The Use of EO Data for Integrated Monitoring of Agricultural Resources and Disaster Impacts

Title: An GNN-based earth's surface anomalies detection framework

Prof. Zhi GAO

武漢大學 WUHAN UNIVERSITY

NUS National University of Singapore

December 18, 2023

Outline

- **About me**
- Background and Motivation
- Method
- Experiments
- Conclusion and Future Work

The School of Remote Sensing and Information Engineering at Wuhan University

Wuhan University:

- **Location:** Situated in Wuhan, Hubei Province, Central China
- **Reputation:** Among the top-ranked universities in China, with a strong emphasis on research and innovation
- **Campus:** Famous for its scenic campus, especially the iconic cherry blossoms and historic buildings


The School of Remote Sensing and Information Engineering:

- **Leadership:** The discipline of remote sensing at Wuhan University ranks first in various international rankings, significantly influencing global remote sensing development.
- **Prestige:** Recognized as a top institution in China and globally, known as the cradle of talent in surveying and remote sensing

Personal Profile

Position:

- Full Professor
- Deputy Dean of School of Remote Sensing and Information Engineering, Wuhan University

Academic Contributions:

- Leading National Natural Science Foundation Major Program: Remote Sensing on-orbit Real-time Diagnosis for the Earth's Surface Anomalies
- Multiple leading research achievements in the field of "Perception, Localization, and Cooperative Control of Intelligent Unmanned Systems"

Outline

- About me
- **Background and Motivation**
- Method
- Experiments
- Conclusion and Future Work

Background

- **Various earth's surface anomalies caused by natural or human factors (natural disasters, ecological damage, etc.) occur on a global scale and are characterized by high frequency, high impact and heavy losses.**
- **Timely monitoring and early warning of earth surface anomalies has become a major need to ensure healthy and stable social and economic development.**

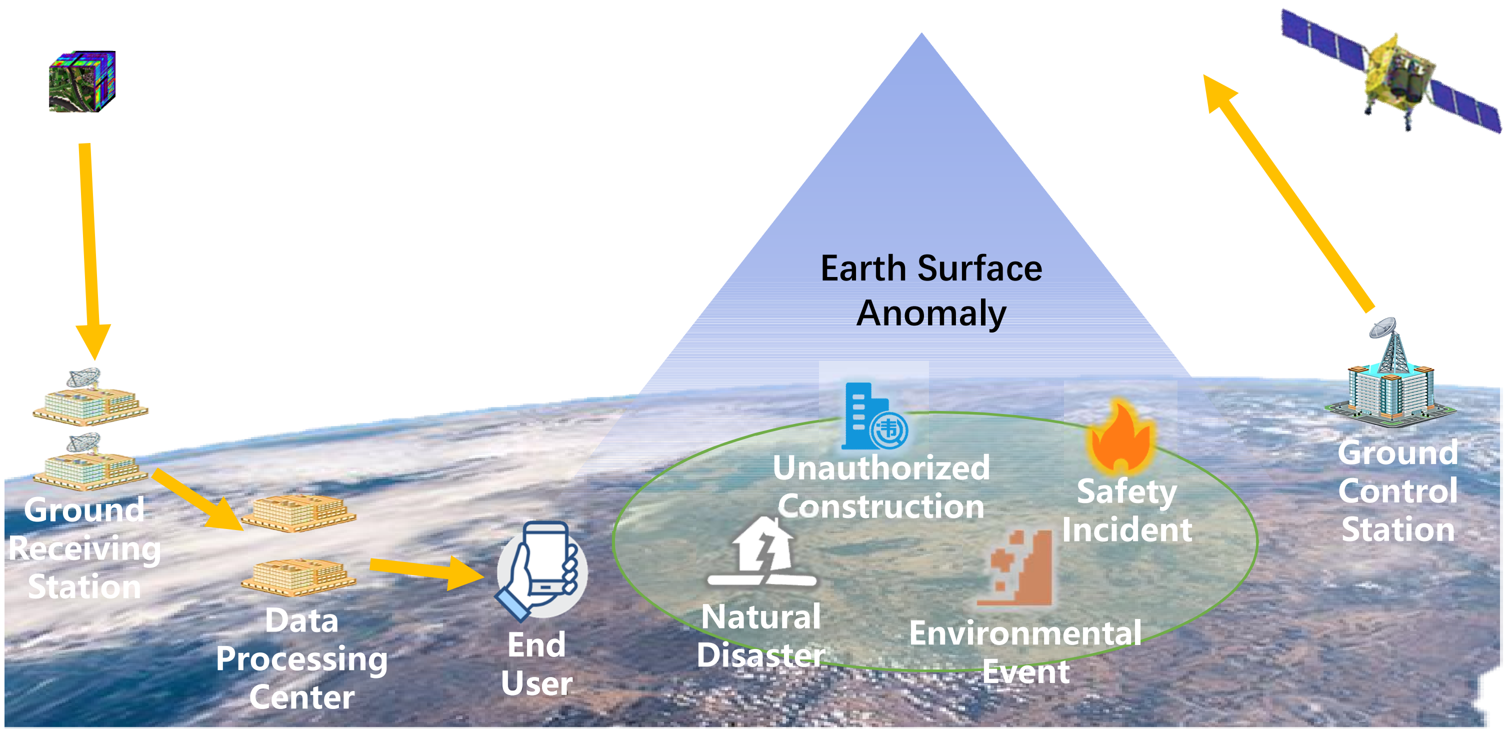
Background

- **Remote Sensing Detection and Segmentation**
- **Large-scale, Non-contact, Dynamic, etc.**

Before and After Satellite Images of the Earthquake-Affected Areas in Turkey

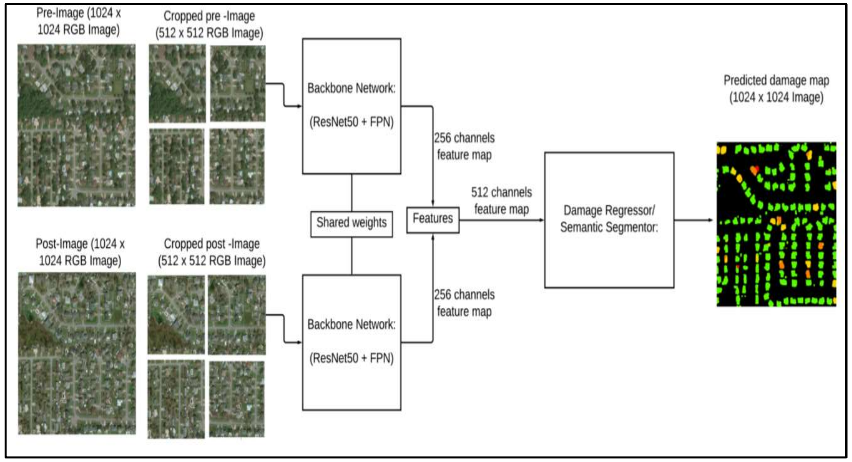
Background

Intelligent Real-time Extraction of Earth Surface Anomaly Information Based on Massive Remote Sensing Data: A large amount of data is transmitted to the ground for processing within a limited time window, leading to long response time.

