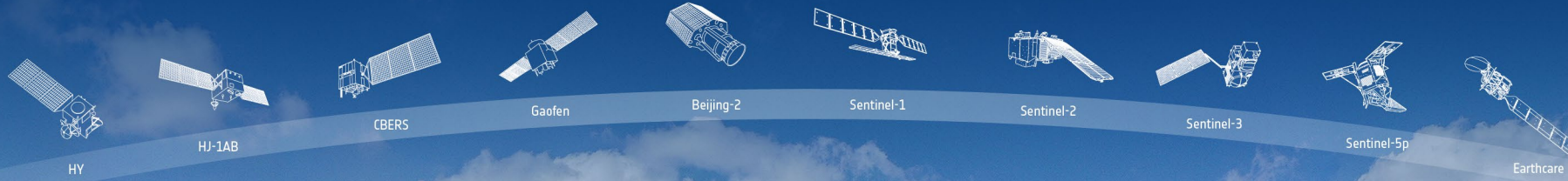




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2025 DRAGON 6 SYMPOSIUM

14-18 JULY 2025

PROJECT ID. 95445

INTEGRATING MULTISOURCE DATA FOR PRECISION FINE-SCALE
MONITORING OF CLIMATE-INDUCED FLOODS AND DROUGHTS





THURSDAY, 17 JULY 2025

ID. 165

PROJECT TITLE: 95445 - INTEGRATING MULTISOURCE DATA FOR PRECISION, FINE-SCALE MONITORING OF CLIMATE INDUCED FLOODS AND DROUGHTS

PRINCIPAL INVESTIGATORS: PROF. WEIWEI GUO AND PROF. MIHAI DATCU

CO-AUTHORS: PROF. ZENGHUI ZHANG AND DR. MADALINA CIUCA

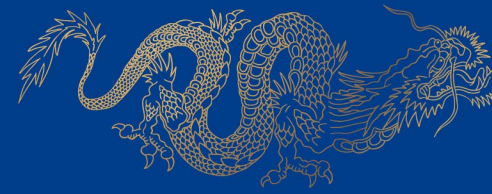
PRESENTED BY: PROF. WEIWEI GUO

Dragon 6 Project Objectives



Objectives	Expected Results
O1. Joint China - ESA EO missions synergy analysis (WP2)	• Characterize the ESA and China EO data for flood and drought monitoring, assessment and prediction tasks. • Develop synergy mechanism and approaches across different resolutions, times, platforms, and data modes to obtain consistent and fine-grained results.
O2. Establish joint EO benchmark datasets for floods and drought monitoring (WP3)	• Curate a large-scale EO benchmark dataset for floods and drought analysis, containing not only ESA and China EO imagery data with different modes, (multispectral, SAR, etc.), but other climate related data - time series of precipitation, moisture, temperature, covering historical flooded and drought regions.
O3. Build a multimodal EO model to climate-related information extraction for multisource and multitemporal EO data (WP4, WP5)	• Develop multi-modal self-supervised representation learning techniques with multi-modal EO data. • Develop self-supervised representation learning techniques for SITS data.
O4. Develop AI-enabled flood and drought prediction model (WP4, WP5)	• Develop hybrid prediction model which combines the physical-based and deep learning algorithm. • Develop a multi-modal deep data fusion method for flood and drought prediction (including weather, satellite imagery and river data, etc).

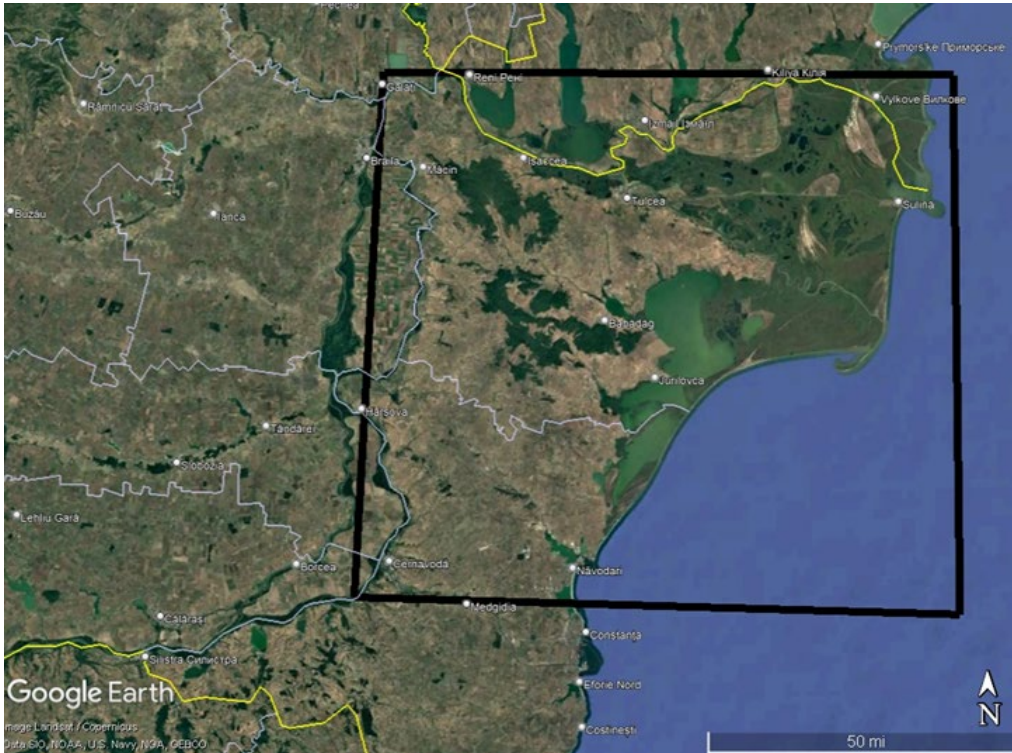
Project Main Study Sites



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 **Danube Delta, Dobrogea Region, Romania**



 **Poyang Lake, Jiangxi Province, China**

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”

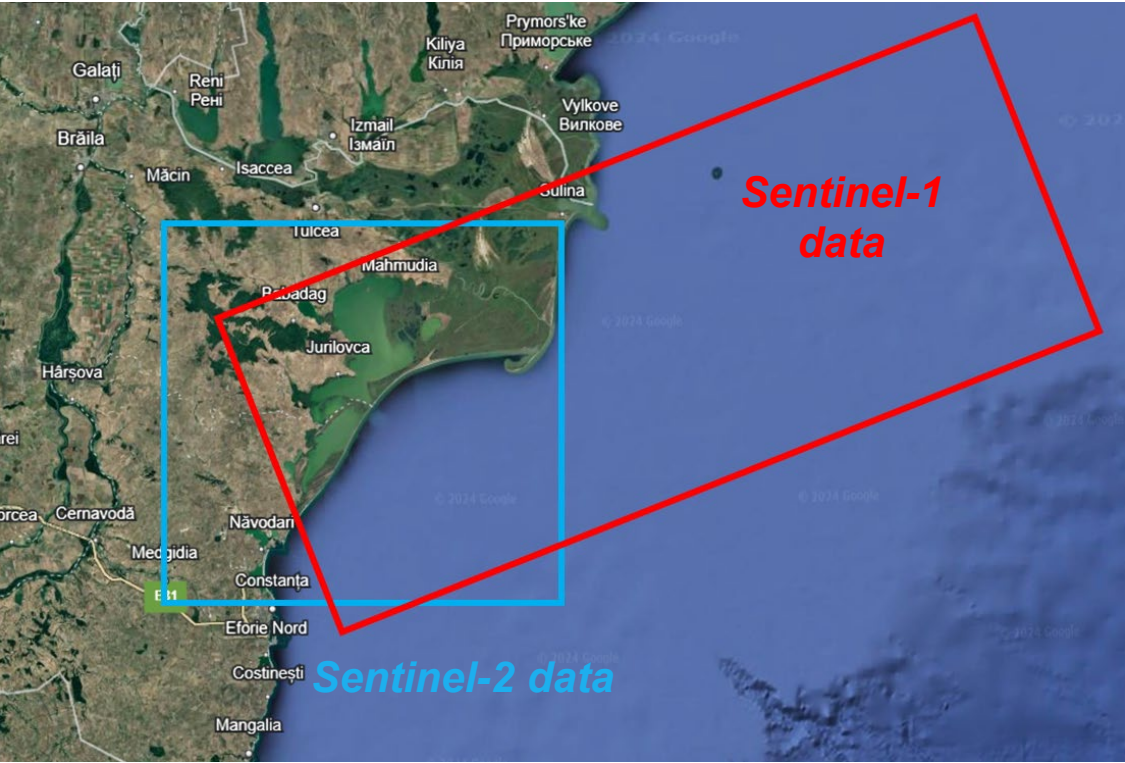
ESA /Copernicus Missions	No. Scenes	ESA Third Party Missions	No. Scenes	Chinese EO data	No. Scenes
1. Sentinel1 (Stripmap, 2017-2028)		1. SPOT6_7		1. FY-3A/B Medium Resolution Spectral Imager (MERSI) 2016-2020	
2. Sentinel2 (MSI, L2a, 2017-2028)		2.Worldview_Geoeye_Quickbird_HighResOptical		2. FY-3A/B Micro-Wave Radiation Imager (MWRI) 2016-2020	
3. Sentinel-4 - Future Access		3. ICEYE (2018-2028)		3. FY-4A/B AGRI - Advanced Geosynchronous Radiation Imager (2024-2028)	
4. Sentinel-5 (UVNS, L1) - Future Access		4. TerraSAR_X (2018-2028)		4. GF-6 WFV (Wild field Camera) (2024-2028)	
5. ENVISAT (2005-2012)		5. PAZ		5. Jilin-1 High Resolution Optical Imager (JL1-GP01 and JL1-GP02) (2024-2028)	
6. AEOLUS		6.		6. Luojia-1A (LJ1-01) (2024-2028)	
7. EARTHCARE - Future Access		Total:		7. SDGSAT-1 MSI Multispectral Imager (2024-2028)	
Total:				Total:	
Issues:		Issues:		Issues:	
5. Level 2A: Scientific aerosol/cloud profile product		1. SPOT_6_7_Color_or_bundle_all_production_levels - MONO - Total No. of km2 = 8000		Considered for Future Access	
6. ASAR IM,AP,WS,GM (PRI and SLC)		2. VIEW_READY_STEREO_PAN - resolution 30cm - - Total No. of km2 = 8000		FY-3F - Feng Yun -Polar-orbiting Meteorological Satellite	
		3. Strip		FY-3C/D for future MWRI data access (after 2019)	
		4. Basic_Products_StripMap		FY-4C Geostationary Meteorological Satellite (from 2024)	
		5. StripMap mode (SM)		HJ-2E SAR S-BAND & HJ-2F SAR S-BAND	
				JL1-GP01 and JL1-GP02 requires payment for access	
				SDGSAT-1 needs proposal to access	



