

# RS IMAGE INTERPRETATION FROM DATA PERSPECTIVE

## Diversity, Richness, Scalability (DiRS) :

*On Benchmarking Remote Sensing Image Interpretation*

Gui-Song Xia

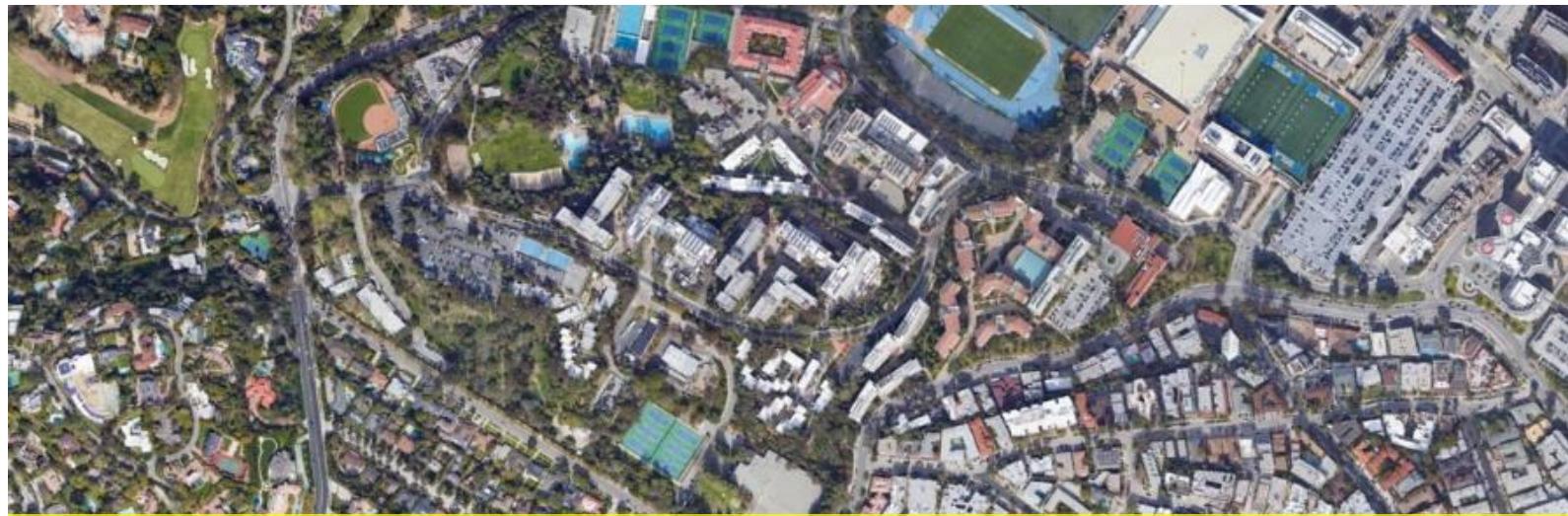
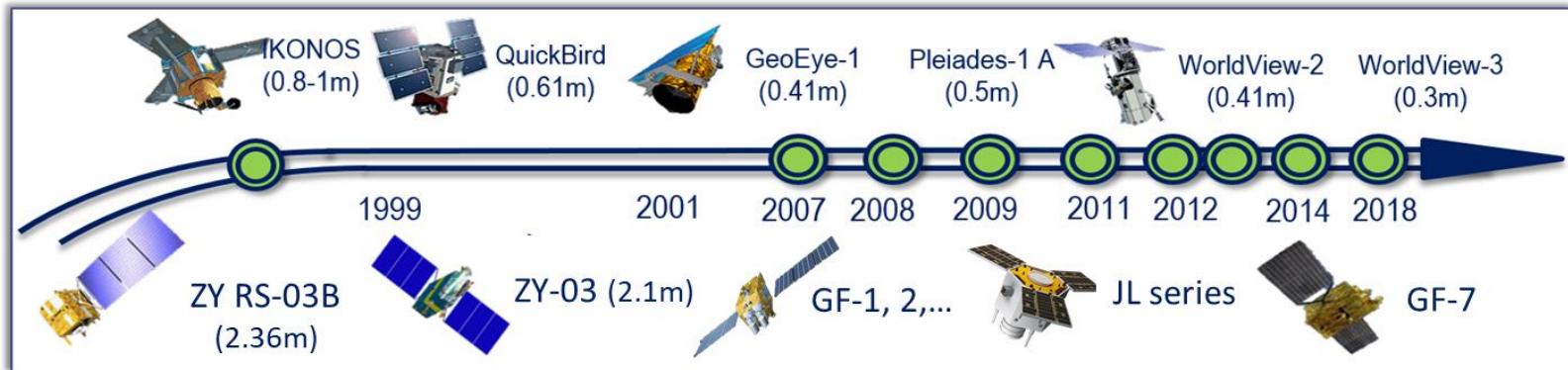
guisong.xia@whu.edu.cn

School of Computer Science, Wuhan University  
Institute of Artificial Intelligence, Wuhan University  
State Key Lab. LIESMARS, Wuhan University

Jun. 1, 2020

# Advanced RS Technology

RS technology has significantly improved the earth observation ability.



The characterization of features on the earth surface.

# Applications of RS Images

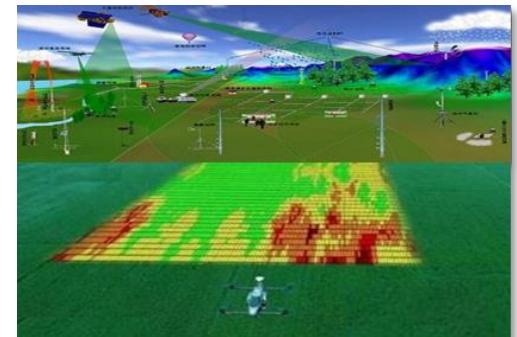
Interpretation of RS images plays important roles in many real-world applications.



National security



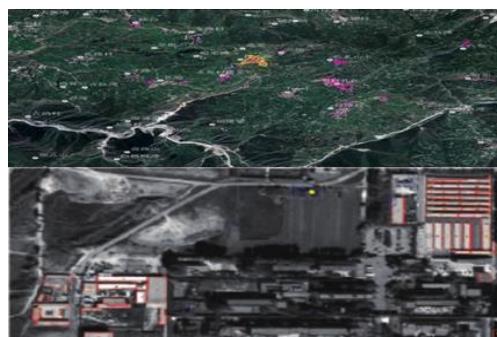
High definition map



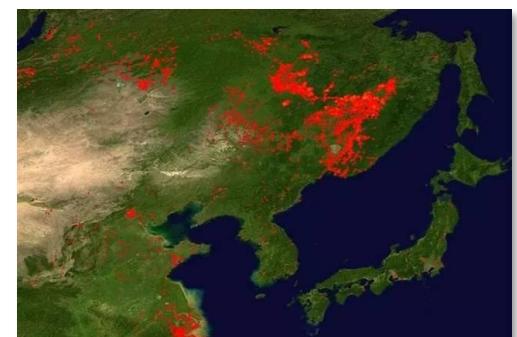
Precision agriculture



Smart city



Disaster assessment



Environ. monitoring

# Applications of RS Images

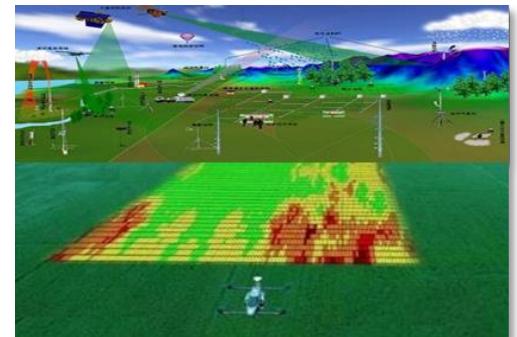
Interpretation of RS images plays important roles in many real-world applications.



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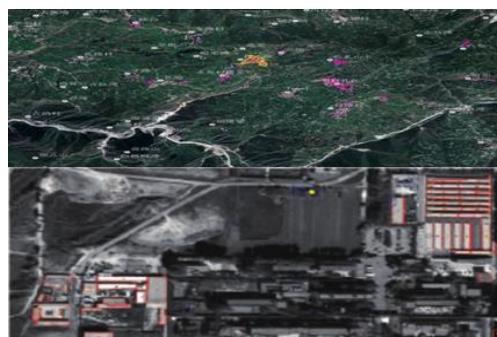
High definition map