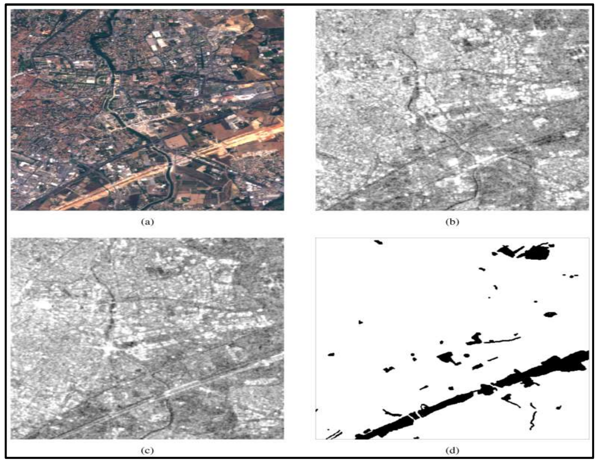


Background

- **The current research mainly focus on post-doc analysis by incorporating additional temporal and modal data.**
- **Data availability, data preprocessing, and data labeling pose challenges for rapid response to earth's surface anomalies.**



Assessment of Building Damage Using Multi-Temporal Method

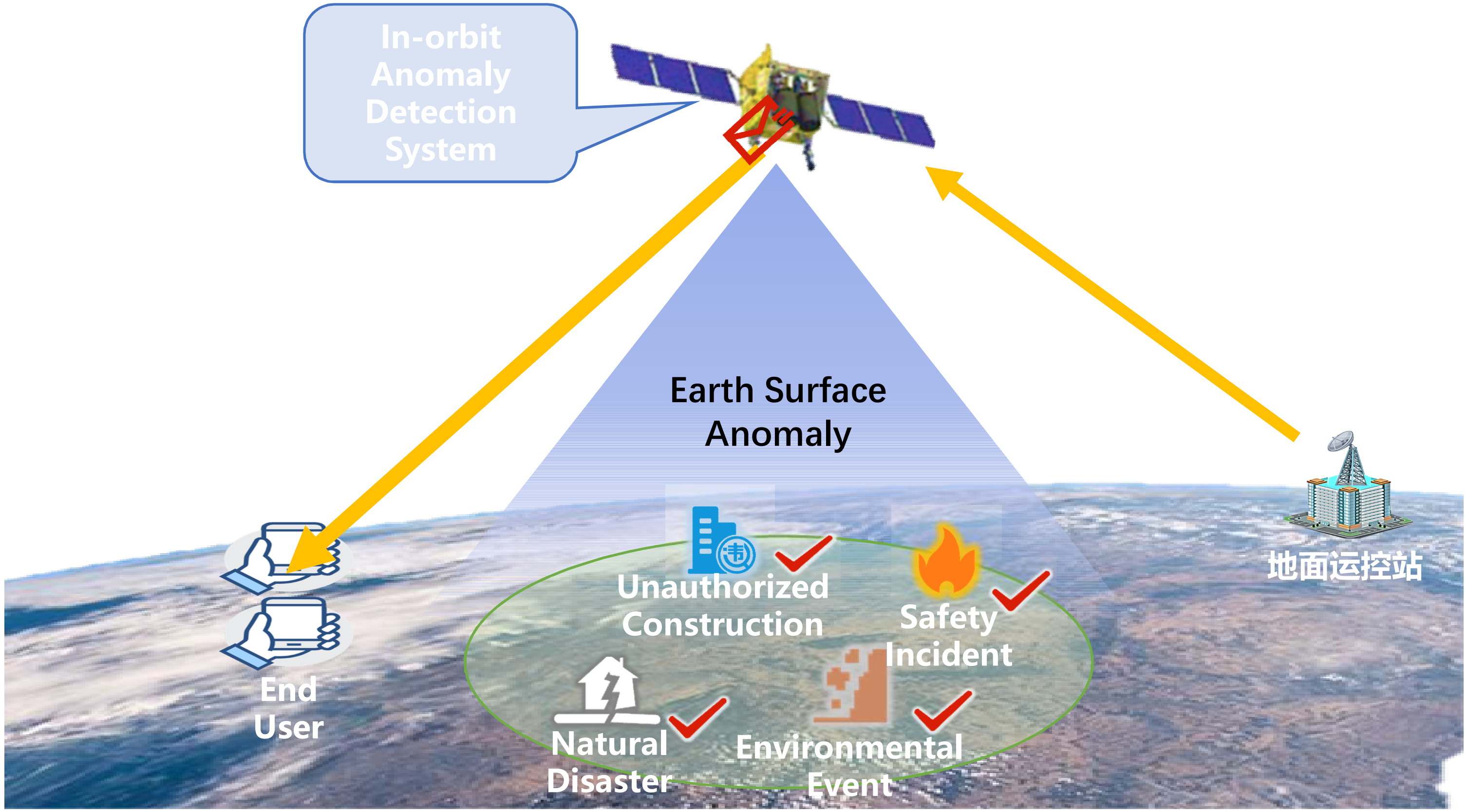


Extracting Disaster-Affected Areas Using Multi-Modal Method

Weber, E., Kané, H. Building disaster damage assessment in satellite imagery with multi-temporal fusion. 2020.
Saha, S., Shahzad, M., Ebel, P., Zhu, X.X.: Supervised change detection using prechange optical-sar and postchange sar data. 2022

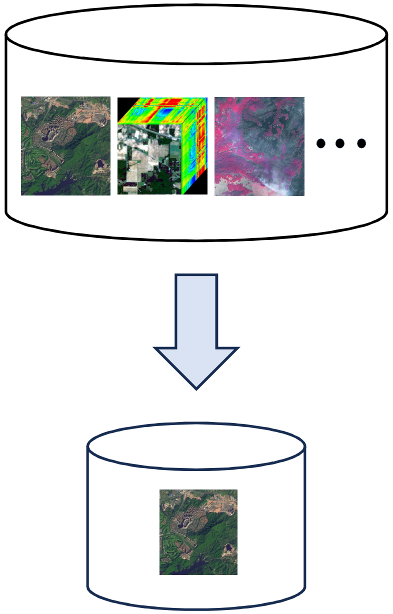
Motivation

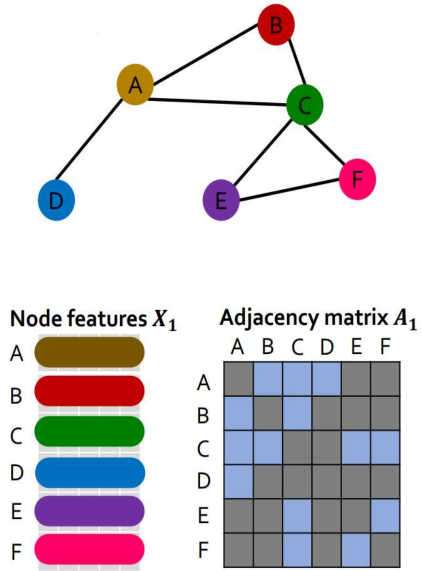
Our solution is building a highly intelligent model capable of addressing multi-tasks under constraint resource. Efficiently integrating and intelligently interpreting multi-source remote sensing data under limited conditions in space.



Motivation

- **Reduce detection time and save valuable time for response.**





Anomaly	Flood
	Landslide
	Debrisflow
	Hurricane
	Wildfire
	Earthquake
	Volcano
	Tornado
	Tsunami
	Fire
	Bushfire
Normal	

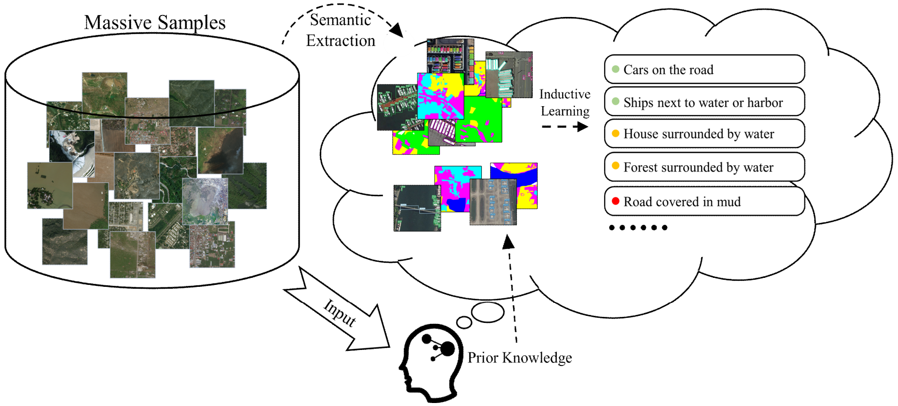
Simpler Data

Lightweight and tailored model

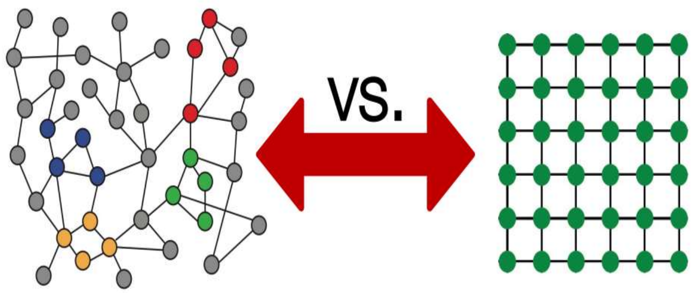
1 vs all

Motivation

- **We use graph neural networks as the core model, aiming to enable the model to explicitly capture semantic relationships between different geoentities and use them for inference.**
- **Irregular structure, Explicitly modeling relationships, Flexibility, etc.**



