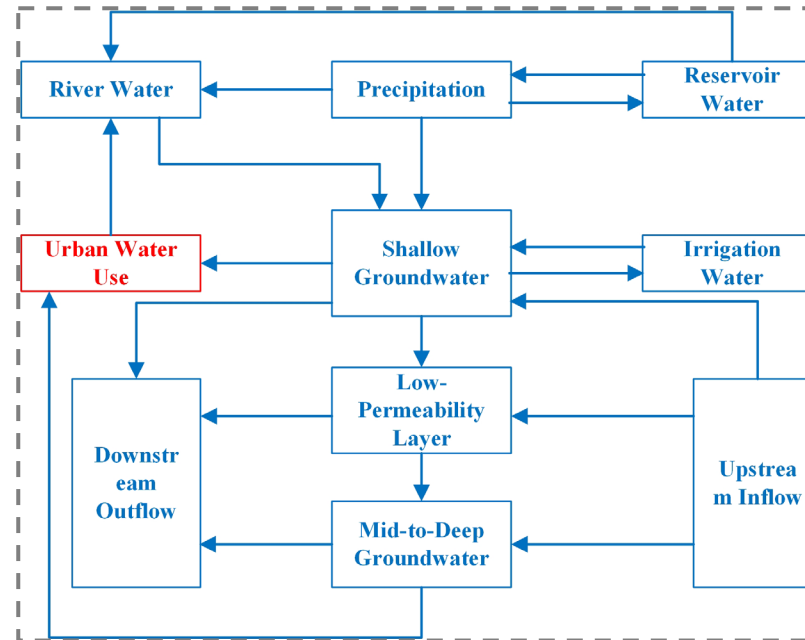
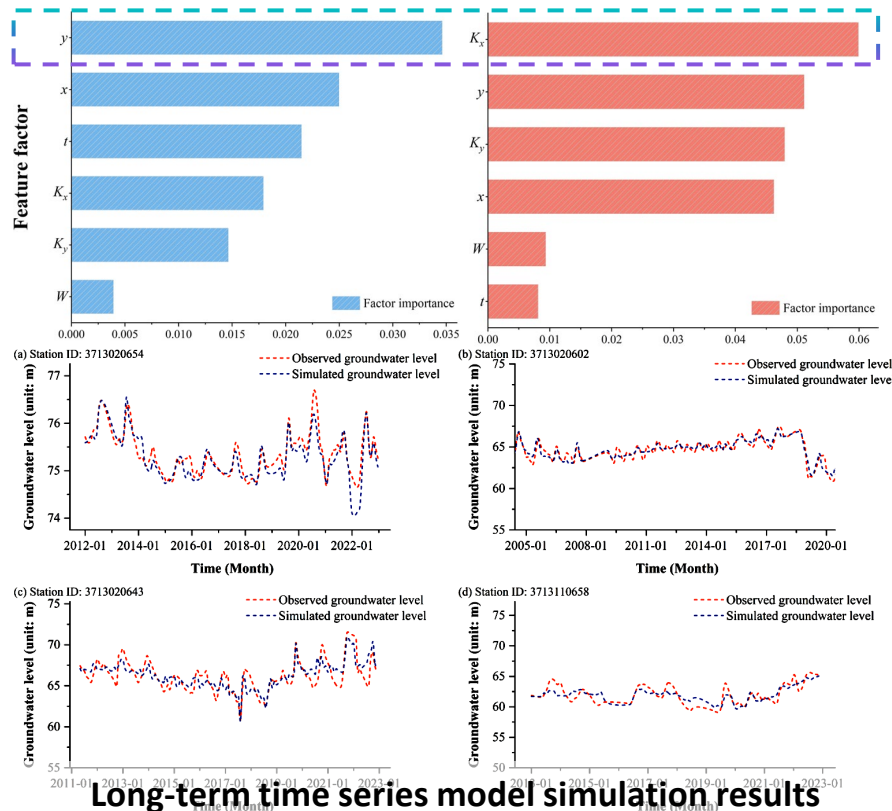