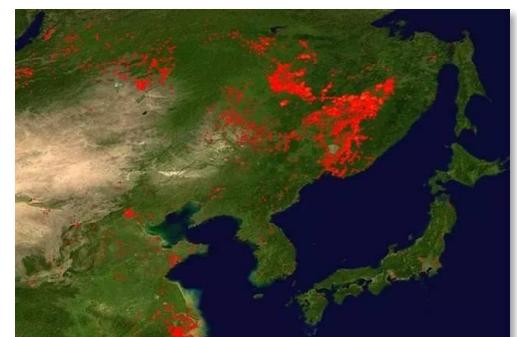
Precision agriculture



Smart city



Disaster assessment



Environ. monitoring

# Interpretation of RS Images

**Current situation:** Increasing demands for automatic interpretation



Satellites on-orbit

- **Variation:** difference in spectral, spatial, and temporal properties

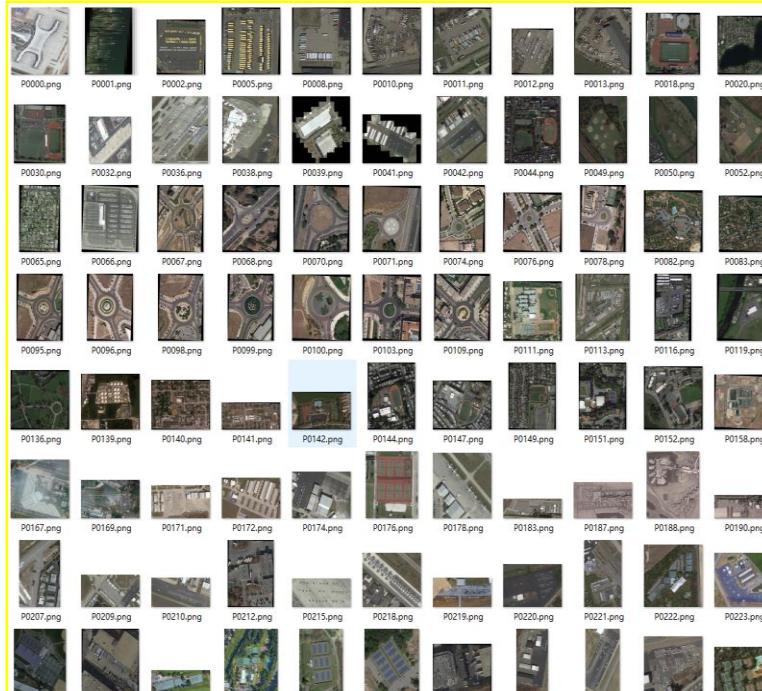


Image acquisition

- **Inconsistency:** multi-modal, multi-source RS images

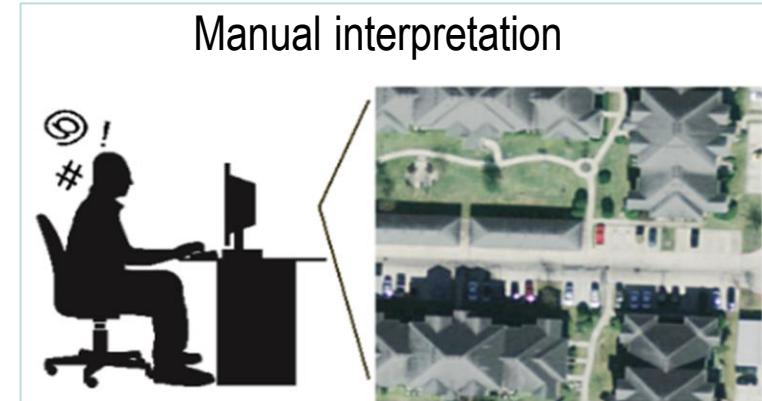
# Interpretation of RS Images

**Current situation:** Increasing demands for automatic interpretation



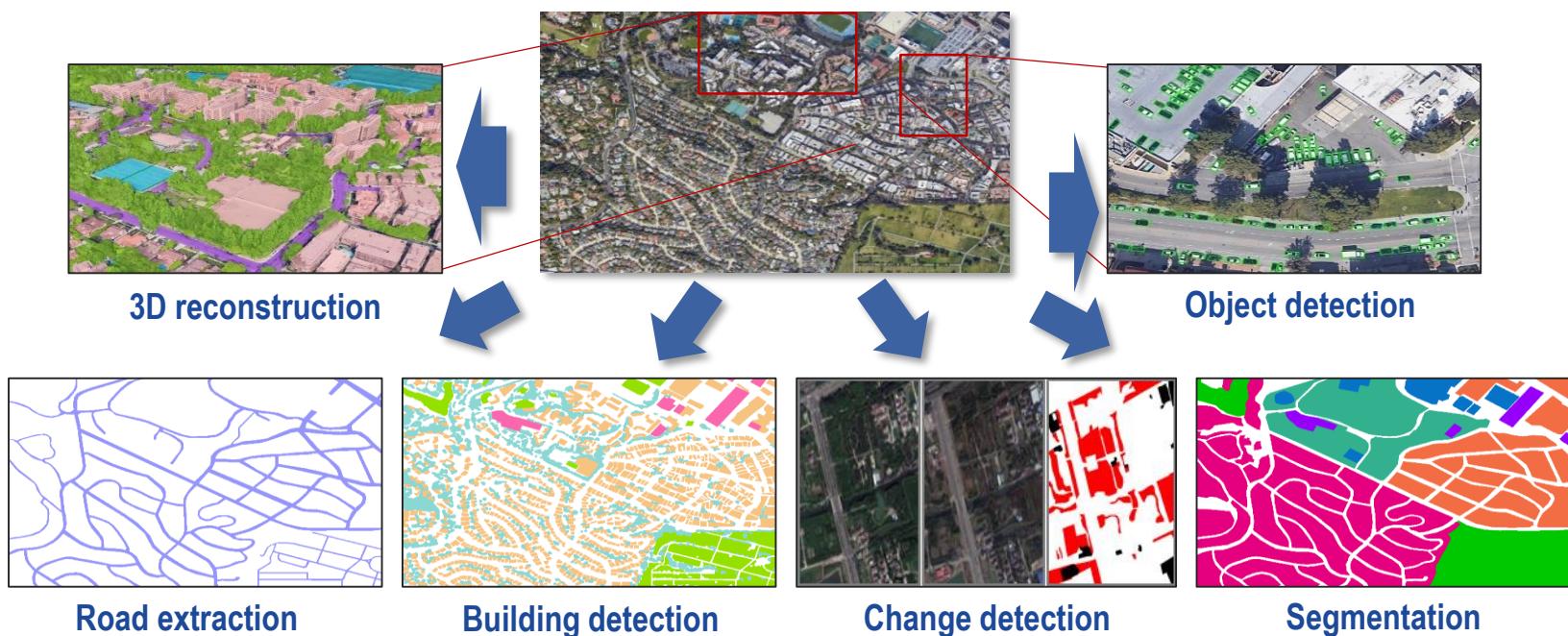
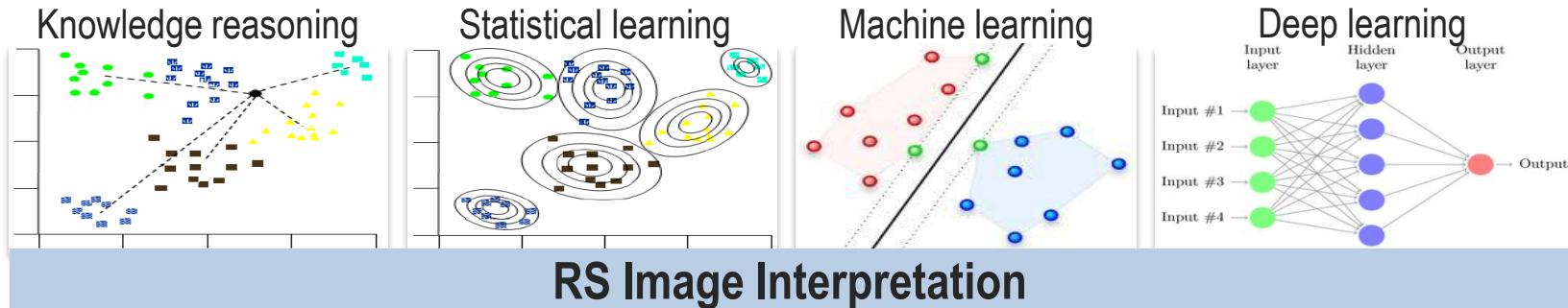
Large volume of images

- **Challenge:** geometrical shapes, textural attribute, structural characteristic ...



# Blooming Data-driven methods

Content interpretation: data-driven methods for RS image interpretation.



- Huge-volume RS images **v.s.** *limited data with labels*
- Increasing number of datasets with *different purposes and standards*
  - The **ever-growing volume of RS images** is acquired while very **few of them are annotated** with valuable information.
  - The **generalization ability of algorithms** for interpreting RS images is of great urgency to be enhanced.
  - The **Representative and large-scale RS image datasets** with accurate annotations is demanded to narrow *the gap between algorithm development and real applications*.
  - There is a **lack of public platforms** for systematic evaluation and fair comparison among different algorithms.



# Outline

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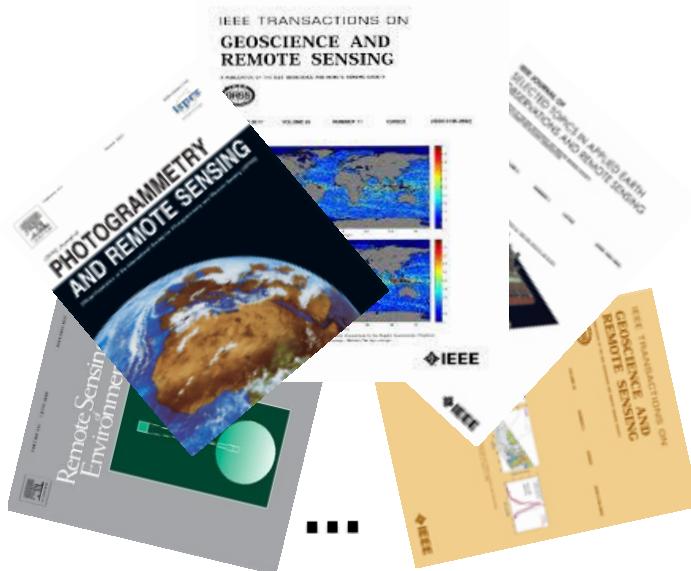
- Background
- **Research Focus in the Past Decade**
- Principles to Benchmark RS Image Interpretation
- An Example: Million-AID
- Challenges and Perspectives
- Conclusions

# Focus in the Past Decade

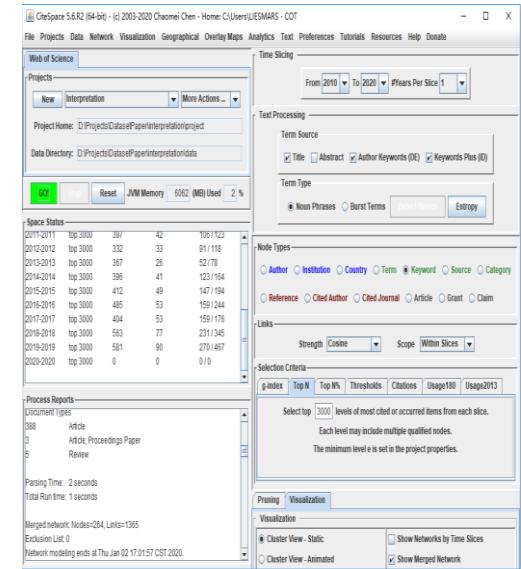


## ■ A systematic investigation to the literature

- **Journals with good reputation:** *ISPRS J. P&RS, RSE, TGRS* ...
  - **Meta-data for analysis:** 11, 337 retrieved articles over the past decade
  - **Bibliometric analysis:** title/topic/keywords ... concerning image interpretation