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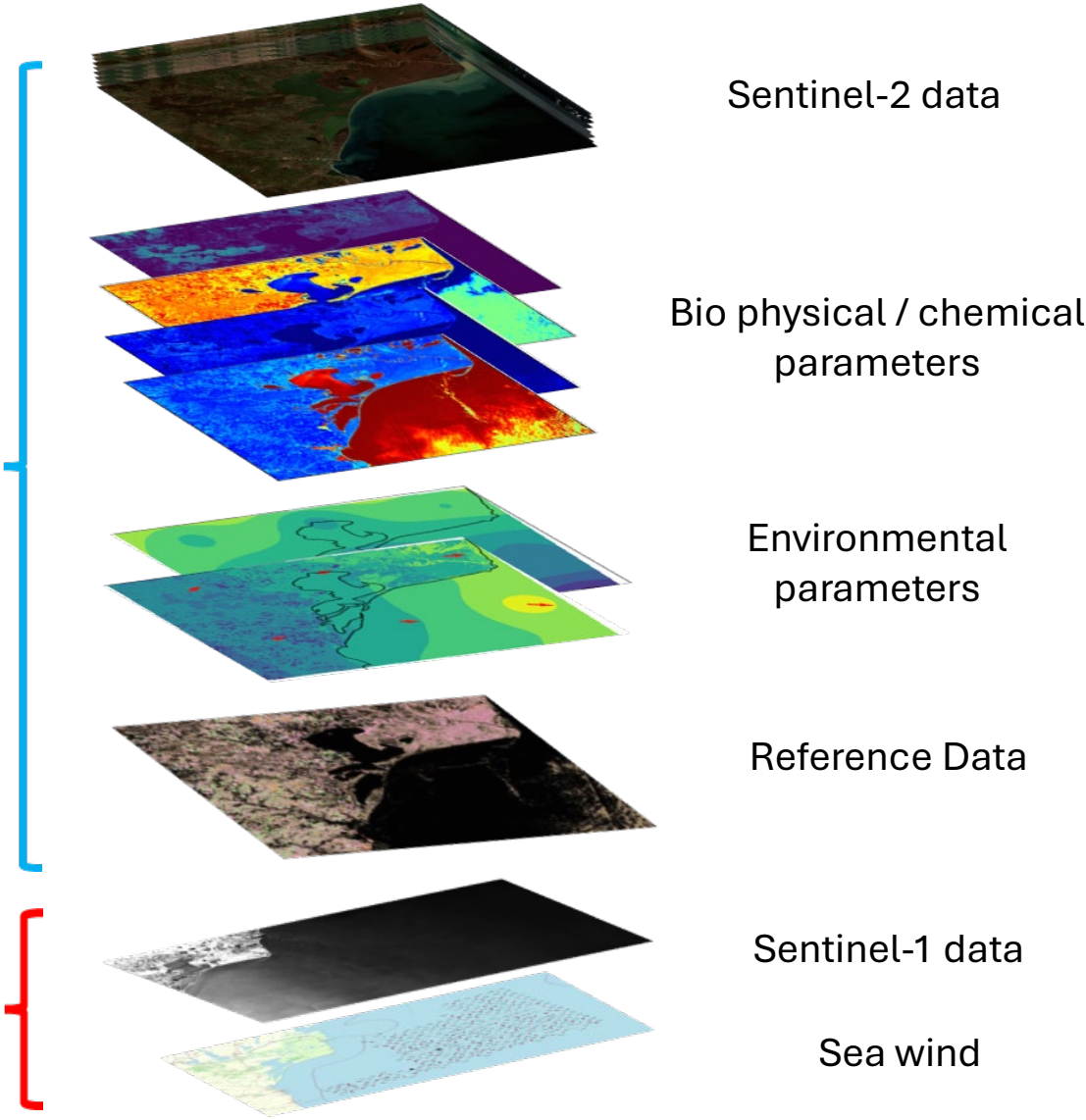


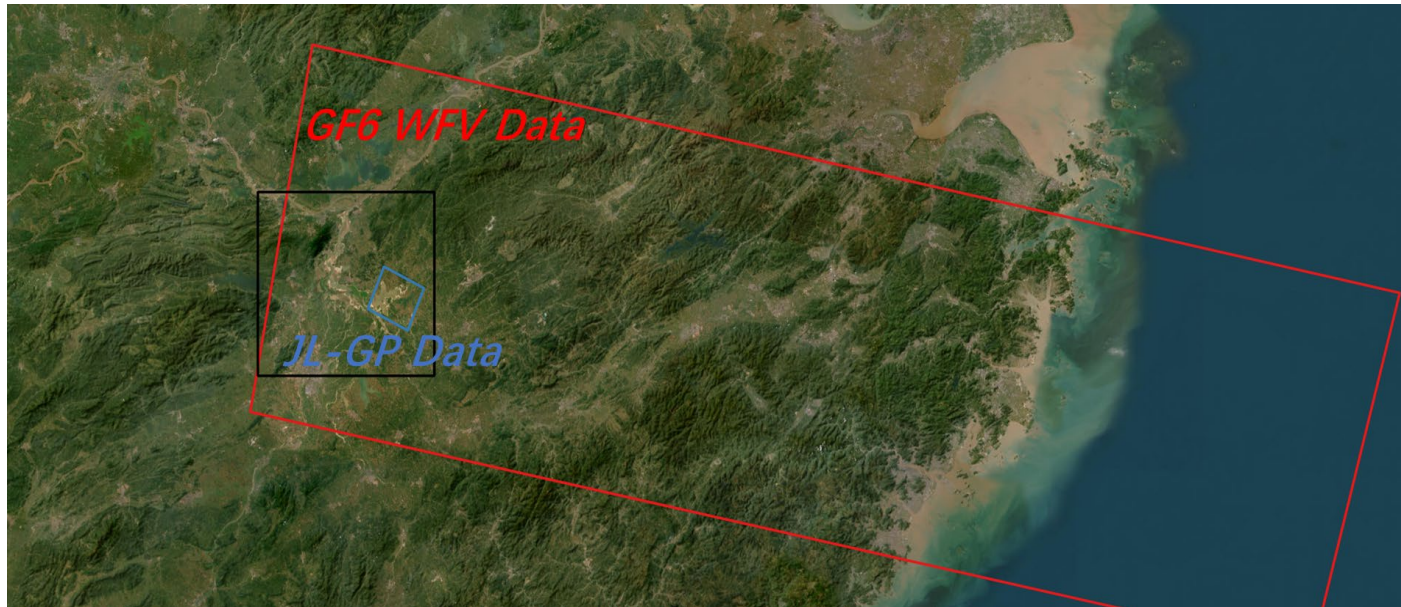
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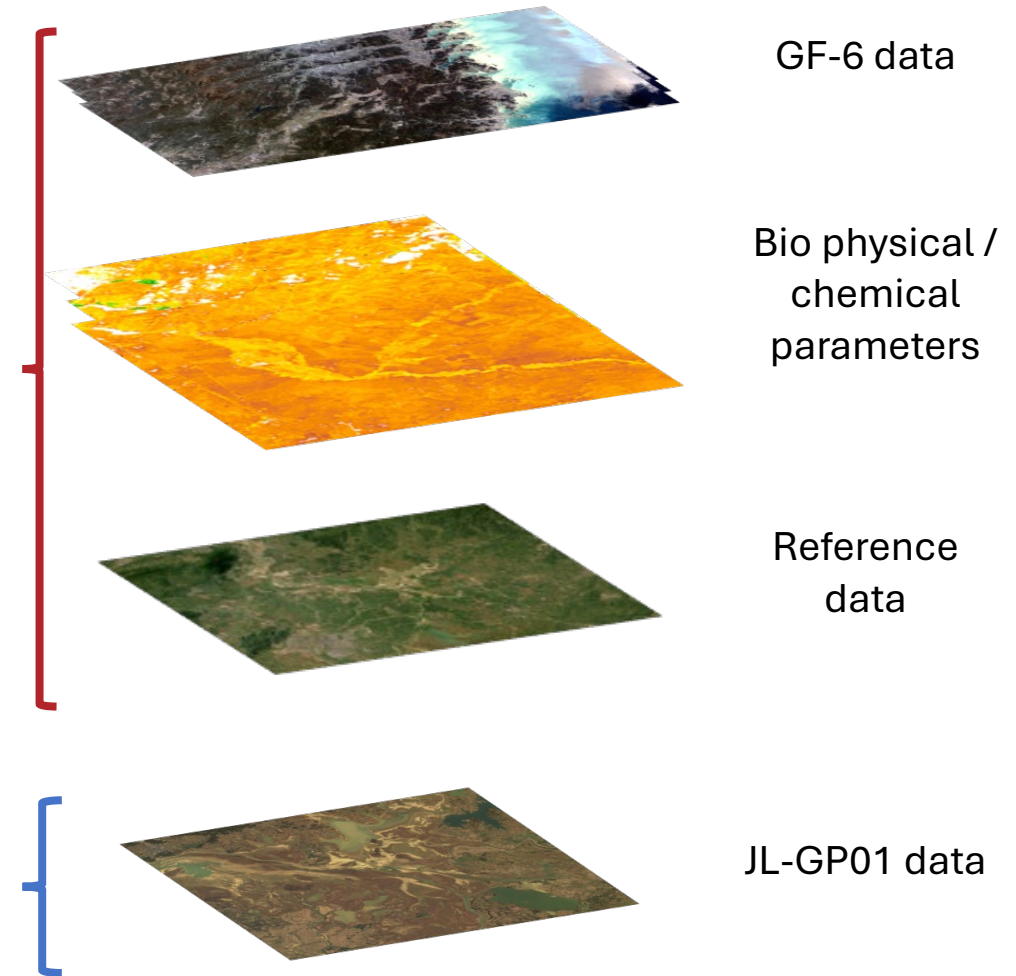
Danube Delta, Dobrogea Region, Romania

