Joint Technical Symposium on Digital Geosciences & Geotechnology

Registration (08:30 – 09:00)

09:00 – 09:05

Ir Tony HO
Chairman, Geotechnical Division, The Hong Kong Institution of Engineers

Welcome Address

09:05 – 09:15

Ir Dr Raymond CHEUNG, JP
Head of Geotechnical Engineering Office, Civil Engineering and Development Department, HKSAR Government

Opening Speech

Morning Session

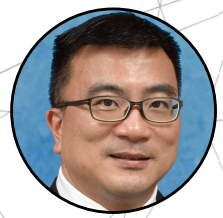
09:15 – 10:00

Prof John SHI
Chair Professor in Geographic Information Science and Remote Sensing, The Hong Kong Polytechnic University

Keynote Speech:
Geospatial Intelligence for Geosciences and Geotecchnology

Theme (1) : Advances in Remote Sensing and Smart Technologies

10:00 – 10:25



Mr Jeffrey WONG
Chief Geotechnical Engineer, Geotechnical Engineering Office, Civil Engineering and Development Department, HKSAR Government

Detector in the Air : 2020 Airborne LiDAR Survey

10:25 – 10:50

Ir Sammy CHEUNG
Deputy Head of Geotechnical Engineering Office (Island), Civil Engineering and Development Department, HKSAR Government

Excellence with Technology Innovation: Dreamers and Realists

10:50 – 11:00 **Break**

Theme (2) : Applications of Artificial Intelligence and Machine Learning

11:00 – 11:25

Prof Y H WANG
Professor and Associate Department Head, Department of Civil and Environmental Engineering, The Hong Kong University of Science and Technology

Vertical AI – An Integrated Solution for A Smart and Resilient City

11:25 – 11:50

Dr Louis WONG
Associate Professor and Director of MSc in Applied Geosciences, Department of Earth Sciences, The University of Hong Kong

Automatic Rock Type Classification using Computer Vision-based Artificial Intelligence Technique – Feasibility and Challenges

11:50 – 12:15

Dr W Z HOU
Engineering Geologist, GeoRisk Solutions

Smart NTHS with Applications of Artificial Intelligence and Computer Vision – Case Studies in Hong Kong

12:15 – 12:30 **Panel Discussion (Morning Session)**

Joint Technical Symposium on Digital Geosciences & Geotechnology

Afternoon Session

14:00 – 14:45		**Prof K K PHOON** Chair Professor and Provost, Singapore University of Technology and Design	**Keynote Speech:** Project DeepGeo – Data-driven 3D Subsurface Mapping

Theme (2) : Applications of Artificial Intelligence and Machine Learning

14:45 – 15:15		**Prof H W HUANG** Distinguished Professor, Tongji University	Long-term Deformation Monitoring and Analysis of Shield Tunnel by Smart Sensoring
15:15 – 15:45		**Dr Z Q LIU** Senior Engineer, Norwegian Geotechnical Institute	Machine Learning and Landslide Studies
15:45 – 15:55		**Break**	

Theme (3) : Innovations and Project Applications

15:55 – 16:20		**Ir Philip KIRK** Technical Director, Aurecon New Zealand Limited	3-D Ground Models in a World of Digital Twins
16:20 – 16:45		**Ir Stuart MILLIS** Associate Director, Ove Arup & Partners Hong Kong Ltd	Total Digital Design
16:45 – 17:10		**Ir Simon LEUNG** Chief Resident Engineer, AECOM Asia Company Limited	Digital Journey to Improved Blasting
17:10 – 17:35		**Ir Stephen MAK** Deputy Project Manager, Hyder-Meinhardt Joint Venture	New Digital Paradigm for Geotechnical Works under Trunk Road T2 and Cha Kwo Ling Tunnel
17:35 – 17:50		**Panel Discussion (Afternoon Session)**	
17:50 – 17:55		**Ir Kevin STYLES** Chairman, Hong Kong Regional Group, Geological Society of London	**Closing Remark**

Joint Technical Symposium on Digital Geosciences & Geotechnology

Hong Kong, 16 September 2021

Organisers:

HKIE THE HONG KONG INSTITUTION OF ENGINEERS 香港工程師學會
Geotechnical Division 岩土分部

The Geological Society
serving science, profession & society
Hong Kong Regional Group

HKGES HONG KONG GEOTECHNICAL SOCIETY 香港岩土工程學會 Since 2003

Supporting Organisations:

AGS (HK) 香港岩土及岩土環境工程專業協會 ASSOCIATION OF GEOTECHNICAL & GEOENVIRONMENTAL SPECIALISTS (HONG KONG)
Association of Geotechnical & Geoenvironmental Specialists (Hong Kong)

GEOLOGICAL SOCIETY OF HONG KONG 香港地質學會 / GEOLOGICAL SOCIETY OF HONG KONG Professional Branch
The Geological Society of Hong Kong

I·M3 Hong Kong
Hong Kong Branch, The Institute of Materials, Minerals and Mining

CityU Department of Architecture and Civil Engineering 香港城市大學 City University of Hong Kong
Department of Architecture and Civil Engineering, City University of Hong Kong

Department of Civil and Environmental Engineering 土木及環境工程學系
Department of Civil and Environmental Engineering, The Hong Kong Polytechnic University

香港科技大學 THE HONG KONG UNIVERSITY OF SCIENCE AND TECHNOLOGY
Department of Civil and Environmental Engineering, The Hong Kong University of Science & Technology

香港大學 THE UNIVERSITY OF HONG KONG
Department of Civil Engineering, The University of Hong Kong

DES 地球科學系 Department of Earth Sciences The University of Hong Kong
Department of Earth Sciences, The University of Hong Kong

LSGI DEPARTMENT OF LAND SURVEYING AND GEO-INFORMATICS 土地測量及地理資訊學系
Department of Land Survey and Geo-Informatics, The Hong Kong Polytechnic University

EARTH SYSTEM SCIENCE PROGRAMME
FACULTY OF SCIENCE · THE CHINESE UNIVERSITY OF HONG KONG
Earth System Science Programme, The Chinese University of Hong Kong

THE HONG KONG POLYTECHNIC UNIVERSITY
香港理工大學

智慧城市研究院
Smart Cities Research Institute

Geospatial Intelligence for Geosciences and Geotechnology

John Shi (史文中), Chair Professor
Director, PolyU-Shenzhen Technology and Innovation Research Institute

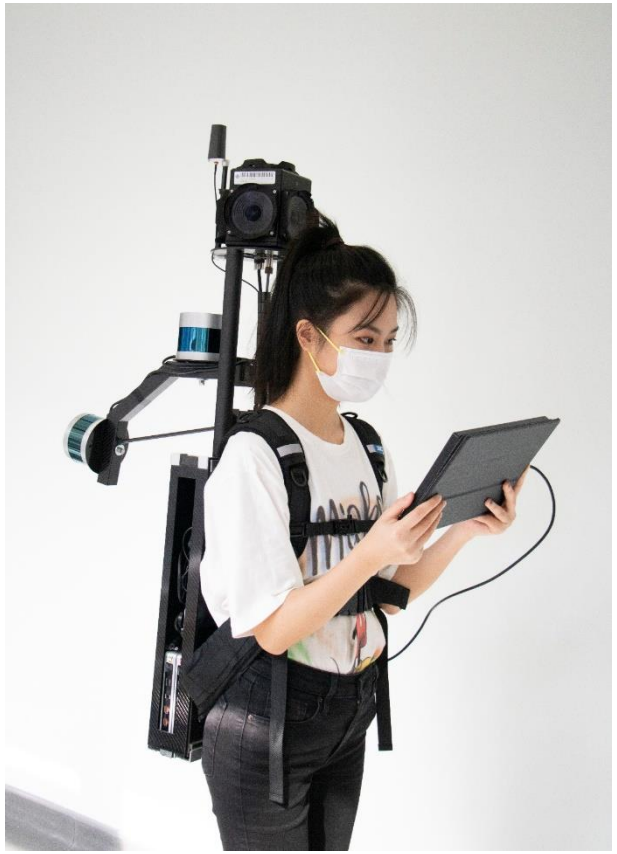
Sept 16 2021

1. 3D Mobile Mapping

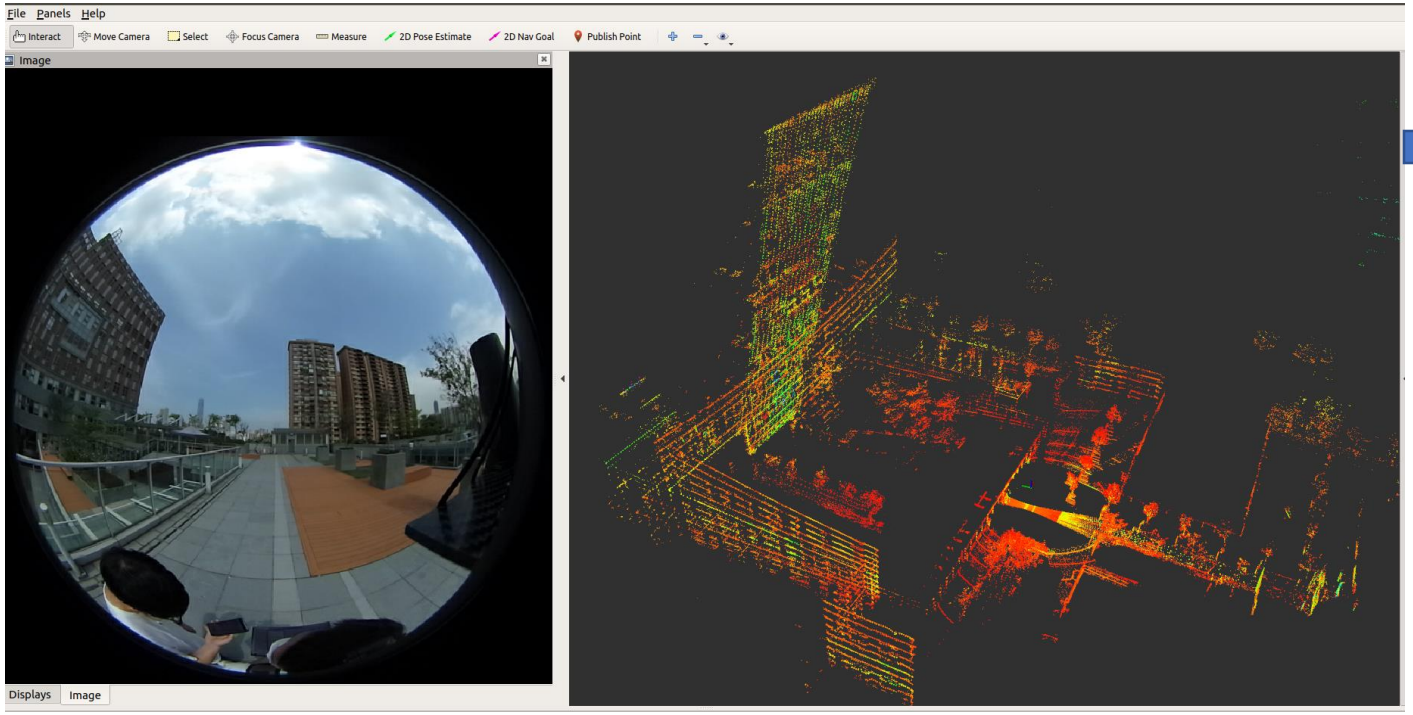
3D mobile mapping

3D Mobile Mapping System – S²DAS

- Indoor and outdoor continuous seamless mapping
- Centimeter-level high accuracy
- Lightweight, easy to carry
- Flexibility: mapping in GPS-denied complex environments
- Real-time 3D data acquisition
- Integrated data processing software
- Utilizes Simultaneous Localization and Mapping (SLAM) technology

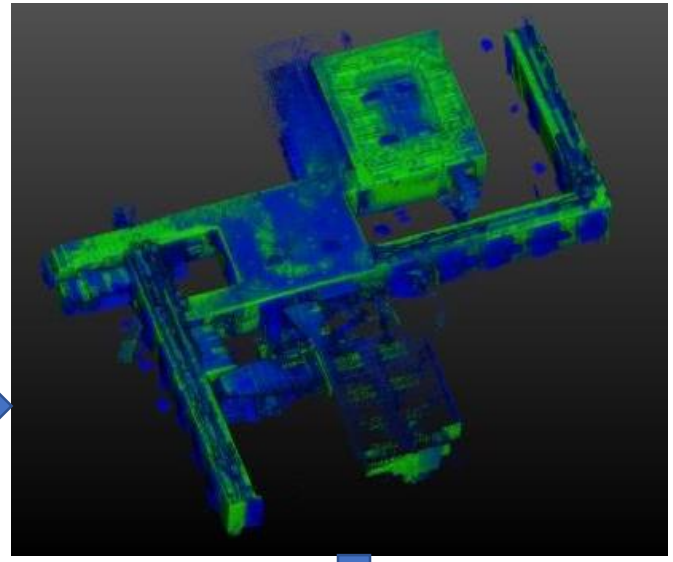


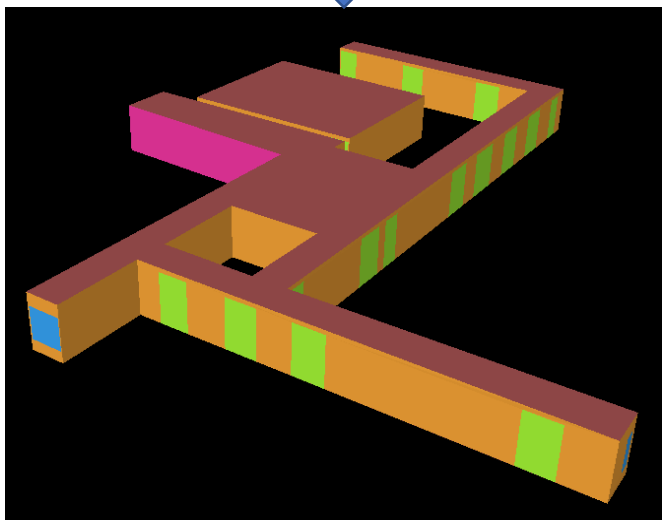
Software



1. Image & Point LiDAR scan

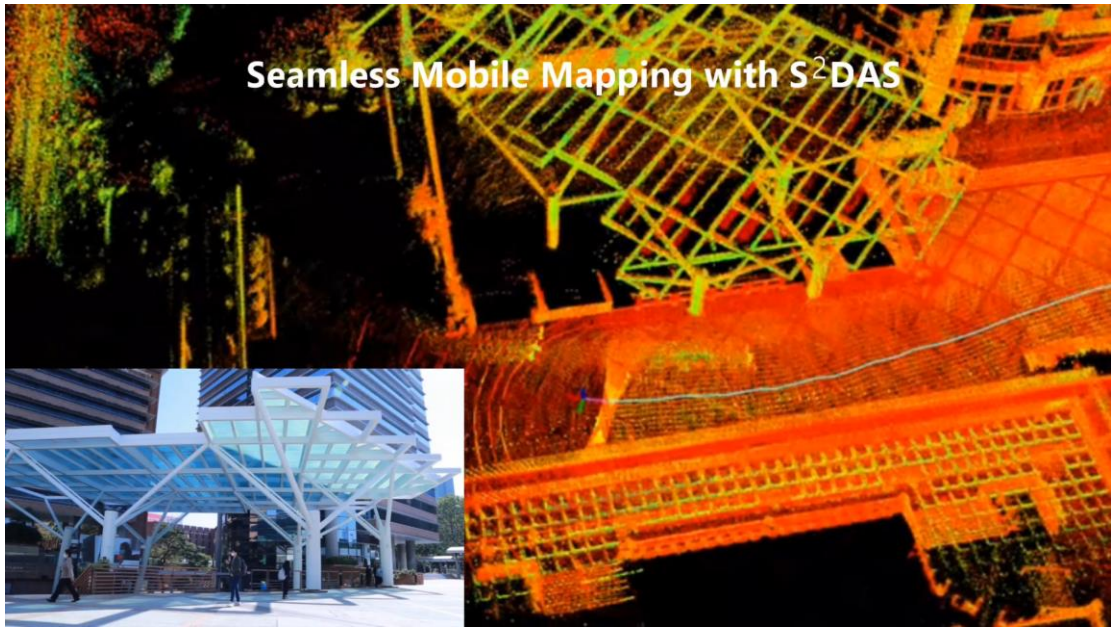
2. Point cloud map

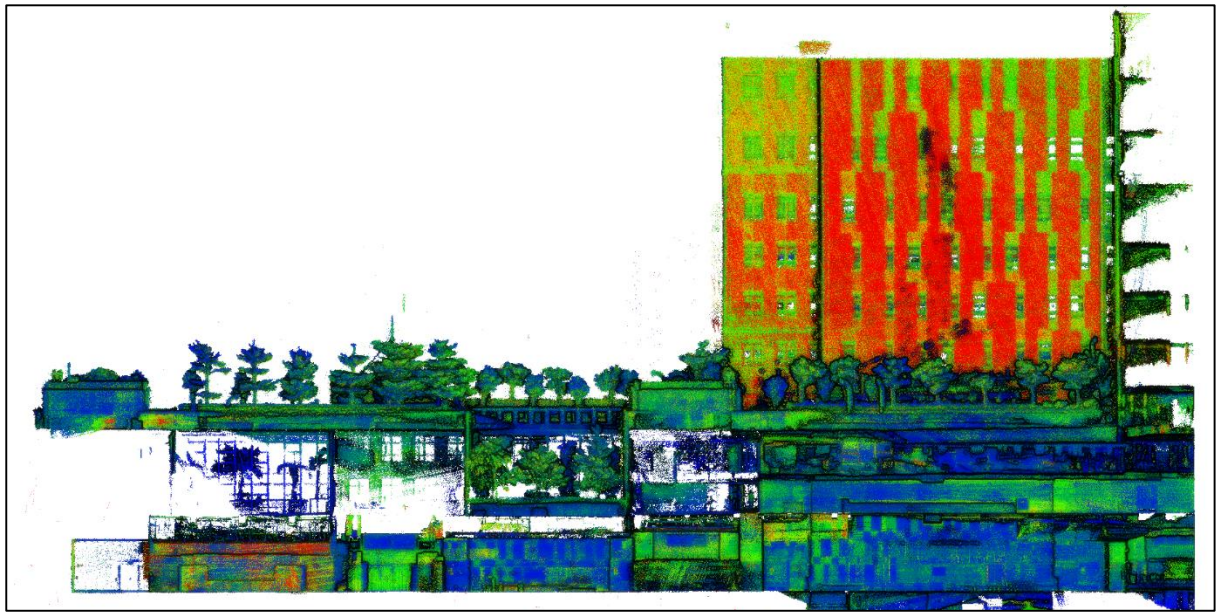




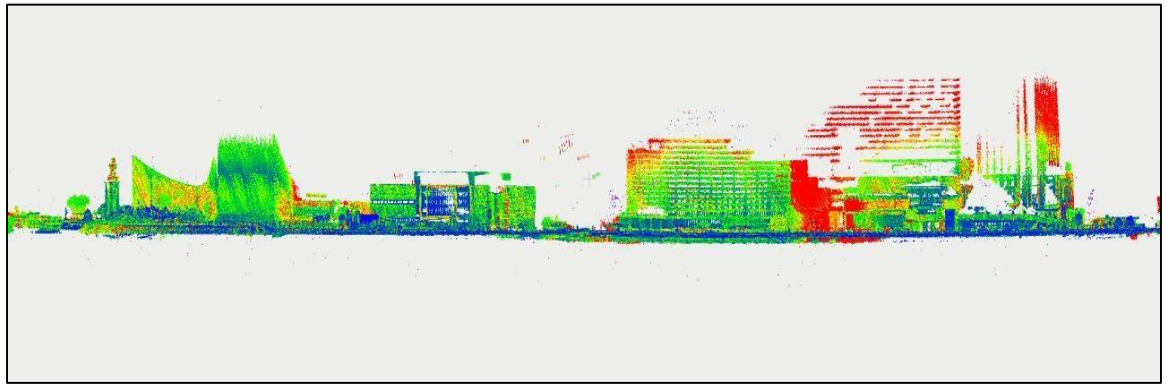
3. Model

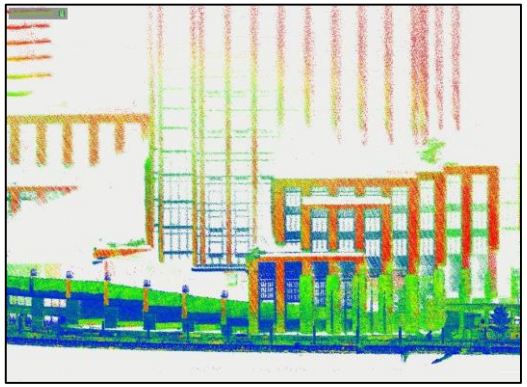
3D mobile mapping: Indoor & outdoor, complex, wide scenes





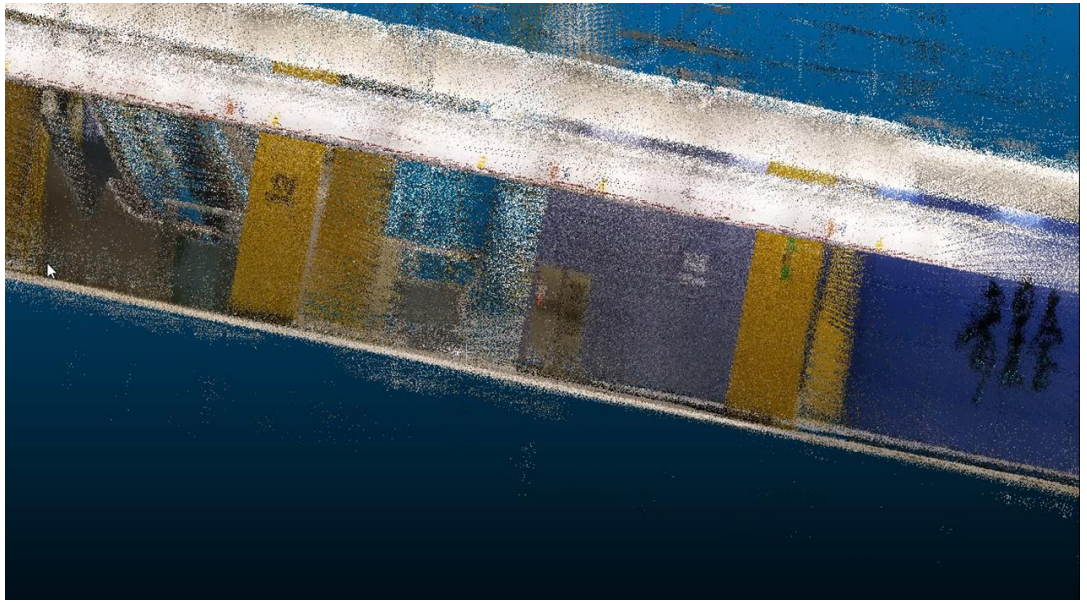
The Hong Kong Polytechnic University Campus

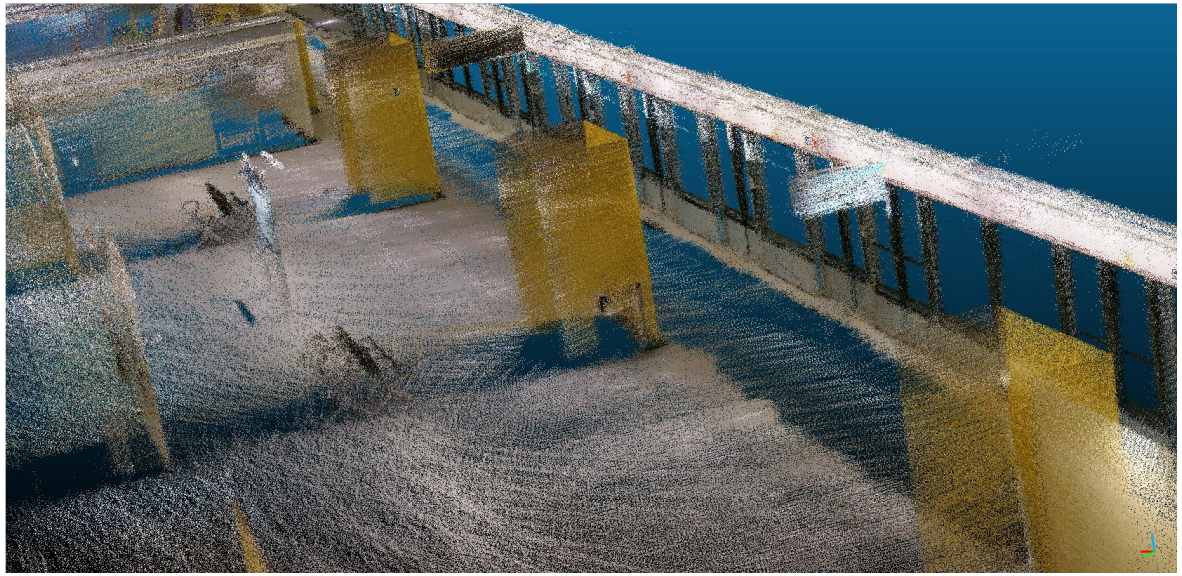


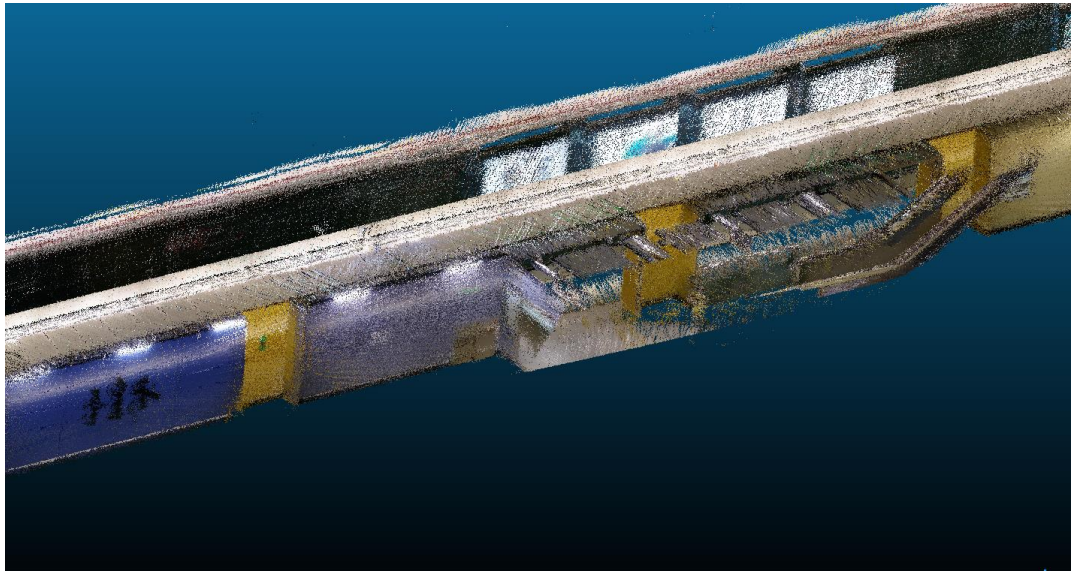


Victoria Harbor – Avenue of Stars

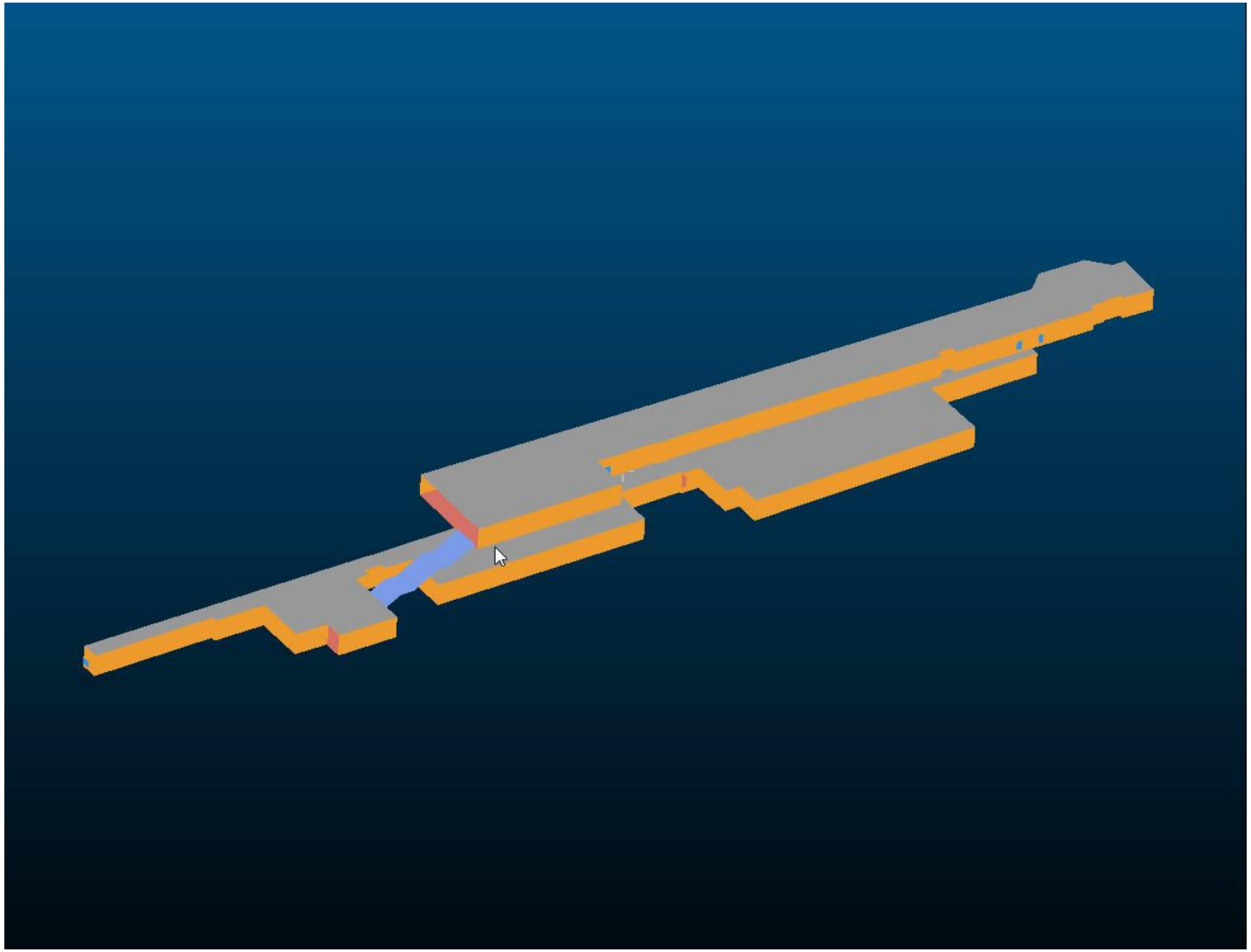
Colorized Point Cloud (MTR)







3D Model (MTR)



Street View

Street view

3D mobile mapping application: Oversized module transportation in MiC

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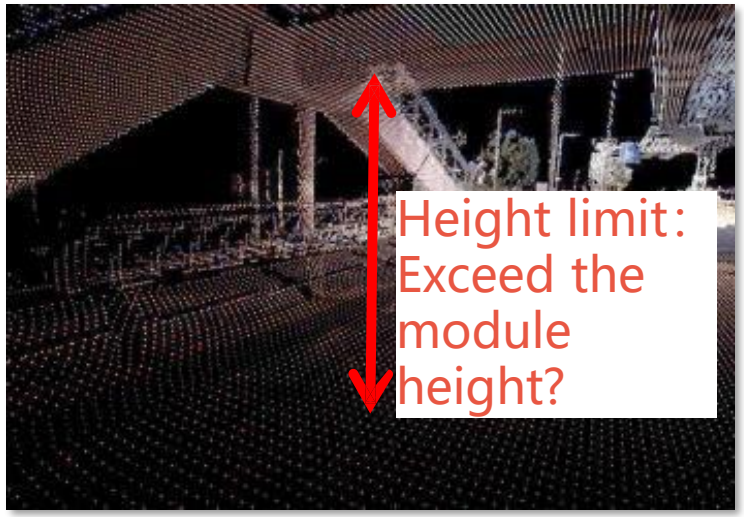
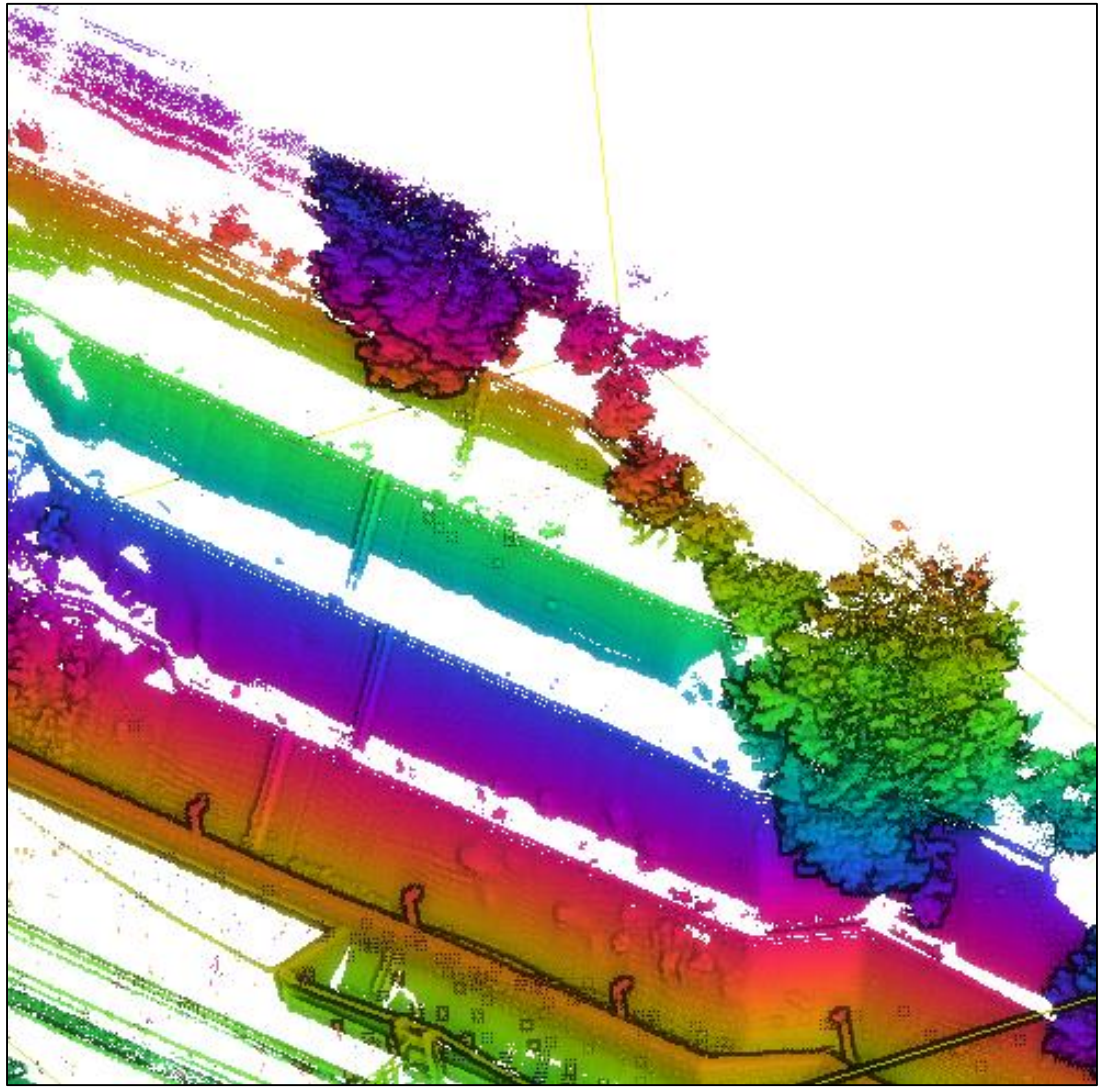
https://www.devb.gov.hk/filemanager/en/content_1044/20201115_12.html

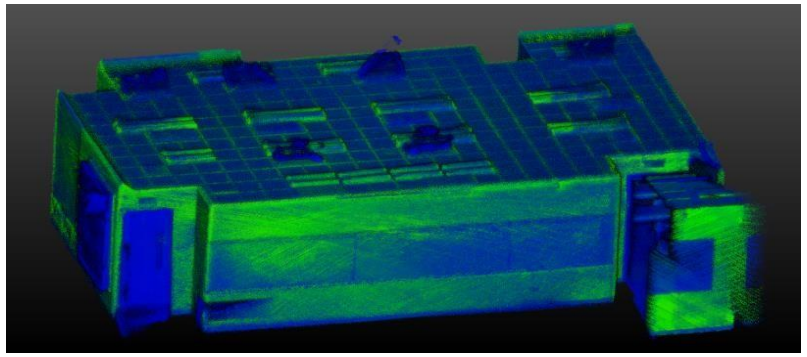


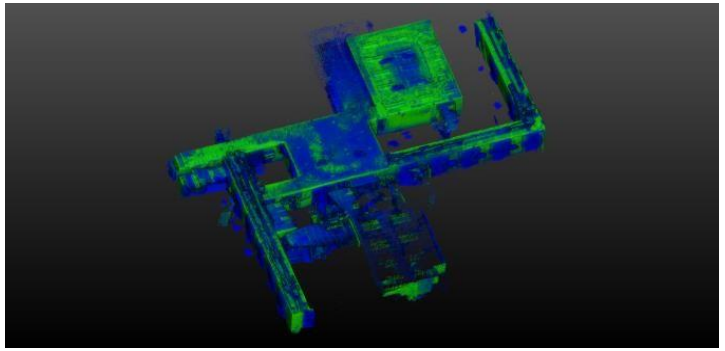
- Due to the large size of oversized modules, some road sections are difficult to pass during the transportation of modules.
- We use the 3D mobile mapping system to conduct 3D mapping of critical narrow road sections, and perform vehicle sweptpath analysis to accurately determine the location of obstructed road sections and provide the best route for smooth transportation
- We collaborate with the Hong Kong Construction Industry Council to promote the application of Modular Integrated Construction (MiC) in Hong Kong

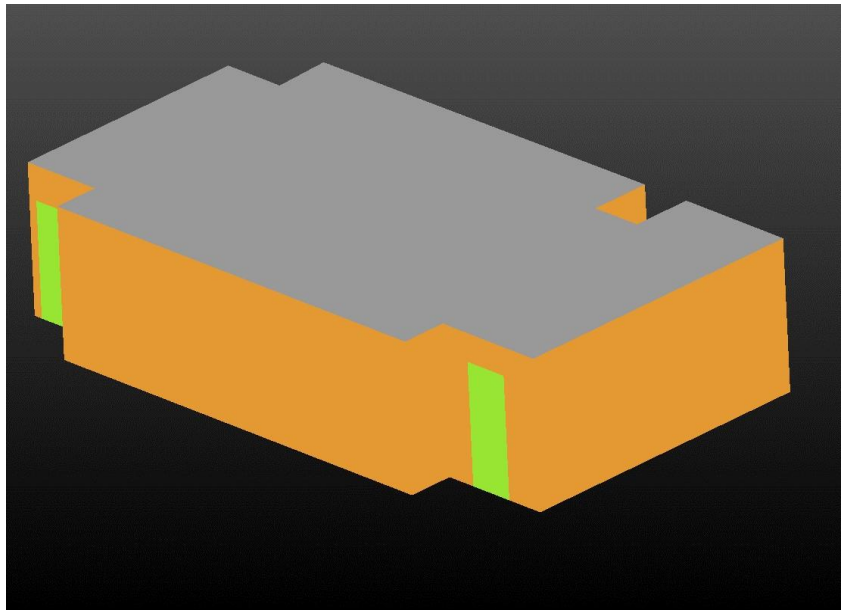
3D mobile mapping application: Slope mapping

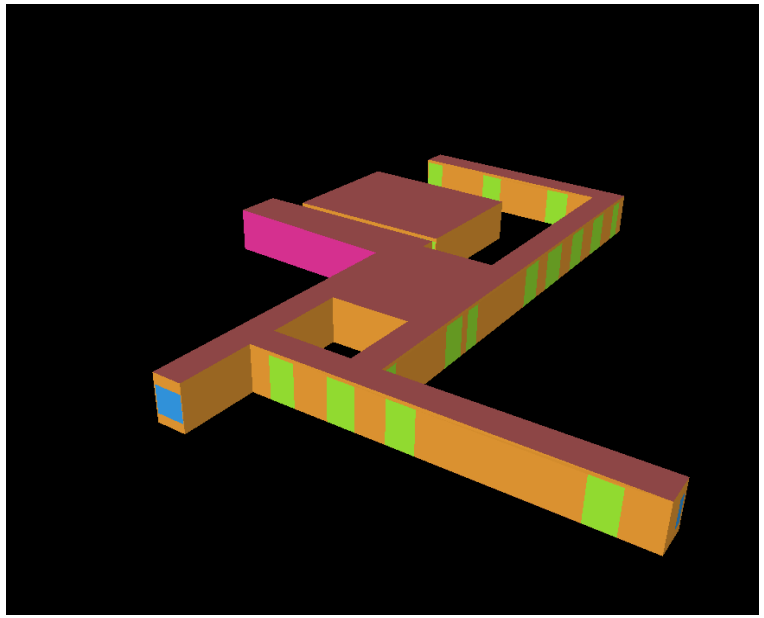


3D mobile mapping application: Support to BIM generation for old buildings in Hong Kong



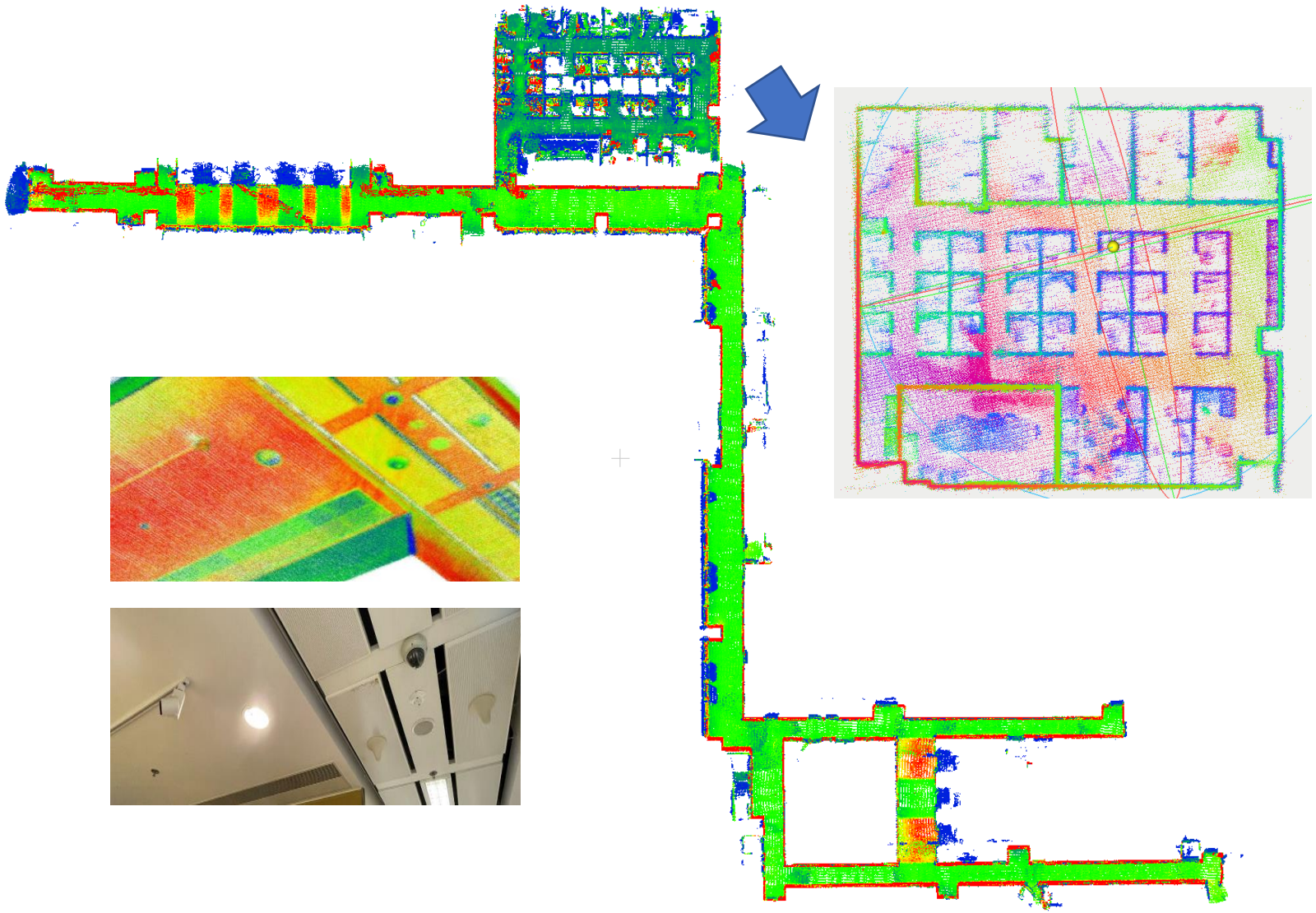






- Automatically identify and generate 3D models of windows and doors from the point cloud
- Automatically generate 3D models of rooms
- Supporting the generation of Building Information Model (BIM) to realize data conversion

3D mobile mapping application: Indoor firefighting



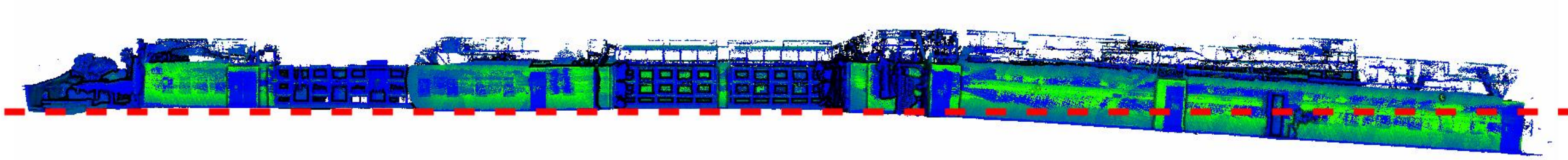
- Create realistic 3D models of indoor scenes
- Automatic identification of doors, windows, fire prevention facilities and other objects
- Used for fire evaluation simulation and evacuate route planning

3D mobile mapping application: Forest inventory

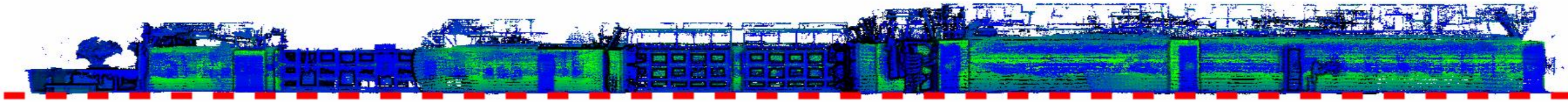
- Automatically compute two key forest inventory variables:
- Tree height
- Diameter at breast height (DBH)

Comparison with existing technologies

2. Building Floor



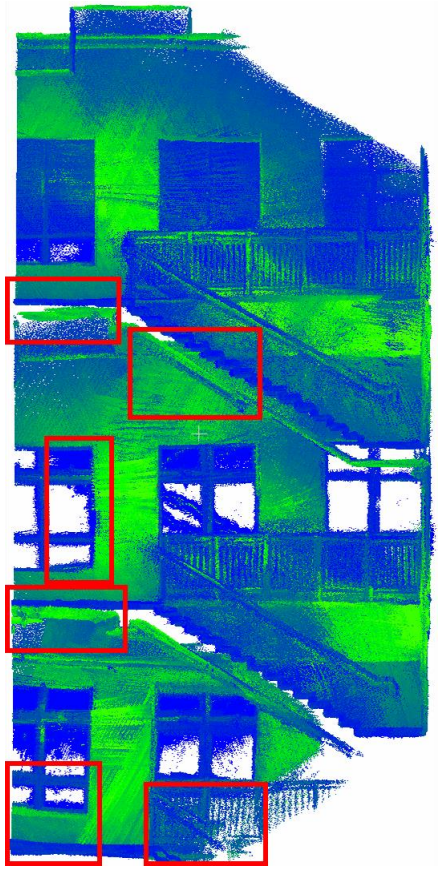
(a) Front view by other method



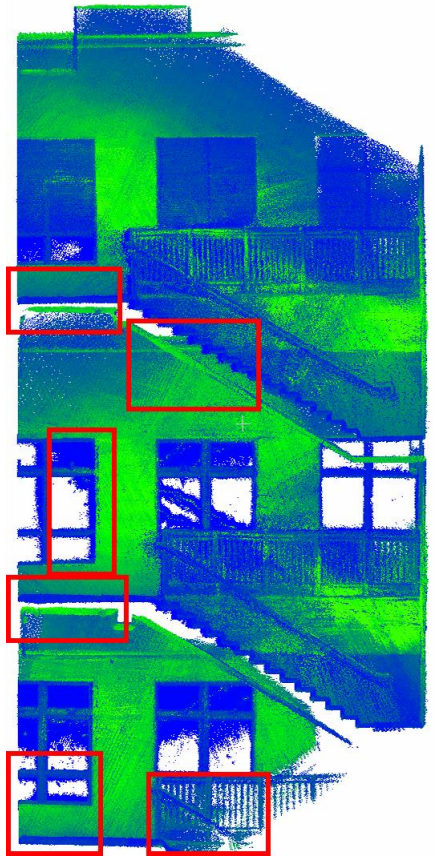
(b) Front view by our method

Comparison with existing technologies

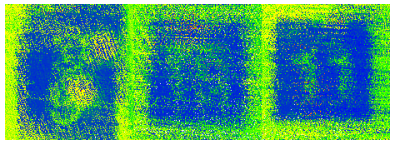
3. Staircase



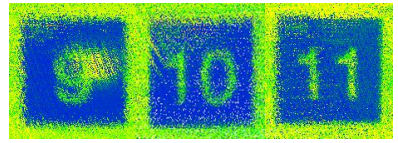
(a) Other's method



(b) Ours



(c) Other's method



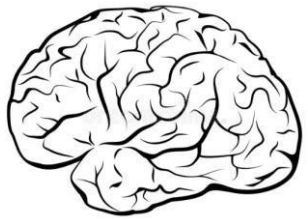
(d) Ours

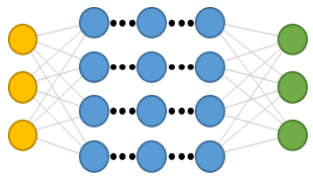
Staircase test between other and our method; (a) and (b) are an overview of mapping results; (c) and (d) are floor numbers on the wall extracted from both maps; colors are rendered by the intensity of points

2. AI for Remote Sensing Object Recognition

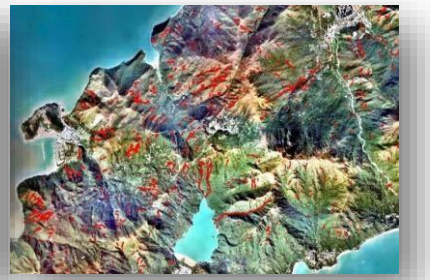
AI-based remote sensing object recognition

Remote Sensing Technology

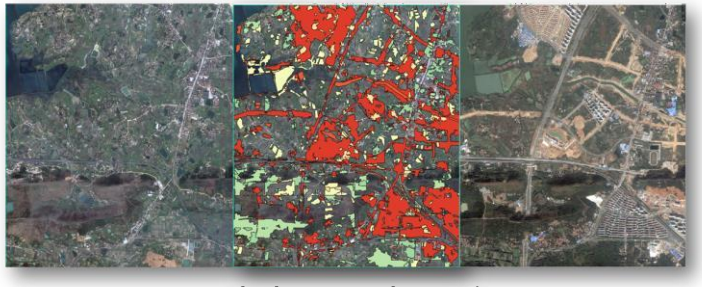




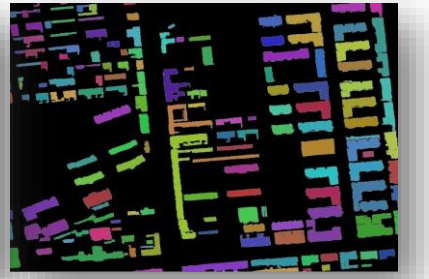
AI



Landslide recognition



Land change detection

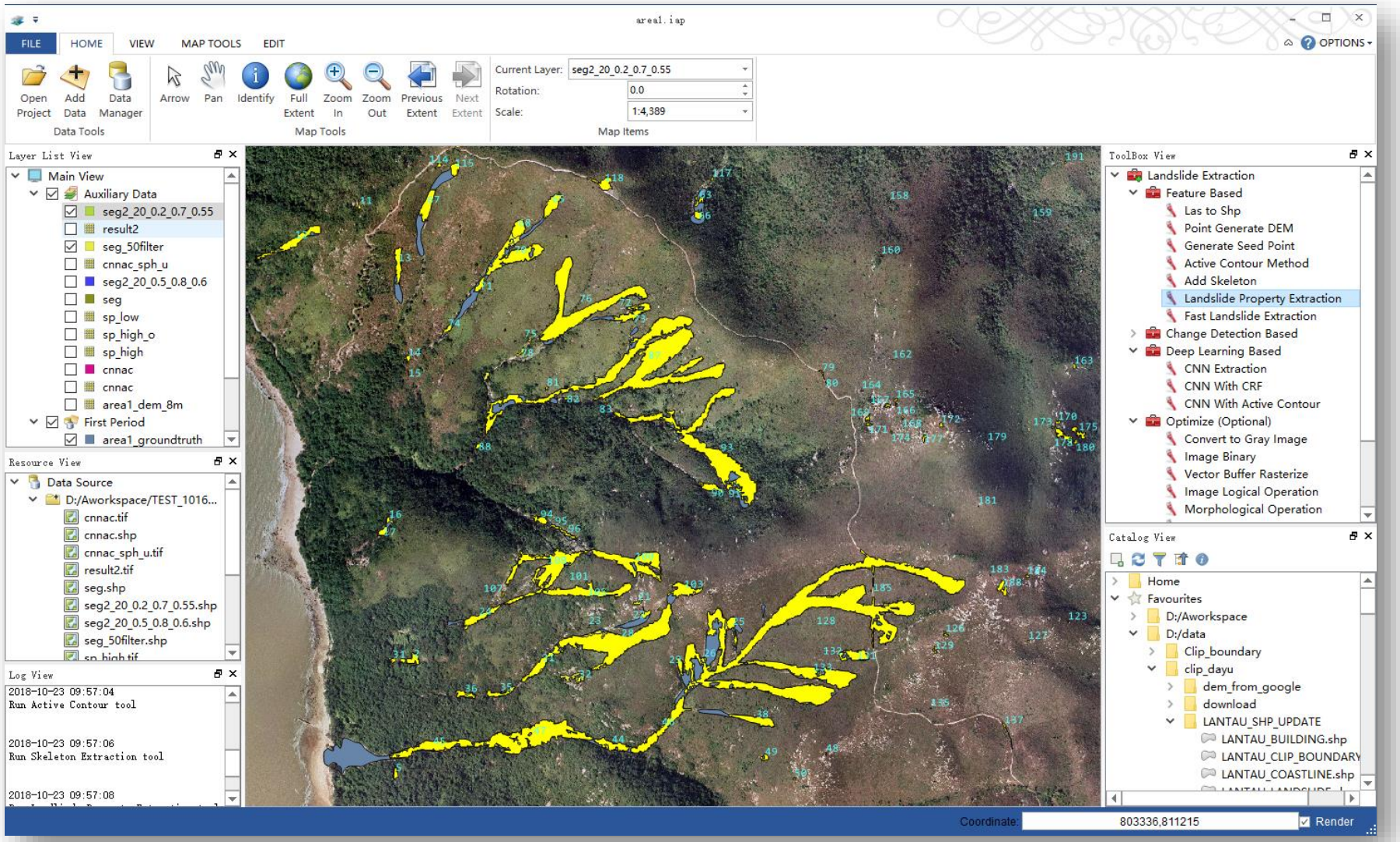


Building extraction

Vehicle recognition and traffic statistics

Landslide Recognition

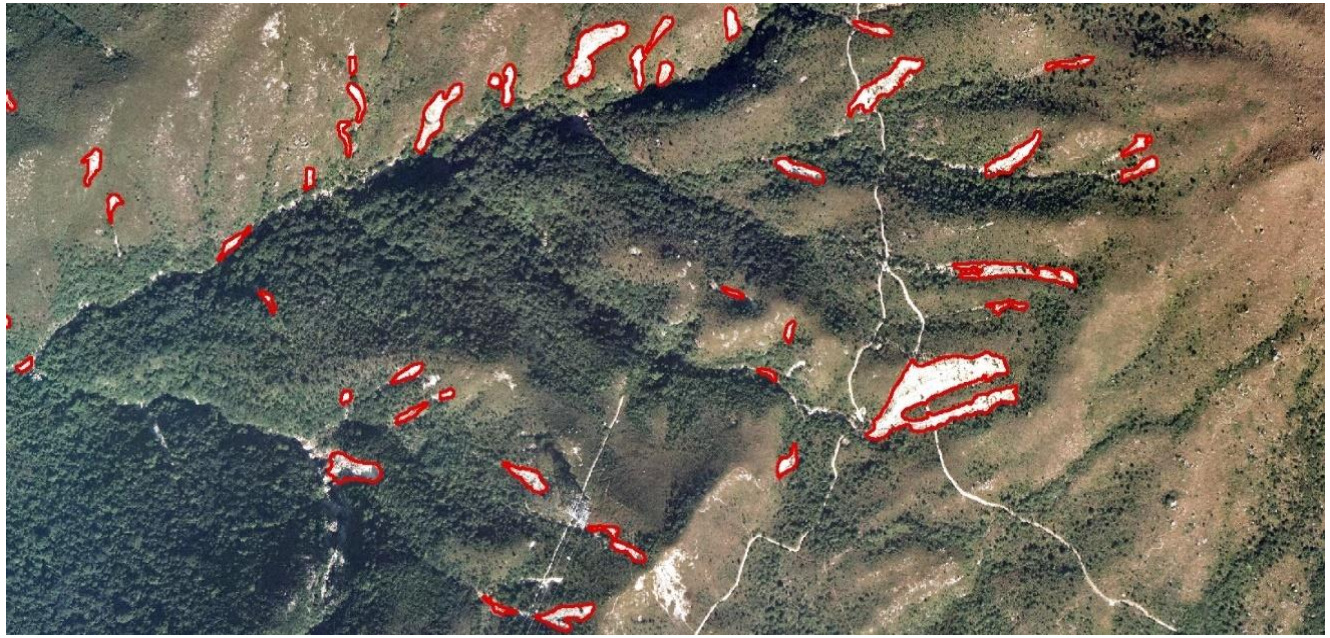
AI-based Landslide Recognition

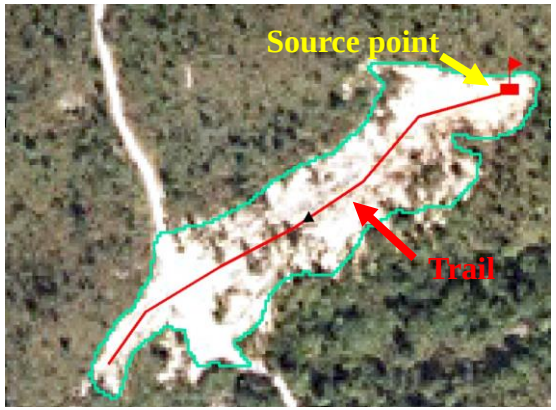


AI-based landslide detection and mapping

AI-based landslide recognition

- We developed a series of AI-based landslide recognition methods and a software system, with the following advantages:
  - **High efficiency**: 8 times higher than traditional manual method
  - **High accuracy**: with the accuracy of up to over 90%
  - **Rich landslide information**: the recognition result includes the boundary, area, height, trail and other information of the landslide.
- This technology is adapted by Hong Kong Government and local industry.

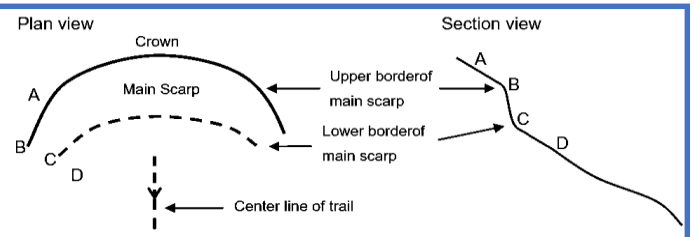




Landslide treatment in Hong Kong

Semi-automatic approach for identifying locations of shallow debris slides/flows based on lidar-derived morphological features

Step 1

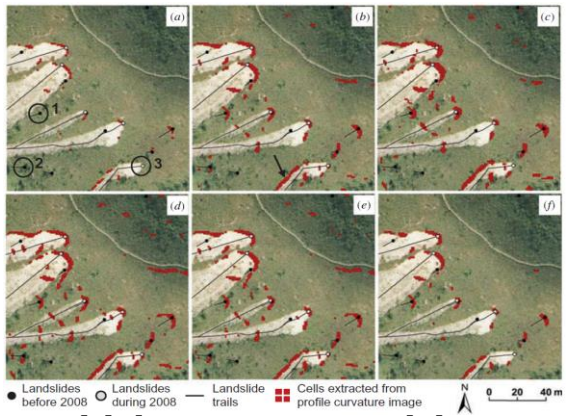


Landslide morphological features

$$I_i = (z_i - \bar{z}) \sum_{j=1}^{n} w_{ij}(z_j - \bar{z})/m_2 \; m_2 = \sum_{i=1}^{n} (z_i - \bar{z})^2/n.$$

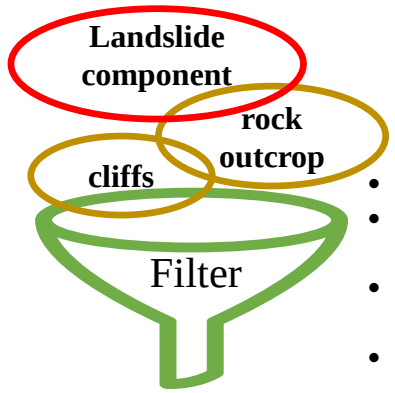
$$w_{ij} = \begin{cases} 1 \text{ if } A_{ij} = S_i \text{ and } d_{ij} \le D \\ 0 \text{ else} \end{cases} \quad i,j = 1, \ldots, n,$$

Local Moran's I (LMI) Calculation
Significance level thresholding



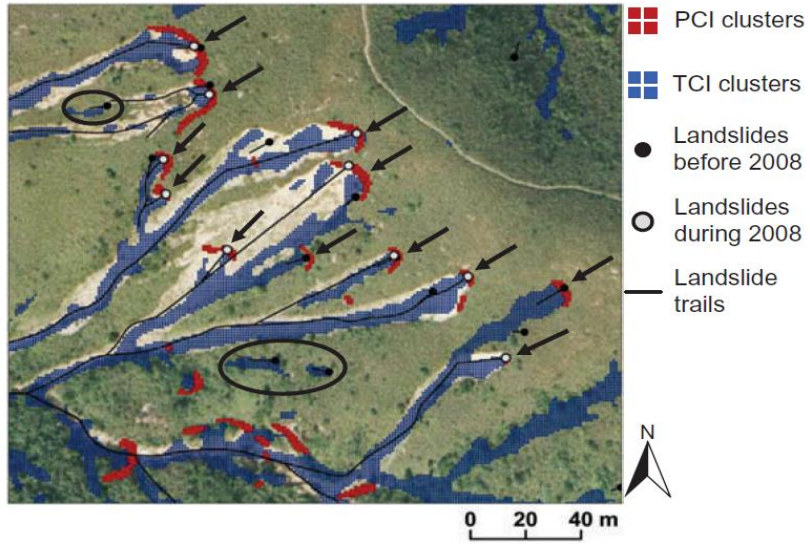
Landslide component candidates

Step 2



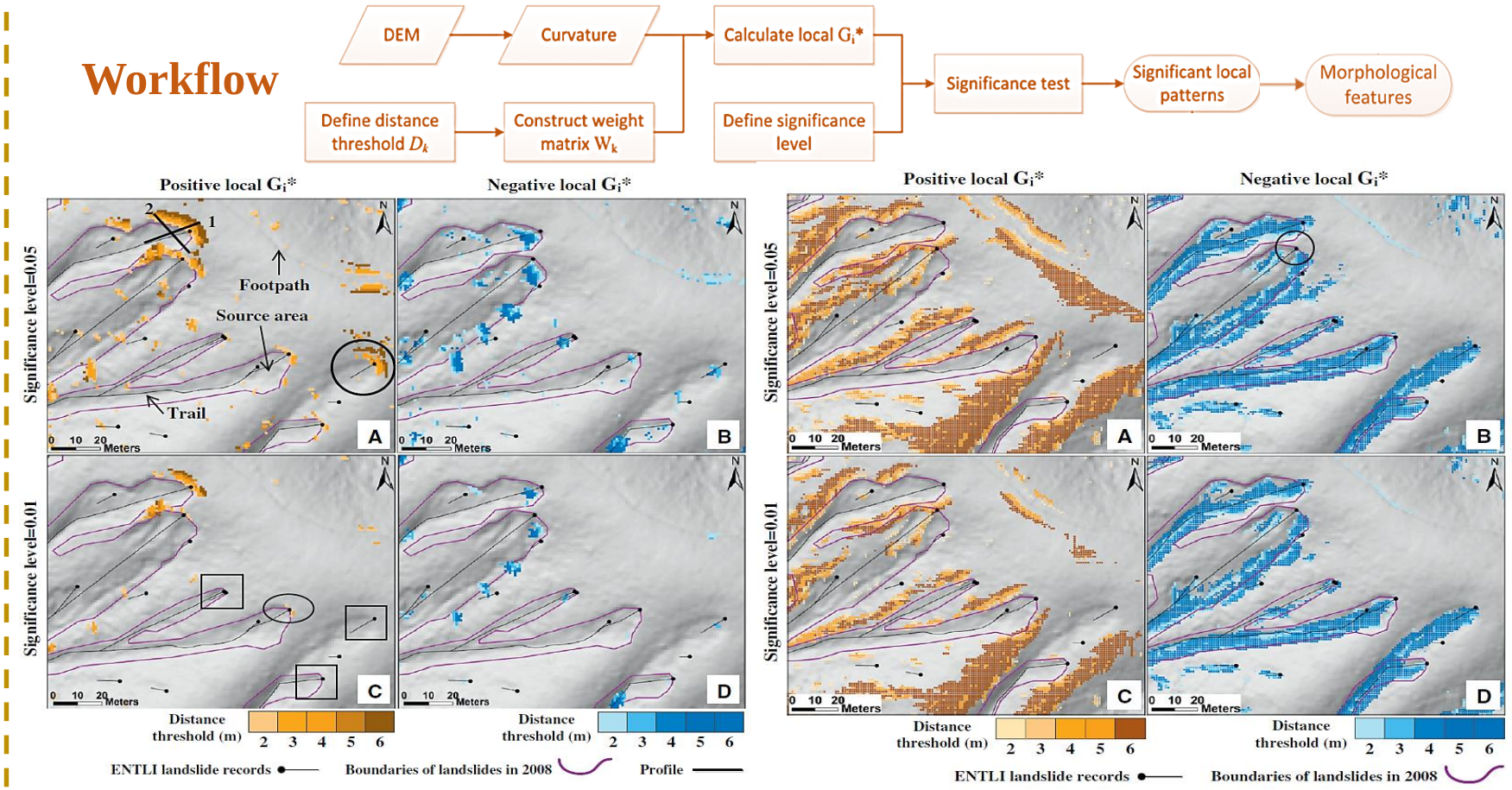
Four Discrimination Rules

- Cluster shape
- Slope gradients downslope of cluster
- Relative location between 2 clusters
- Difference in mean slope direction



Susu Deng & Wenzhong Shi (2014) Semi-automatic approach for identifying locations of shallow debris slides/flows based on lidar-derived morphological features, International Journal of Remote Sensing, 35:10, 3741-3763, DOI: 10.1080/01431161.2014.915438

Extraction of multi-scale landslide morphological features based on local G_i^* using airborne LiDAR-derived DEM

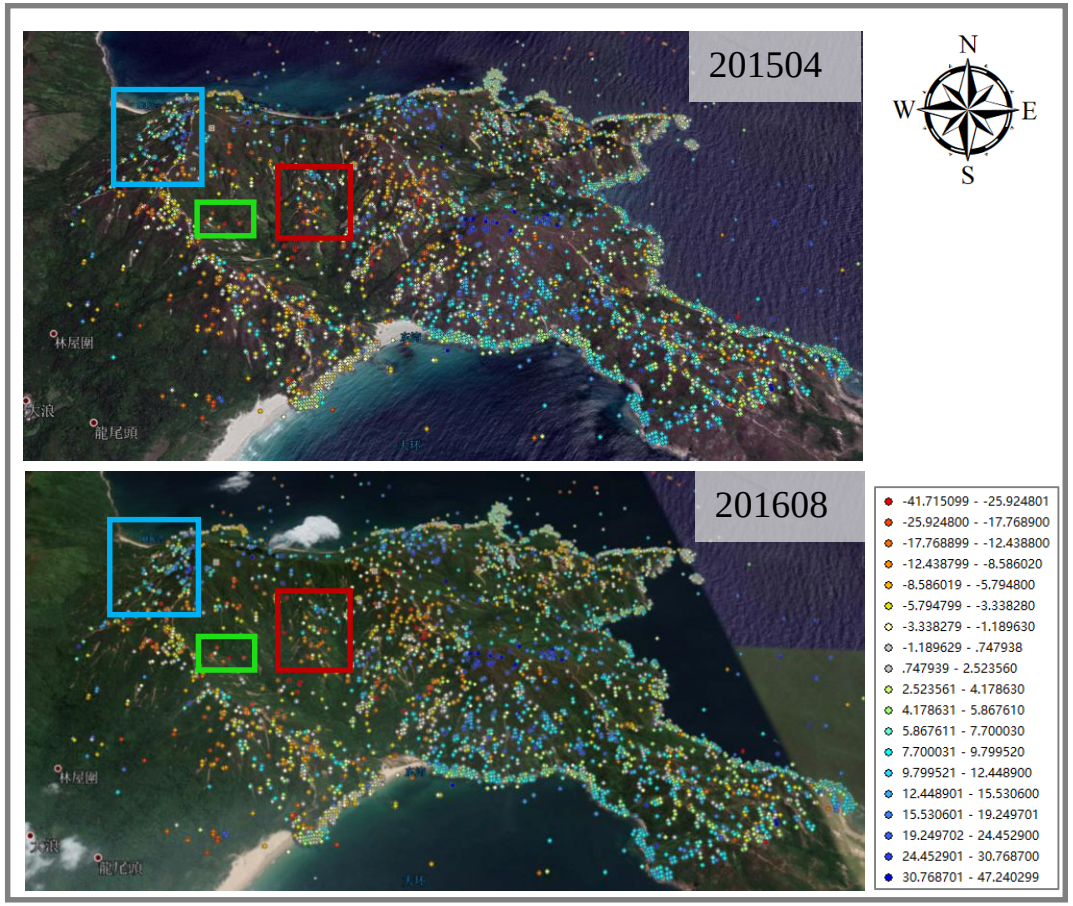


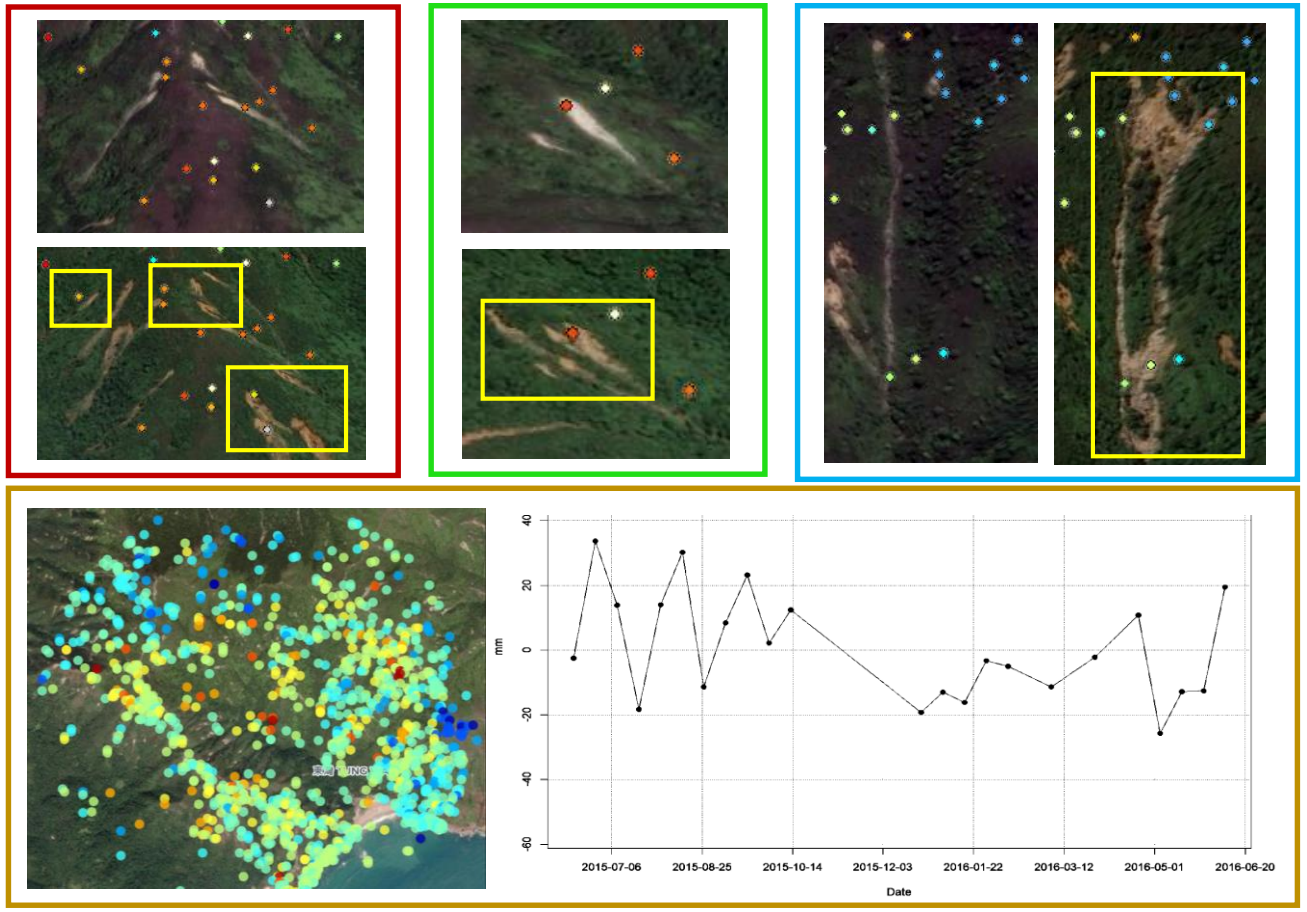
Cells extracted from the profile curvature image through identifying the significant local patterns of clustering of high or low profile curvature values at different significance levels.