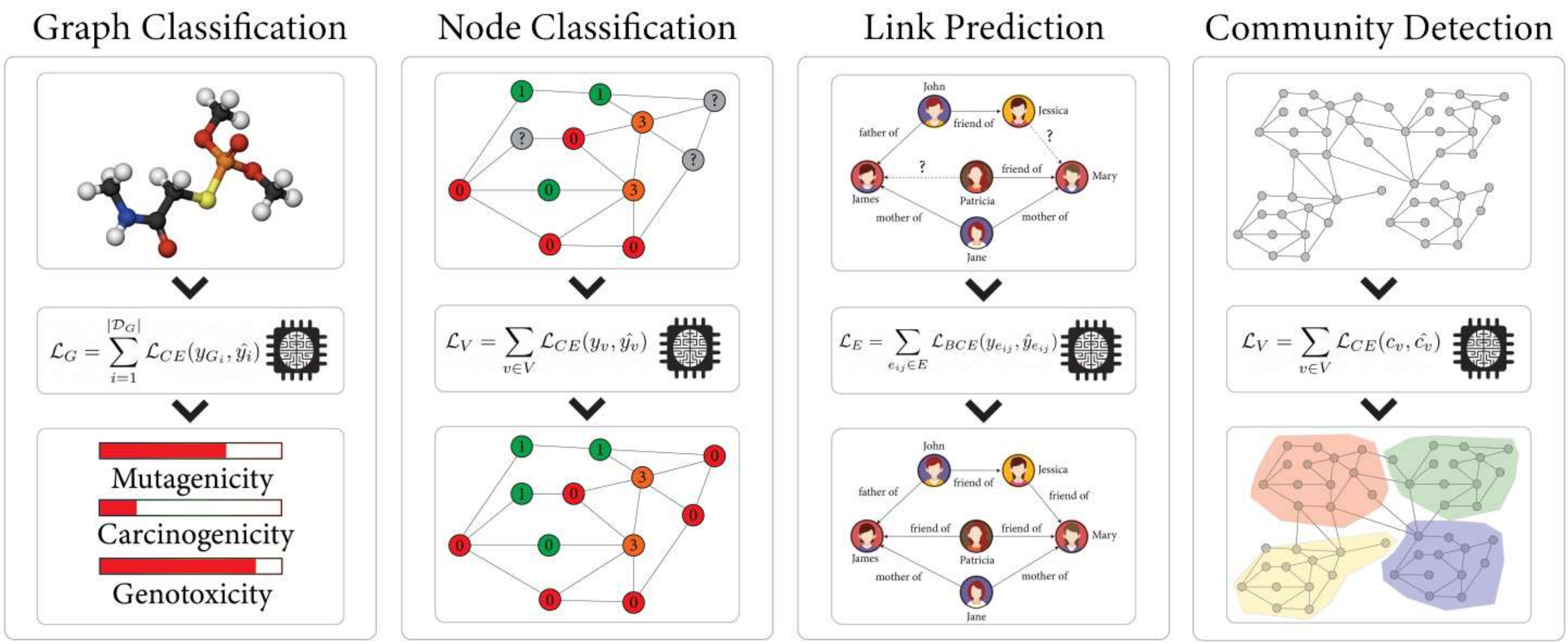
Simulated Process of Human Brain Interpret Satellite Images



Comparison of Graph and Regular Grid Image

Motivation

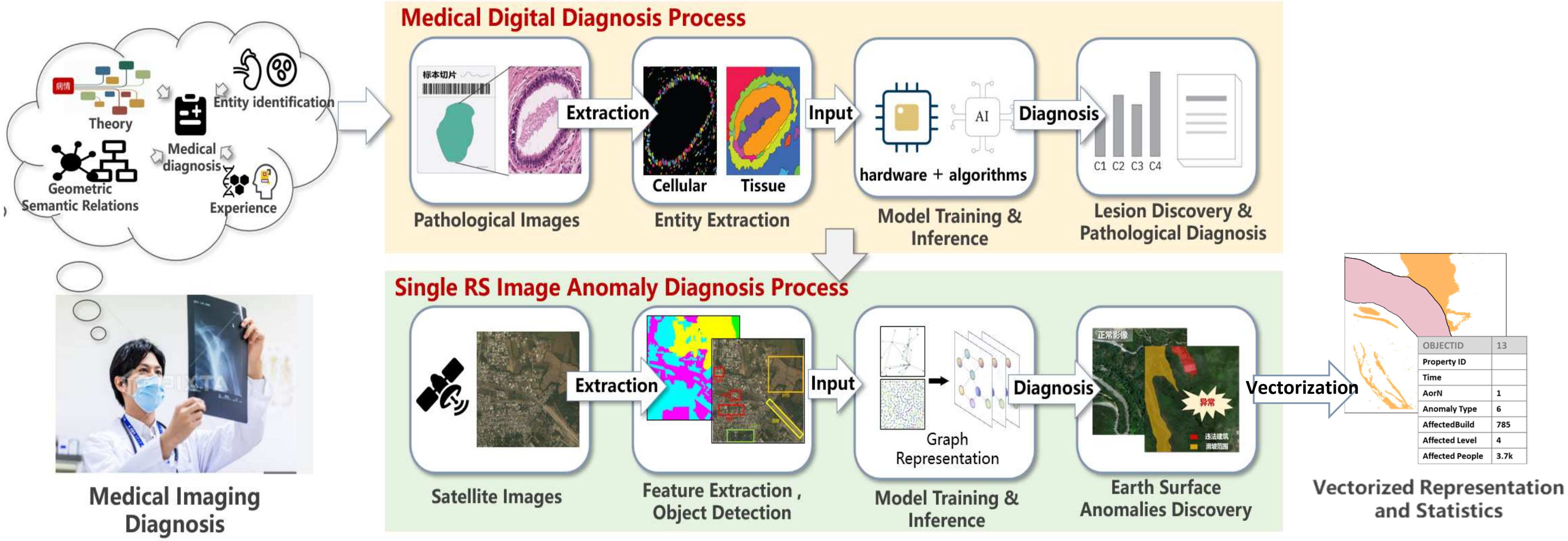
- **After graph generation through node representation and topological construction, various tasks can be carried out based on GNNs' flexibility, and it is widely applied in fields such as medicine and social networks.**



An overview of major deep graph learning tasks

Motivation

Inspired by the AI-based synergistic approach of doctors in diagnosing diseases at the cellular and tissue levels. We process satellite remote sensing images into graph structures at different levels, including geometric and semantic, facilitating earth surface anomaly detection.



Simulating Doctor's Diagnostic Process for Earth's Surface Anomaly Detection

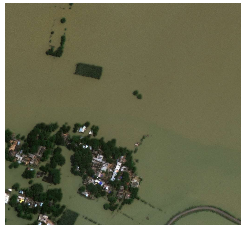
Motivation

Image-level detection: Simple, Fast, Robust, Low Granularity, Suitable for Large-scale Applications
Pixel-level segmentation: High Accuracy, Fine Granularity, Detailed Information
Vector Data: Interpretability, Integration with other geospatial layers, Data Interoperability:

Anomaly Landslide

Anomaly Tsunami

Anomaly Vocalno

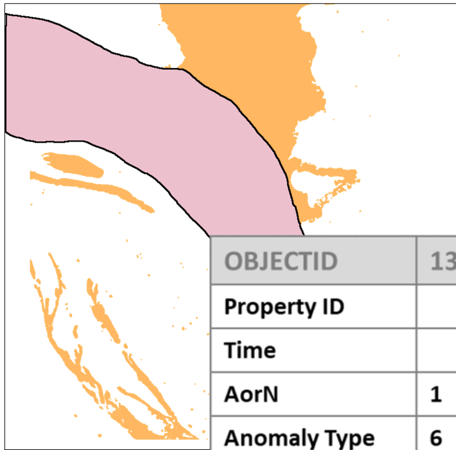


Anomaly Flood

WHAT

Semantic segmentation result

WHERE



OBJECTID	13
Property ID	
Time	
AorN	1
Anomaly Type	6
AffectedBuild	785
Affected Level	4
Affected People	3.7k