Catalin-Andrei Miu and M. Datcu, "Causal drought risk assessment fusing meteo data and satellite image time series: case study of Nuntasi lake," *2024 Advanced Topics on Measurement and Simulation (ATOMS)*, Constanta, Romania, 2024, pp. 31-33, doi: 10.1109/ATOMS60779.2024.10921575





Poyang Lake: GF-6 & JL-GP Footprints



Dragon 6 Project Schedule and Planning



Batch 3 KickOff: April 2025

2025

- Synergy comparison, generation of analysis ready time series (EO & climate data) **WP2, WP3**
- Data pre-processing, preliminary analysis **WP4, WP5**

2026

- Continuous data integration **WP3**
- Advanced data analysis **WP4, WP5**
- Presentation at Dragon symposium 2026 **WP6**
- Preparation of one or more journal papers

2027

- Continuous data integration **WP3**
- Advanced data analysis **WP4, WP5**
- Presentation at Dragon symposium 2027 **WP6**

2028-2029

- Working towards final analysis **WP4, WP5**
- Presentation at Final Dragon6 symposium **WP6**
- Preparation of one or more journal papers **WP6**

Young Scientists contributions in Dragon 6



Chinese Young Scientists

Name	Institution	Poster title	Contribution including period of research
Limeng Zhang	Shanghai Jiaotong University	MMCD: Memory-Based Multimodal Change Detection	Develop algorithms on Satellite image Time series and change detection.
Yanpu Ying	Tongji University		Develop spatial-temporal prediction algorithms on Satellite image Time series and change detection, and climate-related data.

European Young Scientists

Madalina Ciuca – National University of Science and Technology Politehnica Bucharest
Catalin Miu – National University of Science and Technology Politehnica Bucharest
Chandrabali Karmakar – National University of Science and Technology Politehnica Bucharest



MMCD: Memory-Based Multimodal Change Detection

Change detection across multi-sensor images acquired at different times

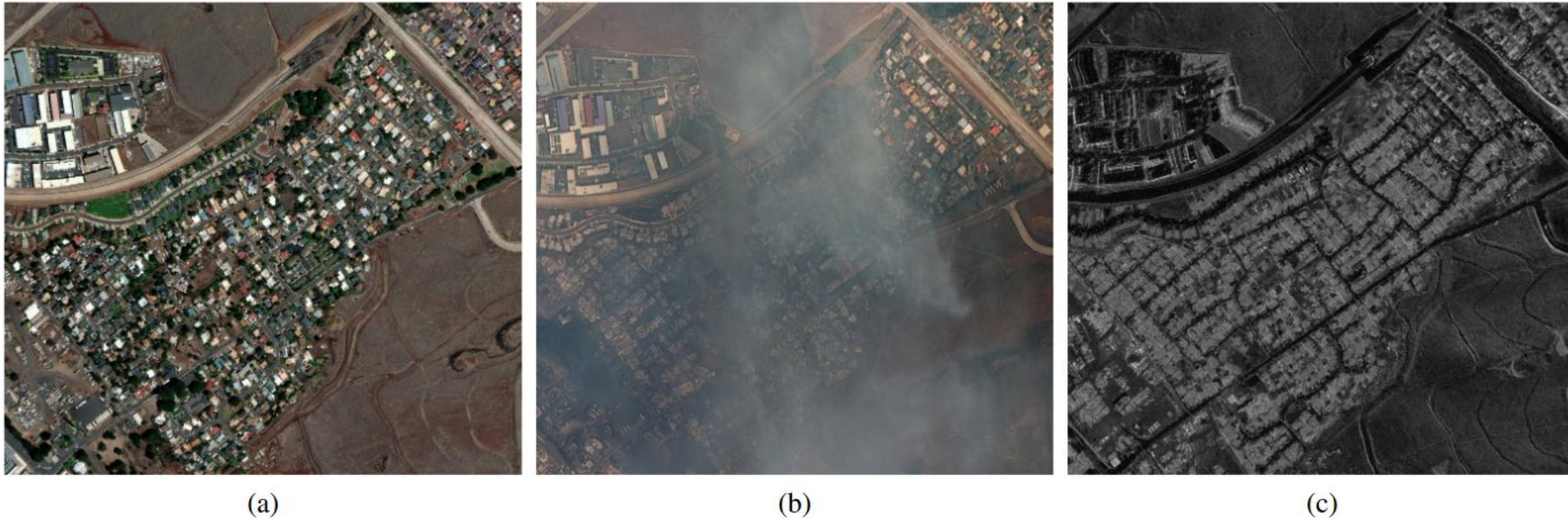


Fig. 1 An example of the wildfire occurring in Maui, Hawaii, USA, August 2023. (a) Pre-event optical imagery (Maxar). (b) Postevent optical image (Maxar) with land-cover features obscured by smoke from wildfires. (c) Post-event SAR imagery (Capella Space) unaffected by smoke, clearly showing disaster area.

Overview of Chinese YSs research (1)

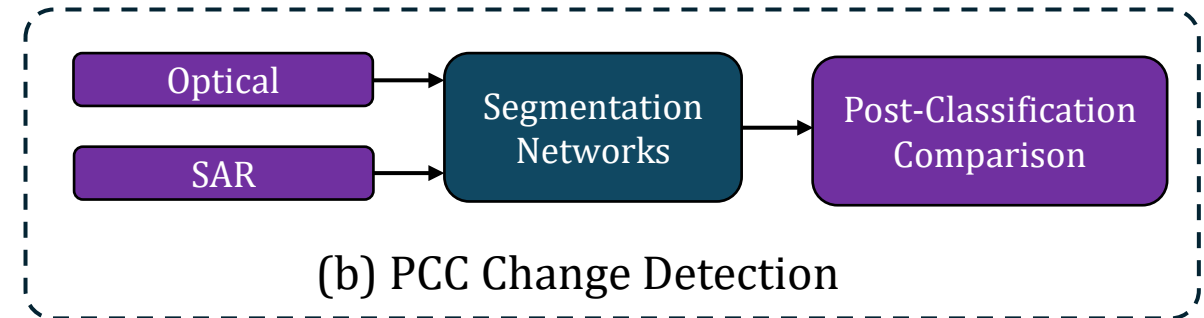
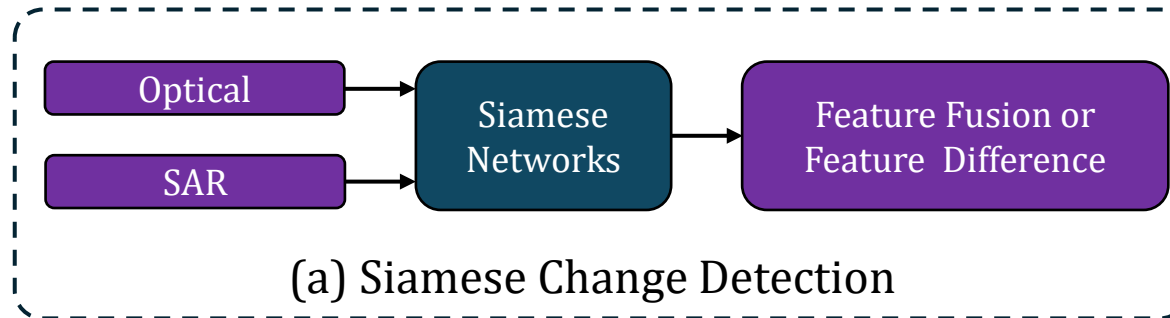


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- Change Detection Paradigm



- Tuning Foundation Models

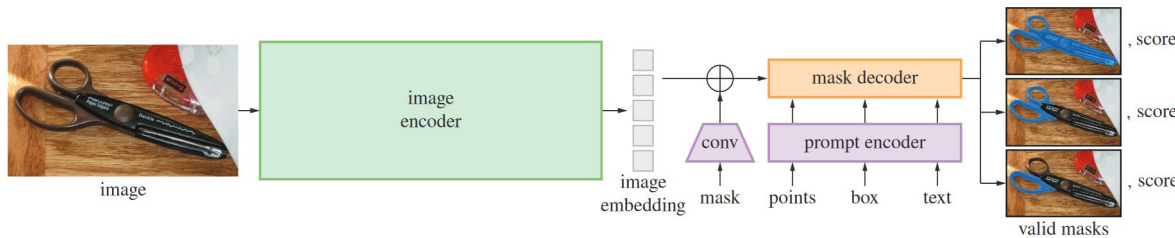


Fig.3 SAM Framework. Trained on an extremely large-scale dataset, SAM possesses powerful feature extraction capabilities. With appropriate tuning, the model can be adapted to the remote sensing domain, enhancing change detection performance.

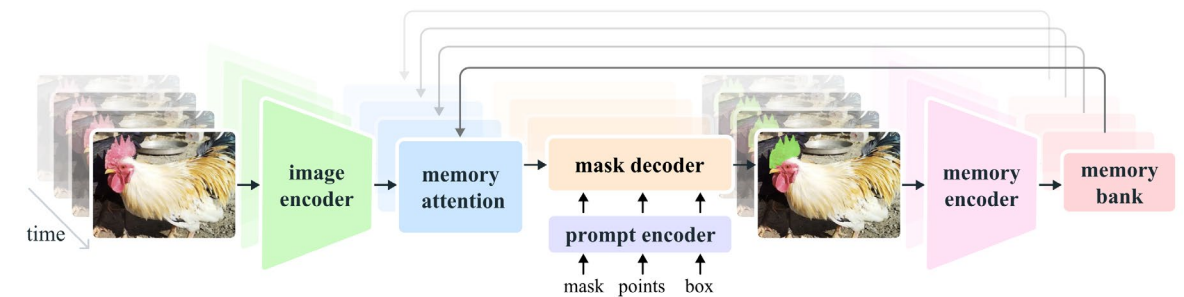


Fig.4 SAM2 extends SAM to video sequences by incorporating memory, enhancing accuracy and efficiency. Each frame is stored in a memory bank, where memory attention integrates features across time, effectively leveraging multi-temporal information for change detection.