Cells extracted from the tangential curvature image through identifying the significant local patterns of clustering of high or low tangential curvature values at different significance levels.

Shi W, Deng S, Xu W. Extraction of multi-scale landslide morphological features based on local Gi* using airborne LiDAR-derived DEM[J]. Geomorphology, 2018, 303: 229-242.

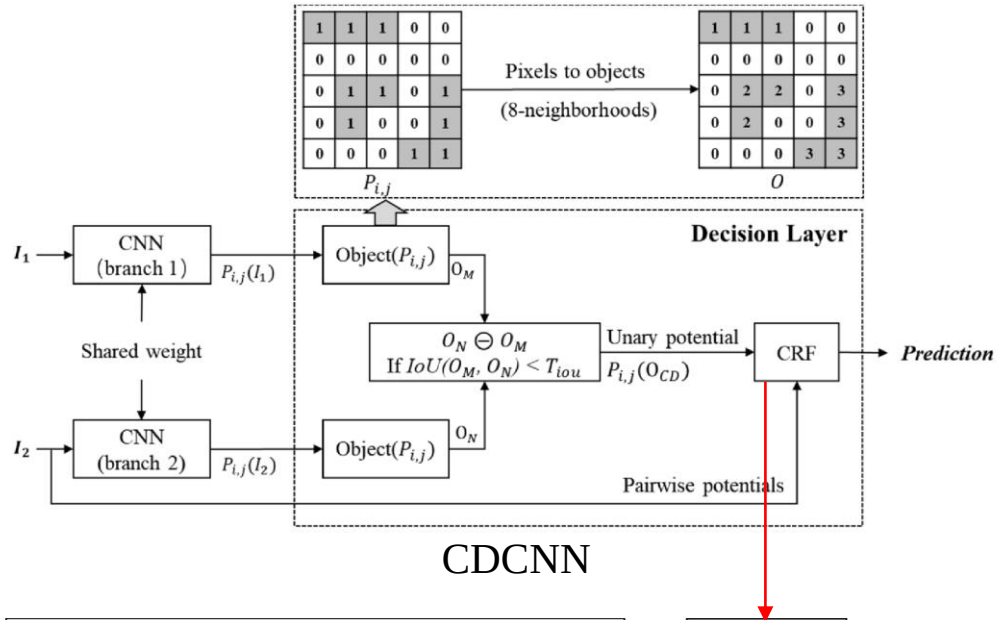
Landslide deformation monitoring based on PS-InSAR



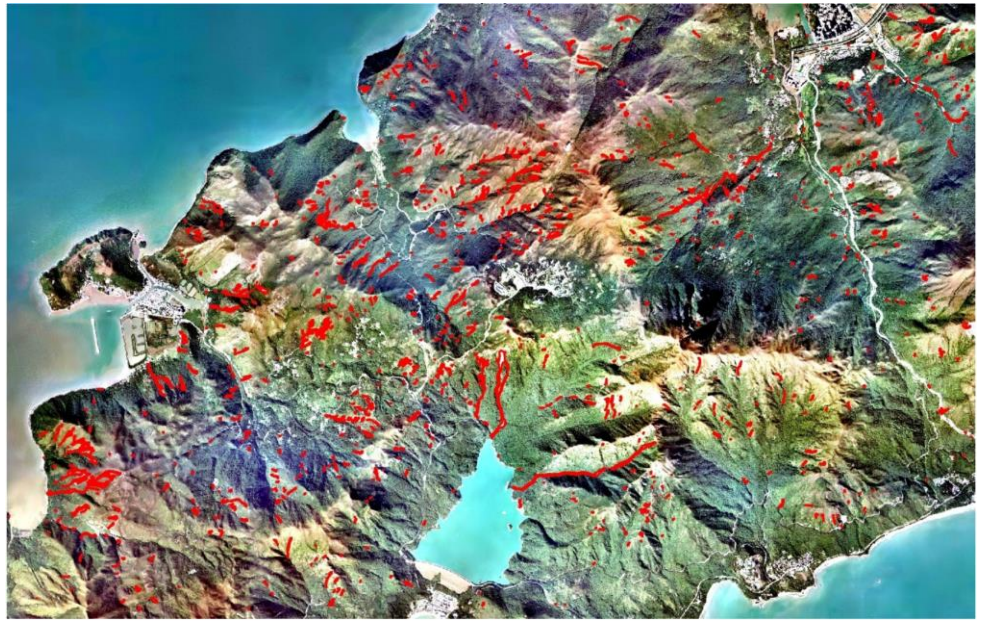


We used a total of 23 interferograms from July 2015 to June 2016 to monitor the deformation of the landslide in **Sai Kung**. According to the average deformation velocity of PS points, it can be found that the severe deformation is often accompanied by the formation of new landslides. This conclusion can further provide data for the analysis of landslide susceptibility.

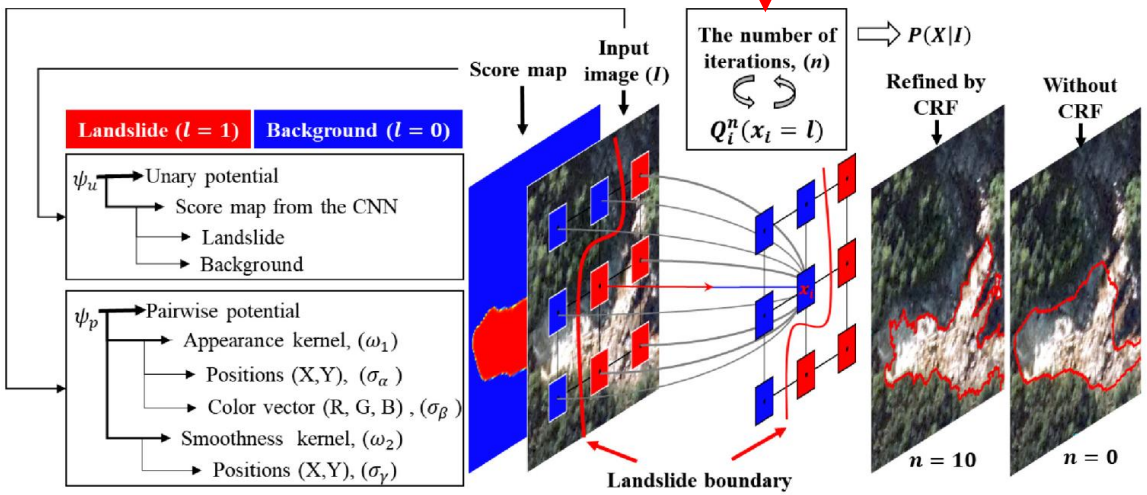
AI-based Landslide Extraction



CDCNN

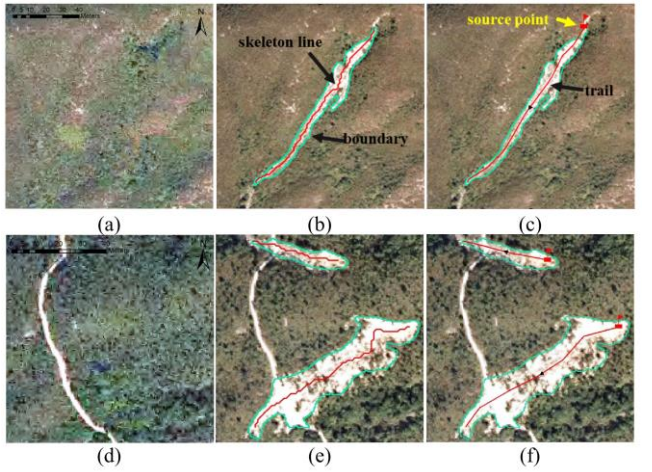


Result in Lantau Island, HK



Using CRF to refine landslide boundary

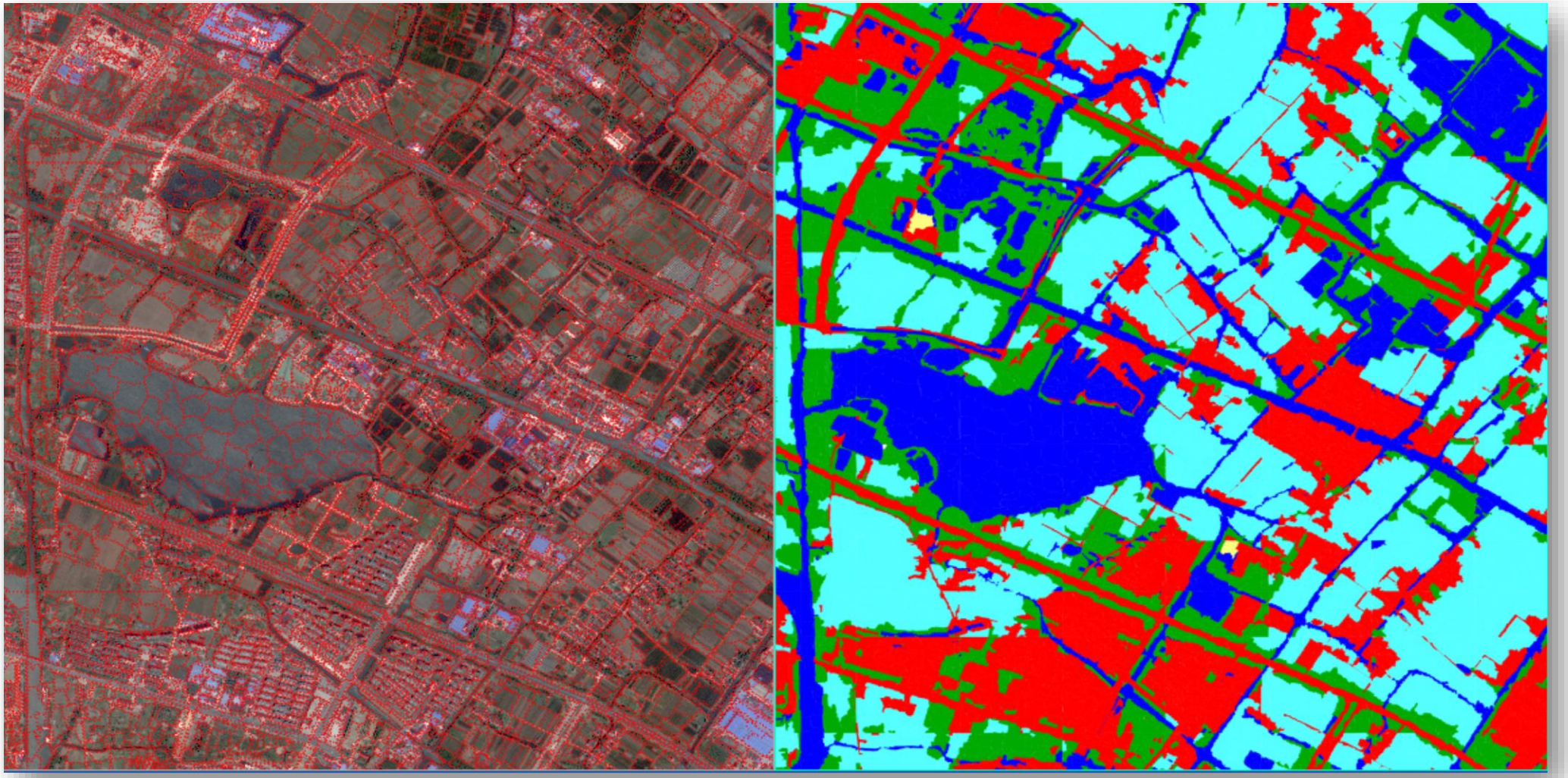
Details



Shi, W., M. Zhang, H. Ke, X. Fang, Z. Zhan & S. Chen (2020) Landslide recognition by deep convolutional neural network and change detection. IEEE Transactions on Geoscience and Remote Sensing, 1-19.

Classification and Change Detection

Classification

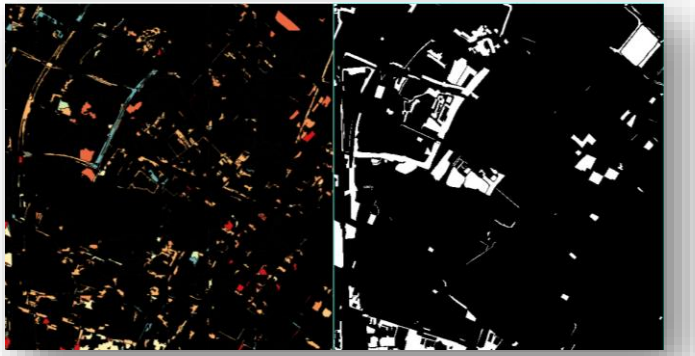


AI-based classification based on multispectral RS images

Change Detection

Bi-temporal image

AI Model



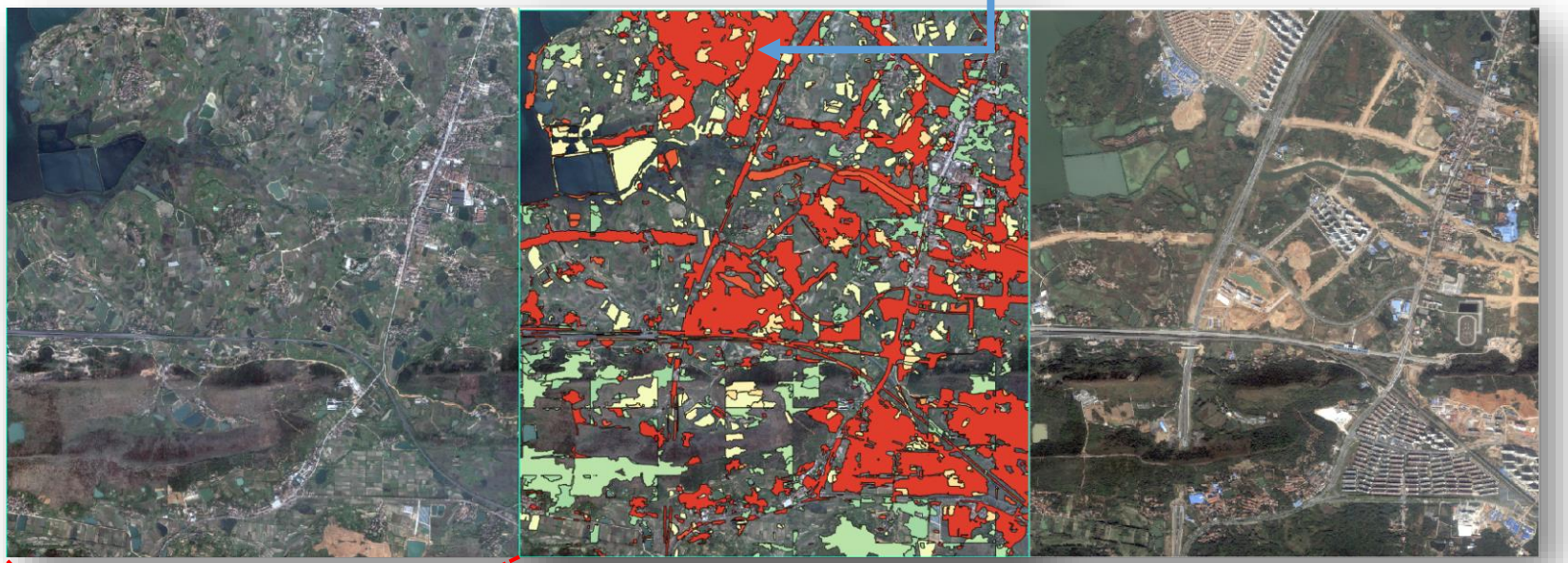
Results with change direction

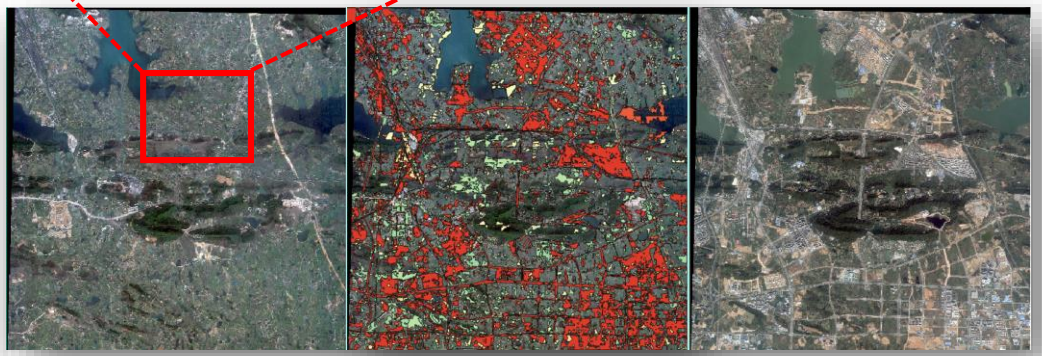
First period image

From grassland change to construction land

From-to change map

Second period image





First period image

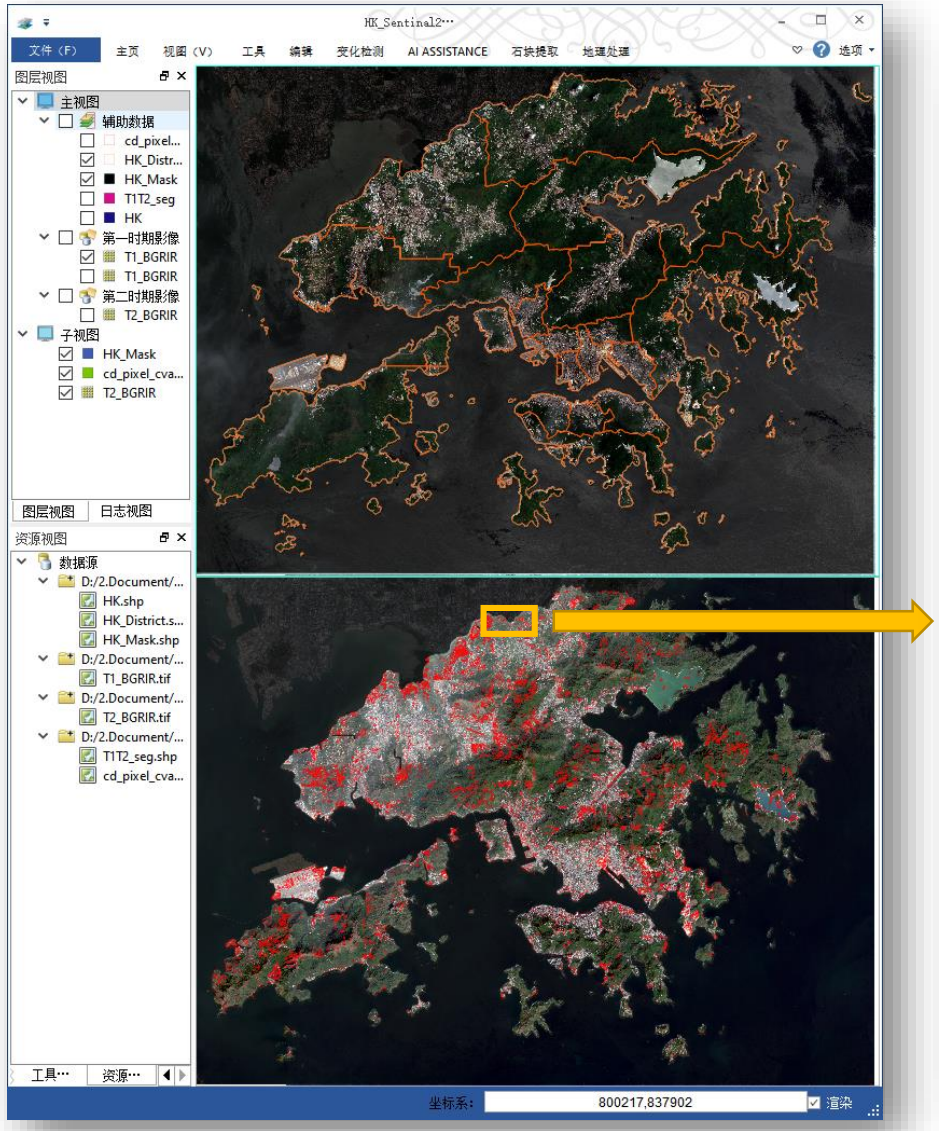
From-to change map

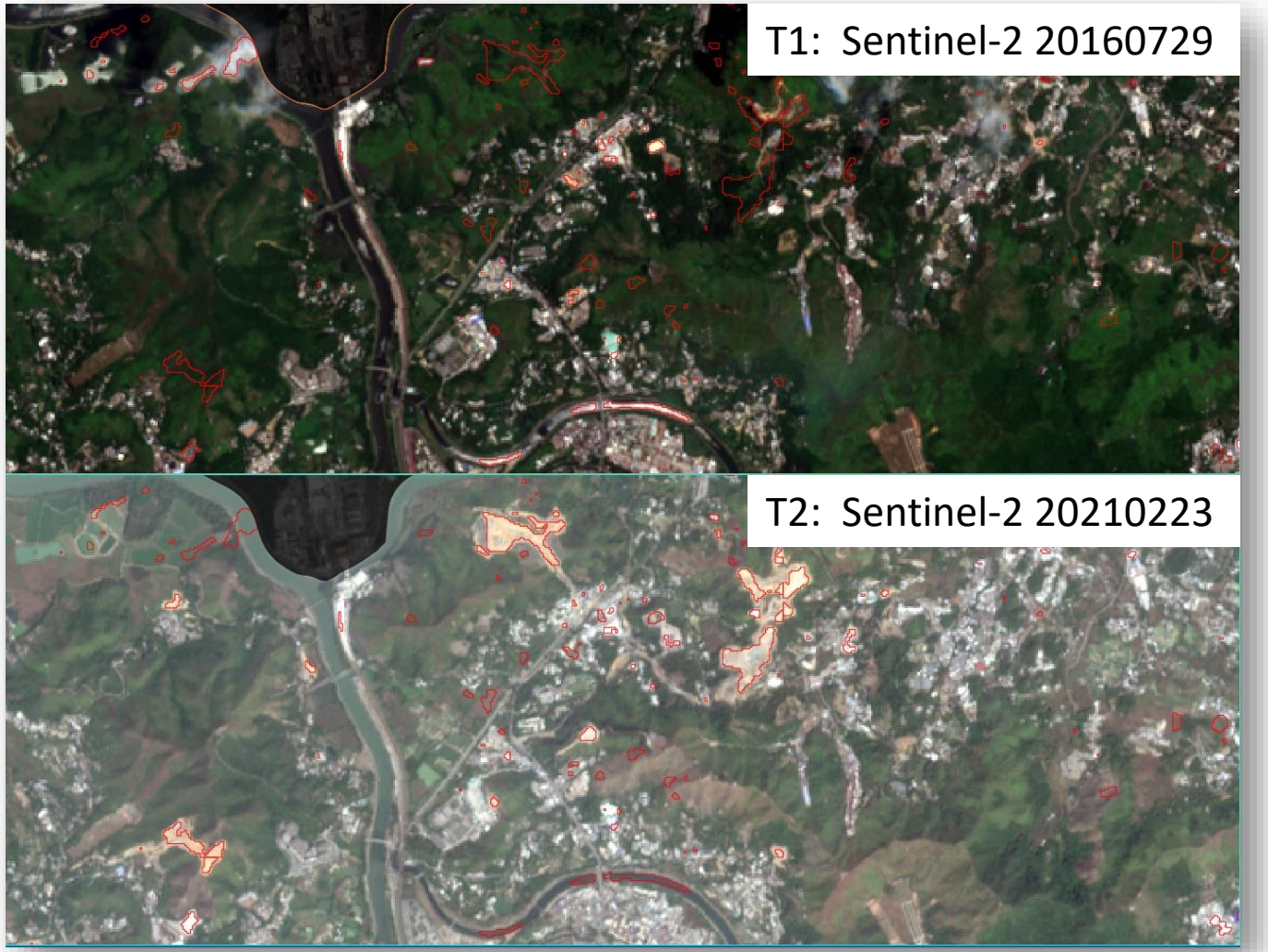
Second period image

	IAID	DN	OldType	NewType	ChangeType	Prob
1	76344	2	耕园草	建设用地	耕园草-建设用地	0.452594..
2	76343	4	耕园草	林地	耕园草-林地	0.522596..
3	76338	15	水系	耕园草	水系-耕园草	0.732666..
4	76336	15	水系	耕园草	水系-耕园草	0.853052..
5	76335	15	水系	耕园草	水系-耕园草	0.864527..
6	76332	2	耕园草	建设用地	耕园草-建设用地	0.385371..
7	76329	3	耕园草	水系	耕园草-水系	0.685129..
8	76328	14	水系	林地	水系-林地	0.825752..
	76325	4	耕园草	林地	耕园草-林地	0.612526..

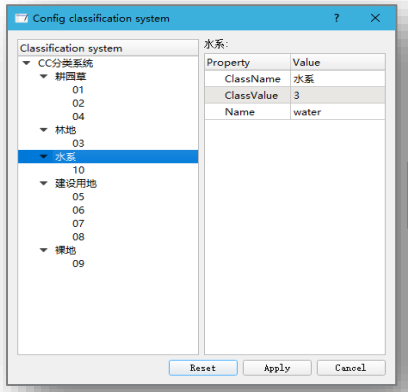
Change direction

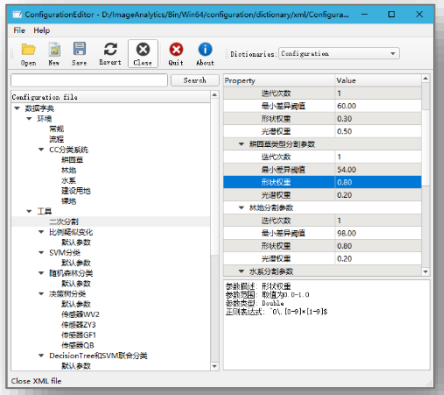
Land Cover Change Detection in Hong Kong

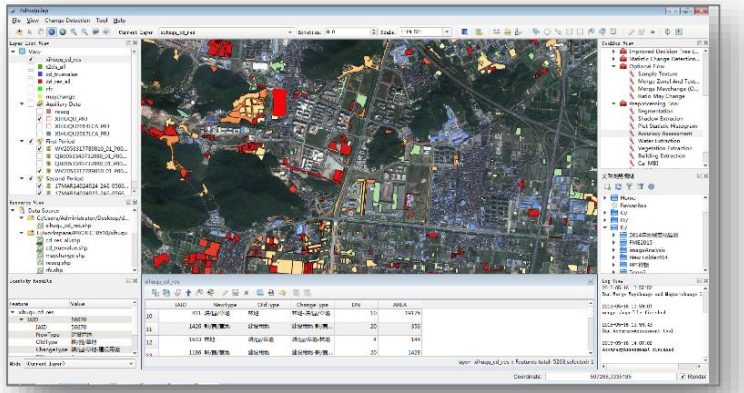




Classification and Change Detection Flow







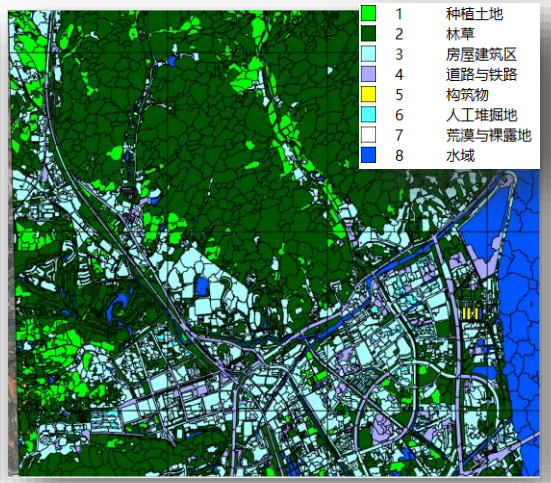
Applications in

- Jiangsu
- Zhejiang
- Beijing

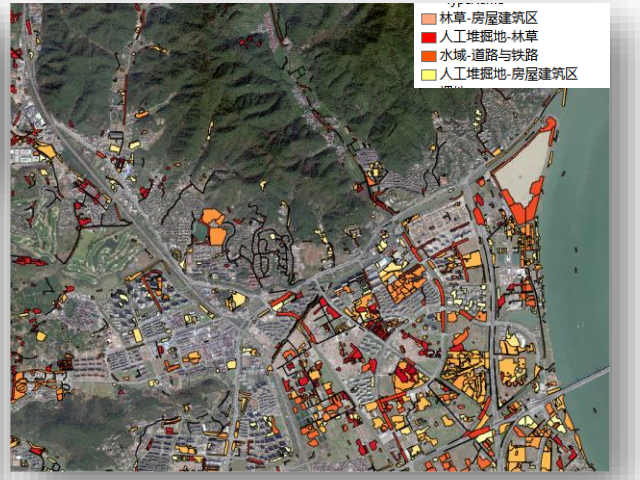
West Lake area in Zhejiang Province

T1: WV2 Satellite Imagery (2m)

T2: WV2 Satellite Imagery (2m)



Classification (T2)



Post-classification based change detection

Change Detection

Grass ->Water

Construction landuse ->Grass

Forest -> Construction landuse

Bare soil -> Grass

Water -> Grass

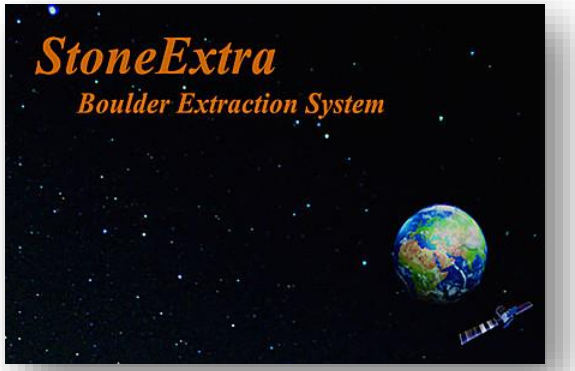
Grass -> Construction landuse

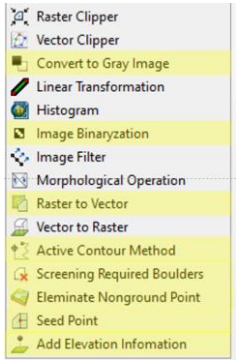
Typical land use changes in urban area

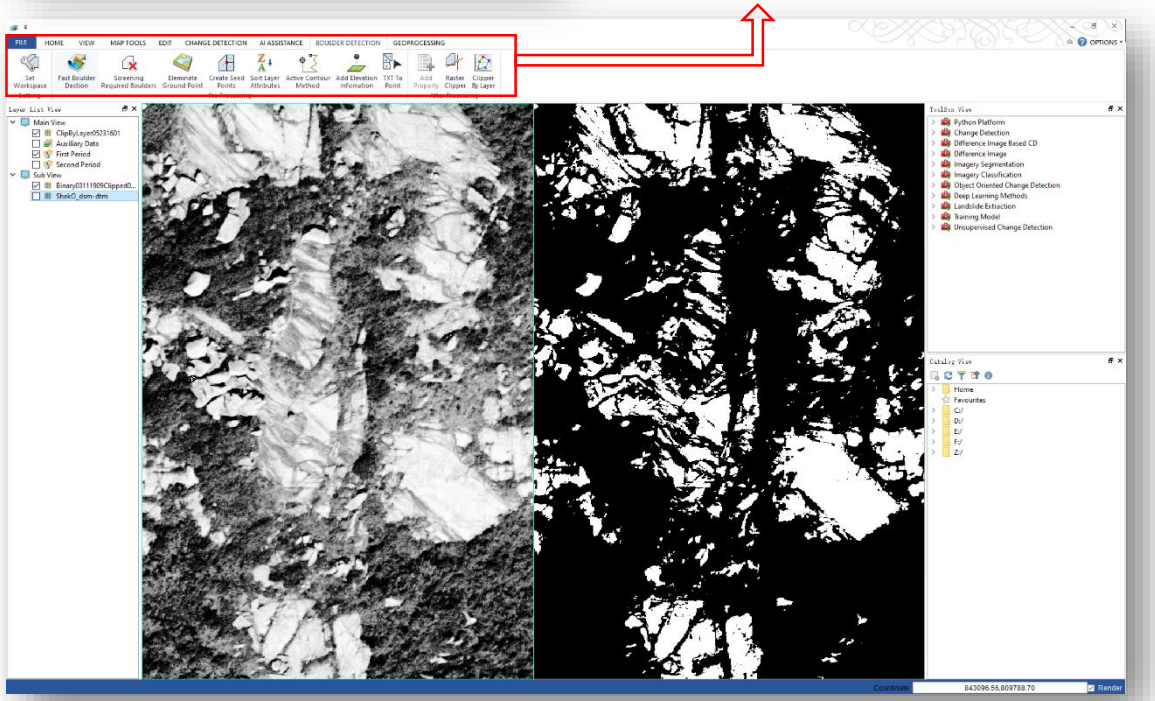
Boulder Detection

Boulder Detection

- StoneExtra-Boulder Extraction System

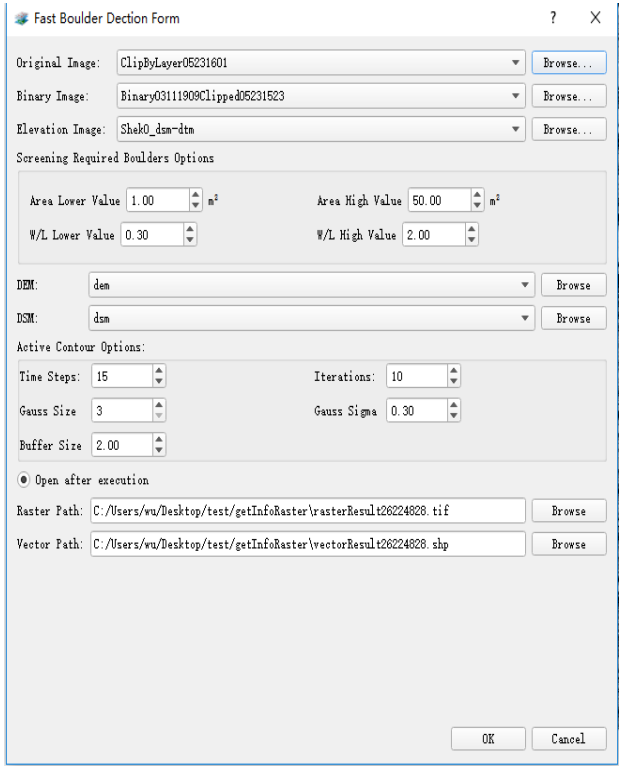


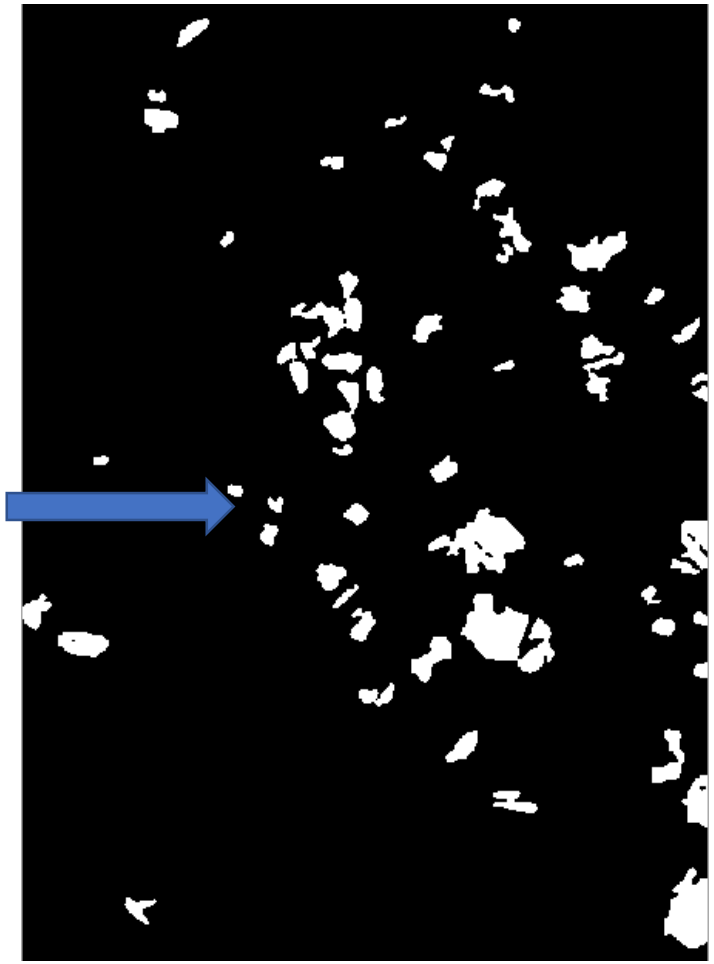




Boulder Detection

Automatic processing system

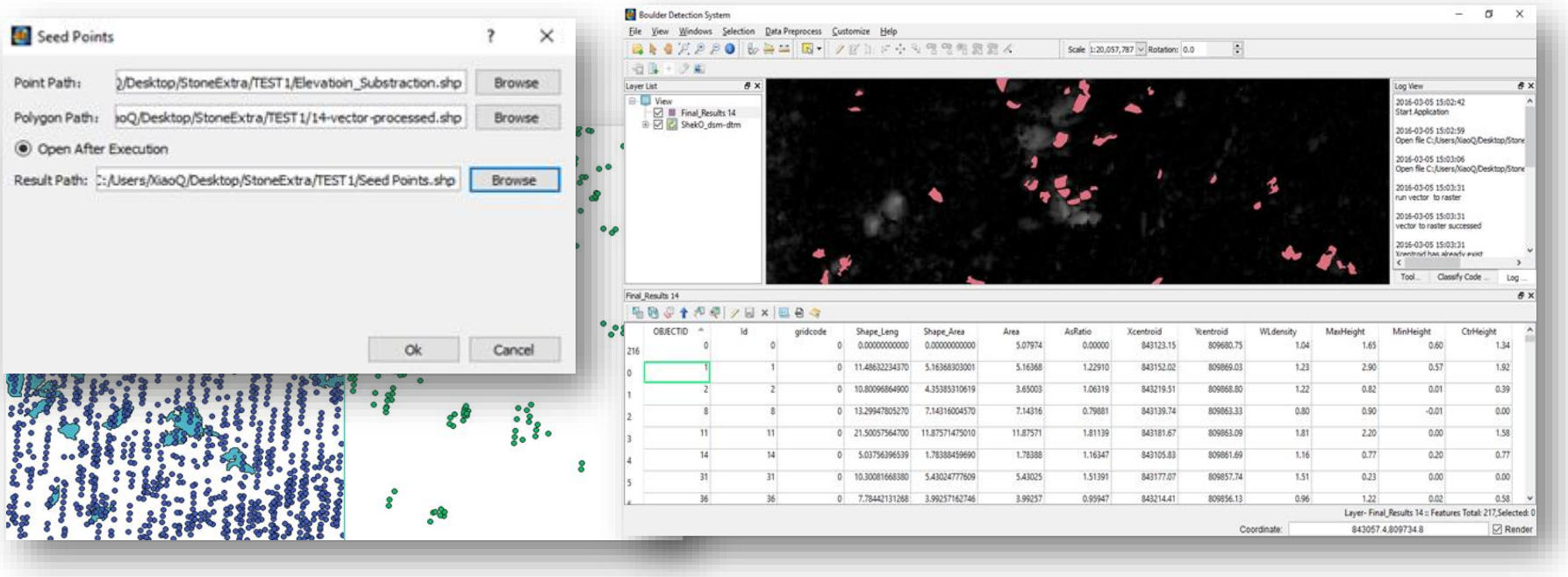




Boulder Detection

An application case in Hong Kong

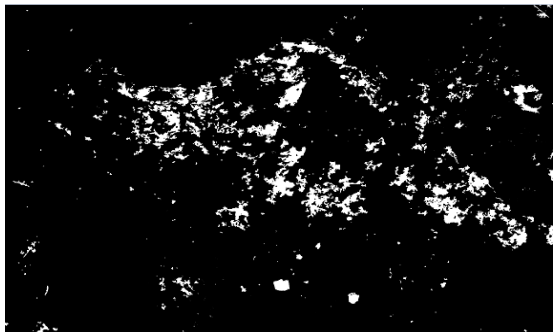
- StoneExtra has been put into use in two projects held during 2014 to 2016, which were completed corporately by Civil Engineering and Development Department(HKSAR) and Hong Kong Polytechnic University.
- These two projects are mainly focus on automatically detecting boulders on deep hillside which will greatly facilitate the stabilization and mitigation work to the boulders.



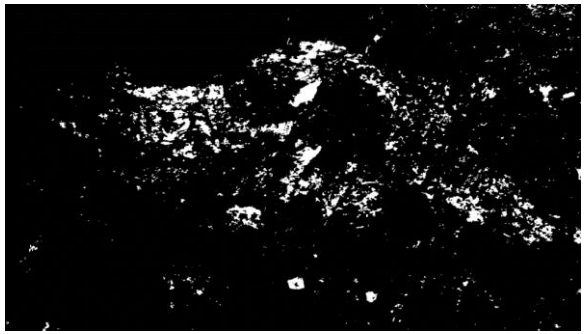
Outcrop Detection

Outcrop Detection

Area 1

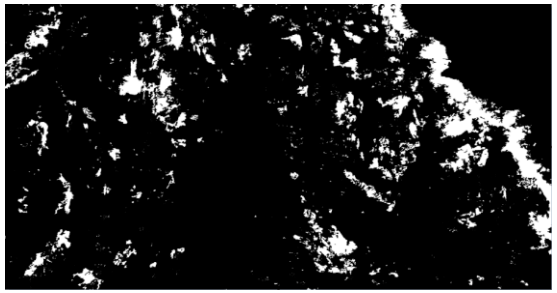


Ground Truth

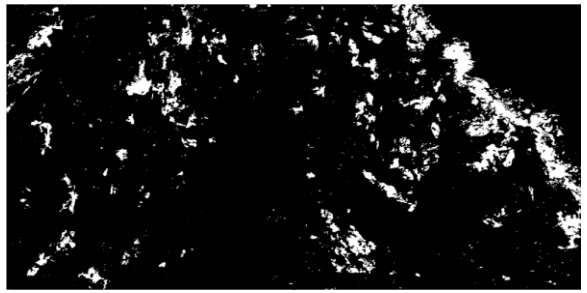


Predict

Area 2

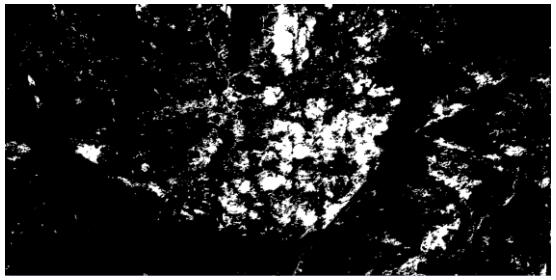


Ground Truth

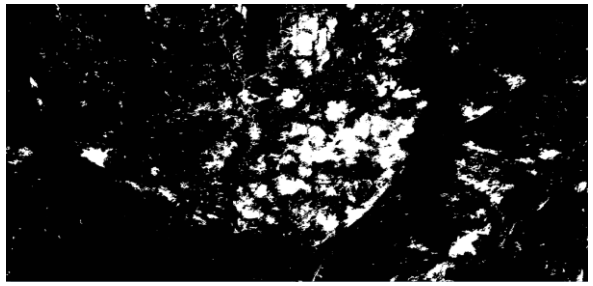


Predict

Area 3



Ground Truth



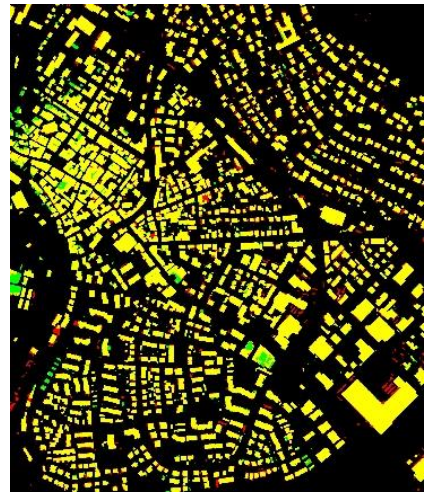
Predict

Building Extraction

Building Extraction

Image

nDSM



Pixel-based evaluation

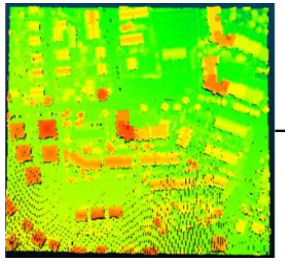
True detection, false detection, and missed detection are colored in yellow, red, and blue.

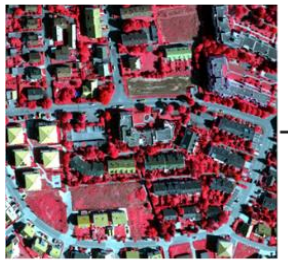
Building extraction result of the whole Vaihingen dataset

- Automatic building extraction via adaptive iterative segmentation with LiDAR data and high spatial resolution imagery fusion.
- An automatic building extraction method with **LiDAR data and high-resolution remote sensing imagery fusion**. The proposed method **had no parameters** to set and **requires no samples**.

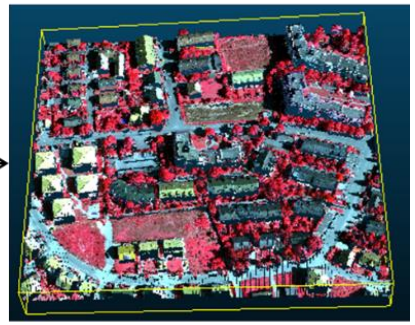
Chen, S. X., W. Z. Shi, M. T. Zhou, Z. Min & P. F. Chen (2020) Automatic building extraction via adaptive iterative segmentation with LiDAR data and high spatial resolution imagery fusion. Ieee Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 13, 2081-2095.

3D Building Change Detection





Matching



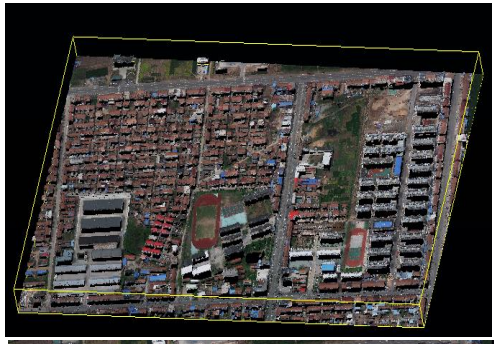
（X,Y,Z）+（IR,R,G）→（X,Y,Z,IR,R,G）

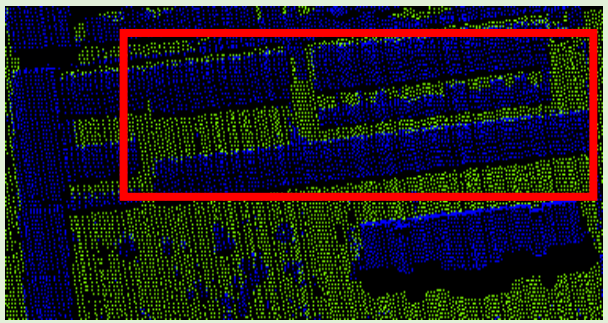
Information fusion of point cloud and image

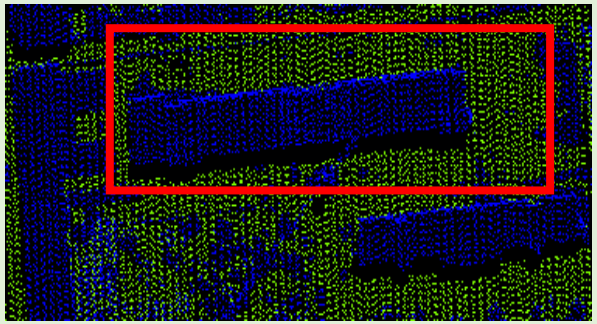
Filtering

Segmentation

Classification



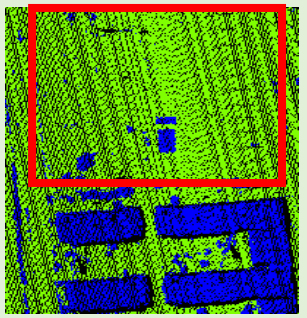


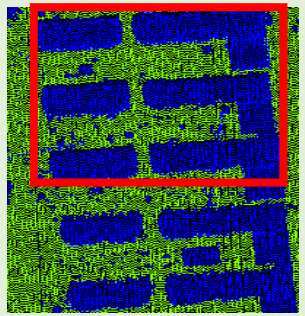


First period

Reconstructed

Second period



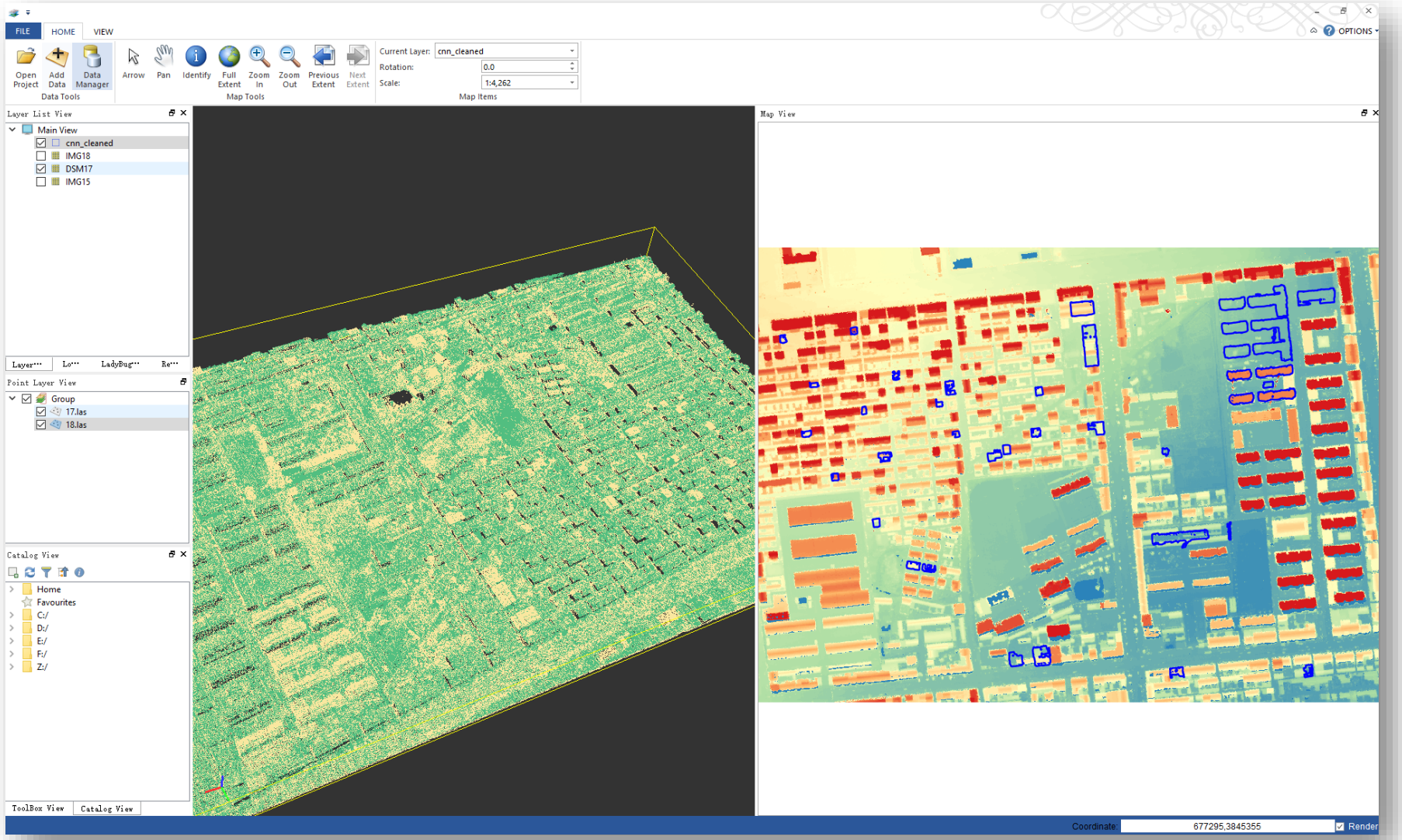


First period

Newly-built

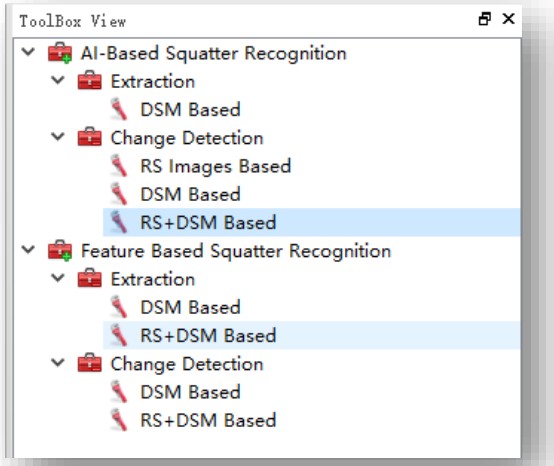
Second period

3D Building Change Detection



Squatter Recognition

Squatter Recognition



Squatter Recognition

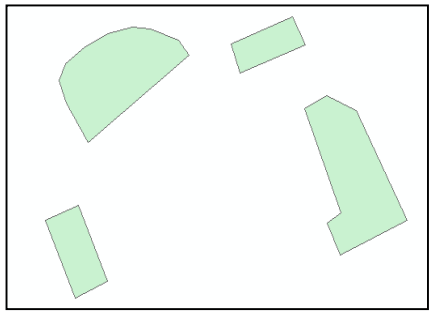
Our results,
overlaid with 2018 DOM

Reference change map, overlaid
with 2019 DOM

2018 DOM

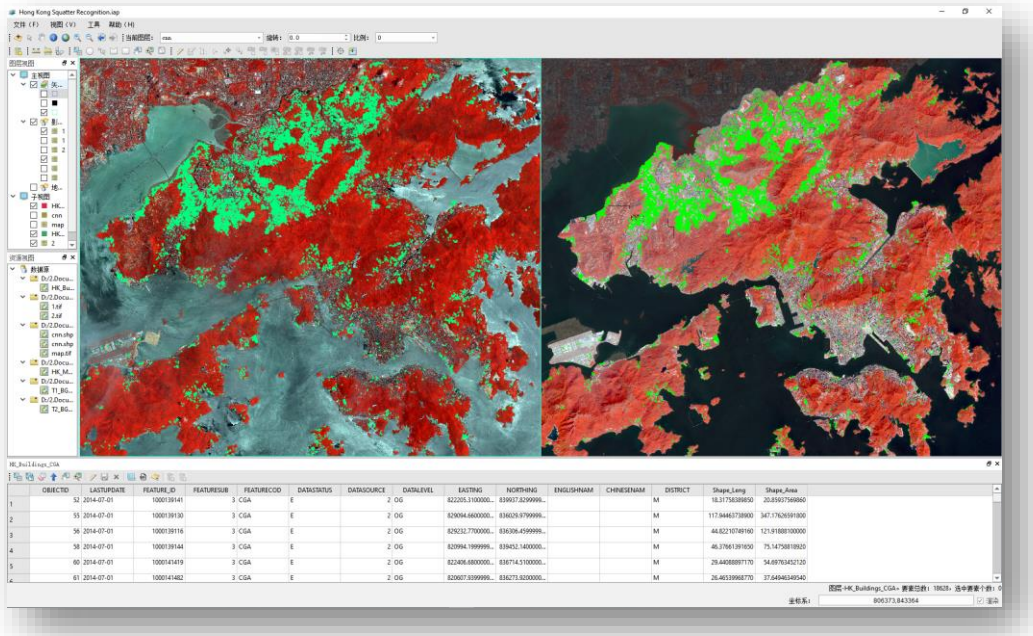
2019 DOM

Detected squatter area
changes

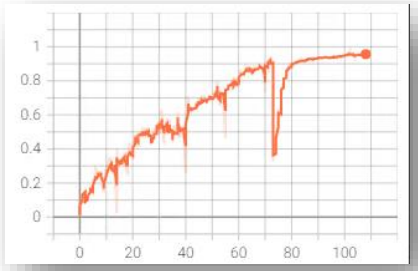


Reference change
map

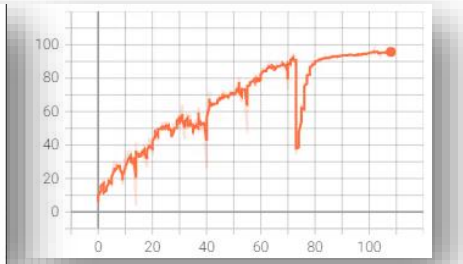
Squatter Recognition



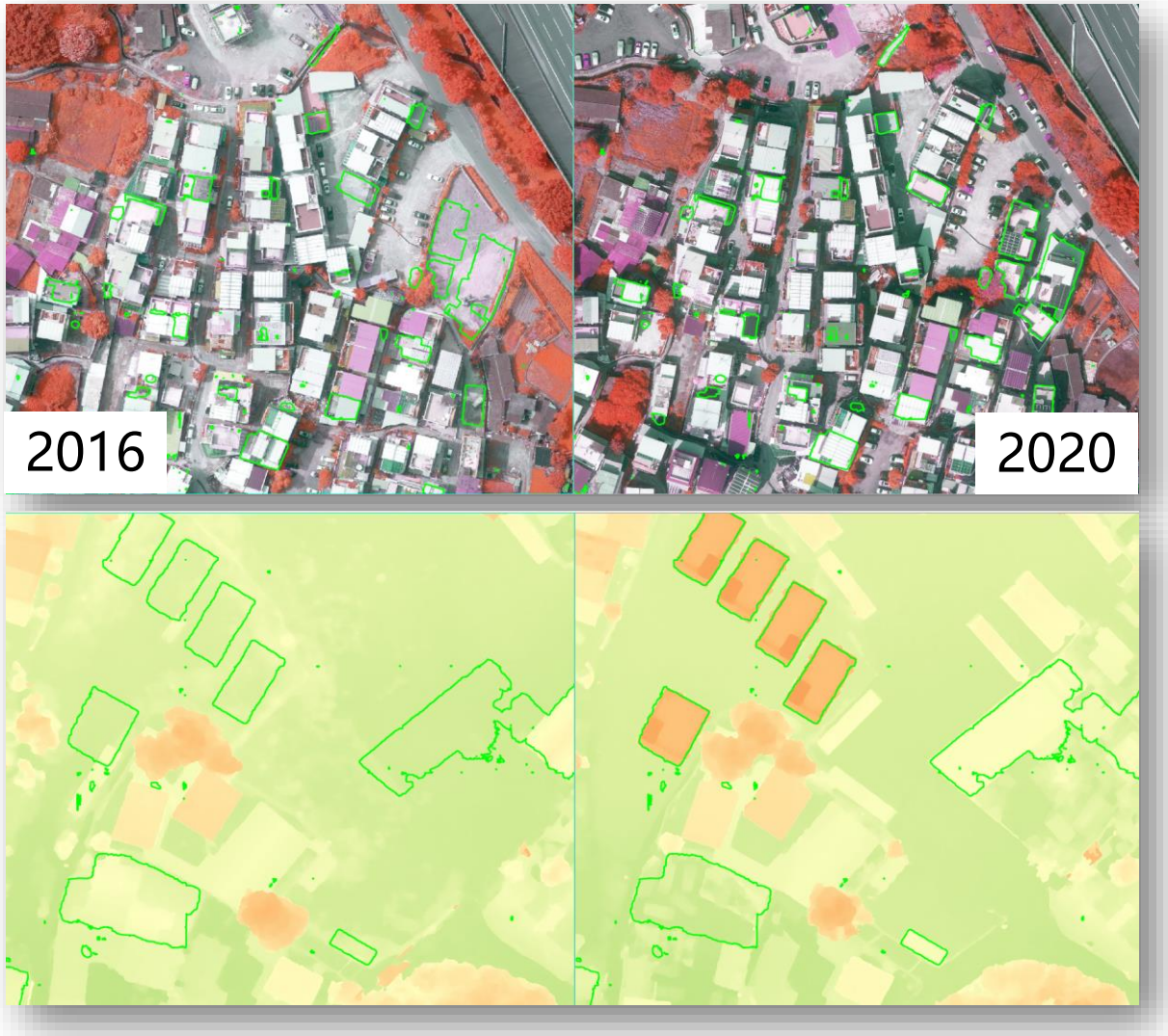
Cottage Area/Temporal Structure distribution in Hong Kong, from ***iB5000 Digital Topographic Map***



Kappa



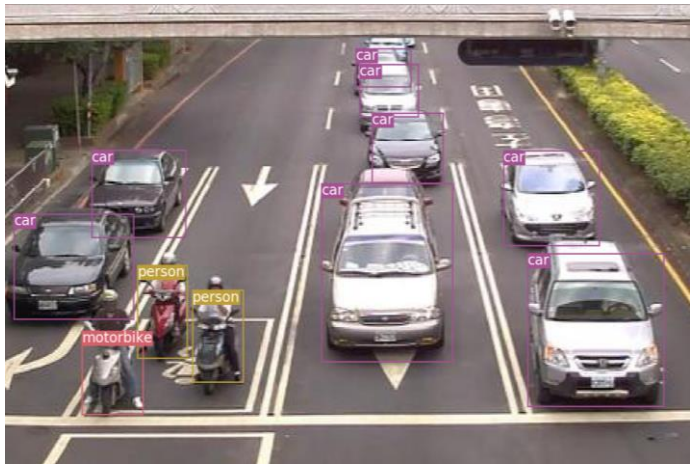
F1-Score



AI-based Squatter Change Detection Based on Aerial Image (upper) & DSM (lower)

Object Detection and Tracking from Image and Video

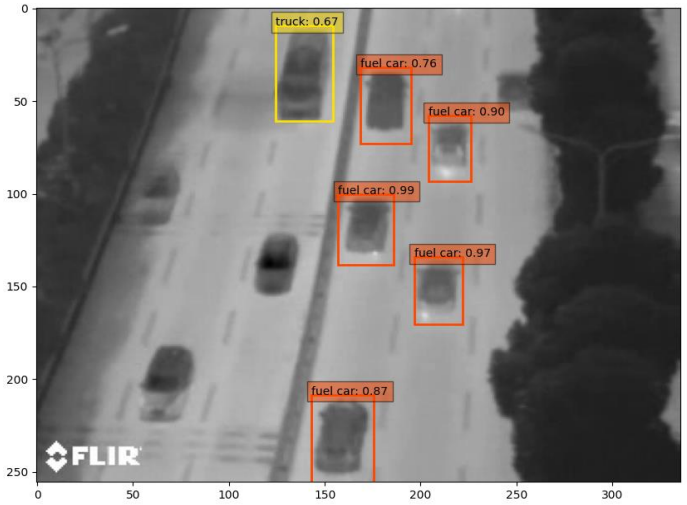
UAV



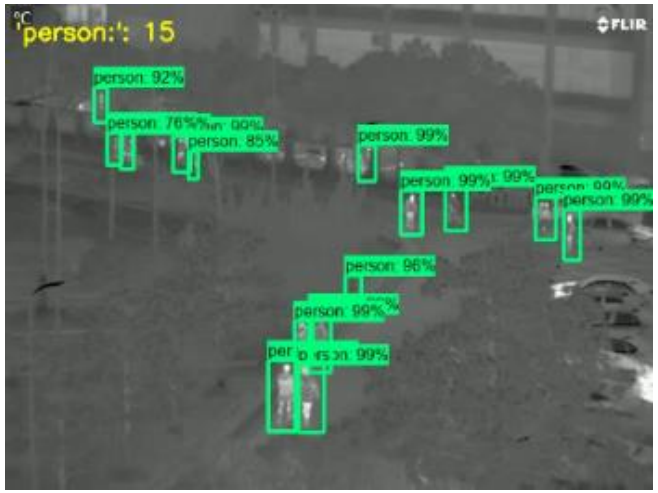
Vehicle detection

Aircraft detection

Optical and thermal infrared cameras

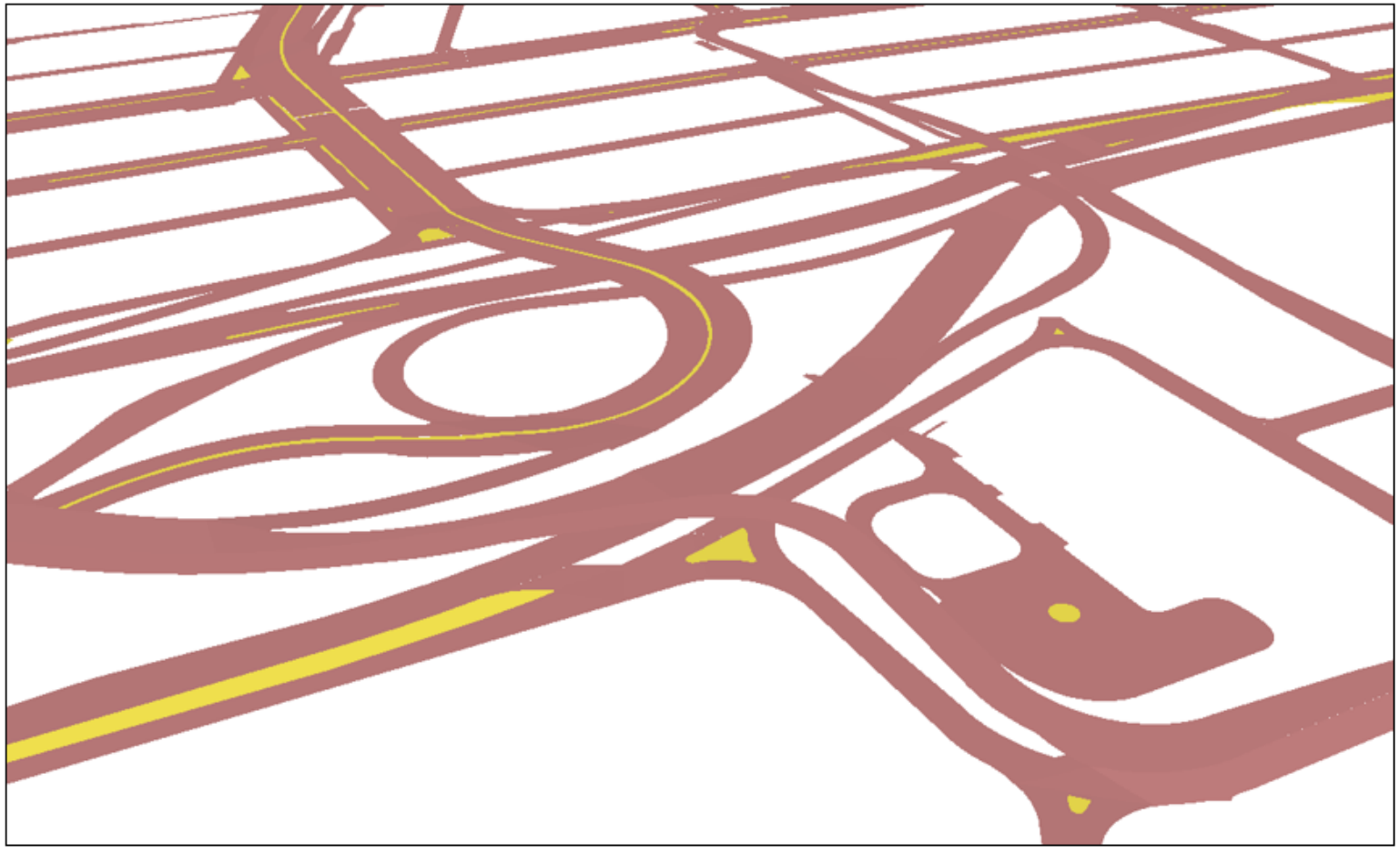


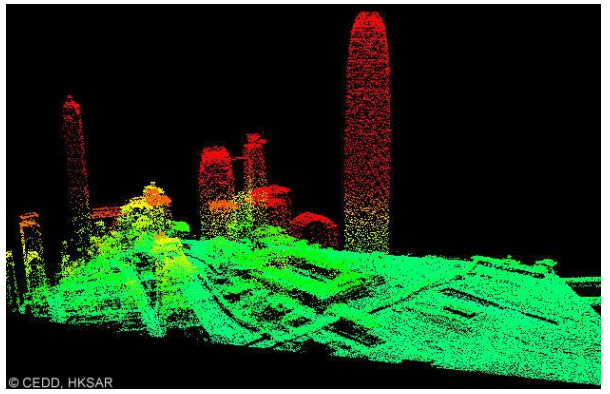
TIR image-based vehicle detection

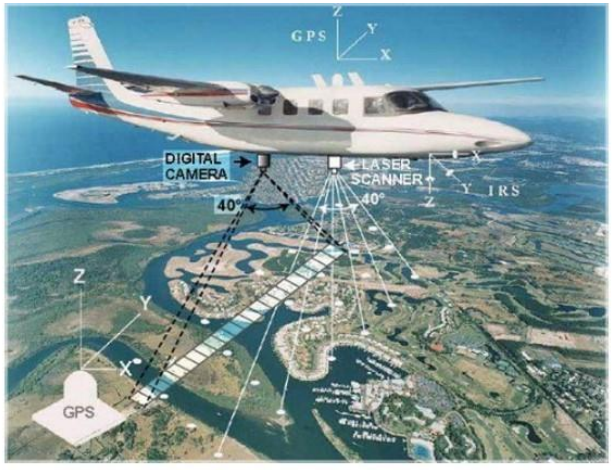


TIR image-based pedestrain detection

3D Road Mapping from LiDAR







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3. Urban Spatiotemporal Big Data Platform

Urban spatiotemporal big data platform

- The management and sharing of urban data faces many problems: complexity of multi-source data, barriers between different software systems/platforms, and difficulties in data interoperability between different stakeholders, etc.