## Selected journals

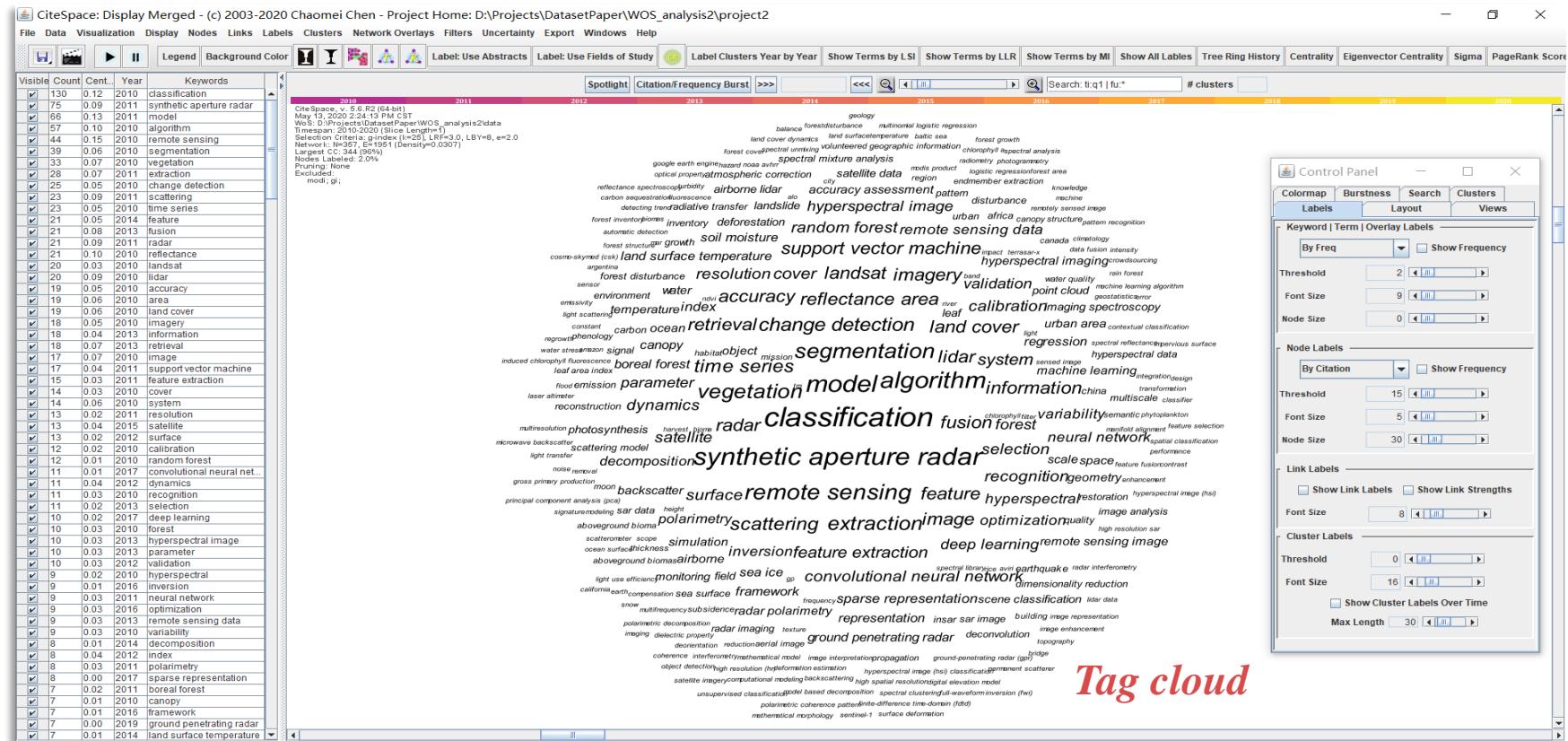


# Meta-data

## Bibliometric analysis

# Frequency Terms

- Interpretation mainly focus on **classification** tasks (scene, object, land cover ...)
- **Segmentation** and **change detection** occupy prominent positions
- **Algorithm** and **model** play significant roles in RS image interpretation



# Citation Bursts

- **Deep learning/CNN** climb to the top for RS image interpretation since 2017
- **Data Set** confirms its key role in data-driven interpretation schemes since 2019

## *Top 5 Keywords with the Strongest Citation Bursts*

Year	Keywords	Strength	Duration	Year	Keywords	Strength	Duration	Year	Keywords	Strength	Duration
2011	atmospheric correction	2.27		2014	surface	2.08		2017	convolutional neural network	3.19	
	endmember extraction	1.86			scattering model	1.95			deep learning	2.90	
	segmentation	1.63			landslide	1.62			sparse representation	2.31	
	object detection	1.24			extraction	1.59			field	2.27	
	reflectance spectroscopy	1.24			reflectance	1.23			radiative transfer	1.81	
2012	hyperspectral data	2.24		2015	time series	2.17		2018	regression	2.70	
	signal	1.87			hyperspectral imaging	2.10			random forest	2.45	
	backsactter	1.41			remote sensing	2.00			dimentionality reduction	2.20	
	model	1.37			subsidence	1.74			reconstruction	2.20	
	optical property	1.28			water quality	1.74			machine learning	1.91	
2013	object	2.45		2016	inversion	2.96		2019	ground penetrating radar	3.72	
	urban area	2.45			simulation	2.84			water	3.19	
	monitoring	2.04			information	2.44			emission	2.12	
	hyperspectral image	1.85			point cloud	2.37			temperature	1.79	
	algorithm	1.68			restoration	2.28			propagation	1.59	

# Available Datasets for Interpretation

## ■ RS *scene classification* datasets

Dataset	#Cat.	#Images per cat.	#Images	Resolution (m)	Image size	Year
UC-Merced	21	100	2,100	0.3	256 × 256	2010
WHU-RS19	19	50 to 61	1,013	up to 0.5	600 × 600	2012
RSSCN7	7	400	2,800	—	400 × 400	2015
SAT-4	4	89,963 to 178,034	500,000	1 to 6	28 × 28	2015
SAT-6	6	10,262 to 150,400	405,000	1 to 6	28 × 28	2015
BCS	2	1,438	2,876	—	600 × 600	2015
RSC11	11	~100	1,232	~0.2	512 × 512	2016
SIRI-WHU	12	200	2,400	2	200 × 200	2016
NWPU-RESISC45	45	700	31,500	0.2 to 30	256 × 256	2016
AID	30	220 to 420	10,000	0.5 to 8	600 × 600	2017
RSI-CB256	35	198 to 1,331	24,000	0.3 to 3	256 × 256	2017
RSI-CB128	45	173 to 1,550	36,000	0.3 to 3	128 × 128	2017
RSD46-WHU	46	500 to 3,000	117,000	0.5 to 2	256 × 256	2017
EuroSAT	10	2,000 to 3,000	27,000	10	64 × 64	2018
PatternNet	38	800	30,400	0.06 to 4.7	256 × 256	2018

## ■ RS *object detection* datasets

Datasets	Annot.	#Cat.	#Instances	#Images	Image width	Year
TAS	HBB	1	1,319	30	792	2008
SZTAKI-INRIA	OBB	1	665	9	~800	2012
NWPU-VHR10	HBB	10	3,651	800	~1,000	2014
DLR 3k	OBB	2	14,235	20	5,616	2015
UCAS-AOD	OBB	2	14,596	1,510	~1,000	2015
VEDAI	OBB	9	3,640	1,210	512 / 1,024	2016
COWC	CP	1	32,716	53	2,000–19,000	2016
HRSC2016	OBB	26	2,976	1,061	~1,100	2016
RSOD	HBB	4	6,950	976	~1,000	2017
CARPPK	HBB	1	89,777	1,448	1280	2017
LEVIR	HBB	3	11,028	22,000	800	2018
VisDrone	HBB	10	54,200	10,209	2,000	2018
xView	HBB	60	1,000,000	1,413	~3,000	2018
DOTA	OBB	15	188,282	2,806	800–4,000	2018
HRRSD	HBB	13	55,740	21,761	152–10,569	2019
DIOR	HBB	20	192,472	23,463	800	2019

# Available Datasets for Interpretation

## ■ RS *semantic segmentation* datasets

Datasets	#Cat.	#Images	Resolution (m)	#Bands	Image size	Year
Kennedy Space Center	13	1	18	224 bands	512×614	2005
Botswana	14	1	30	242 bands	1476×256	2005
Salinas	16	1	3.7	224 bands	512×217	—
University of Pavia	9	1	1.3	115 bands	610×340	—
Pavia Centre	9	1	1.3	115 bands	1096×492	—
ISPRS Vaihingen	6	33	0.09	IR,R,G,DSM,nDSM	~2,500×2,500	2012
ISPRS Potsdam	6	38	0.05	IR,RGB,DSM,nDSM	6,000×6,000	2012
Massachusetts Buildings	2	151	1	RGB	1,500×1,500	2013
Massachusetts Roads	2	1,171	1	RGB	1,500×1,500	2013
Indian Pines	16	1	20	224 bands	145×145	2015
Zurich Summer	8	20	0.62	NIR, RGB	1,000×1,150	2015
Inria Dataset	2	360	0.3	RGB	1,500×1,500	2017
EVlab-SS	10	60	0.1 to 2	RGB	4,500×4,500	2017
RIT-18	18	3	0.047	6 bands	9,000×6,000	2017
WHU Building-Aerial Imagery	2	8,189	0.3	RGB	512×512	2019
WHU Building-Satellite Imagery I	2	204	0.3 to 2.5	RGB	512×512	2019
WHU Building-Satellite Imagery II	2	17,388	2.7	RGB	512×512	2019
So2Sat LCZ42	17	400,673	10	10 bands	32×32	2019
SEN12MS	33	180,662 triplets	10 to 50	up to 13 bands	256×256	2019
UAVid	8	420	—	RGB	~4,000×2,160	2020
GID	15	150	0.8 to 10	4 bands	6,800×7,200	2020