Overall Architecture

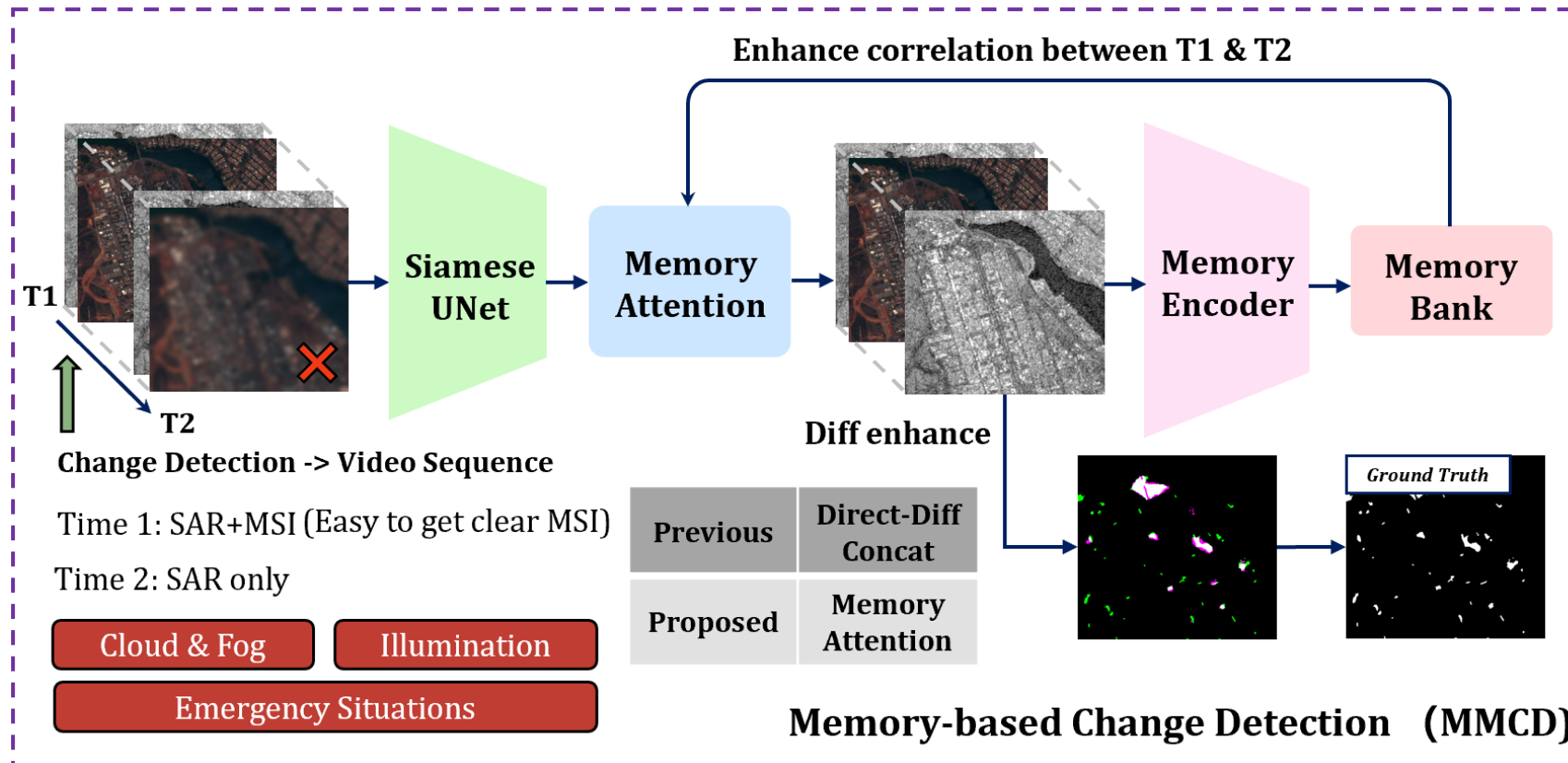


Fig.2 Motivation of the proposed MMCD. Introduce concept of memory into the multimodal change detection by utilizing historical information when post-time optical images are unusable due to degradation.

Overview of Chinese YSs research (1)



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Onera Satellite CD (OSCD) dataset , a popular multimodal change detection dataset

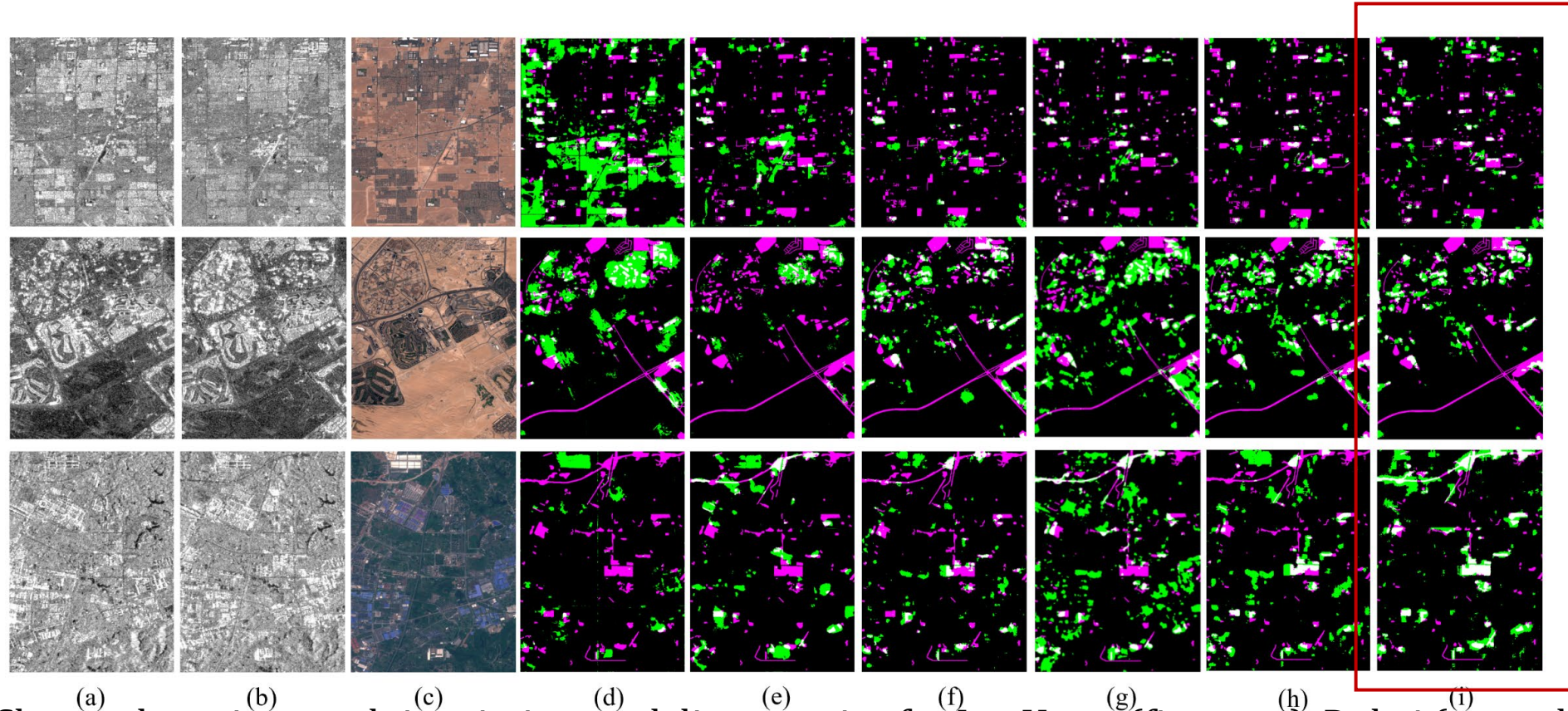


Fig.5 Change detection result in missing modality scenarios for Las Vegas (first row), Dubai (second row) and Chongqing (last row): (a) SAR image captured at T1. (b) SAR image captured at T2. (c) Optical image captured at T1. (d) Result of EF-CNN (e) Result of FC-Siam-conc. (f) Result of MSCD. (g) Result of Siamese. (h) Result of SmaDS. (i) Result of the proposed MMCD. The colors white, green, magenta, and black denote TP, FP, FN and TN, respectively.



- Experiment Results

Method	Prec	Rec	Acc	F1
EF-CNN	0.180	0.218	88.58	0.197
EF-UNet	0.220	0.390	89.70	0.277
Siamese-CNN	0.189	0.272	89.68	0.223
FC-Siam-conc	0.202	0.357	89.96	0.258
FC-Siam-diff	0.220	0.321	90.71	0.261
Fres-UNet	0.225	0.364	88.60	0.278
MSCD	0.364	0.237	91.91	0.287
DS-UNet	0.256	0.334	91.53	0.290
Siamese-UNet	0.220	0.470	89.10	0.303
Siamese-UNet-TTA	0.270	0.410	91.28	0.321
SmaDS	0.341	0.327	91.26	0.334
MMCD (proposed)	0.384	0.378	93.66	0.381

Table 1. Change detection results with pre-SAR, post-SAR and pre-optical images.

- Abaltion Results of Two Inputs.

Method	Data Setting	Prec	Rec	F1
EF-UNet [8]	Pre: optical, Post: SAR	0.100	0.600	0.171
Siamese-UNet [15]	Pre: optical, Post: SAR	0.154	0.291	0.201
SmaDS [16]	Pre: optical, Post: SAR	0.265	0.173	0.209
MMCD (proposed)	Pre: optical, Post: SAR	0.208	0.376	0.268
EF-UNet [8]	Pre: SAR, Post: SAR	0.140	0.610	0.229
Siamese-UNet [15]	Pre: SAR, Post: SAR	0.182	0.350	0.240
SmaDS [16]	Pre: SAR, Post: SAR	0.171	0.423	0.244
MMCD (proposed)	Pre: SAR, Post: SAR	0.283	0.307	0.295

Table 2. Change detection results for two input scenarios

- Ablation Results of Proposed Module.