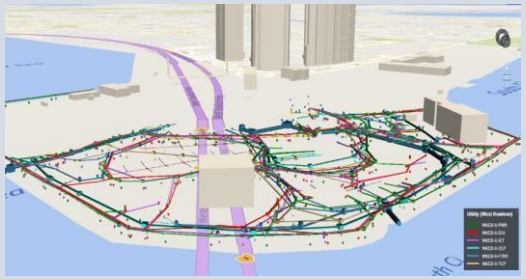
- Our team developed a comprehensive urban spatio-temporal data platform to manage and visualize the data from real world more realistically on the platform in three dimensions.

- The platform supports cross-platform operation via web browsers, multi-source and multi-industry urban data, and spatial analyses.

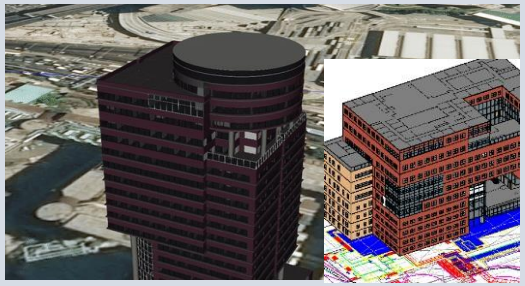
- The platform can serve as the data infrastructure for smart applications in many fields, such as transportation, environment, and economy.

Data management and application scenarios

Multi-dimensional city model
- 2.5D city model
- 3D detailed building model

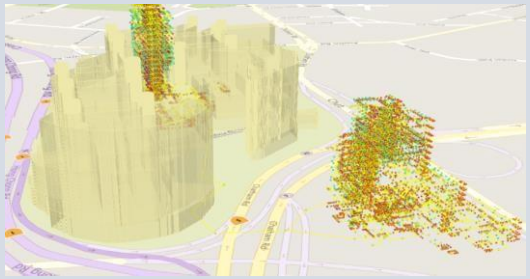


Underground space
- Utility visualization
- Underground space visualization

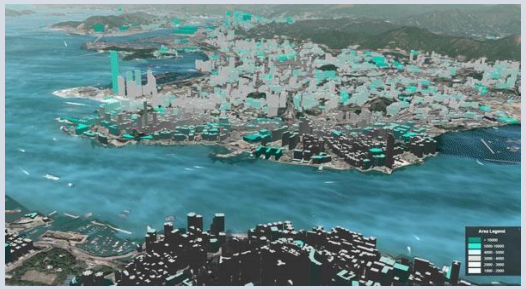


BIM&GIS integration
- Building semantic information
- Spatial location information

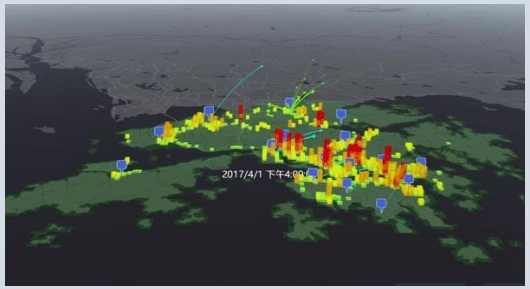
Multi-source spatial data
- UAV scanning data
- LiDAR scanning data



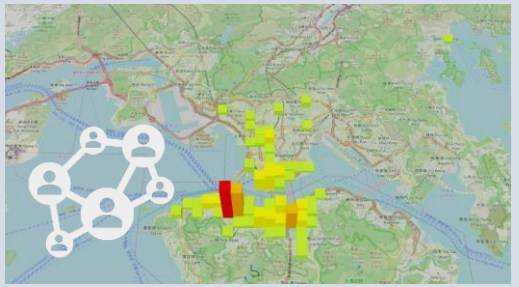
Positioning and navigation
- Indoor-outdoor pedestrian navigation



Urban analysis
- Building density
- City skyline planning

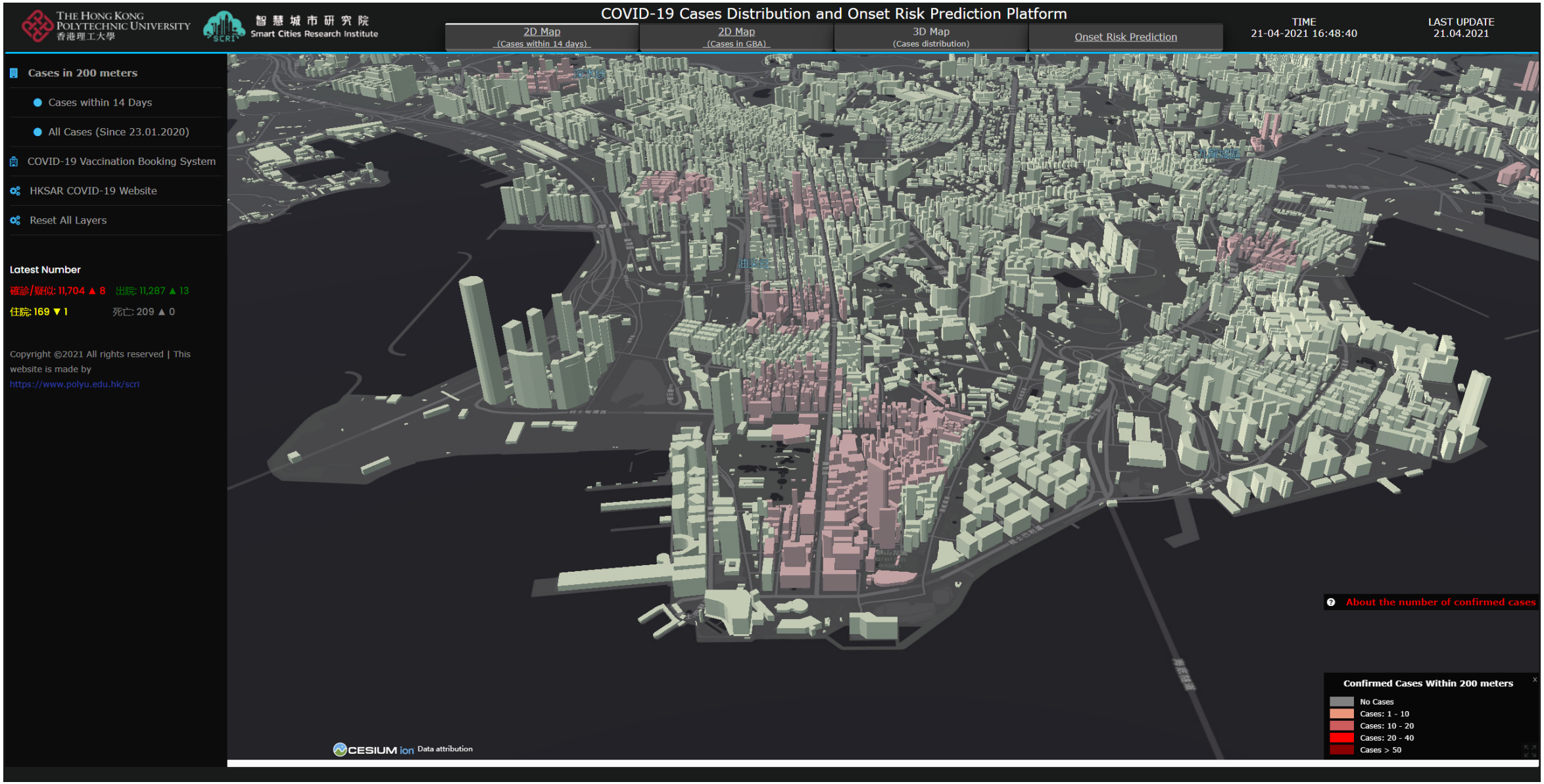


Smart mobility
- Logistics data visualization
- 3D road network

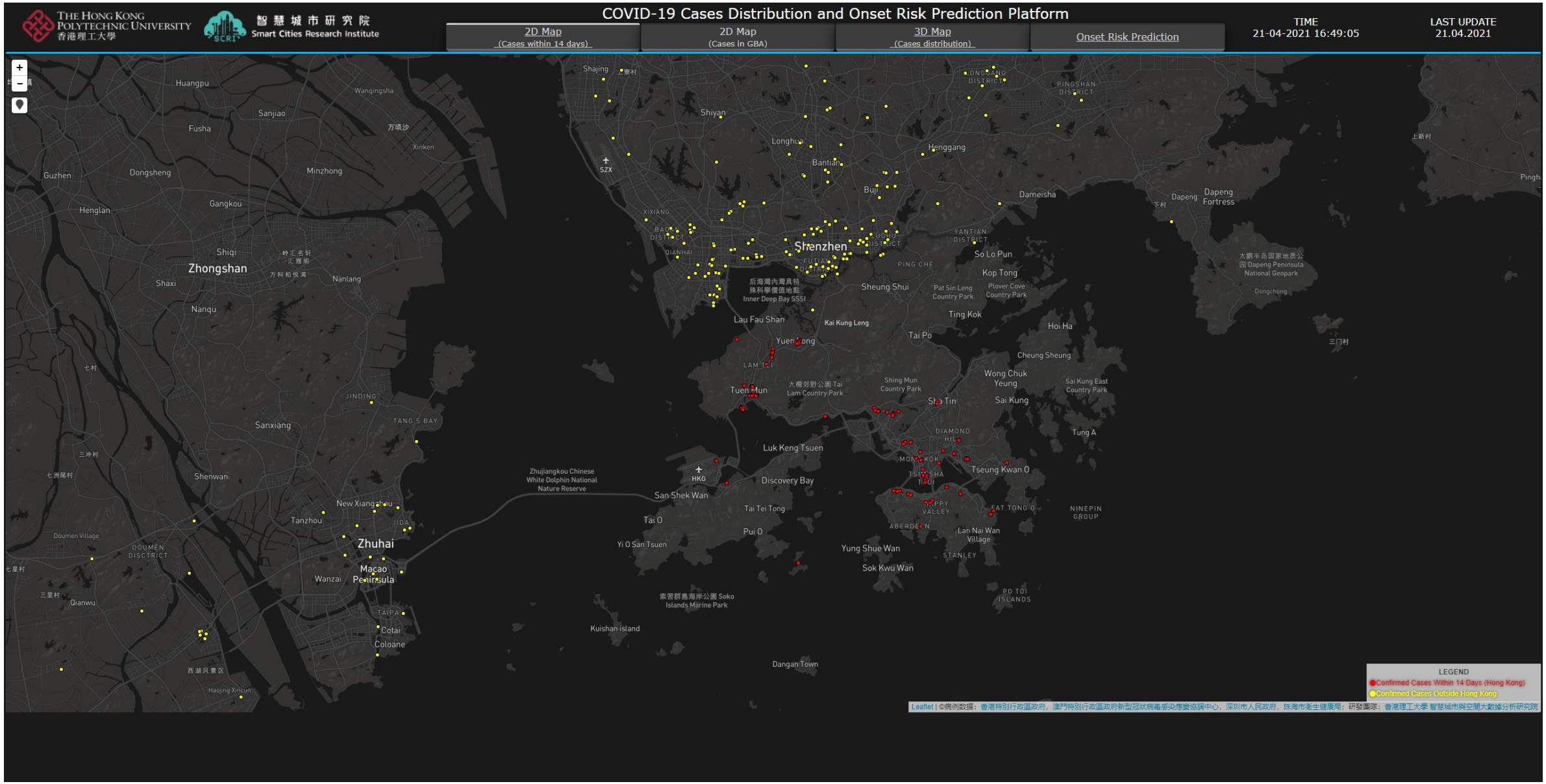


Smart economy
- Tourist hotspot mining

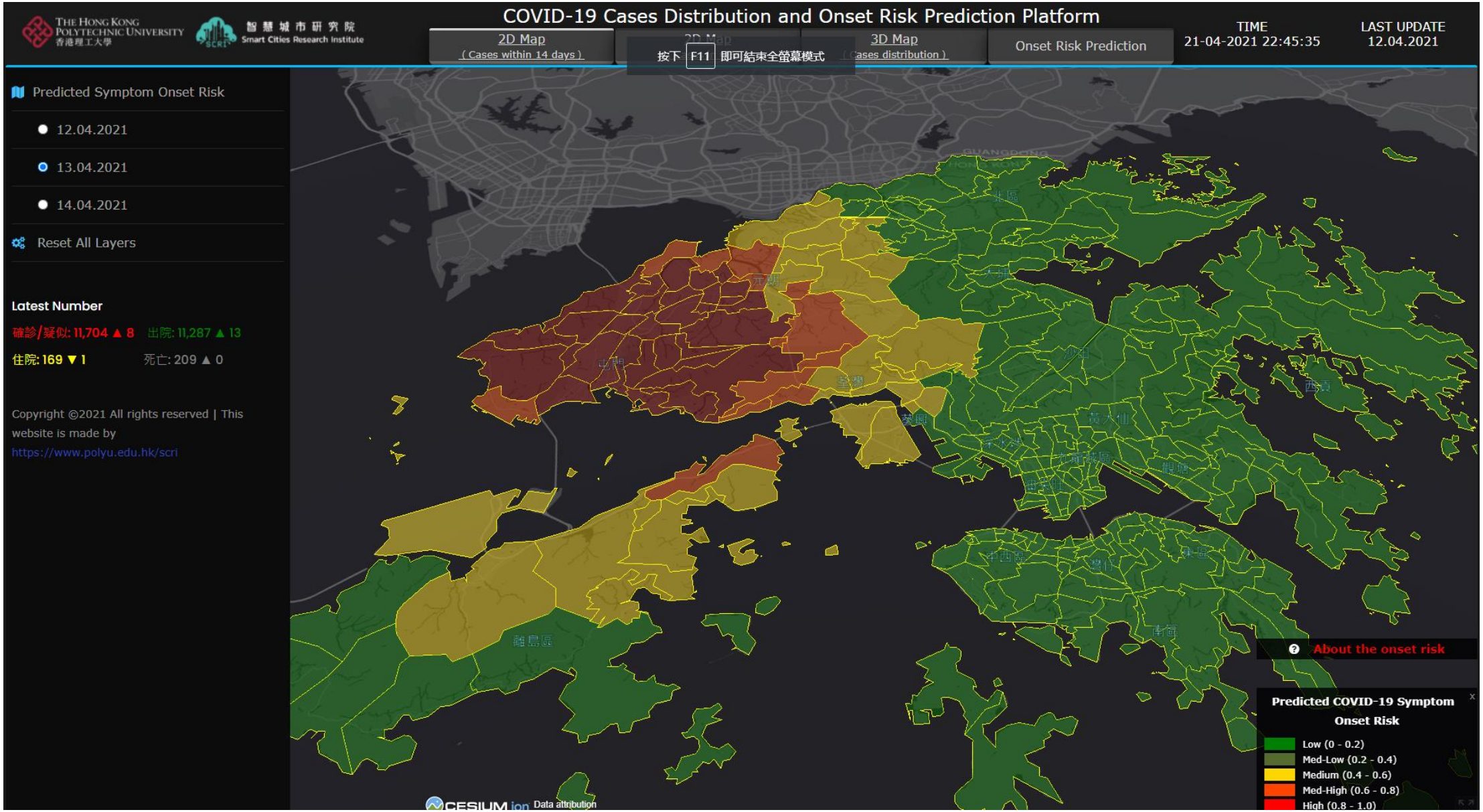
COVID-19 sub-platform: Query and 3-D visualization of No. of confirmed cases in surroundings of buildings



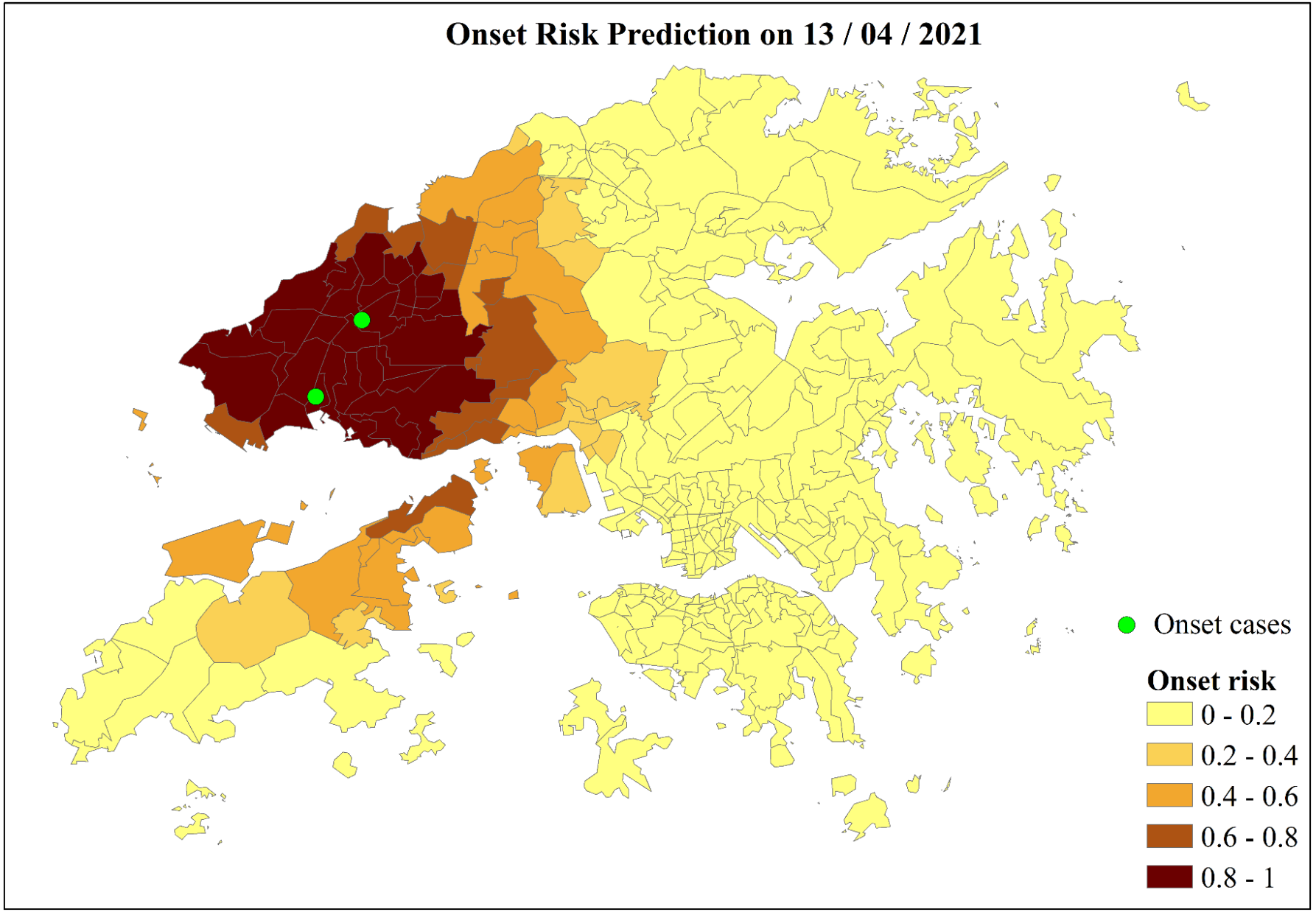
COVID-19 sub-platform: Confirmed cases distribution in the GBA



COVID-19 sub-platform: Symptom onset risk prediction in 291 Tertiary Planning Units (TPUs) in Hong Kong



COVID-19 Symptom onset risk prediction and actual onset cases on 13 Apr 2021



Summary

- We have developed a series of cutting-edge technologies and integrated solutions for smart city development
  - 3D mobile mapping
  - AI-based remote sensing object recognition
  - Spatiotemporal big data platform

- In the future, these cutting-edge technologies will be more widely applied to serve the smart city development of Hong Kong with emphasis on geo-applications.

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智慧城市研究院
Smart Cities Research Institute

Thank you!

John Shi
lswzshi@polyu.edu.hk

Detector in the Air – 2020 Airborne LiDAR Survey

Jeffrey Wong
Chief Geotechnical Engineer/Planning
Geotechnical Engineering Office
Civil Engineering and Development Department

OUTLINE

Why Remote Sensing and Airborne LiDAR?

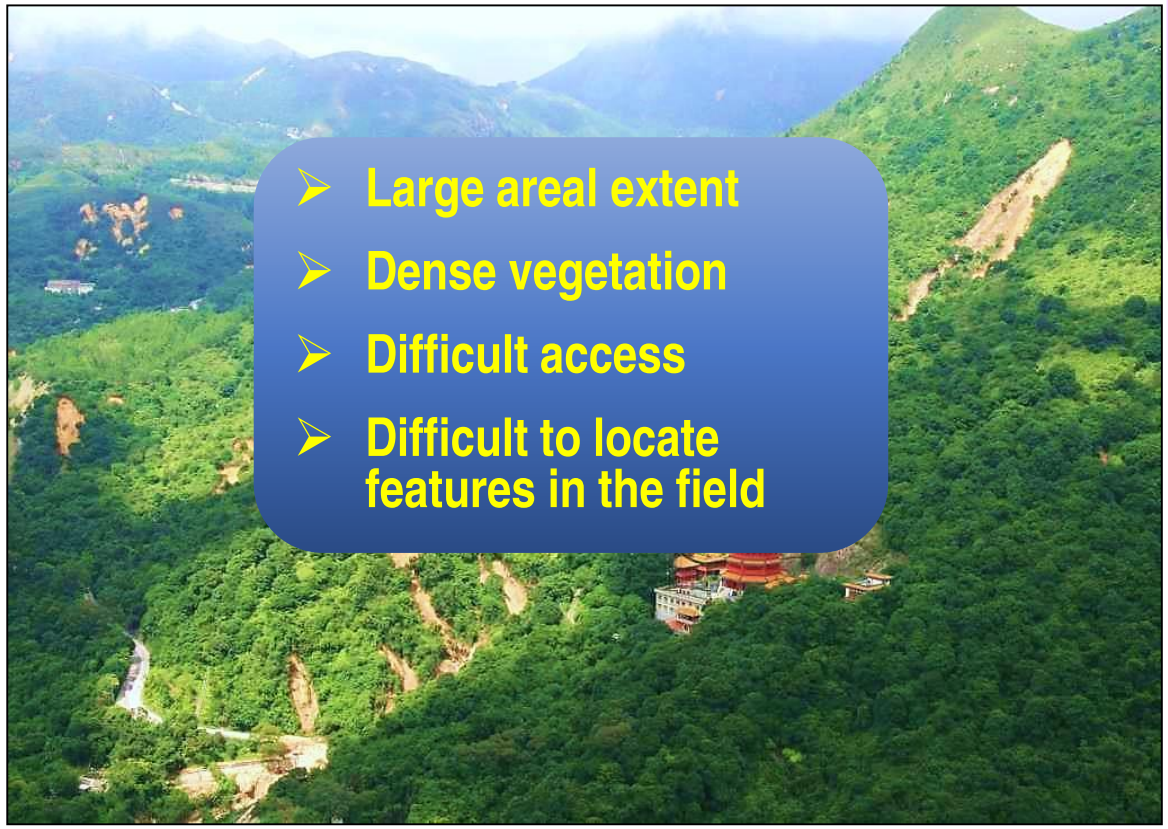
Territory-wide Airborne LiDAR Surveys

Applications of LiDAR Data in Geotechnical Studies

- ✓ ~300 new landslides on natural terrain each year
- ✓ High resolution topographic information is essential to landslide studies

CEDD

WHY REMOTE SENSING



The Geotechnical Engineering Office has been applying different remote sensing techniques to acquire topographic information to support natural terrain hazard assessments

Digital and Remote Sensing Technologies

Aerial Photograph Interpretation

Artificial Intelligence and Virtual Reality

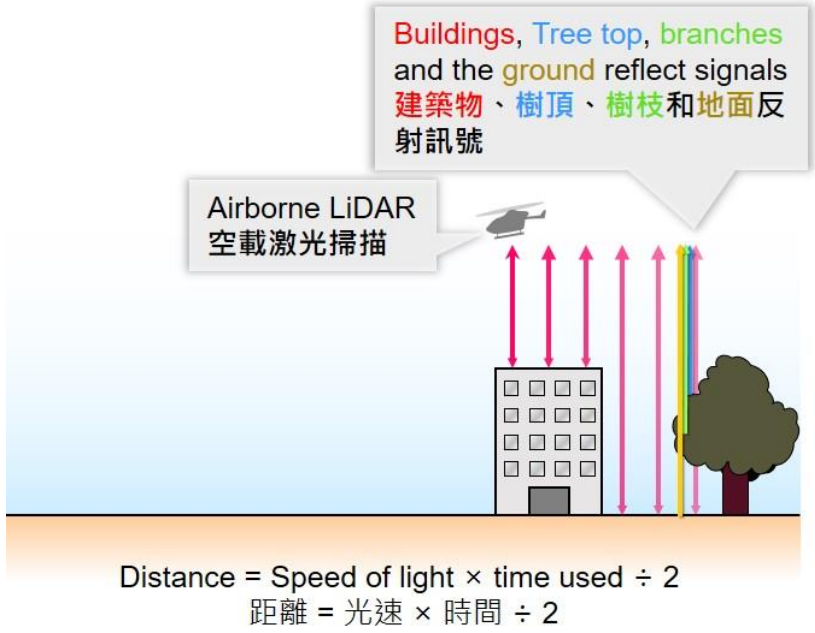
80s' 90s' 00s' Now

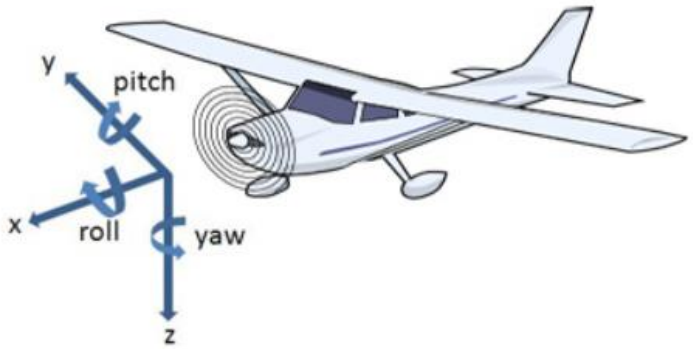
Advantages for Remote Sensing

- Collect ground information over large spatial areas, particularly for remote areas with low accessibility
- Enable characterization of natural features or physical objects on the ground
- Allow observation of ground surface/features on a systematic basis
- Less labour intensive
- Some techniques are weather-permitting

What is LiDAR

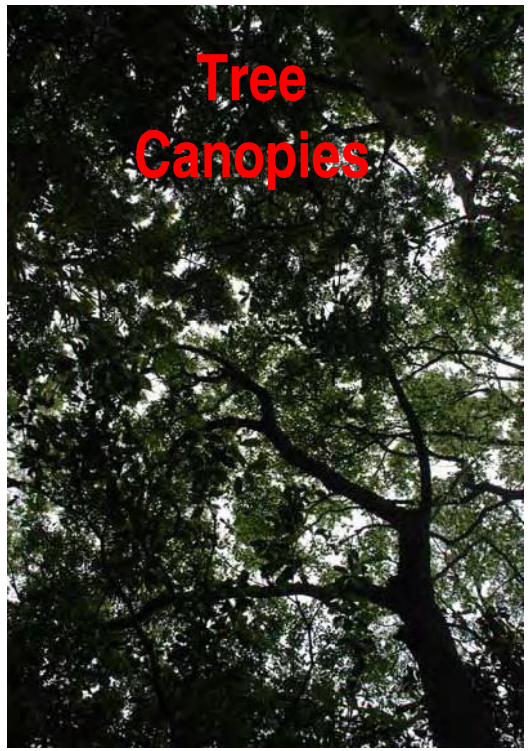
- Light detection and ranging (LiDAR) was invented around the 1960s to measure positions of objects from aircraft rapidly for military use.
- **Laser scanner** - determines range (distance) by emitting laser pulses to the ground and measuring the time for the reflected signals to return to the receiver at the scanner along the flight path.
- To ensure the distances to surfaces are correctly calculated, precise location and angle of the LiDAR system are determined by
  - **Global Navigation Satellite System (GNSS)** - measures x, y and z coordinates
  - **Inertial Measuring Unit (IMU)** - records pitch, roll and yaw of the aircraft
  - Detailed positioning infrastructure and services by Lands Department



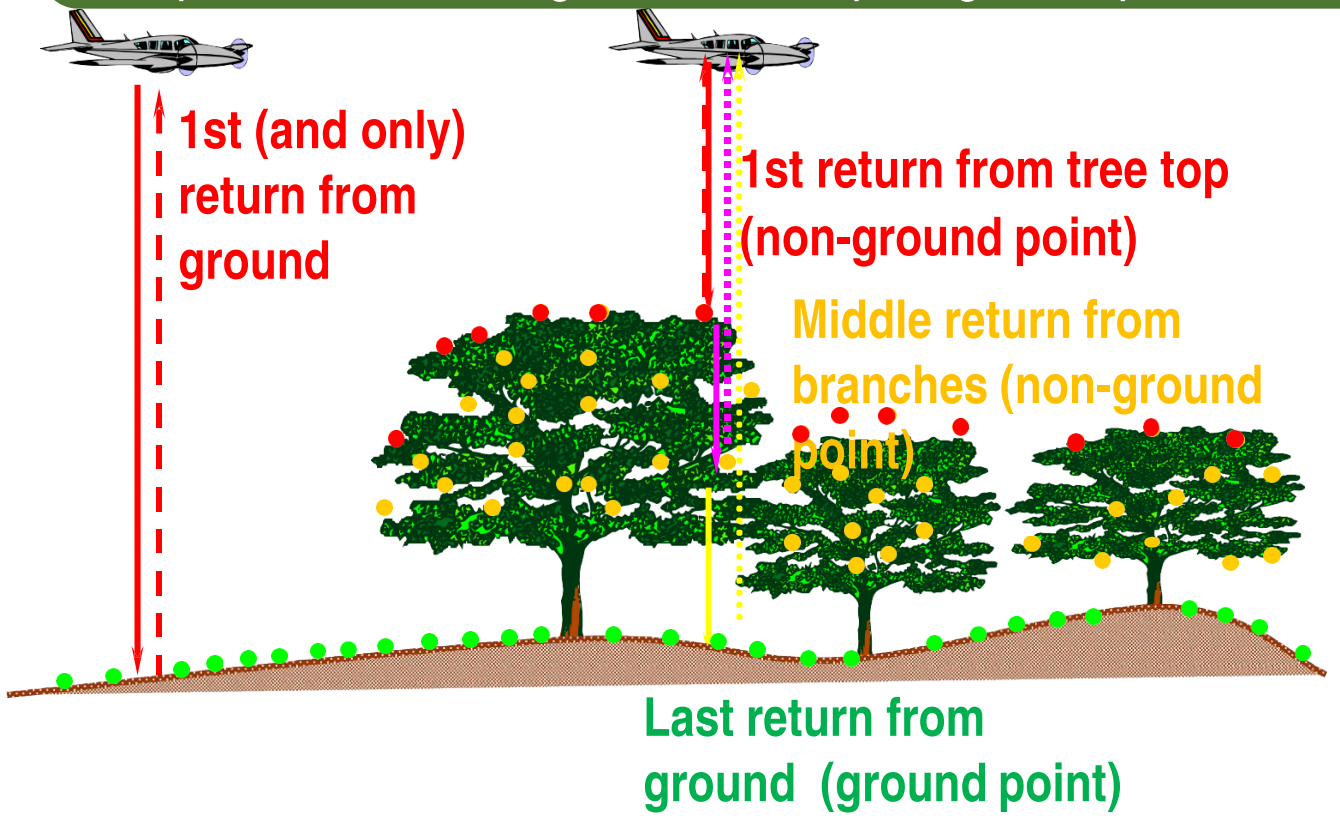


WHY AIRBORNE LIDAR

Challenges of Topographic Survey in Hillside



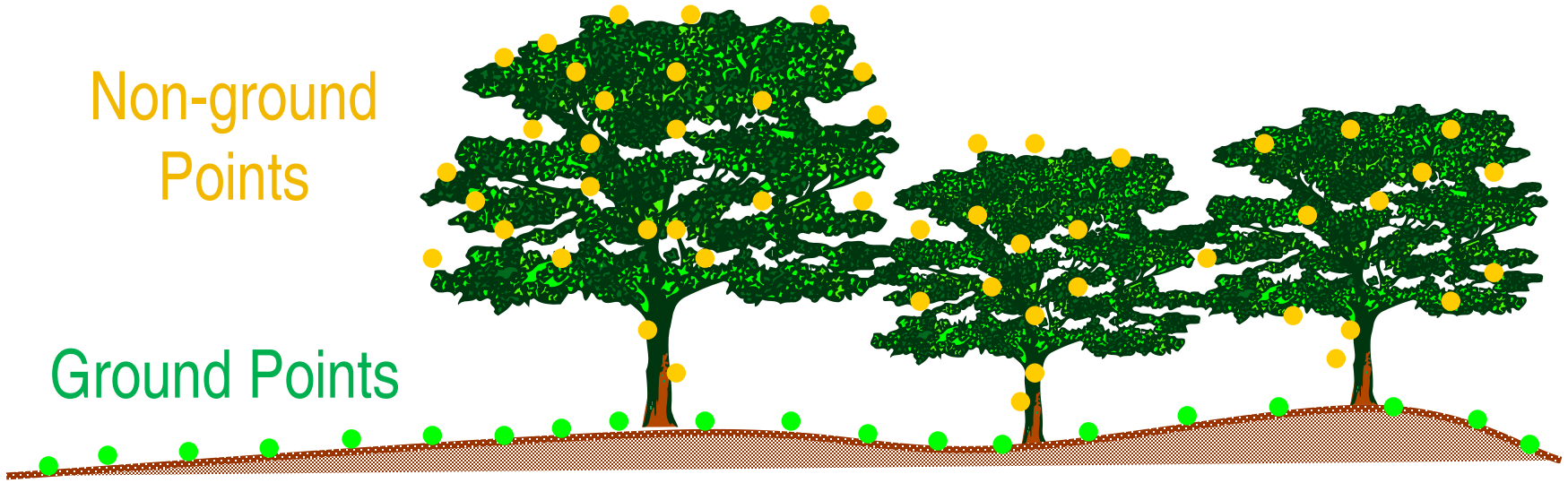
LiDAR signals travelling in the form of a cone enables a **multi-return capability** – penetrates the vegetation to acquire ground points



Information including the x-, y-, z-coordinates, return no., total no. of return of the signal pulse and intensity value

Point Classification & Virtual Deforestation

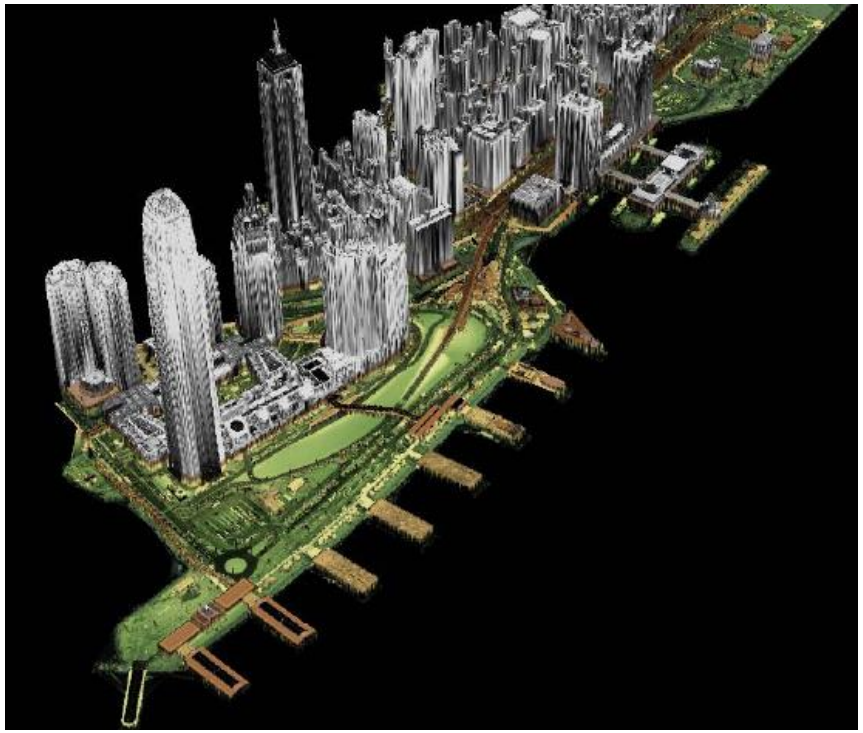
The first return surface formed by the first signal returned from each location is referred to as a digital surface model (DSM). The first returned signal can be a ground point or non-ground point (tree canopy, buildings, etc.)



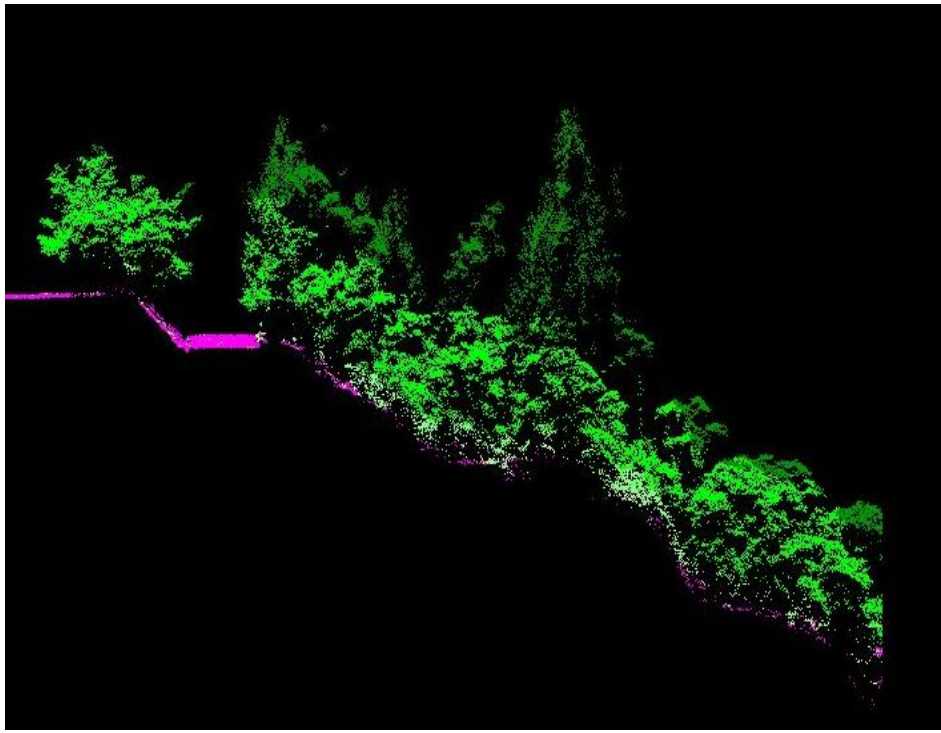
By characterising the received signals using sophisticated data processing, data points from non-ground objects such as buildings and vegetation cover can be removed for acquiring ground surface data points to produce ground or bare earth surface, i.e. digital terrain model (DTM), containing only topographic information.

CEDD

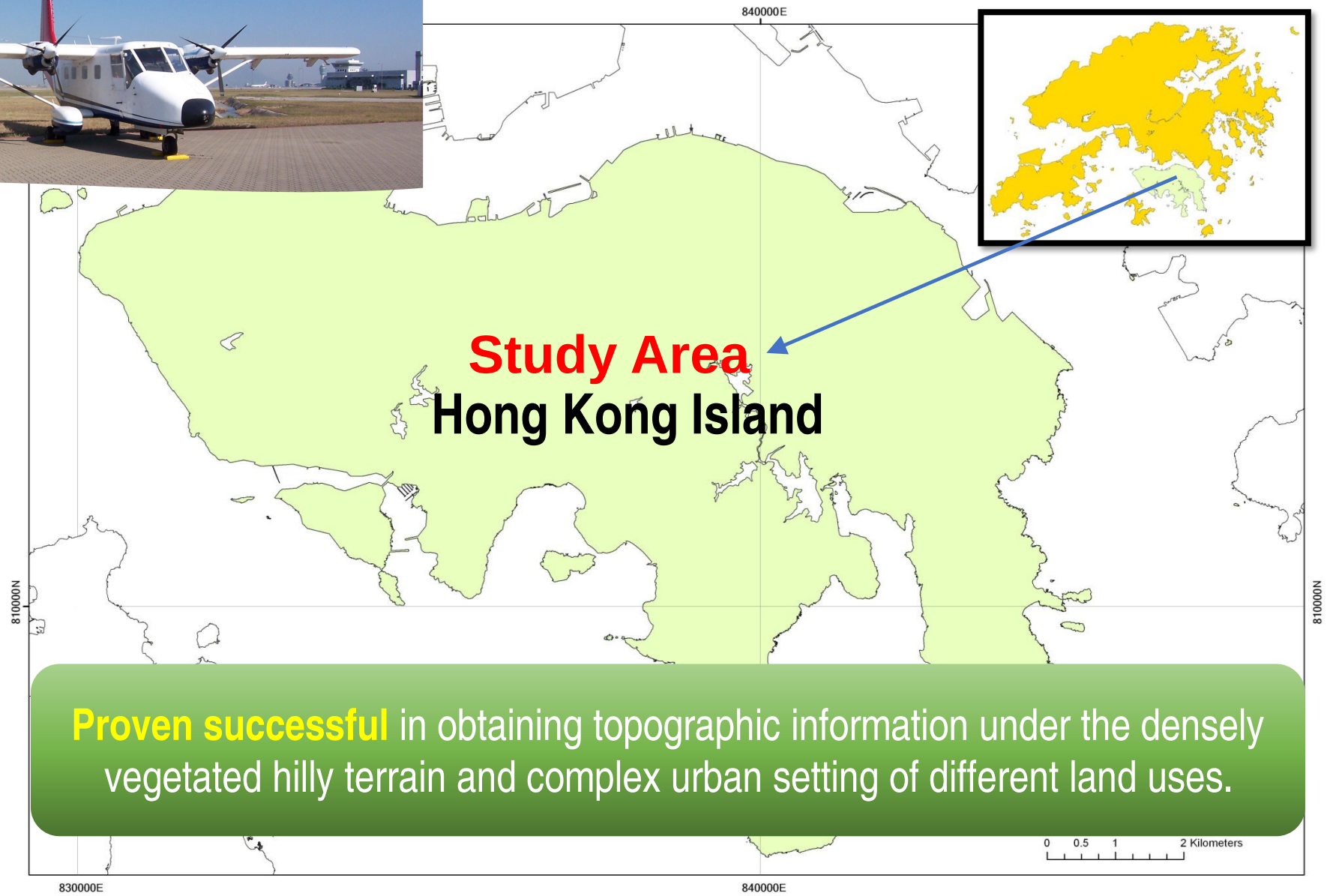
Multi-disciplinary Applications of LiDAR Datasets



- 3D Cityscape Modelling
- Urban Planning
- Tree Management
- Geotechnical



PILOT STUDY ON AIRBORNE LIDAR SURVEY (2006)



Proven successful in obtaining topographic information under the densely vegetated hilly terrain and complex urban setting of different land uses.

THE 1ST TERRITORY-WIDE AIRBORNE LiDAR SURVEY (2010)

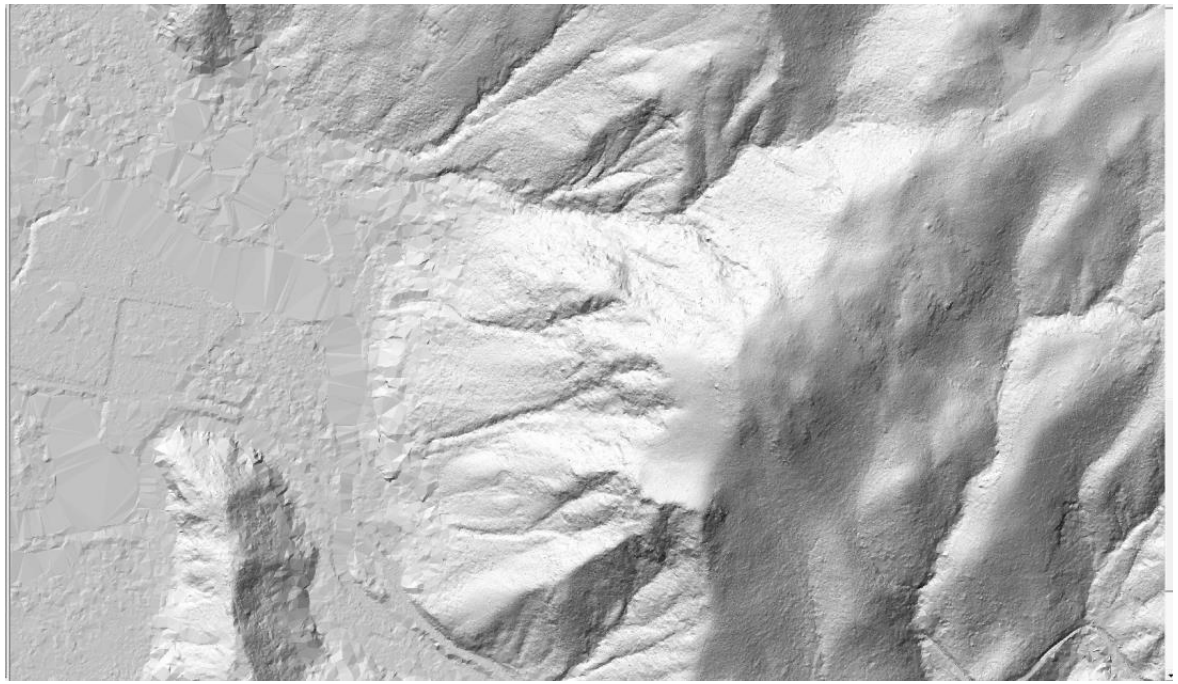
Data Capture Period:	**Dec 2010 to Jan 2011**
Total Flight Time:	**44 flying hours**
Total Flight Length:	**4,700 km**
Medium of Data Capture:	**Fixed wing aircraft**
Flying Height:	**3,300 feet to 3,800 feet (mostly at 3,500 feet)**

CEDD

Generation of Digital Terrain Model

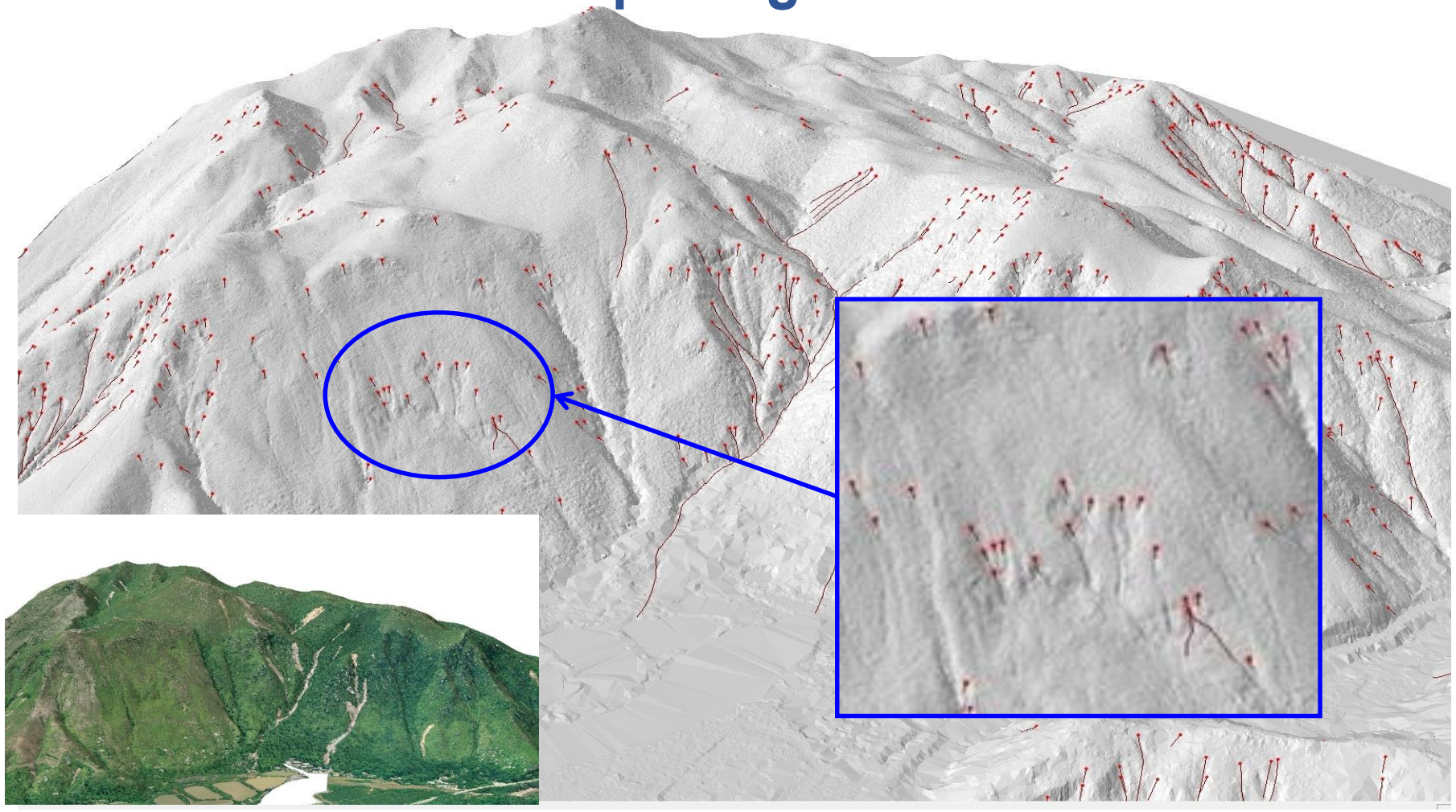
2008 Landslides in Wang Hang, Lantau Island

Aerial Photo



Digital Terrain Model Generated by LiDAR Data

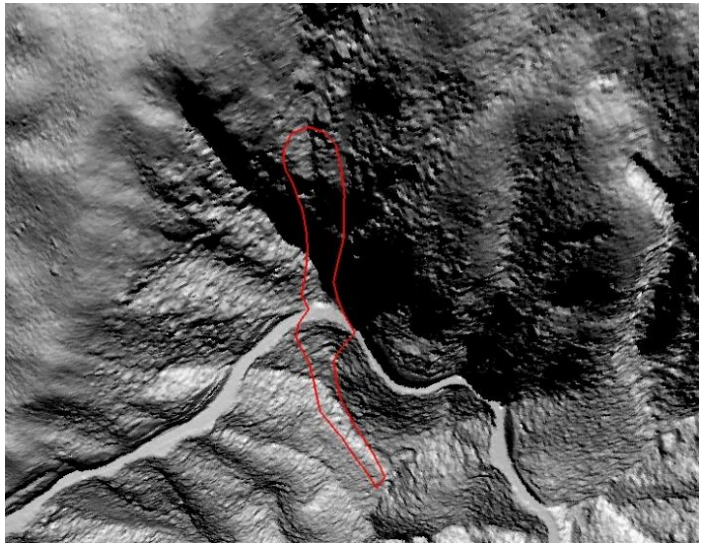
Identification of Geomorphological Features



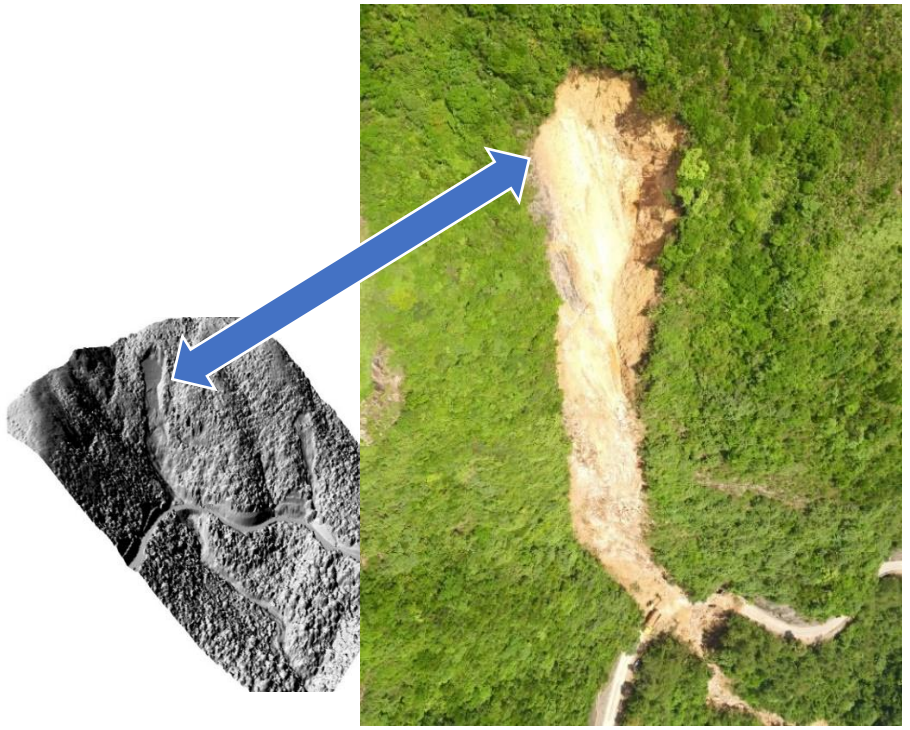
The DTM generated from the airborne LiDAR data clearly shows the geomorphological features on natural hillside (e.g. landslide scars), providing a reliable source of terrain data for assessing natural terrain hazards.

