RS IMAGE INTERPRETATION FROM A DATA PERSPECTIVE

Diversity, Richness, Scalability (DiRS) :

On Benchmarking Remote Sensing Image Interpretation

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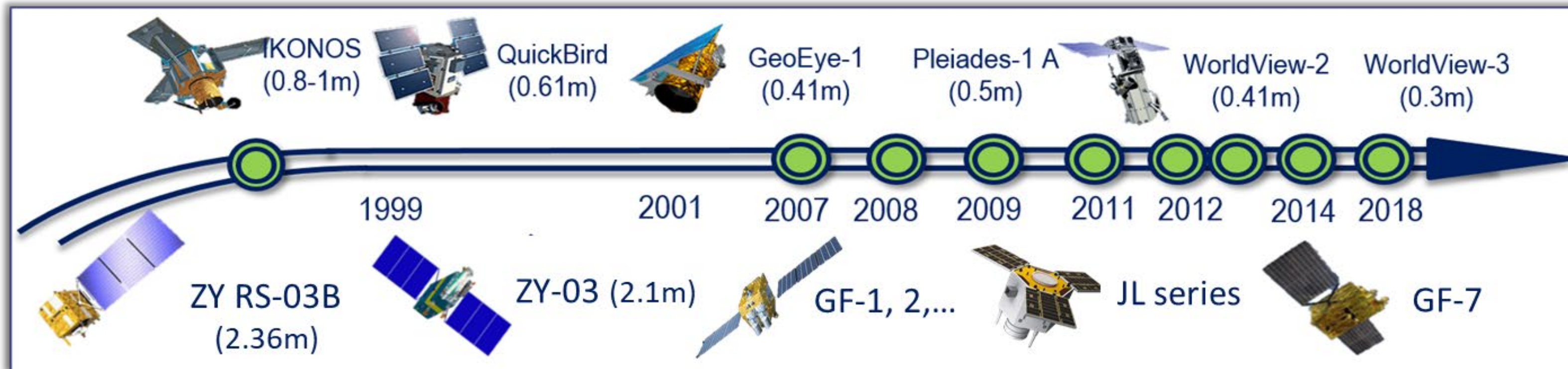
Advanced RS Technology

RS technology has significantly improved the earth observation ability.

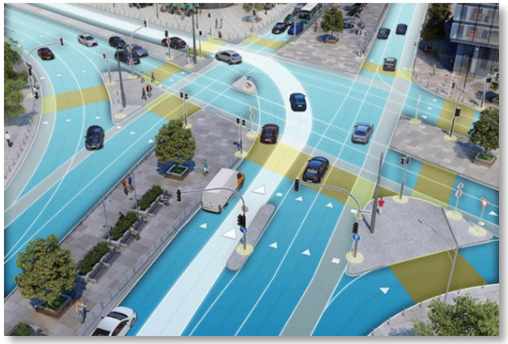


The characterization of features on the earth surface.

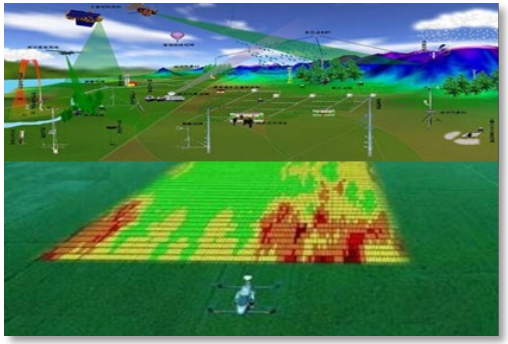
Applications of RS Images

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

National security

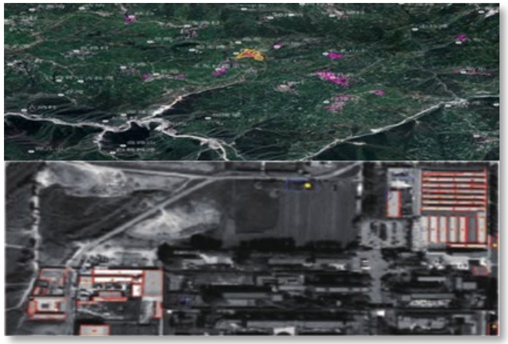


High definition map

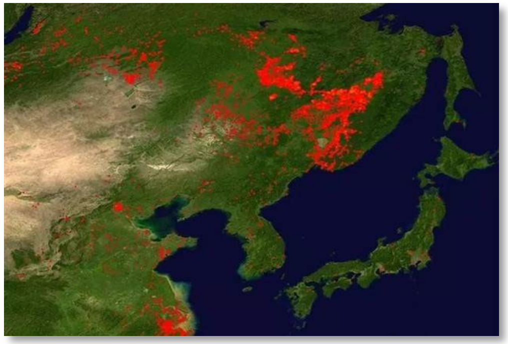


Precision agriculture

Smart city



Disaster assessment



Environ. monitoring

Interpretation of RS Images

Current situation: Increasing demands for automatic interpretation

Satellites on-orbit

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

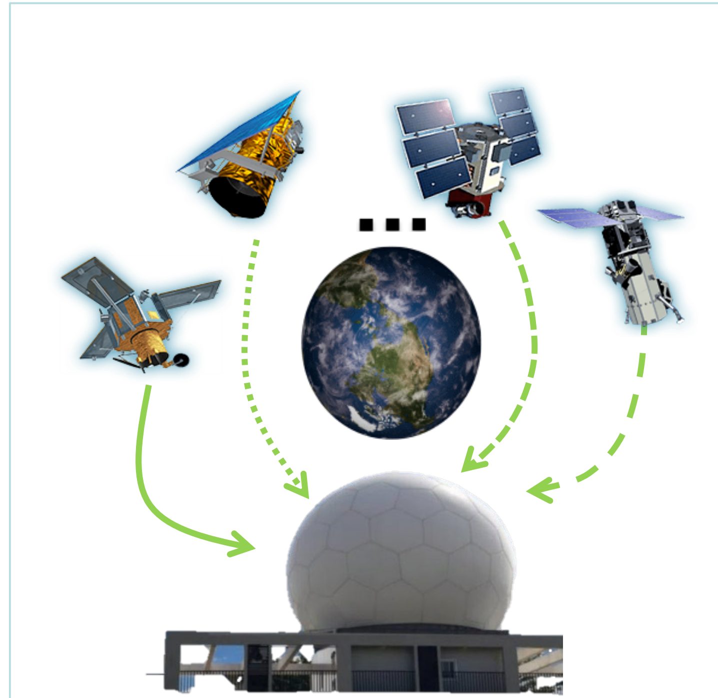
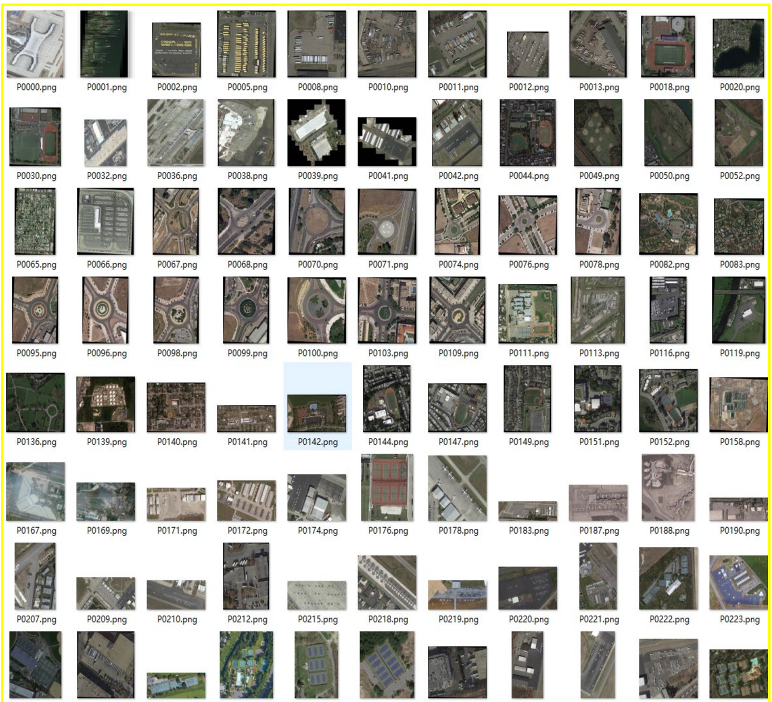