Method	Prec	Rec	Acc	F1
MMCD-DEM	0.327	0.315	89.76	0.321
MMCD-MEM	0.319	0.364	90.56	0.340
MMCD-SAR	0.283	0.307	91.73	0.295
MMCD (proposed)	0.384	0.378	93.66	0.381

Table 3. Ablation results of DEM and MEM module.



Diff-MRCD: Diffusion-Based Multi-Resolution Change Detection for Remote Sensing Imagery

- Data obtained from different platforms faces challenges such as varying resolutions and modalities.

- Multimodal Change Detection



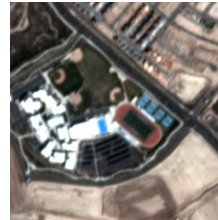
Platform1



Platform2

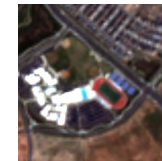
Has gained a lot attention.

- Multi-resolution Change Detection



T1-HR

Platform1



T2-LR

Platform2



GT

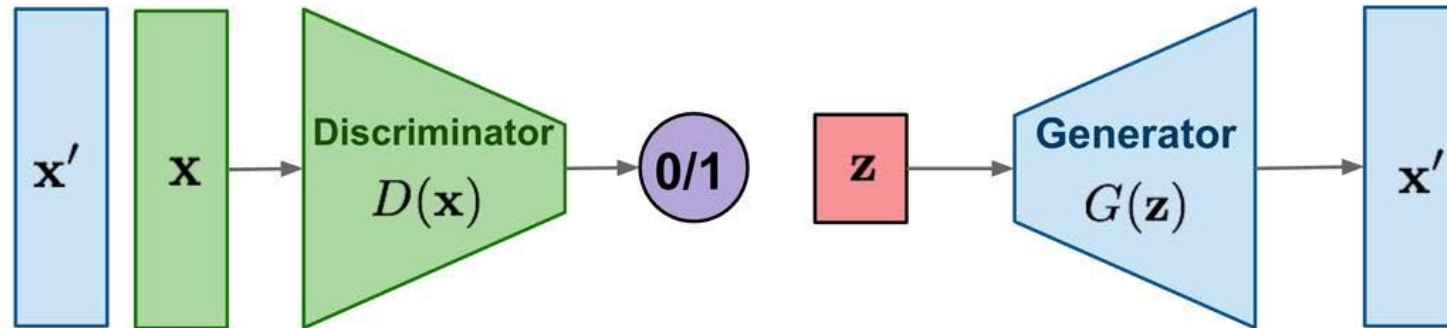
- 1) Direct resize. → Data distribution discrepancies result in degradation.
- 2) Super-resolution.
- 3) Map from one resolution to another resolution. → An overemphasis on mapping details may impair generalization performance in scenarios with substantial resolution variations.



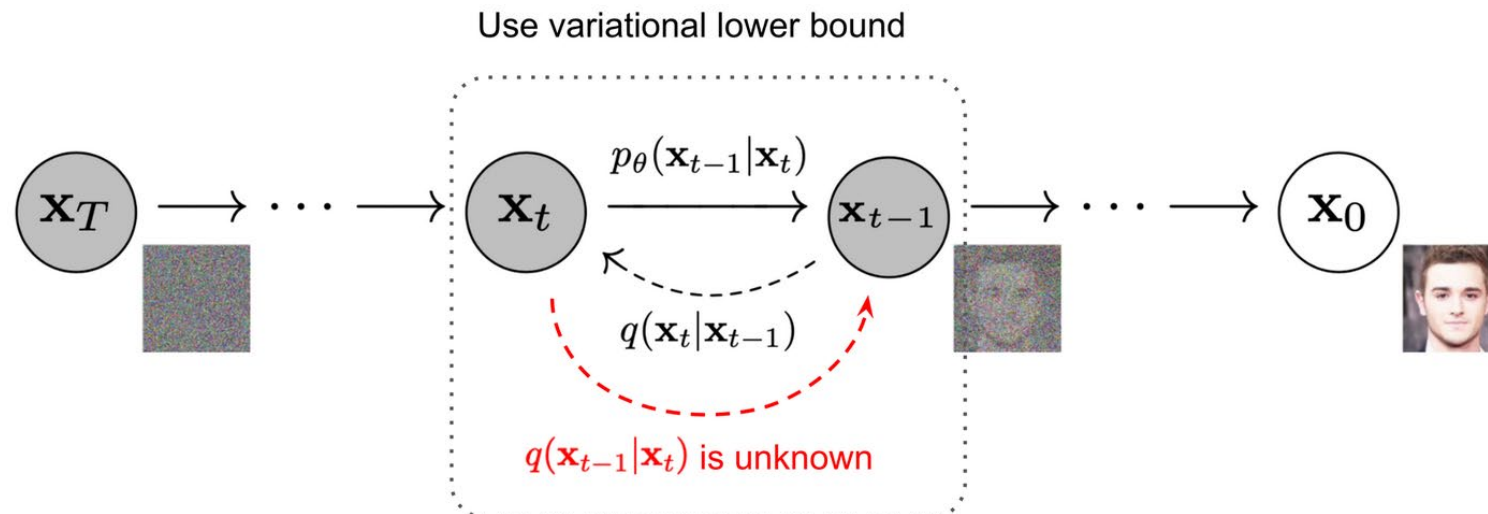
Diff-MRCD: Diffusion-Based Multi-Resolution Change Detection for Remote Sensing Imagery

- GANs

GAN: Adversarial training



- Diffusion Module (DDPM)





Diff-MRCD: Diffusion-Based Multi-Resolution Change Detection for Remote Sensing Imagery

Overall Architecture

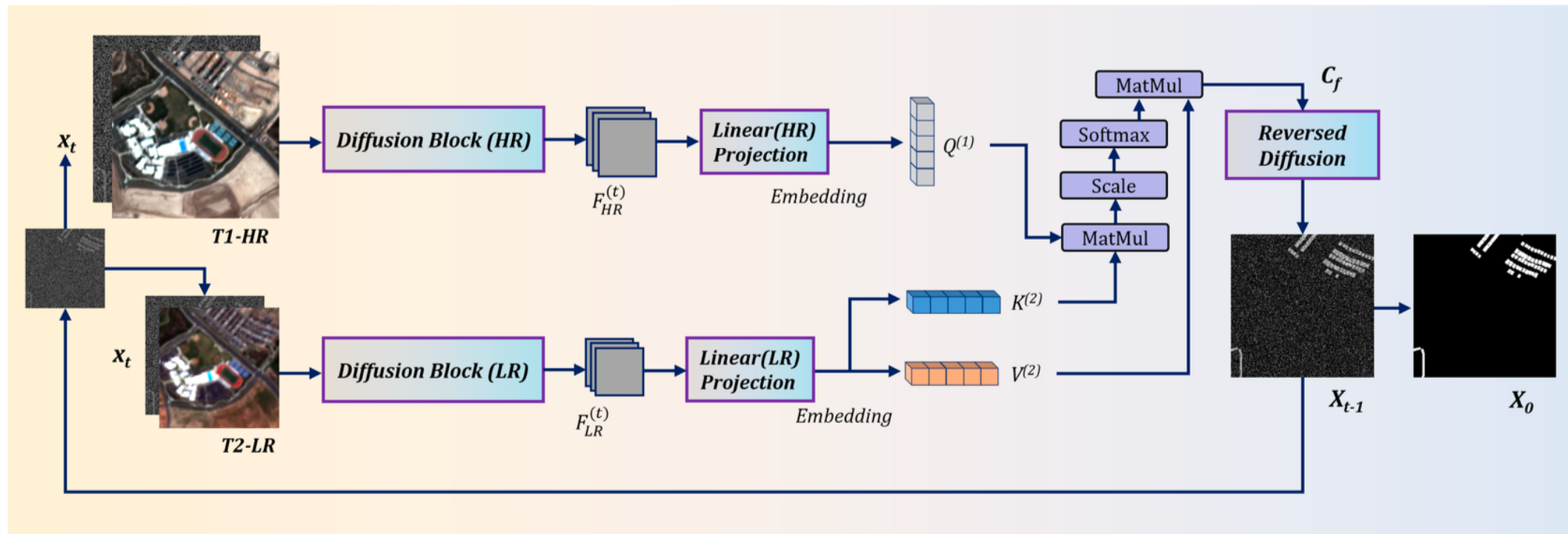


Fig. 1. An overview of the proposed Diffusion-Based Multi-Resolution Change Detection (Diff-MRCD) framework: For inputs with different resolutions, separate forward diffusion blocks are used to add noise. The extracted features are aligned through linear projection and a feature alignment module. Then, the aligned features are gradually restored through the reverse process to directly generate the change map for the next iteration. During inference, the model takes two images from different time points as input and generates the change detection map.