## ■ RS *change detection* datasets

Datasets	#Cat.	#Image pairs	Resolution (m)	#Bands	Image size	Year
SZTAKI AirChange	2	13	1.5	RGB	952×640	2009
AICD	2	1000	0.5	115 bands	800×600	2011
Taizhou Data	4	1	30	6 bands	400×400	2014
Kunshan Data	3	1	30	6 bands	800×800	2014
Yancheng	4	2	30	242 bands	400×145	2018
Urban-rural boundary of Wuhan	20	1	4/30	4/9 bands	960×960	2018
Hermiston City area, Oregon	5	1	30	242 bands	390×200	2018
OSCD	2	24	10	13 bands	600×600	2018
Quasi-urban areas	3	1	0.5	8 bands	1,200×1,200	2018
WHU Building-Change Detection	2	1	0.2	RGB	32,207×15,354	2018
Season-varing Dataset	2	16,000	0.03 to 0.1	RGB	256×256	2018
ABCD	2	4,253	0.4	RGB	160×160	2018
HRSCD	6	291	0.5	RGB	10,000×10,000	2019
MtS-WH	9	1	1	NIR, RGB	7,200×6,000	2019
LEVIR-CD	2	637	0.5	RGB	1,024×1,024	2020
SCDN	30	4,214	0.5 to 3	RGB	512×512	2020

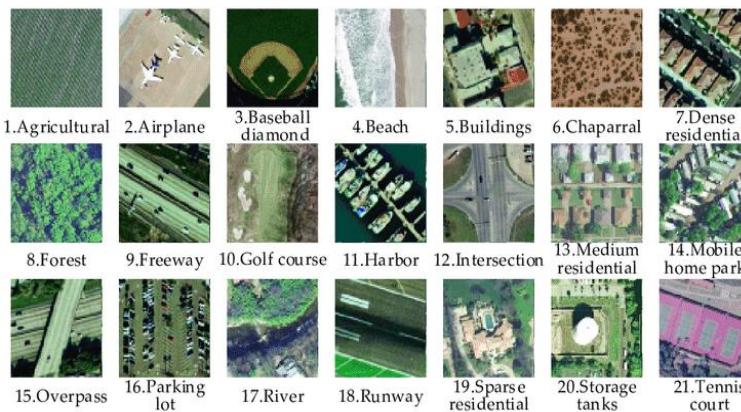
# Some Critical Reviews

## ■ Categories involved in interpretation

- **Small number** of categories, content interpretation for **certain objects**
- Categories with **equal relationship**, chaotic management for semantic information
- Complex semantic categories and relationships in real applications, e.g., LULC

## ■ Dataset annotation

- Nearly all **manually annotated** by experts, extensive **labor remains to relieve**
- **Visualization for large scale, high spectral RS images** annotation is demanded
- **Lack of interchange** with application departments for efficient data annotation



UC Merced, 21 classes, 2100 images



NPWU VHR, 800 images, manually annotated

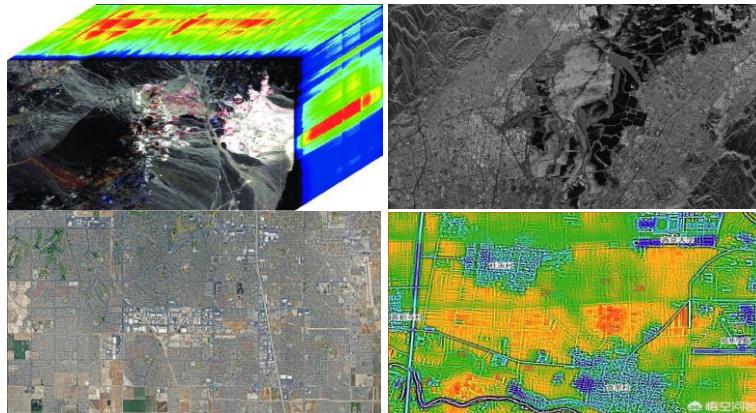
# Some Critical Reviews

## ■ Image source

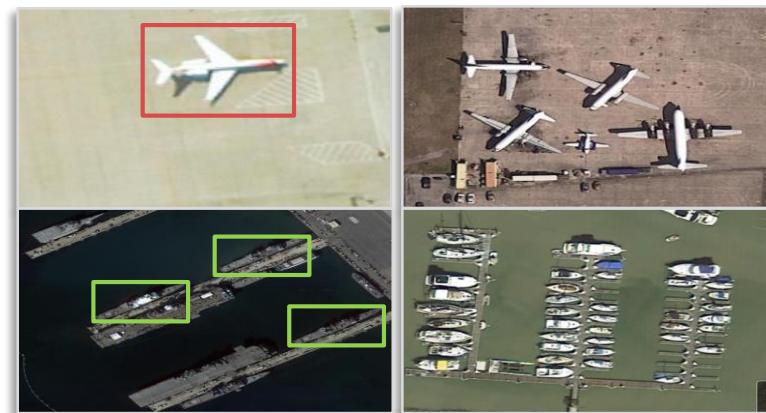
- Optical images (Google Earth) as data standard since spatial pattern, visual texture, structural information are more concerned (e.g., for scene/object recognition)
- High spectral, SAR images for abnormal object detection by the physical property

## ■ Dataset scale

- *Limited number, size of chipped images, performance saturation* of algorithms
- *Lack of image variation, sample diversity*, and *content representation*, causing *weak generalization ability* of interpretation algorithms



Multi-modal image source



Simple scenes and complex reality



# Outline

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- Background
- Research Focus in the Past Decade
- **Principles to Benchmark RS Image Interpretation**
- An Example: Million-AID
- Challenges and Perspectives
- Conclusions

# Principles to Benchmark RS II

## ■ Toward real-world scenarios *rather than specific algorithms*

- Model training, testing, and screening for practical applications
- Rich samples of variation in background, scale, imaging conditions, ...

## ■ Annotation by application sides *rather than algorithm developers*

- Label images and samples considering practical challenges in application



Images



Annotators

Algorithm designer

Application personnel



Algorithm oriented

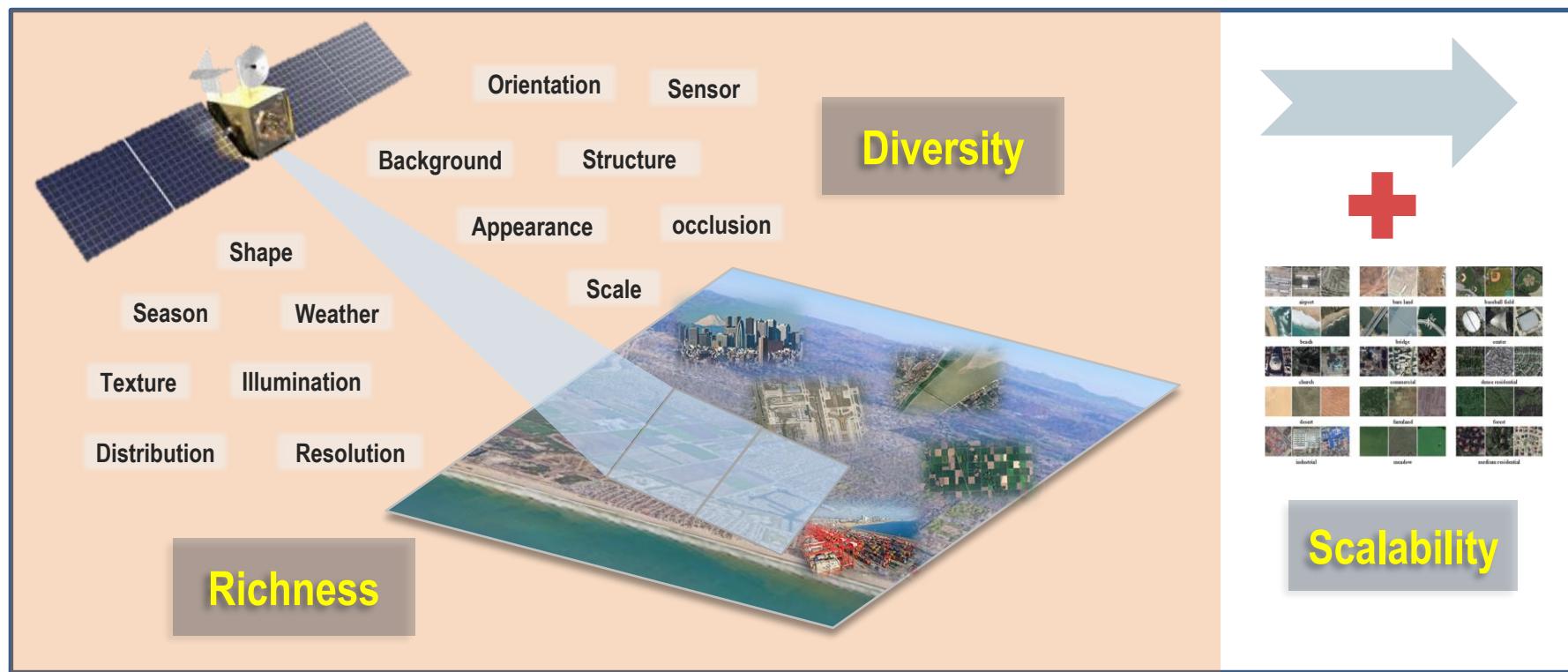


Application oriented



## ■ DiRS for dataset construction

- **Diversity**: between-/within-class diversity, complementarity of features
- **Richness**: large-scale images, sufficient samples, diverse characteristics ...
- **Scalability**: sufficient space for new data involvement, sustainable availability