Image acquisition

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

Interpretation of RS Images

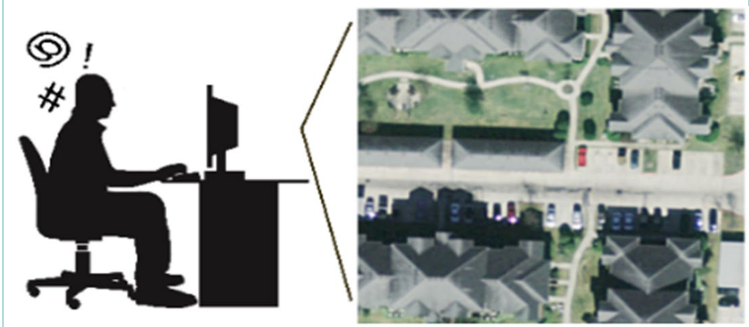
Current situation: Increasing demands for automatic interpretation

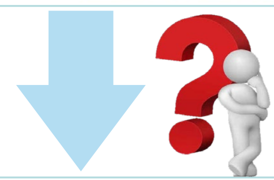


Large volume of images

- **Challenge:** geometrical shape, textural attribute, structural characteristic …

Manual interpretation

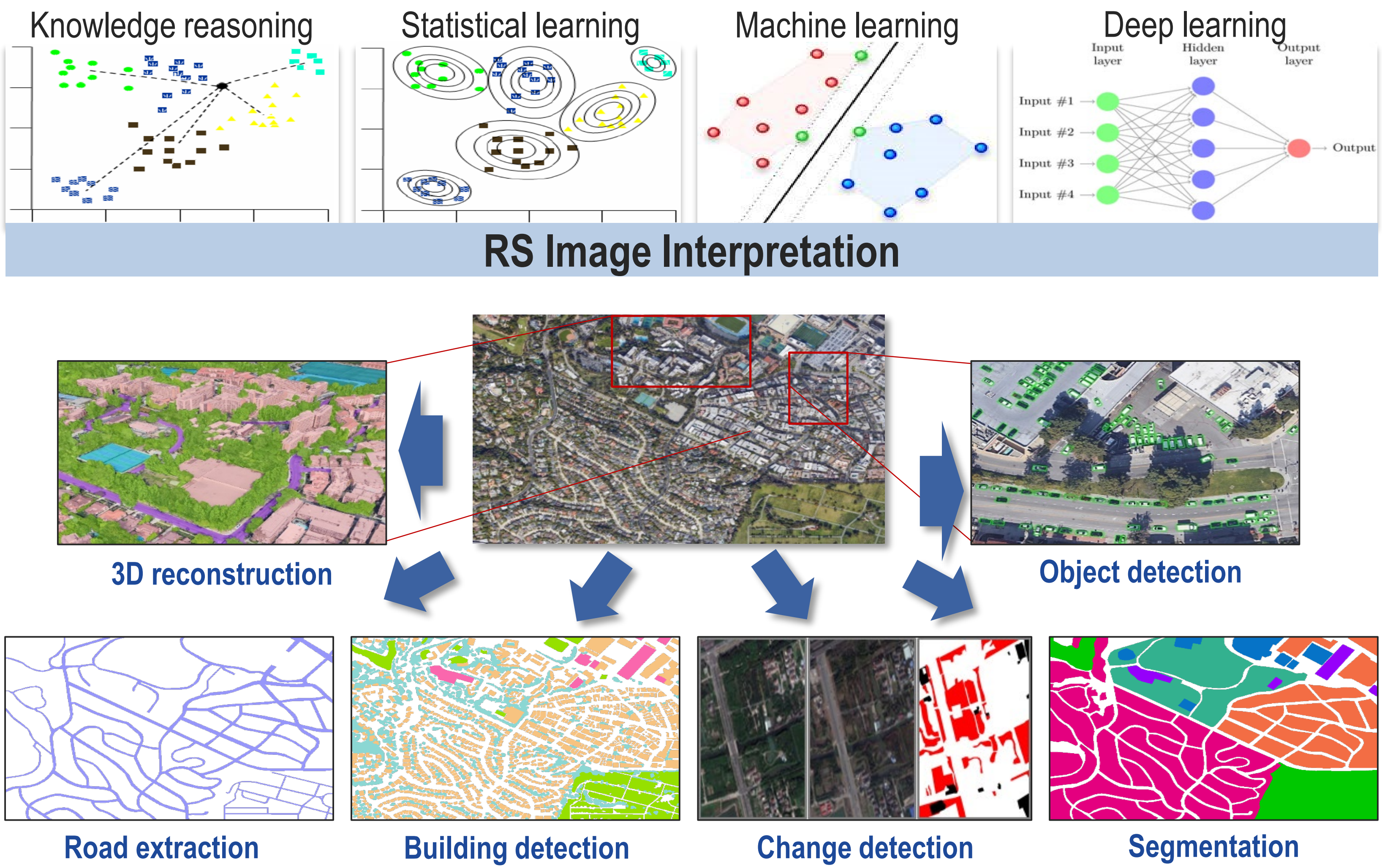




Automatic interpretation

Blooming Data-driven methods

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



Motivation

CAPTAIN
COMPUTATIONAL AND PHOTOGRAMMETRIC VISION

- **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.

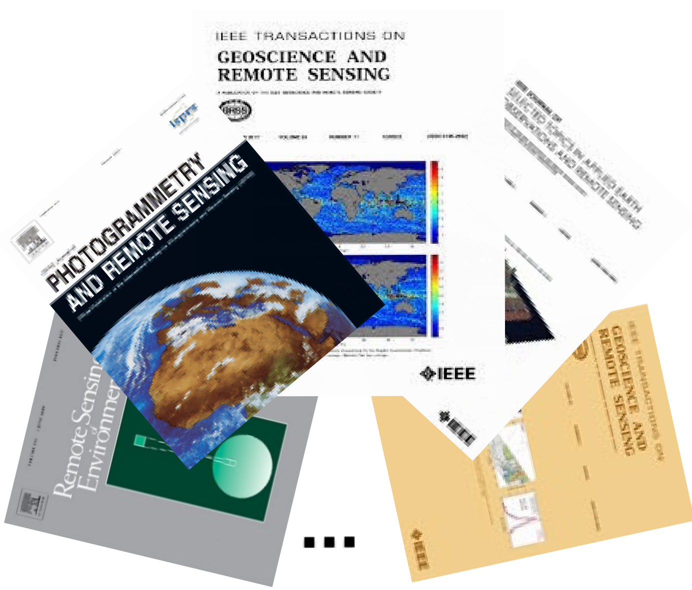
Outline

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

Focus in the Past Decade

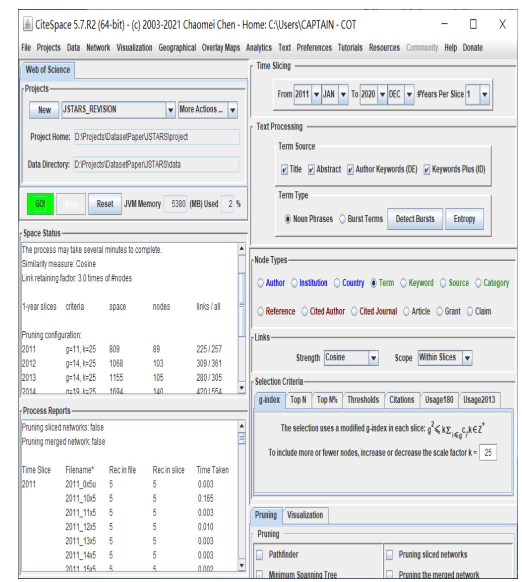
■ A systematic investigation to the literature

- **Journals with good reputation:** *ISPRS J. P&RS, RSE, TGRS …*
- **Meta-data for analysis:** 5, 827 surveyed articles over the past decade
- **Bibliometric analysis:** title/topic/keywords … concerning image interpretation