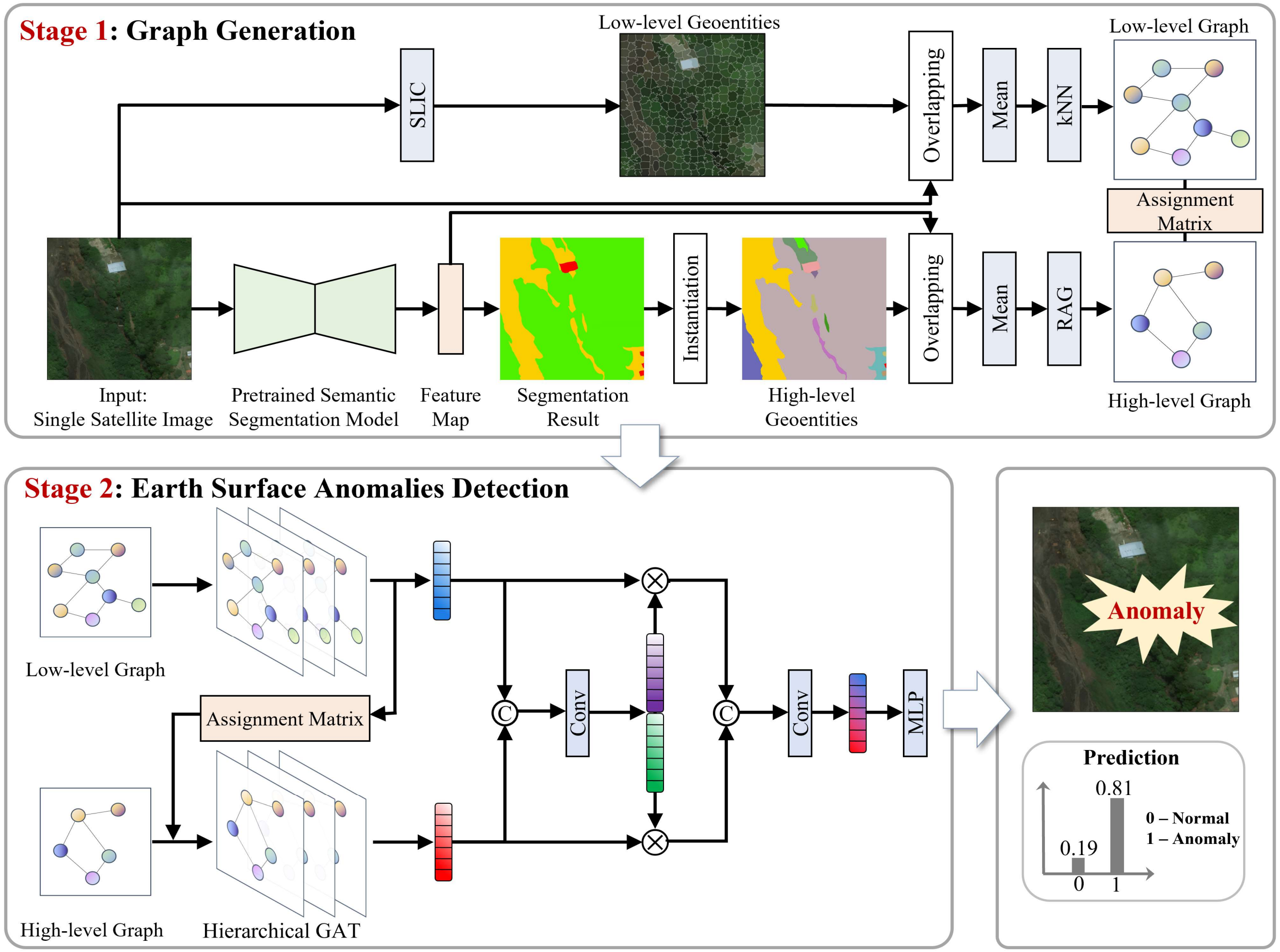
Vectorized representation

Outline

- About me
- Background and Motivation
- **Method**
  - **Graph Generation and Anomaly Detection**
  - **Anomaly Segmentation and Representation**
- Experiments
- Conclusion and Future Work

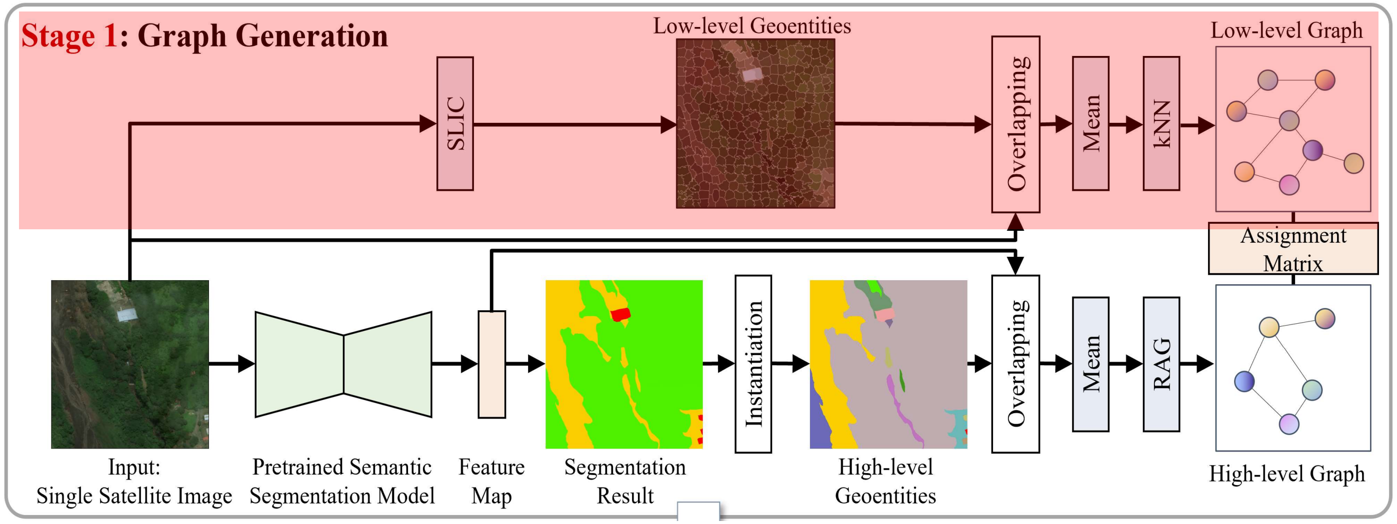
Method: Graph Generation and Anomaly Detection

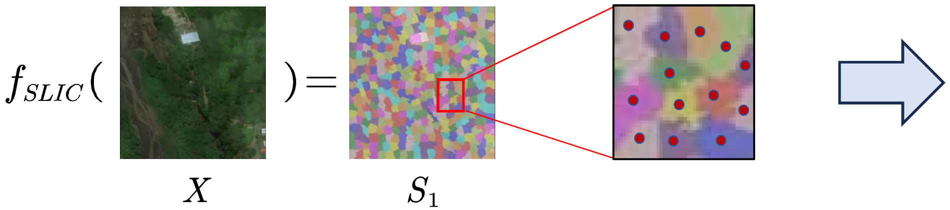
- **A hierarchical geometry-to-semantic fusion GNN framework**



Method： Graph Generation and Anomaly Detection

- Graph Building—How to generate hierarchical graph?