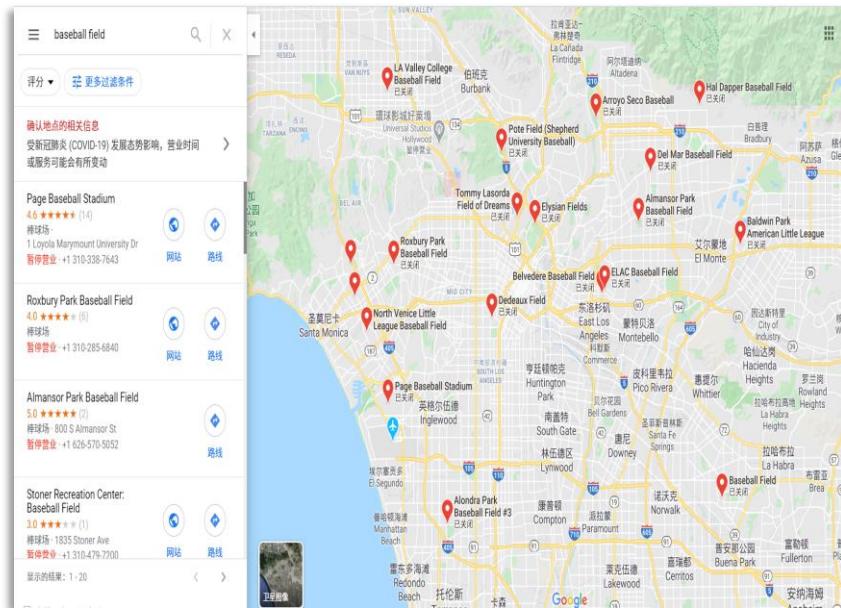


# Geographic Information Integration

## ■ Coordinates Collection for RS Image Acquisition

### ■ Geographic information utilization

- Rich positional data with millions of point, line and region objects
- Inherent semantic tags for interested image extraction with Map API



baseball field

更多过滤条件

确认地点的相关信息  
受新冠肺炎 (COVID-19) 发展态势影响，营业时间或服务可能会有所变动

Page Baseball Stadium  
4.6 ★★★★ (14)  
棒球场  
1 Loyola Marymount University Dr  
暂停营业: +1 310-335-7643

Roxbury Park Baseball Field  
4.0 ★★★★ (1)  
棒球场  
暂停营业: +1 310-285-6840

Almansor Park Baseball Field  
5.0 ★★★★★ (2)  
棒球场  
暂停营业: +1 626-570-5052

Stoner Recreation Center: Baseball Field  
3.0 ★★★★ (1)  
棒球场  
暂停营业: +1 310-479-7700



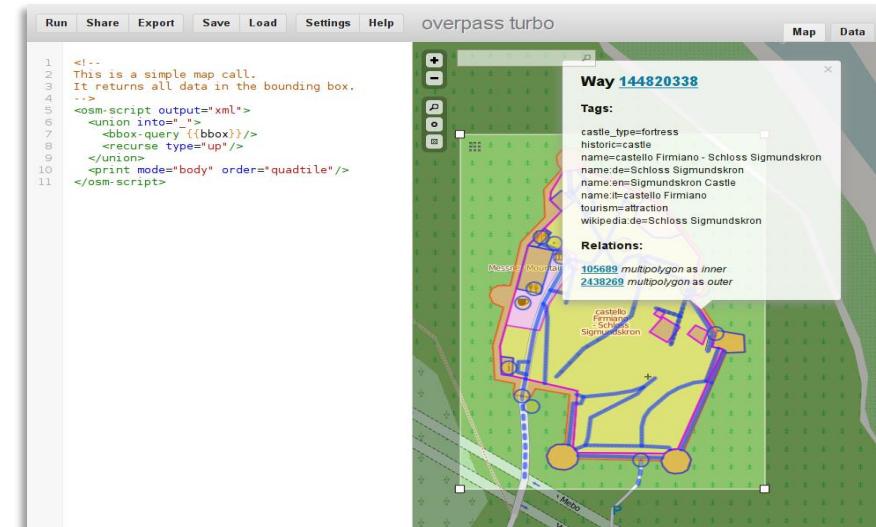
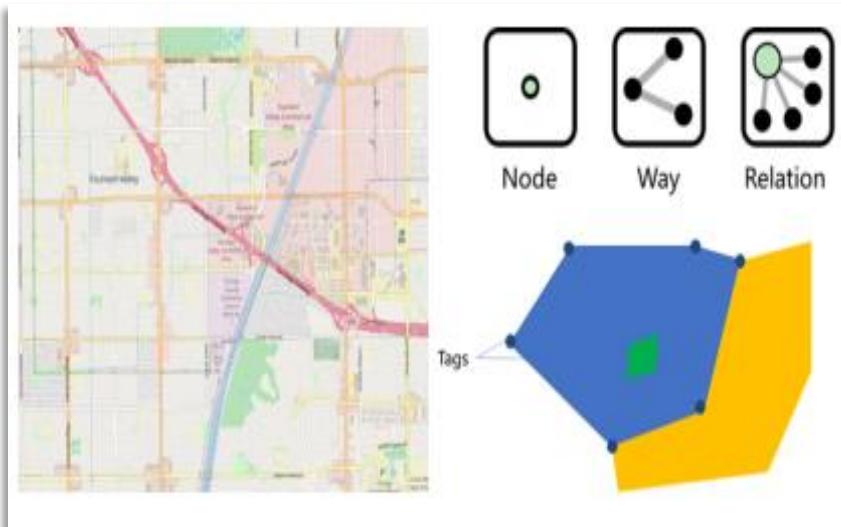
Searched baseball fields using Google Map API

# Geographic Information Integration

## ■ Coordinates Collection for RS Image Acquisition

### ■ Open source data

- Geographic data with rich semantic information that is timely updated, low cost and with large amount, e.g., OSM, WikiMapia ...
- Excellent interface for data customization, elements aligned with different maps



The screenshot shows the overpass turbo interface. At the top, there are buttons for Run, Share, Export, Save, Load, Settings, Help, and a search bar. The main area has tabs for Map and Data. On the left, there is a code editor with the following XML query:

```
1 <!--
2 This is a simple map call.
3 It returns all data in the bounding box.
4 -->
5 <osm-script output="xml">
6   <union into="">
7     <bbox-query {bbox}>/>
8     <recurse type="up"/>
9   </union>
10  <print mode="body" order="quadtile"/>
11 </osm-script>
```

On the right, a map displays a complex polygonal area representing a castle. A tooltip for a way is shown, listing tags such as castle, historic-architecture, historic-castle, name=Schloss Firmiano - Schloss Sigmundskron, name\_en=Sigmundskron Castle, name\_it=castello Firmiano, tourism=attraction, and wikipedia.de=Schloss Sigmundskron. Below the map, a legend indicates that 105698 multipolygon is the inner and 2438269 multipolygon is the outer boundary.

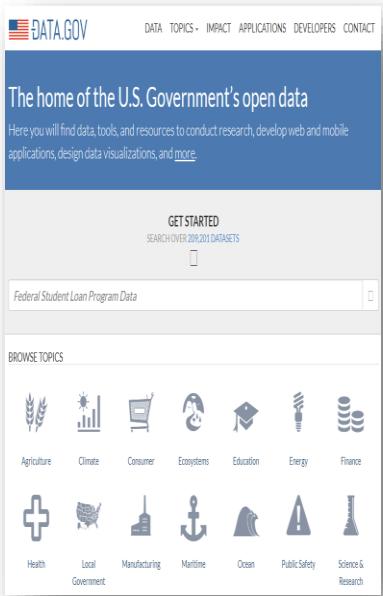
Elements of interest extracted from OSM

# Geographic Information Integration

## ■ Coordinates Collection for RS Image Acquisition

### ■ Geodatabase integration

- Public geodatabases released by the state institutions and communities
- Domain-specific geodatabase that is publicly available



The home of the U.S. Government's open data. Here you will find data, tools, and resources to conduct research, develop web and mobile applications, design data visualizations, and more.

GET STARTED  
SEARCH OVER 200,000 DATASETS

Federal Student Loan Program Data

BROWSE TOPICS

- Agriculture
- Climate
- Consumer
- Ecosystems
- Education
- Energy
- Finance
- Health
- Local Government
- Manufacturing
- Maritime
- Ocean
- Public Safety
- Science & Research



Transportation.gov Geospatial at the Bureau of Transportation Statistics

Search for open data

Data by Mode

- Rail
- Aviation
- Roads
- Transit
- Marine

Data by Category

- Performance
- Safety
- Freight
- Energy and Environment



HIFLD Open Data

This site provides National foundation-level geospatial data within the open public domain that can be useful to support community preparedness, resilience, research, and more. The data is available for download as CSV, KMZ, Shapefile, and accessible via web services to support application development and data visualization.

Find Data

Search HIFLD Open

Explore All Data

National Bridge Inventory

Transit Stations

Interstate Highways

Water System

Protestant Churches

ESRI Open Data Hub

.....

Public geodatabases available for image coordinates collection

# Annotation methodology

## ■ Manual Annotation

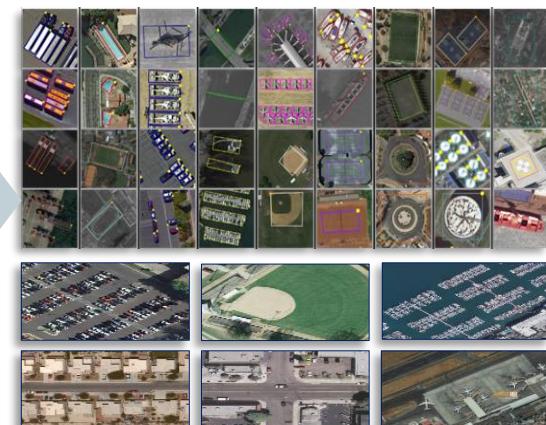
- Accuracy guarantee, but labor-intensive and time-consuming
- Hard to meet the scale requirements particularly for data-driven methods

## ■ Automatic Annotation

- Reduce the cost of annotation by leveraging learning models
- Bias problem deriving from the initialization data and model capability