Selected journals

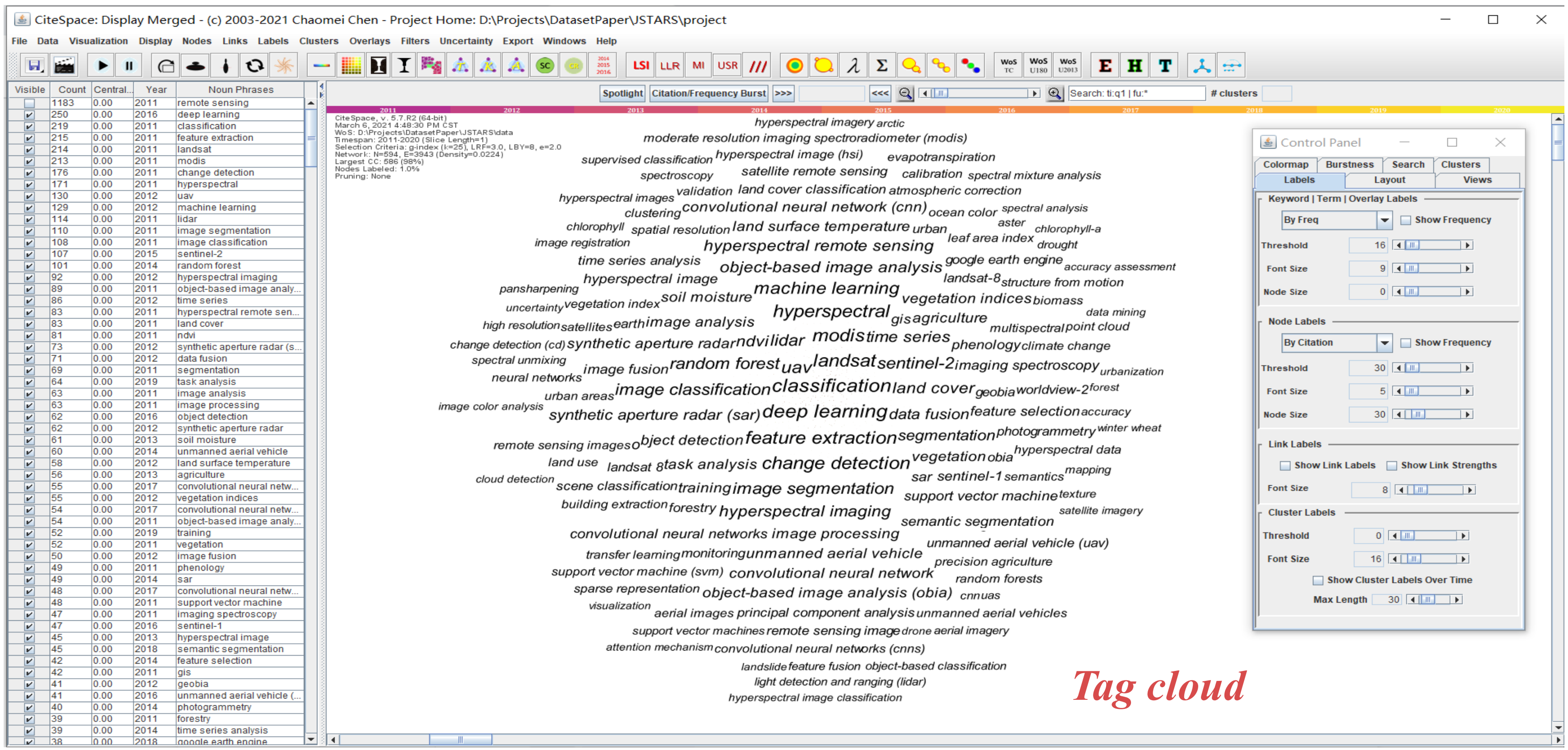
Meta-data



Bibliometric analysis

Frequency Terms

- Interpretation mainly focus on ***classification*** tasks (*scene*, *land cover*, …)
- ***Change detection***, ***segmentation,*** and object detection occupy prominent positions
- ***Deep learning*** and ***feature extraction*** play significant roles in RS image interpretation



Available Datasets for Interpretation

- RS *scene classification* datasets

Dataset	#Cat.	#Images per cat.	#Instances	Resolution (m)	Image size	GL/IT/SP	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
Planet-UAS	17	–	40,480	3 to 5	256×256	✓✓✓	2017
RSD46-WHU	46	500 to 3,000	117,000	0.5 to 2	256×256	×××	2017
MASATI	7	304 to 1,789	7,389	–	512×512	×××	2018
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
fMoW	62	–	132,716	0.5	74×58 to 16,184×16,288	✓✓✓	2018
WiDS Datathon 2019	2	–	20,000	3	256×256	×××	2019
Optimal-31	31	60	1,860	–	256×256	×××	2019
BigEarthNet	43	328 to 217,119	590,326	10,20,60	20×20;60×60;120×120	✓✓✓	2019
CLRS	25	600	15,000	0.26 to 8.85	256×256	×××	2020
MLRSN	46	1,500 to 3,000	109,161	0.1 to 10	256×256	×××	2020

- RS *object detection* datasets

Datasets	Annot.	#Cat.	#Instances	#Images	Resolution (m)	Image width	GL/IT/SP	Year
TAS	HBB	1	1,319	30	–	792	×××	2008
OIRDS	OBB	5	1,800	900	up to 0.08	256 to 640	✓✓✓	2009
SZTAKI-INRIA	OBB	1	665	9	–	∼800	×××	2012
NWPU-VHR10	HBB	10	3,651	800	0.08 to 2	∼1,000	×××	2014
DLR-MVDA	OBB	2	14,235	20	0.13	5,616	××✓	2015
UCAS-AOD	OBB	2	14,596	1,510	–	∼1,000	×××	2015
VEDAI	OBB	9	3,640	1,210	0.125	512;1,024	✓××	2016
COWC	CP	1	32,716	53	0.15	2,000 to 19,000	✓××	2016
HRSC2016	OBB	26	2,976	1,061	–	∼1,100	×××	2016
RSOD	HBB	4	6,950	976	0.3 to 3	∼1,000	×××	2017
CARPK	HBB	1	89,777	1,448	–	1,280	××✓	2017
SSDD/SSDD+	HBB/OBB	1	2,456	1,160	1 to 15	∼500	××✓	2017
SpaceNet1-6*	Polygon	1	859,982	–	up to 0.3	–	✓✓✓	2018
LEVIR	HBB	3	11,028	22,000	0.2 to 1	800	×××	2018
VisDrone	HBB	10	54,200	10,209	–	2,000	×××	2018
xView	HBB	60	1,000,000	1,413	0.3	∼3,000	✓×✓	2018
DOTA-v1.0	OBB	15	188,282	2,806	up to 0.3	800 to 13,000	×××	2018
ITCVD	HBB	1	29,088	173	0.1	3,744;5,616	×××	2018
WHU building dataset	Polygon	1	221,107	25,420	0.075 to 2.7	512	×××	2018
DeepGlobe Building	Polygon	2	302,701	24,586	0.3	650	××✓	2018
OpenSARShip	Chip	1	11,346	41	∼10	–	✓✓✓	2018
CrowdAI Mapping Challenge	Polygon	1	2,910,917	341,058	–	300	×××	2018
Airbus Ship Detection Challenge	Polygon	1	∼131,000	208,162	–	768	×××	2018
iSAID	Polygon	15	655,451	2,806	up to 0.3	800 to 4,000	×××	2019
HRRSD	HBB	13	55,740	21,761	0.15 to 1.2	152 to 10,569	×××	2019
DIOR	HBB	20	192,472	23,463	0.5 to 30	800	×××	2019
DOTA-v1.5	OBB	16	402,089	2,806	up to 0.3	800 to 13,000	×××	2019
SAR-Ship-Dataset	HBB	1	5,9535	43,819	up to 3	256	××✓	2019
AIR-SARShip	HBB	1	2,040	300	1;3	1,000	✓✓✓	2020
HRSID	HBB	1	16,951	5,604	0.5;1;3	800	××✓	2020
RarePlanes	Polygon	1	644,258	50,253	0.3	–	✓×✓	2020
DOTA-v2.0	OBB	18	1,793,658	11,268	up to 0.3	800 to 20,000	×××	2020

Available Datasets for Interpretation

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- RS *semantic segmentation* datasets

Datasets	#Cat.	#Images	Resolution (m)	#Channels	Image size	GL/IT/SP	Year
Kennedy Space Center	13	1	18	224	512×614	✗✓✓	2005
Botswana	14	1	30	242	1,476×256	✗✓✓	2005
Salinas	16	1	3.7	224	512×217	✗✗✓	–
University of Pavia	9	1	1.3	115	610×340	✗✗✓	–
Pavia Centre	9	1	1.3	115 bands	1,096×492	✗✗✓	–
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	145×145	✓✓✓	2015
Zurich Summer	8	20	0.62	NIR, RGB	1,000×1,150	✓✓✓	2015
SPARCS Validation	7	80	30	11	1,000×1,000	✓✓✓	2016
Biome	4	96	30	11	∼9,000×9,000	✓✓✓	2017
Inria	2	360	0.3	RGB	5,000×5,000	✗✗✗	2017
EvLab-SS	10	60	0.1 to 2	RGB	4,500×4,500	✗✗✓	2017
RIT-18	18	3	0.047	6	9,000×6,000	✓✓✓	2017
CITY-OSM	3	1,671	0.1	RGB	2,500×2,500 to 3,300×3,300	✗✗✗	2017
Dstl-SIFD*	10	57	up to 0.3	up to 16	∼3,350×3,400	✓✗✓	2017
IEEE GRSS Data Fusion Contest 2017	17	30	1,4	9	643×666;374×515	✓✓✓	2017
IEEE GRSS Data Fusion Contest 2018	20	1	1	48	4,172×1,202	✓✓✓	2018
Aeroscapes	11	3,269	–	RGB	720×1,280	✗✗✗	2018
DLRSD	17	2,100	0.3	RGB	256×256	✗✗✗	2018
DeepGlobe Land Cover	7	1,146	0.5	RGB	2,448×2,448	✗✗✓	2018
So2Sat LCZ42	17	400,673	10	10	32×32	✓✗✓	2019
SEN12MS	33	180,662 triplets	10 to 50	up to 13	256×256	✓✗✓	2019
95-Cloud	1	43,902	30	NIR,RGB	384×384	✓✗✓	2019
Shakeel et al.	1	2,682	0.3	RGB	300×300	✗✗✗	2019
ALCD Cloud Masks	8	38	10	RGB	1,830×1,830	✓✓✓	2019
SkyScapes	31	16	0.13	RGB	5,616×3,744	✗✗✗	2019
DroneDeploy	7	55	0.1	RGB	up to 12,039×13,854	✗✗✗	2019
Slovenia LULC	10	940	10	6	5,000×5,000	✓✓✓	2019
LandCoverNet	7	1,980	10	NIR,RGB	256×256	✓✓✓	2020
UAVid	8	420	–	RGB	∼4,000×2,160	✗✗✓	2020
GID	15	150	0.8 to 10	4	6,800×7,200	✓✓✓	2020
LandCover.ai	3	41	0.25,0.5	RGB	9,000×9,500;4,200×4,700	✓✗✗	2020
Agriculture-Vision	9	94,986	0.1;0.15;0.2	NIR,RGB	512×512	✗✗✓	2020
S2CMC*	18	513	20	13	1,024×1,024	✓✓✓	2020