Overview of Chinese YSs research (2)



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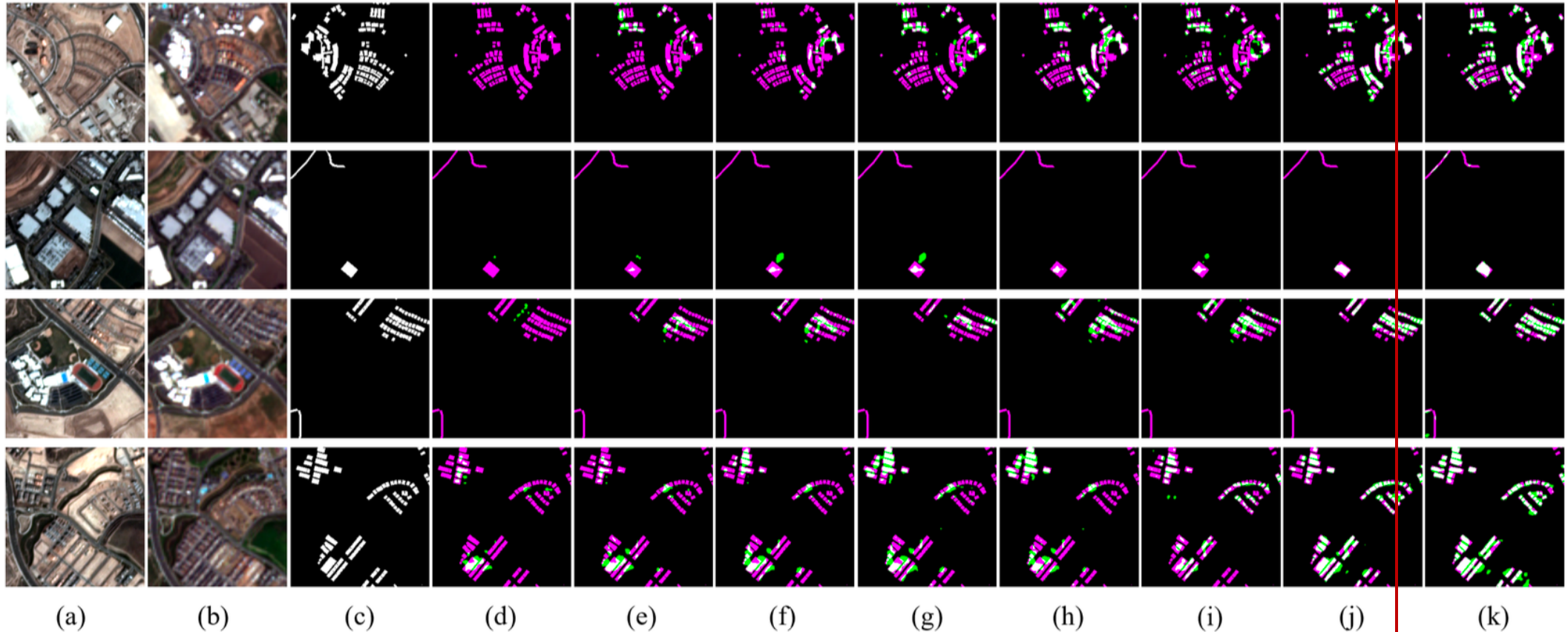


Fig. 2. Change detection results in multi-resolution scenarios for the DECD dataset. (a) Pre-time HR image. (b) Post-time LR image. (c) Change label. (d) Result of EF-EF [10]. (e) Result of STANet [12]. (f) Result of BIT [11]. (g) Result of SUNet [8]. (h) Result of SRCDDNet [4]. (i) Result of SLICD [5]. (j) Result of Diff-MRCD-base. (k) Result of the proposed Diff-MRCD. The colors white, green, magenta, and black denote TP, FP, FN, and TN, respectively.

Overview of Chinese YSs research (2)



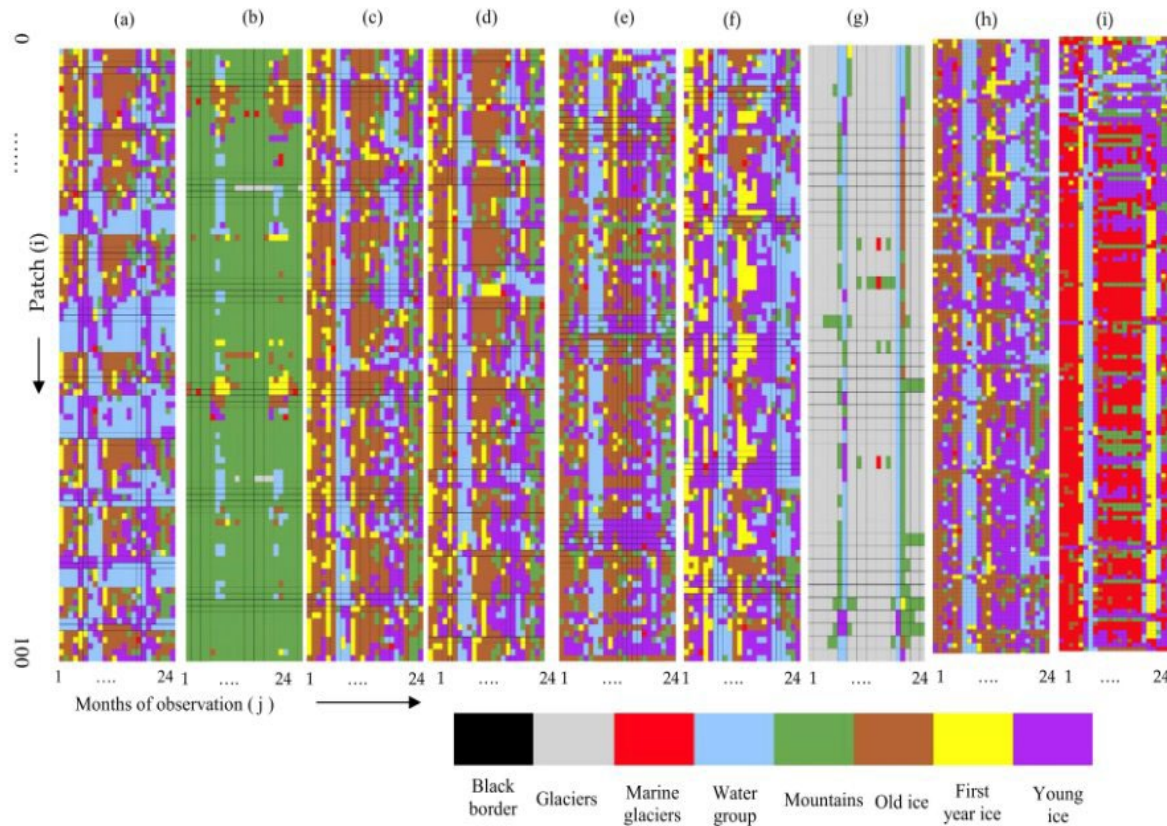
The DECD [1] is a comprehensive multi-resolution dataset designed for change detection, developed based on DynamicEarthNet

TABLE I
CHANGE DETECTION RESULTS USING PRE-HIGH RESOLUTION
AND POST-LOW RESOLUTION IMAGES. VALUES IN THE TABLE ARE
EXPRESSED AS PERCENTAGES.

Method	Prec	Rec	Acc	F1
FC-EF [10]	27.85	19.23	92.47	22.75
FC-Siam-Conc [10]	29.56	19.74	92.91	23.67
FC-Siam-Diff [10]	27.31	23.58	91.76	25.31
STANet [12]	43.71	24.54	94.58	31.43
BIT [11]	38.82	45.23	93.77	41.78
SUNet [8]	36.17	57.92	96.33	44.53
SRCDNet [4]	27.99	62.39	97.64	38.64
SILICD [5]	46.47	53.34	98.12	49.67
Diff-MRCD-base	47.24	58.12	99.05	52.12
Diff-MRCD (our)	46.52	68.08	99.43	55.27