→ THE EUROPEAN SPACE AGENCY

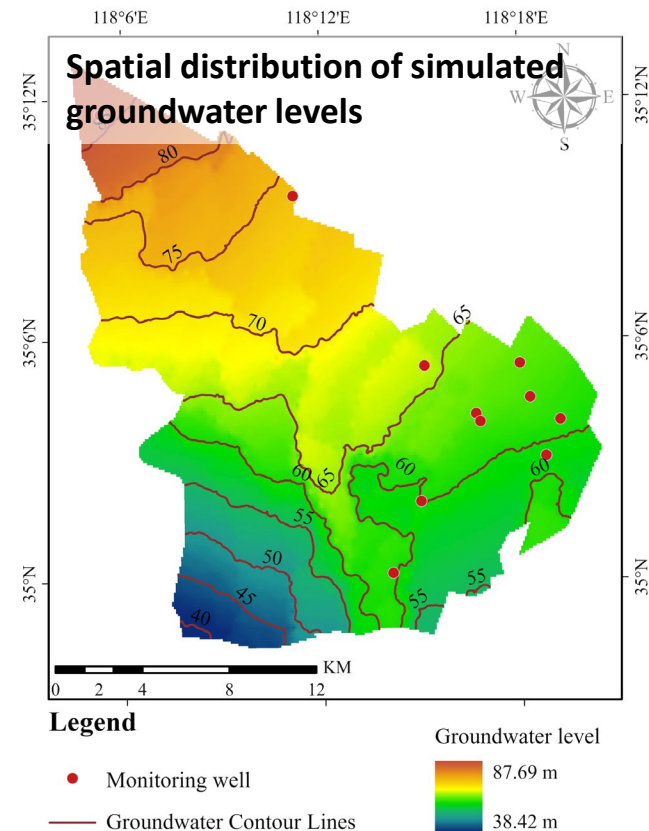
The SHAP (SHapley Additive exPlanations) framework is employed to interpret the prediction outputs of both the MLP and the PINNs models, quantifying the global constraining effect of physical mechanisms on network training.

While the MLP model captures local spatial variability at monitoring points, the PINNs model—by integrating physical constraints into its loss function—demonstrates stronger physical consistency and significantly amplifies the contribution of the hydraulic conductivity factor as a driving factor.

Factor importance in MLP v.s. PINNs



Data Framework: Remote Sensing Big Data – Reanalysis Datasets – Station-based Small Data