Emergency Landslide Studies

- Provide dataset for comparison of change in topography at different times.
- Support landform analysis and landslide volume estimate, which assist emergency landslide response and design of mitigation measures



Generation of **pre-landslide terrain model** from territory-wide airborne **LiDAR data**



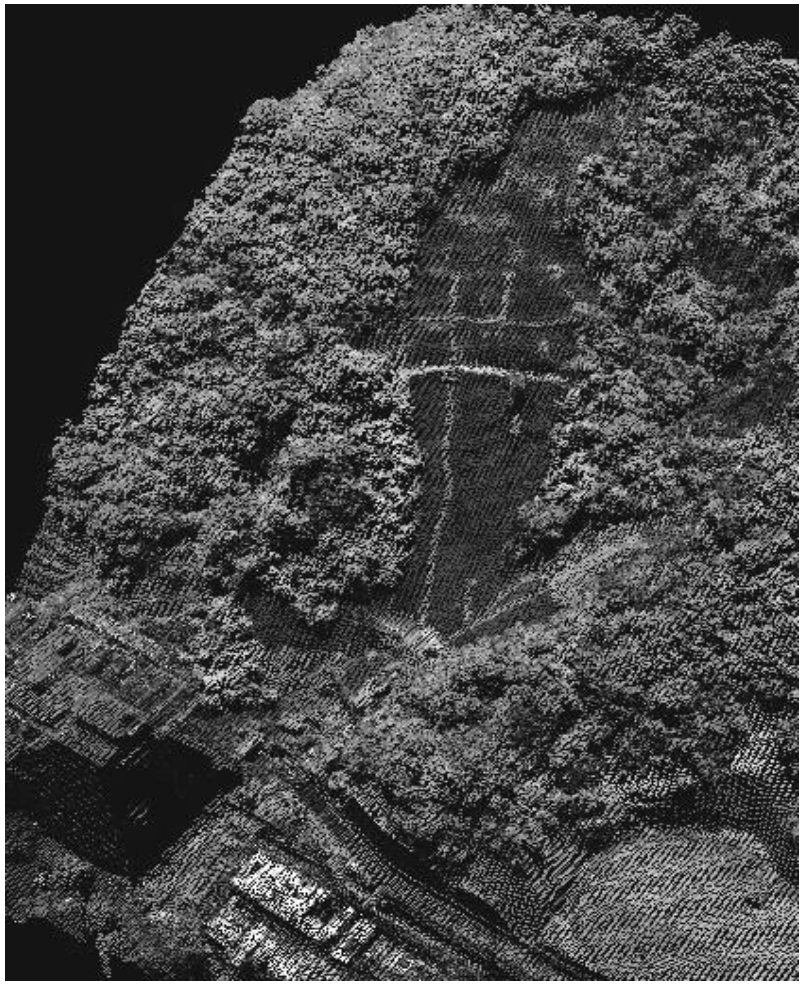
Post-landslide digital surface model produced from **UAV photos**

Completed Flexible Barriers

CEDD

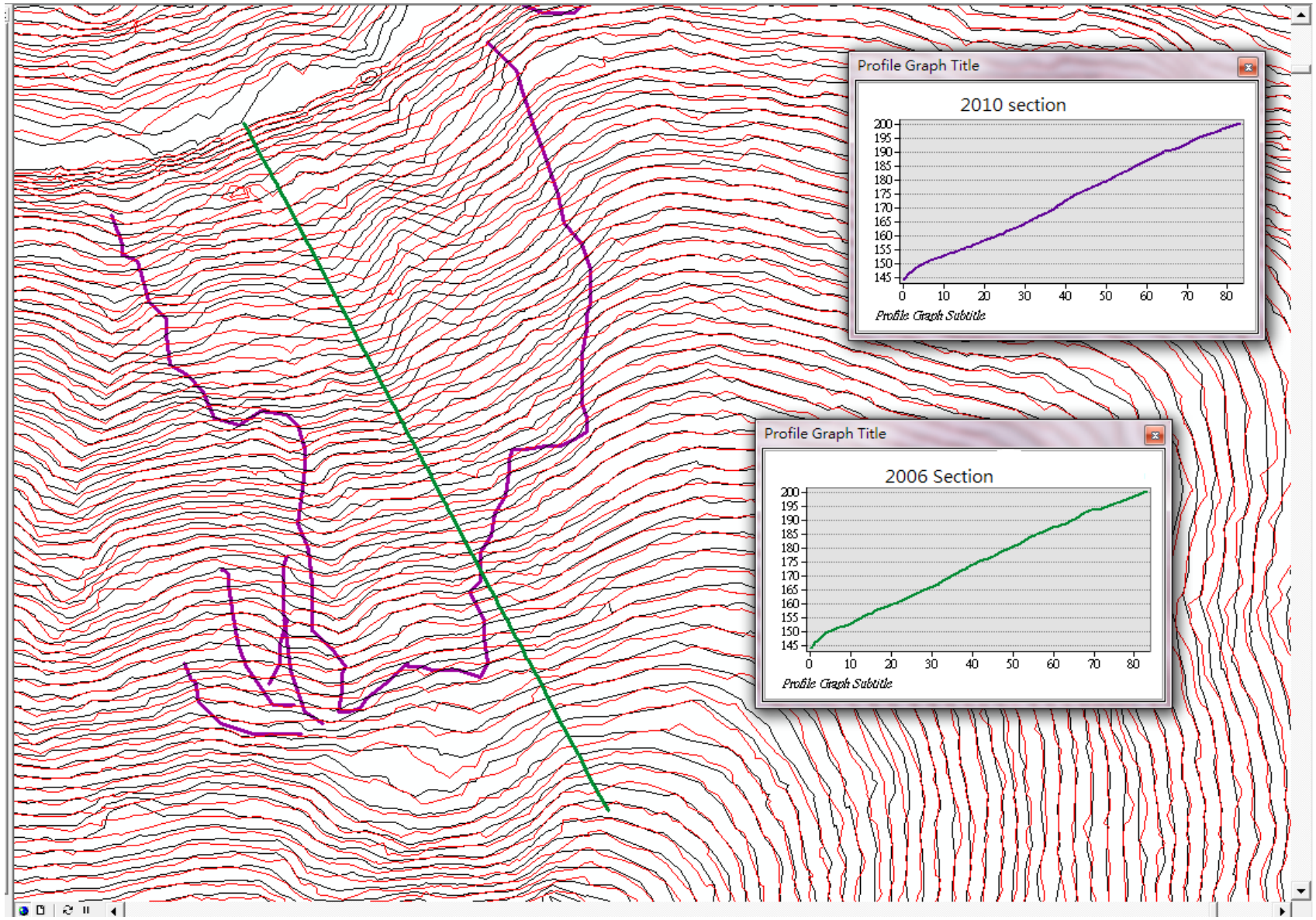
Detection of Landform Change (1)

2006 LiDAR
(all returns, points by intensity)



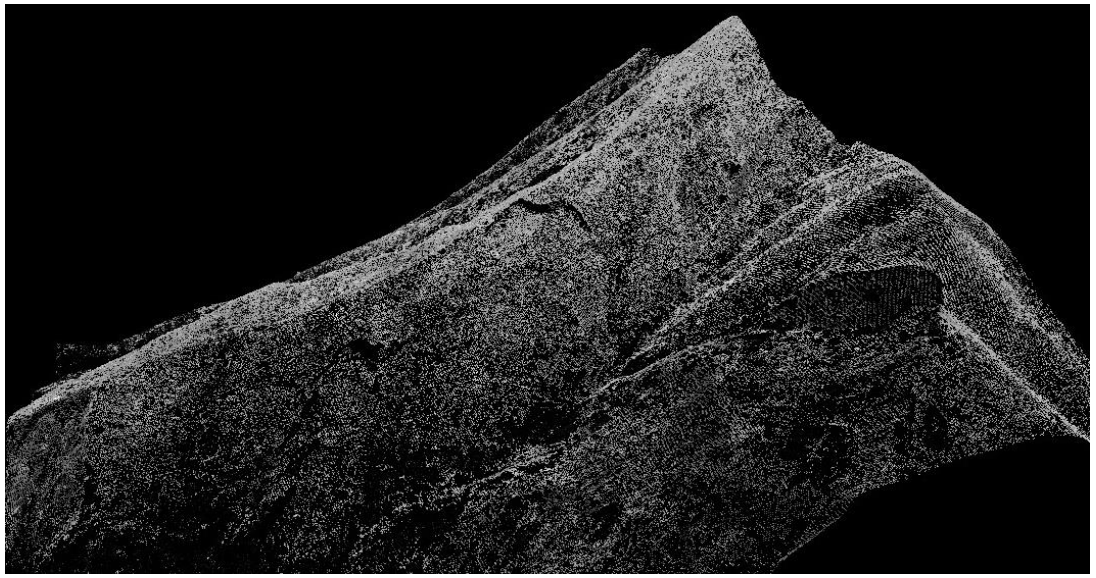
2010 LiDAR
(all returns, points by intensity)

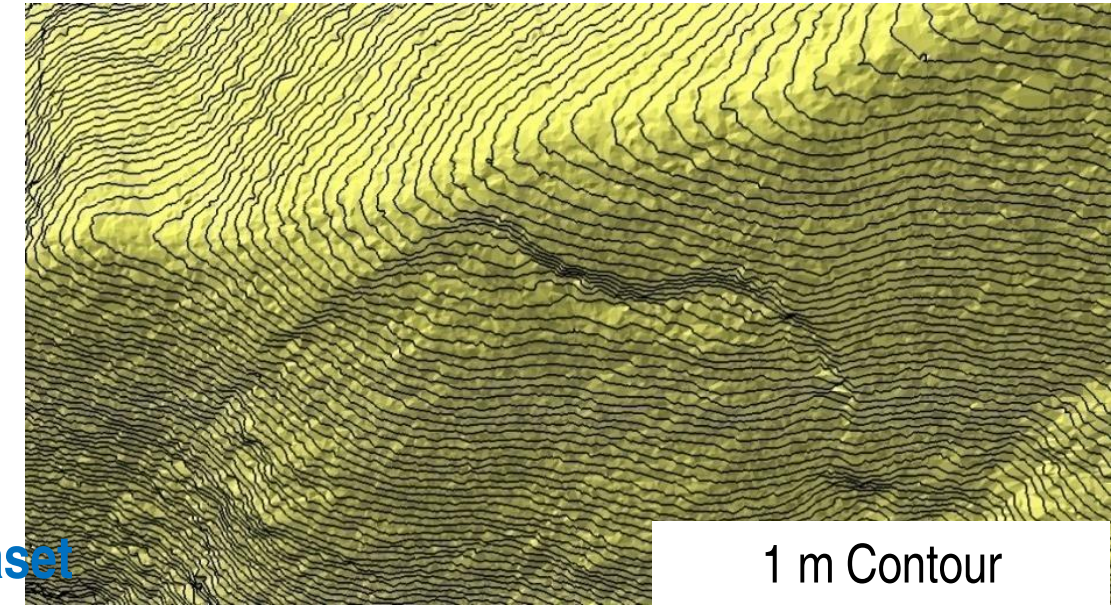
Detection of Landform Change (2)



Extraction of Terrain Characteristics

Tension Crack in Ma On Shan





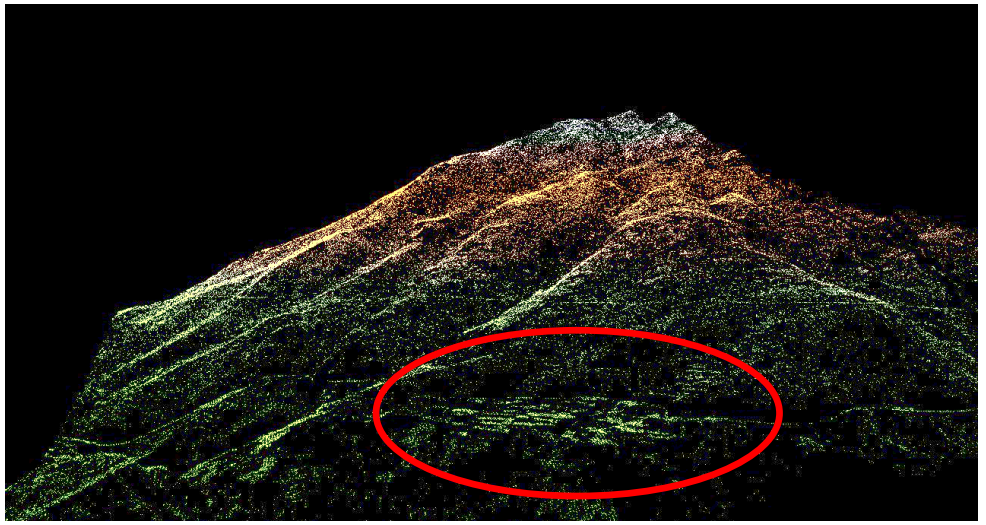
Contour Map by LiDAR DTM Dataset

1 m Contour

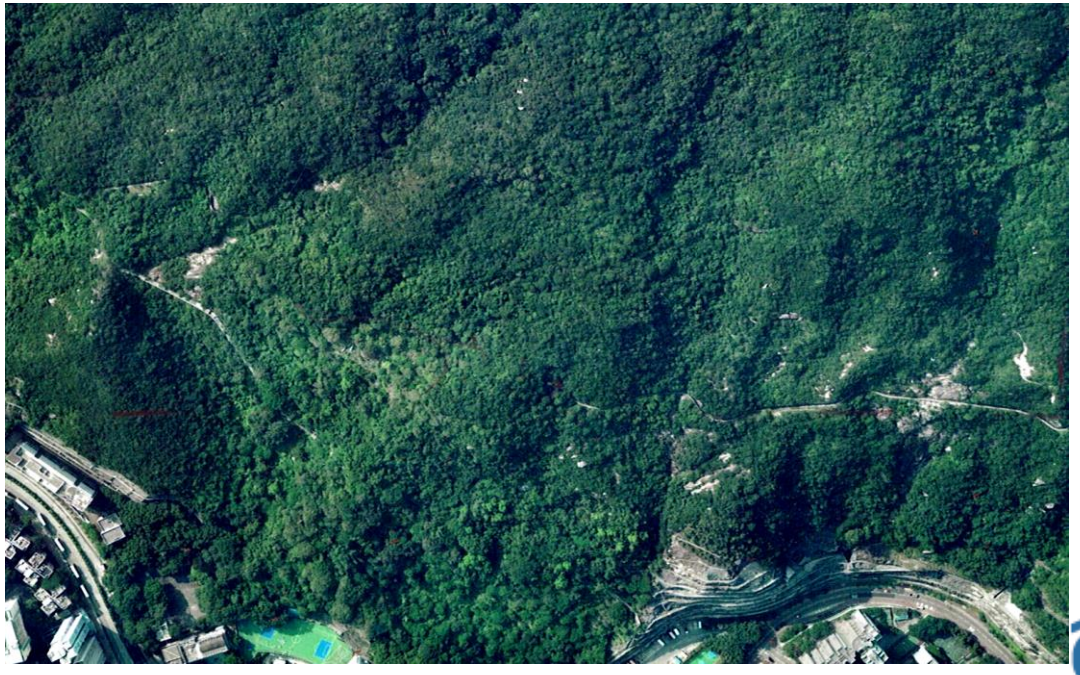
Identification of Old Cut and Fill Terraces

Shau Kei Wan

1963 Aerial Photo



2010 LiDAR Point Cloud Data



2009 Aerial Photo

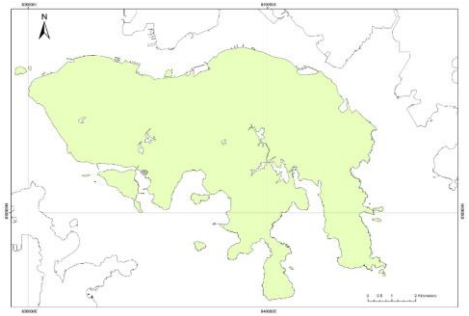
CEDD

THE 2ND TERRITORY-WIDE AIRBORNE LiDAR SURVEY (2020)

Data Capture Period:	Dec 2019 to Feb 2020
Total Flight Time:	84 flying hours
Total Flight Length:	8,600 km
Medium of Data Capture:	Helicopter
Flying Height:	1,500 feet to 6,000 feet (mostly at 2,000 feet)

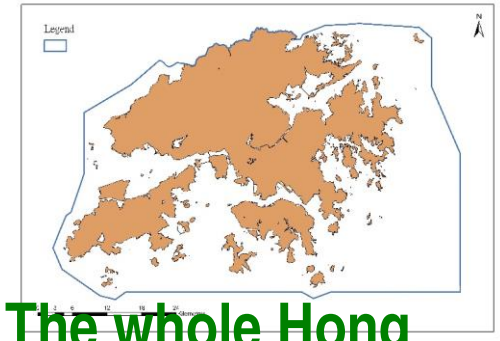
Comparison of the Airborne LiDAR Surveys (1)

Pilot LiDAR Survey (2006)



Hong Kong Island

Territory-wide LiDAR Surveys (2010, 2020)



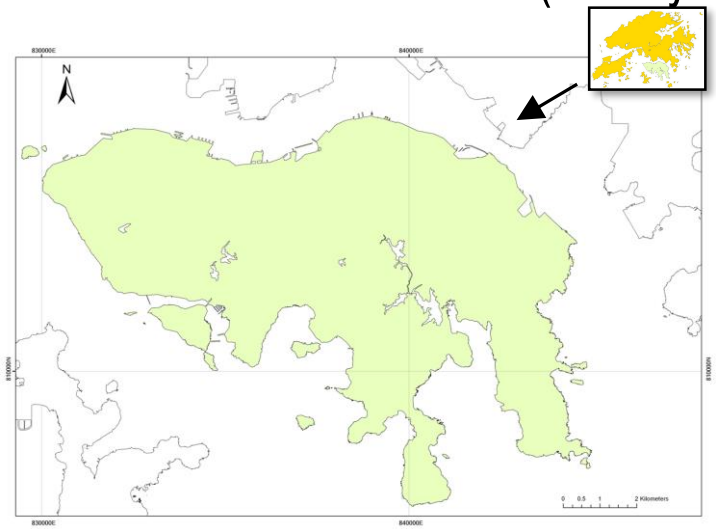
The whole Hong Kong

	2006	2010	2020
Maximum Point Spacing:	1.3 m	0.5 m	0.25 m
Horizontal Accuracy:	0.3 m	0.3 m	0.3 m
Vertical Accuracy: (Flat Open Terrain)	0.13 m	0.1 m	0.1 m
Max. no. of Pulse Return:	4	4	8

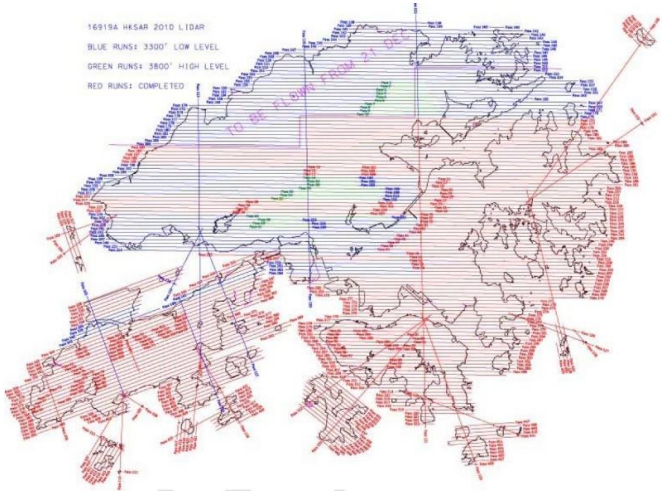
Comparison of the Airborne LiDAR Surveys (2)

Pilot Airborne LiDAR Survey (2006)
Fixed-wing Aircraft

(mostly at 3,500 feet)



Territory-wide Airborne LiDAR Survey (2010)
Fixed-wing Aircraft

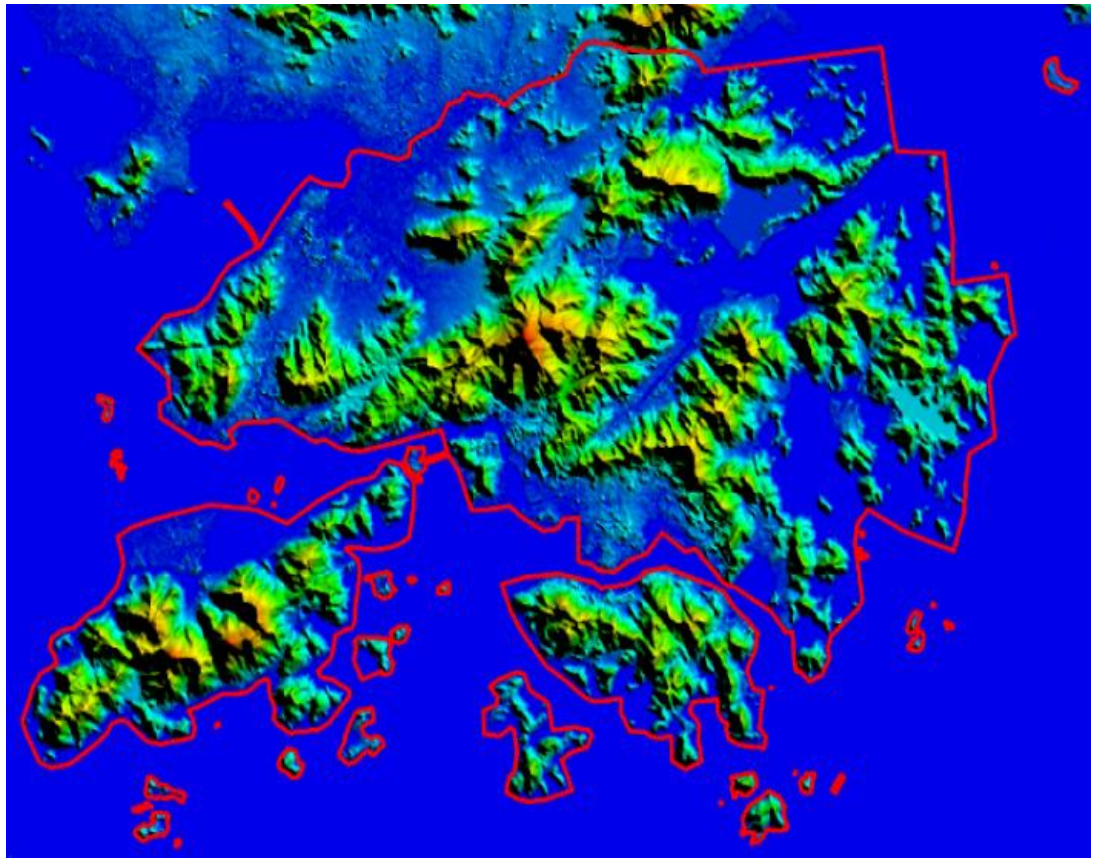


Territory-wide Airborne LiDAR Survey (2020)
Helicopter

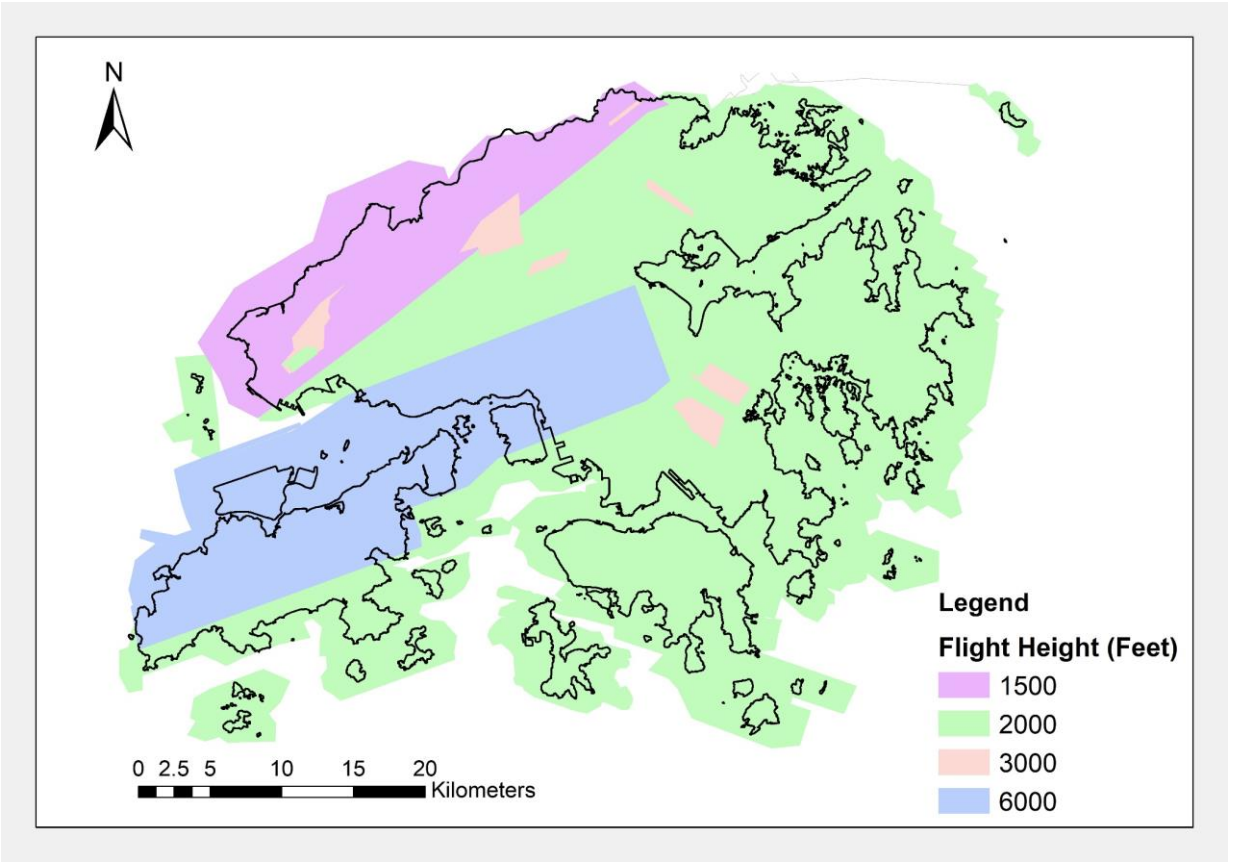
(mostly at 2,000 feet)

2020 LiDAR Survey – Key Considerations in Planning of Flight Paths

1. Topography



2. Airspace of Nearby Airports



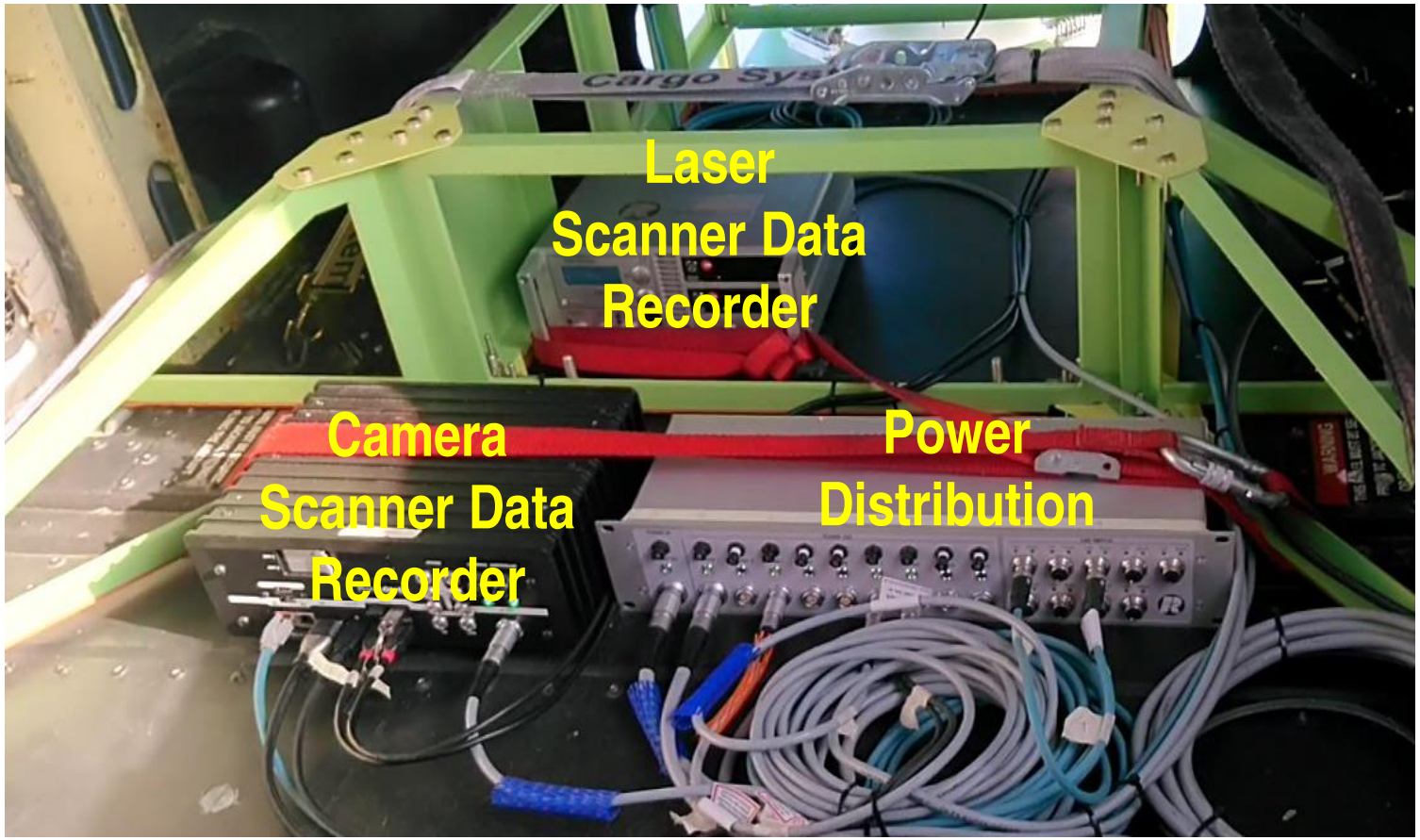
40% swath overlapping with adjacent flight lines

System Configuration (1)

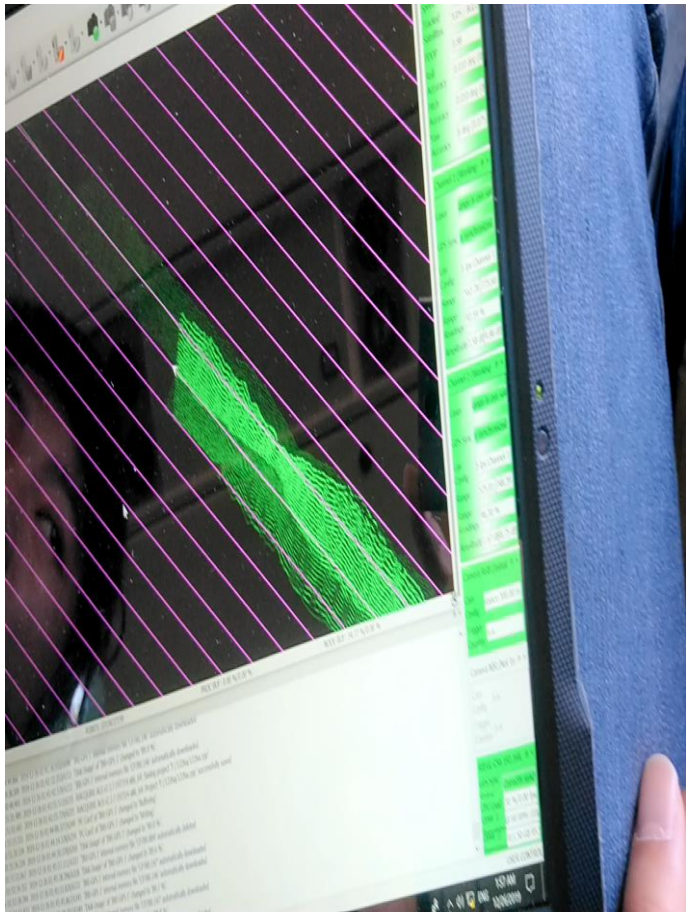
GNSS Receiver

Laser Scanner

System Configuration (2)

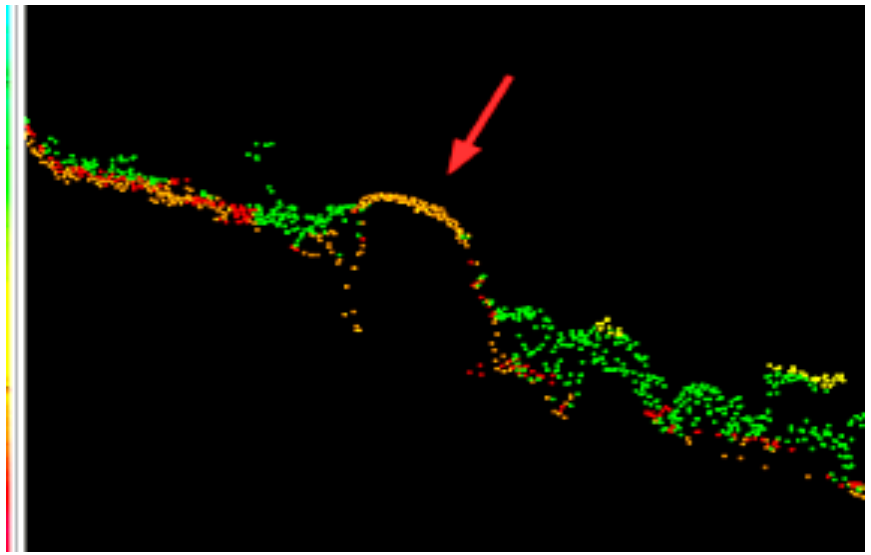


Data Capturing

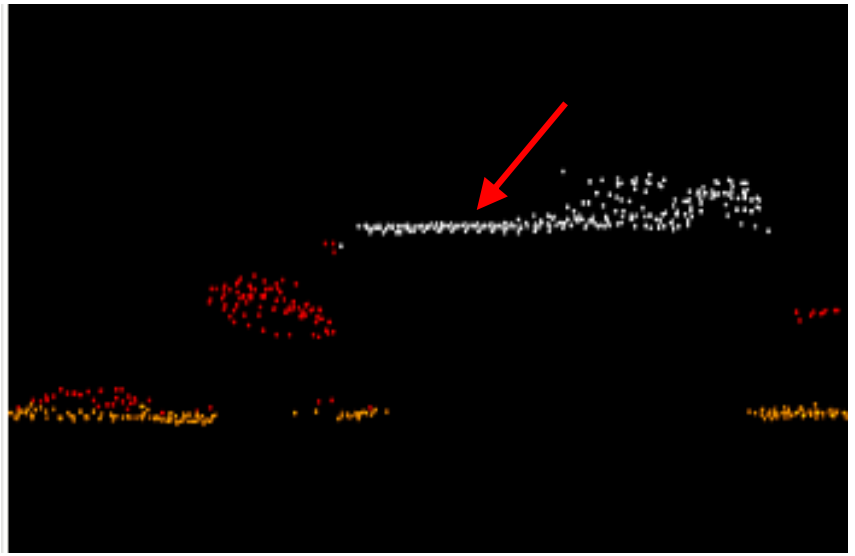


Data Processing

- Step 1: Automatic classification of LiDAR data points by specialist software.
- Step 2: Manual checking and adjustment of classification data.
- Orthophotos produced by Lands Department provided a good reference for data classification; the imagery captured during LiDAR acquisition was also used.
- Complicated terrain conditions with the presence of steep hillslope, thick vegetation and high-density buildings may result in defects in the software/algorithm for processing LiDAR data.



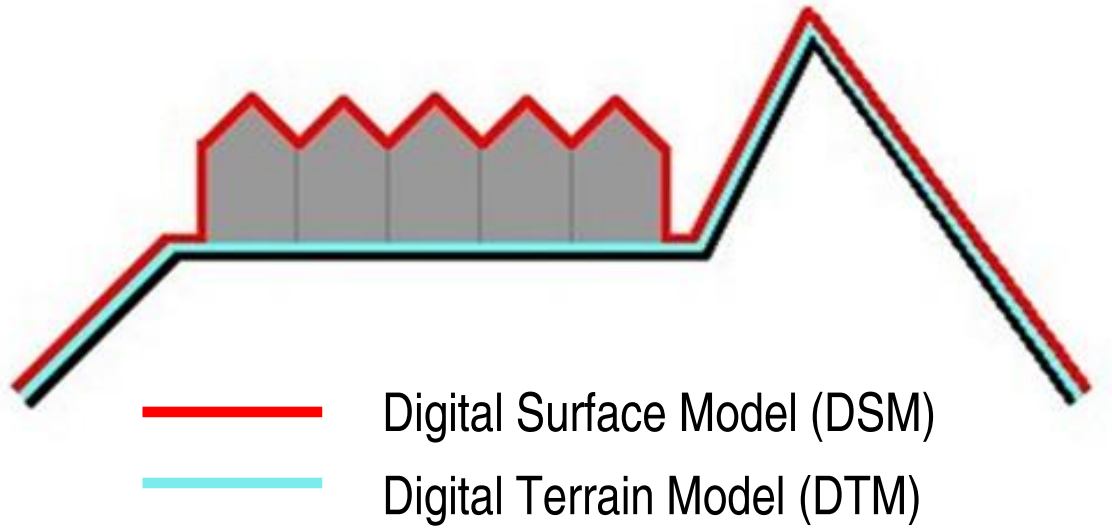
Manual Reclassification of Vegetation to Ground



Manual Reclassification of Vegetation to Building

Key Datasets under the 2020 Airborne LiDAR Survey

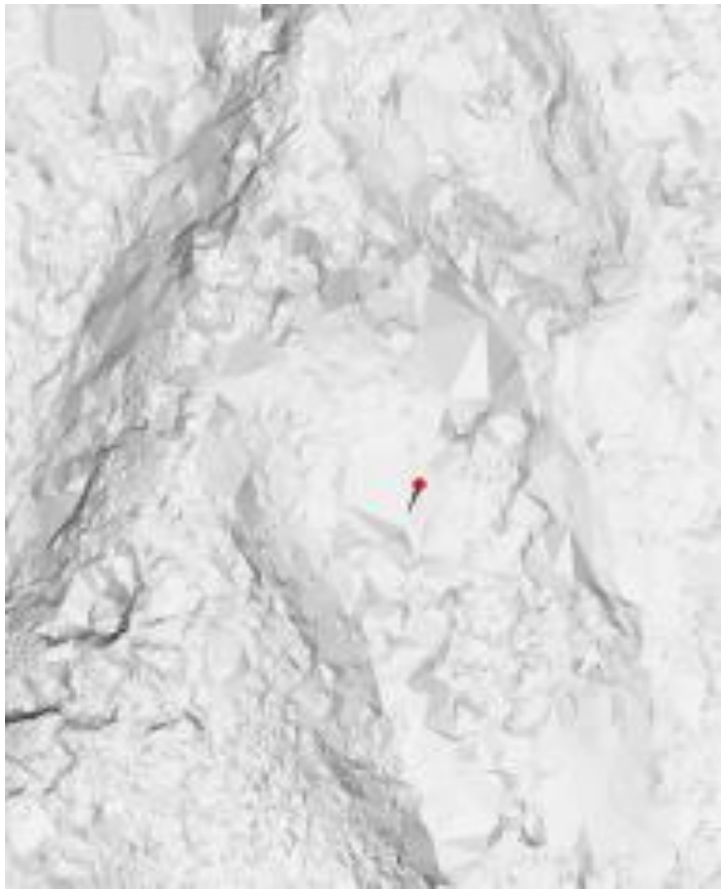
- Raw data points
- Classified data points (ground, low-, middle- and high-vegetation, building, water, electric tower, etc.)
- Digital terrain models
- Digital surface models



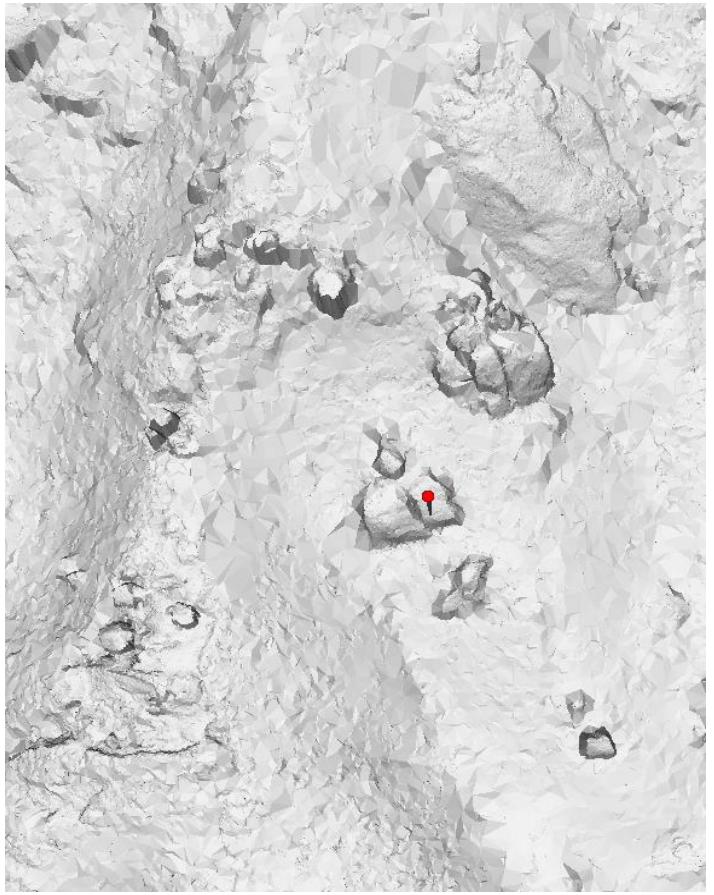
APPLICATIONS OF LiDAR DATA IN GEOTECHNICAL STUDIES

Natural Hillslope with Rock Outcrops

Aerial Photograph
(2010)

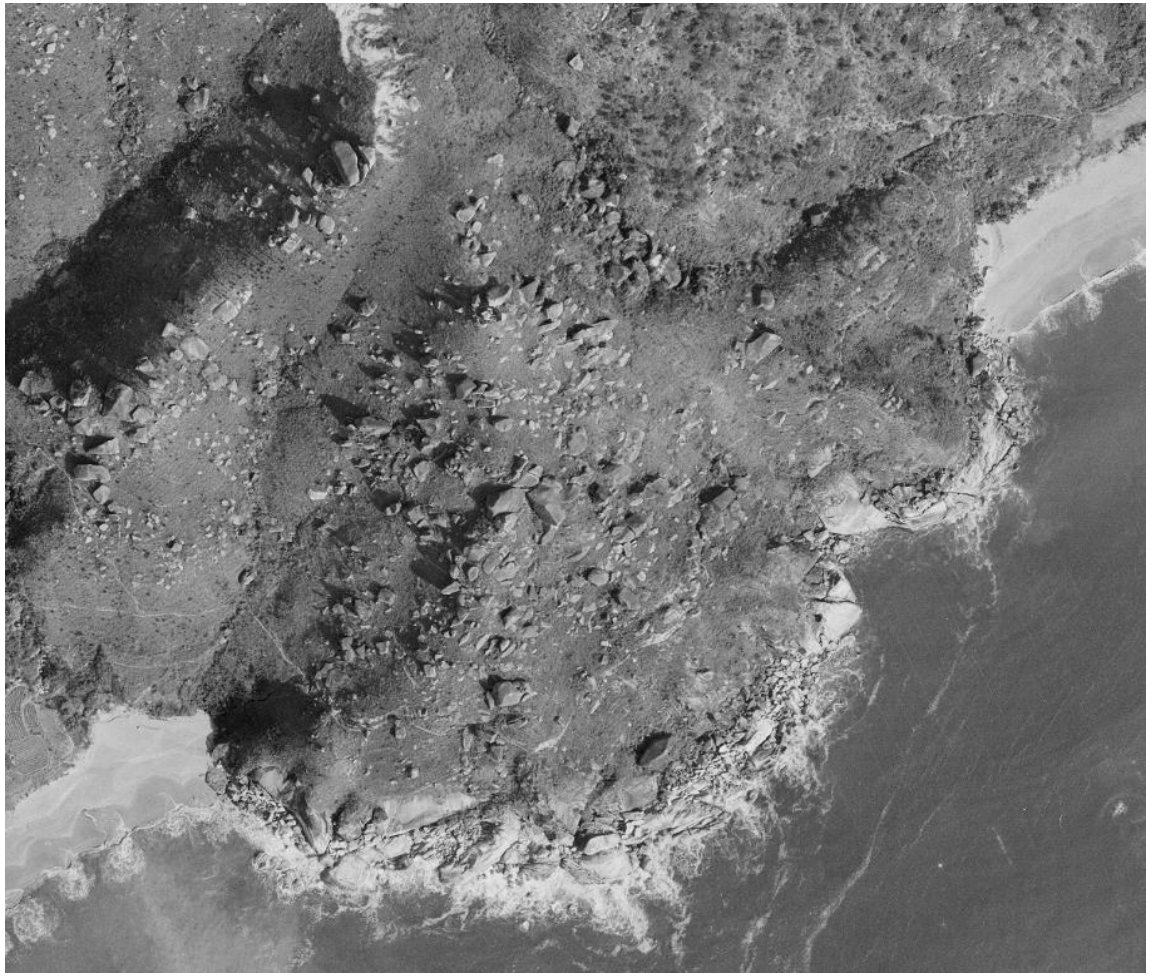


DTM
(2010 LiDAR Dataset)

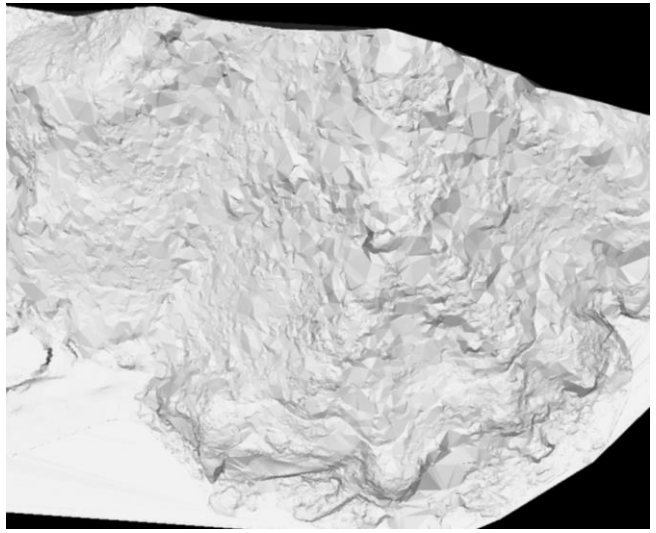


DTM
(2020 LiDAR Dataset)

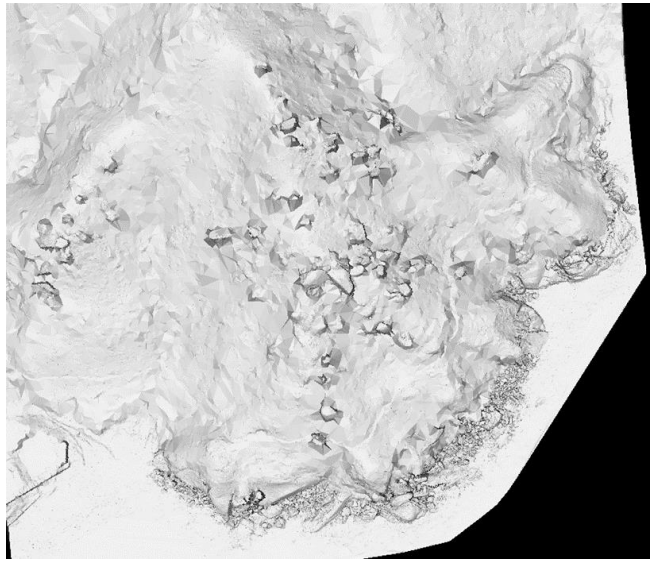
Boulder Field in South Lantau



Aerial Photograph
(1963)

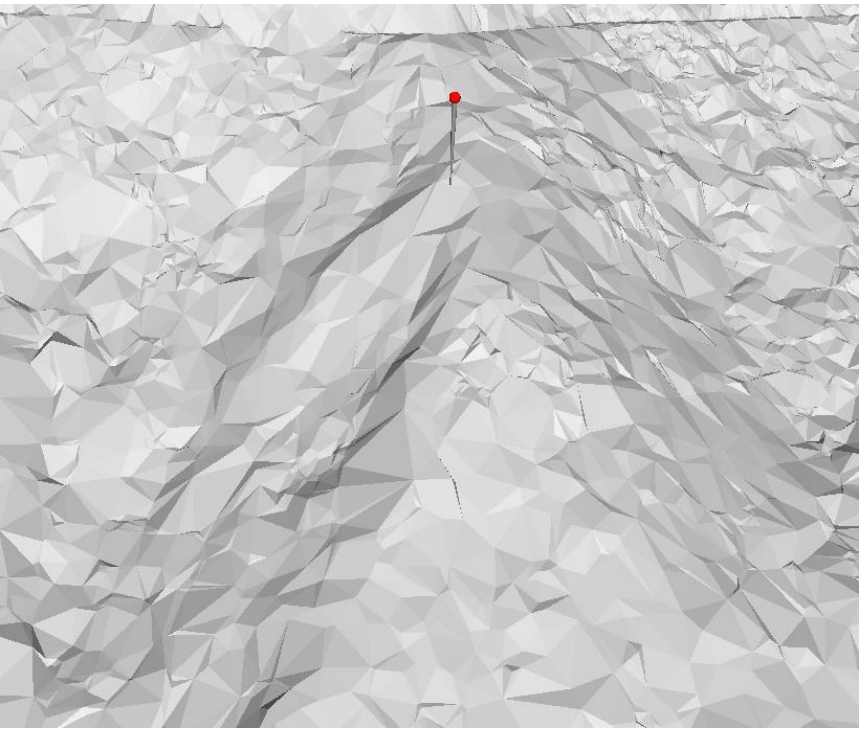


DTM
(2010 LiDAR Dataset)

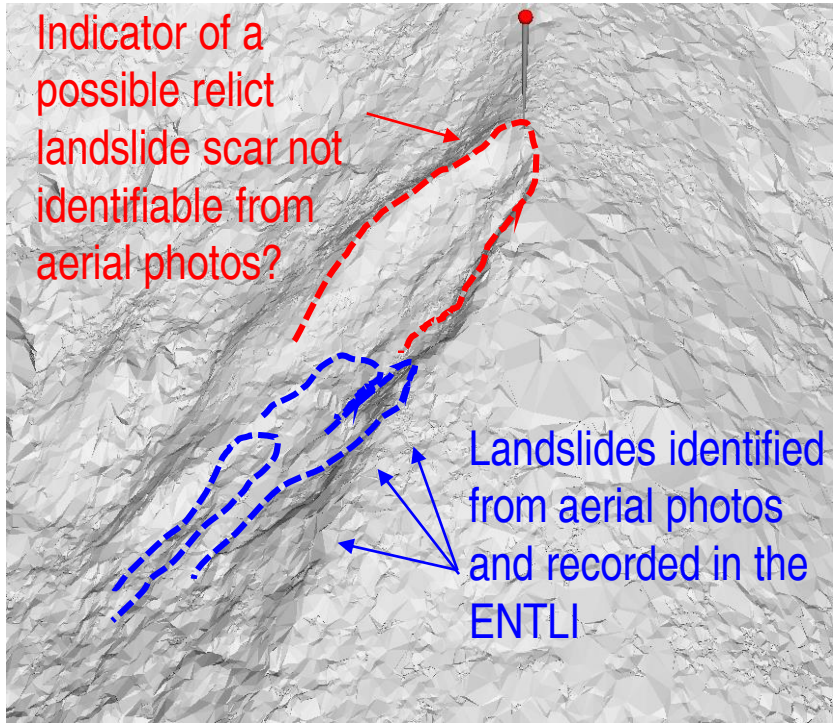


DTM
(2020 LiDAR Dataset)

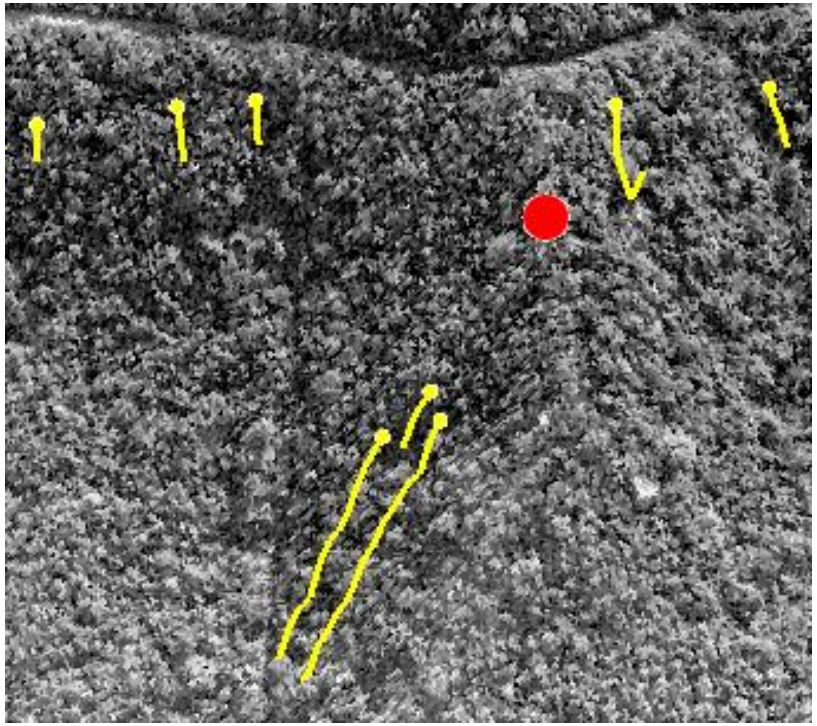
More Detailed DTM generated from 2020 LiDAR Survey Datasets



DTM
(2010 LiDAR Dataset)



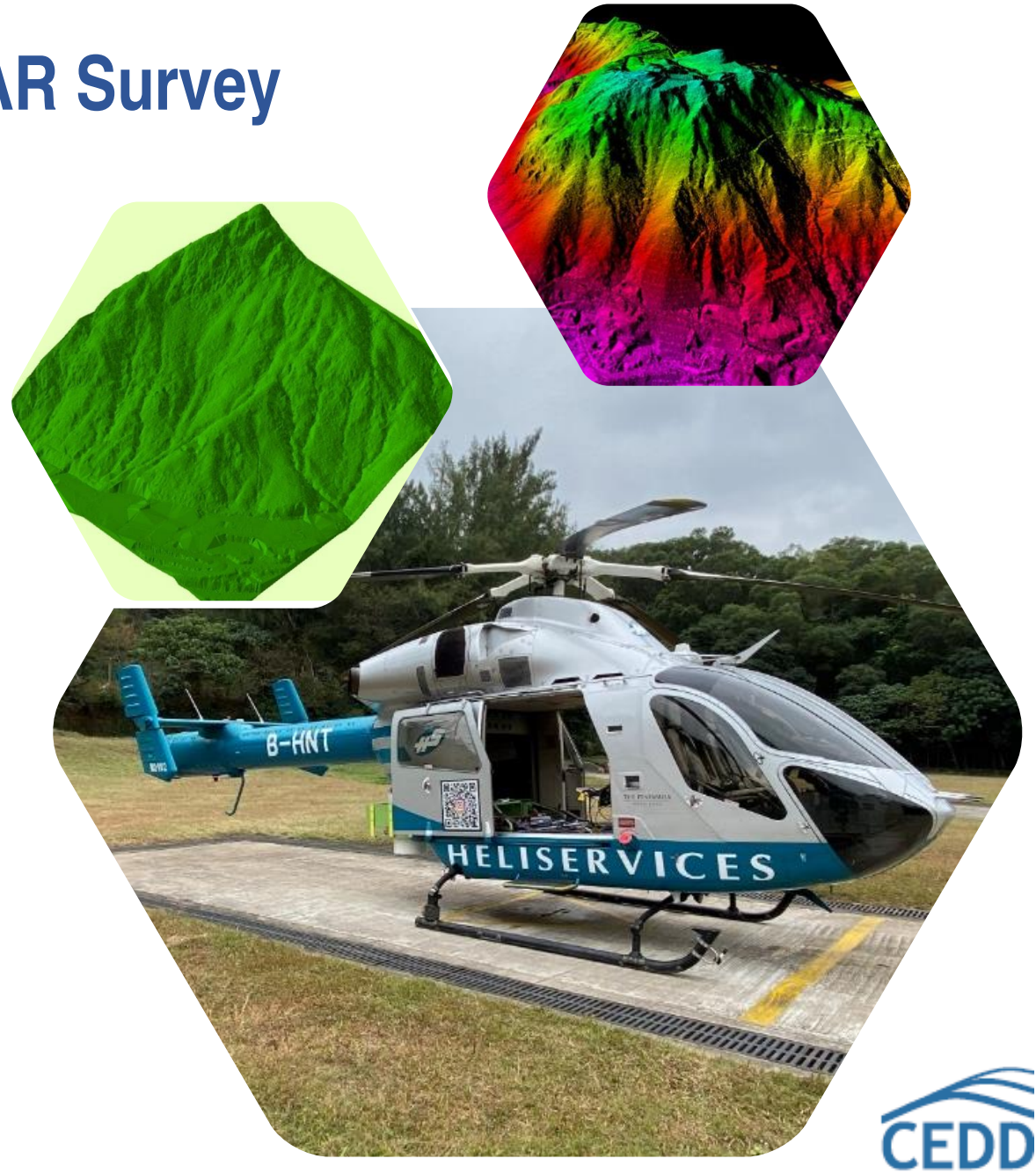
DTM
(2020 LiDAR Dataset)



ENTLI Dataset/1963
Aerial Photograph -
No Record Identified for
the Possible Scars

Advancements in the 2020 LiDAR Survey

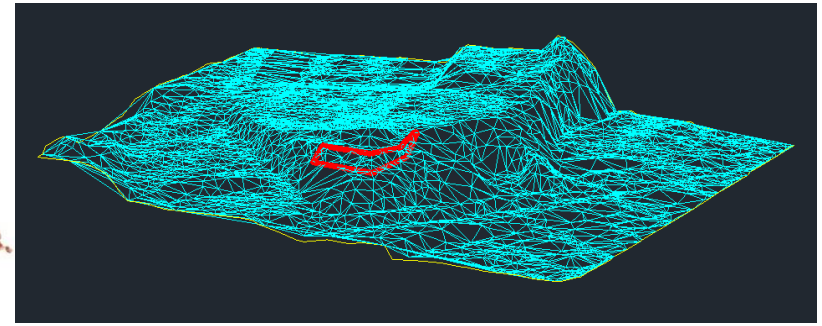
- *Higher point density and resolution of 16 points/m²* – **4 times higher** than the first airborne LiDAR survey in 2010.
- *Enhanced penetration* – capable of recording **8 returned signals** (4 returned signals in 2010) allowing better penetration through dense vegetation and more accurate capturing of ground profiles.
- *Improved accuracy* – Higher data accuracy is expected from a low flying height at about **2,000 feet** in the majority of Hong Kong by helicopter (compared to 3,500 feet flying height of fixed-wing aircraft used in 2010). The lower flying height also means that the survey had a better chance to avoid cloud covers.



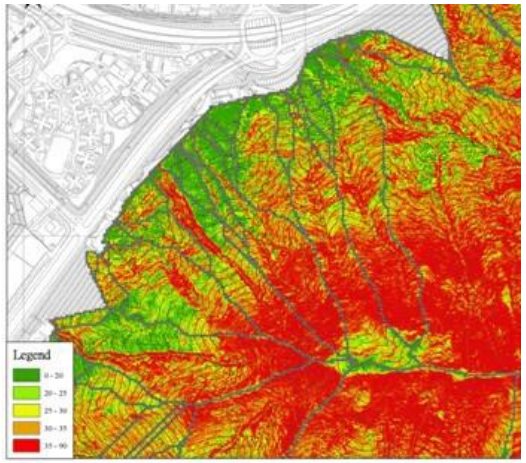
CEDD

Improved Digital Terrain Model for Geotechnical Studies

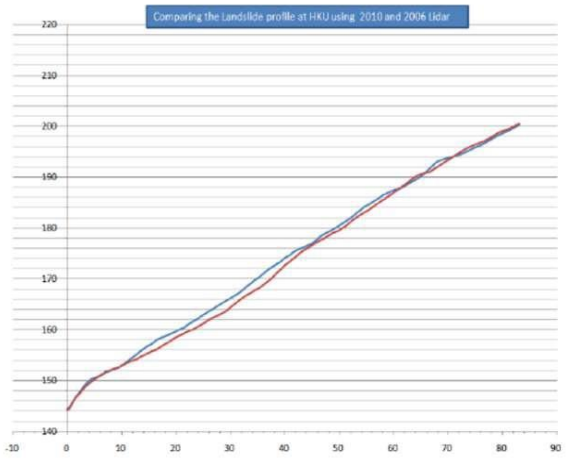
Digital Terrain Model



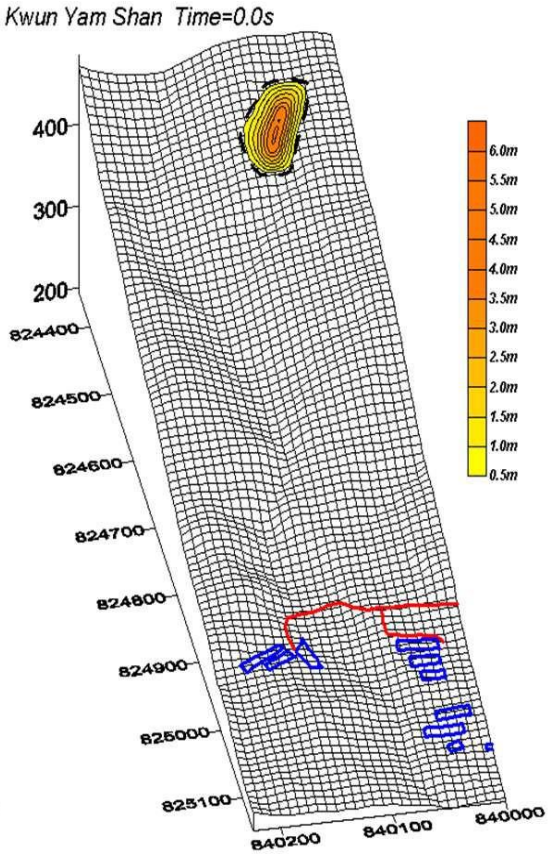
Generation of Site-specific Topographic Model



Slope Angle Map



Landform Change Giving Hint of Ground Detachment



Debris Mobility Modelling

GEO Open Data Portal

The territory-wide airborne LiDAR datasets are available for public use since April 2021.

Website：
https://www.geomap.cedd.gov.hk/GEOOpenData/tc/Default.aspx

Conclusion

- Remote sensing techniques provide spatially continuous data, enhance safety and efficiency.
- LiDAR, especially airborne LiDAR, can obtain accurate topographic information for a large area for geotechnical studies effectively.
- Airborne LiDAR is well applied to inaccessible and vegetated areas, which supplements traditional survey methods.
- High resolution terrain models are generated and non-ground objects are identified.
- The data obtained are useful to landslide risk management and multi-disciplinary applications.

THANK YOU

Excellence with Technology Innovation:

Dreamers and Realists

Ir Sammy Cheung
Geotechnical Engineering Office
Civil Engineering and
Development Department

Geotechnical Engineering Office

many severe landslides occurred in the 70s

Civil Engineering and Development Department

Geotechnical Engineering Office

manage and control geotechnical engineering works related to the safe and economic utilization and development of land, provide emergency services to support government in mitigate landslide risks

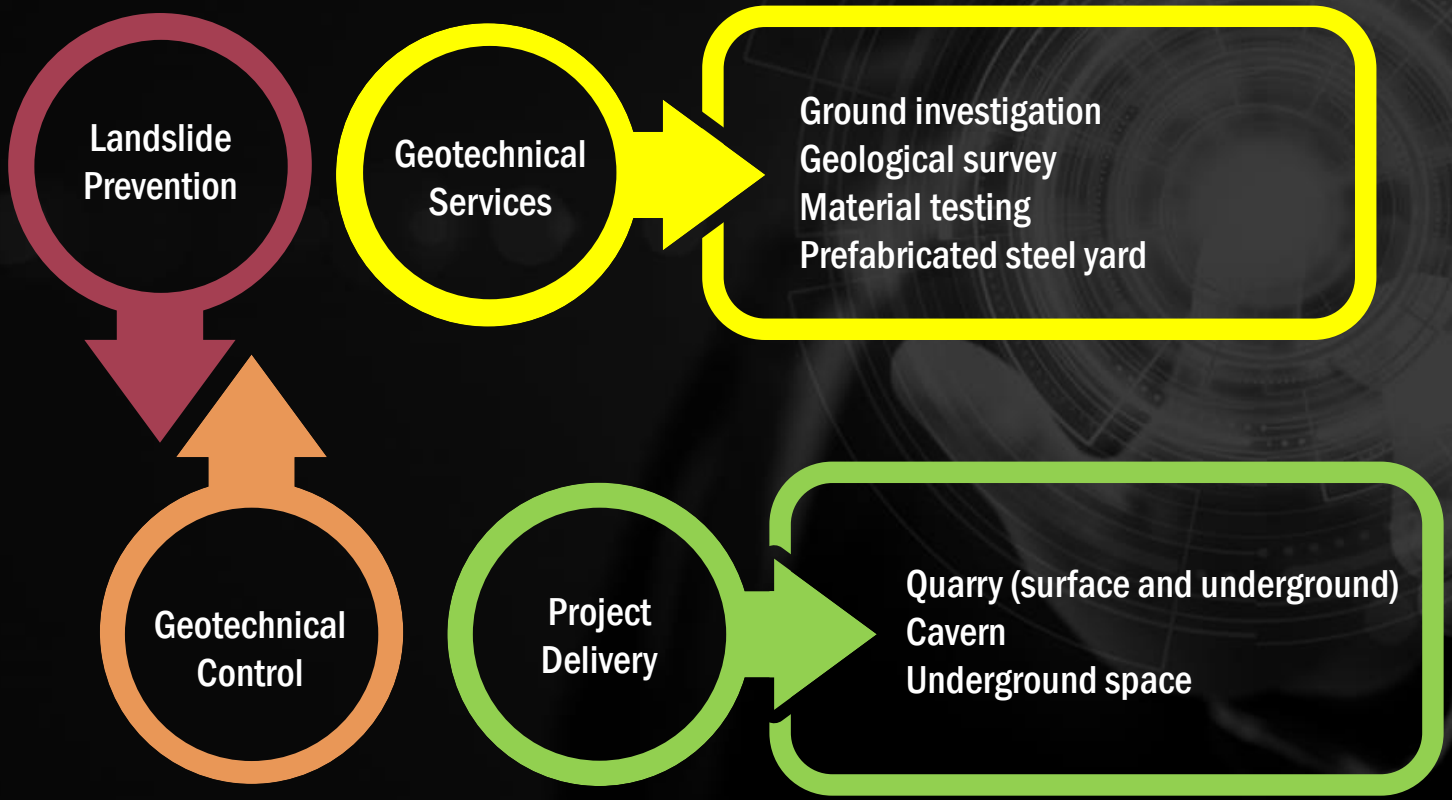
Civil Engineering Office

implement engineering works mainly in the areas of port and coastal engineering; and site formation and reclamation works, public and marine filling, formulation of overall public filling strategy and programme, planning and operation of barging points and fill banks.

Development Offices

Plan and implement engineering projects related to major infrastructure developments in Hong Kong

Geotechnical Engineering Office
our services are expanding



Geotechnical Engineering Office

innovation has been a part of our success

Evolving in response to experience, continual improvement initiatives and technological advancement, we now have in place one of the best slope engineering and landslide risk-management systems in the world.

Chief Executive, 2017

Geotechnical Engineering Office

innovation has been a part of our success

Asian Magazine: Hong Kong leading the world in slope management

Success factors

...

Innovation and technology

Geotechnical Engineering Office

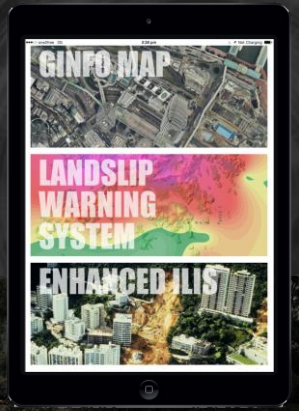
examples of our achievements in using innovative solutions

Slope Information System

Comprehensive inventory of registered slopes in HK (since 1999)

Airborne Lidar survey covering entire Hong Kong (2006, 2011, 2020)

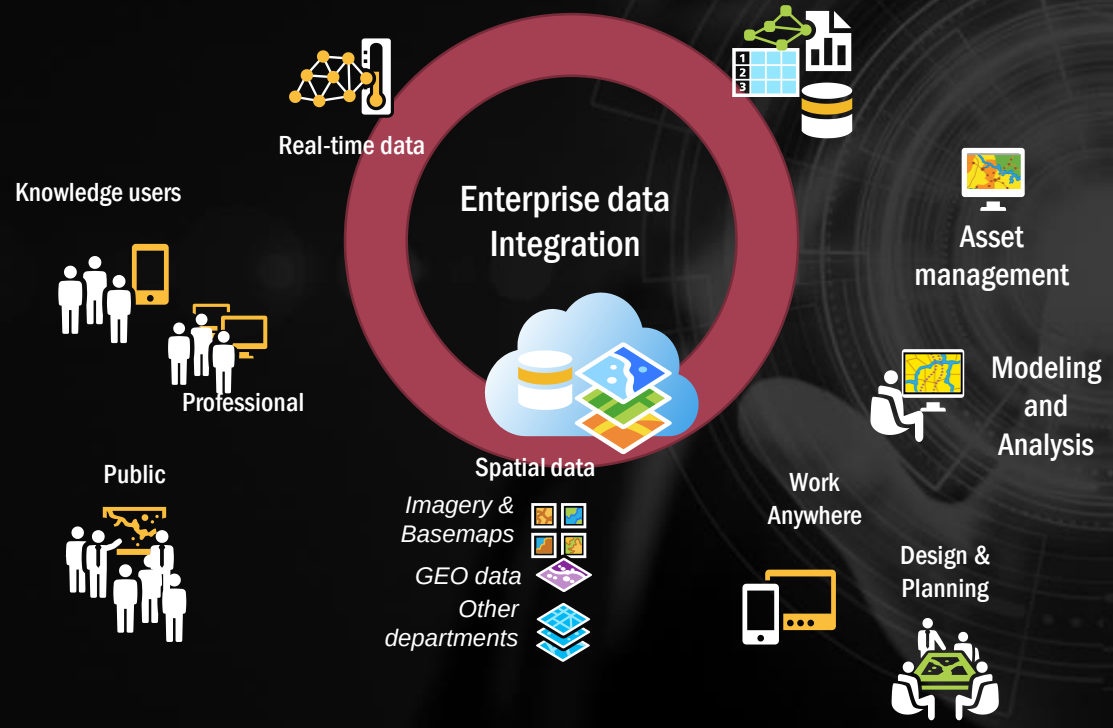
Mobile Applications



Integrated GEO System on mobile platform (2012)

Geotechnical Engineering Office

examples of our achievements in using innovative solutions



Geotechnical Information Infrastructure for systematic management of GEO data

GEO Drive for Technology Innovation

Construction 2.0

Time to change

Innovation is one of the key pillars in the Construction 2.0 advocated by the Government to strengthen and enhance the sustainability and long term growth prospects of Hong Kong construction industry.

Innovation offers us the momentum to excel our services and achieve the best in quality, safety and productivity.

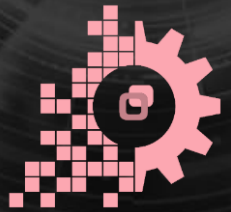
GEO Drive for Technology Innovation

Four Pillars on Innovation

Fostering a vibrant culture of I&T and nurturing talents within GEO

Strengthening technological collaboration with practitioners

Identifying and applying technologies for applications



Implementing suitable I&T in engineering practices

Our people, our asset

Competence matrix of GEO staff in innovation and technology subjects

knowledge users

power users

expert users

leading development

applying advanced application

perform day-to-day tasks

GEO Drive for Technology Innovation

key technological areas

Robotics & Automation

Artificial Intelligence

Digital Technology & IoT

Novel Technology

GEO Drive for Technology Innovation
key technological areas

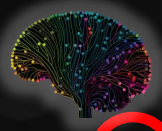
Automation

11

Smart Construction

8

Artificial Intelligence



19

BIM

12

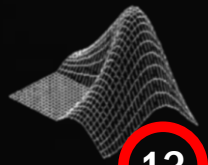
GIS

10

Digital Twin

8

Numerical Tools



13

IoT and smart sensors

6

Novel Material

11

Remote Sensing

11

VR & AR

5

Robotic

10

We have a vision

Dreamers operate in a special mode, always looking for opportunities to create value in novel ways

GEO Drive for Technology Innovation

our recent endeavor in robotic solutions

GEO Drive for Technology Innovation

our recent endeavor in robotic solutions

Are you fascinated by working with them?

Robotic Solutions
the Enthusiasts

GEO Drive for Technology Innovation

our recent endeavor in robotic solutions

How can they help in our services?