Source image

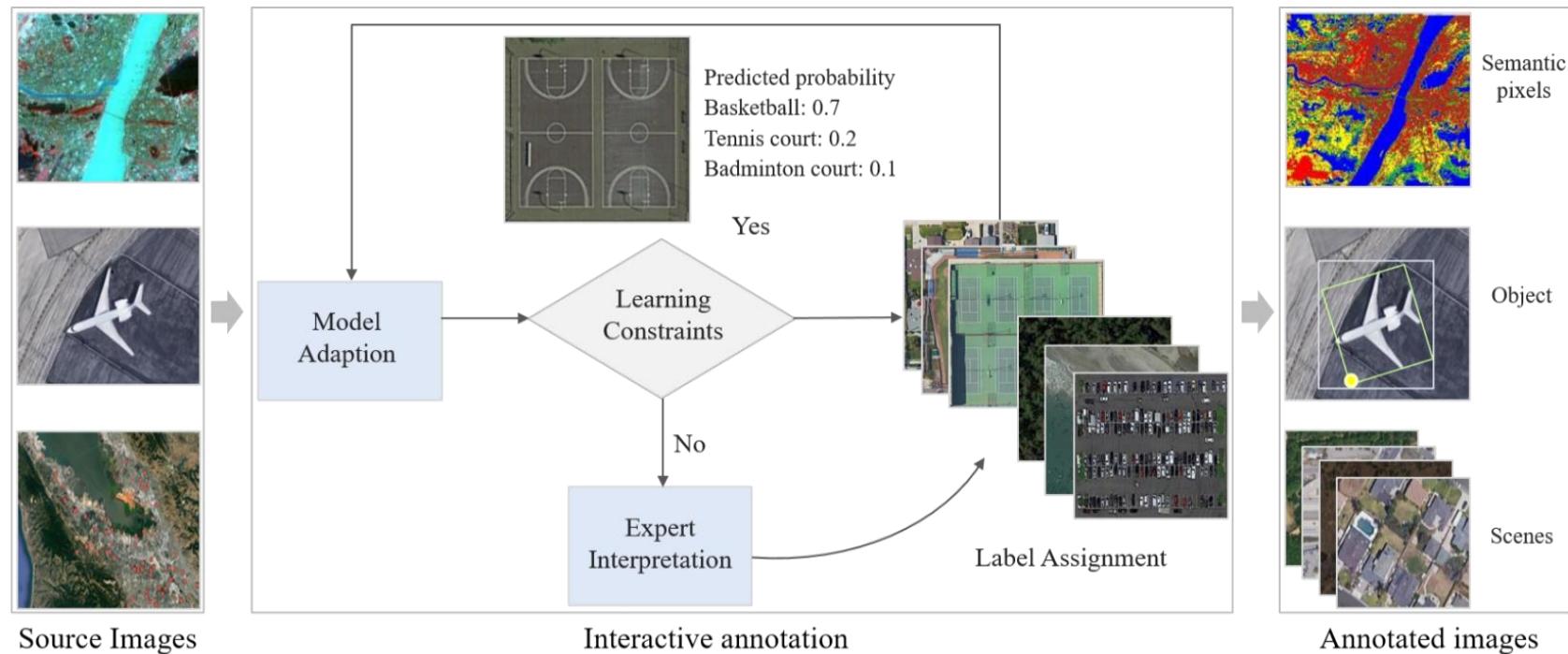


Annotated samples

# Annotation methodology

## ■ Interactive Annotation

- Annotation with human-computer interaction, semi-automatic annotation
- Guarantee for quality and efficiency, toward large-scale dataset construction



General workflow of Semi-automatic annotation in RS images

# Quality Assessment

- **Rules and Samples:** annotation without ambiguity, specific samples for instructions
- **Training of Annotators:** well-qualified annotators for dataset quality guarantee
- **Multi-stage Pipeline:** annotation task decomposition
- **Grading and Reward:** incentive mechanism for incompetent/competent annotators
- **Multiple Annotations:** merge multiple accurate annotations
- **Annotation Review:** expert/peer review and quality rating
- **Spot Check and Assessment:** gold data for annotation quality assurance



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- **An Example: Million-AID**
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## ■ Scene Classification

- High-level knowledge expression to RS image contents
- Semantic information recognition to local areas of RS images



Forest

Grass land

Parking lot

Resid. area

Indus. area

Water

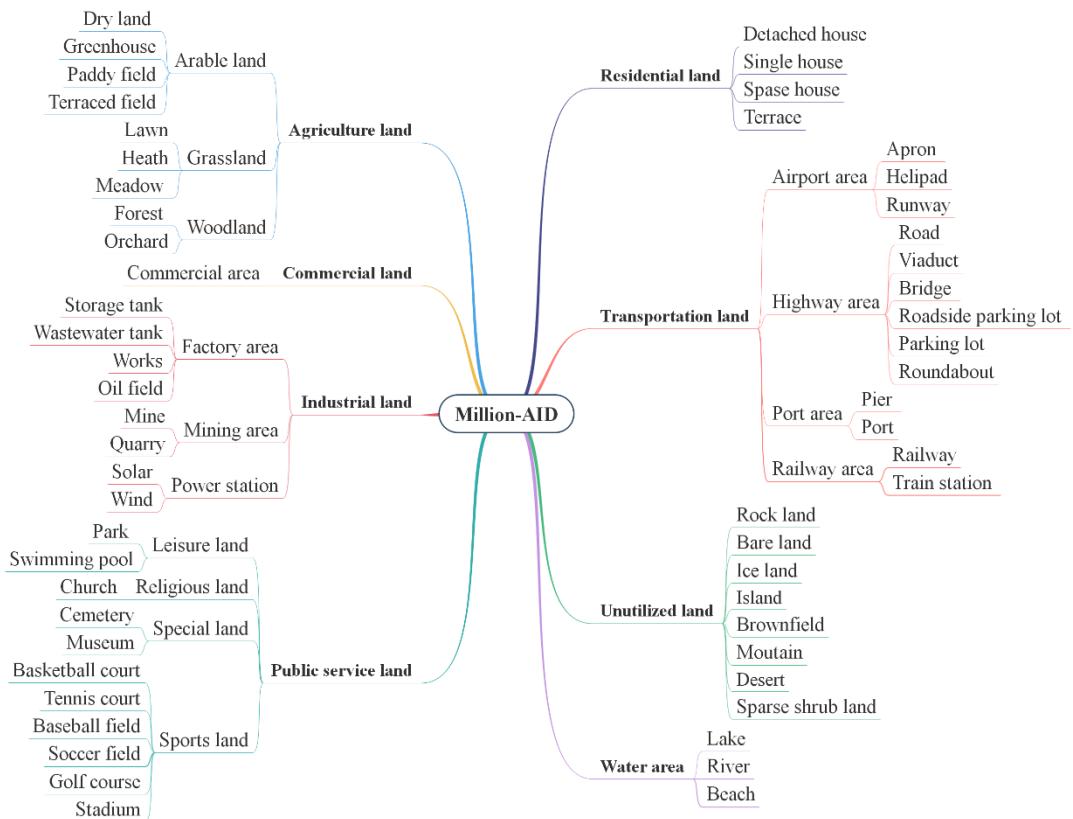
Other

## ■ Category Organization

### Chinese Land Use Classification Criteria



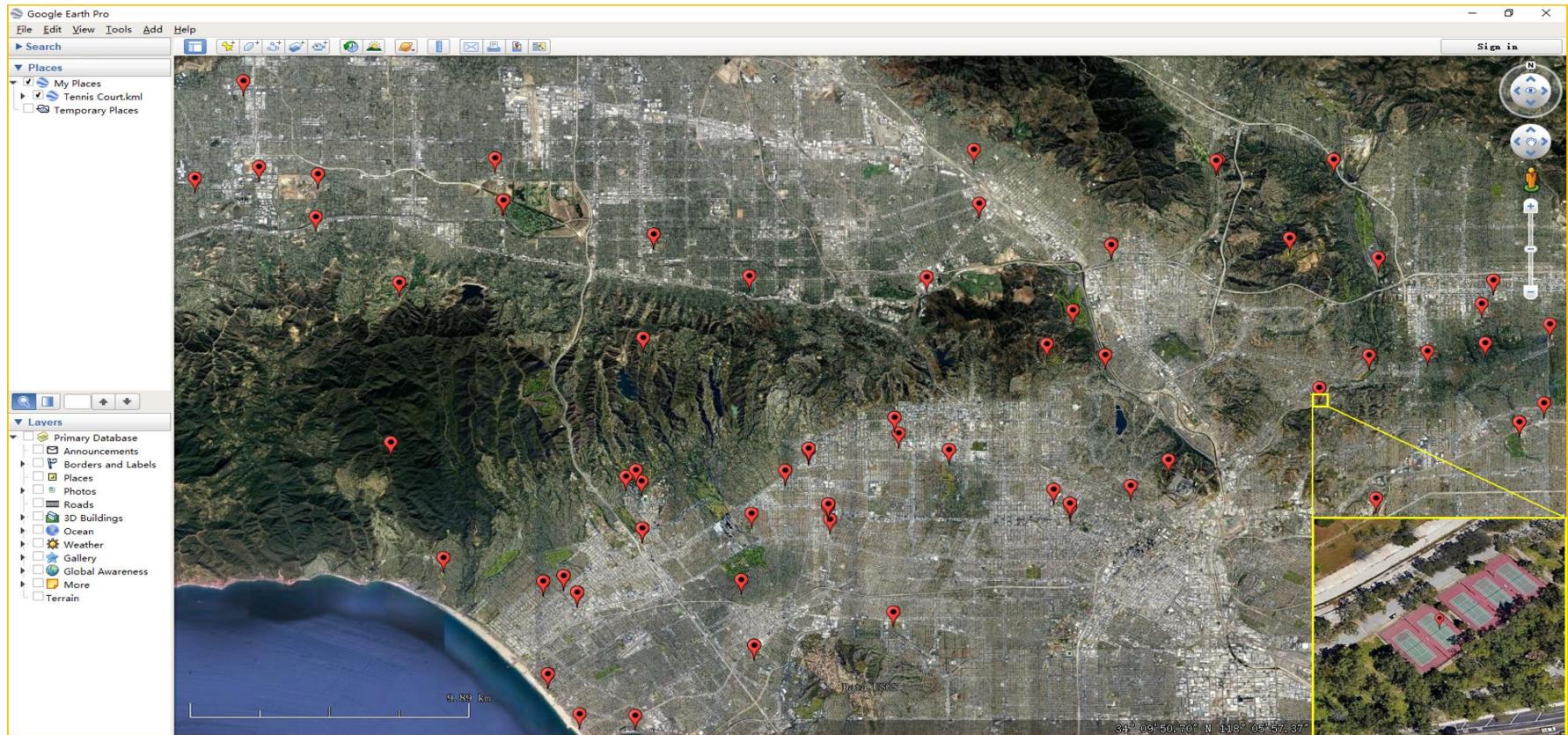
**8 major categories with 57 sub-categories**