Introduction

Hydrological Processes

Mechanical Response

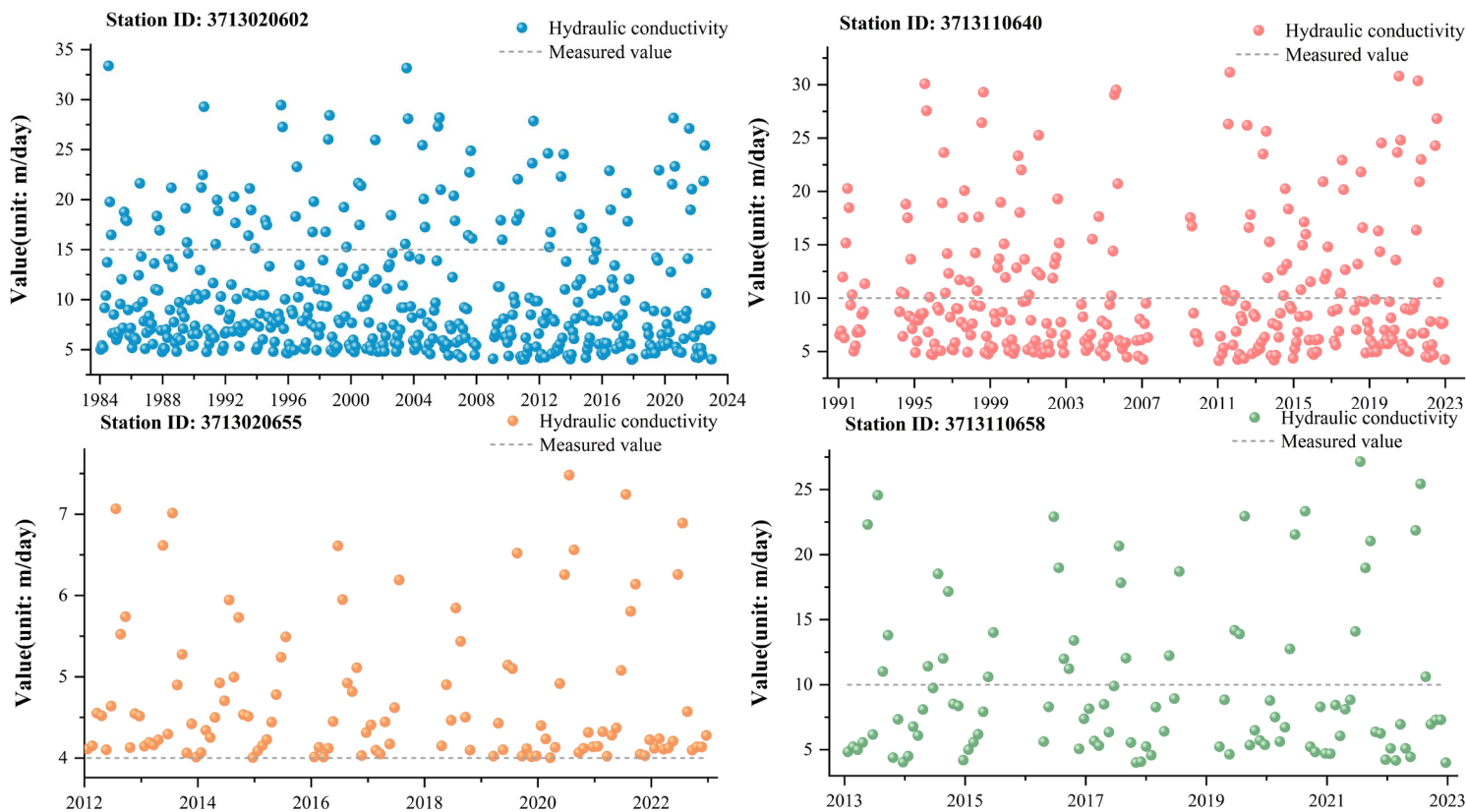
Fracture Evolution

Hydraulic conductivity inversion via PINNs

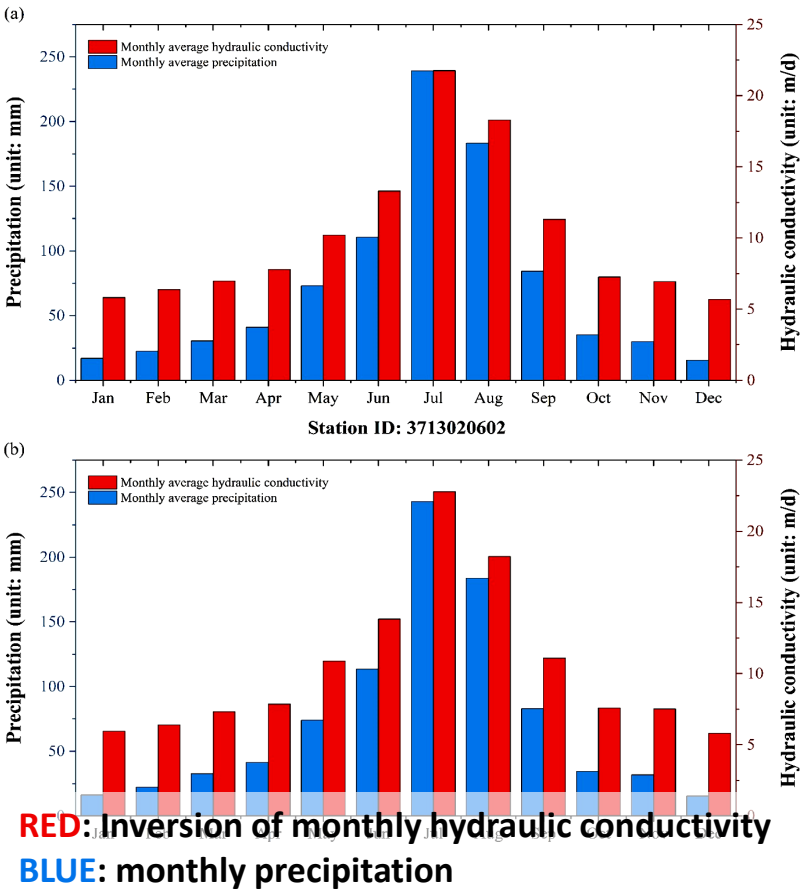


A significant correlation between temporal variations in hydraulic conductivity and precipitation events: during the peak rainfall season (Jun.–Aug.), hydraulic conductivity increases with precipitation inputs, followed by a gradual decline in dry and normal-flow periods.