Robotic Solutions

the circumstances that robots can help

Landslide inspection where the environment is hazardous and in poor condition

Robotic Solutions

the circumstances that robots can help

Hazardous situation during inspection of landslide sites

Robotic Solutions

the circumstances that robots can help

Hazardous situation during inspection of landslide sites

Robotic Solutions

the circumstances that robots can help

Rugged terrain that we traverse and collect field data

Robotic Solutions

the circumstances that robots can help

slope inspection and site works

Robotic Solutions

the circumstances that robots can help

huge slope that we need to carry out inspection

Robotic Solutions
advanced quadrupled robot

- **Feb 2020** — Initial discussion with Boston Dynamic
- **Jun 2020** — Invitation of Quotation (Leasing Dog)
- **Aug 2020** — Arrival of Spot in Hong Kong
- **Sep 2020** — Site Trial (Man-made Slope, Natural Terrain & Dis-used Tunnel)
- **Dec 2020** — New remote sensing tools
- **Mar 2021** — Remote Control Capability
- **Jun 2021** — Landslide Inspection

Robotic Solutions
advanced quadrupled robot

AI Lens
(AWS Deeplens)

Additional Lighting

Handheld LiDAR
scanner mounted on
SPOT

High resolution
camera using
GoPRO

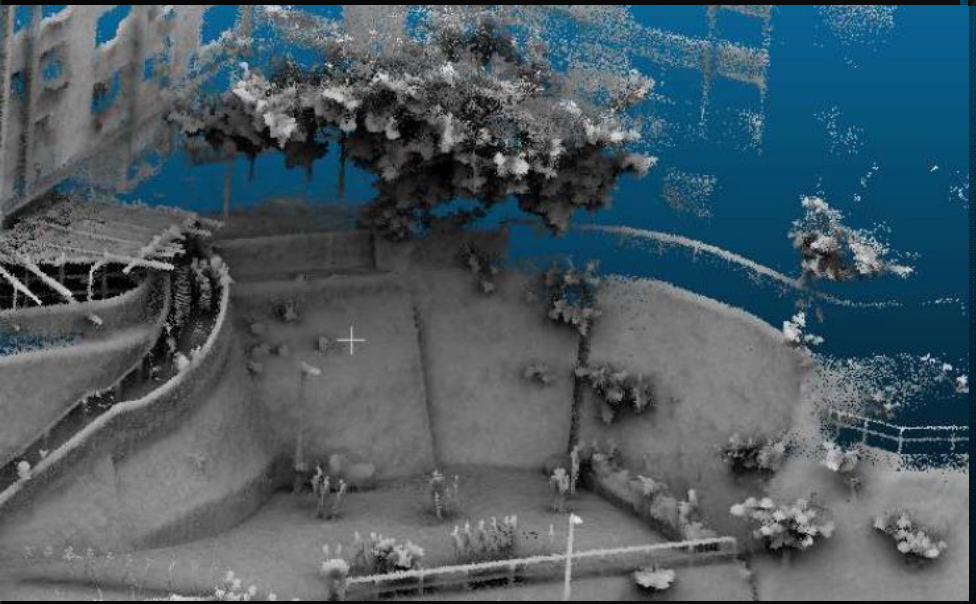
Quick assembly of sensors and
camera on Boston Dynamics SPOT

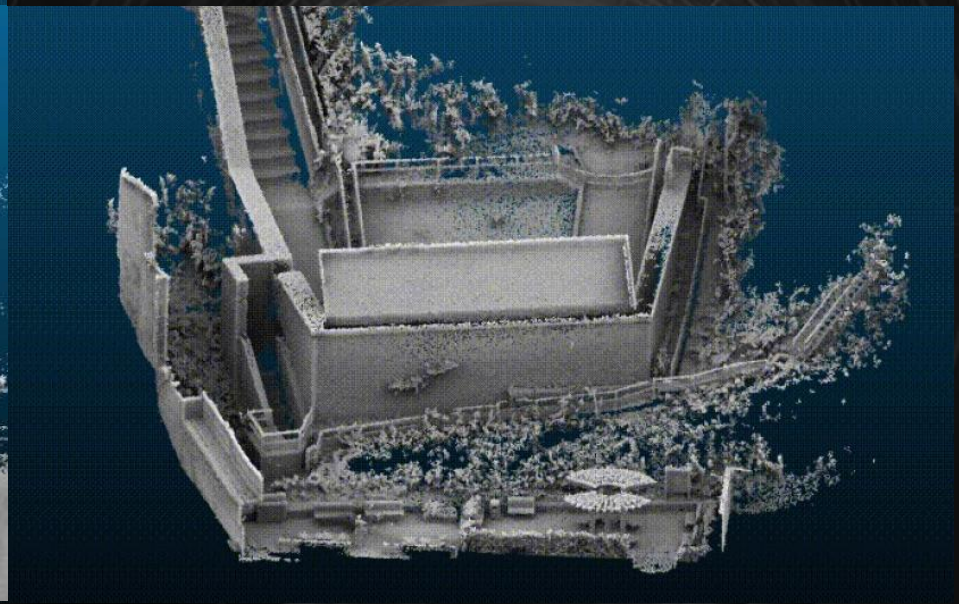
Robotic Solutions
advanced quadrupled robot

inspection at landslide site

Robotic Solutions

advanced quadrupled robot

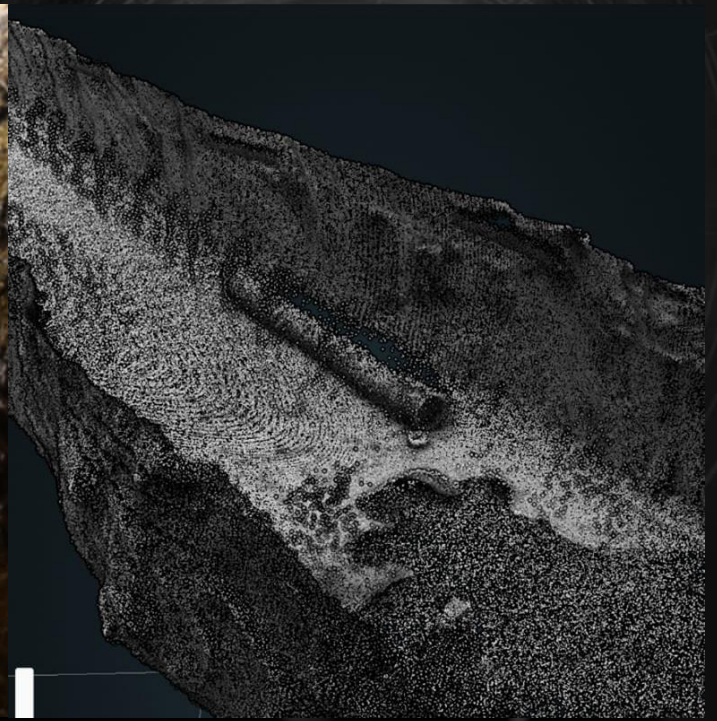




digital model captured by handheld LiDAR scanner

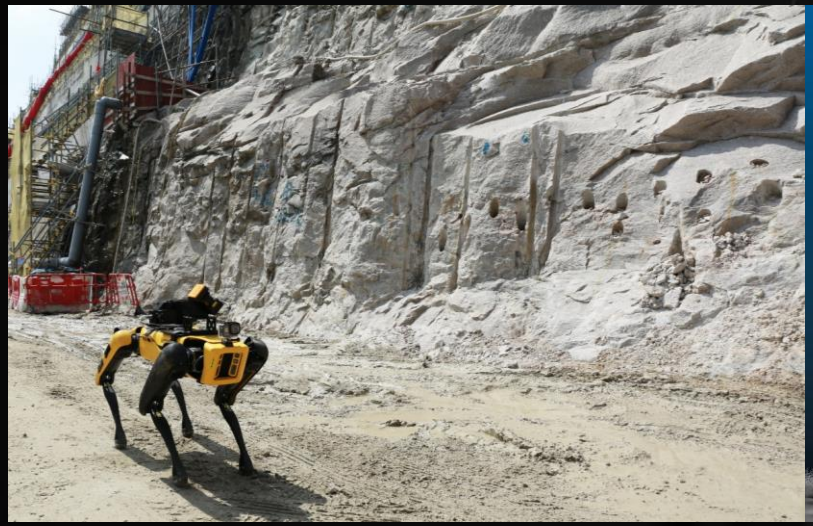
Robotic Solutions

advanced quadrupled robot



Robotic Solutions

advanced quadrupled robot



rock slope formed by open blasting

Lidar Image of rock slope

data capturing at construction site

Robotic Solutions

advanced quadrupled robot

cavern construction site

Robotic Solutions

advanced quadrupled robot

5G

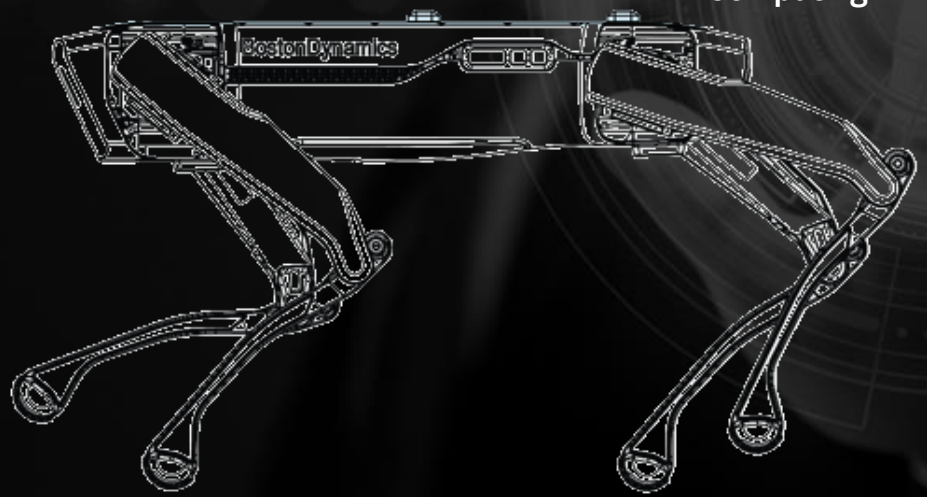
Long Range Control

Vision

EDGE

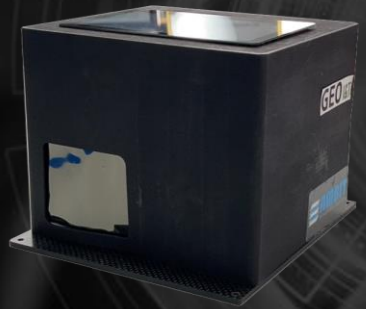
Computing

Sensors/
Data
Collection



mobile platform for traversing rugged terrain

Robotic Solutions
advanced sensors



Advanced 360 cameras

GPU Accelerated
AI computers

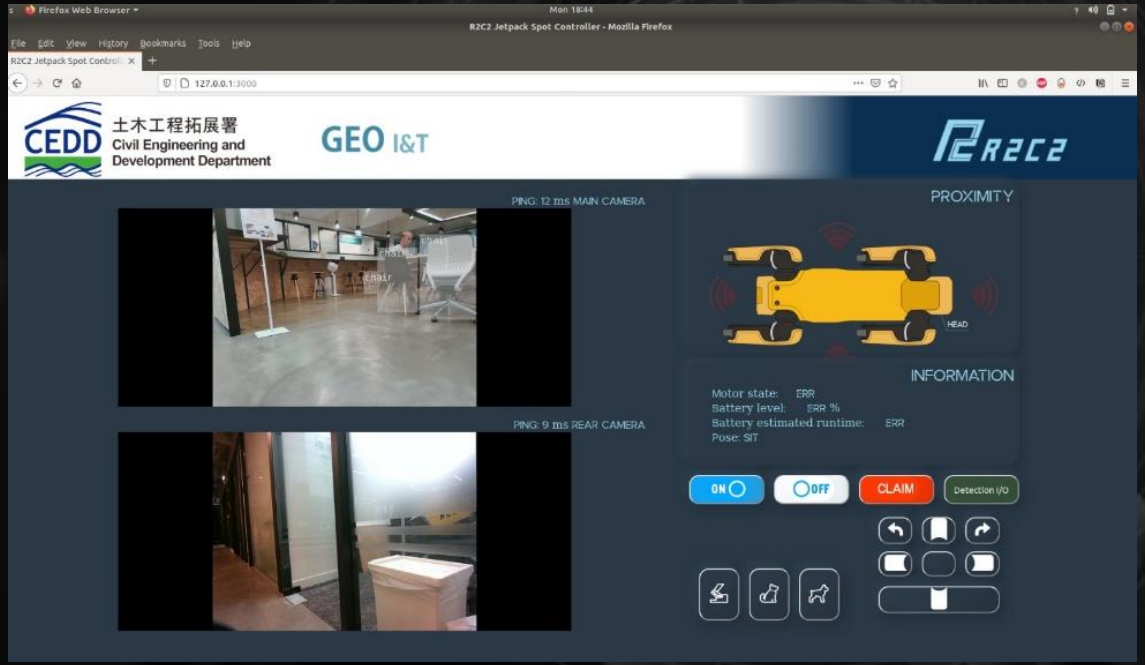
Lightweigtht
LiDAR

Robotic Solutions
advanced sensors

Robotic Solutions
advanced sensors

Robotic Solutions

long-range communication on advanced quadrupled robot



GPU Accelerated AI computers

Advanced cameras (IR camera, depth camera, 360 camera, solid state LiDAR)

Robust long range communication for robotic control

Robotic Solutions

a variety of data capture sensors on advanced quadrupled robot

Robotic Solutions

advanced quadrupled robots on actual mission

landslide inspection at Black’s Link

Robotic Solutions

mobility limitation of the advanced quadrupled robot

working with Boston Dynamic in improving the mobility

Robotic Solutions
rugged terrain

Robotic Solutions

spider robot prototype

Robotic Solutions

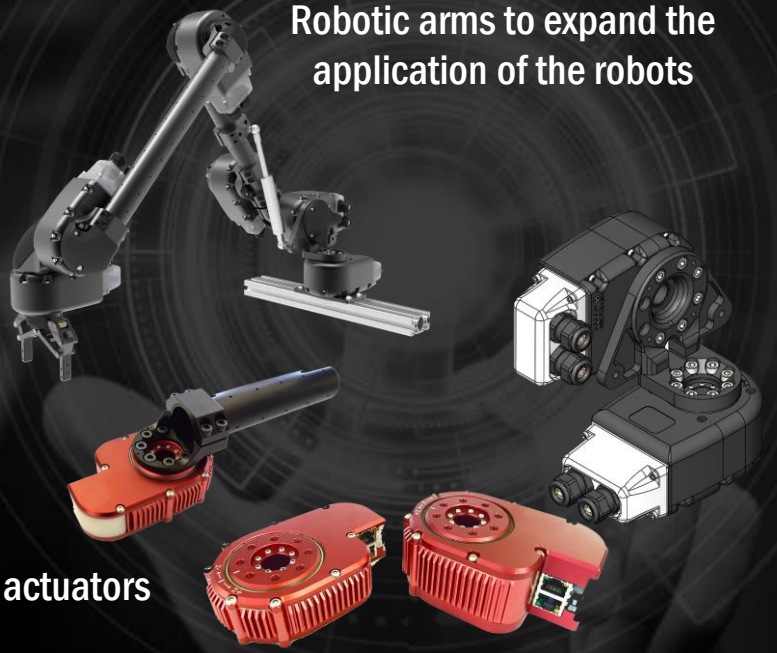
Hebi - tready

Robotic Solutions

Hebi - tready

Assemble tready in
collaboration with CUHK

Robotic arms to expand the
application of the robots



actuators

香港中文大學（深圳）
The Chinese University of Hong Kong, Shenzhen

机器人与人工智能实验室
Robotics & Artificial Intelligence Laboratory

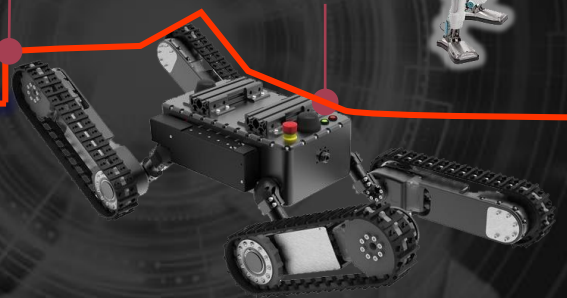
Robotic Solutions

Hebi - tready

Feb 2020

Aug 2020

Sep 2021



Our journey on robotic applications will continue

GEO Drive for Technology Innovation

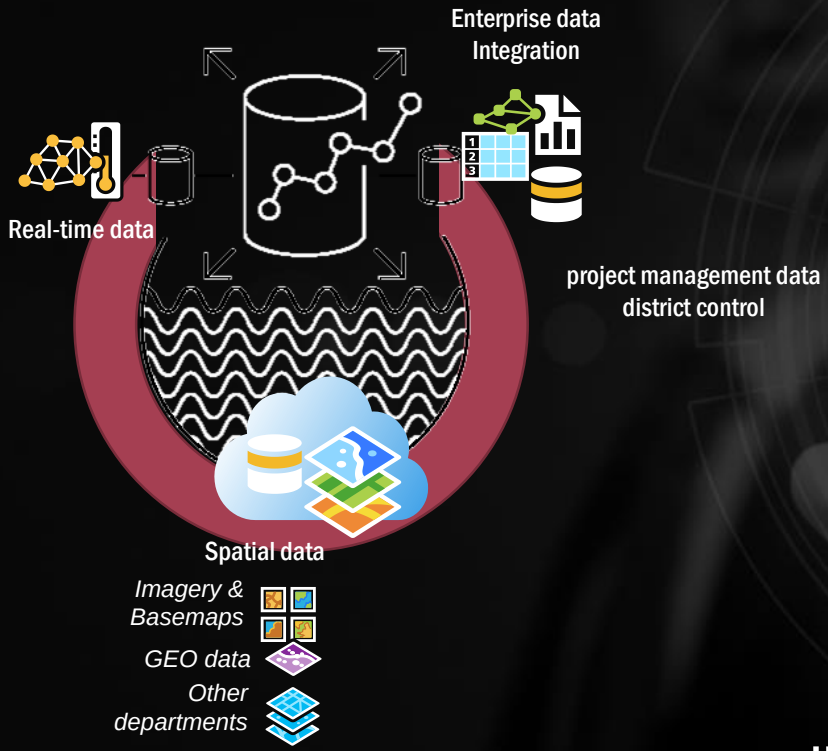
We need ambitious leaders whom they do not content to carry out the business as usual, but willing to upend convention and wield their vision for the future.

GEO Drive for Technology Innovation

Prerequisites of ambitious leaders

- conceiving (potentially) great ideas
- excitement in exploring and validating high-impact opportunities;
- communicating and promoting ideas and concepts
- realizing the resulting potential
- pragmatic and accepting failure

Biggest Dream?



GEO data amalgamates into data lake

Hey, GEO

Can you tell me when this slope was upgraded and who were the consultants responsible for the upgrading works?

GEO Drive for Technology Innovation

Pandemic has forced corporations to make sweeping changes to confront the new normal and technology has been the lifeline for many companies, government and people.

cloud and AI

cloud and AI

digitalisation

hybrid workplaces

e-commerce

consumer behaviour changes

travel grounded

virtual visit

GEO Drive for Technology Innovation

Natural disasters caused by climate change become more frequent and damaging

Chances are only for the
people who are prepared.
Whoever react fast, survive

THANK YOU

Geotechnical Engineering Office
Civil Engineering and Development Department

Sammy Cheung

sammypycheung@cedd.gov.hk

Joint Symposium on Digital Geosciences & Geotechnology

Theme (2) : Applications of Artificial Intelligence and Machine Learning

Vertical AI – An integrated solution for a smart and resilient city

Ir. Prof. Wang Yu-Hsing and DESR Lab

Department of Civil and Environmental Engineering

16 September 2021

香港科技大學
THE HONG KONG UNIVERSITY OF SCIENCE AND TECHNOLOGY

GREAT Smart Cities

DESRlab Data-Enabled Scalable Research Laboratory

GREAT Smart Cities Center

DESR

Data

Enabled

Scalable

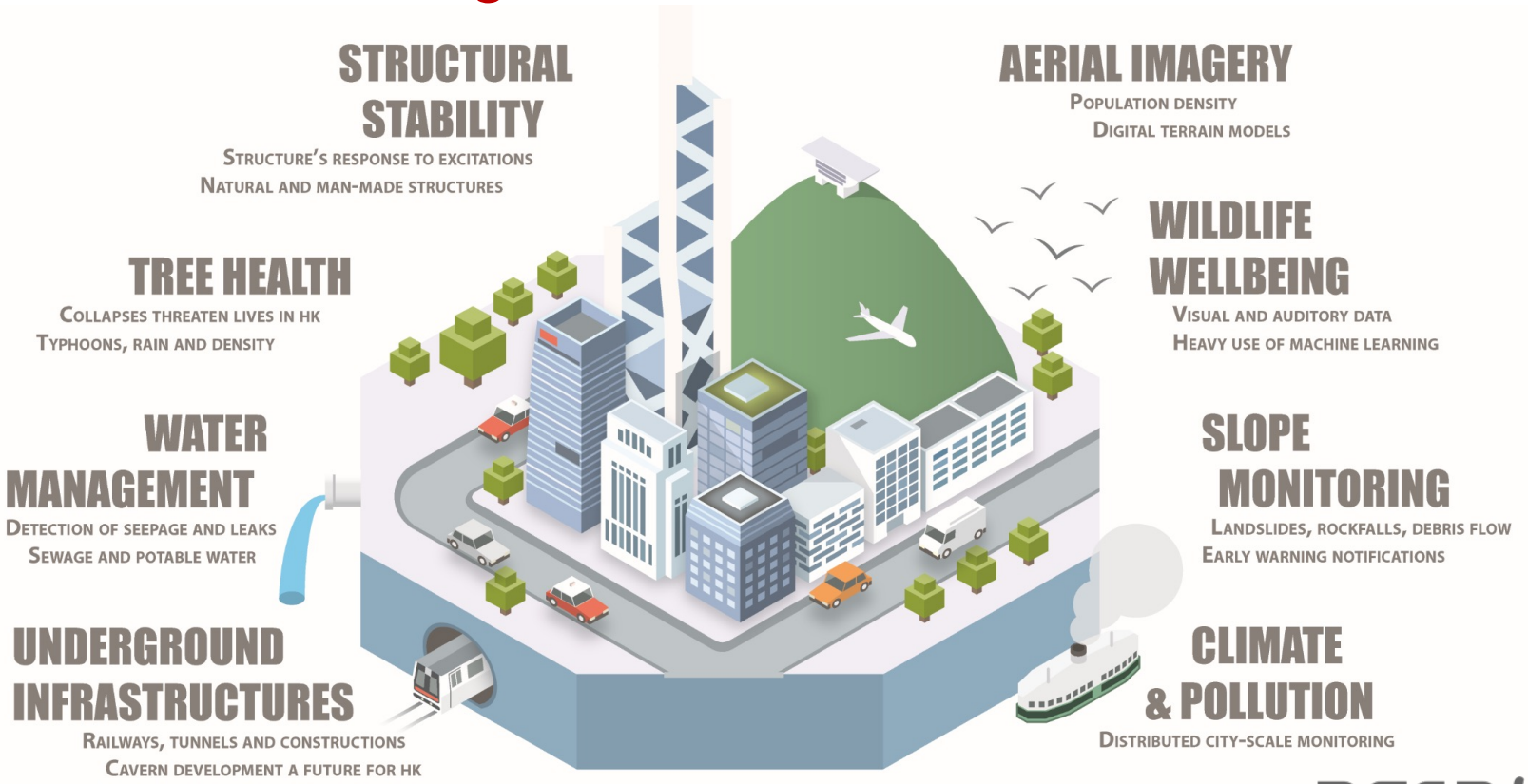
Research

DESRlab

Data-Enabled Scalable Research Laboratory

Our mission:

innovating fundamental Smart City infrastructural technologies to connect citizens and decision-making.



DESRlab
Data-Enabled Scalable Research Laboratory

Smart City Is Not About Money

Smart City Is About Integration

DESRlab
Data-Enabled Scalable Research Laboratory

Vertical AI

Sensor Design

Data Collection

Big Data

Artificial Intelligence

Semantic Integration

Smart & Resilient City

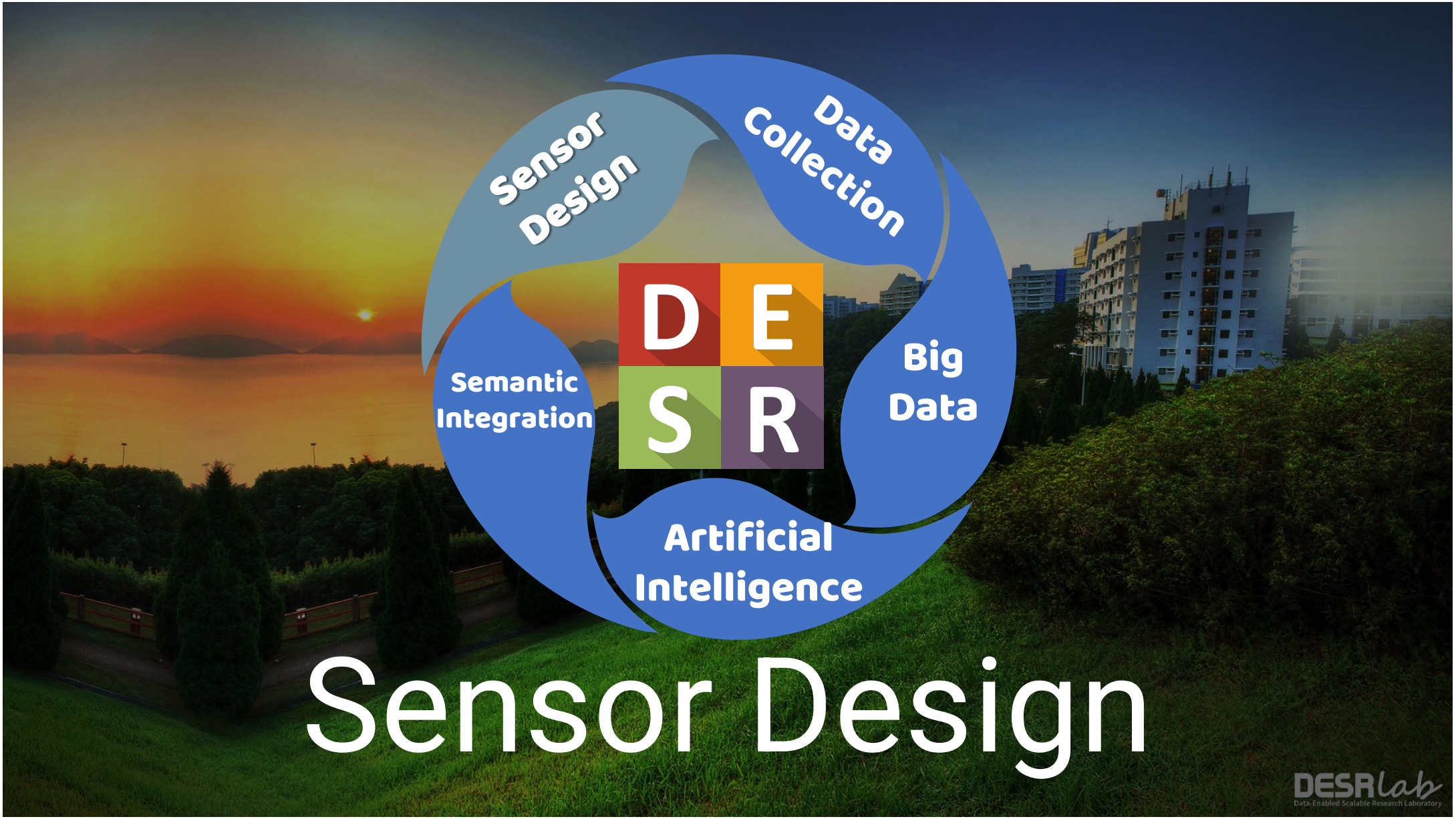
Vertical Integration

An Integrated

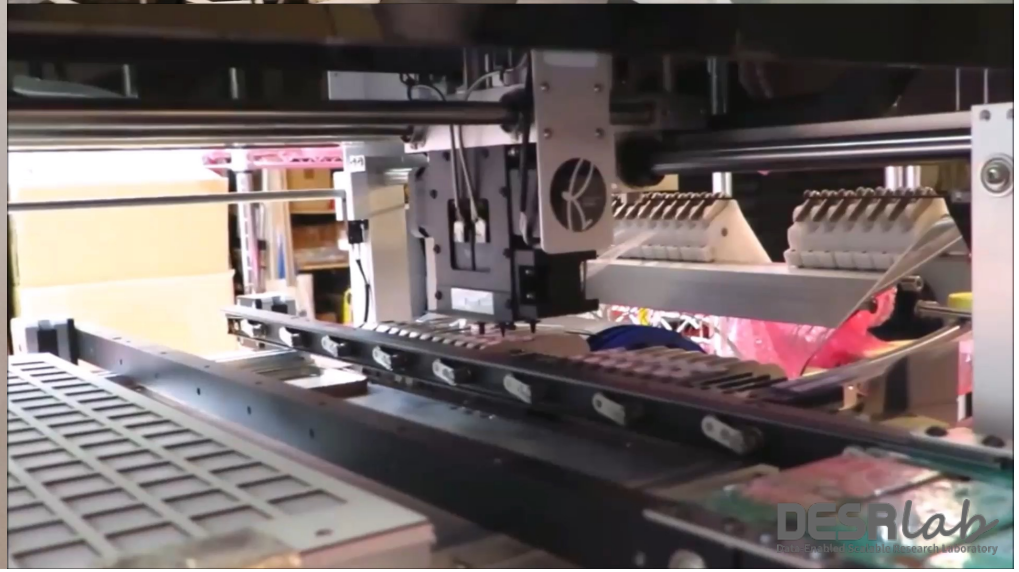
Human-Robot-AI

Symbiotic Solution for Smart and Resilient Cities

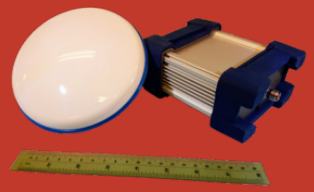
Human-Robot-AI Partnership


Sensor Design
Data Collection
Big Data
Artificial Intelligence
Semantic Integration
D E
S R
Sensor Design
DESRlab
Data-Enabled Scalable Research Laboratory

DESRLab in Action

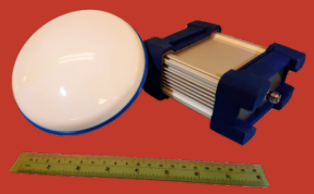
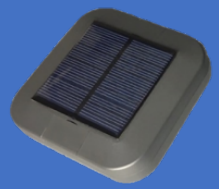


Sensor Technology Matrix

	Dynamic	Static
Permanent	Geo-IoT 	DESR-node
Portable	Marble	RTK-GNSS

DESRlab
Data-Enabled Scalable Research Laboratory

Sensor Technology Matrix

	Dynamic	Static
Permanent	Geo-IoT 	DESR-node 
Portable	Marble	RTK-GNSS

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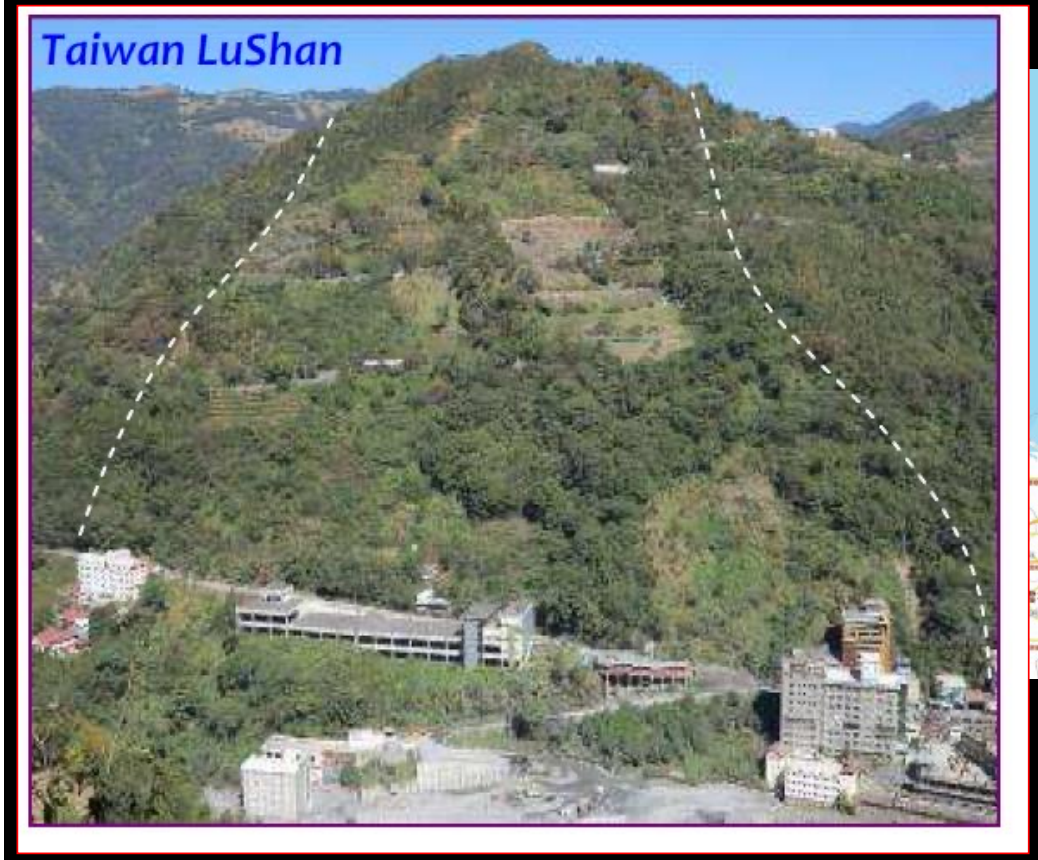
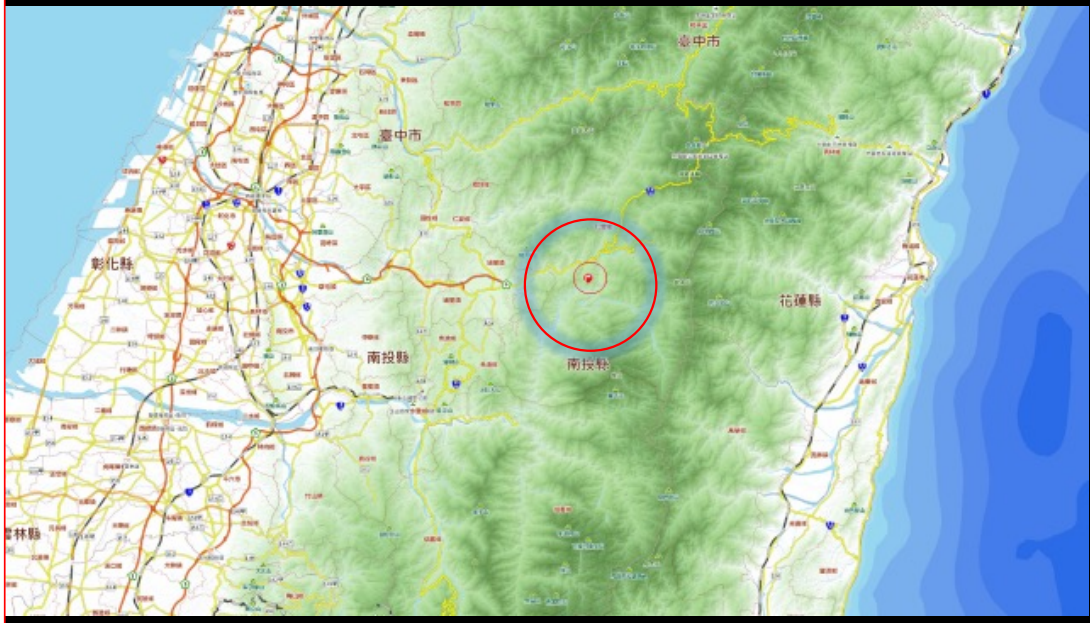
Data-Enabled Scalable Research Laboratory

Landslide monitoring





Lushan,
Central Part of Taiwan

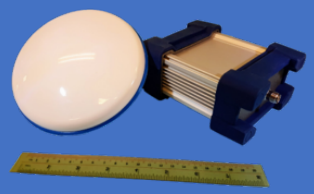
DESRlab
Data-Enabled Scalable Research Laboratory

GPS Antenna
Solar Panel
with Battery
Control Module
Sensor Module
Lu Shan, Taiwan

Fault-tolerance
Over the air
Flexible
Sichuan, China
DESRLab

DESR Lab

Sensor Technology Matrix

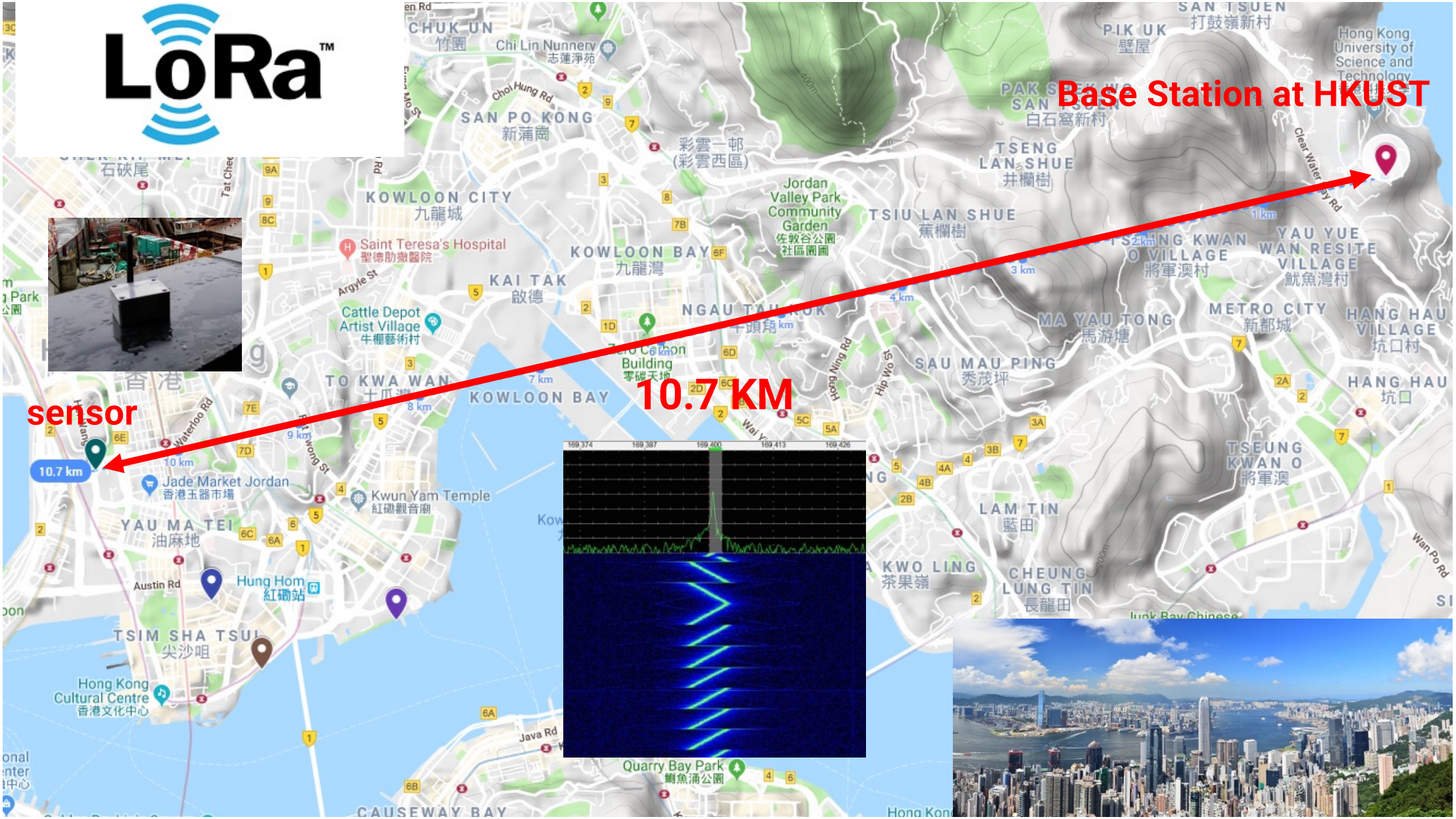
	Dynamic	Static
Permanent	Geo-IoT 	DESR-node
Portable	Marble	RTK-GNSS

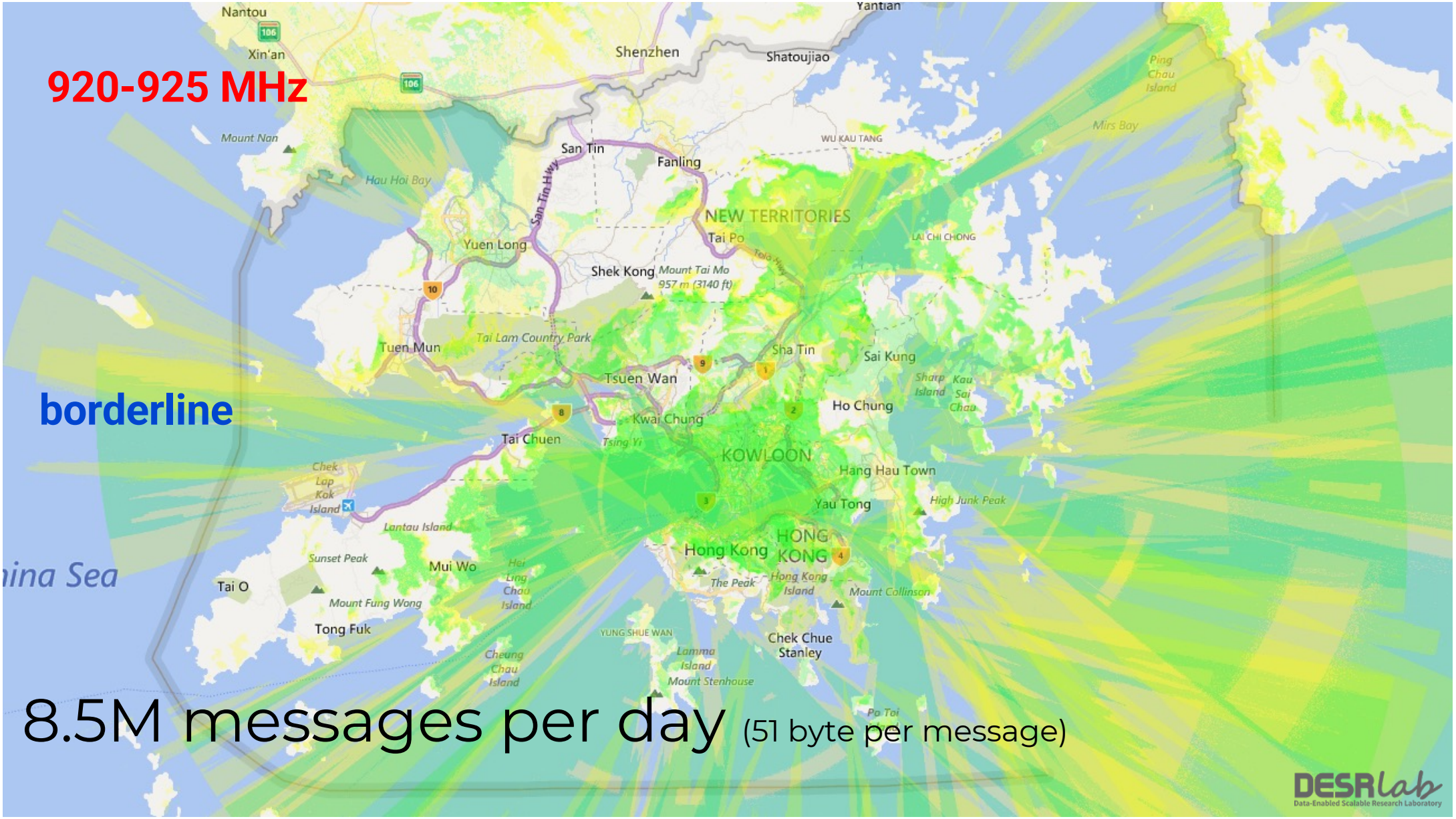
LoRa™

Low Power, Wide Area networking

DESRlab
Data-Enabled Scalable Research Laboratory

Wide Area Sensing Network (LoRa)


LoRa™
Base Station at HKUST
sensor
10.7 KM
10.7 km
CHUK UN
竹園
Chi Lin Nunnery
志蓮淨苑
SAN PO KONG
新蒲崗
KOWLOON CITY
九龍城
KOWLOON BAY
九龍灣
KAI TAK
啟德
TO KWA WAN
土瓜灣
Saint Teresa's Hospital
聖德肋撒醫院
Cattle Depot Artist Village
牛棚藝術村
Jordan Valley Park Community Garden
佐敦谷公園
社區園圃
彩雲一邨
(彩雲西區)
TSENG LAN SHUE
井欄樹
TSIU LAN SHUE
蕉欄樹
PIK UK
壁屋
SAN TSUEN
打鼓嶺新村
Hong Kong University of Science and Technology
SAU MAU PING
秀茂坪
MA YAU TONG
馬游塘
METRO CITY
新都城
HANG HAU VILLAGE
坑口村
HANG HAU
坑口
YAU YUE WAN RESITE VILLAGE
魷魚灣村
TSEUNG KWAN O
將軍澳
LAM TIN
藍田
KWO LING
茶果嶺
CHEUNG LUNG TIN
長龍田
YAU MA TEI
油麻地
Jade Market Jordan
香港玉器市場
Kwun Yam Temple
觀音廟
Austin Rd
Hung Hom
紅磡站
TSIM SHA TSUI
尖沙咀
Hong Kong Cultural Centre
香港文化中心
Quarry Bay Park
鰂魚涌公園
CAUSEWAY BAY
Java Rd
Choi Hung Rd
Argyle St
Waterloo Rd
Hong Ning Rd
Hip Wo St
Wan Po Rd
Clear Water Bay Rd



8.5M messages per day (51 byte per message)

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Data-Enabled Scalable Research Laboratory

LoRaWAN-based sensor system, Internet of Tree Things (IoTT)

香港賽馬會慈善信託基金
The Hong Kong Jockey Club Charities Trust
同心同步同進 RIDING HIGH TOGETHER

JOCKEY CLUB SMART CITY TREE MANAGEMENT PROJECT
賽馬會智慧城市樹木管理計劃

香港科技大學
THE HONG KONG UNIVERSITY OF SCIENCE AND TECHNOLOGY

Sustainable Smart Campus as a Living Lab

THE HONG KONG POLYTECHNIC UNIVERSITY
香港理工大學

地球之友 friends of the earth

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II. LoRa Gateway

LoRaWAN networking

LoRaWAN networking

Interactive Data Visualizations

I. DESR-node (the tree sensor)

III. Data center (network and application servers)

Spider Sense (smart barrier)
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Source: Mr. Kenneth Ho (Deputy Head), GEO, CEDD

Combing the power of IoT and AI

AIoT (Artificial Intelligence of Things)

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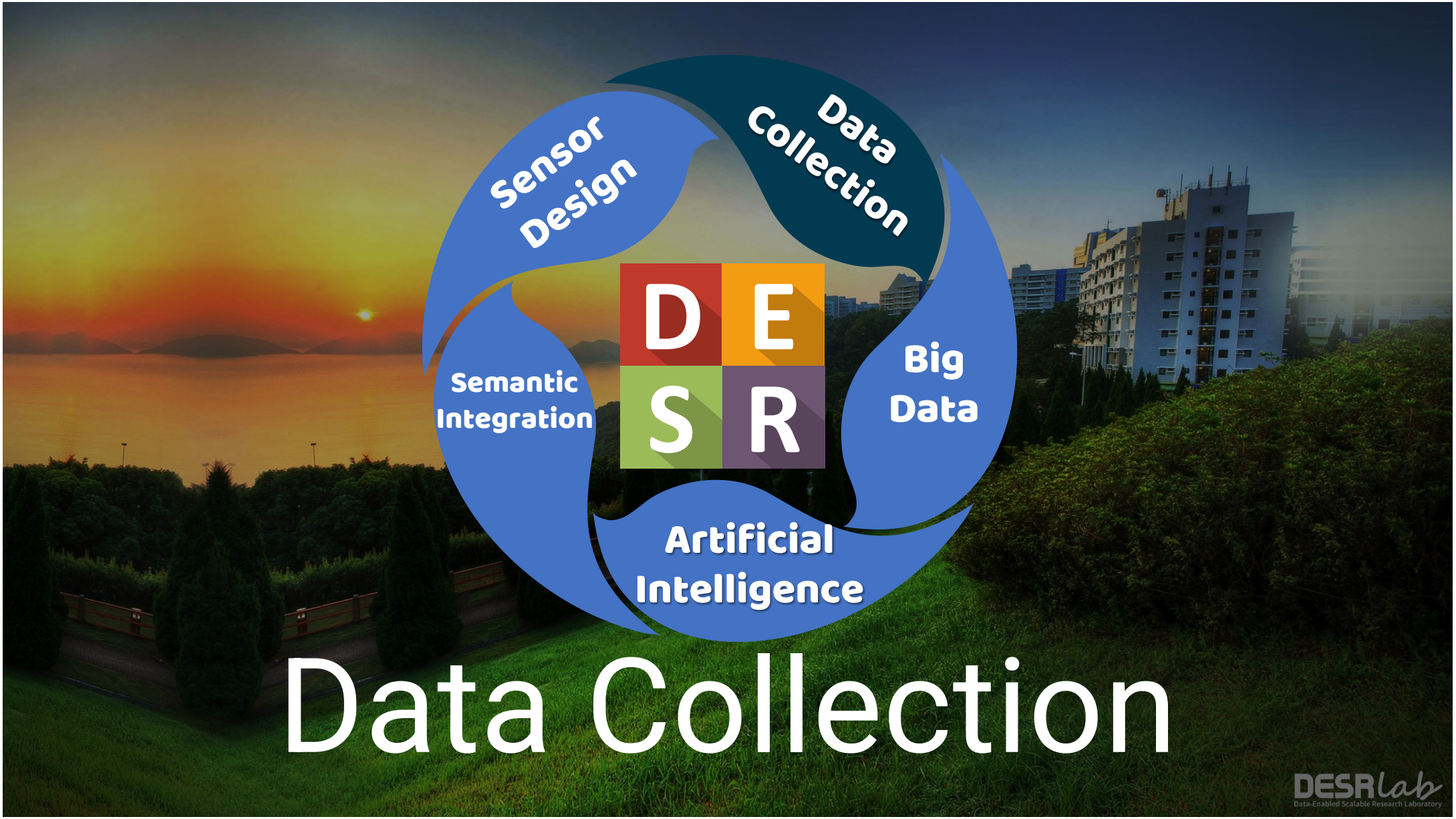
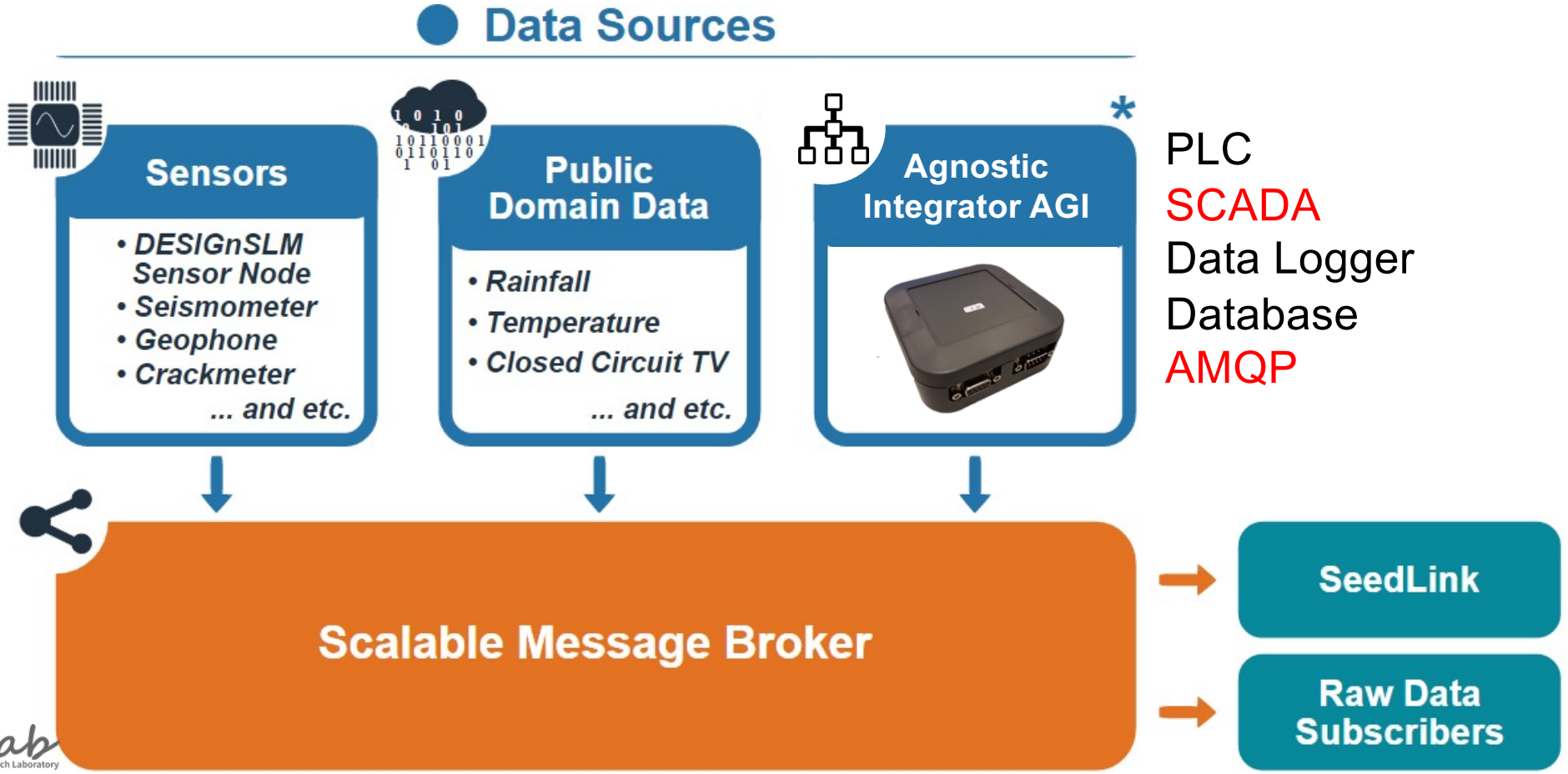

Sensor Design
Data Collection
Big Data
Artificial Intelligence
Semantic Integration
D E S R
Data Collection
DESRlab
Data-Enabled Scalable Research Laboratory

Unified Data Collection



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Agnostic integrator

RS232

Other Sensors

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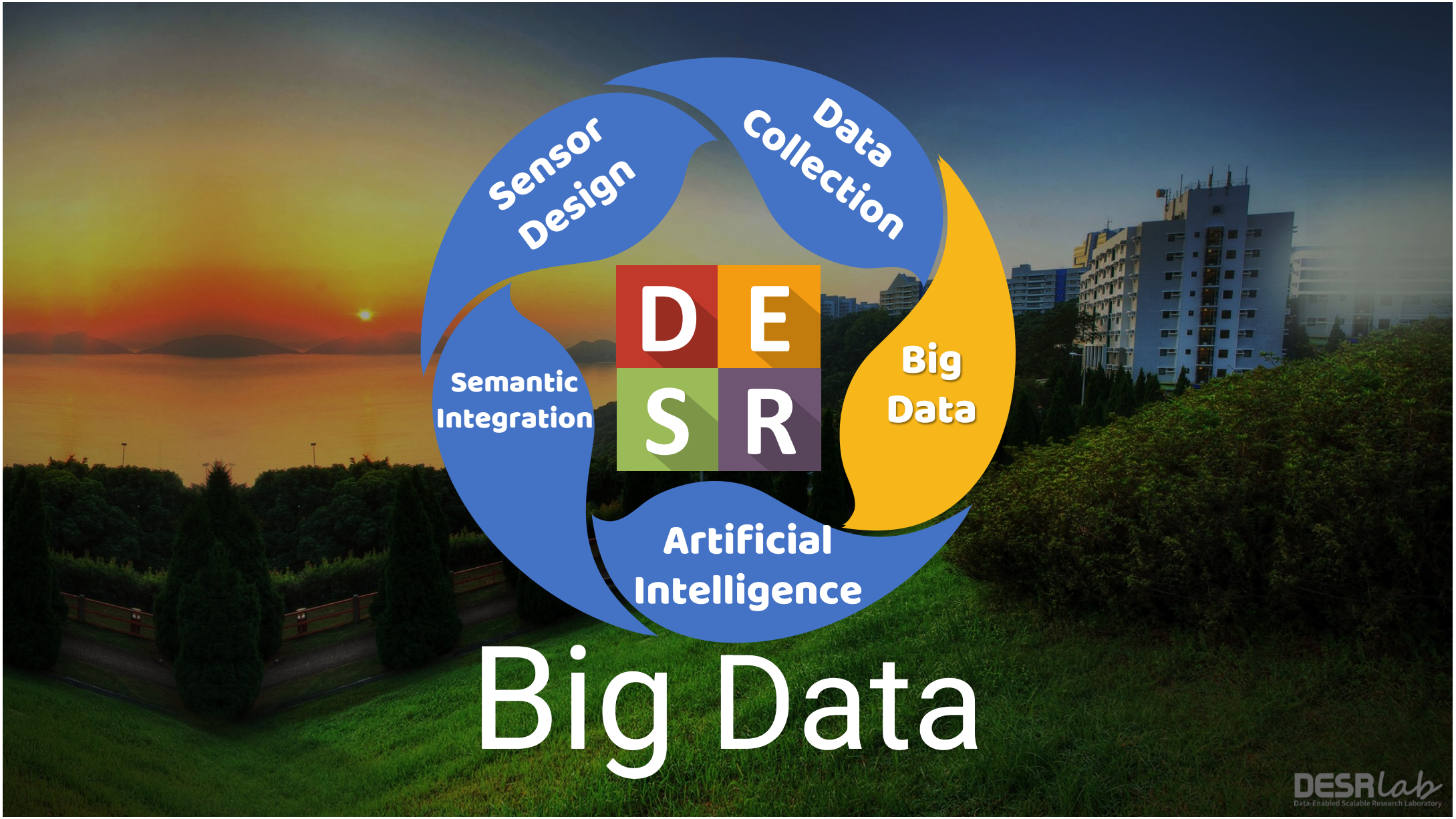
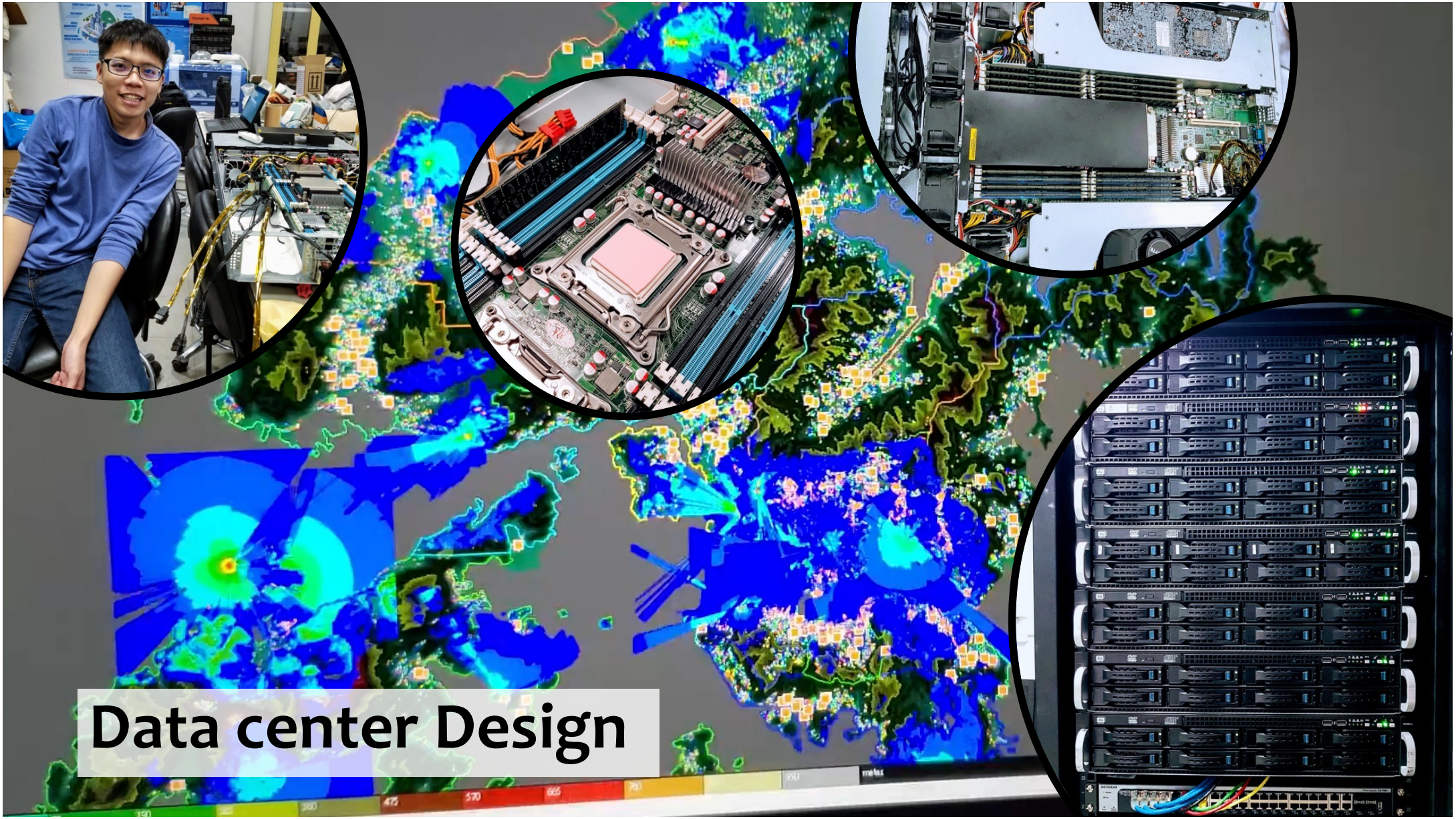
Data-Enabled Scalable Research Laboratory

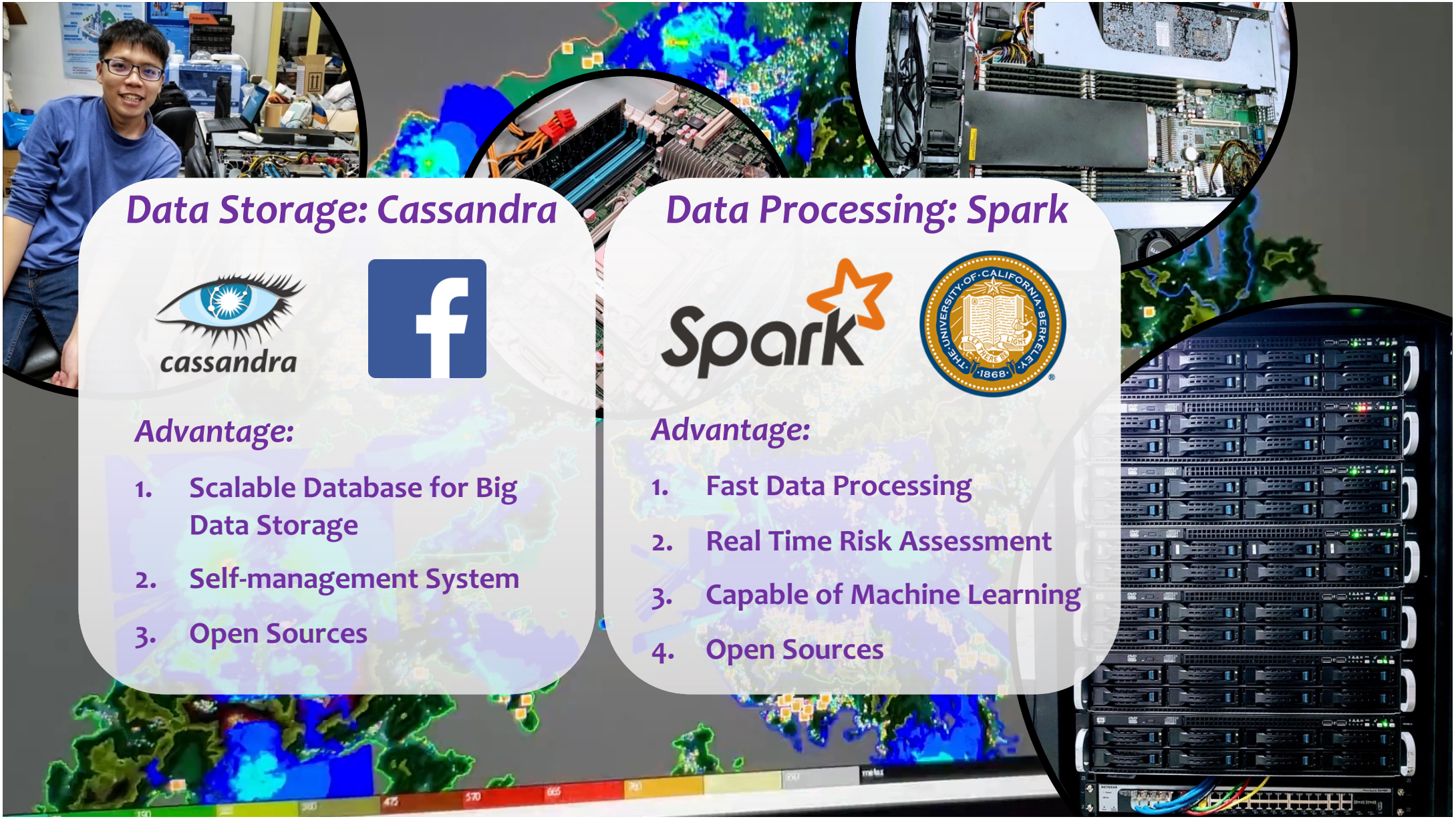
Patent-pending Military Grade Trusted Data Loggers

- On-device battery, DGPS location
- Guarantied Delivery to Server
- GPS Time Sync
- Data Compression
- Redundant CPU, Storage, Power, Sensor, Networking
- Self-monitoring and recovery
- Trusted Platform Modules-based security architecture
- Secure Boot
- Trusted Computing Group (TCG) standards
- Common Criteria (EAL4+) and FIPS security certification
- Transport Layer Security (TLS) for all data transfer

DESRlab
Data-Enabled Scalable Research Laboratory


Sensor Design
Data Collection
Big Data
Artificial Intelligence
Semantic Integration
D E S R
Big Data
DESRlab
Data-Enabled Scalable Research Laboratory


Data center Design



Data Storage: Cassandra

cassandra

Advantage:

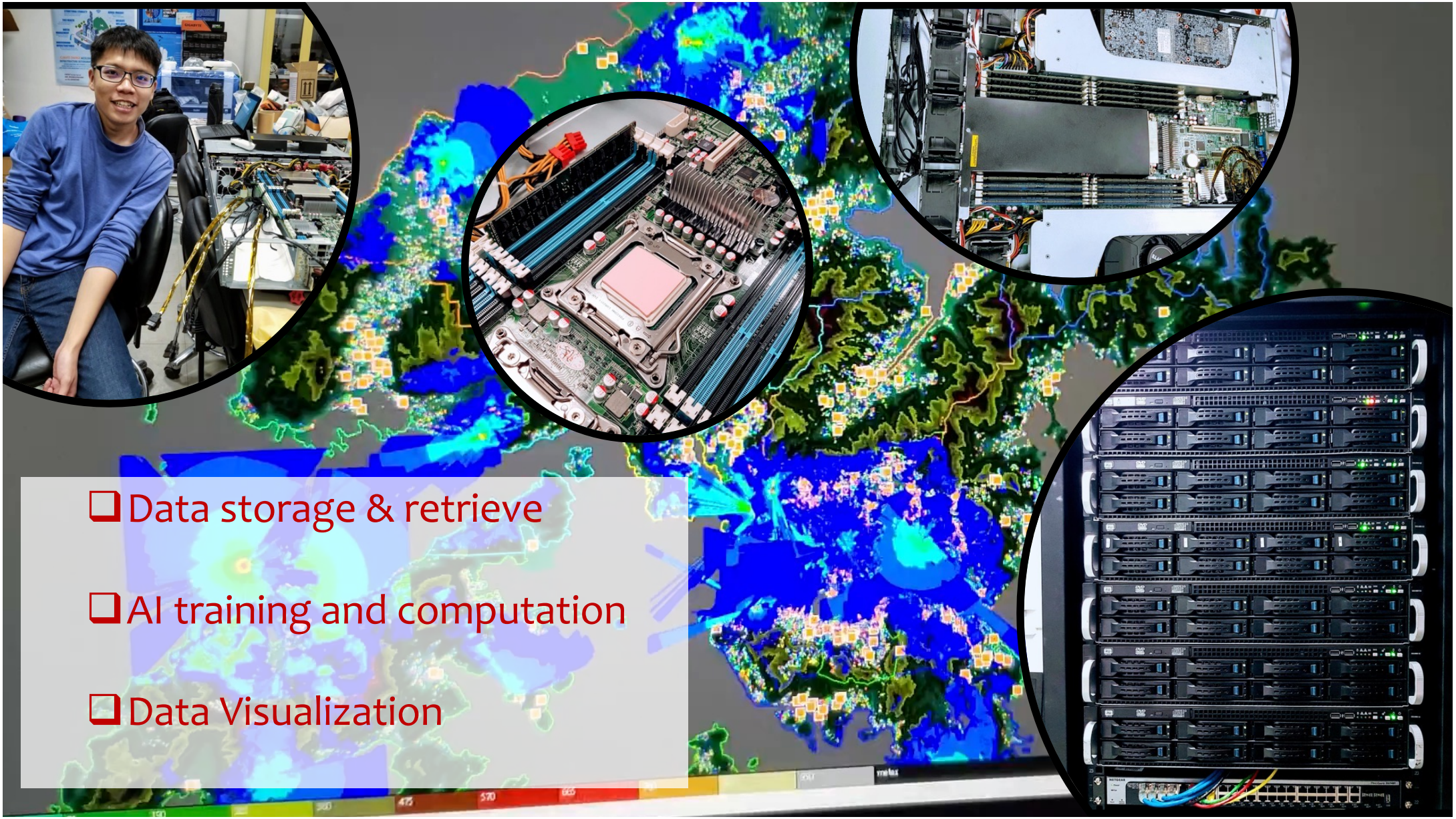
1. Scalable Database for Big Data Storage
2. Self-management System
3. Open Sources

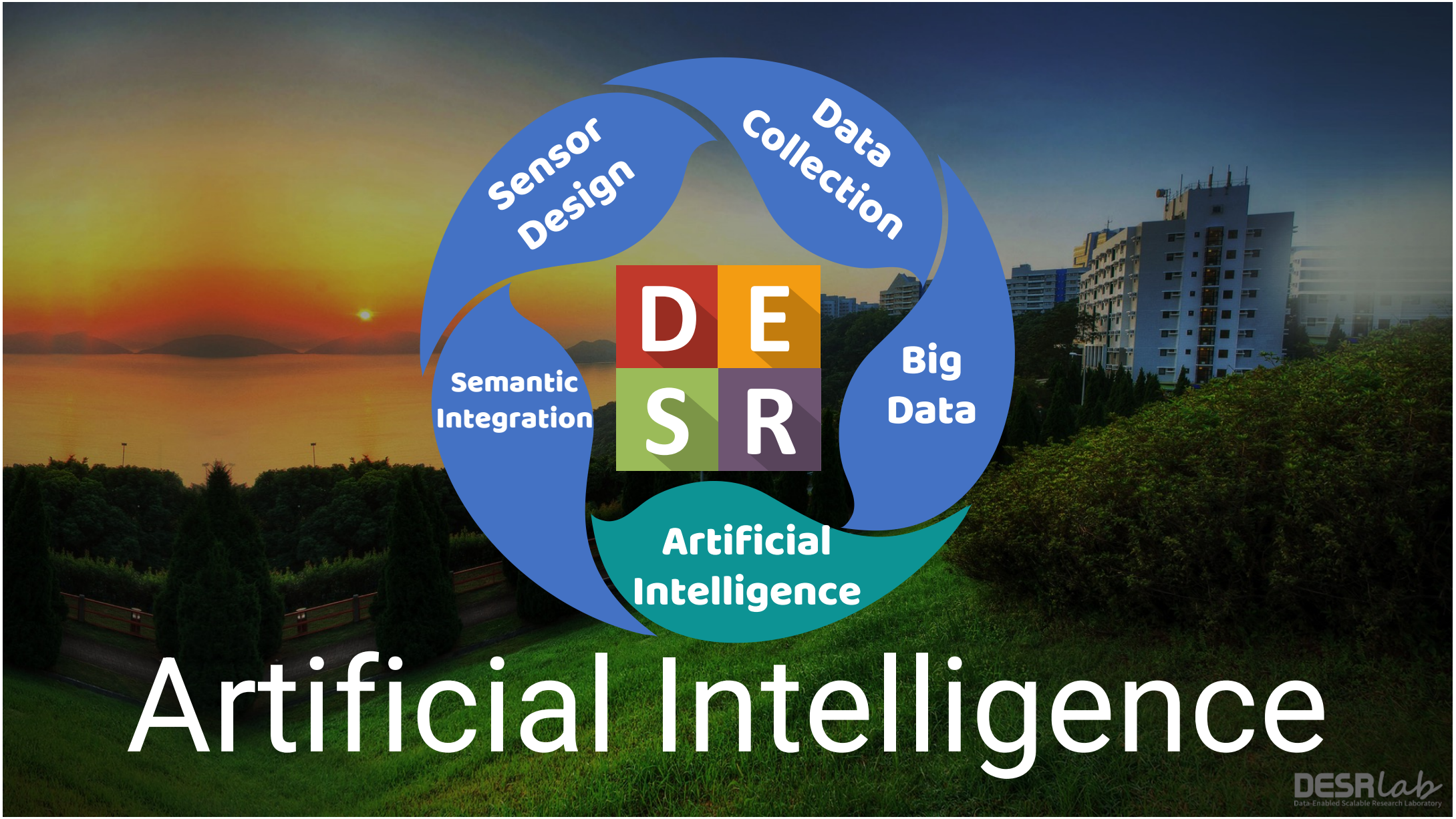
Data Processing: Spark

Spark

Advantage:

1. Fast Data Processing
2. Real Time Risk Assessment
3. Capable of Machine Learning
4. Open Sources


❑ Data storage & retrieve
❑ AI training and computation
❑ Data Visualization


Sensor Design
Data Collection
Semantic Integration
Big Data
Artificial Intelligence
D E S R
Artificial Intelligence
DESRlab
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AlphaGo
Deep Learning
DESRlab
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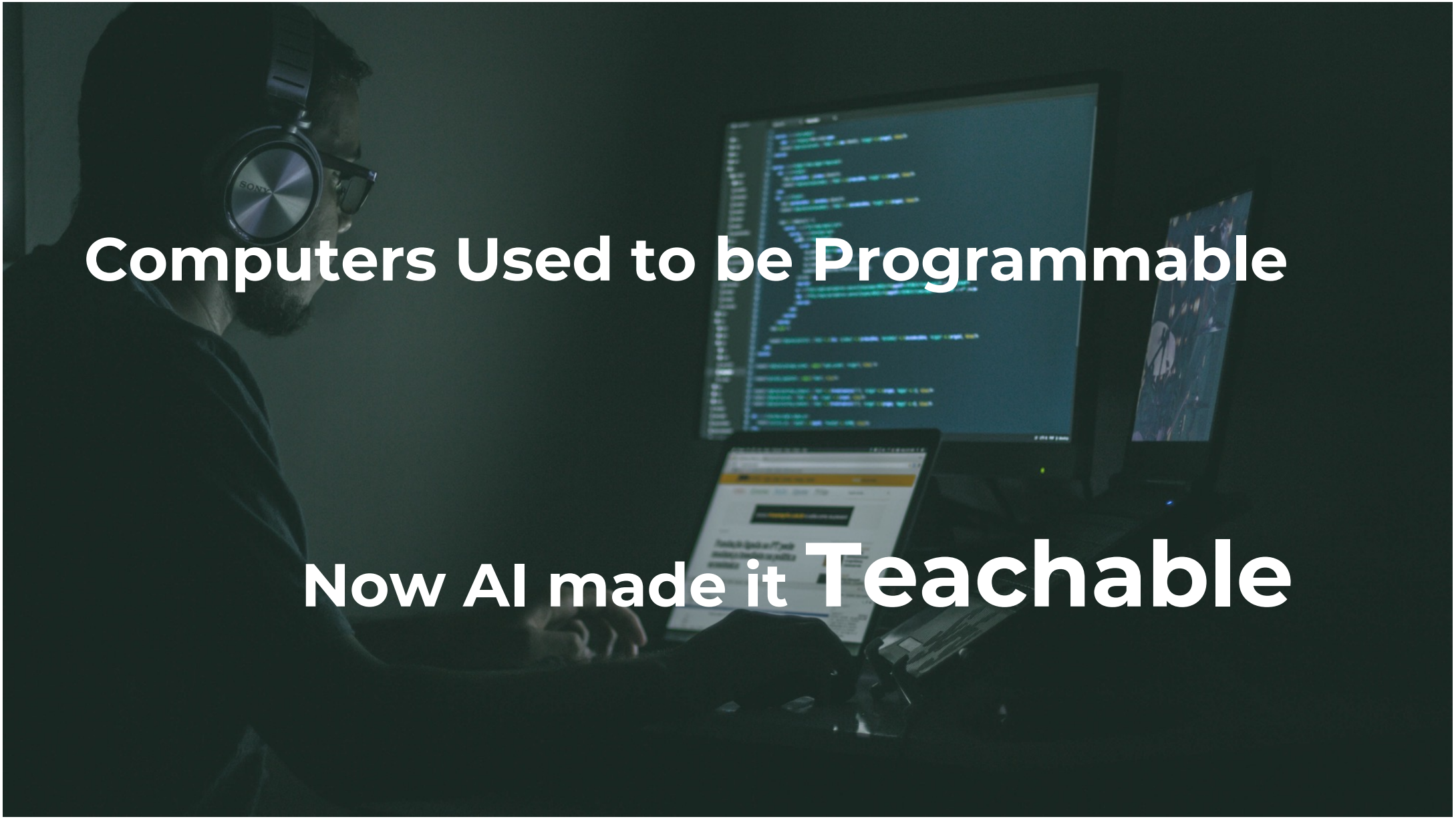
AI isn't the future; **It's the now.**

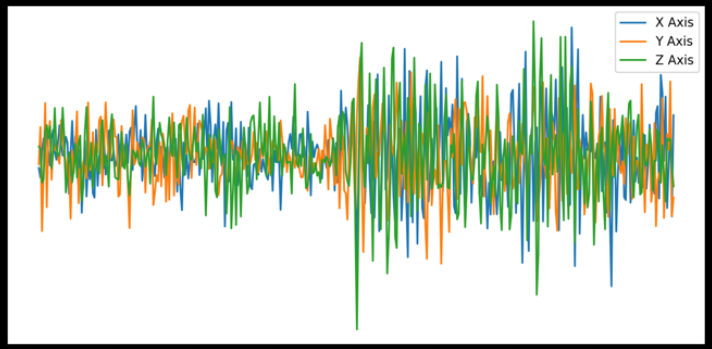
Already more than half of Fortune 500 CEOs say their company is using these technologies to improve efficiency.