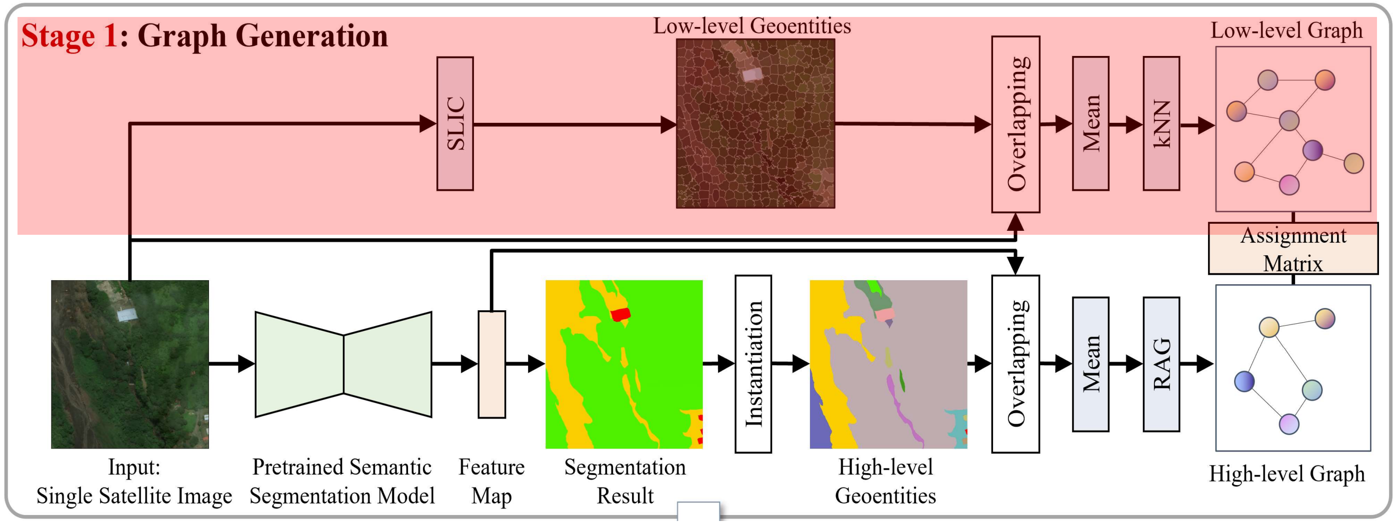


$$N(v_i) = \frac{1}{m}\sum_{j=1}^{m}\begin{bmatrix} R_j \\ G_j \\ B_j \end{bmatrix}, \; v_i \in V_{low}$$

Achanta, R., Shaji, A., Smith, K., Lucchi, A., Fua, P., Süsstrunk, S.: Slic superpixels compared to state-of-the-art superpixel methods. IEEE TPAMI. 2012.

Method：Graph Generation and Anomaly Detection

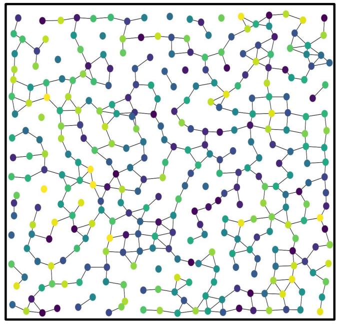
- **Graph Building—How to generate hierarchical graph?**



Constructing low-order graph topologies

k-Nearest Neighbors Algorithim:

$$u \in \{w | D(v,w) \leq d_k \wedge D(v,w) < \tau_{dist}, \forall w, v \in V_{low}\}$$

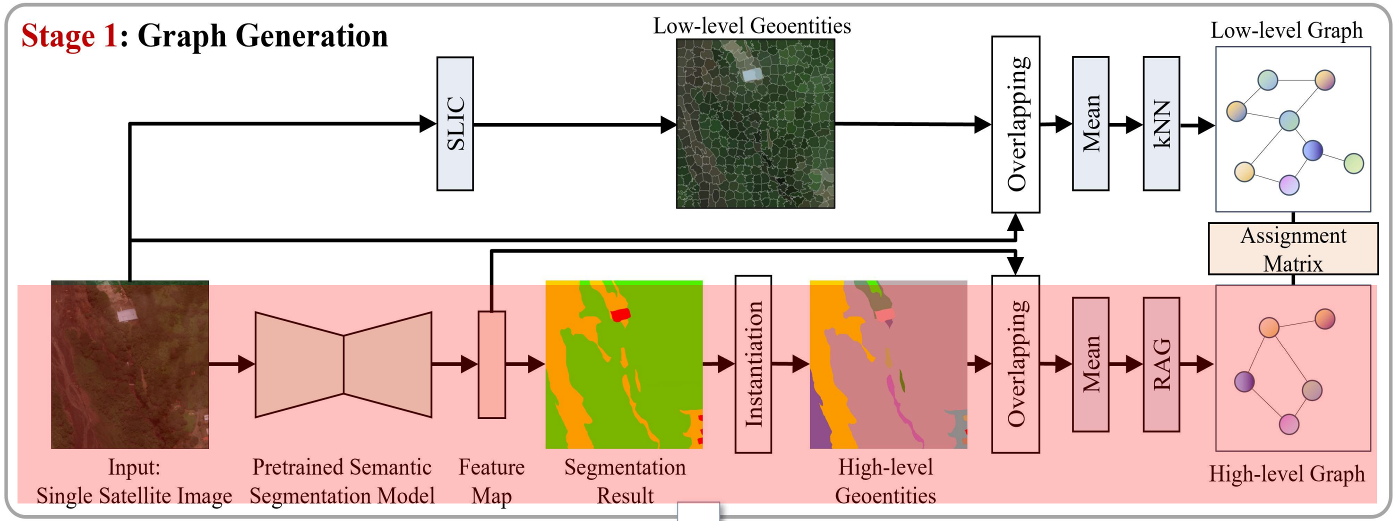


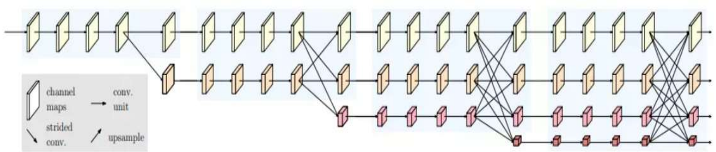
G_{low}

Fix, Evelyn, and Joseph Lawson Hodges. Discriminatory analysis. Nonparametric discrimination: Consistency properties. 1989.

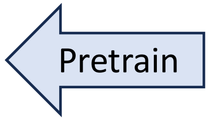
Method：Graph Generation and Anomaly Detection

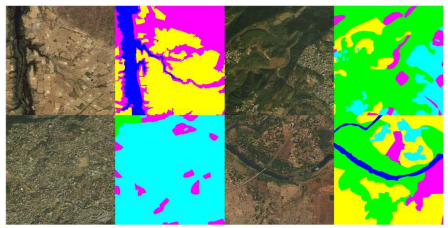
- Graph Building—How to generate hierarchical graph?