This alignment between hydraulic conductivity inversion results and precipitation dynamics—consistent with fundamental physical principles—confirms the robust physical interpretability of the PINNs model.



Results of hydraulic conductivity parameter inversion using the PINN model



Peridynamics (PD) model v.s. traditional models



中国科学技术交流中心
China Science and Technology Exchange Center



→ THE EUROPEAN SPACE AGENCY

Methods	Authors and time	Model size
Finite difference method (FDM)	Wang et al, 2013	3500×2800×1335 m
Finite element method (FEM)	Bray et al, 1994	107×30.5×61 cm
	Panda et al, 2015	1500×12000 feet
Interface Elements (IEs)	Ye et al, 2018	15000 km ²
	Li et al, 2021	600×165×50 m

The above numerical models are fundamentally rooted in **continuum mechanics theory**.

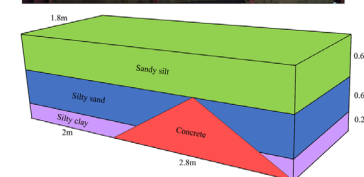
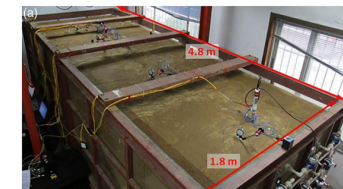
However, earth fissuring represents **a discontinuous geological phenomenon by nature!**

Traditional models struggle with discontinuities, but PD excels:

- ❑ Nonlocal integral formulation avoids mesh dependency
- ❑ Simulates arbitrary crack paths without a priori knowledge

A sandbox experiment was conducted in this study, yielding the following results:

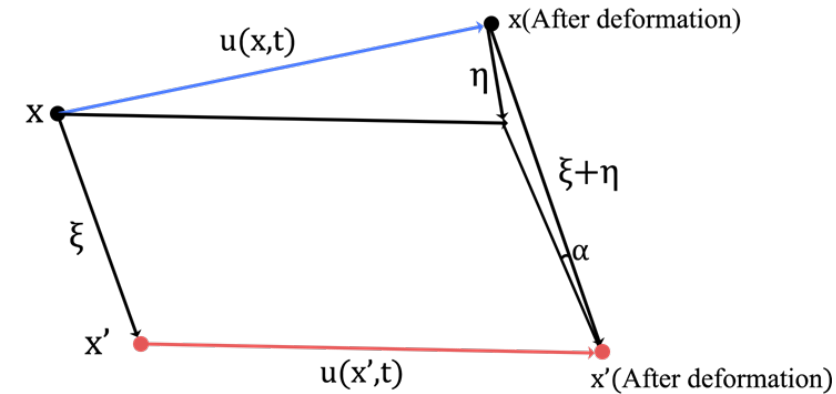
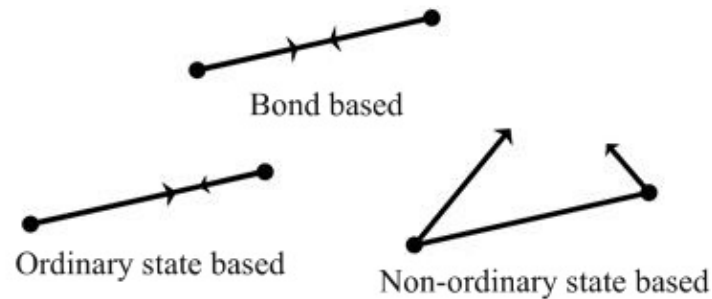
- ❑ Predicted fissure length: 1.8 m (match with observation)
- ❑ Width/depth discrepancies (0.5 mm vs. 3.5 mm) highlight stress concentration effects





The Peridynamics (PD) method (proposed by Silling in 2000) has demonstrated successful applications in solid mechanics across both macroscale and microscale problem domains. This approach can be taxonomically categorized into two principal frameworks:

- **Bond-based model**: comparatively simple but limited;
- **State-based model** (ordinary / nonordinary state-based model): possible to incorporate general material models.