The hierarchical scene category network of Million-AID

## ■ Semantic Coordinates Collection

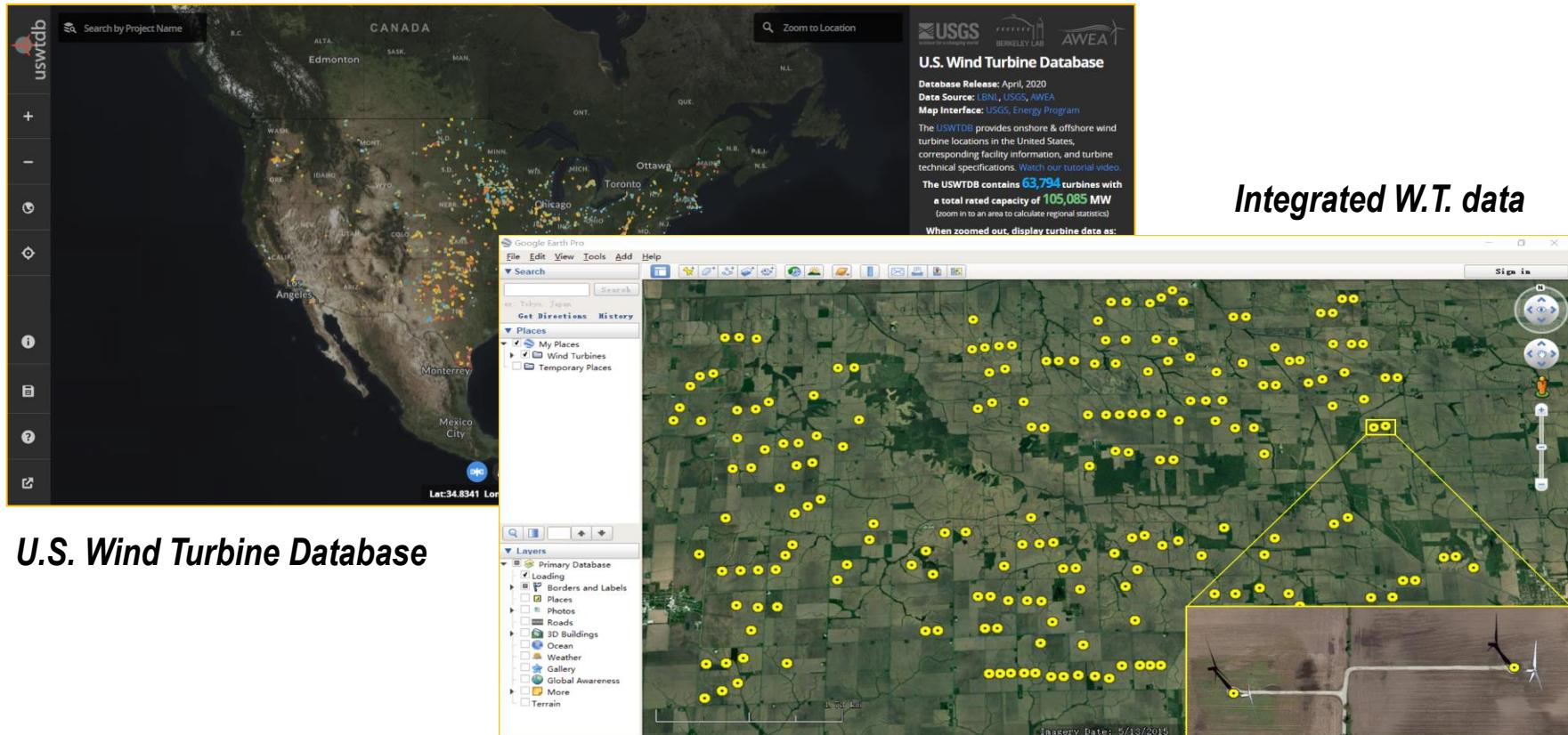
### ■ Point coordinates using Google Map API



The points of searched tennis courts shown in Google Earth. We consider the tennis courts as point ground features. In this case, we use Google Map API for coordinates collection.

## Semantic Coordinates Collection

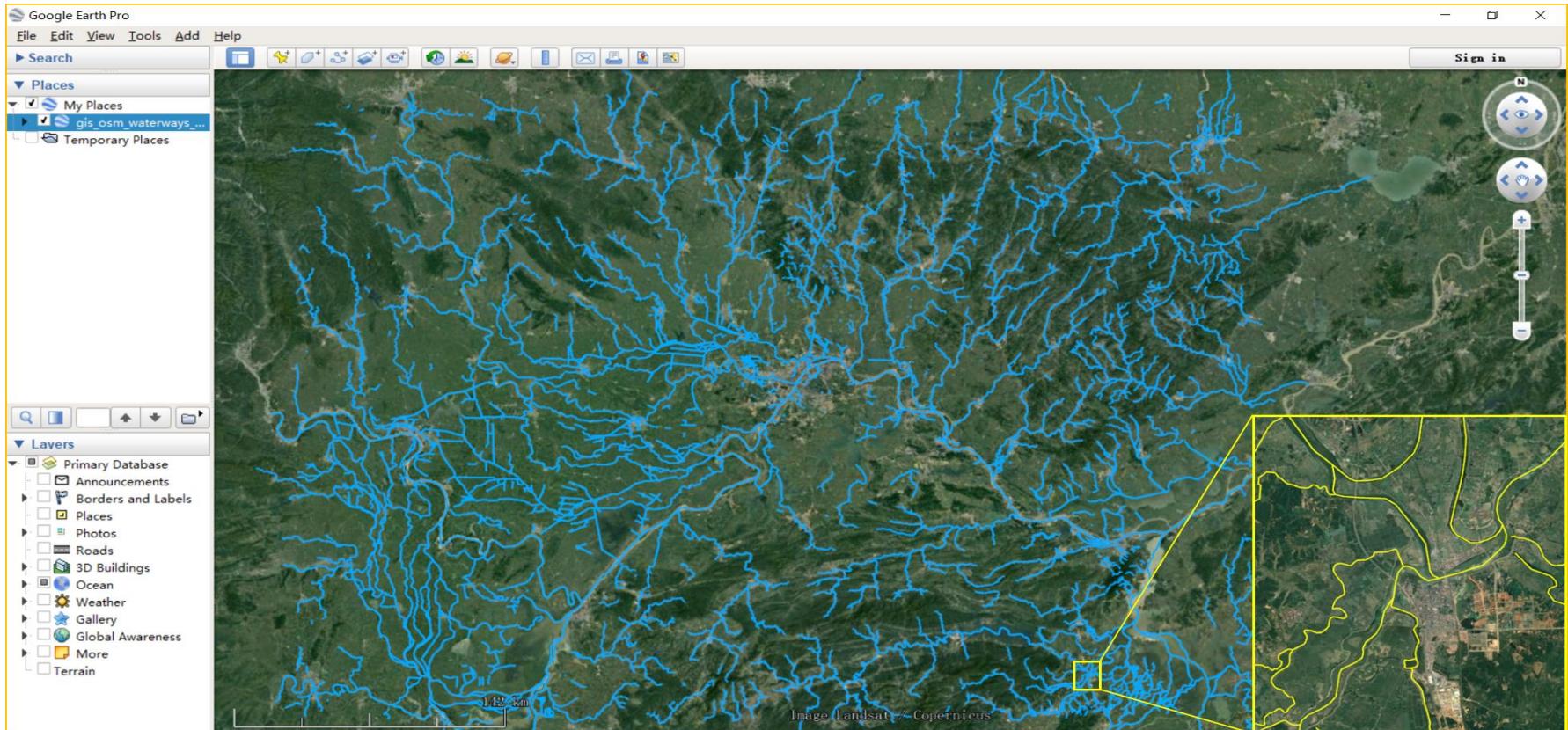
### Point coordinates integrated from Geodatabase



The points of wind turbines extracted from USWTDB and integrated in Google Earth. Generally, over 60, 000 objects of wind turbines can be collected by the database.

## ■ Semantic Coordinates Collection

### ■ Line features extracted from OSM



The river lines within a local area of China collected from OSM and displayed in Google Earth

## Semantic Coordinates Collection

### Plane features customized on OSM

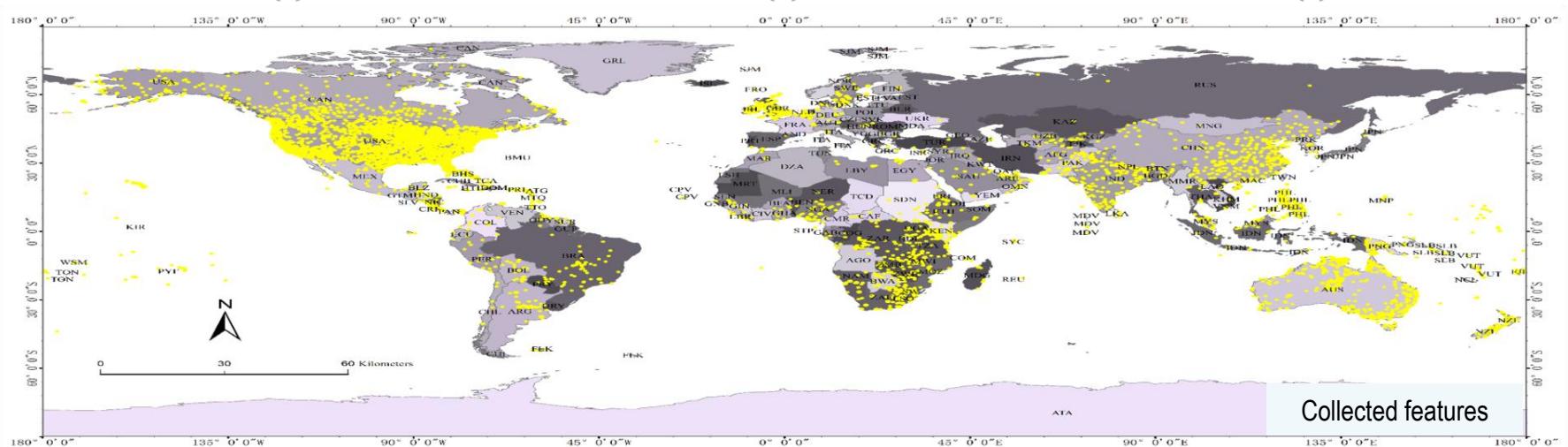


aeroway	aerodrome
ele	37
iata	VRC
icao	RPUV
length	1886
name	Virac Airport
operator	Civil Aviation Authority of the Philippines
source	Wikipedia
wikidata	
wikipedia	

Semantic tags

```
<osm-script>
<union>
<query type="way">
<has-kv k="aeroway" regv="aerodrome"/>
<has-kv k="name" regv="[a|A]irport$|机场$"/>
</query>
<query type="relation">
<has-kv k="aeroway" regv="aerodrome"/>
<has-kv k="name" regv="[a|A]irport$|机场$"/>
</query>
<recurse type="relation-way"/>
</union>
<union>
<item/>
<recurse type="down"/>
</union>
<print/>
</osm-script>
```

Data customization



The illustration of searching scenes of airports around the world. An airport in OSM contains a large amount of tags, which can be employed to search airports with specific semantic key-value labels.