Visual Analysis of Class Evolution in Temporal Series



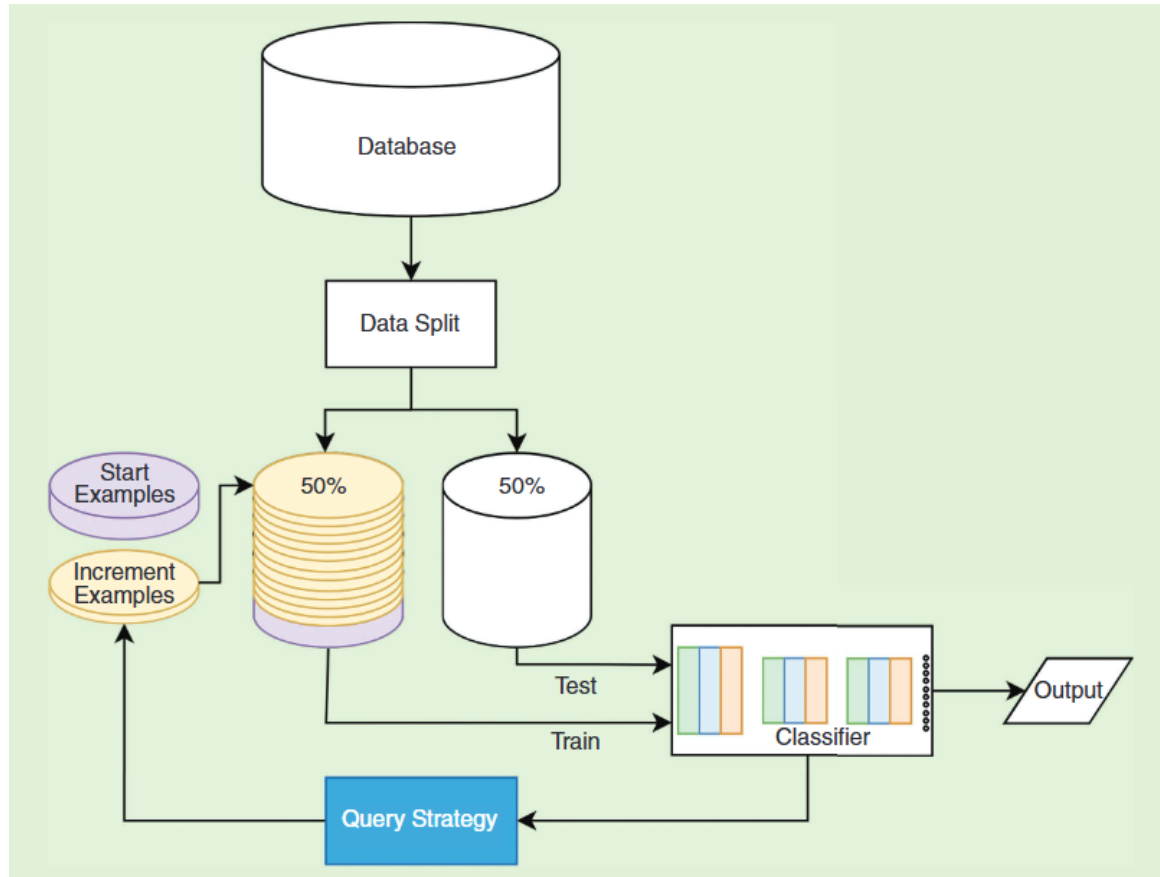
Classification from single observation

Sea-ice cover extracted from Sentinel-1 observations

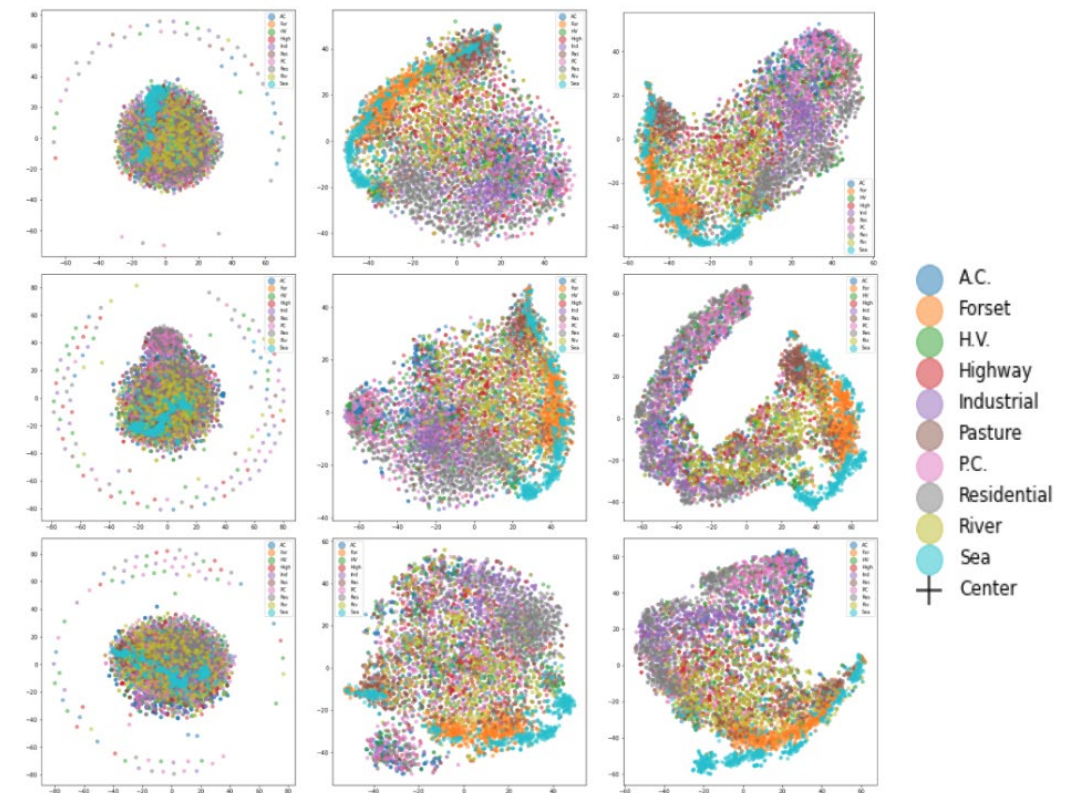




Active Learning

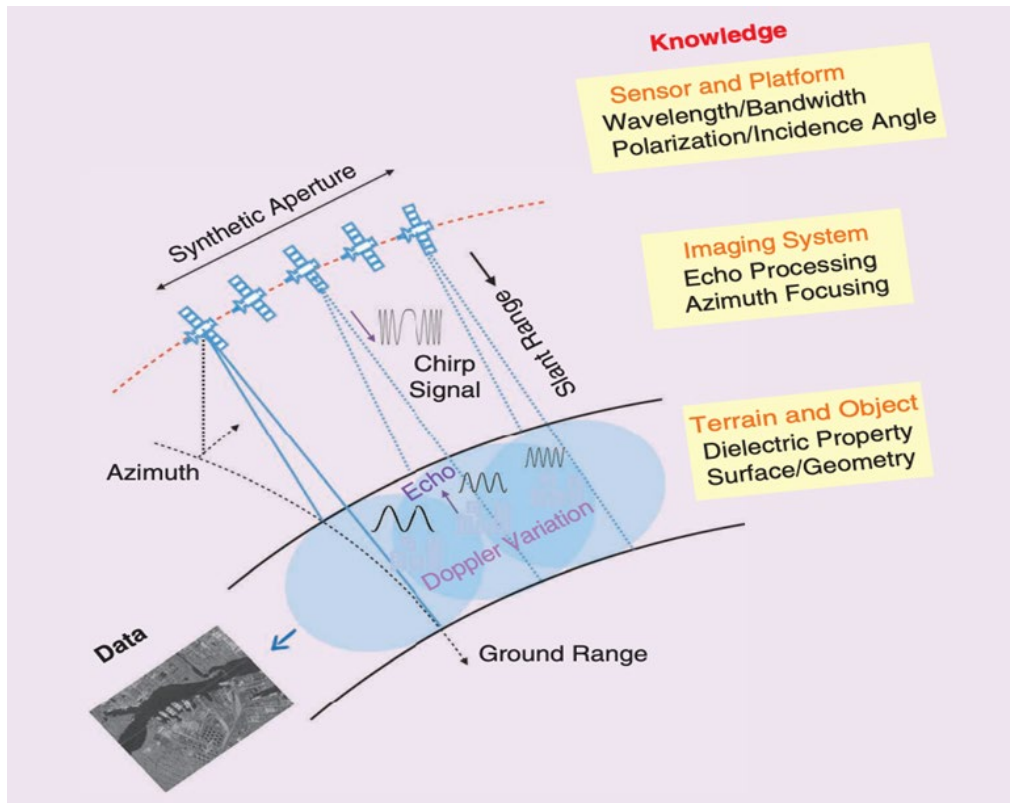


Optimization of training data under annotation constraints

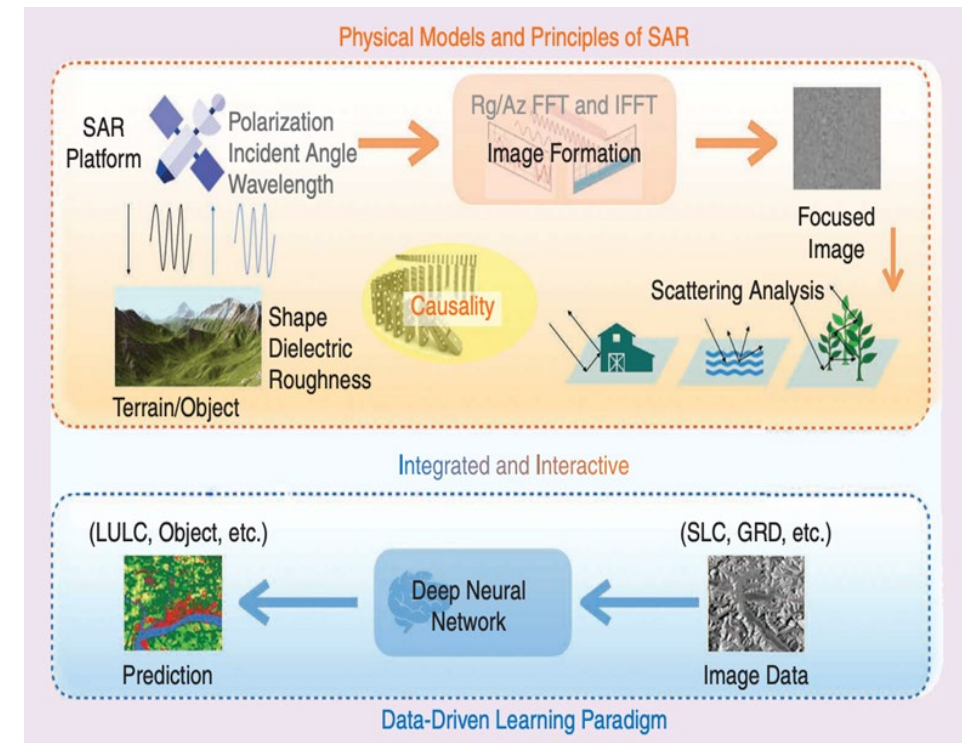




Explainable, Physics-Aware AI for SAR



Paradigm integrating and interacting with physical knowledge of SAR





Hybrid Architectures: DNN, Signal Processing, Physical Models

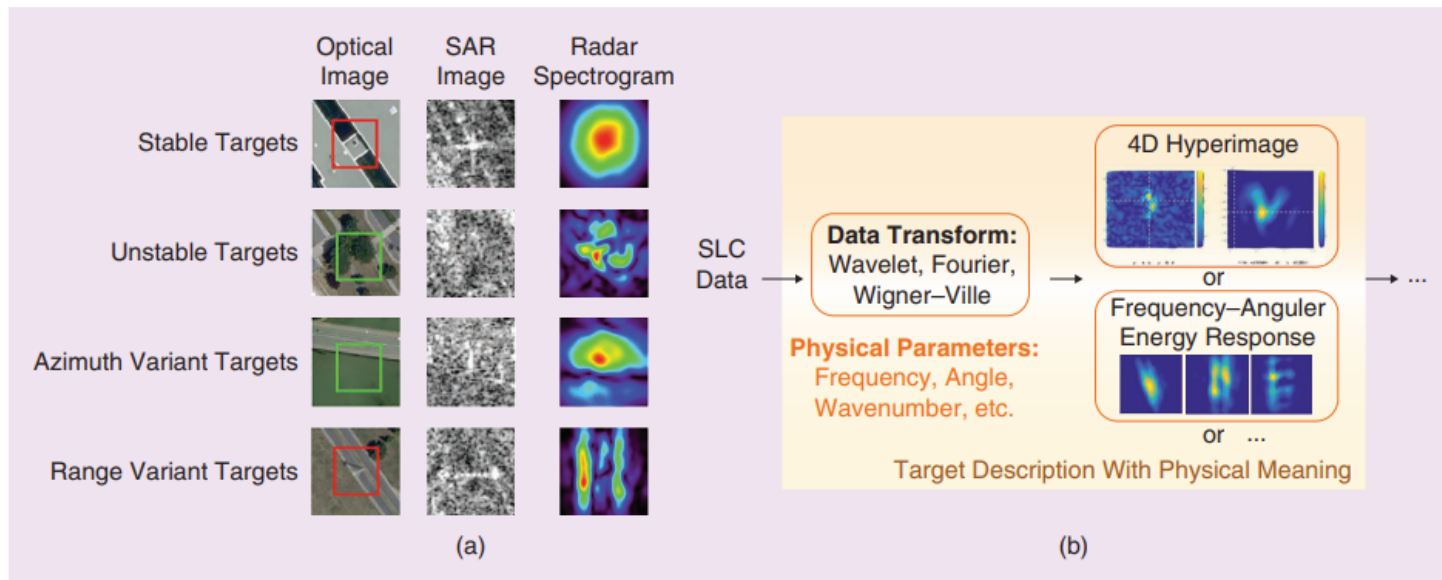
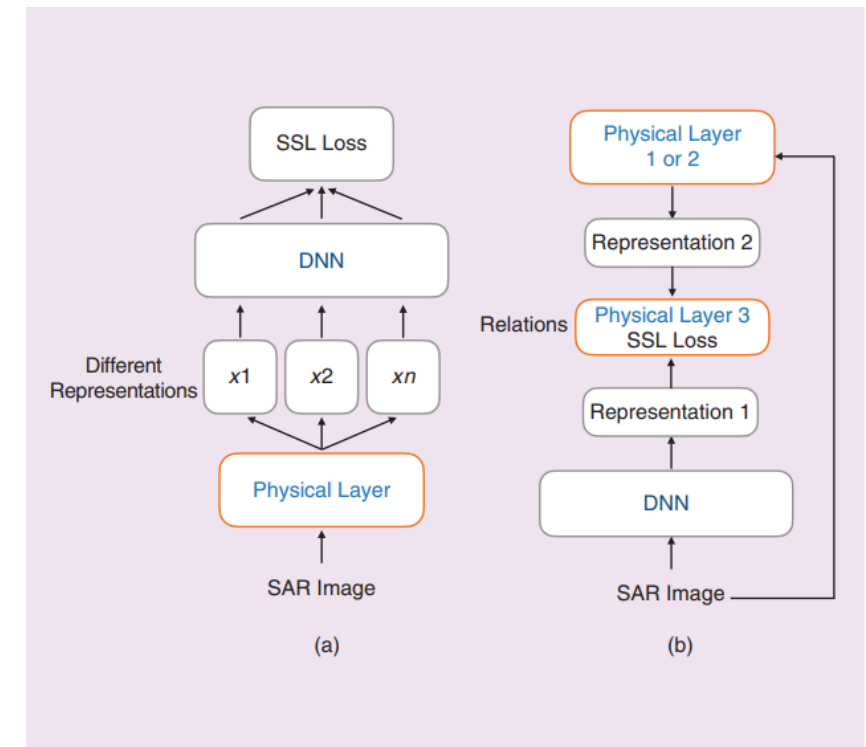