HRNet



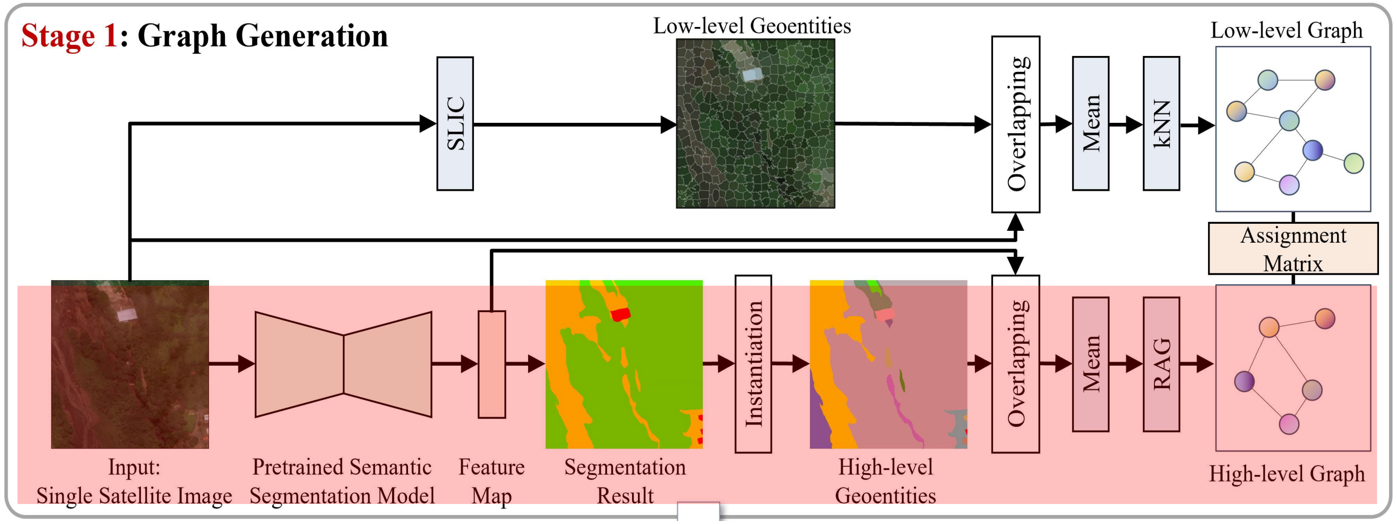


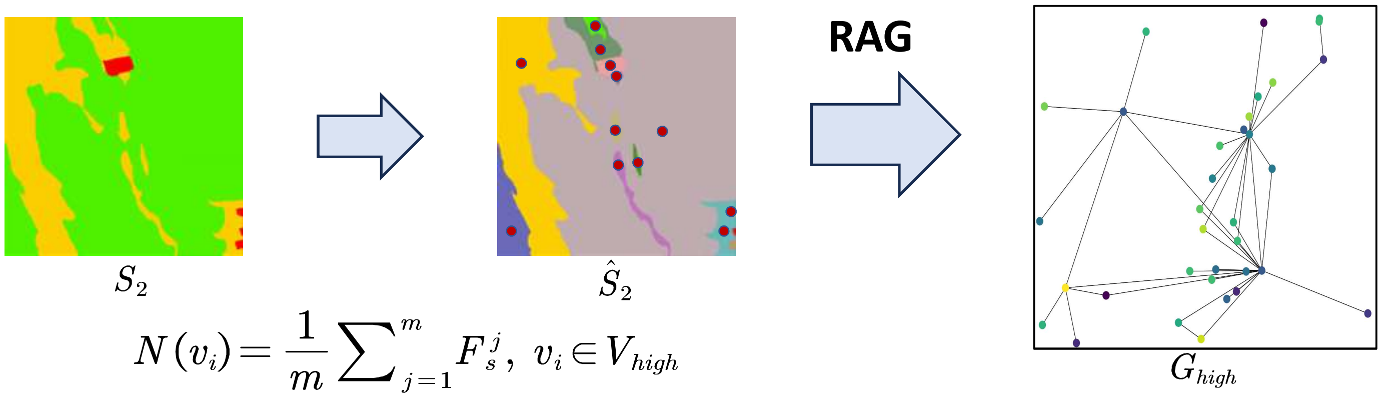
DeepGlobe Dataset

Wang, Jingdong, et al. Deep high-resolution representation learning for visual recognition. IEEE TPAMI. 2020.
Demir, Ilke, et al. Deepglobe 2018: A challenge to parse the earth through satellite images. CVPR Workshop. 2018.

Method： Graph Generation and Anomaly Detection

- Graph Building—How to generate hierarchical graph?

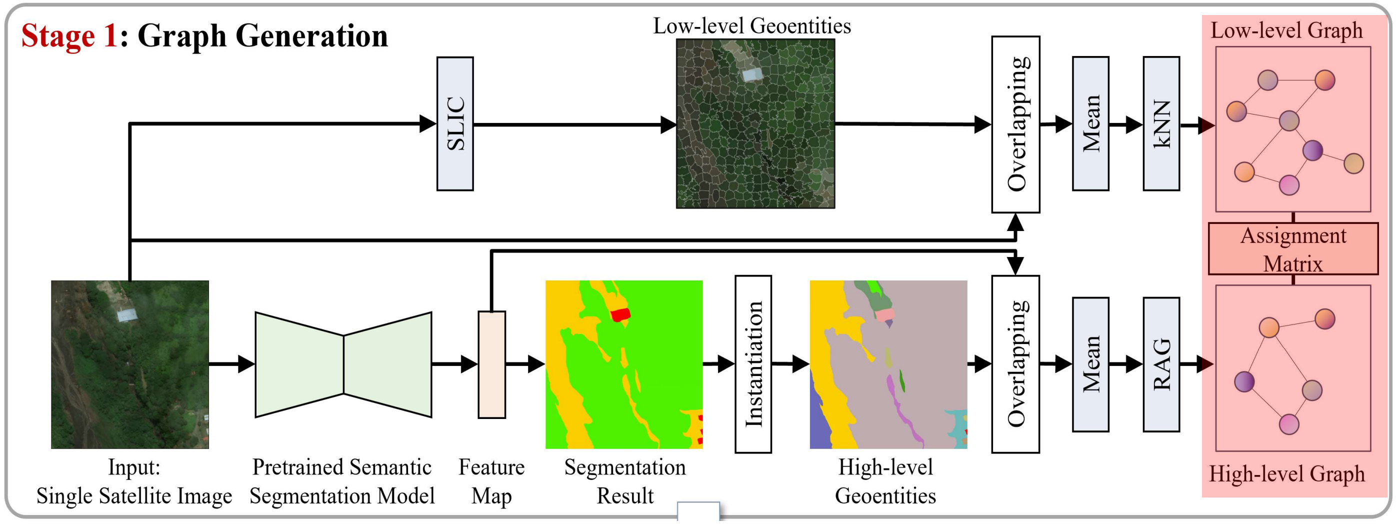




$$N(v_i) = \frac{1}{m}\sum_{j=1}^{m} F_s^j,\ v_i \in V_{high}$$

Method：Graph Generation and Anomaly Detection

- Graph Building—How to generate hierarchical graph?

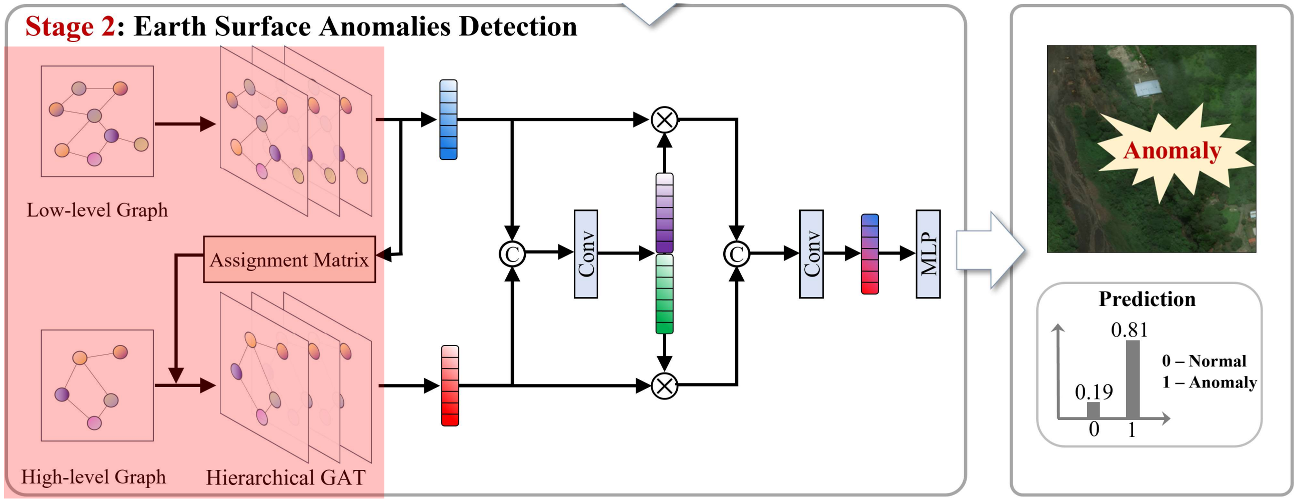


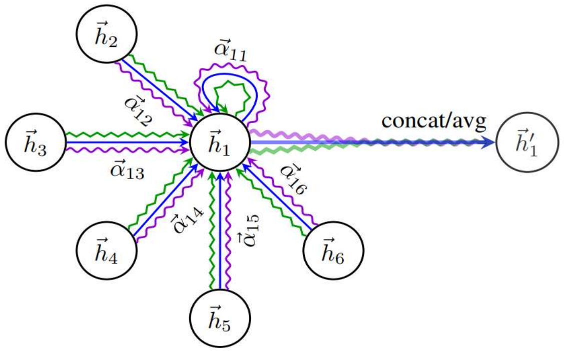
$$A_{low \to high}[i, j] = \begin{cases} 1 & \text{if} i^{\text{th}} \text{ low-level geoentity} \in j^{\text{th}} \text{ high-level geoentity} \\ 0 & \text{otherwise} \end{cases}$$

$$G_{joint} := \{G_{low}, G_{high}, A_{low \to high}\}$$

Method: Graph Generation and Anomaly Detection

- **Anomaly Detection: How to learn from graph?**





$$h_i^{(l)} = \sigma\Big(\sum_{j\in N_i} \alpha_{ij}^{(l)} W^{(l)} h_j^{(l-1)} + b^{(l)}\Big),$$