density acceleration force vector state field loading force density

$$\rho(x)\ddot{u}(x,t) = \int_{\mathcal{H}_x} \{\underline{T}[x,t]\langle x' - x \rangle - \underline{T}'[x,t]\langle x - x' \rangle\} dVx' + b(x,t)$$

spherical neighborhood of radius δ centered at x

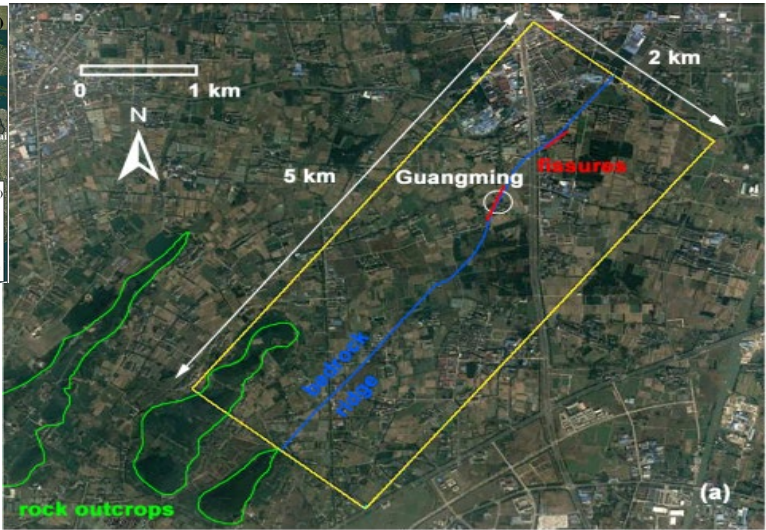
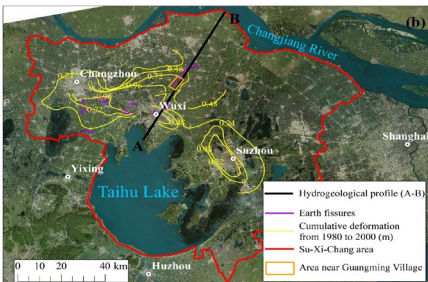
Simulation of Earth Fissures via PD method



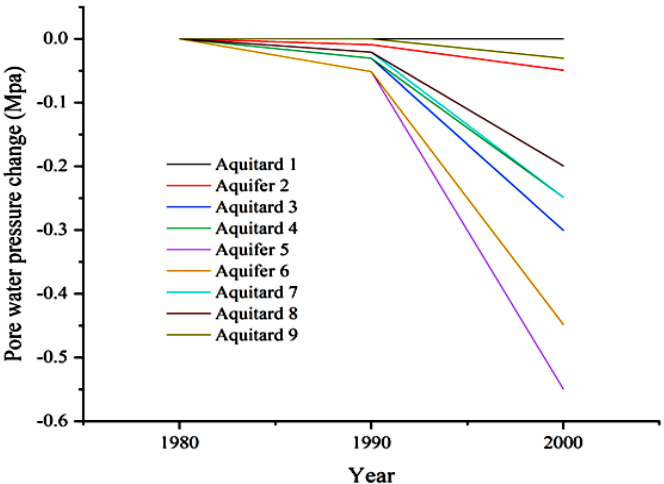
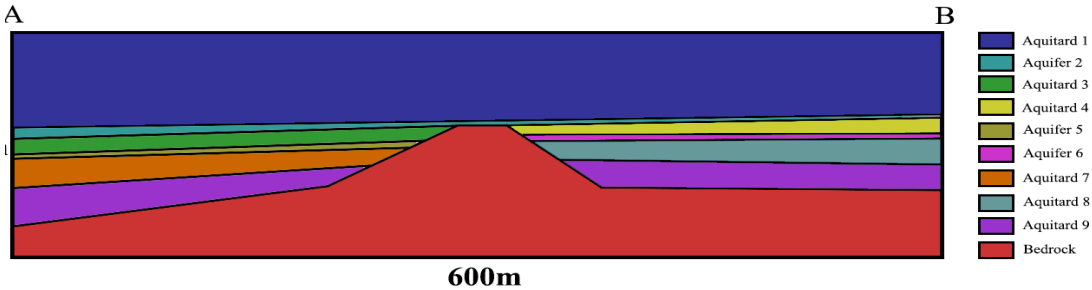
中国科学技术交流中心
China Science and Technology Exchange Center



THE EUROPEAN SPACE AGENCY



Material parameters		
	Elastic modulus E (Gpa)	Poisson's ratio ν
Aquifer	18.0	0.25
Aquitard	3.6	0.25



The model framework comprises bedrock, three aquifers, and seven aquitards, with the peridynamic (PD) domain spanning 600×35×170 m.