- RS *change detection* datasets

Datasets	#Cat.	#Image pairs	Resolution (m)	#Channels	Image size	GL/IT/SP	Year
SZTAKI AirChange	2	13	1.5	RGB	952×640	✗✓✗	2009
AICD	2	1,000	0.5	115	800×600	✗✗✗	2011
Taizhou Data	4	1	30	6	400×400	✓✓✓	2014
Kunshan Data	3	1	30	6	800×800	✓✓✓	2014
Cross-sensor Bastrop	2	4	30,120	7,9	444×300; 1,534×808	✓✓✓	2015
MtS-WH	9	1	1	NIR, RGB	7,200×6,000	✓✓✓	2017
Yancheng	4	2	30	242	400×145	✓✓✓	2018
GETNET dataset	2	1	30	198	463×241	✗✓✓	2018
Urban-rural boundary of Wuhan	20	1	4/30	4, 9	960×960	✓✓✓	2018
Hermiston City, Oregon	5	1	30	242	390×200	✓✓✓	2018
OSCD	2	24	10	13	600×600	✓✓✓	2018
WHU building dataset	2	1	0.2	RGB	32,507×15,354	✓✓✓	2018
Season-varing dataset	2	16,000	0.03 to 0.1	RGB	256×256	✗✗✗	2018
ABCD	2	16,950	0.4	RGB	128×128;160×160	✗✓✗	2018
California flood dataset	2	1	5,30	RGB,11	1534×808	✓✓✓	2019
López-Fandiño et al.	5	2	20	224	984×740; 600×500	✗✓✓	2019
xBD	6	11,034	up to 0.8	RGB	1,024×1,024	✓✓✓	2019
HRSCD	6	291	0.5	RGB	10,000×10,000	✓✓✓	2019
LEVIR-CD	2	637	0.5	RGB	1,024×1,024	✗✗✗	2020
SECOND	30	4,214	0.5 to 3	RGB	512×512	✗✗✗	2020
Google Dataset	2	1,067	0.55	RGB	256×256	✓✓✗	2020
Zhang et al.	2	4	2;2.4;5.8	NIR, RGB	1,431×1,431; 458×559; 1,154×740	✓✓✓	2020
Hi-UCD	9	1,293	0.1	RGB	1,024×1,024	–/–/Y	2020
SpaceNet7	–	24	4	RGB	–	✓✓✓	2020
S2MTCP	2	1,520	up to 10	13	600×600	✓✓✓	2021

Some Critical Reviews

Categories involved in interpretation

- ***Small number*** of categories, content interpretation for ***specific 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, hyper-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