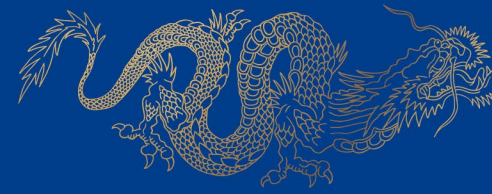


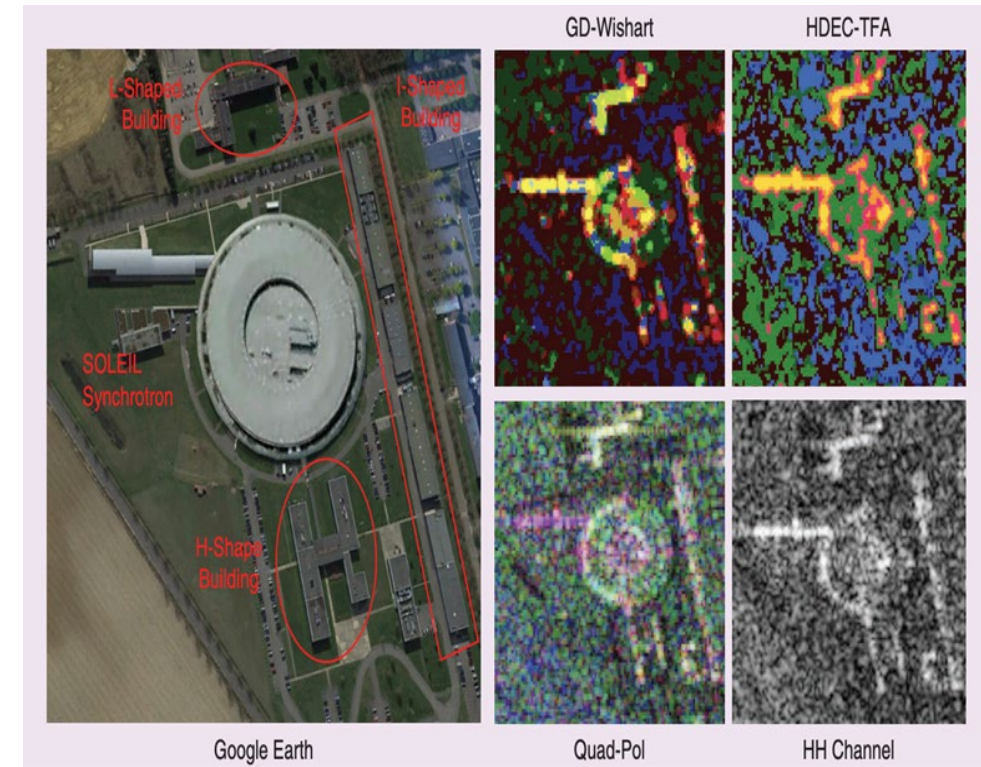
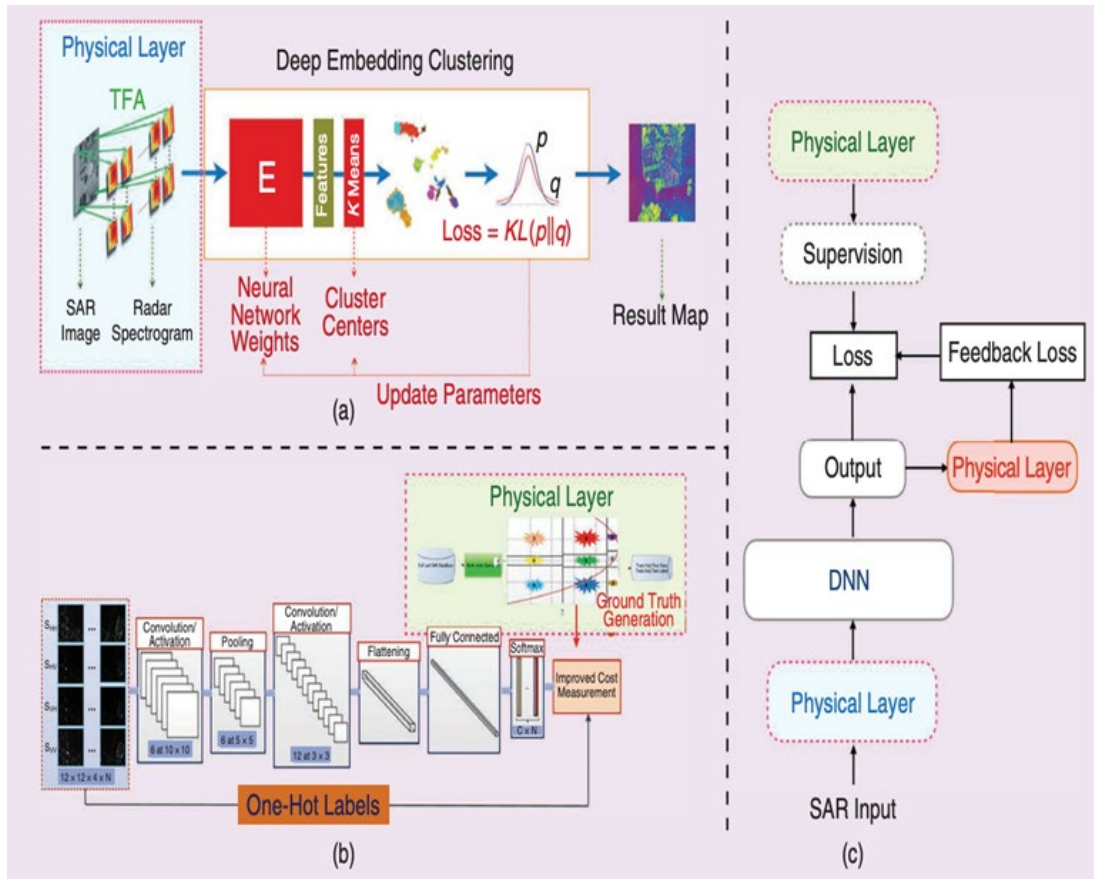
FIGURE 4. Physical layer 2: image formation. (a) Targets are characterized by sliding bandpass filtering in the Fourier domain. (b) On the basis of the image formation principle and target scattering model, the physical layer generates the rich target description with physical meaning.





Hybrid Architectures: DNN, Signal Processing, Physical Models

Model trained with PolSAR data predicts quad-pol signatures from single polarization observations

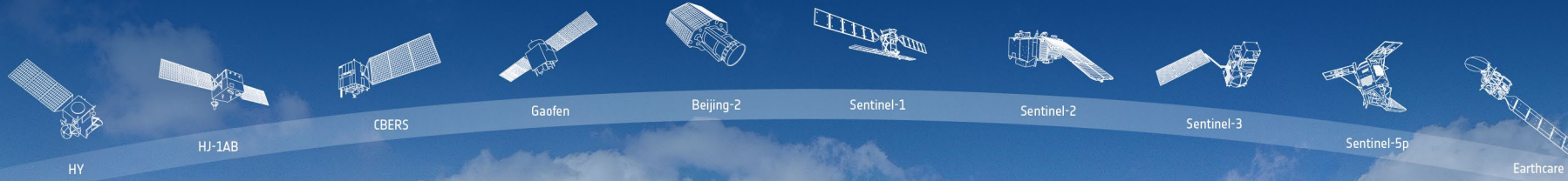




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THANK YOU! Q&A?