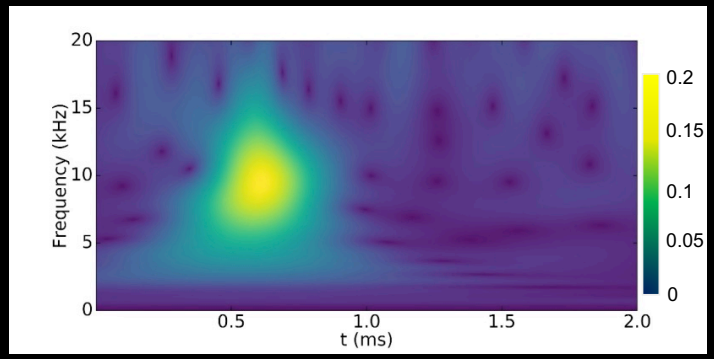
Artificial Intelligence in Construction Market Estimated to Generate a Revenue of $2,642.4 Million by 2026, Growing at a CAGR of 26.3% from 2019 to 2026 - Exclusive Business Report by Research Dive

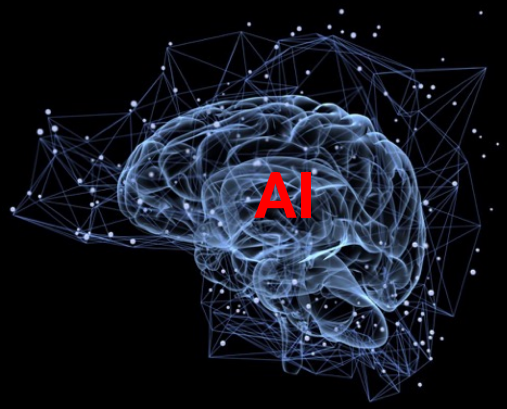

Computers Used to be Programmable
Now AI made it Teachable

To process...

Time series data (frequency domain)

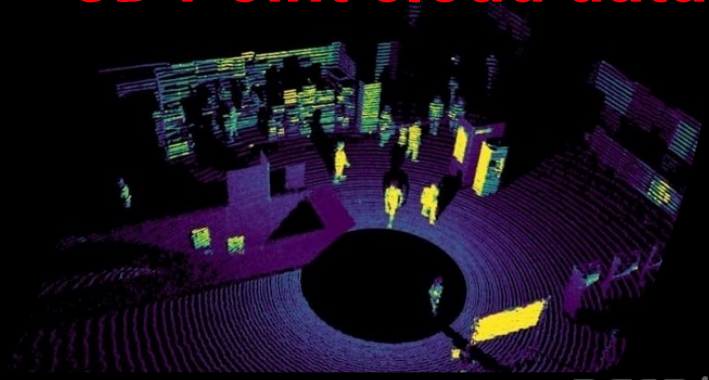






2D Image data

3D Point cloud data



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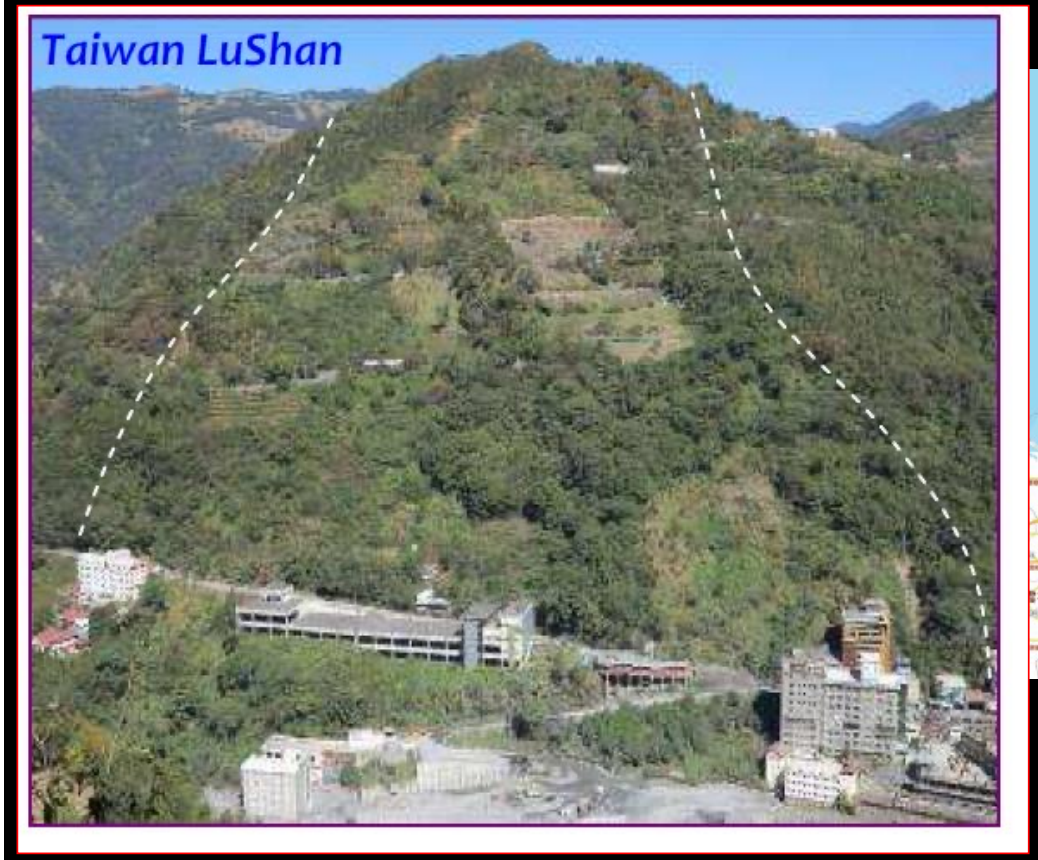
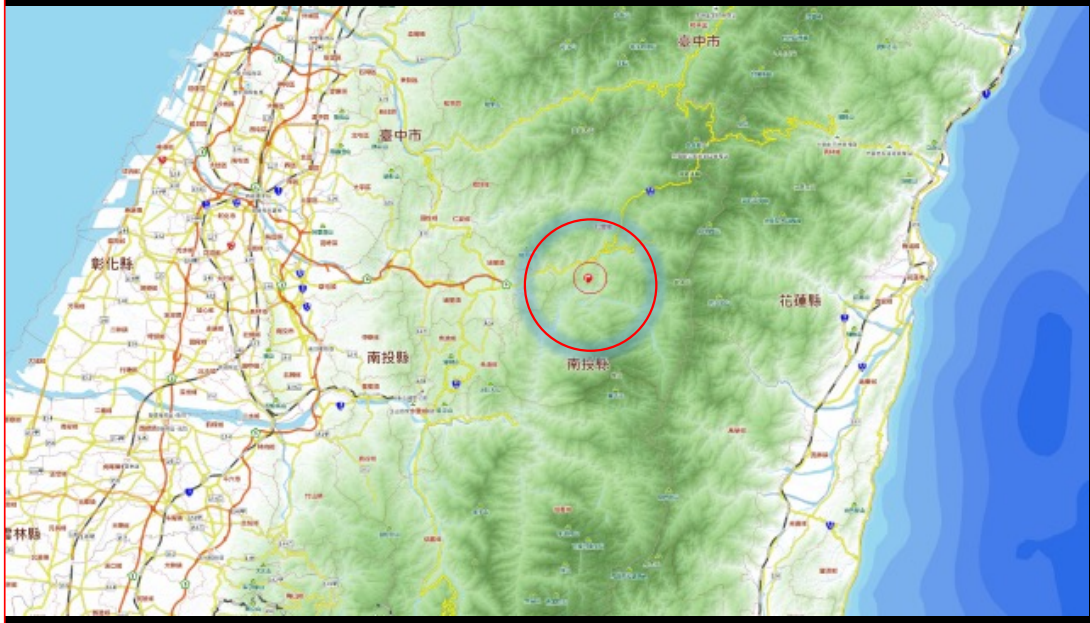
Landslide monitoring





Lushan,
Central Part of Taiwan
(starting from 2013)

DESRlab
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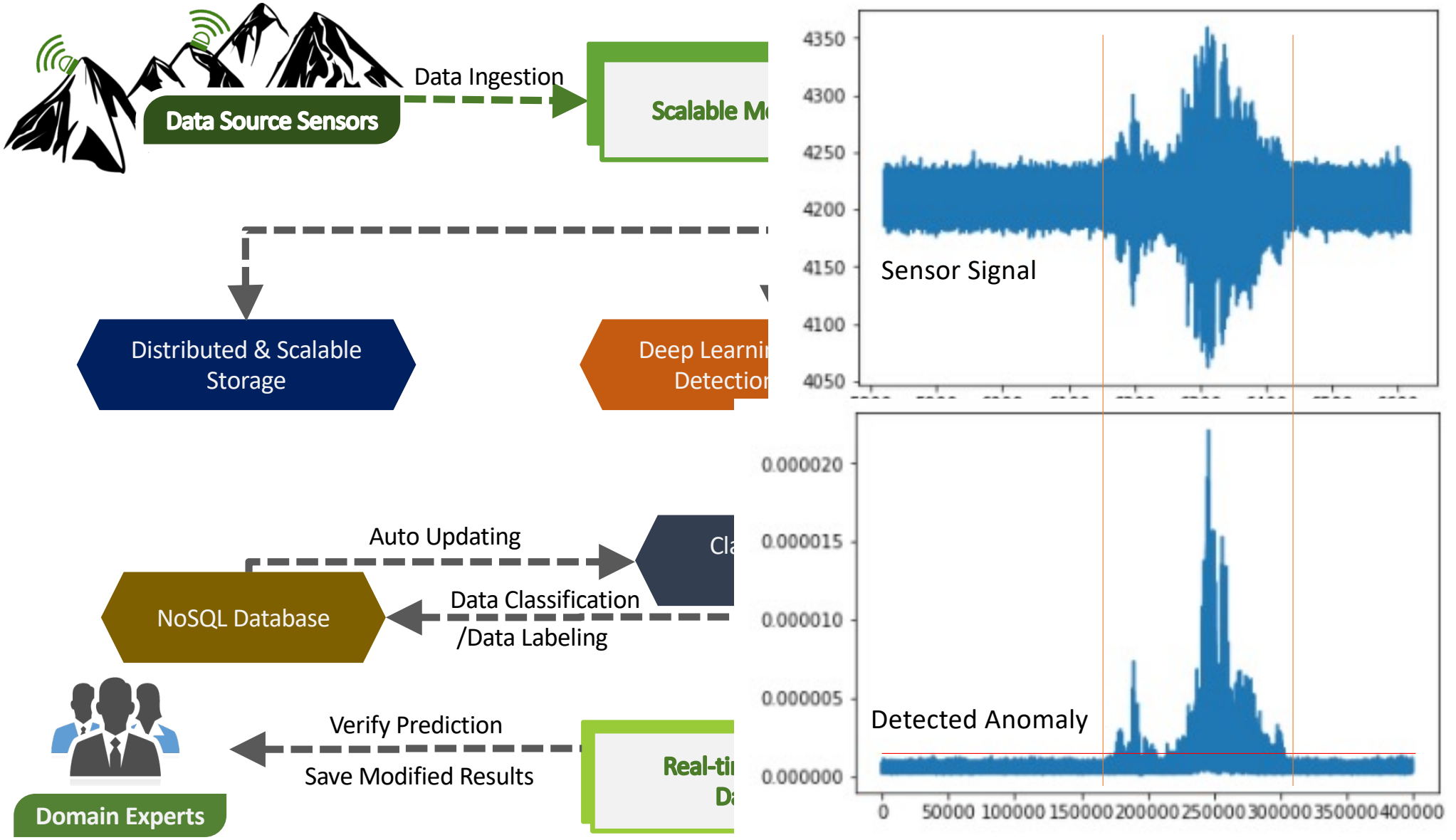
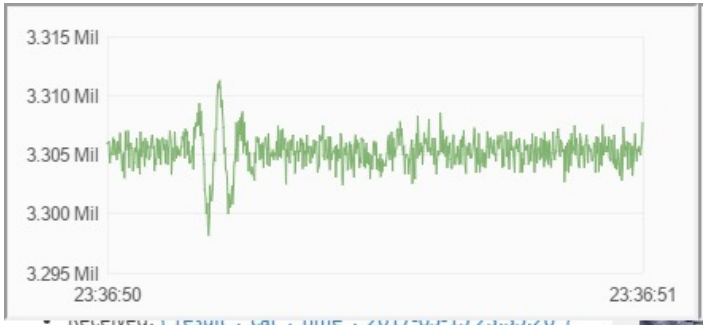
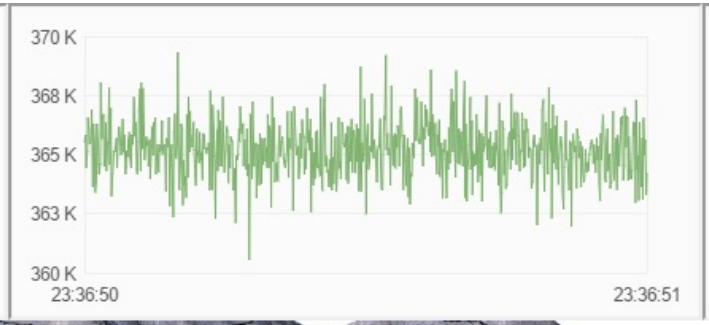
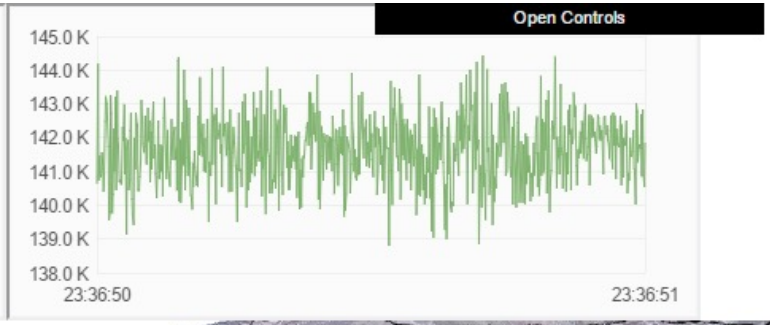
GPS Antenna
Solar Panel
with Battery
Control Module
Sensor Module
Lu Shan, Taiwan

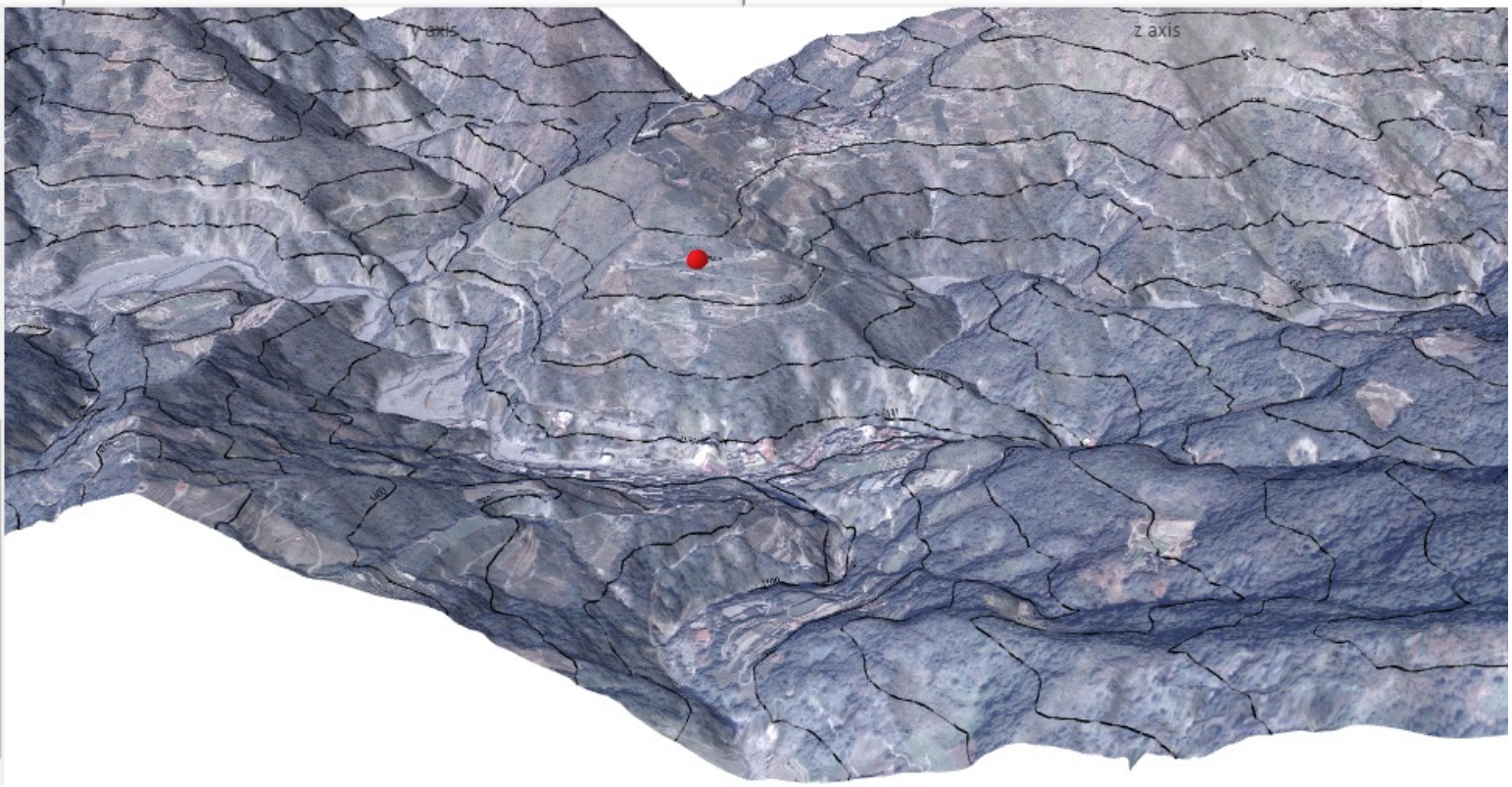

Data Source Sensors
Data Ingestion
Scalable M
Distributed & Scalable Storage
Deep Learni
Detectio
Auto Updating
Cl
NoSQL Database
Data Classification /Data Labeling
Verify Prediction
Save Modified Results
Real-ti
D
Domain Experts
Sensor Signal
Detected Anomaly
4350
4300
4250
4200
4150
4100
4050
0.000020
0.000015
0.000010
0.000005
0.000000
0
50000
100000
150000
200000
250000
300000
350000
400000







- Received: {"result":"abnormal wave","time":"2017-05-15 23:35:22"}
- Received: {"result":"car","time":"2017-05-15 23:35:24"}
- Received: {"result":"car","time":"2017-05-15 23:35:25"}
- Received: {"result":"car","time":"2017-05-15 23:35:27"}
- Received: {"result":"car","time":"2017-05-15 23:35:29"}
- Received: {"result":"earthquake","time":"2017-05-15 23:35:33"}
- Received: {"result":"car","time":"2017-05-15 23:35:35"}
- Received: {"result":"car","time":"2017-05-15 23:35:37"}
- Received: {"result":"car","time":"2017-05-15 23:35:41"}
- Received: {"result":"car","time":"2017-05-15 23:35:44"}
- Received: {"result":"car","time":"2017-05-15 23:35:51"}
- Received: {"result":"car","time":"2017-05-15 23:35:56"}
- Received: {"result":"car","time":"2017-05-15 23:36:22"}
- Received: {"result":"abnormal wave","time":"2017-05-15 23:36:24"}
- Received: {"result":"car","time":"2017-05-15 23:36:29"}
- Received: {"result":"car","time":"2017-05-15 23:36:33"}
- Received: {"result":"car","time":"2017-05-15 23:36:35"}
- Received: {"result":"car","time":"2017-05-15 23:36:41"}
- Received: {"result":"car","time":"2017-05-15 23:36:43"}
- Received: {"result":"abnormal wave","time":"2017-05-15 23:36:50"}



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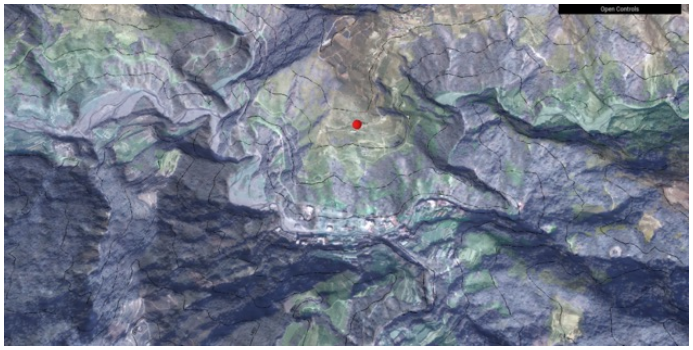
Data Source Sensors

Data Ingestion

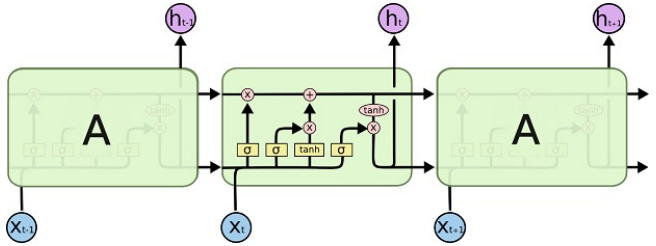
Scalable Message Broker

Sensor Signal



Distributed & Scalable Storage

Deep Learning Anomaly Detection Engine



Abnormal Data Filtering

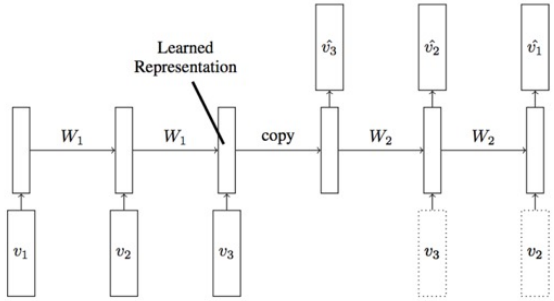
Auto Updating

Classification Engine

NoSQL Database

Data Classification /Data Labeling

Prediction



Domain Experts

Verify Prediction

Save Modified Results

Real-time Interactive Dashboard

DESRlab
Data-Enabled Scalable Research Laboratory

Deep Learning for Landslide inventory mapping

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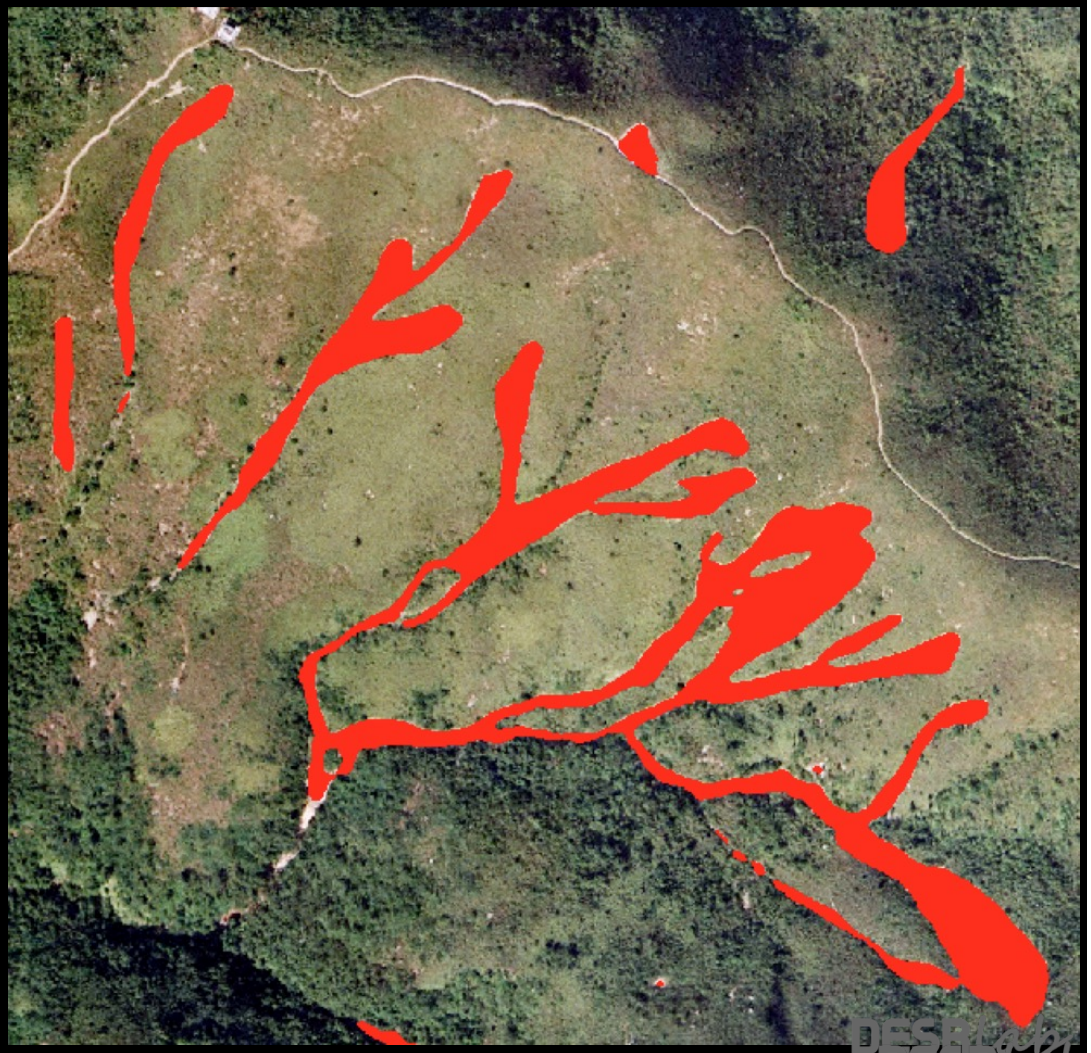
Data-Enabled Scalable Research Laboratory

AI
(deep learning)

DESRlab
Data-Enabled Scalable Research Laboratory

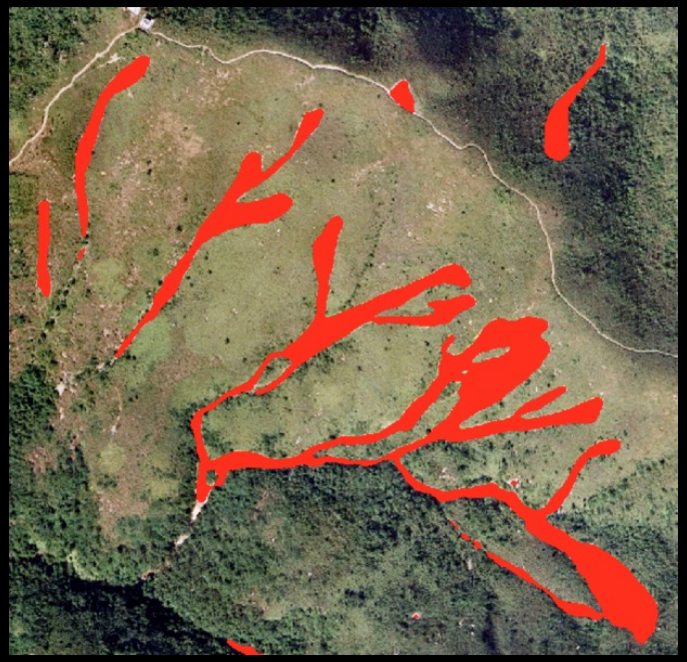
ENTLI (by Human experts)

By deep learning



Su et al. 2020

Sub-area A

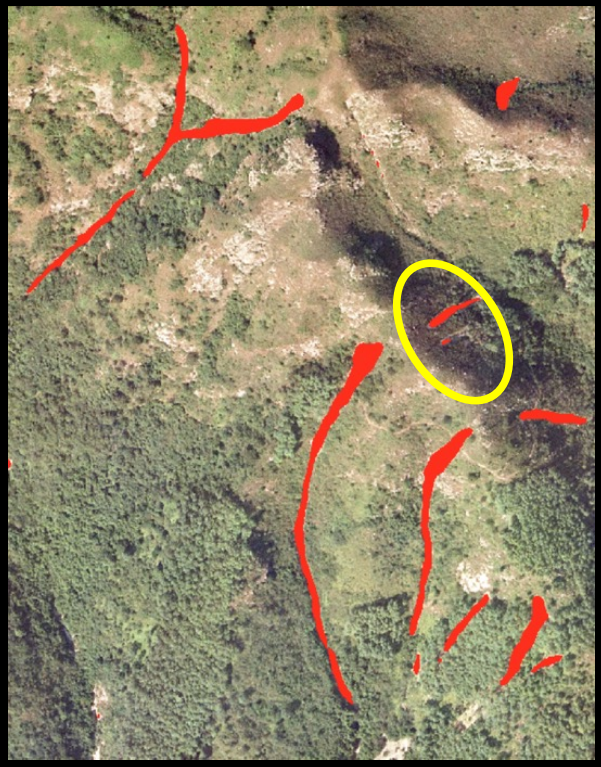


Proposed LanDCNN Model (deep learning)

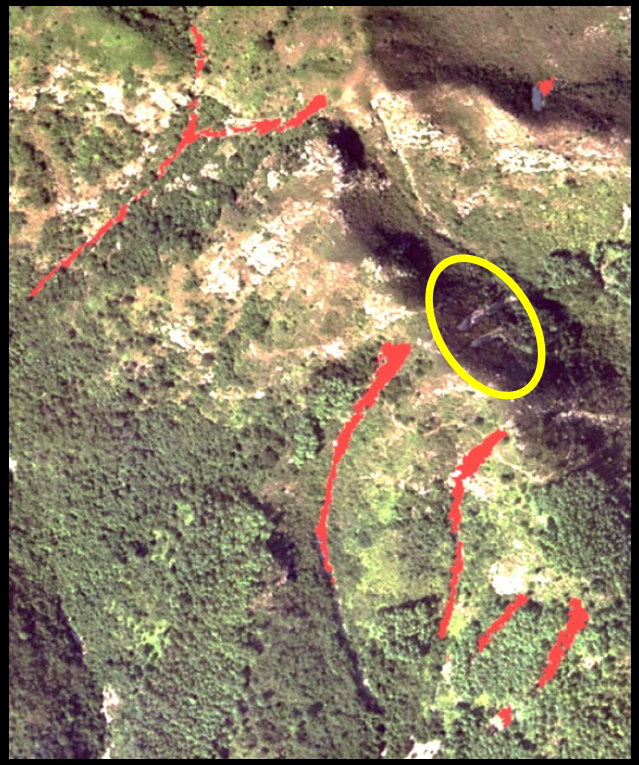
Classical machine learning

Zu et al. 2020

Sub-area B



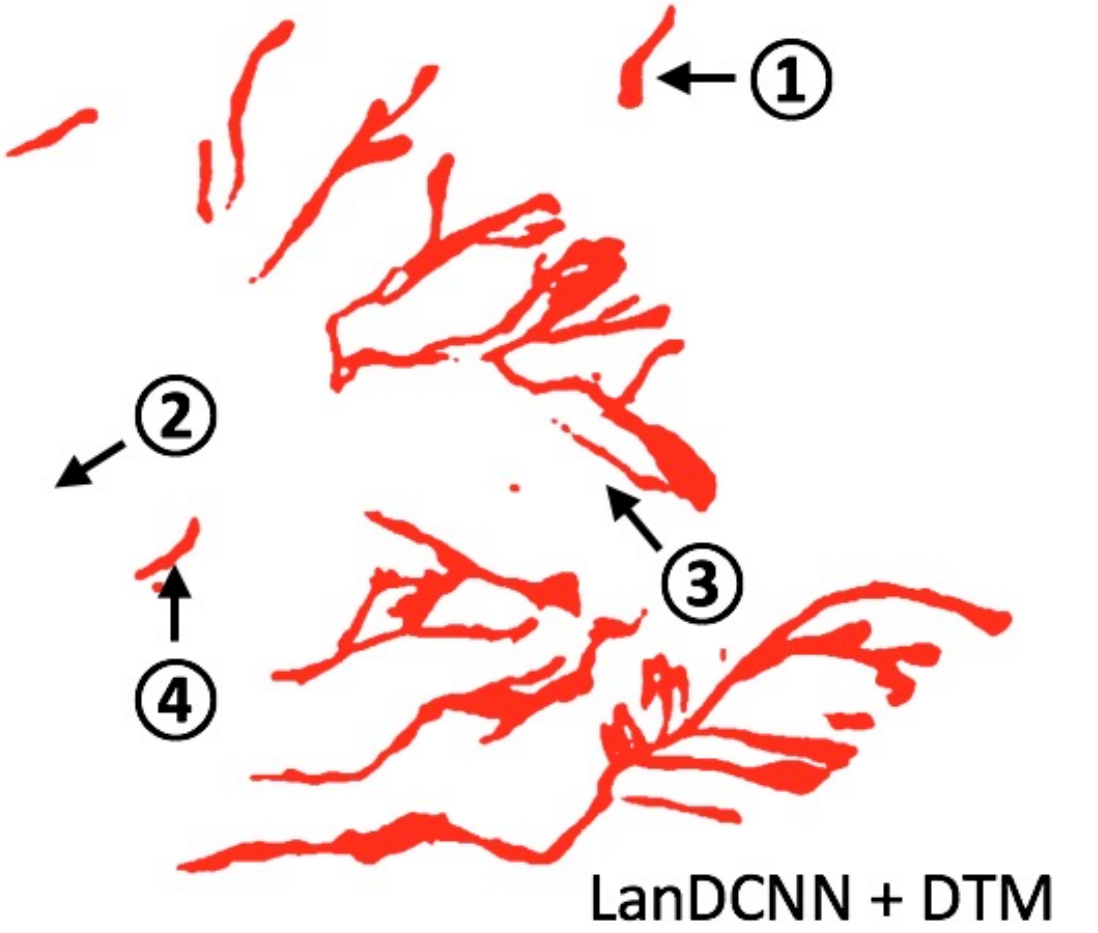
Proposed LanDCNN Model (deep learning model)

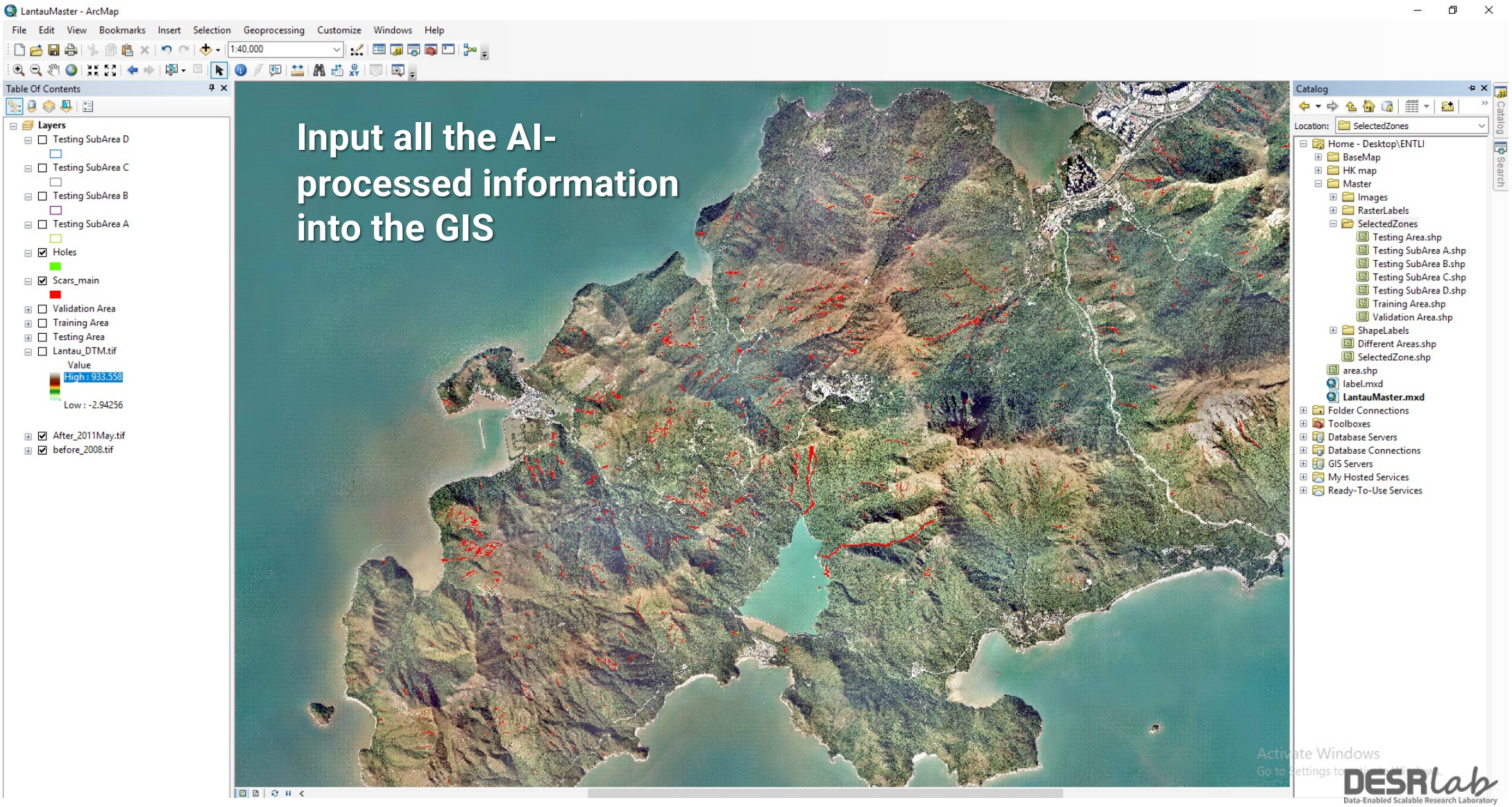


Classical machine learning

Su et al. 2020

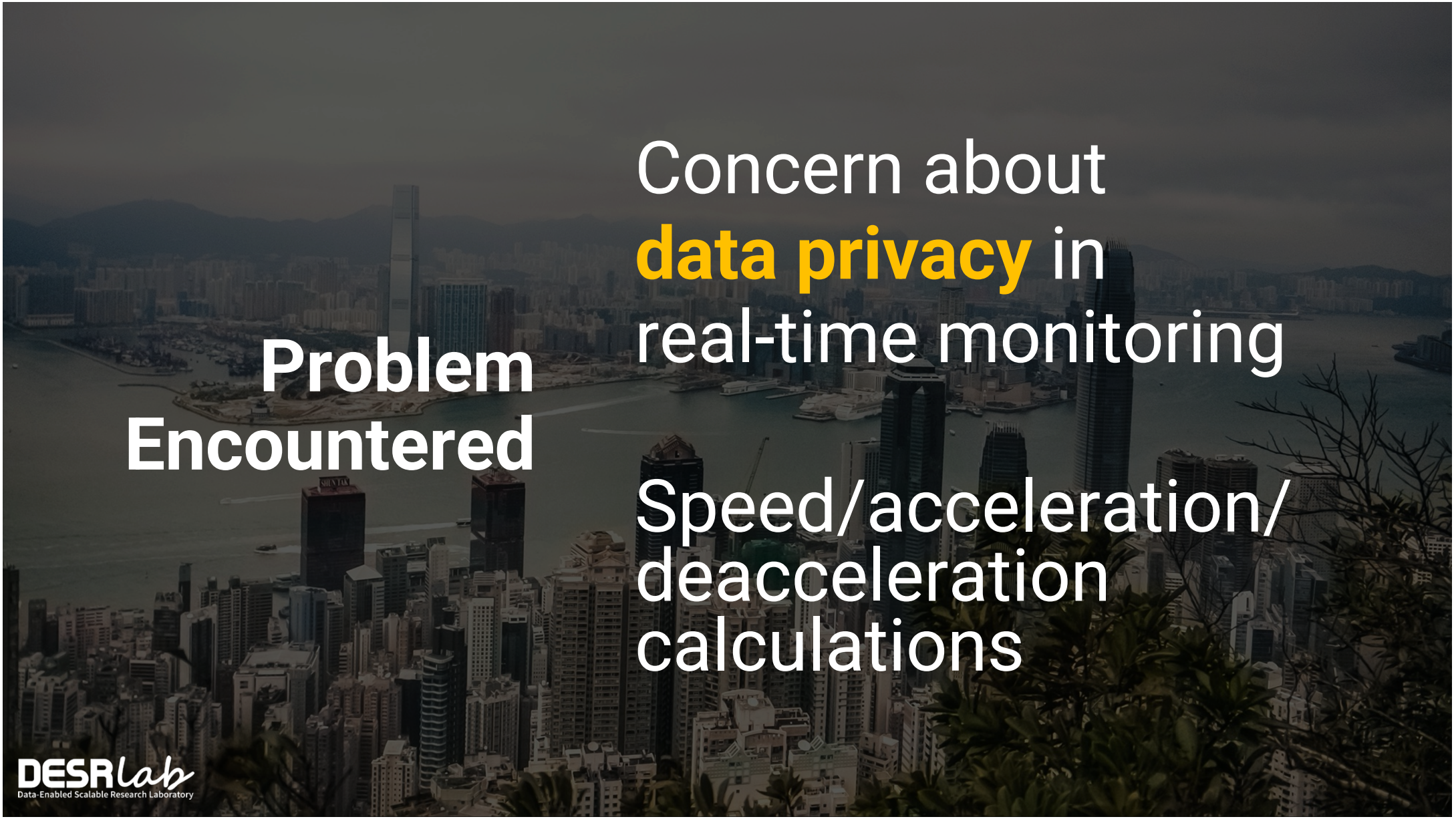
By deep learning




LantauMaster - ArcMap
File Edit View Bookmarks Insert Selection Geoprocessing Customize Windows Help
1:40,000
Table Of Contents
Layers
Testing SubArea D
Testing SubArea C
Testing SubArea B
Testing SubArea A
Holes
Scars_main
Validation Area
Training Area
Testing Area
Lantau_DTM.tif
Value
High : 933.558
Low : -2.94256
After_2011May.tif
before_2008.tif
Input all the AI-processed information into the GIS
Catalog
Location: SelectedZones
Home - Desktop\ENTLI
BaseMap
HK map
Master
Images
RasterLabels
SelectedZones
Testing Area.shp
Testing SubArea A.shp
Testing SubArea B.shp
Testing SubArea C.shp
Testing SubArea D.shp
Training Area.shp
Validation Area.shp
ShapeLabels
Different Areas.shp
SelectedZone.shp
area.shp
label.mxd
LantauMaster.mxd
Folder Connections
Toolboxes
Database Servers
Database Connections
GIS Servers
My Hosted Services
Ready-To-Use Services
Activate Windows
DESRlab
Data-Enabled Scalable Research Laboratory

Deep learning
for Environmental Monitoring &
Conservation
Green AI
DESRlab
Data-Enabled Scalable Research Laboratory

Street air
pollution
from the
vehicle fleet
DESRlab
Data-Enabled Scalable Research Laboratory


Problem Encountered
Concern about data privacy in real-time monitoring
Speed/acceleration/ deacceleration calculations
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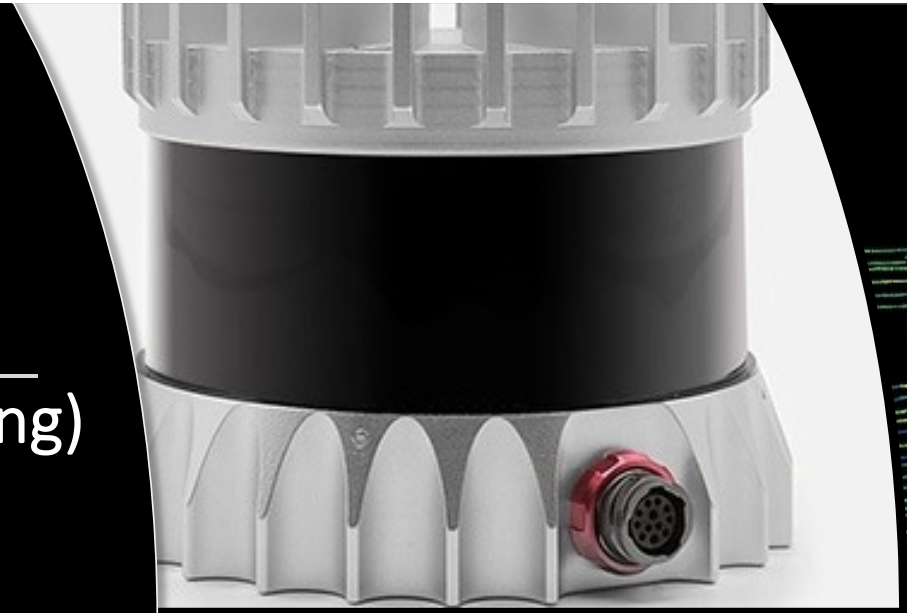
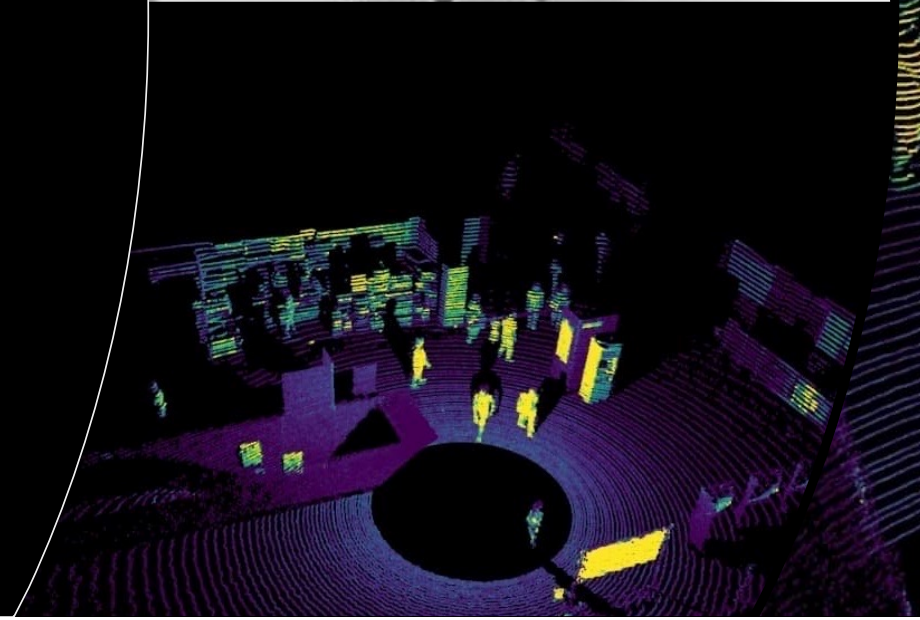
Data-Enabled Scalable Research Laboratory

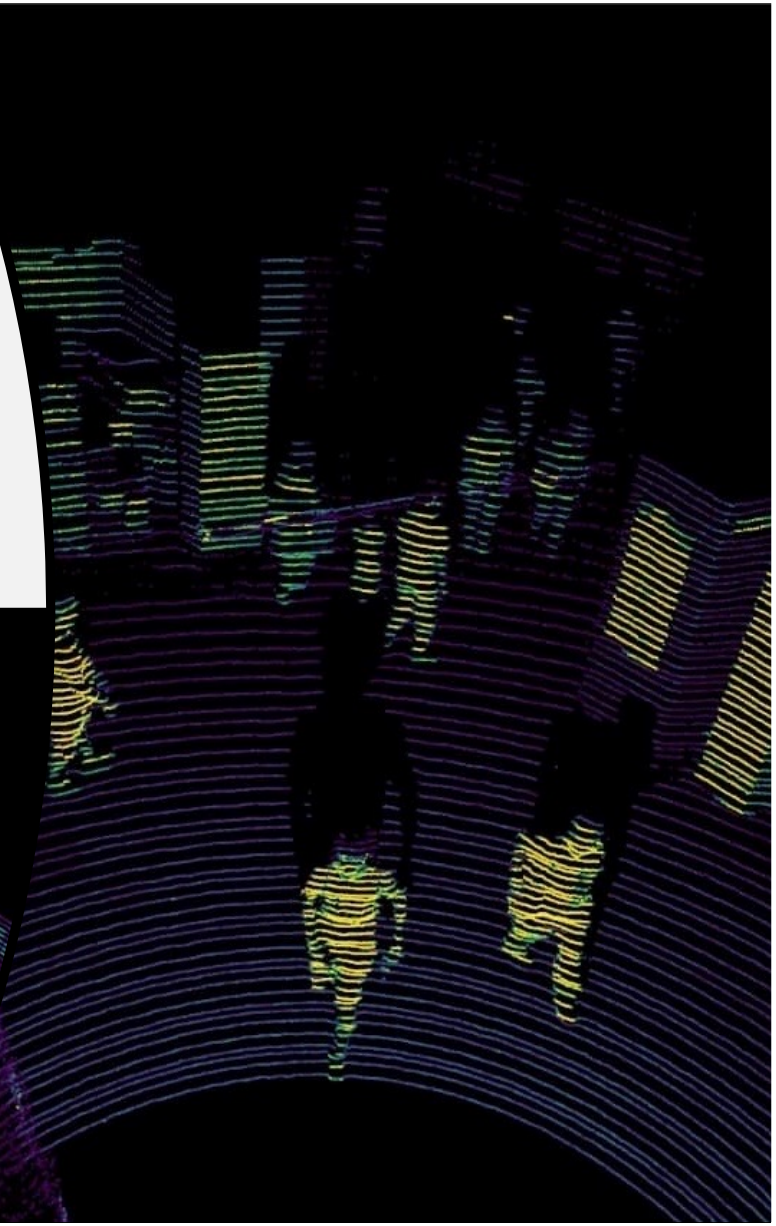
Solution:

LiDAR

(edge computing)







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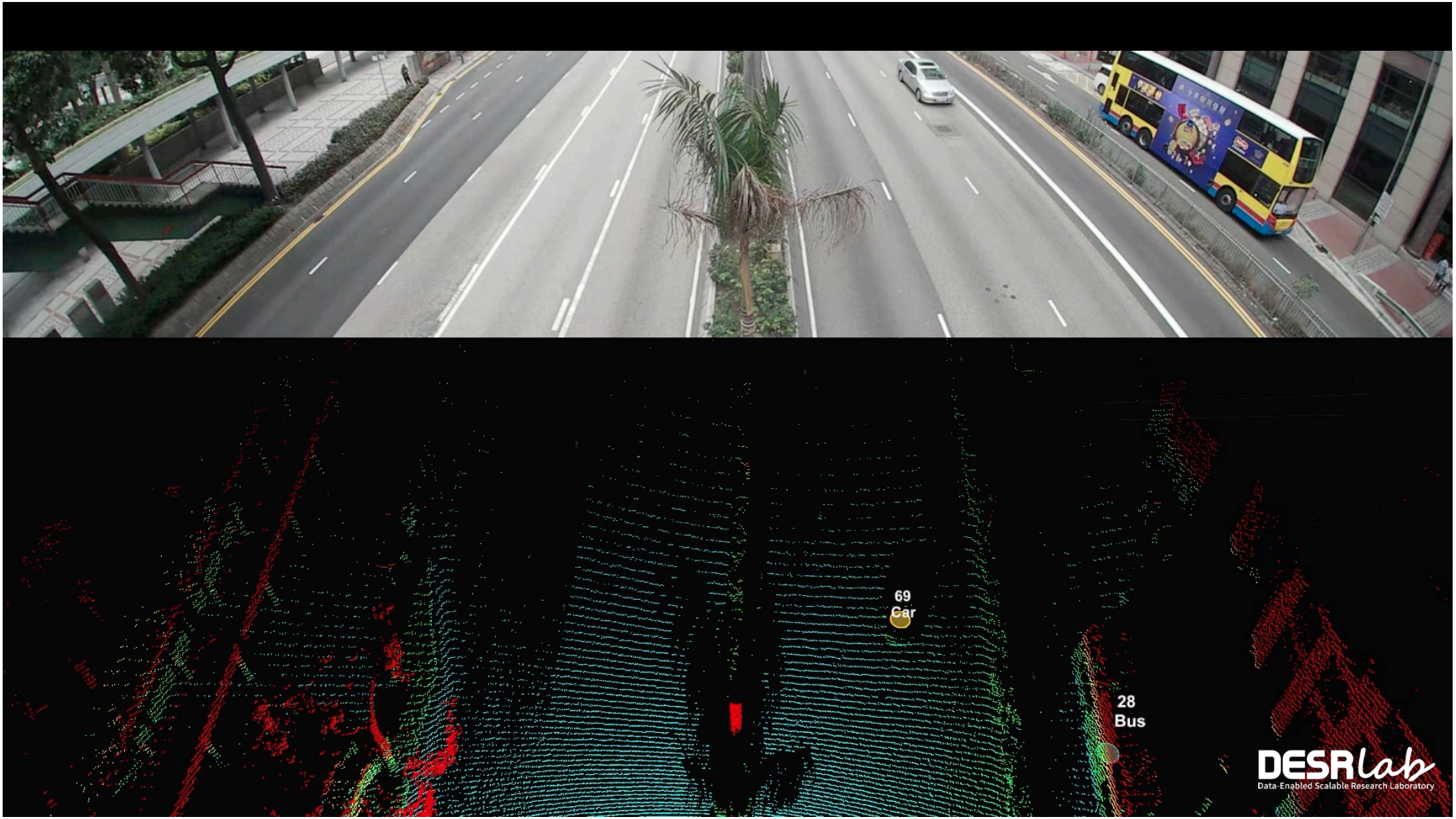
69
Car
28
Bus
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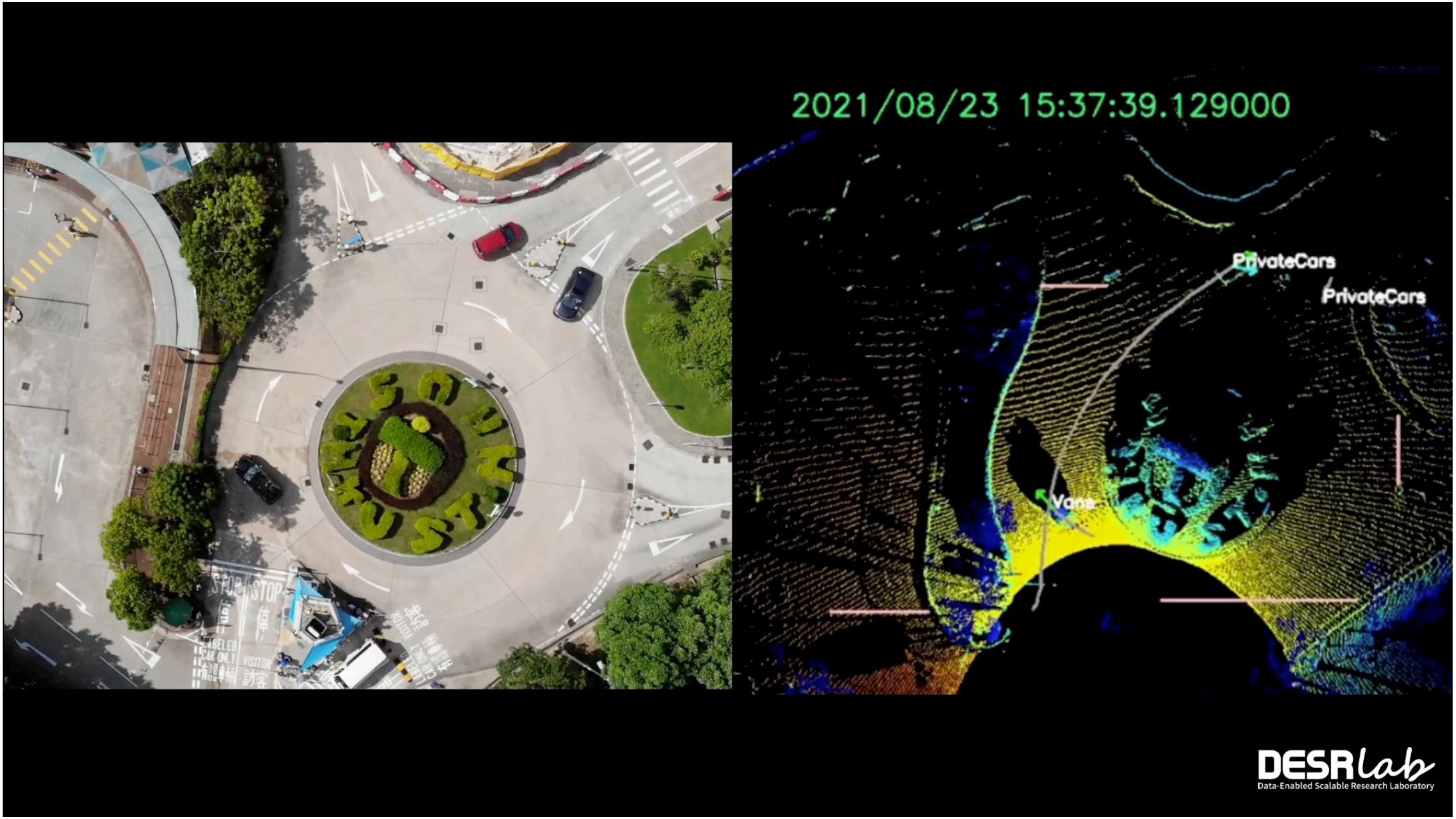
2021/08/23 15:37:39.129000
PrivateCars
PrivateCars
Vans
DESRlab
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Bird watching for the environmental impact assessment
DESRlab
Data-Enabled Scalable Research Laboratory

360° Camera with *Edge AI*

Six 4k cameras to capture high-resolution 360° view

Penfold Park (nesting area)

大白鷺 Great Egret
DESRlab
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小白鷺 Little Egret

DESRlab
Data-Enabled Scalable Research Laboratory

大白鷺 Great Egret
小白鷺 Little Egret
DESRlab
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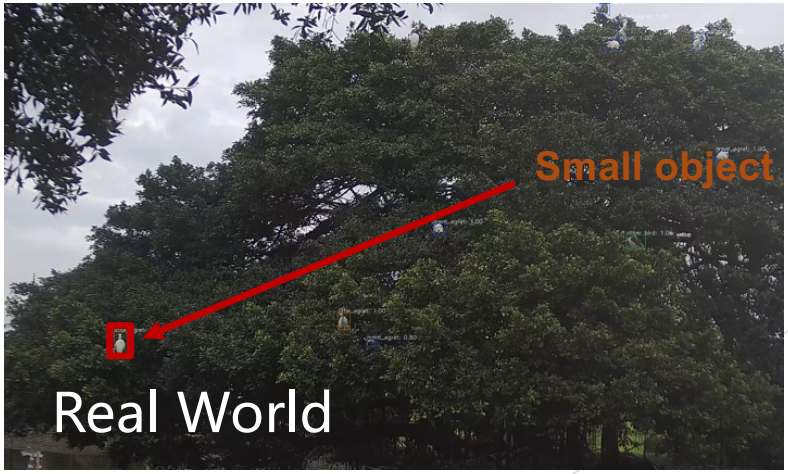
Challenges in model training

1. Bias and limited labelled datasets

- ❑ Common applications: MNIST, ImageNet, CIFAR, COCO
- ❑ Aves classification & detection: CUB-200-211, iNaturalist
  - • **Insufficient**; average no. of images per species: ~59 & ~114
  - • Images of species found at Hong Kong are **limited**
  - • **Small object;** Label data are usually display clear features



Mao et al. 2020

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Challenges in model training

2. Fine-grained object detection

- Subtle features, such as bill/beak color, the color surrounding eyes/lore, color/pattern of plumage, etc.; typically used by human to distinguish different bird species

- Prominent features: pose, orientation, distance to cameras; used by machine learning models to differentiate objects

- The AI models would be confused & misled if inconsistencies are found in the prominent features (partially covered by leaf)

Mao et al. 2020

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Difficulties in model training

3. Features of egrets vary with seasons

- Great egret
  - Breeding season : black bill, breeding plume, neon green lore
  - Normal season : yellow bill, no breeding plume

- Little egret
  - Breeding season : breeding plume, purple/red lore
  - Normal season : no breeding plume

Mao et al. 2020

Domain randomization

Synthesized bird dataset using 3D modelling

- ❑ 3D egret models, with specific attributes (size, shape, color of feathers, posture and flight pattern)
- ❑ Different perspectives of views (orientation angle, distance to camera)

Mao et al. 2020

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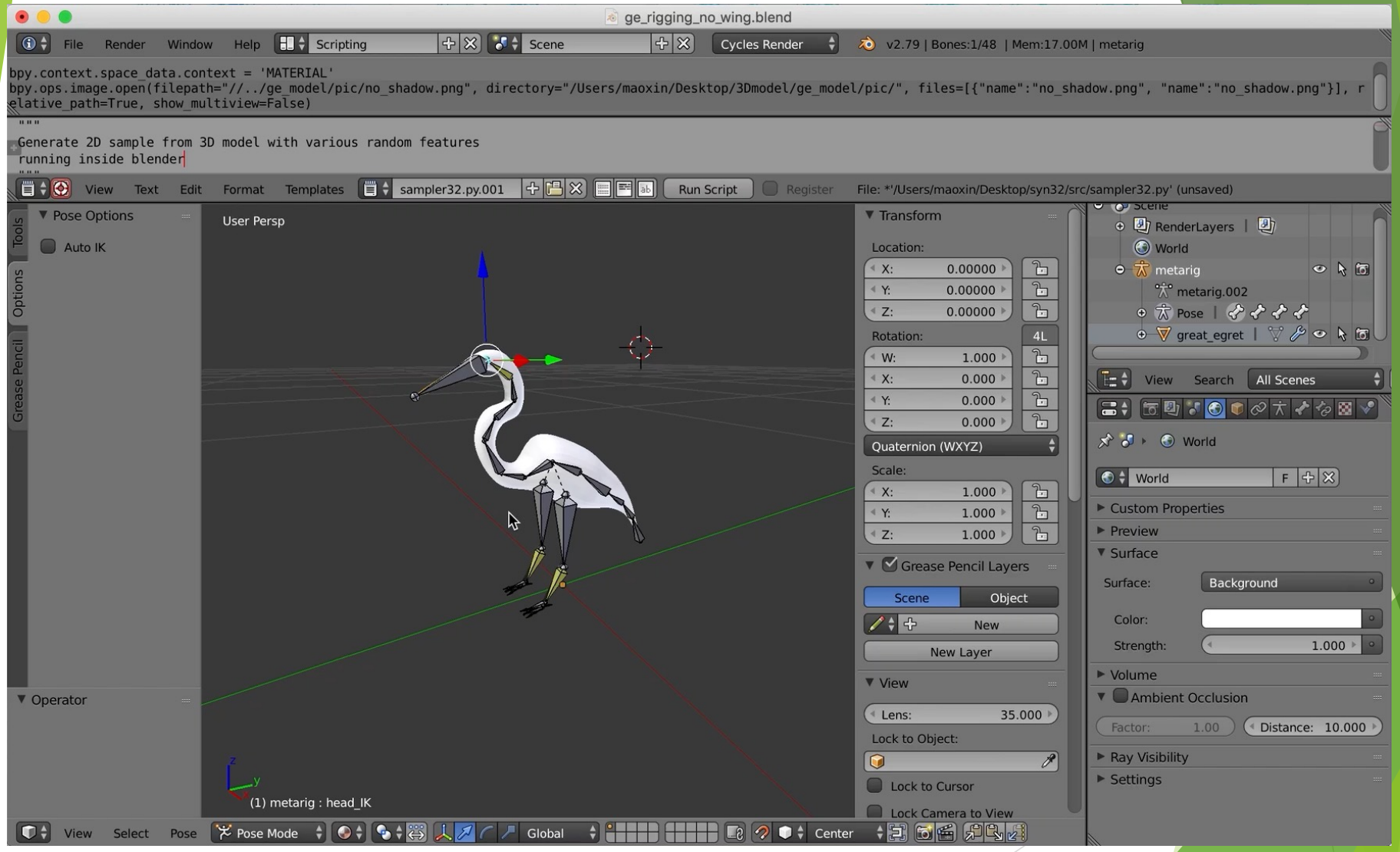

Mao et al. 2020

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Domain randomization

Mao et al. 2020

Results

Detected Birds

Mao et al. 2020

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Detected Birds

Mao et al. 2020

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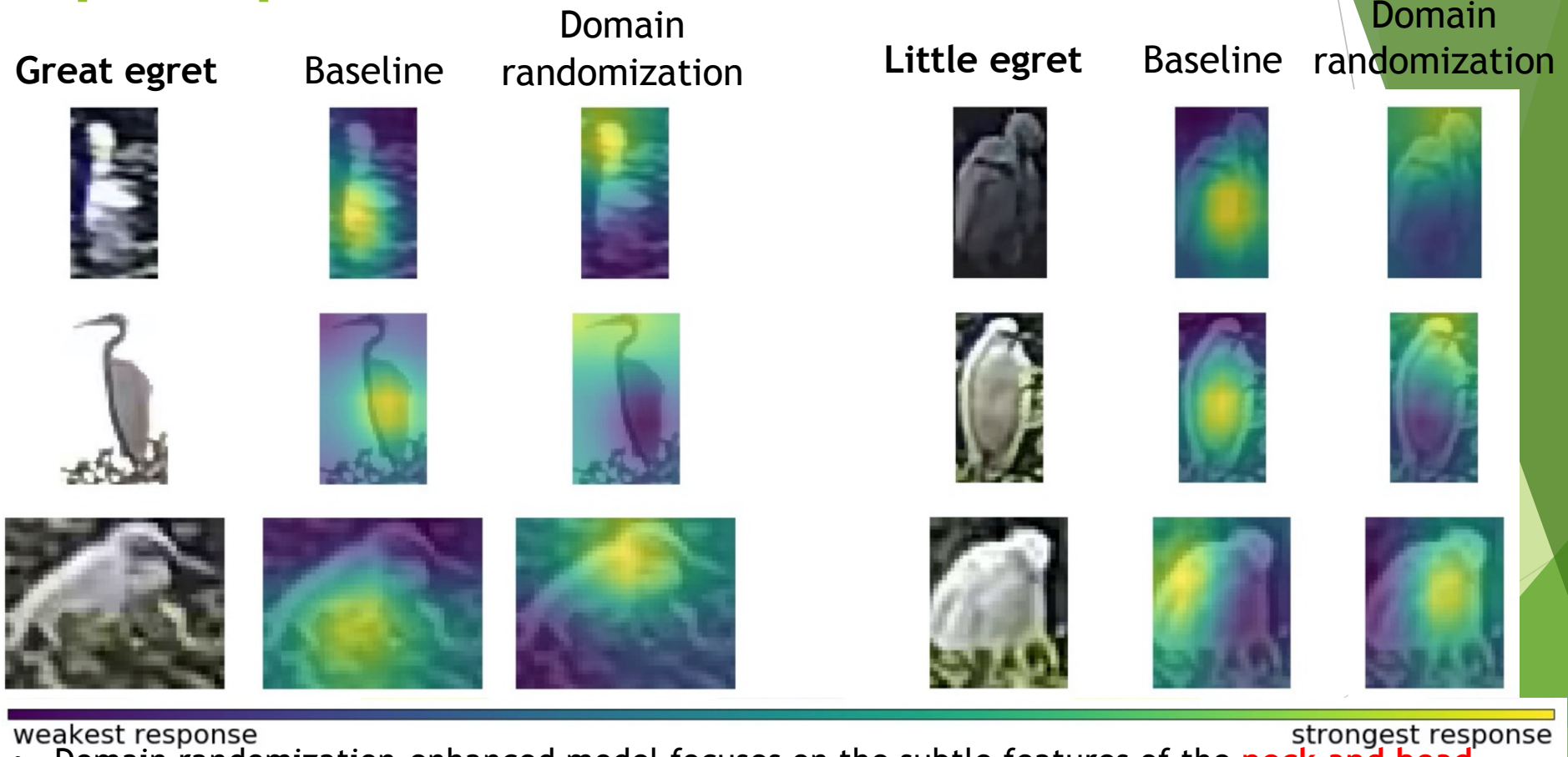
AI perception for bird detection



- Domain randomization-enhanced model focuses on the subtle features of the **neck and head**, (essential fine-grained features used by the experts to distinguish bird species).
- Conventional approach tends to identify bird species from the color and textural features of the body.