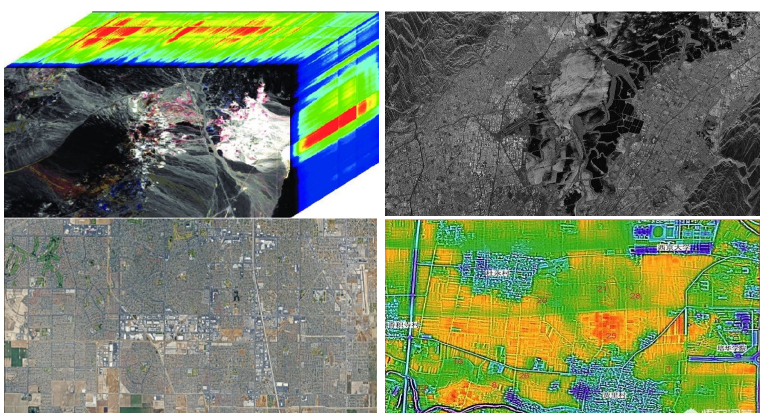
Some Critical Reviews

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



Multi-modal image source

Simple scenes and complex reality

Outline

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

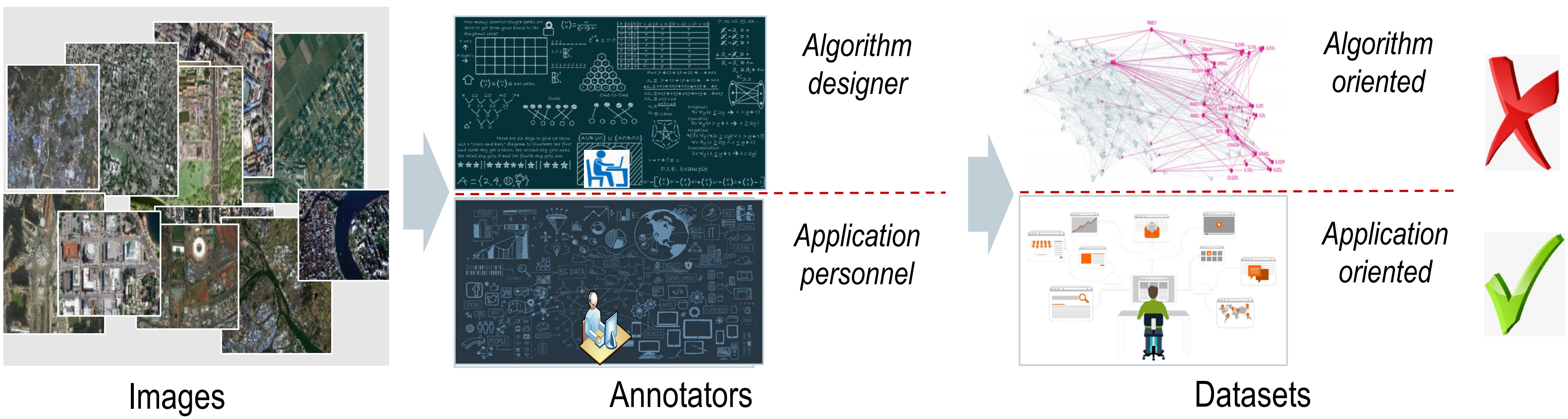
Guidances to Benchmark RS II

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

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

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

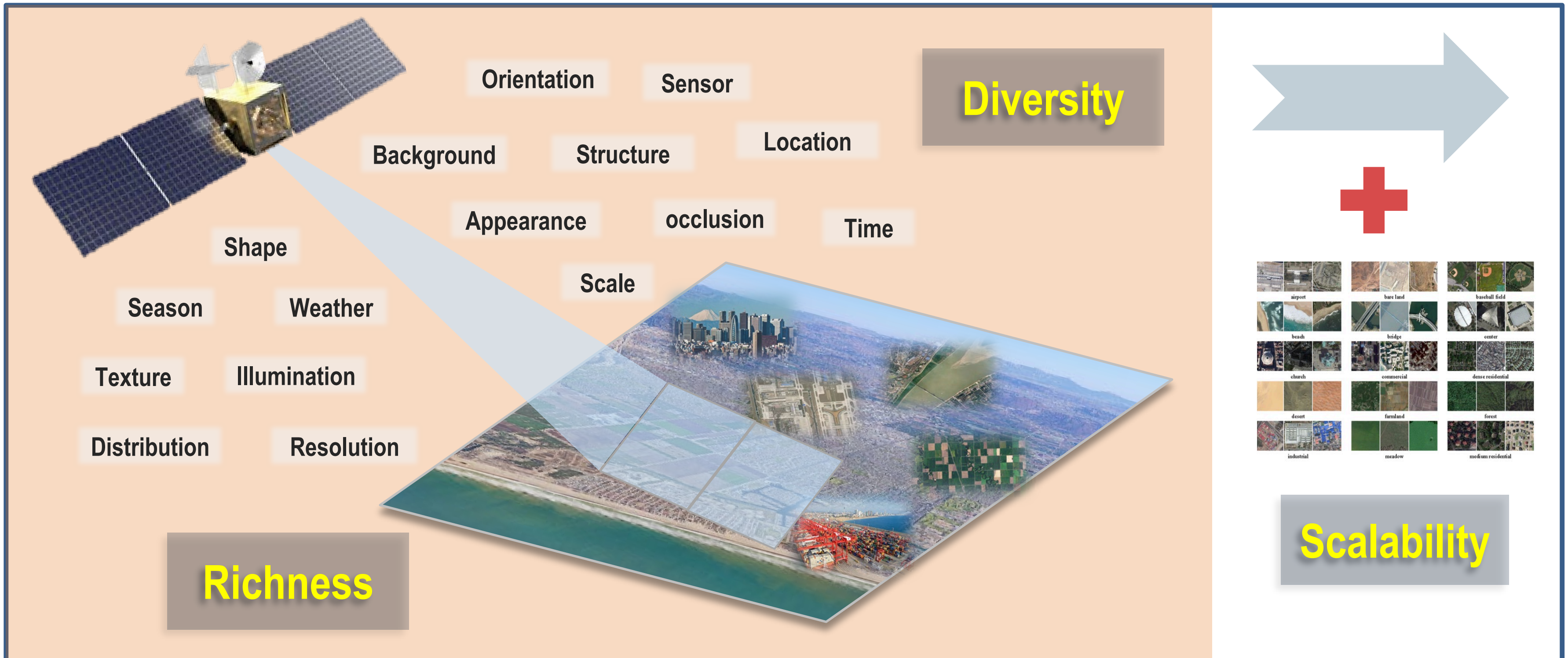
- Label images and samples with consideration of challenges in practical application



DiRS: Guidances to Benchmark RS II

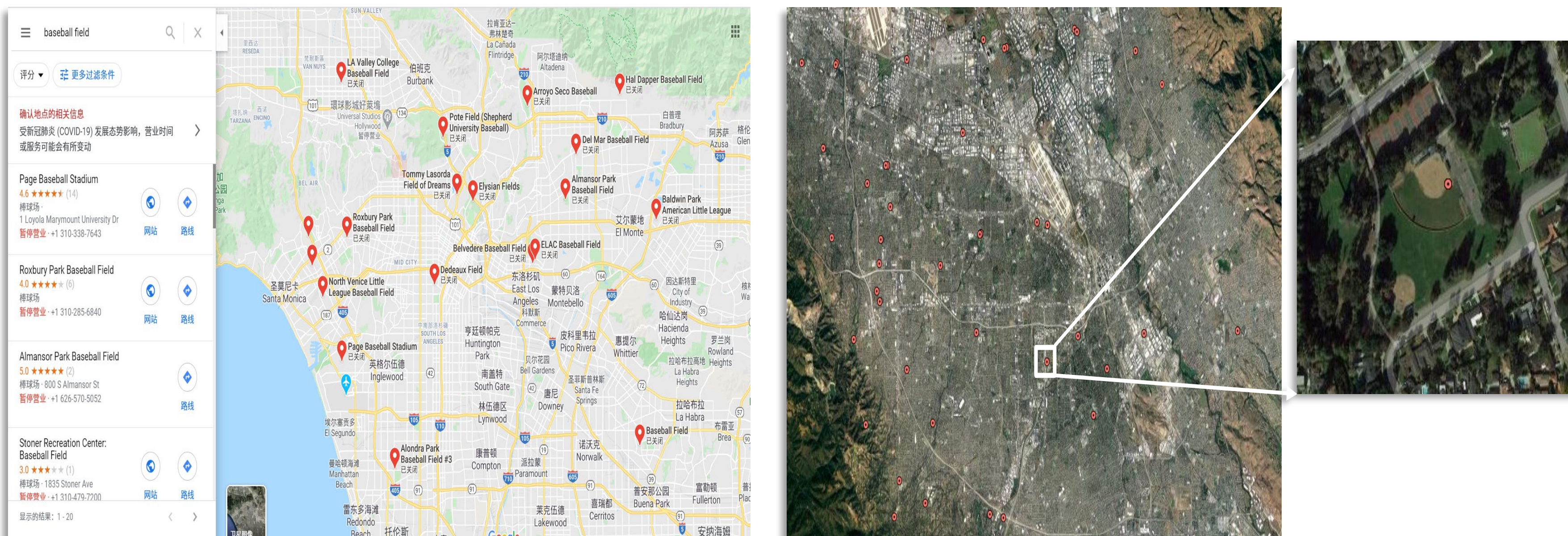
DiRS for dataset construction

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



Geographic Information Integration

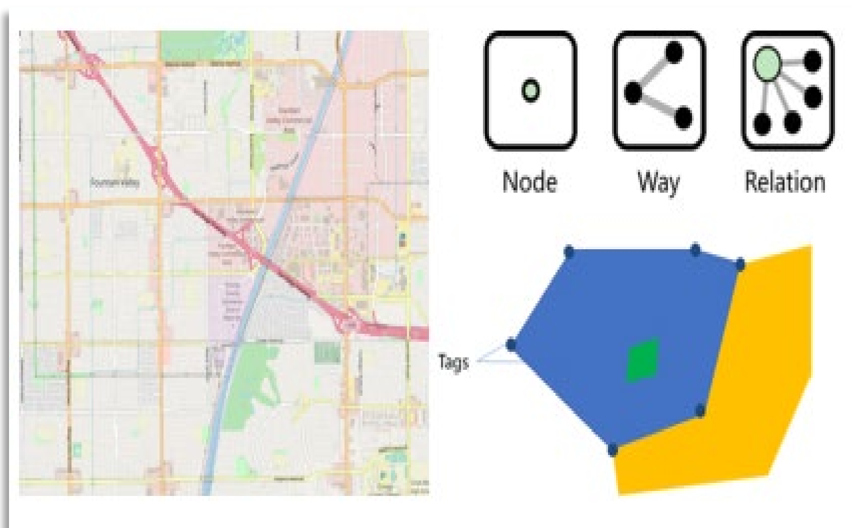
- Coordinates Collection for RS Image Acquisition
  - **Geographic information utilization**
    - Rich positional data with millions of point, line, and region objects
    - Inherent semantic tags for images of interest, image acquisition by Map API

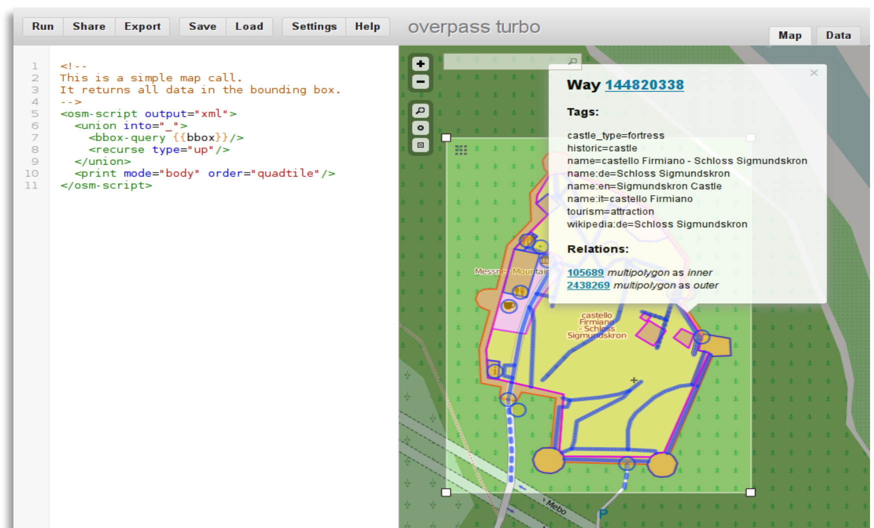


Searched baseball fields using Google Map API

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, information aligned with different maps





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

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 assurance, 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 initialized data and model capability