Bottom: a fixed boundary

The other boundaries: move freely in directions

Soil material:

$\rho = 2200 \text{ kg/m}^3$; the internal friction angle $\varphi = 30^\circ$; the cohesion $c = 0.01 \text{ Mpa}$;

The pore water pressure of each stratum was generalized according to the measured groundwater head (Ye et al. 2019), which was the same with Li et al. (2021).

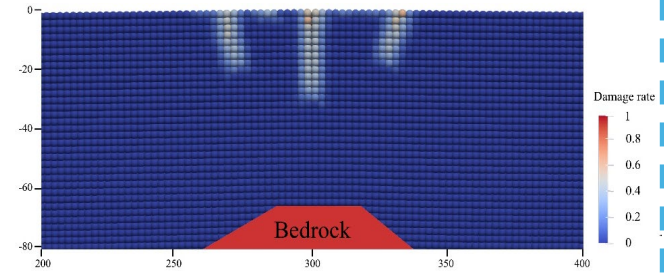
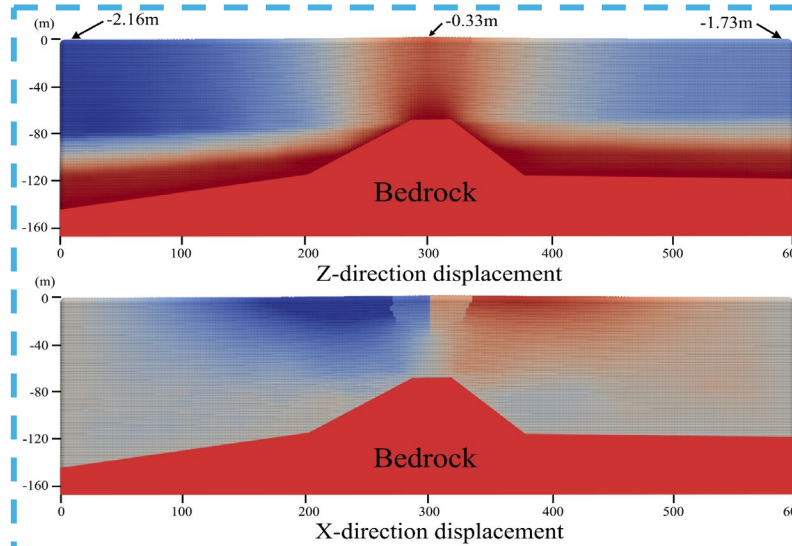
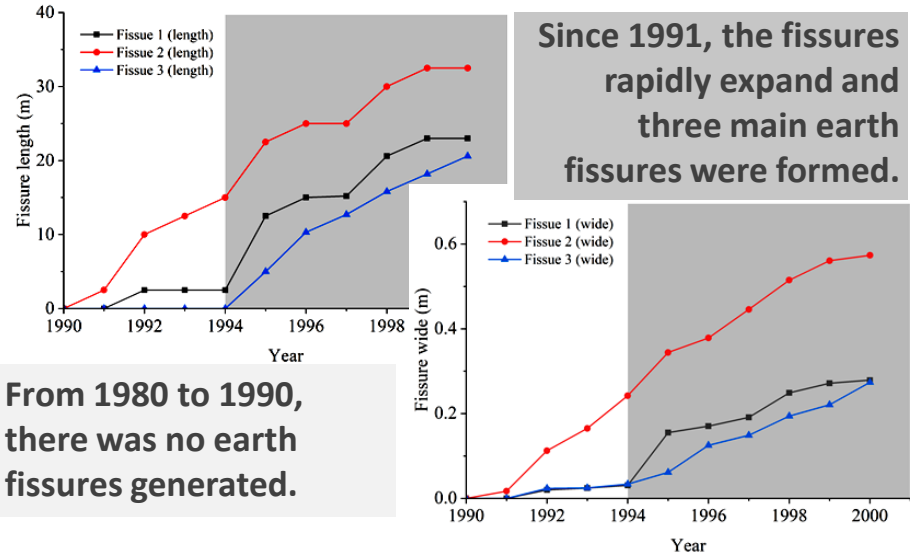
Simulation of Earth Fissures via PD method