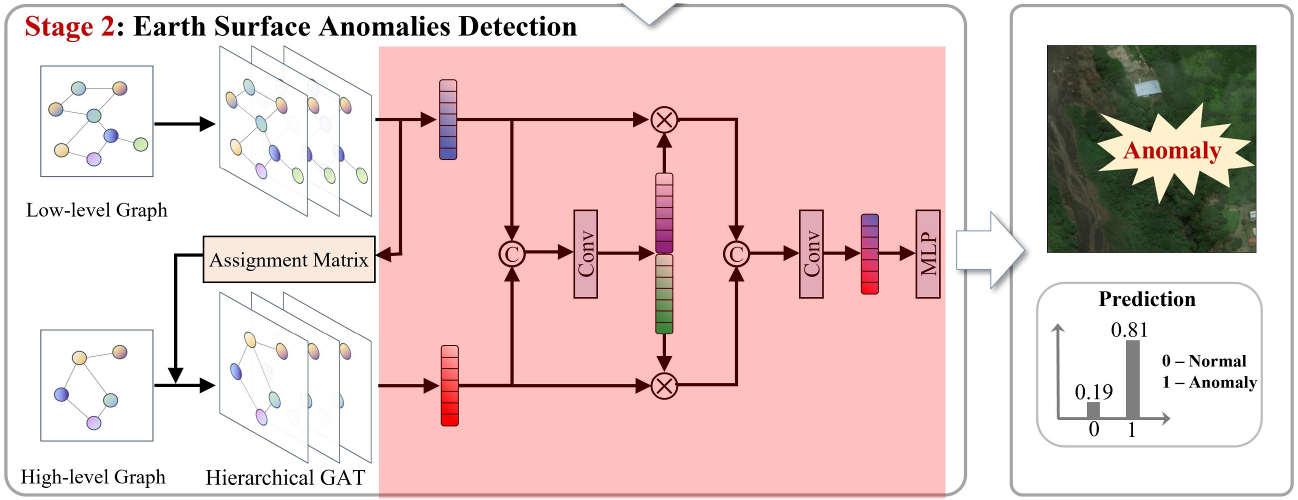
$$\alpha_{ij}^{(l)} = \frac{\exp\left(\mathrm{LeakyReLU}\left(\boldsymbol{a}^{(l)T}\left[W^{(l)}h_i^{(l-1)} || W^{(l)}h_j^{(l-1)}\right]\right)\right)}{\sum_{k\in N_i}\exp\left(\mathrm{LeakyReLU}\left(\boldsymbol{a}^{(l)T}\left[W^{(l)}h_i^{(l-1)} || W^{(l)}h_k^{(l-1)}\right]\right)\right)}$$

Graph Attention Networks (GAT)

Petar Veličković, Guillem Cucurull, Arantxa Casanova, Adriana Romero, Pietro Liò, Yoshua Bengio. Graph attention networks. 2017.

Method： Graph Generation and Anomaly Detection

- Anomaly Detection: How to learn from graph?



$$h_{\text{high}}(w) = \left[H_{\text{high}}(w) || \sum_{v \in M(w)} \hat{h}_{low}(v)\right]$$

$$\mathbf{z} = f(\left[x_{low} \odot a_{low} || a_{high} \odot a_{high}\right])$$

$$[a_{low}, a_{high}] = [\sigma(f([x_{low}, x_{high}]), 1 - \sigma(f([x_{low}, x_{high}])]$$

Method： Anomaly Segmentation and Representation

- Anomaly Segmentation: Main problem

Limited Annotation: Pixel-level labeling is time-consuming and non-trivial
Semantic Complexity: Intra-class diversity, inter-class similarity, scales, etc.
Domain Gap: Heterogeneity across spatial and temporal domain

Domain gap in remote sensing imagery

Semantic complexity in remote sensing imagery

Method： Anomaly Segmentation and Representation

- Anomaly Segmentation: Weakly Supervised labels

Inexact label：

where the training data are given with only coarse-grained labels

Incomplete label：

where only a subset of training data is given with labels

Noisy label：

where the given labels are not always ground-truth

(a) image-level labels

(b) box-level labels

(c) point labels

(d) doodle labels

(a) cat

(b) bus

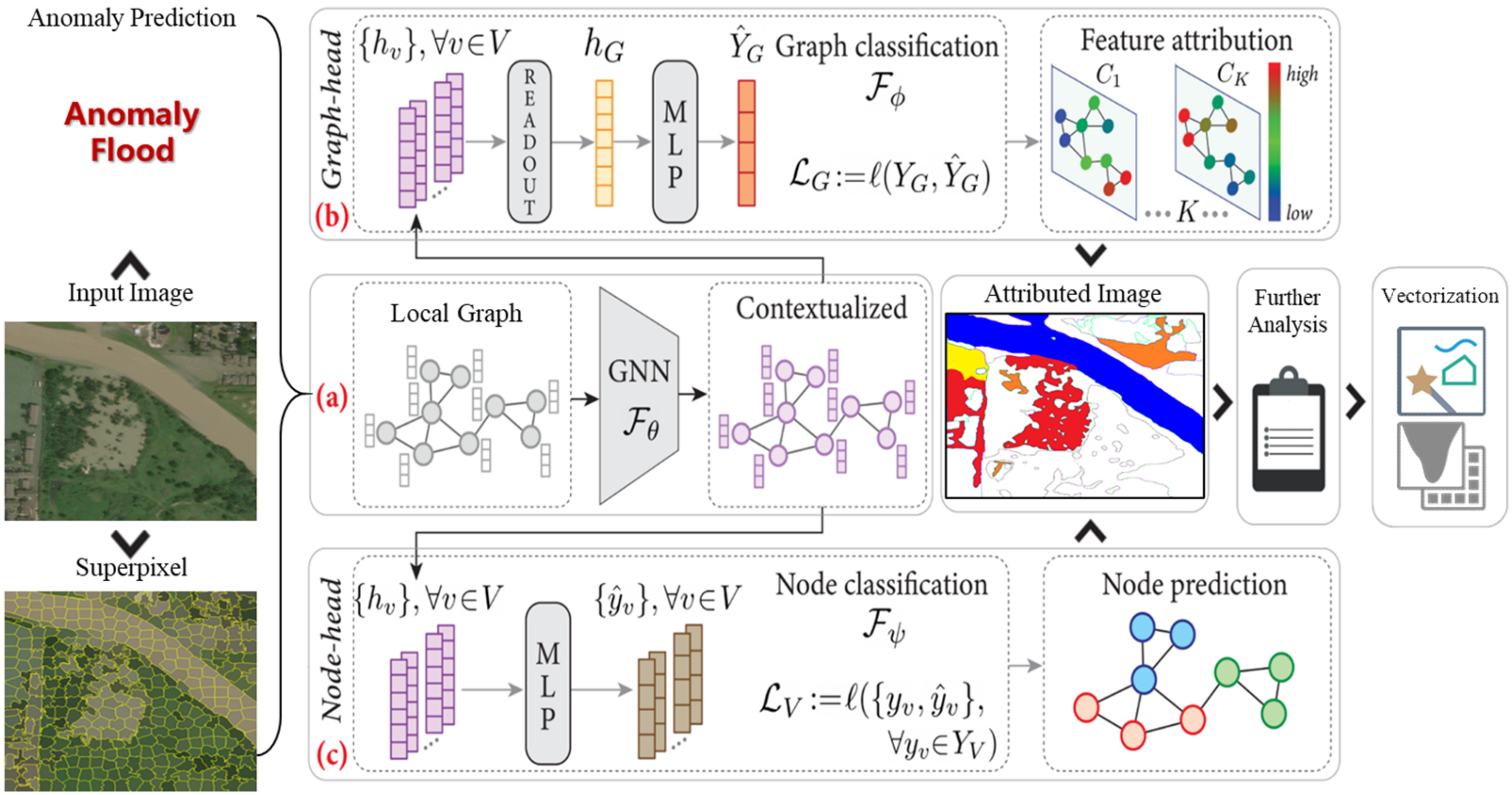
(c) car

(d) chair

Different labels in weakly supervised learnings

Method： Anomaly Segmentation and Representation

- Anomaly Segmentation and Representation:
  Based on image-level anomaly prediction results, attributions are performed on each superpixel node, assessing impact levels and generating a pixel-level attributed image for further analysis.