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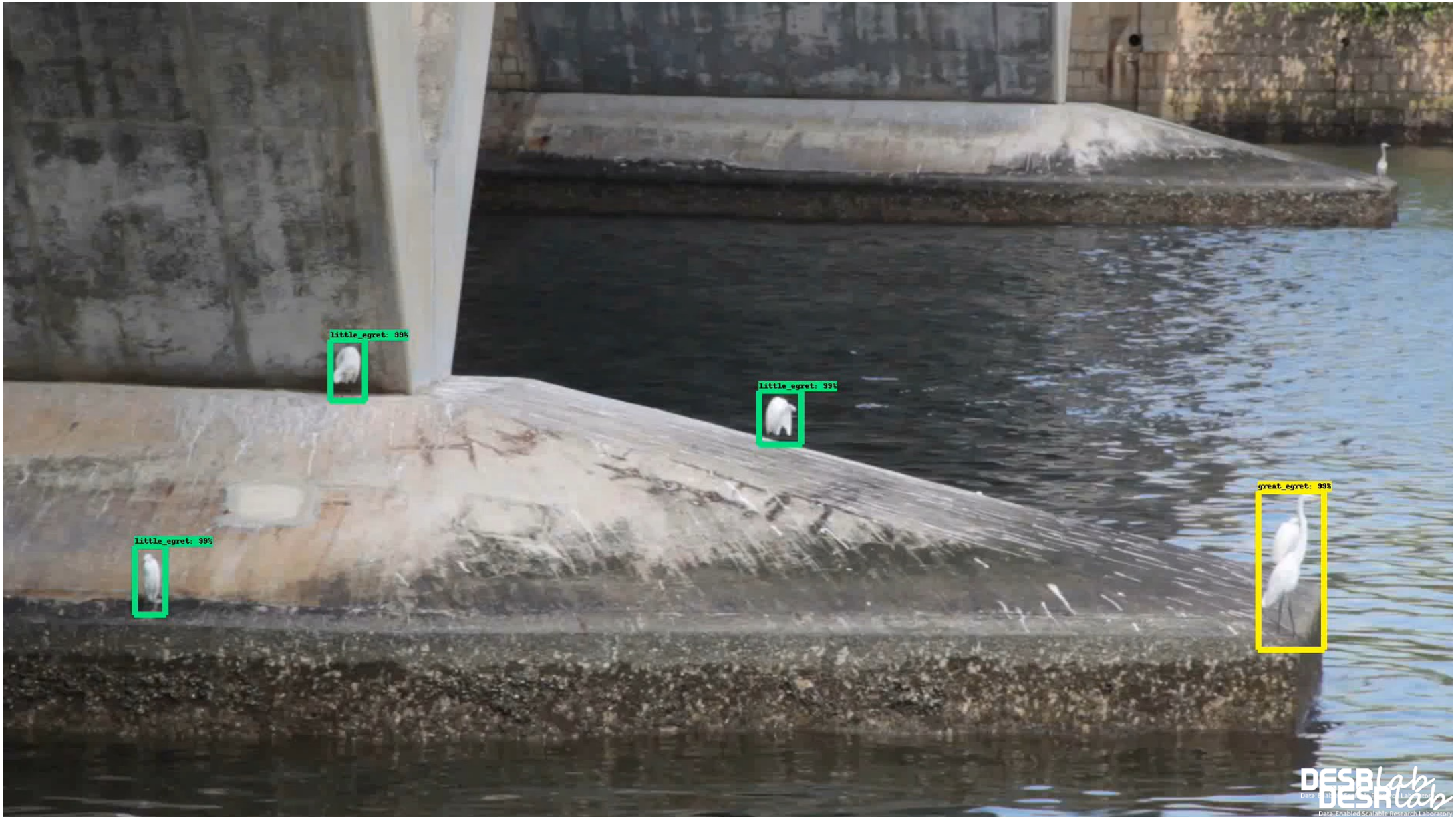
little_egret: 99%
little_egret: 99%
little_egret: 99%
great_egret: 99%
DESBlab
Data-Enabled Scalable Research Laboratory

little egret: 0.46
little egret: 0.53
little egret: 0.43
little egret: 0.37
little egret: 0.47
great egret: 0.50
little egret: 0.45
little egret: 0.33
little egret: 0.46
little egret: 0.35
little egret: 0.26
little egret: 0.39
little egret: 0.49
little egret: 0.48
little egret: 0.42
little egret: 0.29
great egret: 0.52
little egret: 0.51
Mao et al. 2020
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all birds count
date
all birds count
date
great_egret: 1.00
great_egret: 1.00
great_egret: 1.00
great_egret: 0.99
little_egret: 1.00
great_egret: 0.98

Results

Elevation of hot spots: **Great egrets** vs **Little egrets**

- Birds align themselves vertically according to the body size

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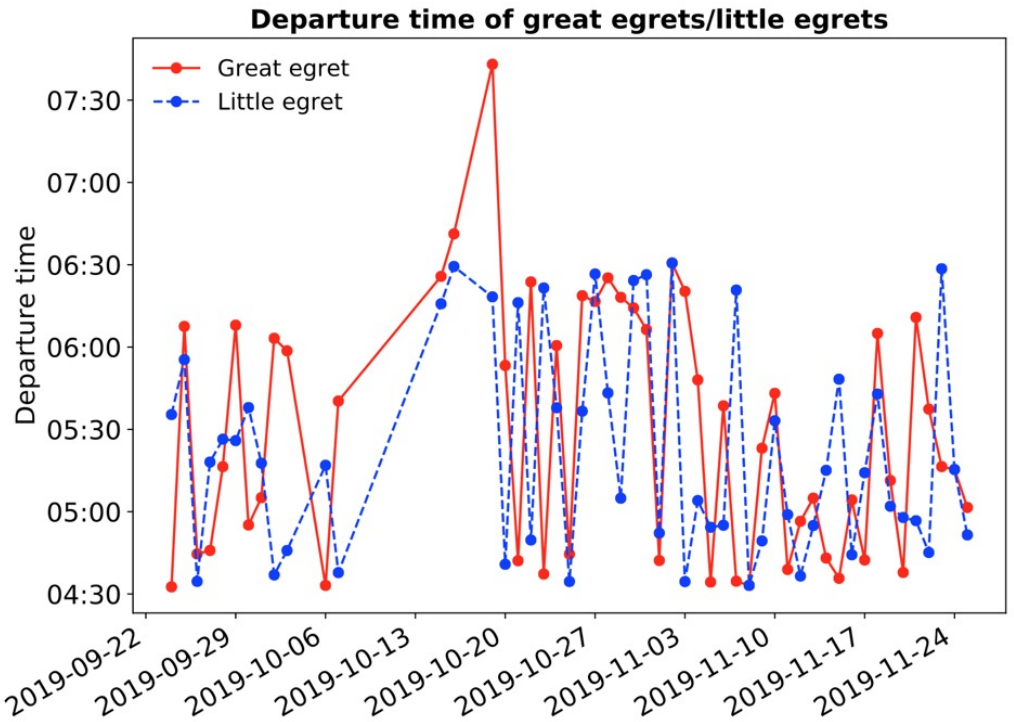
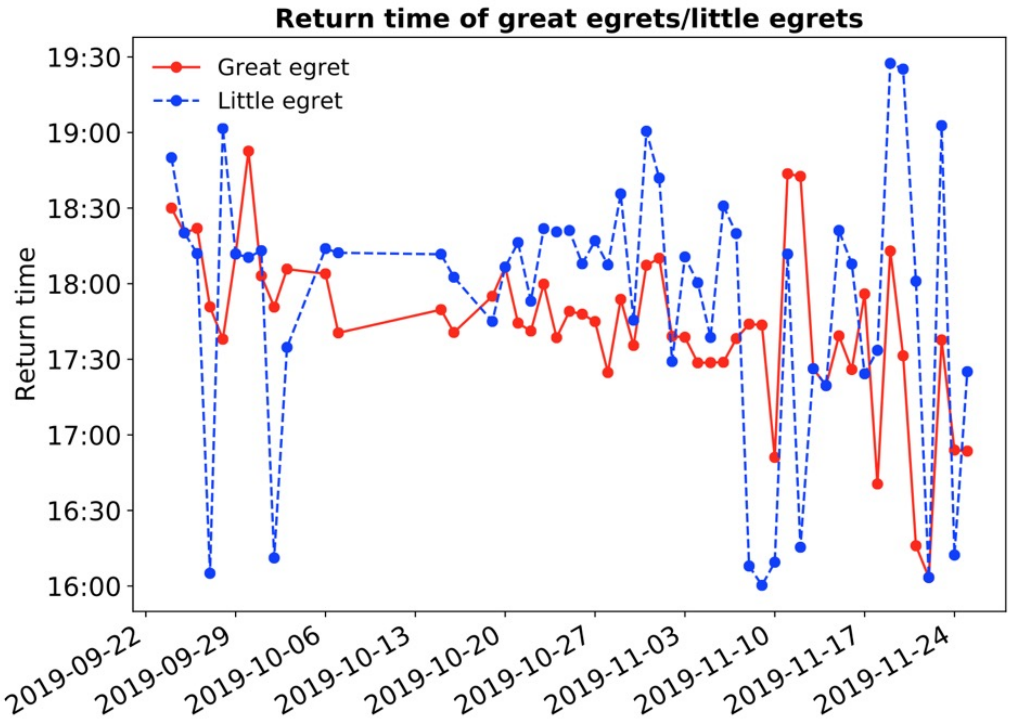
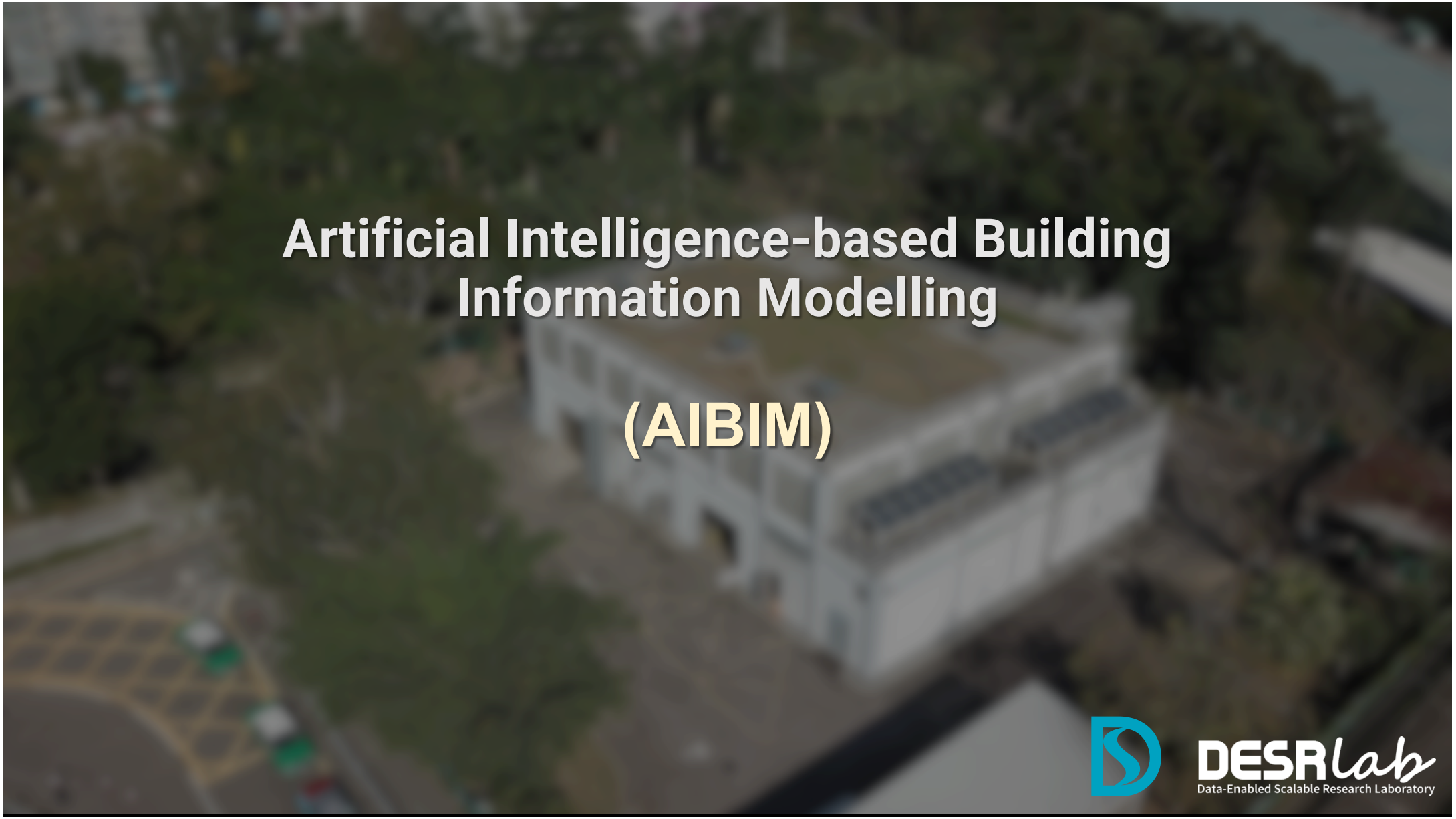
Results

Daily schedule of the great egrets & little egrets





- Great egrets come home a little bit earlier


Artificial Intelligence-based Building Information Modelling
(AIBIM)
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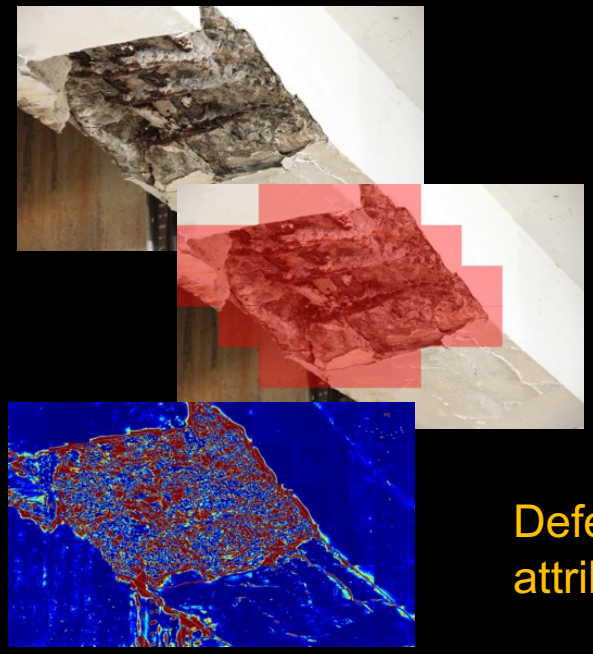
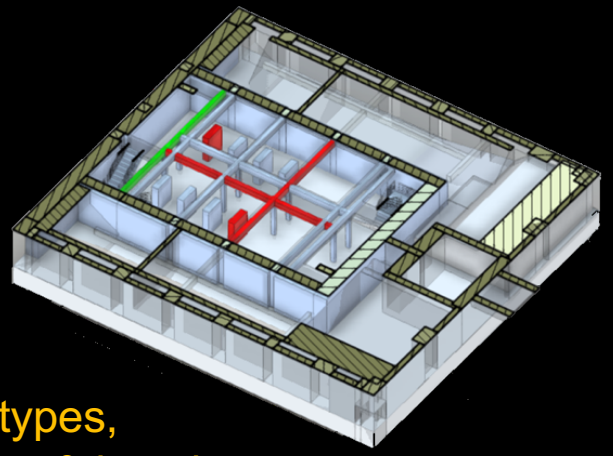
AIBIM Operational Pipeline

Data Collection → **Data Analysis** → **Data Integration**





Defect types,
attributes & locations

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Chow et al. 2021

Smart Data Collection System

Generation 1 (16 Lines)

Generation 2
(128 Lines)

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Chow et al. 2021

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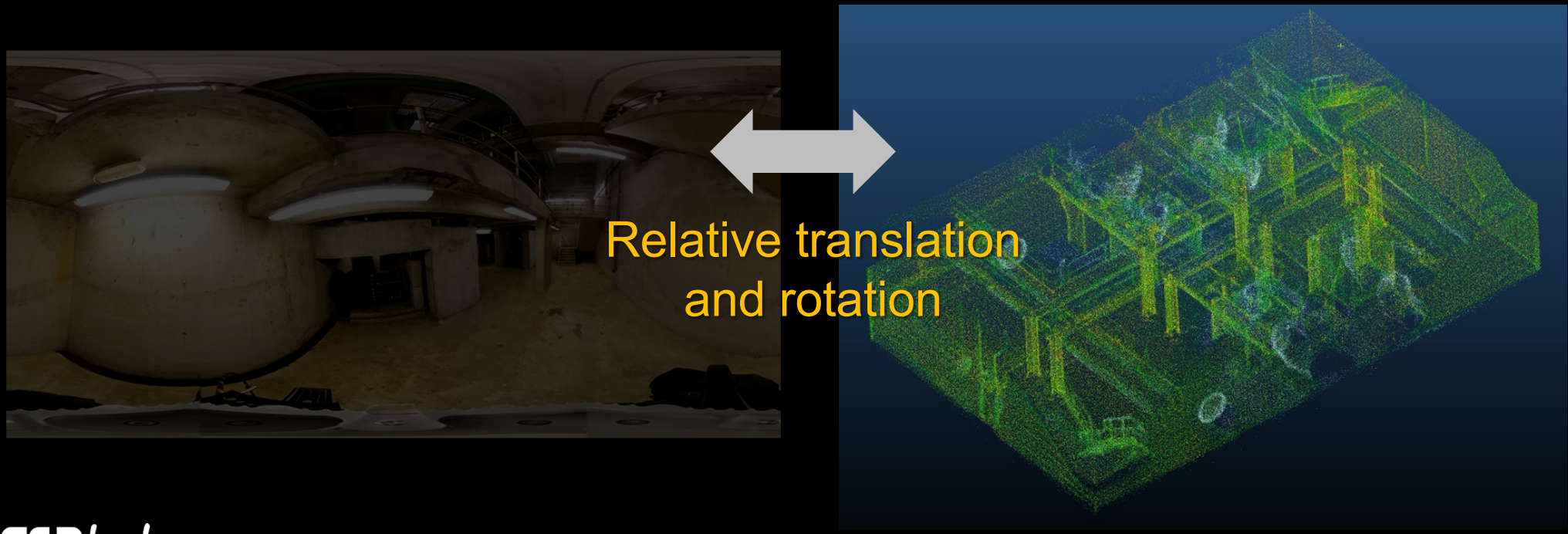
Sensor fusion

- Perform coordinate registration for camera-LiDAR datasets
- Estimate relative pose of LiDAR and camera (translation & rotation)
- Stack point clouds onto equirectangular images



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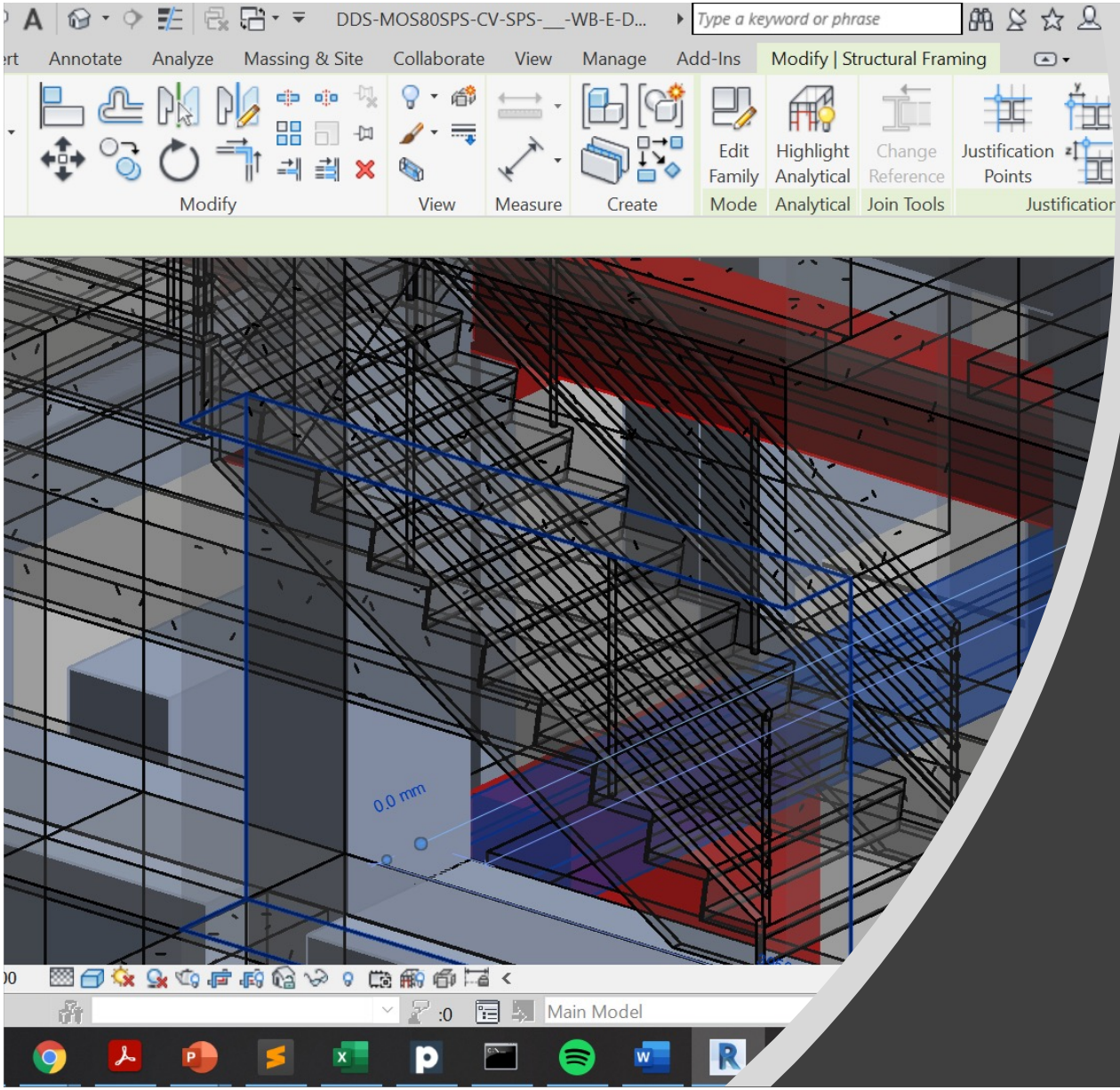
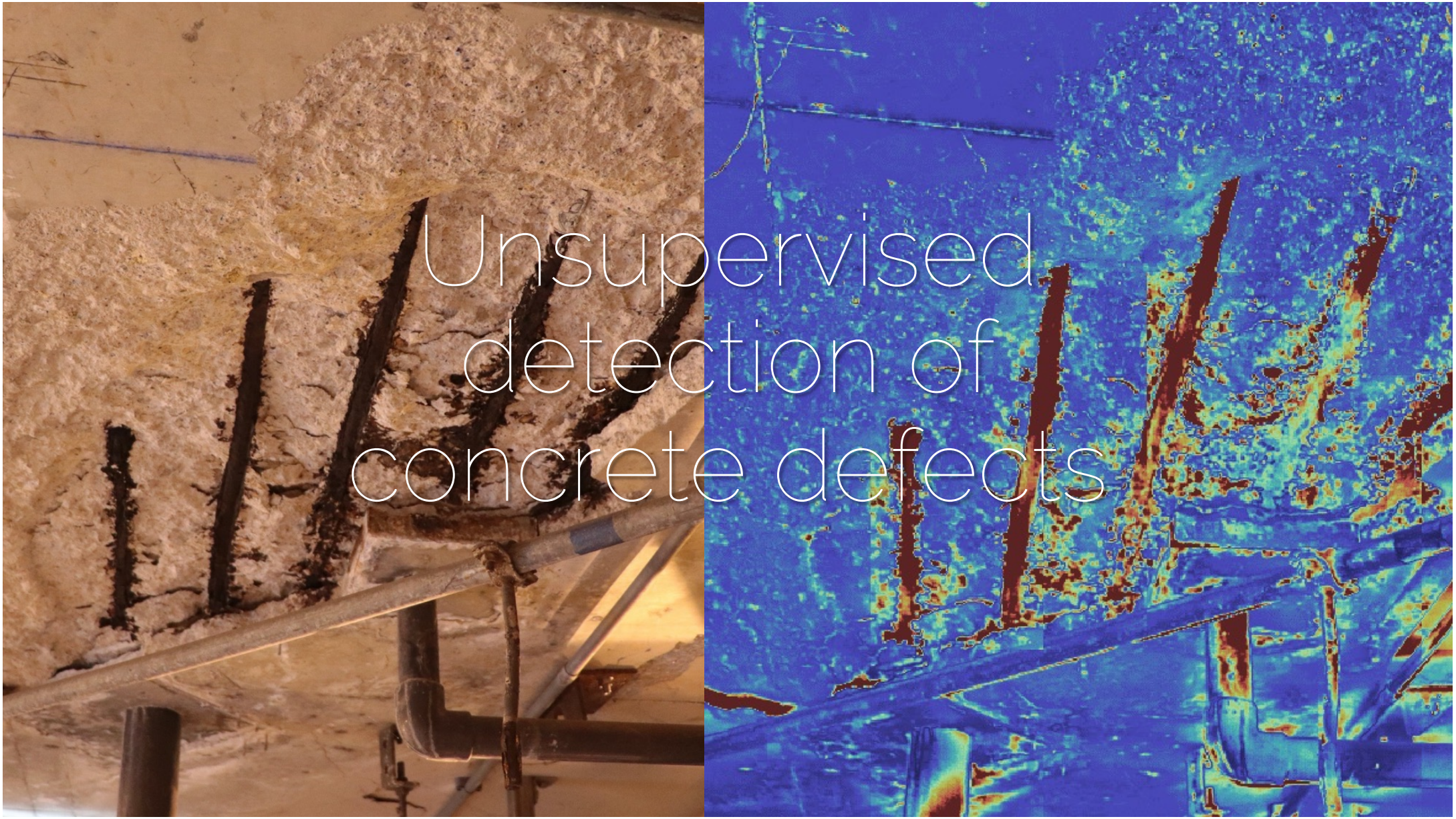
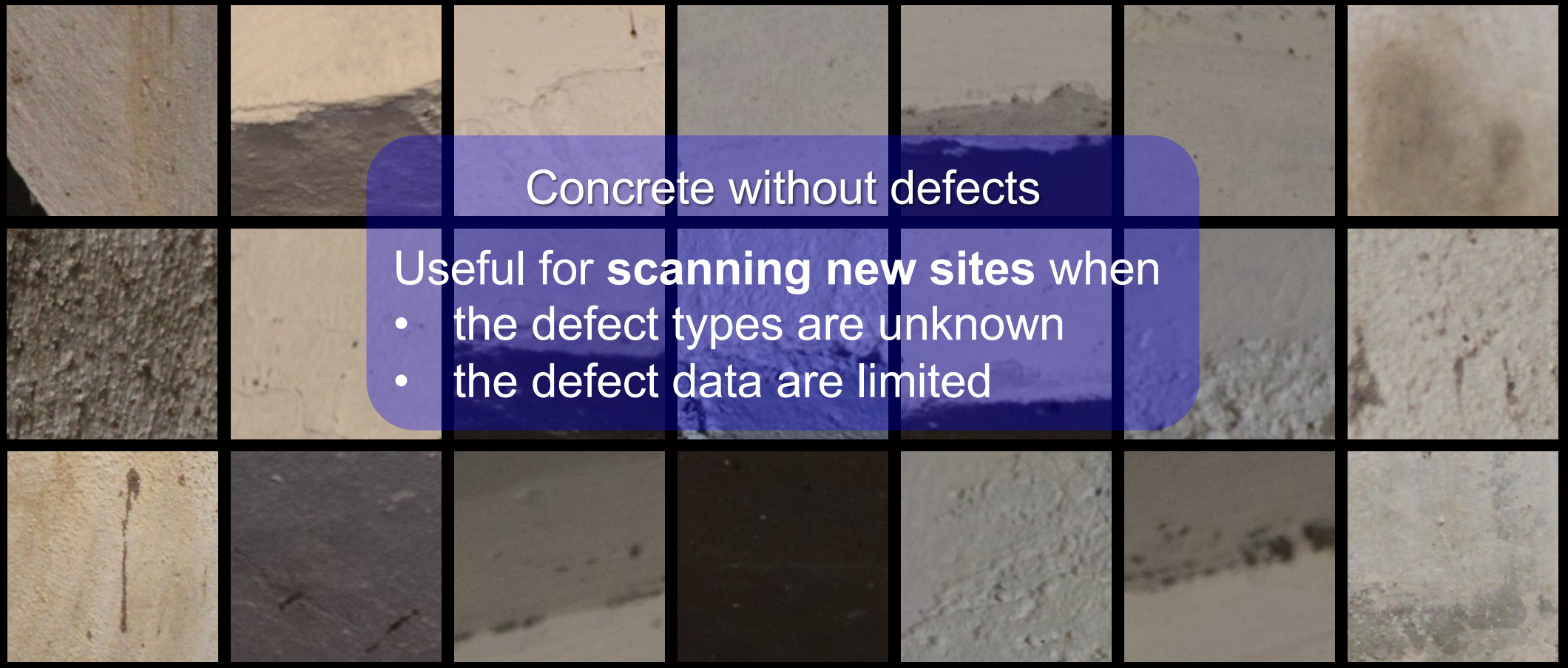


Robot-AI Enabled (GEO)Digital Twin + BIM


Unsupervised
detection of
concrete defects

Anomaly detector



Concrete without defects

Useful for **scanning new sites** when

- the defect types are unknown
- the defect data are limited

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Anomaly detector

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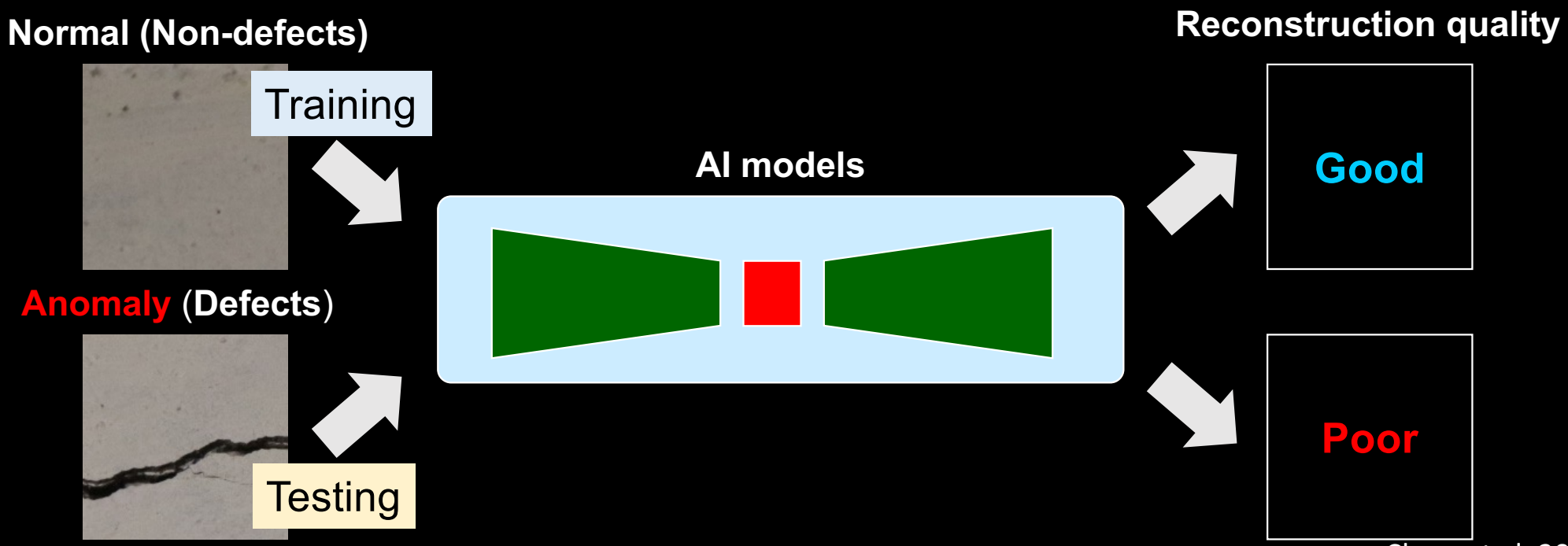
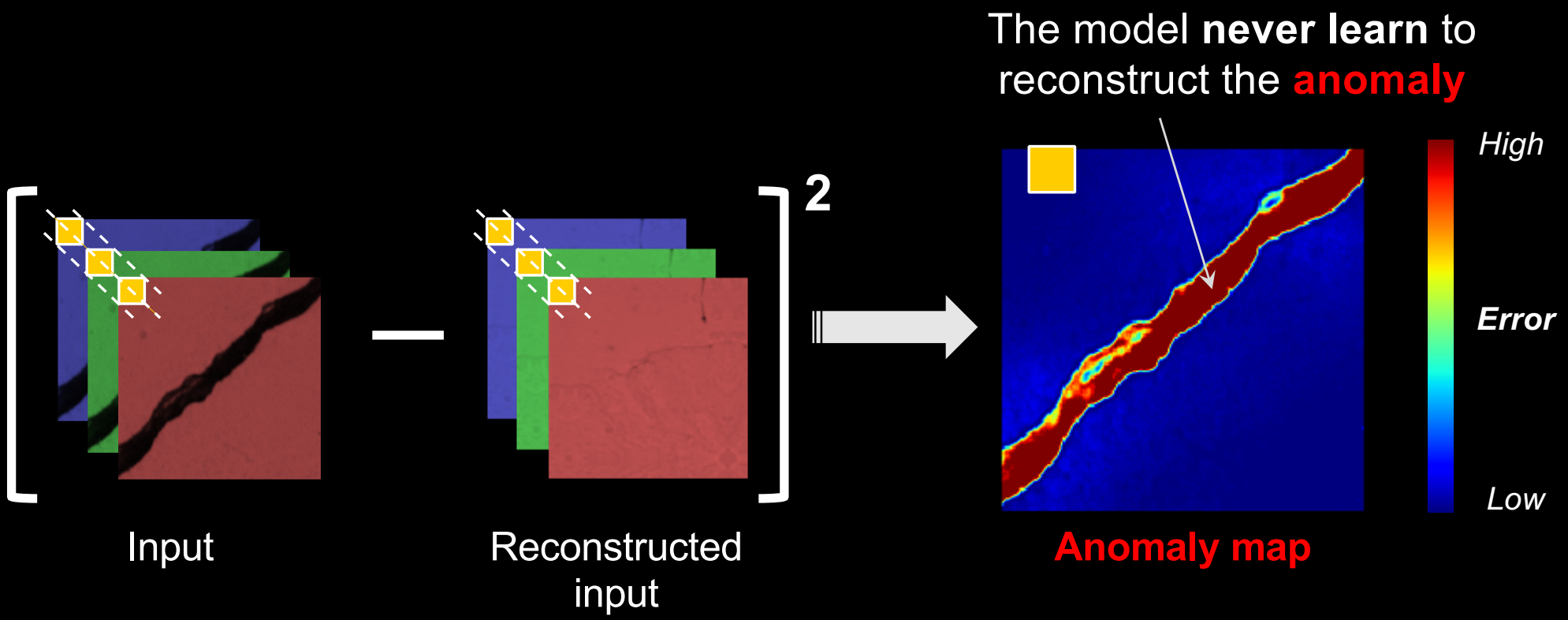
- **Self-learning** to reconstruct the **normal class**
- Never see and learn what are **defects** → **poor reconstruction**
- Unsupervised: **No label** is required



Chow et al. 2020

Anomaly detector



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Chow et al. 2020

Anomaly detector

Cracking

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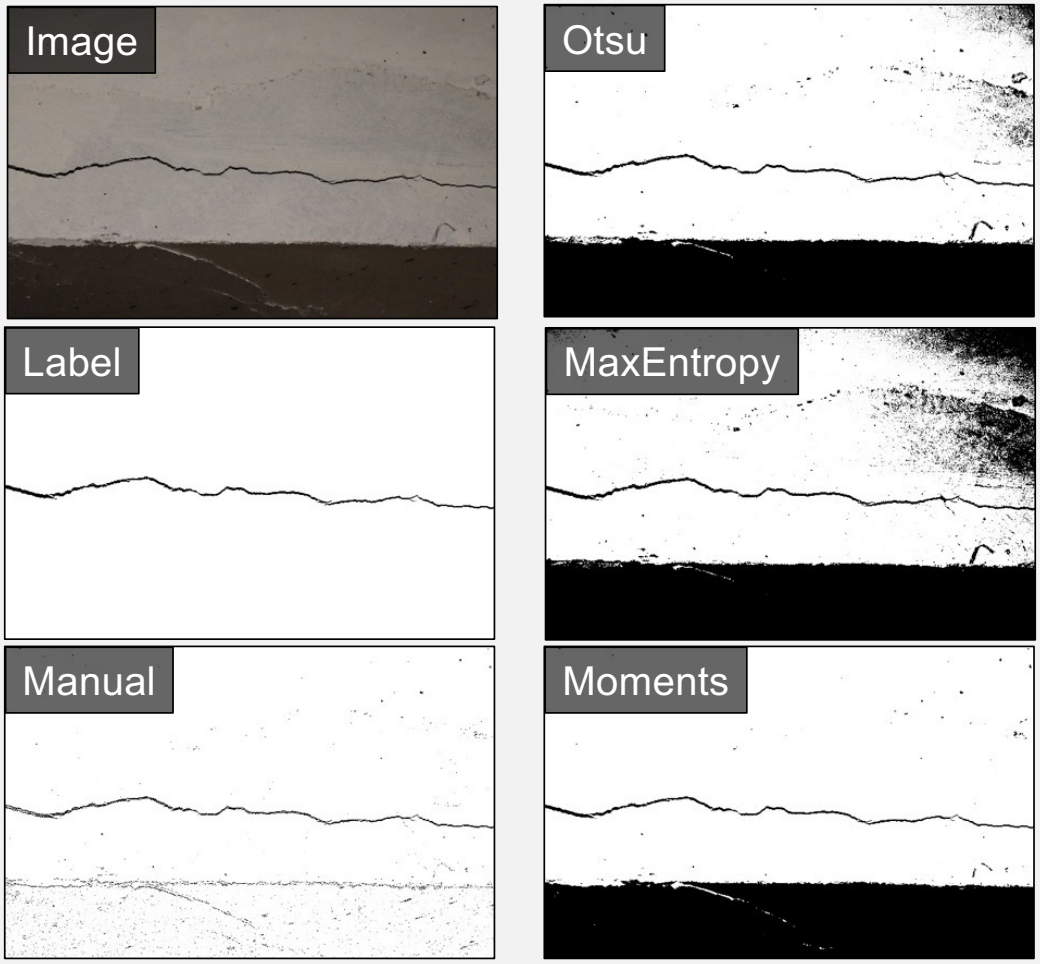
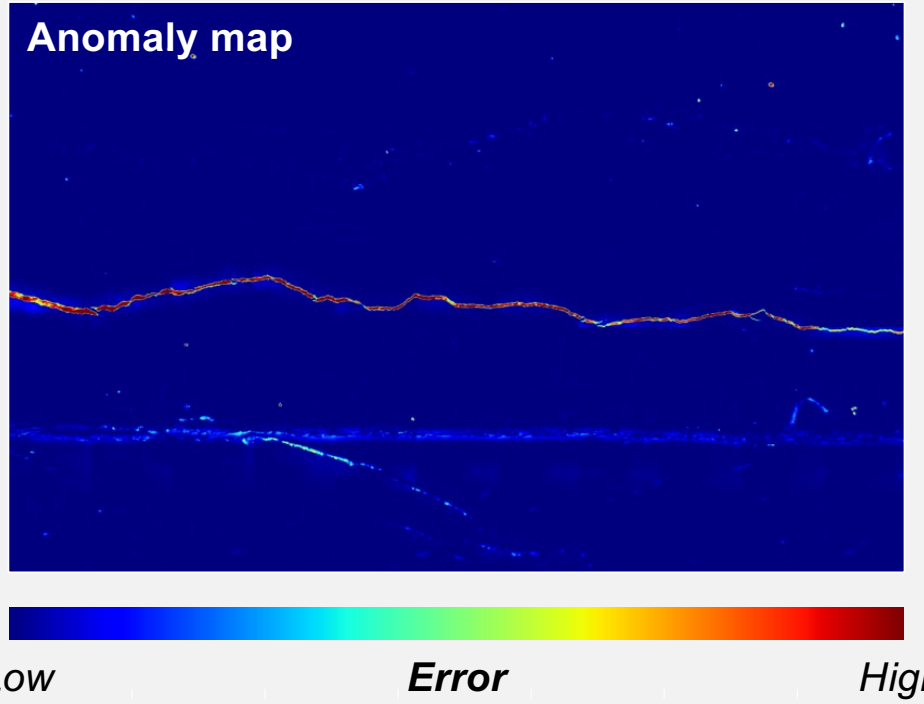


- **Significant differences** between cracks and undamaged surfaces
- Parts are shaded from the light source



Anomaly detector

Spalling

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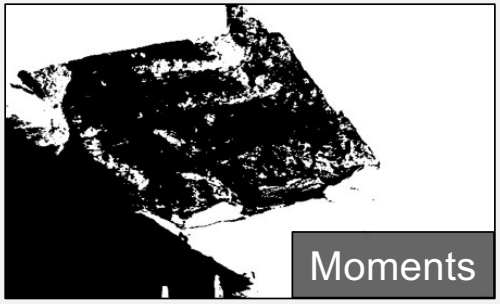
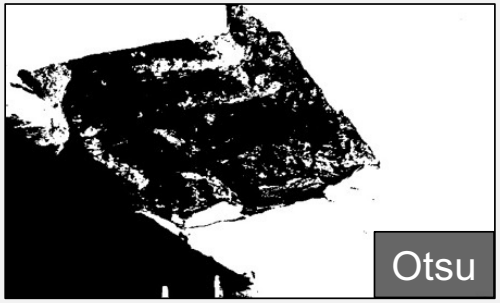
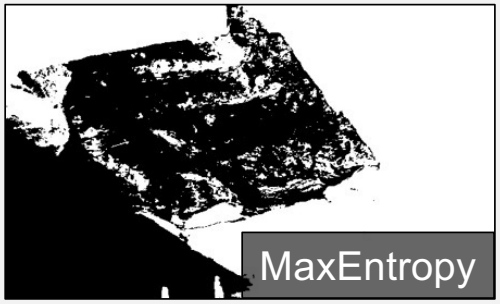
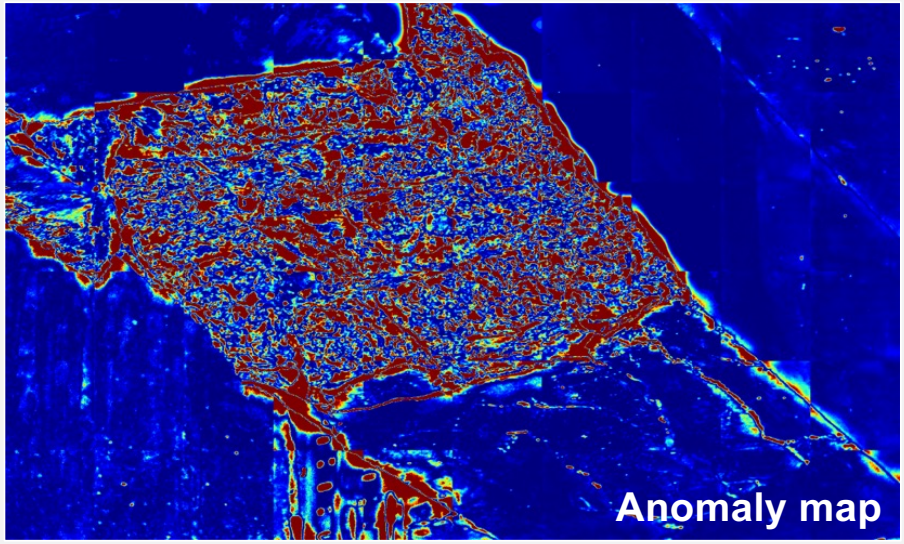




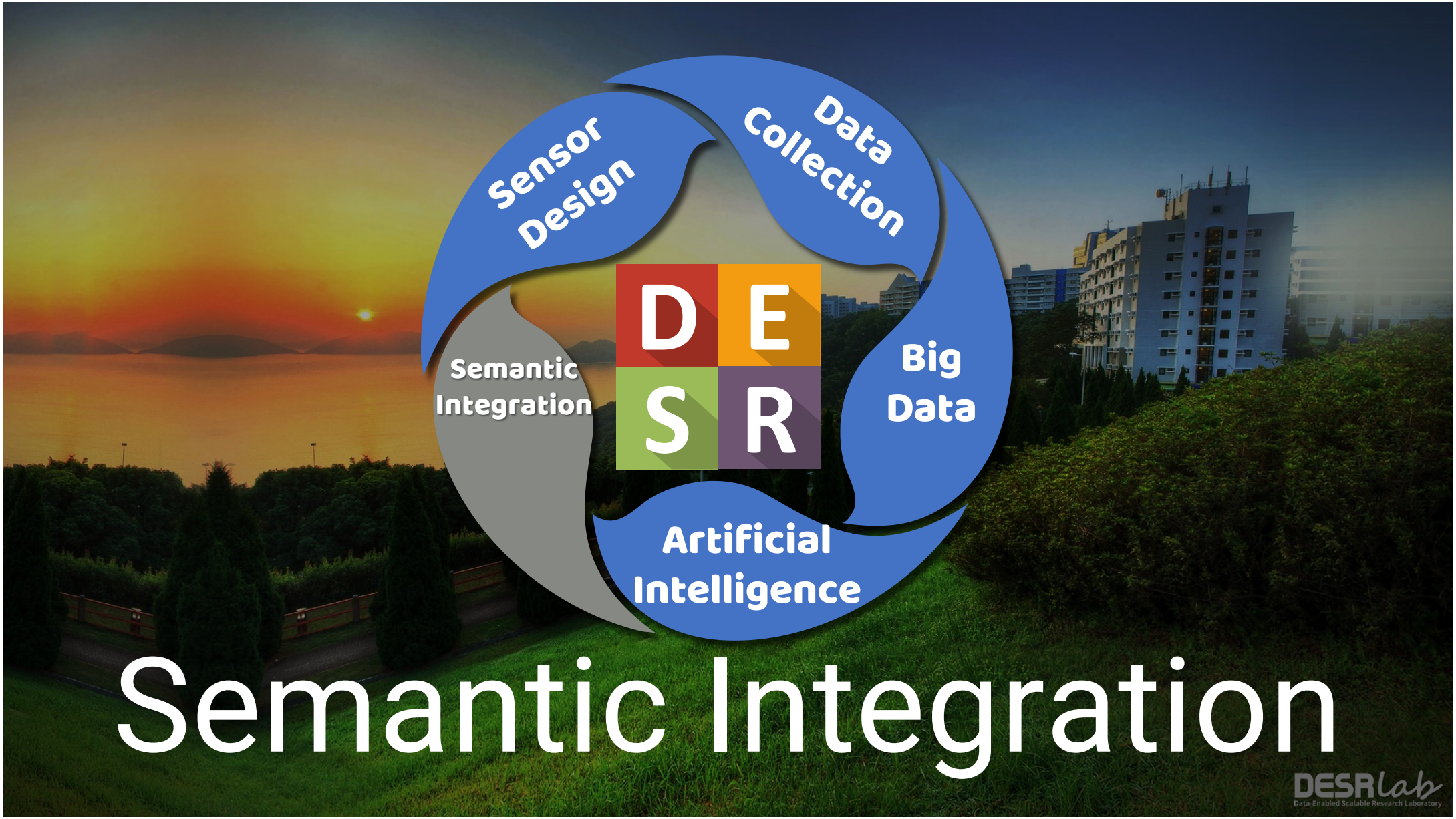


- Significant differences between spalling region and smooth surfaces
- Parts are shaded from the light source



Low ***Error*** *High*

DC/2015/02
08-11-2017
MS17K4M0403
MA CHAI HANG ROAD
FMH4026438B TO FMH4026442
DN450 D/S
016.4
Sewage pipe inspection


Sensor Design
Data Collection
Big Data
Artificial Intelligence
Semantic Integration
D E S R
Semantic Integration
DESRlab
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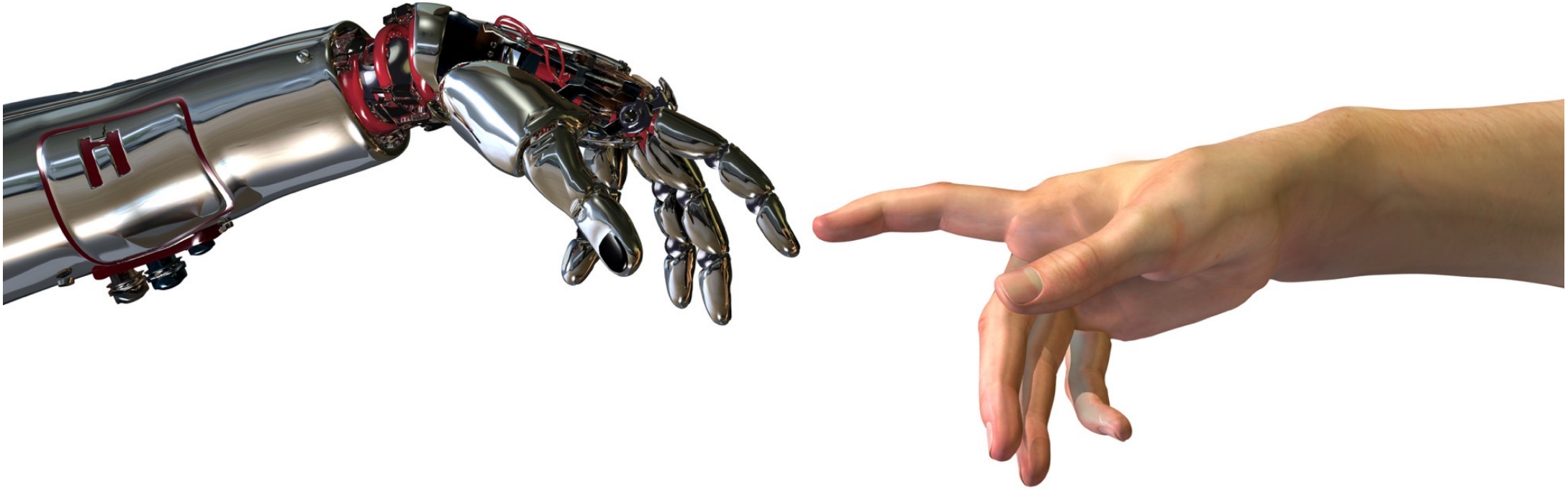
Human-Robot-AI Partnership



Automatic integrated solution

To see things that we should have seen before

Better Decision Making

From NASA

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Thank You
innovating today
imagining tomorrow
25
INNOVATING TODAY
IMAGINING TOMORROW
HKUST
DESRlab

Automatic rock type classification using computer vision-based artificial intelligence technique *feasibility and challenges*

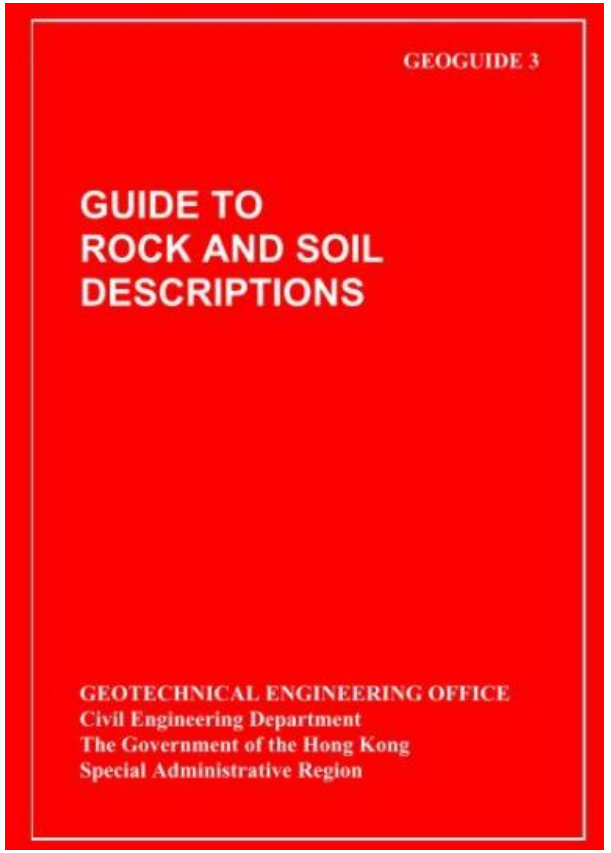
Louis WONG 王毅遠

Associate Professor
Director, MSc in Applied Geosciences
Department of Earth Sciences

Background

The ground is the place where things are most likely to go wrong during a construction project, and the worse the ground, the greater the risk.

The Institution of Civil Engineers (ICE) (1991)



Ground investigations (GIs)

- Soil/rock samples recovered from boreholes
- Logged (described) manually by qualified geologists with reference to Geoguide 3 (GEO, 2017).
- GI reports (description + colour photographs)

Background

Rock identification and classification

- Why?

- How?
  - Manual
  - Computer-aided hand-crafted feature-based rock classification (feature-based classification)

Outline

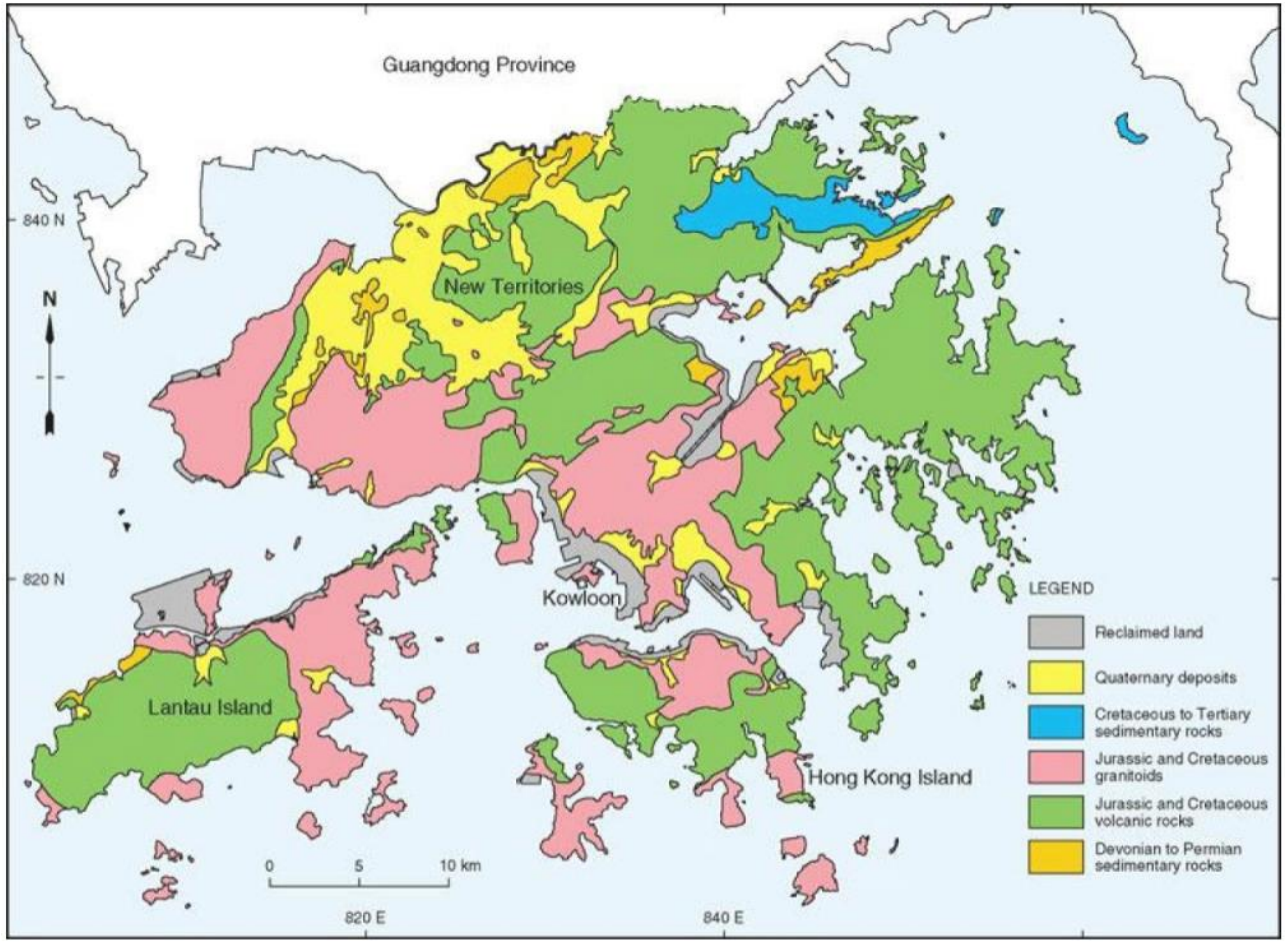
- Background (√)
- Objectives
- Methodology
- Conclusions

Objectives

- automatically classifies common Hong Kong rocks (fresh and weathered)
- predicts rock name + confidence accuracy, e.g. Grade II medium-grained granite (95%)

https://www.learncomputerscienceonline.com/what-is-computer-program/

https://www.universitytranscriptions.co.uk/what-is-a-good-accuracy-level-for-transcription/



https://maps-hong-kong.com/hong-kong-geological-map

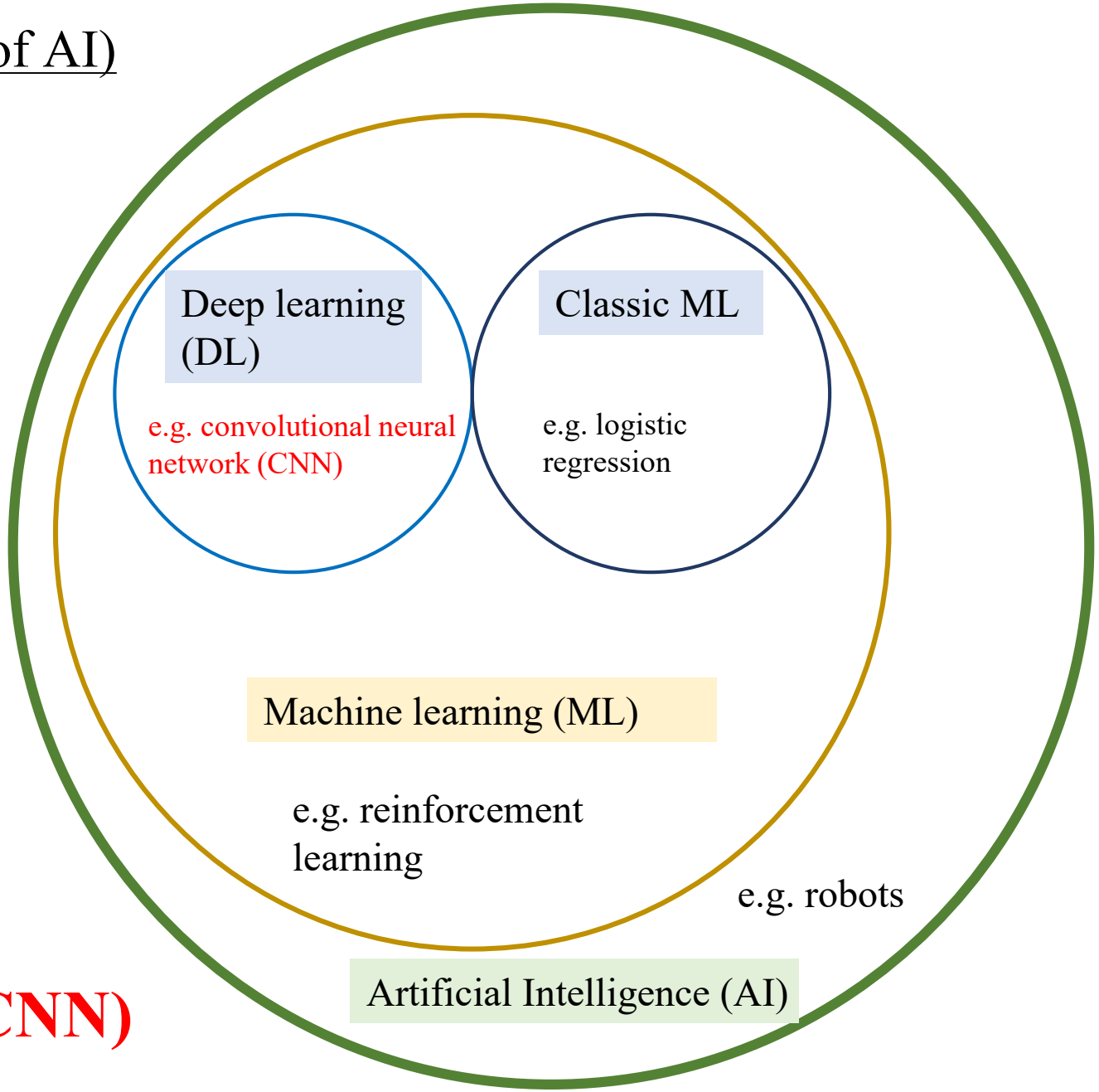
Outline

- Background (√)
- Objectives (√)
- Methodology
- Conclusions

The big family of "AI" (many are subsets of AI)

1. Artificial Intelligence (AI)
learning, reasoning, understanding, grasping truths, seeing relationships, considering meanings, separating fact from belief.