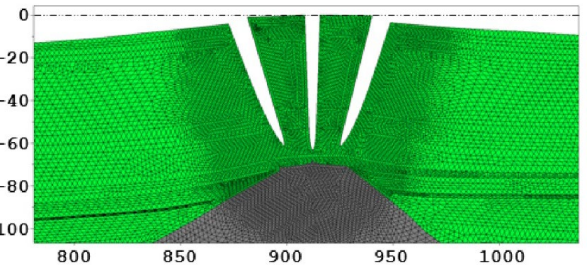
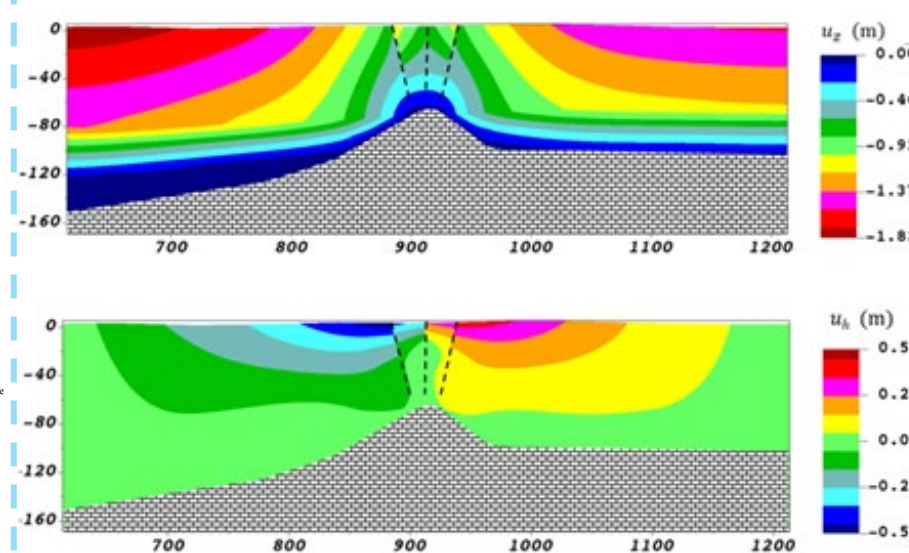
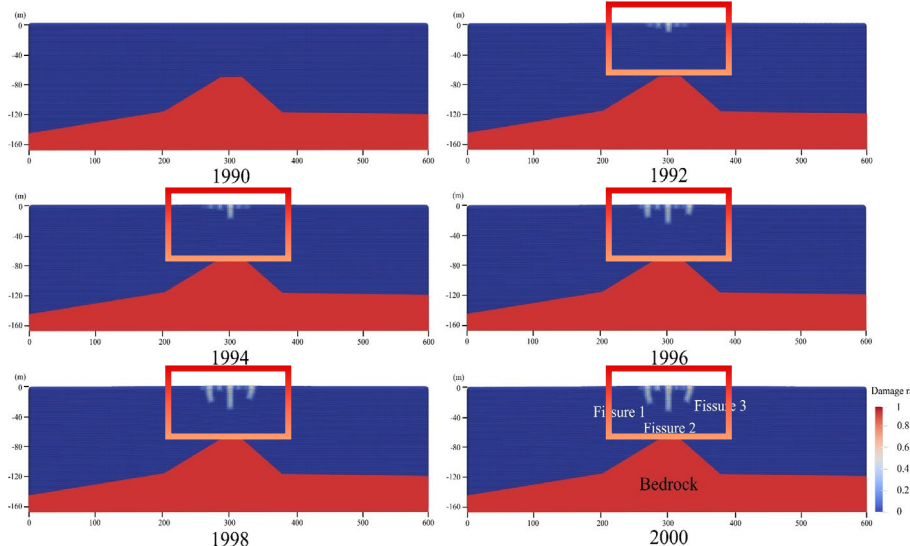
中国科学技术交流中心
China Science and Technology Exchange Center



→ THE EUROPEAN SPACE AGENCY



Notably, beyond the three primary fissures, the PD model also simulates secondary fissures, ensuring that the randomness of fracture planes captures crack propagation paths more consistent with field observations.