## ■ Scene Image Acquisition

- **Image blocks by the line, point, and plane data**

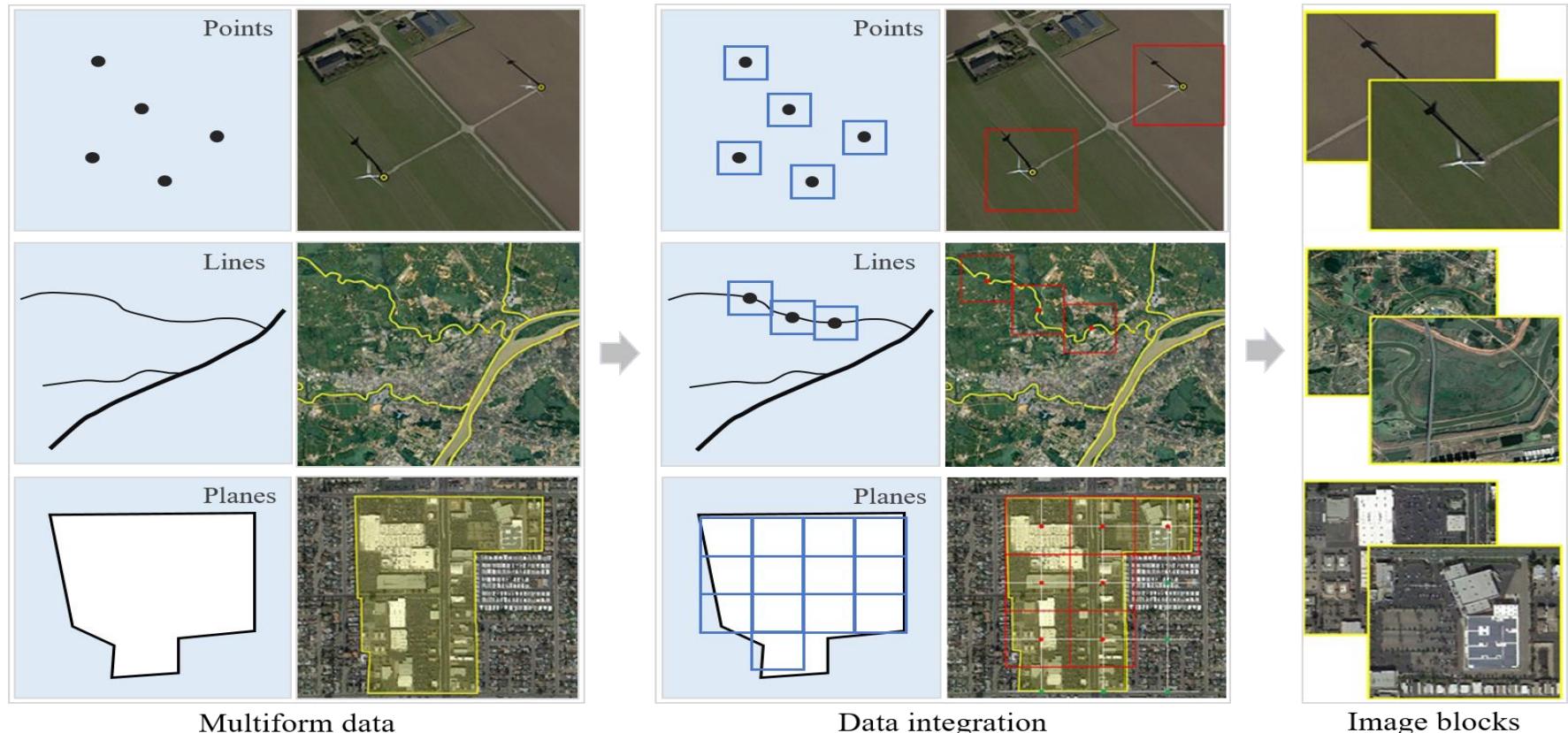
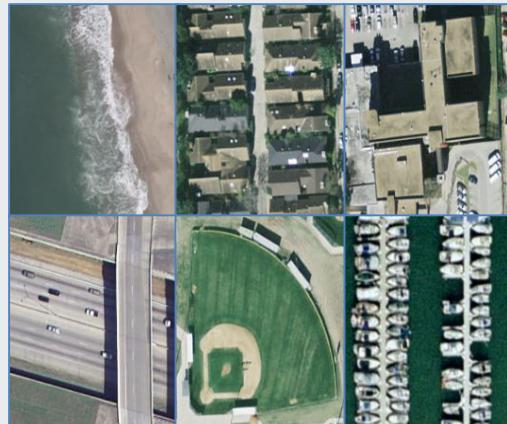


Illustration of the acquisition of RS scene images based on the collected geographic point, line and area data.  
**Points:** centers of scene blocks. **Line:** sampled by intervals. **Plane:** sampled by mesh grids.

## ■ A Glimpse of Comparison

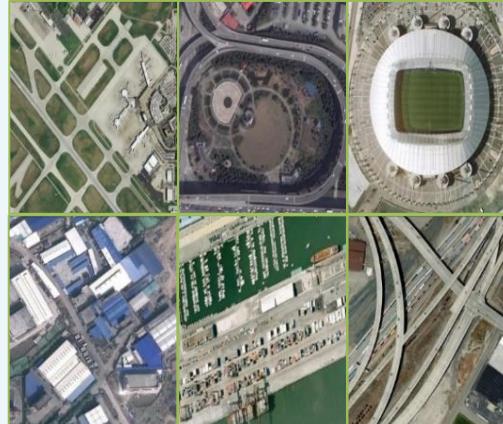
### ■ Million-AID: DiRS, better approximate real applications

UC-Merced



- Categories: 21
- Image size: 256x256
- Resolution: ~ 0.3m
- Number of images: 2100

WHU-RS19



- Categories: 19
- Image size: 600x600
- Resolution: 0.2 ~ 10m
- Number of images: 950

Million-AID



- Categories: 57
- Image size: 114~1024
- Resolution: 0.2 ~ 10m
- Number of images: 100M



# Outline

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- Background
- Research Focus in the Past Decade
- Principles to Benchmark RS Image Interpretation
- An Example: Million-AID
- Challenges and Perspectives
- Conclusions

- How to speed up the annotation process?

## ■ Visualization technology for RS image Annotation

- *High-spectral images*: several selected bands, band transformation ...
- *Large-scale images*: efficient display technology helps to catch the content essence
- *SAR images*: signal expression via physical means

## ■ Annotation Efficiency and Quality Improvement

- *Cooperation with application departments*: convert production data to algorithms
- *Annotation tools*: open-sourced and professional tools for RS image annotation
- *Noisy annotations*: noise cleansing, performance impact, tolerant algorithms

# Challenges and Perspectives



## ■ Speed up the annotation process

### Annotation tools for image dataset construction

No.	Name	Year	Description
1	LabelMe	2008	An online image annotation tool that supports various annotation primitives, including polygon, rectangle, circle, line and point.
2	Video Annotation Tool from Irvine, California (VATIC)	2012	An online tool that efficiently scaling up video annotation with crowdsourced marketplaces (e.g., AMT).
3	LabelImg	2015	A popular graphical image annotation application that labels objects in images with bounding boxes.
4	Visual Object Tagging Tool (VOTT)	2017	An open source annotation and labeling tool for image and video assets, extensible for importing/exporting data to local or cloud storage providers, including Azure Blob Storage and Bing Image Search.
5	Computer Vision Annotation Tool (CVAT)	2018	A universal data annotation approach for both individuals and teams, supporting large-scale semantic annotation for scene classification, object detection and image segmentation.
6	Image Tagger	2018	An open source online platform to create and manage image data and diverse labels (e.g., bounding box, polygon, line and point), with friendly support for collaborative image labeling.
7	Polygon RNN++	2018	A deep learning-based annotation strategy, producing polygonal annotation of objects segmentation interactively using humans-in-the-loop.
8	Makesence.AI	2019	An open source and online image annotation platform, using different artificial model to give recommendations as well as automate repetitive and tedious labeling activities.
9	VGG Image Annotator (VIA)	2019	A simple and standalone manual annotation software for image and video, providing rich labels like point, line, polygon as well as circle and ellipse without project management.



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## ■ A review of annotated datasets for RS image interpretation

- Covering literature published over the past decade
- A systematic review of the existing RS image datasets concerning the current mainstream of RS image interpretation tasks

## ■ Principles to build RS image benchmarks

- DiRS: on creating benchmark datasets for RS image interpretation
- A picture of coordinates collection, methodology for RS image dataset construction

## ■ An example for construction : Million-AID

- A large-scale benchmark dataset for RS image scene classification

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# THANKS



*School of Computer Science, Wuhan University  
Institute of Artificial Intelligence, Wuhan University  
State Key Lab. LIESMARS, Wuhan University*

Gui-Song Xia ([gusong.xia@whu.edu.cn](mailto:gusong.xia@whu.edu.cn))