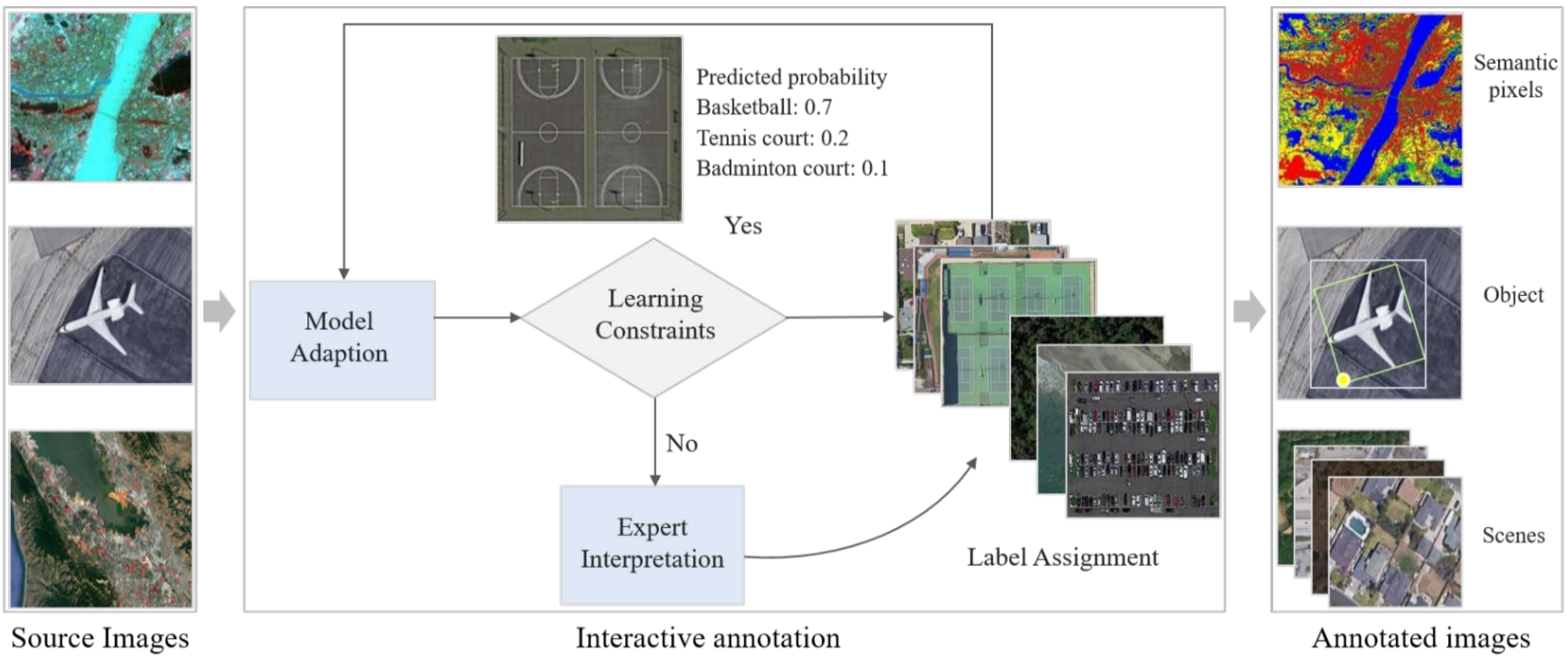
Source image

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, annotated samples for instructions
- ***Training of Annotators:*** well-qualified annotators for dataset quality assurance
- ***Multi-stage Pipeline:*** decomposition of complex annotation tasks
- ***Grading and Reward:*** incentive mechanism for incompetent/competent annotators
- ***Multiple Annotations:*** merge multiple annotations to improve accuracy
- ***Annotation Review:*** expert/peer review and quality rating
- ***Spot Check and Assessment:*** gold data for model adaption and quality evaluation

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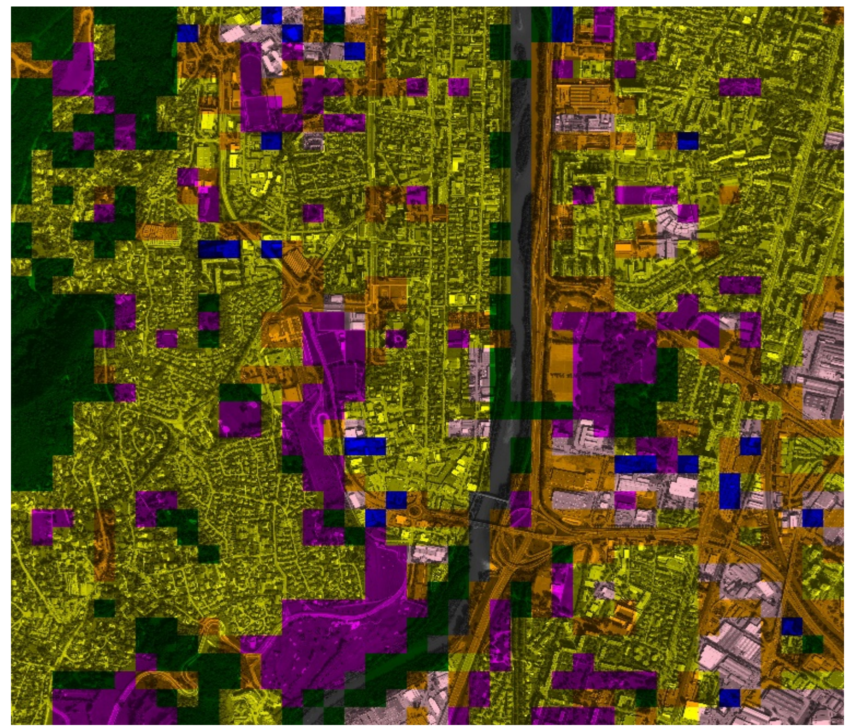
Million-AID

- 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

Million-AID

■ Category Organization

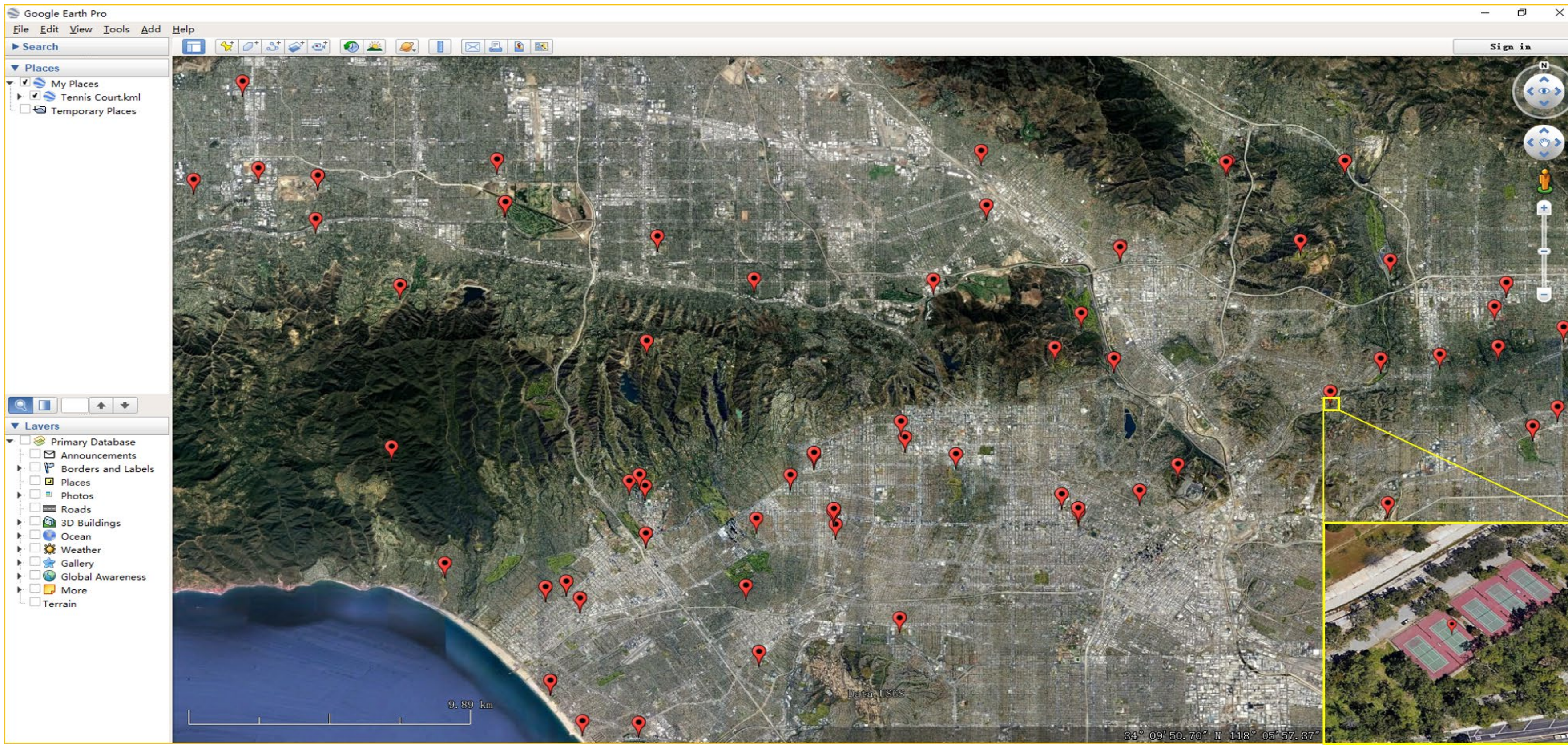
Chinese Land Use Classification Criteria