Introduction

Hydrological Processes

Mechanical Response

Fracture Evolution



Major points:

- ❑ Various processes contributes to the observed land subsidence in Urban area
- ❑ Recent measurement techniques provide information that appears fundamental for:
 - Understanding the change-response processes of water-soil systems at scales from urban area to the sedimentary basin
 - developing and calibrating simple / complex models for the simulation of geomechanical processes
- ❑ Integration of InSAR measurements and physics-informed simulation approaches (e.g., PINNs and peridynamics) produces an important step foreward for a reliable prediction of several geomechanical processes (land subsidence, earth fissuring, etc)

Dragon 6 EO Data Delivery



Data access (list all missions and issues if any). NB. in the tables please insert cumulative figures (since June 2024) 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 /Copernicus Missions	No. Scenes	ESA Third Party Missions	No. Scenes	Chinese EO data	No. Scenes
1. SENTINEL-1	72	1. GRACE	ftp	1.	
2. SENTINEL-2	36	2. ERA-5	12 monthly	2.	
3.		3. GLDAS	12 monthly	3.	
4.		4.		4.	
5.		5.		5.	
6.		6.		6.	
Total:	108	Total:		Total:	
Issues:		Issues:		Issues:	

Schedule, planning & contribution for 2026



中国科学技术交流中心
China Science and Technology Exchange Center



→ THE EUROPEAN SPACE AGENCY

Jul. - Sep. 2025

**Data gathering
(EO and in situ)**

Jan. - Mar. 2026

Implementation

Oct. - Dec. 2025

**Methodology
development**

Apr. - Jun. 2026

**Communication and
Dissemination**

Chinese Young Scientists contributions in Dragon 6



Name	Institution	Poster title	Contribution including period of research
Zijian Wang	Capital Normal University	Groundwater Level Modeling with Physics-Informed Neural Networks: A Novel Physics-Constrained and Transferable Approach	



中国科学技术交流中心
China Science and Technology Exchange Center



→ THE EUROPEAN SPACE AGENCY

Interpretable Physics-Informed Neural Network Groundwater Level Simulation Model: A Case Study of Linyi, Shandong Province, China

Zijian Wang^{1,2}, Huili Gong^{1,2*}, Xiaojuan Li^{1,2}, Lin Guo^{1,2}, Lin Zhu^{1,2}, Beibei Chen^{1,2}, Mingliang Gao^{1,2}, Chaofan Zhou^{1,2}, Yinghai Ke^{1,2}, Wei Lyu^{1,2}

¹Beijing Laboratory of Water Resources Security, Capital Normal University, Beijing, 100048, China

²Key Laboratory of Mechanism, Prevention and Mitigation of Land Subsidence, MOE, Capital Normal University, Beijing, 100048, China

Contact: 4039@cnu.edu.cn; 2220902104@cnu.edu.cn

Driven by global climate change, the frequency of extreme weather and climate events has increased significantly in recent years. Climate change, extreme events, and human activities have exerted a profound impact on regional dual water cycle processes, triggering a series of geological hazards such as karst collapses and land subsidence. Accurate simulation and prediction of groundwater levels have thus become an urgent priority. To address this challenge, this study selects the Linyi monocline hydrogeological unit as the case study area and introduces a Physics-Informed Neural Network (PINN) model for groundwater level simulation, incorporating the 2-D unsteady groundwater flow equation as a physical constraint. Compared with traditional numerical models, the PINN model reduces reliance on detailed regional geological structures and hydrogeological conditions. Unlike conventional neural networks, PINN integrates physical equations into the loss function, enabling the coupling of linear physical constraints with nonlinear neural networks.



中国科学技术交流中心
China Science and Technology Exchange Center



→ THE EUROPEAN SPACE AGENCY



2025 DRAGON 6 SYMPOSIUM

14-18 JULY 2025

Thanks for your attention

PROJECT ID: 95393

PROJECT Title: Use of Earth Observation for Urban Security: addressing heat risk and geological hazards