Outline

- About me
- Background and Motivation
- Method
- **Experiments**
- Conclusion and Future Work

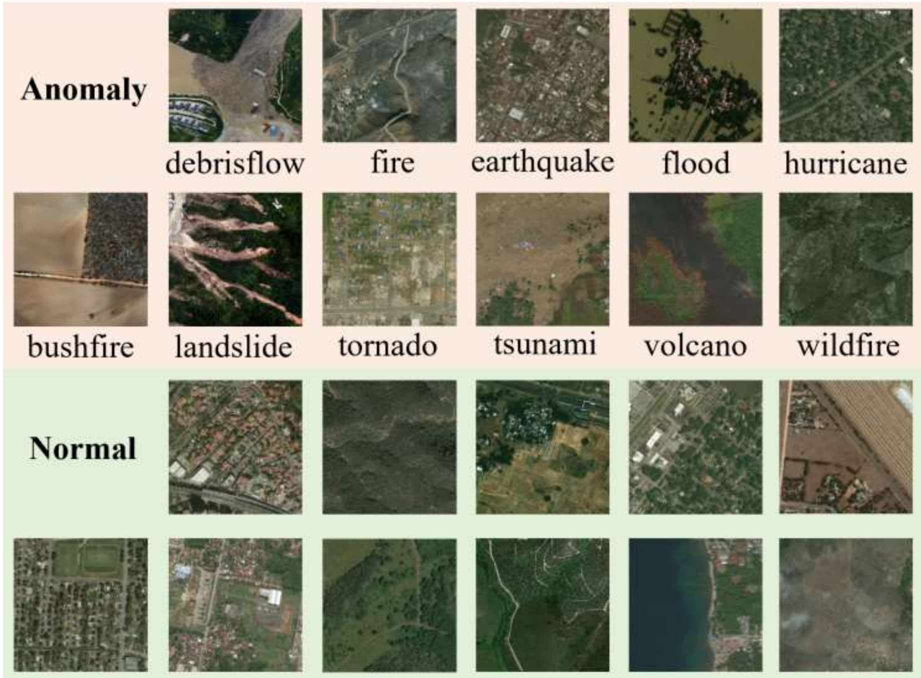
Experiments

- **ESAD (Earth Surface Anomaly Detection) Dataset**
- **13058 samples, 11 classes, high spatial resolution**

The first large-scale benchmark dataset for surface anomaly detection in single images

Class		Num
Anomaly	Flood	647
	Landslide	59
	Debrisflow	48
	Hurricane	1296
	Wildfire	1201
	Earthquake	14
	Volcano	217
	Tornado	254
	Tsunami	107
	Fire	1548
	Bushfire	996
Normal		6671

Statistics of ESAD Dataset



Examples of ESAD Dataset

Experiments

- **Comparison with baselines**

Quantitative result of comparison methods

Method	OA	Recall	AIT	Params
ResNet-50	91.05	90.42	16.63ms	25.61M
MobileNetV3	88.40	88.08	14.98ms	3.8M
ViT-B/32	93.71	93.40	16.67ms	88.21M
HGP-SL-Low	66.85	66.87	2.04ms	0.07M
HGP-SL-High	61.64	61.58	0.28ms	0.14M
HACT-Net	74.53	75.42	2.47ms	0.79M
Our method	83.89	83.86	6.04ms	1.01M

Experiments

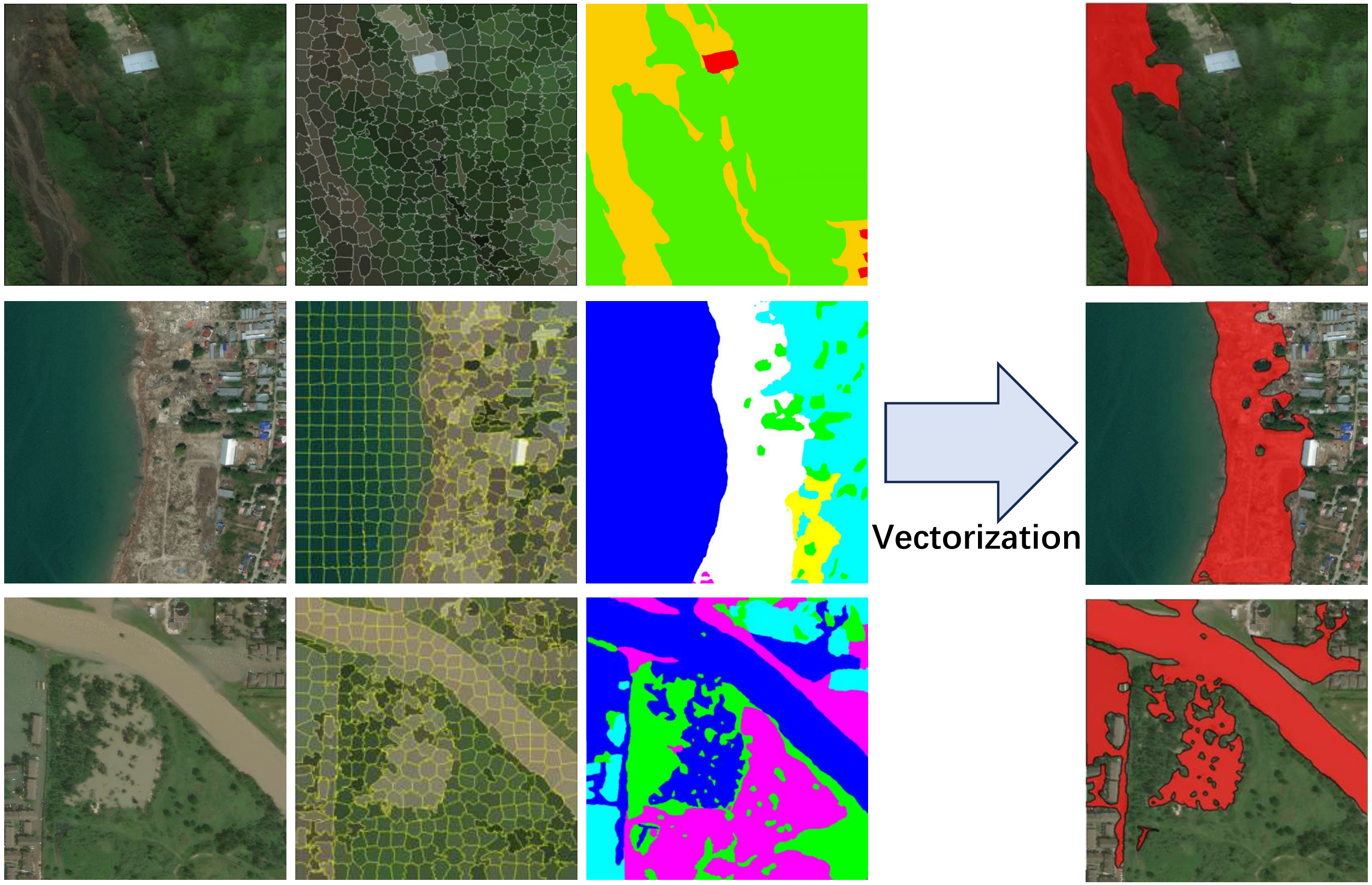
- **Ablation Study**

Ablation Study of Proposed Method

Method	OA	Recall	AIT	Params
GAT-Low	65.15	66.80	2.88ms	0.09M
GAT-High	62.32	68.06	3.42ms	0.21M
Concat-GAT	78.41	77.25	6.92ms	1.02M
Our method	83.89	83.86	6.04ms	1.01M

Experiments

- **Vectorized representation**



OBJECTID	1022
Property UD	
Time	2016
AorN	1
Anomaly Type	2
Affected Build	12
Damage Level	2
Affceted People	40

OBJECTID	87
Property UD	
Time	2019
AorN	1
Anomaly Type	9
Affected Build	1044
Damage Level	3
Affceted People	1,500

OBJECTID	15
Property UD	
Time	2023
AorN	1
Anomaly Type	6
Affected Build	785
Damage Level	4
Affceted People	3,700

Input   Superpixels   Semantic Segmentation   Vectorized Representation

Outline

- About me
- Background and Motivation
- Method
- Experiments
- **Conclusion and Future Work**

Conclusion and Future Work

- **Better model performance**

  Improve overall model precision, recall, reduce the number of model parameters, and improve inference efficiency

- **Larger dataset**

  Construct a dataset with a larger sample size and more comprehensive types of surface anomalies

- **Satellite on-orbit experiment**

  Realize the framework for the deployment and operation of satellites in orbit for the immediate detection and diagnosis of surface anomalies and the downlinking of results

Thanks!

Wechat:

gaozhinus@gmail.com
gaozhinus@whu.edu.cn