8 major categories with 51 sub-categories

The hierarchical scene category network of Million-AID

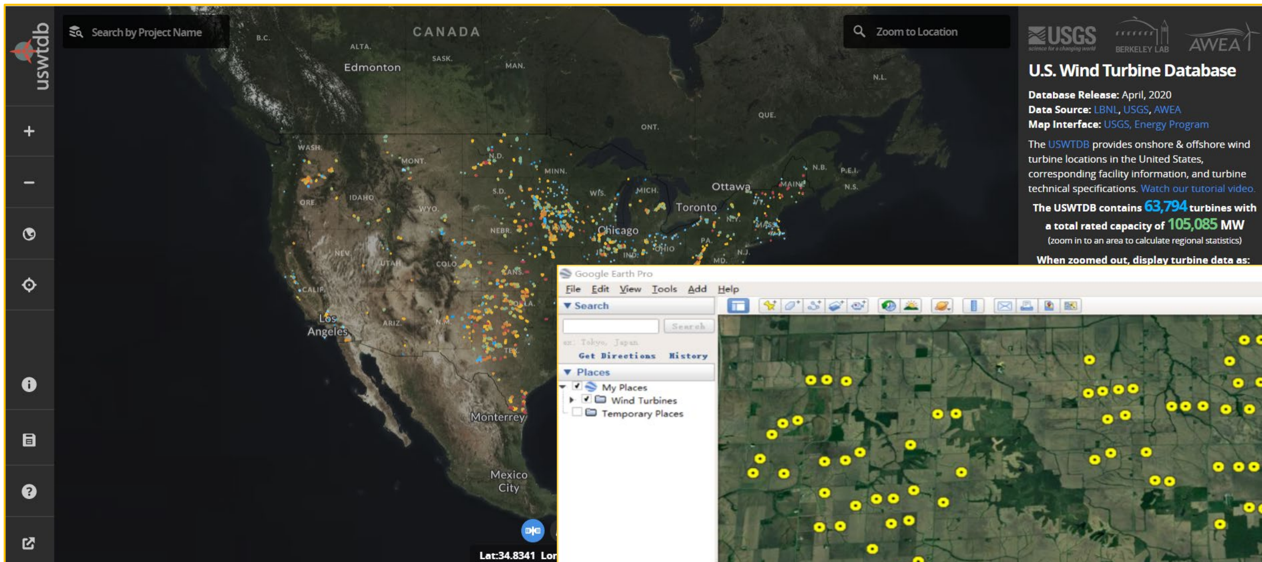
Million-AID

- Semantic Coordinates Collection
  - **Point coordinates obtained by Google Map API**

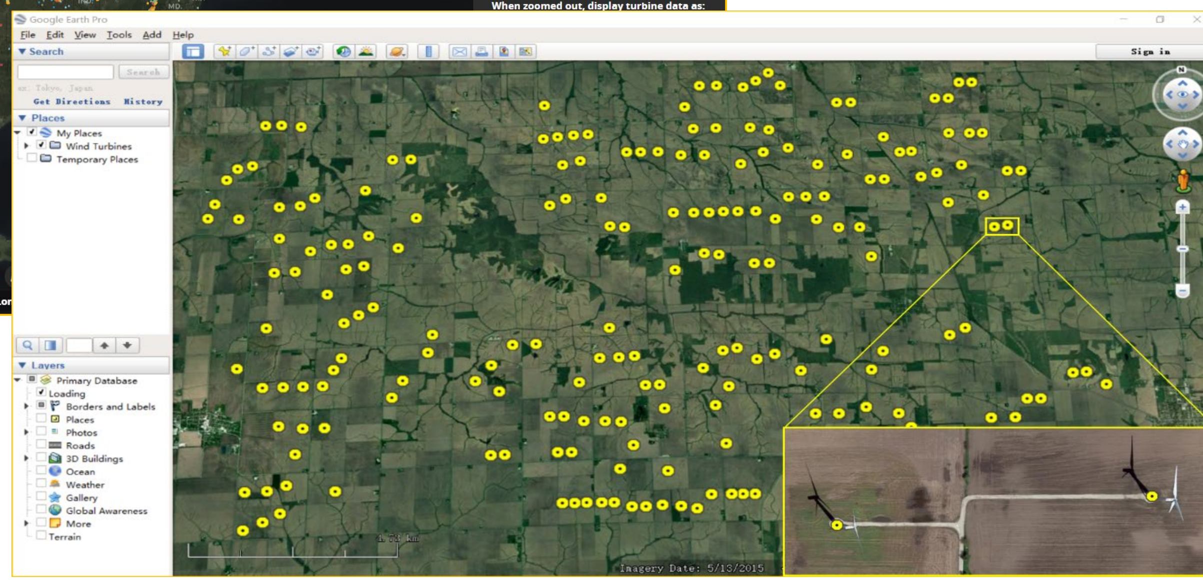


The points of searched tennis courts shown in Google Earth. We consider the tennis courts as point ground features and the Google Map API is employed for coordinates collection.

- Semantic Coordinates Collection
  - **Point coordinates integrated from Geodatabase**



U.S. Wind Turbine Database

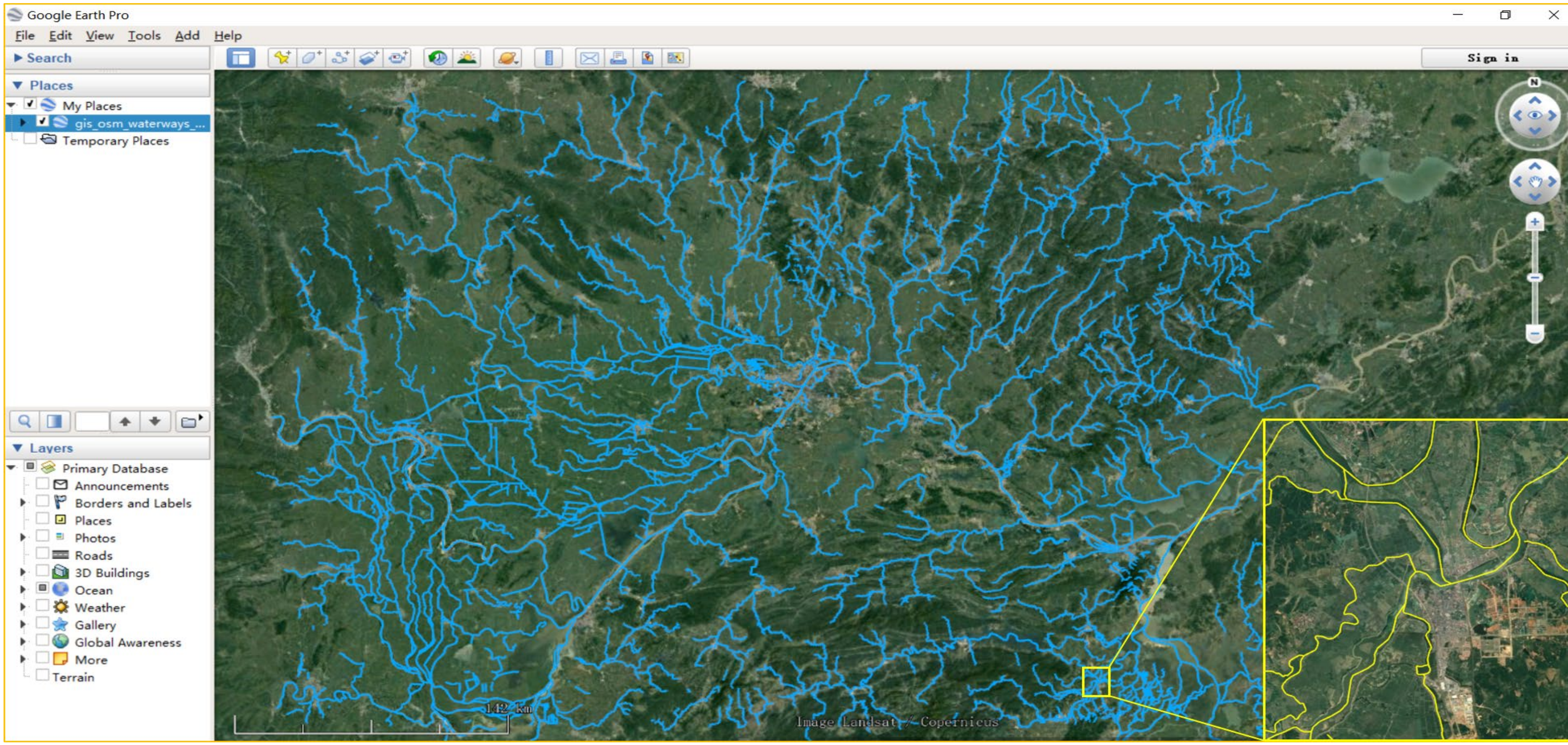


Integrated W.T. data

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

Million-AID

- 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.

Million-AID

- Semantic Coordinates Collection
  - **Plane features customized on OSM**

(a)

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

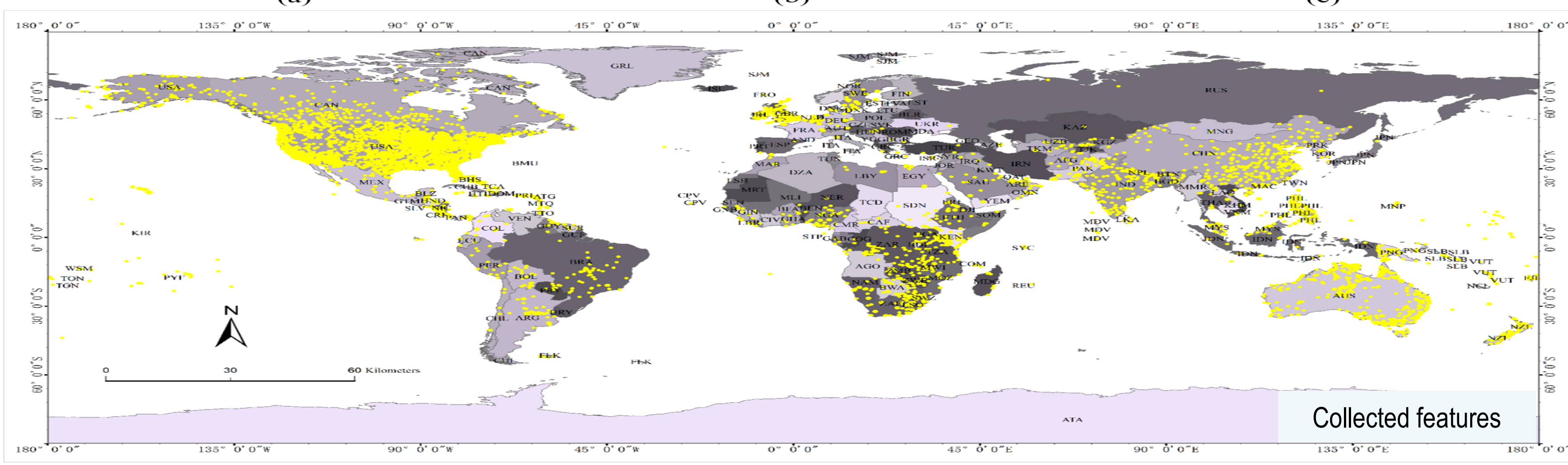
Semantic tags

(b)

```
<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

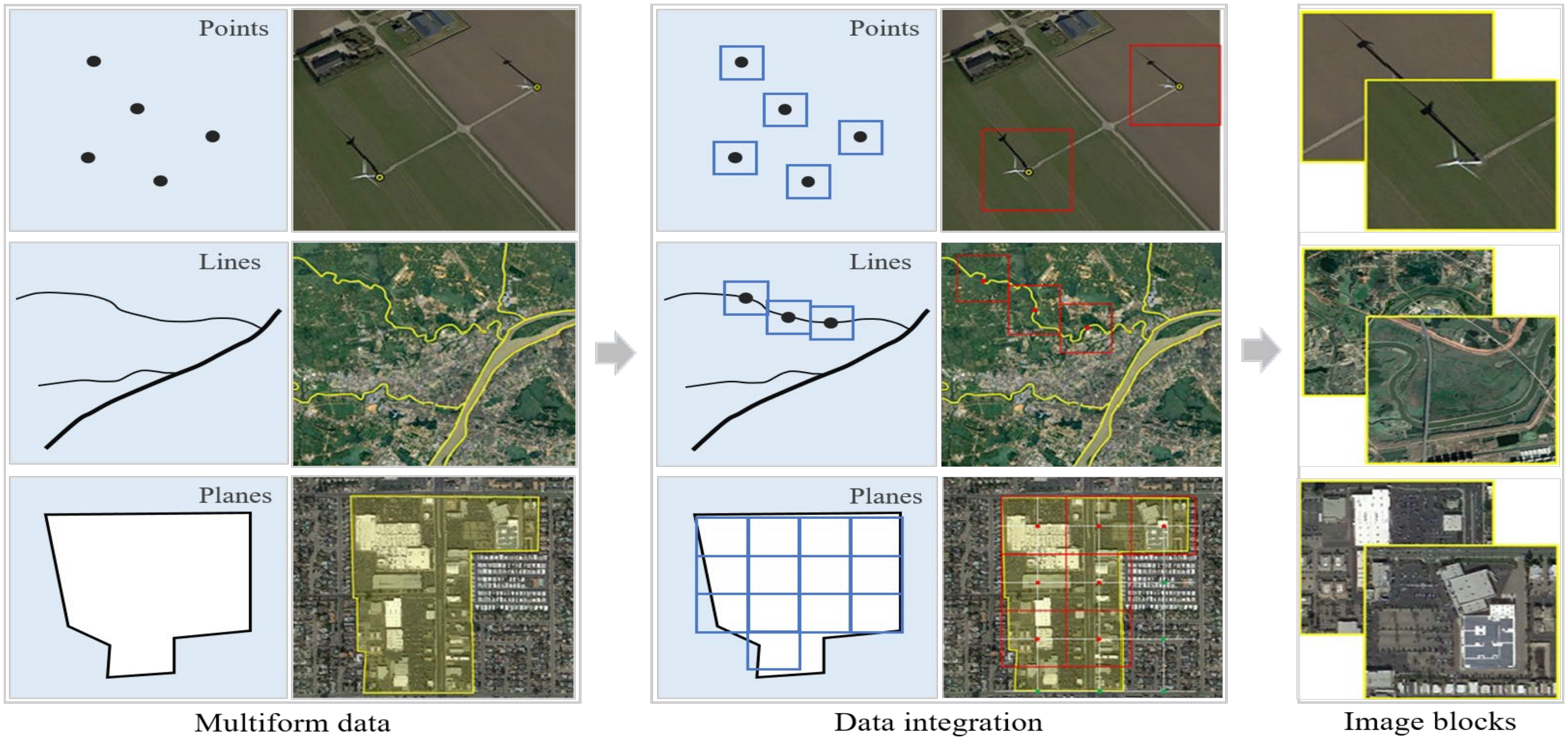
(c)



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

Million-AID

- Scene Image Acquisition
  - Image block produced by the line, point, and plane data



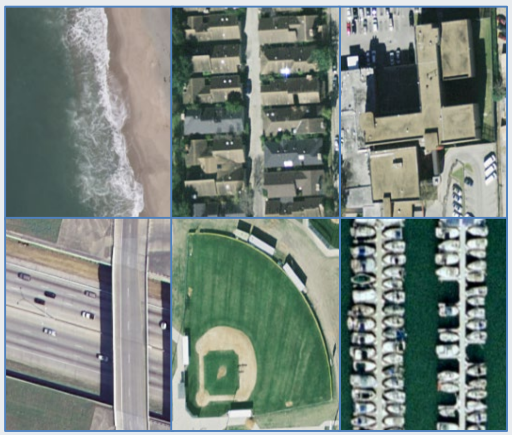
The acquisition of RS scene images based on the collected geographic point, line and area data. ***Points***: centers of scene blocks. ***Lines***: sampled by intervals. ***Planes***: sampled by mesh grids.

Million-AID

A Glimpse of Comparison

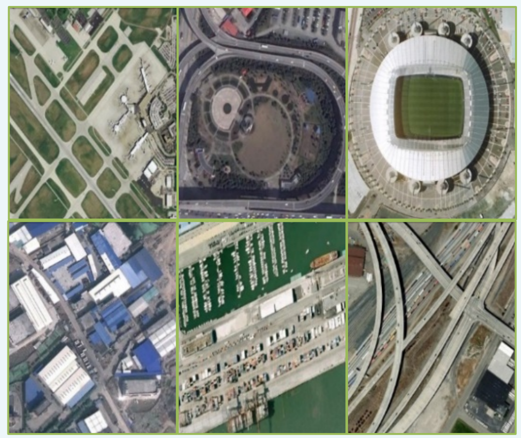
Million-AID: DiRS, better approximate real applications

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： 51**
- **Image size： 110~30,000**
- **Resolution： 0.2 ~ 153m**
- **Number of images： 1M**

Outline

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

Challenges and Perspectives

- How to speed up the annotation process?

- **Visualization technology for RS image Annotation**
  - ***Hyper-spectral images:*** select representative 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, noise tolerant algorithms

Challenges and Perspectives

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- 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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Conclusions

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

Guidances 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 dataset construction : Million-AID

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

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THANKS

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