2. Machine learning (ML)
larger concept containing deep learning and classic ML.



convolutional neural network (CNN)
卷積神經網路

AI Models vs AI Algorithms

- This can be confusing as both algorithm and model can be used interchangeably. Not really!!!

- Model as the specific representation learned from data and the algorithm as the process for learning it.

Model = Algorithm (Data)

- e.g., a *decision tree* or *a set of coefficients* are a model
- e.g., *C5.0* and *Least Squares Linear Regression* are algorithms to learn those respective models.

Machine Learning (ML)

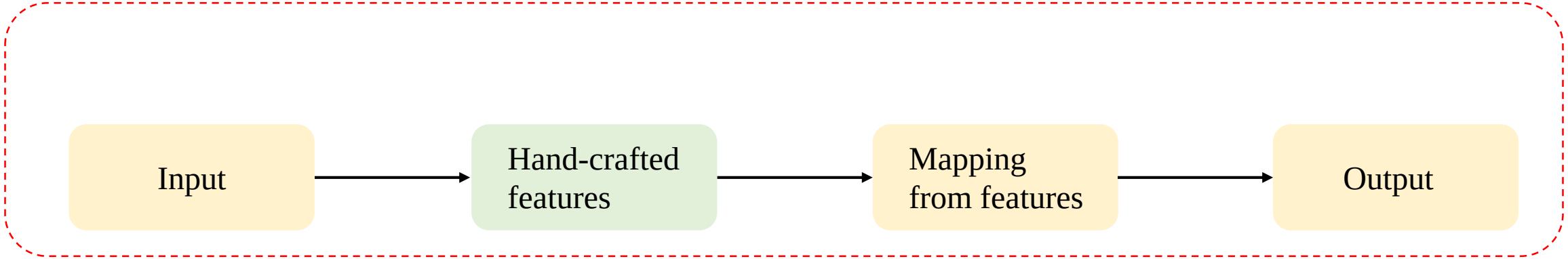
- The goal is to create a simulation of human learning so that an application can adapt to uncertain or unexpected conditions.

- To perform this task, machine learning relies on algorithms to analyze huge datasets.

- The key task is to LEARN a function.

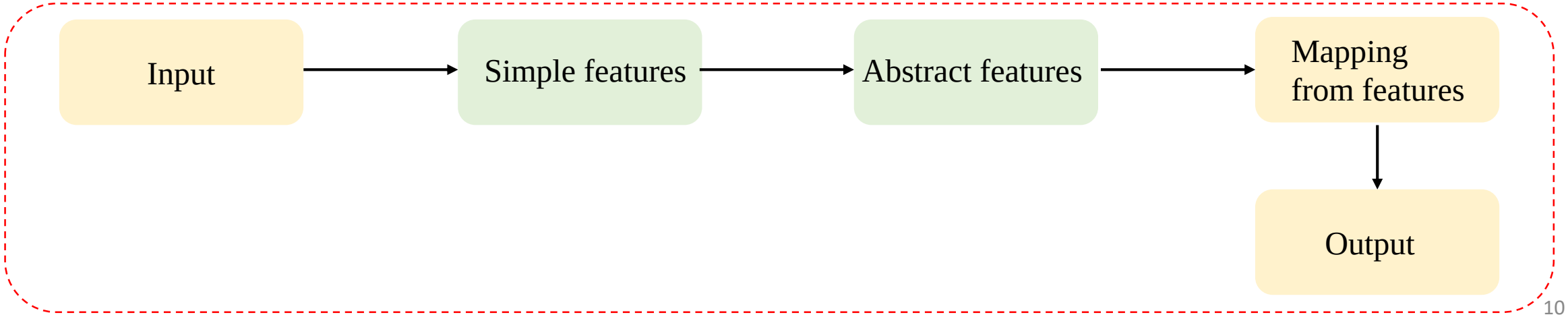
Different workflow

Classic ML



- No need to understand the details of the two flowcharts.
- Just have an intuition that classic ML and DL have similar flowcharts but different representation of features

Deep learning

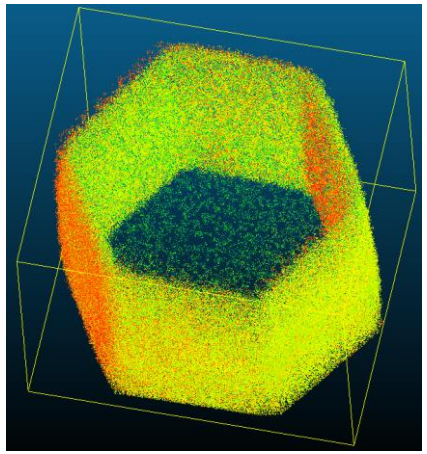


Features for DL (unstructured data)

1-D: i.e. Audio

2-D: i.e. Image

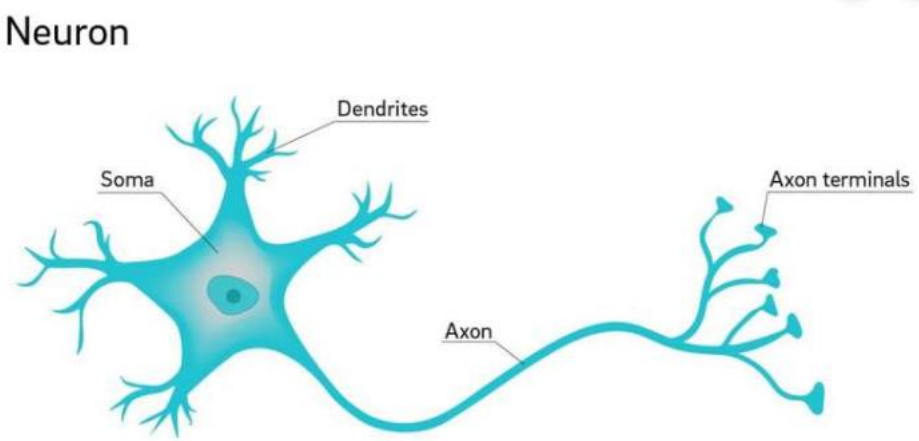
3-D: i.e. Point cloud



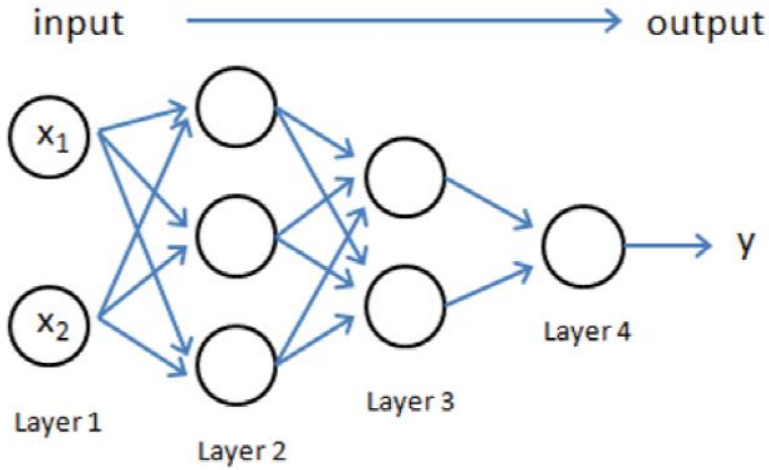
- No need to manually extract features from inputs.
- Algorithms will automatically learn abstract features from simple features, such as RGB values, gray-scale values, etc.
- Then using abstract features to do prediction.

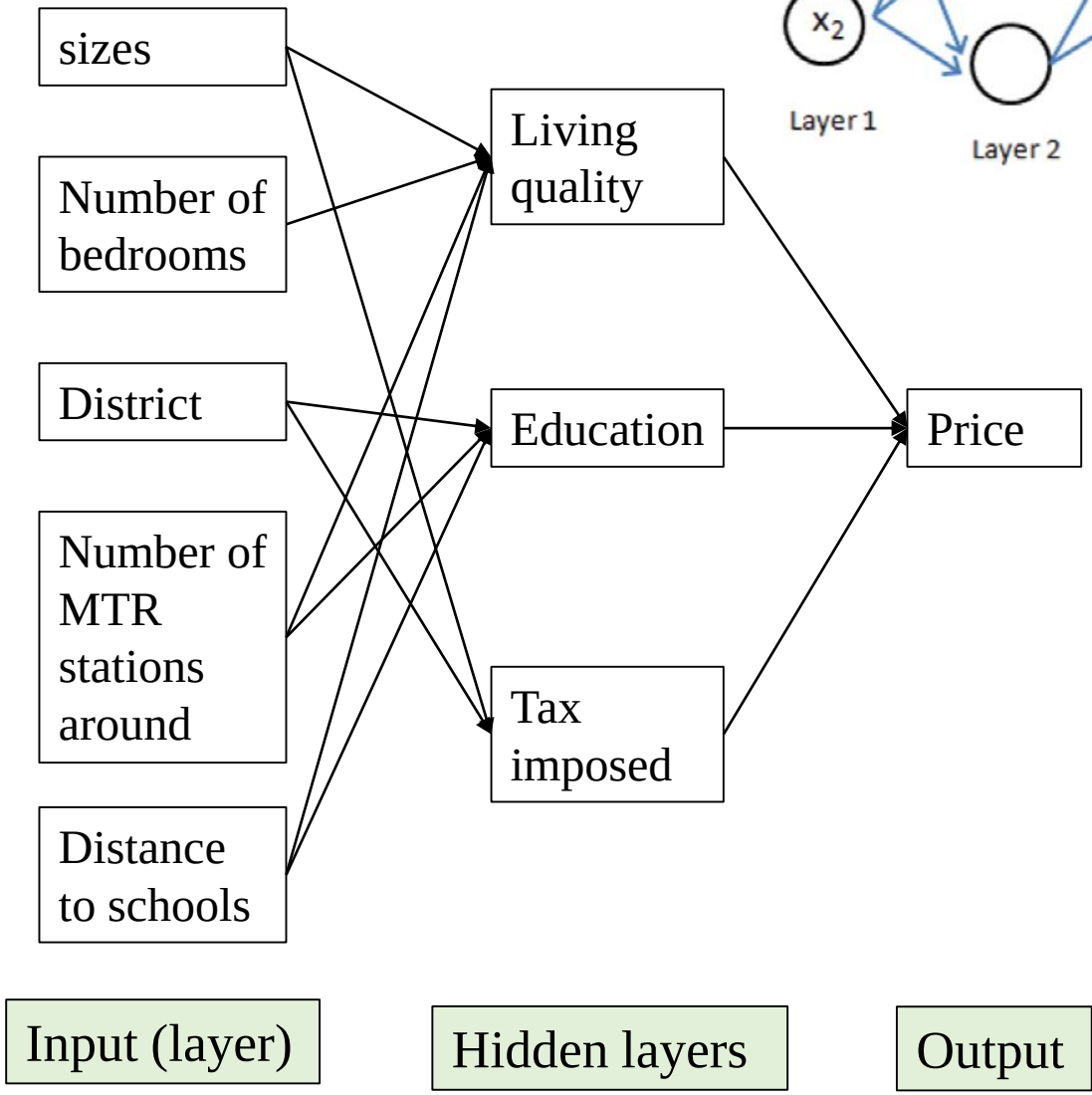
- However, the meaning of abstract features is quite non-interpretable.
- Why some abstract features work is kind of "black-box"

Neurons and hidden layers



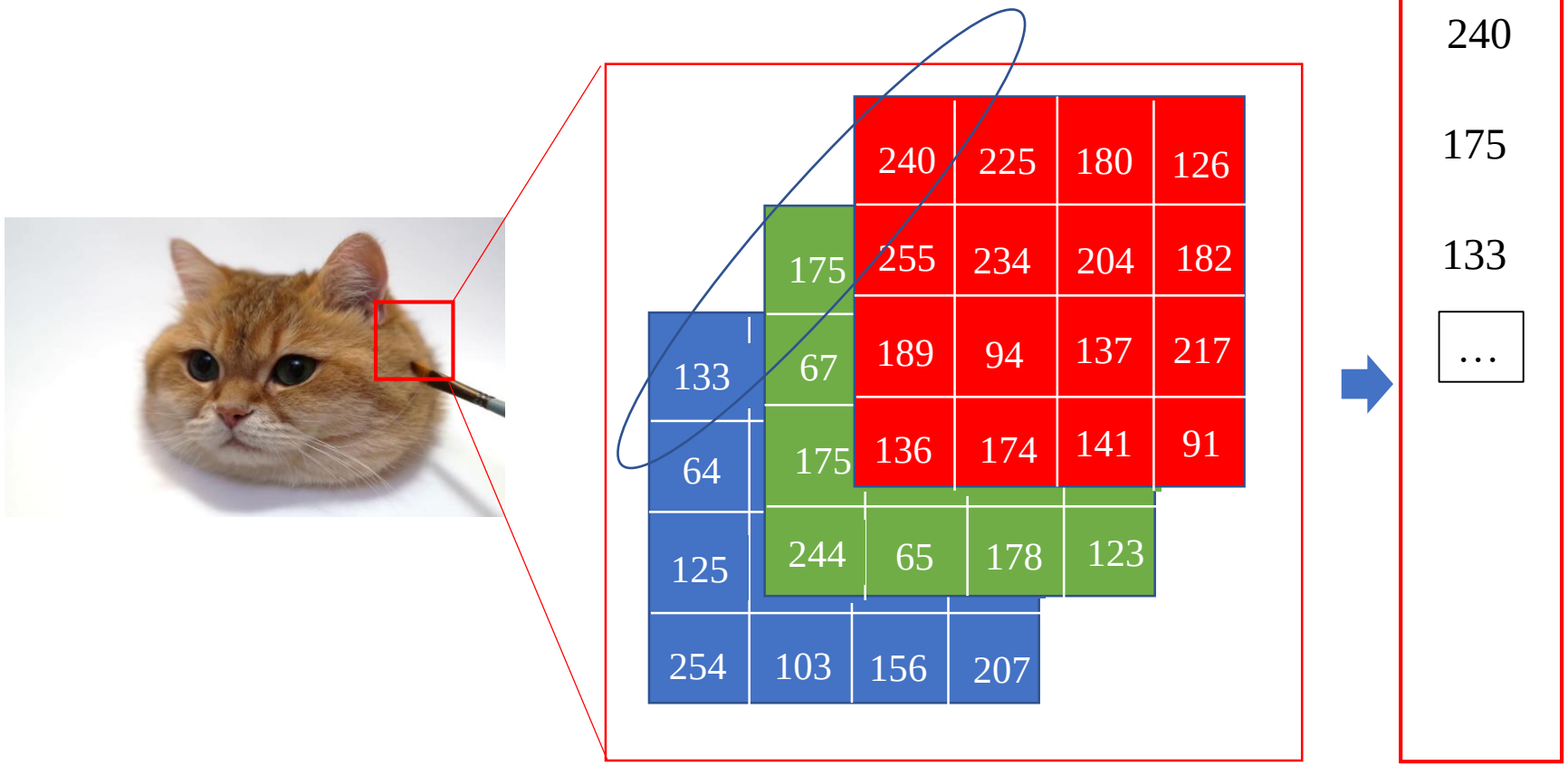
- Neural networks have different **layers**, each one having its own **weights**
- The neural network segregates computations by **layers**
- Weights represent **the strength of the connection** between neurons in the network





Simple features

How a computer read an image? ---Using RGB values



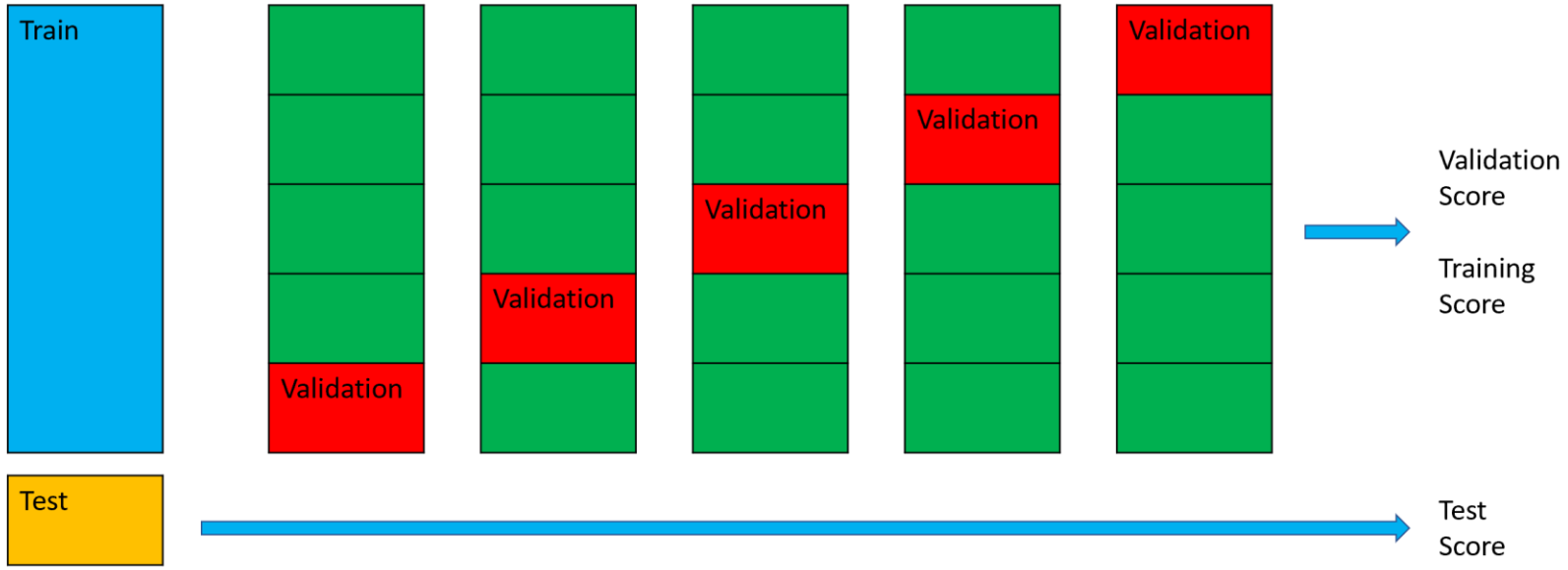
Convert images to numeric data

Methodology (cont'd)

Heavy technical content

(3) AI model training and fine-tuning

1. Splitting data into training, validation, and testing datasets
2. Testing data are always "never-before-seen" ("unseen") data vs training and validation data
3. Training and testing AI CNN models (***MobileNet V2, ResNet18, VGG16, Inception V3, AlexNet***)
4. 5-fold cross-validation strategy for more comprehensive analysis
5. Three evaluation indices - Precision, recall, f1-score (next slide for e.g.)
6. Confusion matrices for error analysis
7. Identification of misclassified testing images
8. **Pick the best performing CNN model**



https://medium.com/analytics-vidhya/training-validation-and-test-set-in-machine-learning-7fab555c1080

Examples (predicted vs actual)

		Predicted class	
		Granite	Tuff
Actual class	Granite	100 (TP)	10 (FN)
	Tuff	20 (FP)	90 (TN)

$$Precision = \frac{TP}{TP + FP}$$

$$Precision = \frac{100}{100+20} = 0.83$$

$$Recall = \frac{TP}{TP + FN}$$

$$Recall = \frac{100}{100+10} = 0.91$$

$$f_1 - score = 2 \times \frac{precision \cdot recall}{precision + recall}$$

$$f_1 - score = 2 \times \frac{0.83 \times 0.91}{0.83 + 0.91} = 0.87$$

Outline

- Background (√)
- Objectives (√)
- Methodology(√)
- Conclusions

Conclusions

Feasibility

- GI records
- Standard logging practice
- Open access

Challenges

- Need good data
- Need large amount of data
- Need image pre-processing and labelling
- Complex geological formation, e.g. Yuen Long Formation?

Thank you!

Louis WONG

LNYWONG@hku.hk

Smart NTHS with Applications of Artificial Intelligence and Computer Vision – Case Studies in Hong Kong

Wenzhu Hou[1], Min Wei[2] & Jonathan Hart[1]

[1]GeoRisk Solutions Limited

[2]Independent AI Specialist

Joint Technical Symposium on Digital Geoscience & Geotechnology

16 September 2021, Hong Kong

Outline

1. **Background** for the Natural Terrain Hazard Study (NTHS) in Hong Kong
2. **Methodology** (Brief history of AI and specific applications in earth sciences)
3. **Challenges** (Adoption of AI tools in NTHS)
4. **Case Study in Hong Kong** (Catchments in Fei Ngo Shan, KLN, and Tuen Mun, N.T.)
5. **Algorithms** (Mask-RCNN and its advantages)
6. **Model training** (Data pre-processing, training samples, parameters, training result)
7. **Training result & model inference** (Assessment of accuracy, limitations)
8. **Smart NTHS** (Proposed framework)

1. Background

- Natural Terrain Hazard Study (NTHS) in Hong Kong
- (1970s, 1977 GCO, 1991 GEO, 2010)
- Landslip Prevention and Mitigation Programme (LPMitP)
- Enhanced Natural Terrain Landslide Inventory (ENTLI)
- (interpreted from 1945 onwards aerial photographs)
- 2010 and 2020 LiDAR survey and pilot studies
- Pilot studies on landslides and climate change
- Digital transformation (BIM, digital twin)
- New technologies (software & hardware)

Po Shan Road landslide (1972)

Shum Wan Road landslide (1995)

Tsing Shan landslide (1990)

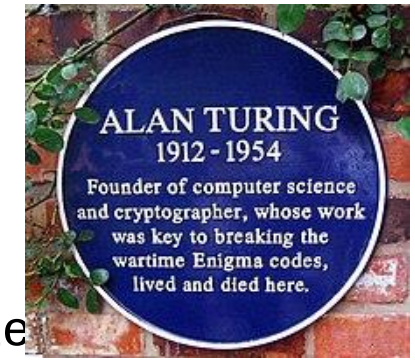
Yu Tung Road landslide (2008)

Photo credit:
hkss.cedd.gov.hk

2. Methodology

- Artificial Intelligence
- (Alan Turing and the Turing test)
- (1956-1974, 1980-1987, 2011 to date)
- Support Vector Machine (SVM)
- Convolutional Neural Network (CNN)
- Conventional classification vs Deep Learning

Computing Machinery and Intelligence, 1950

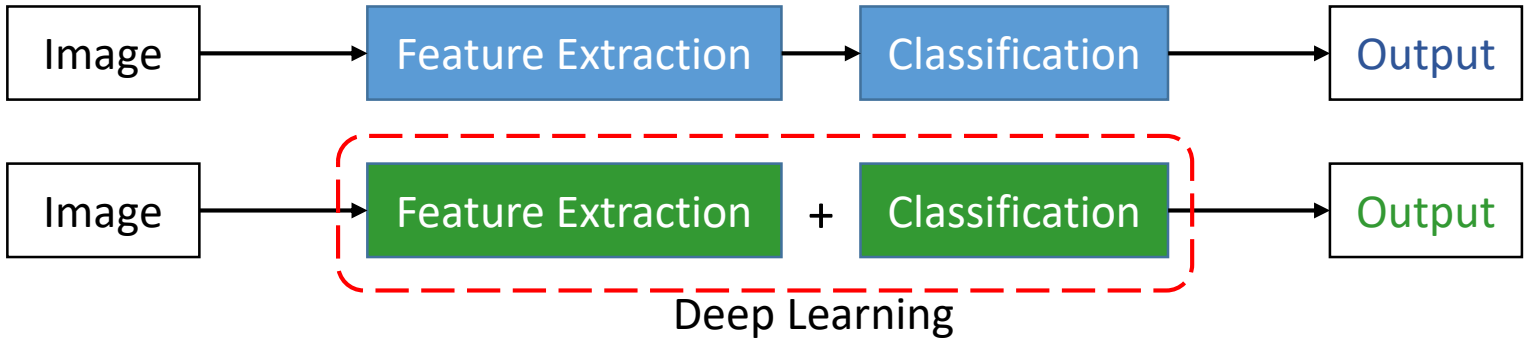


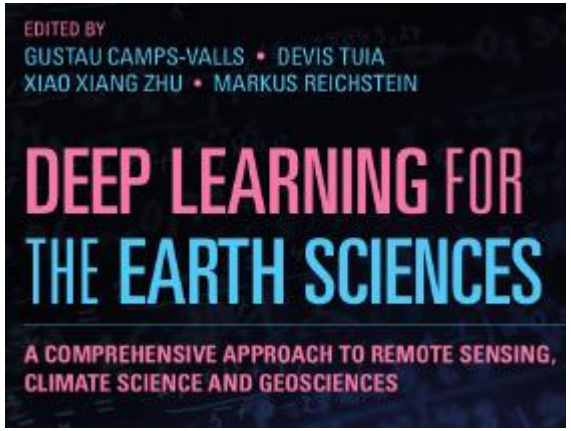
50 yrs after the 1956 Dartmouth Conference
Photo credit: forbes.com

Machine learning for data-driven discovery in solid Earth geoscience

Karianne J. Bergen[1,2], Paul A. Johnson[3], Maarten V. de Hoop[4], Gregory C. Beroza[5]*

2019, *Science*, *363*(6433)





- Deep Learning for the Earth Sciences
- (solid earth, ocean, atmosphere, mining…)

Published in 2021, Chapter 17 by **Prof. LIU, Lin, ESSC, CUHK**
A Review of Deep Learning for Cryospheric Studies

3. Challenges

Journals & Magazines > IEEE Transactions on Knowledg... > Volume: 31 Issue: 8

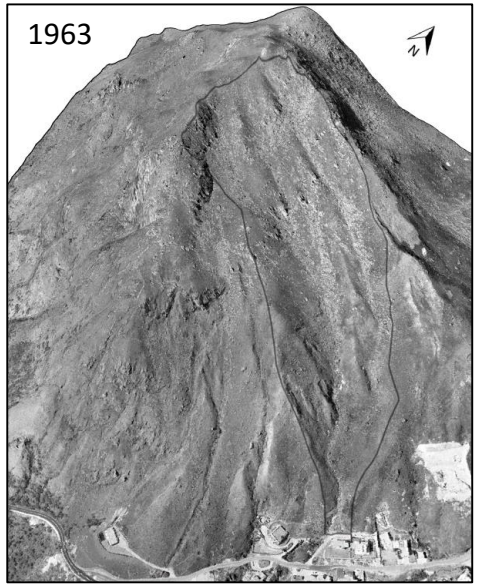
Machine Learning for the Geosciences: Challenges and Opportunities

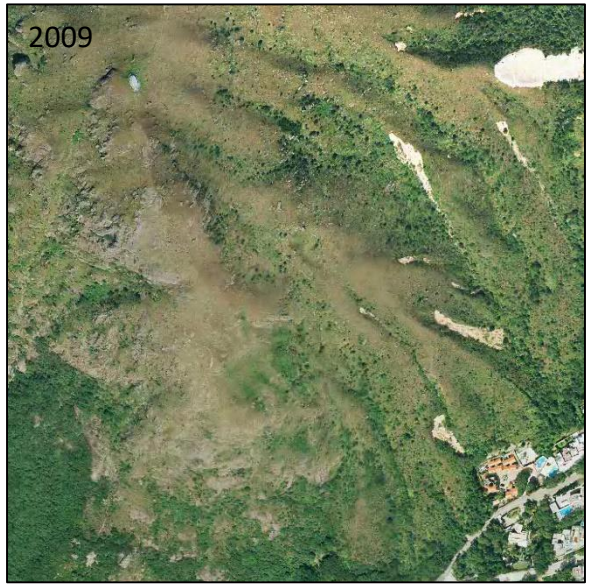
Publisher: IEEE Cite This PDF

- Challenges from properties of geosciences
- "Amorphous boundaries in space and time"
- "Geoscience phenomena also have spatio-temporal structure, are highly multi-variate, follow non-linear relationships (e.g., chaotic), show non-stationary characteristics, and often involve rare but interesting events."
- "…multiple resolutions of space and time, with varying degrees of noise, incompleteness, and uncertainties."
- "…additional challenges due to the small sample size and lack of gold-standard ground truth in geoscience applications."
- Challenges of knowledge transfer from academia to industry
- "…it is difficult to train machine learning models that have good performance across all regions in space and across all time-steps…instead, there is a need to build local or regional models, each corresponding to a homogeneous group of observations."
- *Interdisciplinary collaboration between professional geologists and AI professionals*
- *(many years training requested… smooth collaboration is essential)*

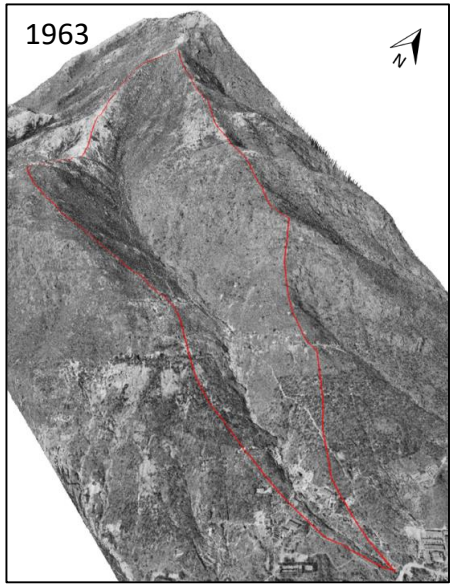
4. Case Study in Hong Kong

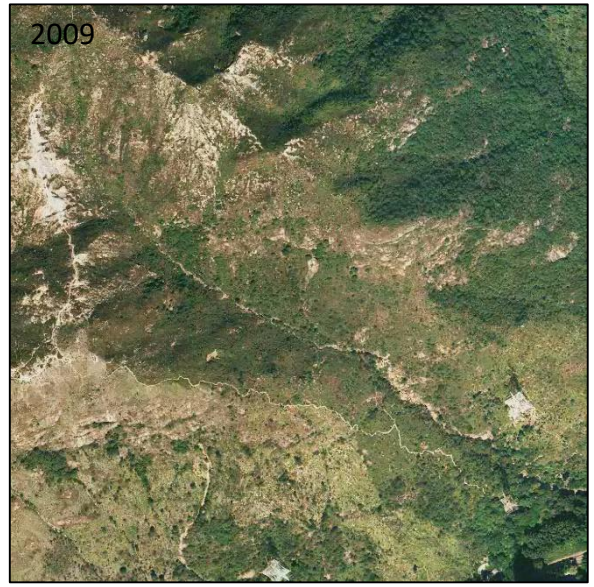
- Feasibility of automatic landslide scar recognition with spatial data (2010 LiDAR data)
- Two study areas combined: One study area is located at Fei Ngo Shan, Kowloon; the other study area is located at Tuen Mun, New Territories
- The case study is further developed from two detailed NTHS[(1)], and designed by the author.





Fei Ngo Shan study area, 1280 x 1280 pixels





Tuen Mun study area, 1280 x 1280 pixels

Note [(1)] - Other publications related to these studies:

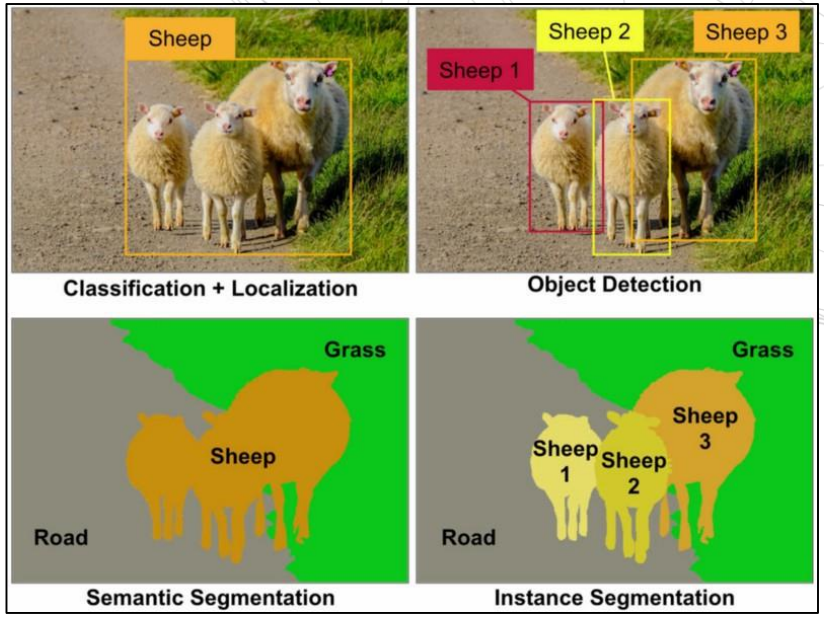
Hou, Wenzhu & Jonathan Hart. Design Event Determination for Natural Terrain Hazards using an Alternative Magnitude-Cumulative Frequency Method – Observations from a Pilot Study in Fei Ngo Shan, Kowloon. (In preparation)

Hou, Wenzhu, Jonathan Hart, Regine Tsui, Alan Ng, & Chi Son Cheung. "Using UAV-based Technology to Enhance Landslide Investigation - A Case Study in Fei Ngo Shan, Kowloon". Full Paper in HKIE Annual Seminar. (2021)

Hou, Wenzhu, Regine Tsui, & Jonathan Hart. "Digital Regolith Mapping from Integrated Sources of LiDAR Data and Historical Imagery – A Case Study in Hong Kong". Abstract in Geological Society of Australia Abstract. (2021)

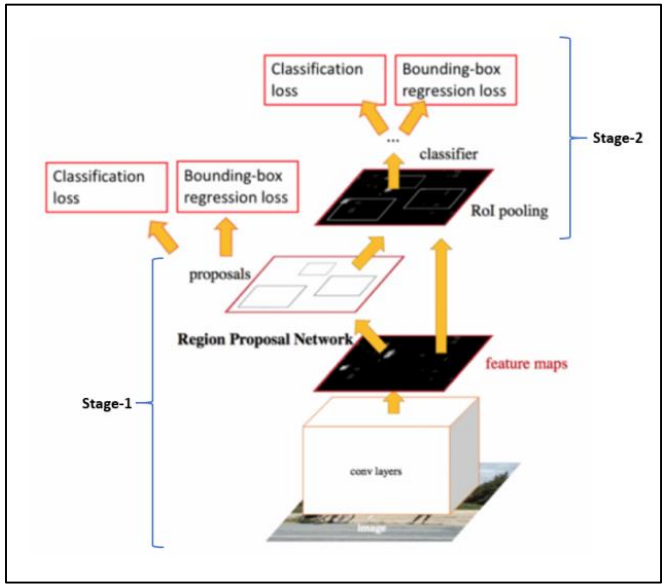
5. Algorithms

- Mask R-CNN for Object Detection and Segmentation
- (The model generates bounding boxes and segmentation masks for each instance of an object in the image. It's based on Feature Pyramid Network (FPN) and a ResNet101 backbone.)
- Source code from https://github.com/matterport/Mask_RCNN
- Included as a tool in ArcGIS Pro

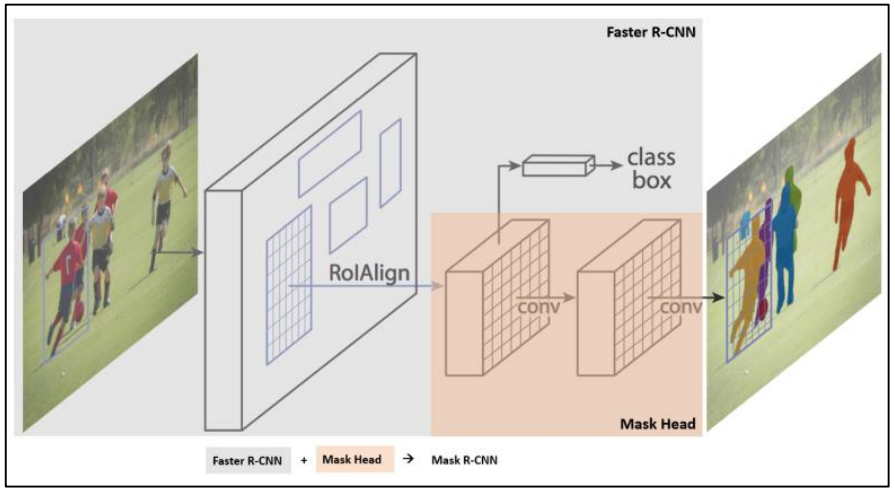


Semantic Segmentation vs *Instance Segmentation*

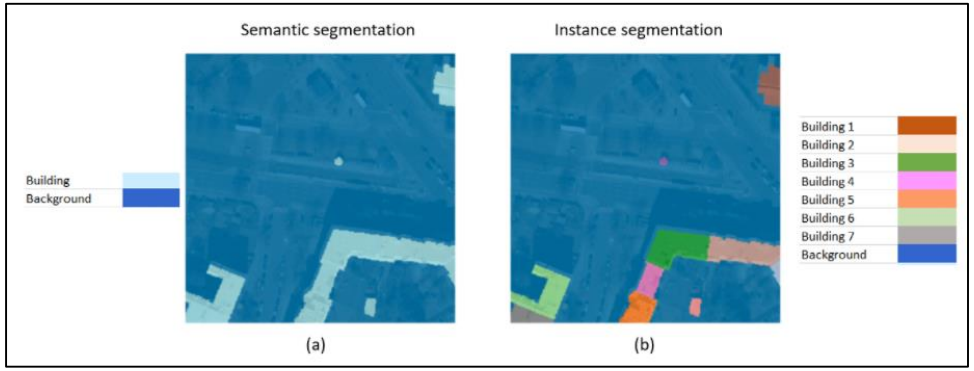
Image credit: https://towardsdatascience.com/



Architecture of the Faster R-CNN



Framework of the Mask R-CNN



Extracted from https://developers.arcgis.com/python/guide/how-maskrcnn-works/

Faster R-CNN predicts object class and bounding boxes.
Mask R-CNN is an extension of Faster R-CNN with additional branch for predicting segmentation masks on each Region of Interest (RoI).

6. Model training

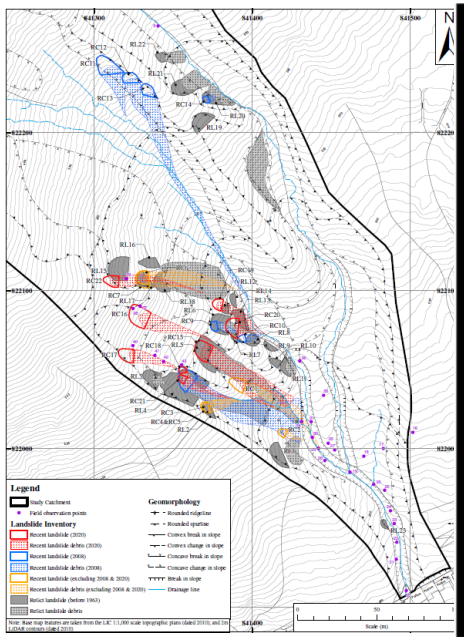
We've also tried different combinations of channels
More details will be provided in the paper.

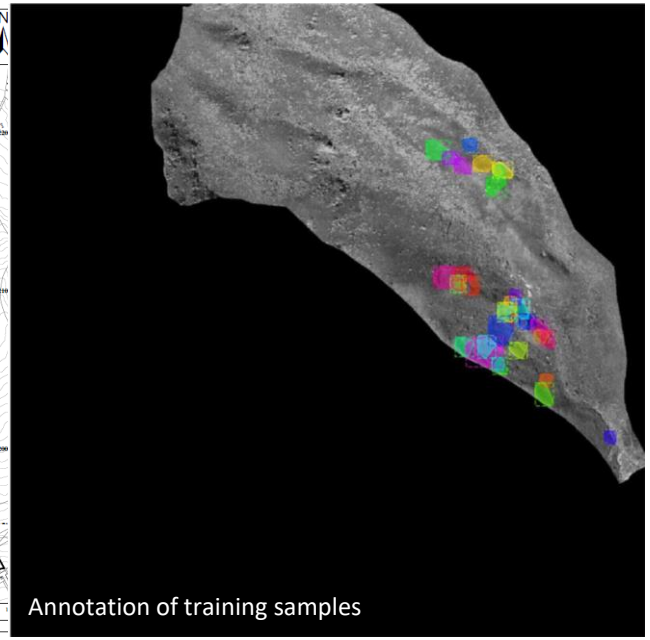
- How many training samples? totally 73 landslide scars in the two corresponding catchments were annotated as training samples (is it sufficient?)
- To overcome the data scale limitation, we use 9 (nine) channels data generated from the Digital Elevation Model (derived from 2010 LiDAR).
- The multi-channel images contain supplementary dimensional-wise information which can be treated as substitution of pixel-wise information for model training.
- Heterogeneous modality were aligned, standardized, and concatenated.

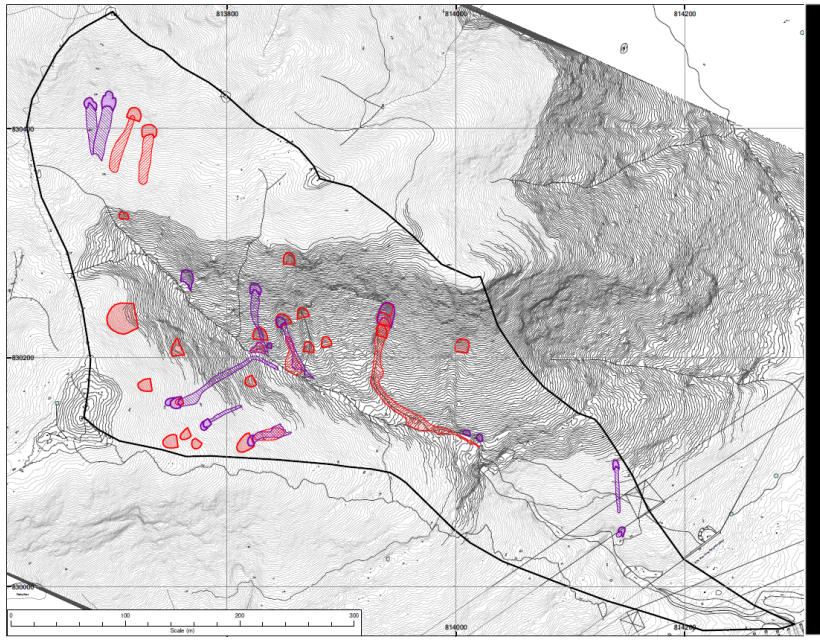
The nine channels are:

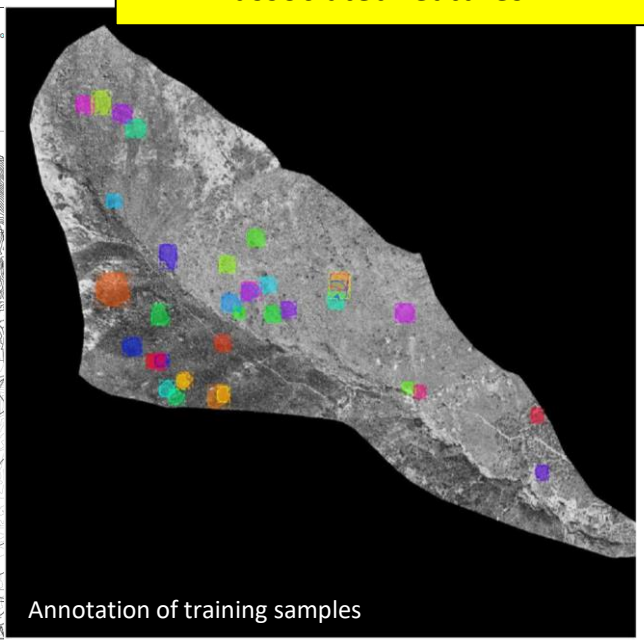
DEM
Slope
Slope roughness
Aspect
Aspect roughness
Landform classification
Curvature
Plan curvature
Profile curvature

These channels are carefully selected to reflect landslide associated features.




Annotation of training samples




Annotation of training samples

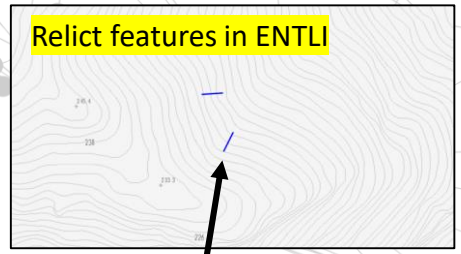
To ensure the robustness of the AI model, only the corresponding catchments, i.e. area investigated by API professionals, were included for model training. That means, the uninvestigated parts of the 1280 x 1280 pixels' images were treated as non-informative areas (the black out area as shown above) during the whole training procedure.

7. Training result and model inference

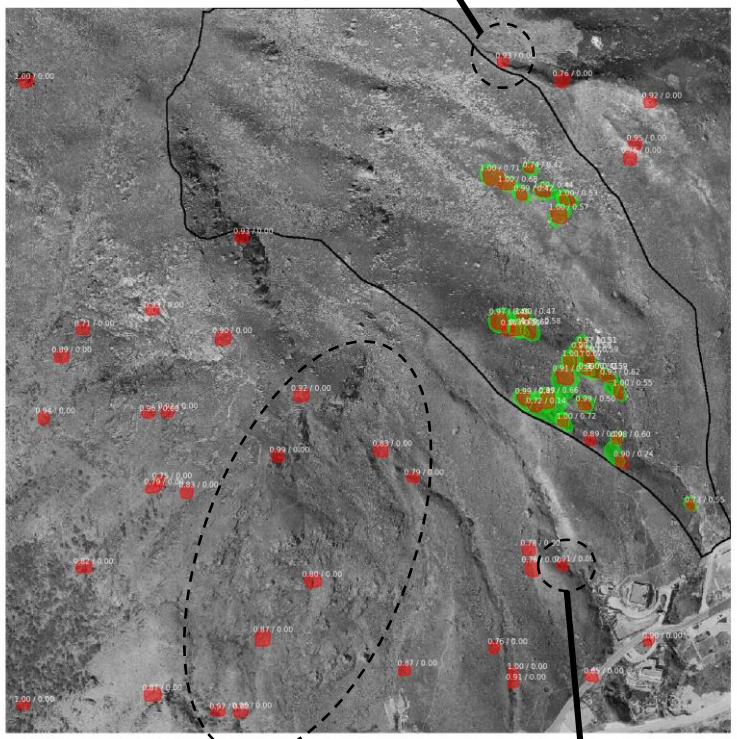
- Initial learning rate 0.001, decrease by a factor of 0.1 when loss stop decreasing.
- Train Average precision 0.821.
- Full 1280 x 1280 pixels images with all information enabled were then used for model inference.
- The results show that, the trained Mask R-CNN can not only clearly detect and segment the landslide scars in the investigated areas,
- but also infer with promising performance in the uninvestigated areas (outside the catchments).
- Limitations: resolution of the 2010 LiDAR, paucity of training samples, bedrock geology, landslide types, field validation…

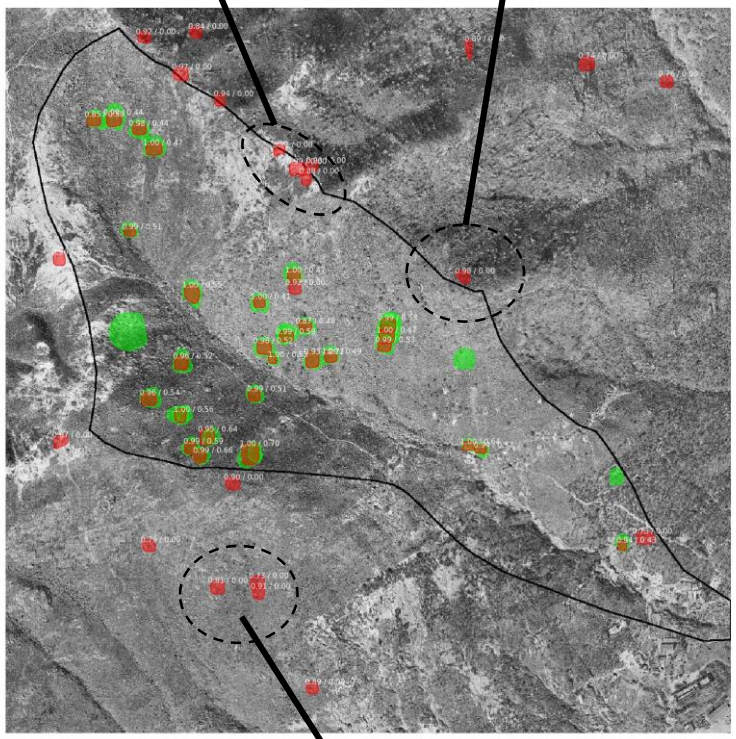
Recent features in ENTLI (2005)

Erosional features which are recognised by AI model but not included in ENTLI

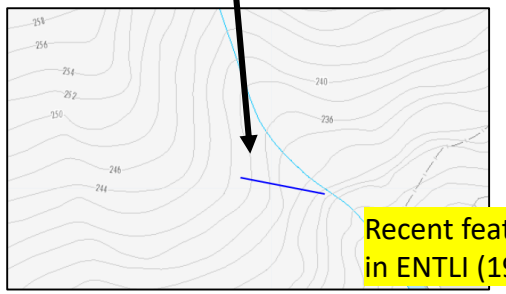


Relict features in ENTLI

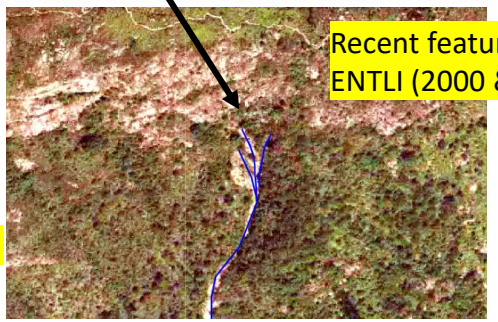




These were preliminarily validated using aerial photos



Recent features in ENTLI (1989)



Recent features in ENTLI (2000 & 2007)

8. Smart NTHS – Proposed Framework

- Our case studies indicate that in NTHS, the use of AI models can enhance professional investigation efforts, at the same time, the inferred results can be used as reliable references for further analysis and research.
- So, what's next?
- GRS ask for support and resources from different sectors of the greater geosciences community (the government, universities, professional societies and the industry)

  – LPMitP special tasks (AI, BIM, Digital Twin)

  – Collaboration with ESSC, CUHK

  – Focus Group 2 of HKRG of GSL

  – CIC research fund

We also propose to develop a package of tool boxes to implement an highly automation process, the **Smart NTHS**, in the geotechnical industry.

✓ Building historical DEM *(collaboration with ESSC CUHK)*

✓ Automated landform mapping *(our LIC report)*

✓ Automated mapping of landslide scars *(this study)*

✓ Automated regolith mapping *(AESC abstract)*

• Automated landslide susceptibility mapping *(study in progress)*

✓ Automated calculation of landslide source volumes *(HKIE abstract)*

✓ Semi-automated design event derivation *(MCF method, our LIC report and HKIE abstract in preparation)*

• Automated generation of initial engineering geological maps and associated cross sections, incorporating previous GI results

Thank you!

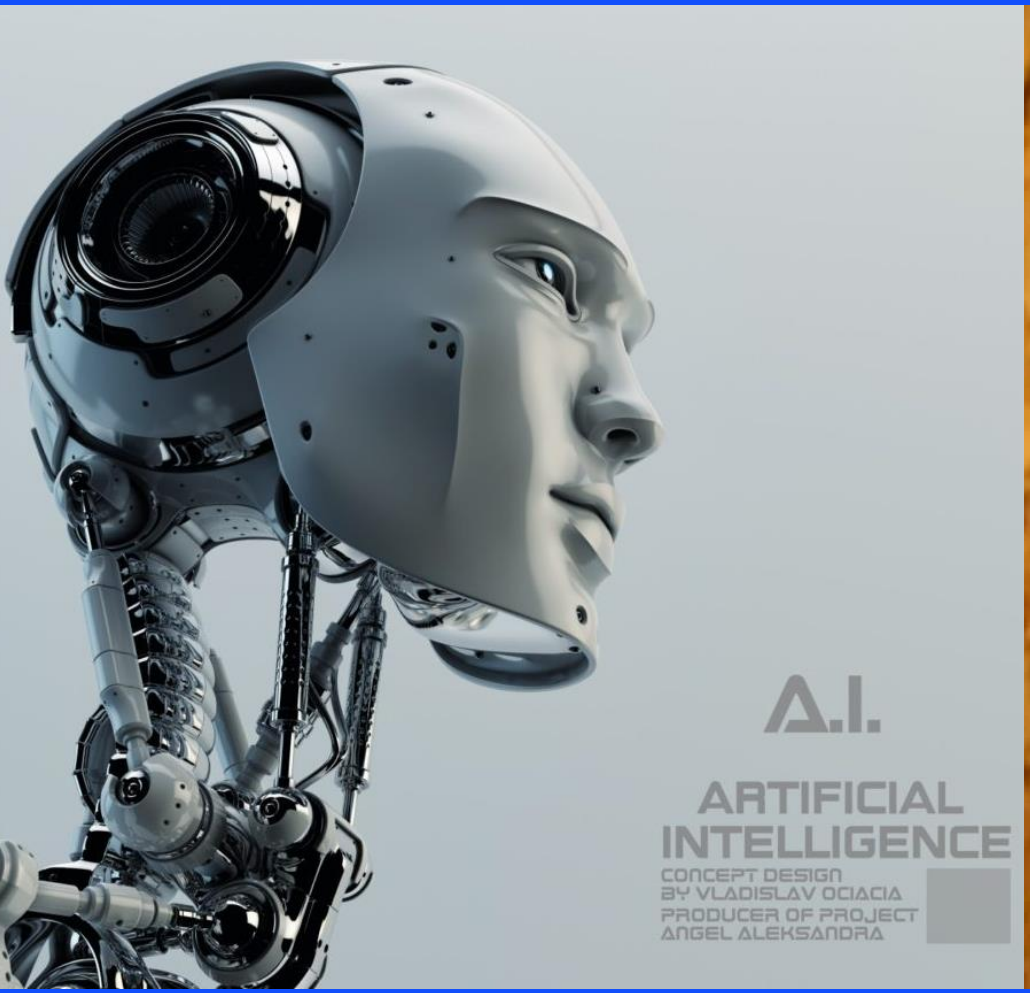
Dr. Wenzhu Hou - Email: whou@georisksolutions.com

(Engineering Geologist with GRS, Facilitator of FG2, HKRG of GSL)

Mr. Jonathan Roy Hart - Email: jhart@georisksolutions.com

(BSc, MSc, DIC, CGeol, Co-Founder, Director and Principal Geologist of GRS)

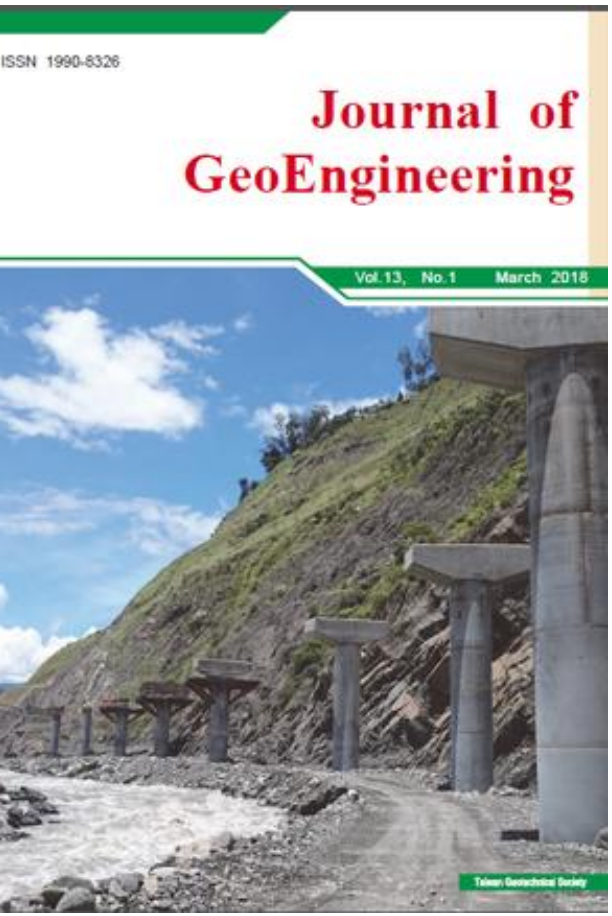
GeoRisk Solutions Limited - www.georisksolutions.com



The Tunnel of Eupalinos or Eupalinian aqueduct is a tunnel of 1,036 m length running through Mount Kastro in Samos, Greece, built in the 6th century BC to serve as an aqueduct.

ACKNOWLEDGMENTS

- IR TONY HO, CHAIRMAN, GEOTECHNICAL DIVISION, THE HONG KONG INSTITUTION OF ENGINEERS (HKIE GD)
- IR JEFFREY WONG, CHIEF GEOTECHNICAL ENGINEER/PLANNING, GEO, CEDD & CHAIRMAN, ORGANIZING COMMITTEE
- COLLABORATORS: JIANYE CHING (NATIONAL TAIWAN UNIVERSITY), TAKAYUKI SHUKU (OKAYAMA UNIVERSITY), HONGWEI HUANG (TONGJI UNIVERSITY), DONGMING ZHANG (TONGJI UNIVERSITY)



Journal of GeoEngineering, Vol. 16, No. 2, pp. 061-073, June 2021
http://dx.doi.org/10.6310/jog.202106_16(2).2

PROJECT DEEPGEO — DATA-DRIVEN 3D SUBSURFACE MAPPING

Kok-Kwang Phoon [1*] and Jianye Ching [2]

ABSTRACT

Data-driven site characterization (DDSC) is defined as any site characterization methodology that relies solely on measured data, both site-specific data collected for the current project and existing data of any type collected from past stages of the same project or past projects at the same site, neighboring sites, or beyond. One key complication is that real data is "ugly". A useful mnemonic is MUSIC-3X (Multivariate, Uncertain and Unique, Sparse, Incomplete, and potentially Corrupted with "3X" denoting three dimensional spatial variations). It is an open question whether DDSC can solve real world subsurface mapping problems based on real world MUSIC-3X data from routine projects with minimum ad-hoc assumptions. The computational challenges are very significant, but some reasonable partial solutions have been obtained recently. One promising solution is Sparse Bayesian Learning (SBL). It is nearly data-driven and it can handle a large scale 3D problem without incurring excessive cost. However, it can only handle one type of field test data. Nonetheless, it is already useful for practice. A 3D SBL version would be made available in Rocscience's Settle3 (three-dimensional soil settlement analysis) in the near future to generate subsurface maps based on cone penetration test data. The second solution is based on a variant of the Gaussian Process Regression (GPR-MUSIC-3X). It can handle multiple field test data by learning the cross-correlation behavior among different soil parameters at a single site of interest. GPR-MUSIC-3X can be enhanced to learn cross-correlation behaviors at multiple sites and thus bring information from "similar" sites in a larger generic database to bear on improving predictions at a single site. Both 3D SBL and GPR-MUSIC-3X are cross validated using a 2D virtual ground and an actual 3D site in Texas. The hunt is on for a "holy grail" mapping approach that is fully data-driven, MUSIC-3X compliant, and is able to exploit all available data including data from similar sites. This is Project DeepGeo (inspired by DeepMind that produces AlphaGo), which constitutes one major research effort in the emerging field of data-centric geotechnics.

Key words: Data-driven site characterization (DDSC), MUSIC-3X, Sparse Bayesian Learning (SBL), Gaussian process regression, data-centric geotechnics.

ice
Institution of Civil Engineers

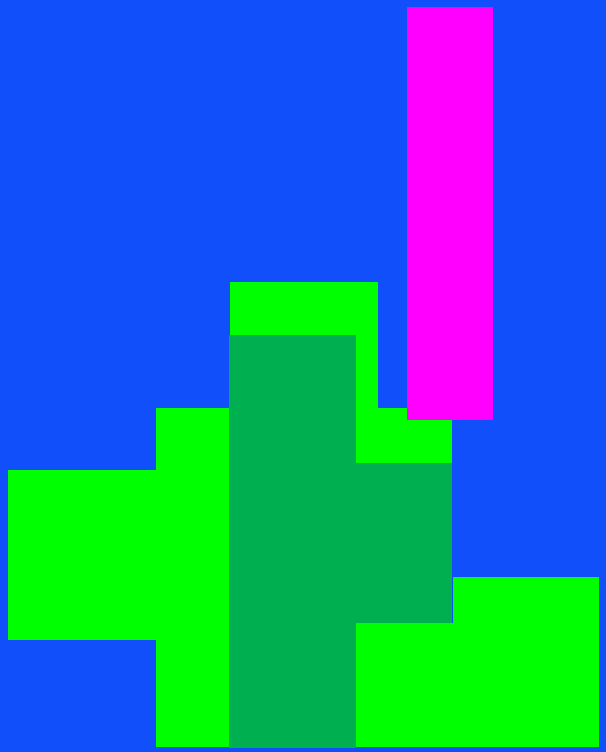
State Of The Nation 2017:
Digital Transformation

INDUSTRY 4.0

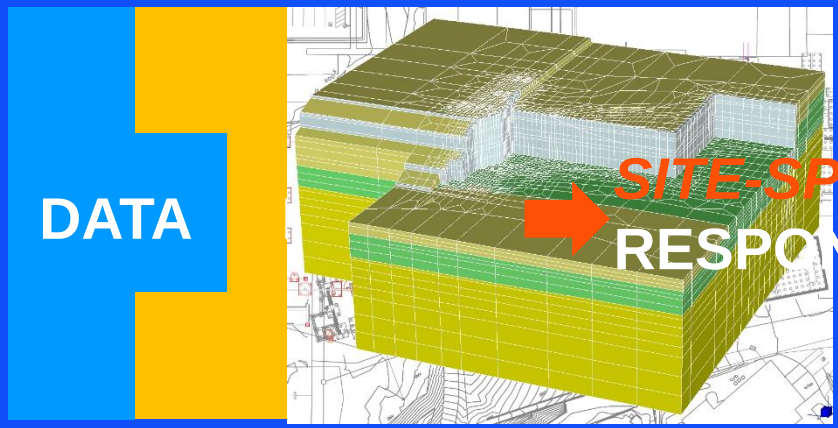
GEO 3.0 → GEO 4.0

- DATA-CENTRIC GEOTECHNICS
- "DIGITAL FIRST" AGENDA
- METHOD TO MAKE SENSE OF *ACTUAL* DATA
- *NOT* INTERPRET DATA TO MAKE SENSE OF METHOD
- "FIT FOR PRACTICE"
- *VALUE* TO *SPECIFIC* SITE/PROJECT

PHYSICS



PHYSICAL
INPUTS: G, s_u

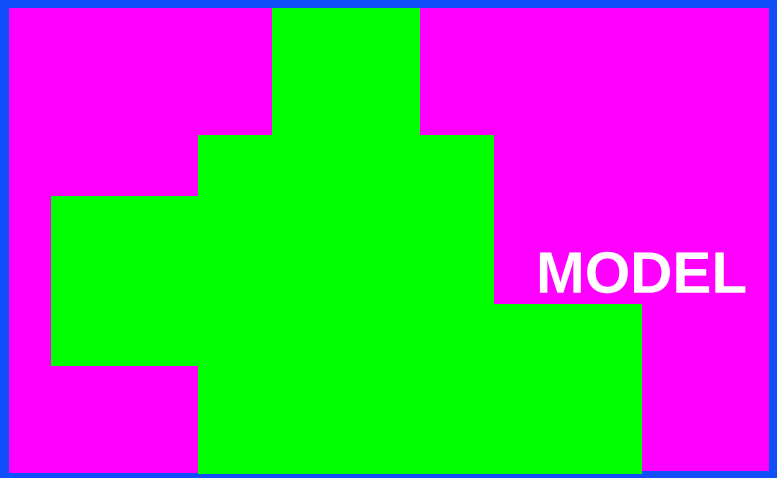


REAL WORLD DATA

CALIBRATION & JUDGMENT

PHYSICAL MODEL

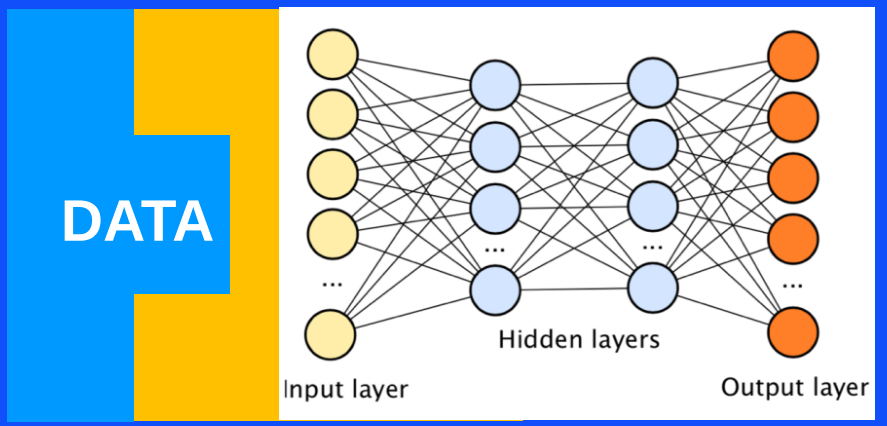
DATA-DRIVEN



LEARNING/
TRAINING

REAL
WORLD
DATA

INPUT LAYER



DATA-DRIVEN
MODEL

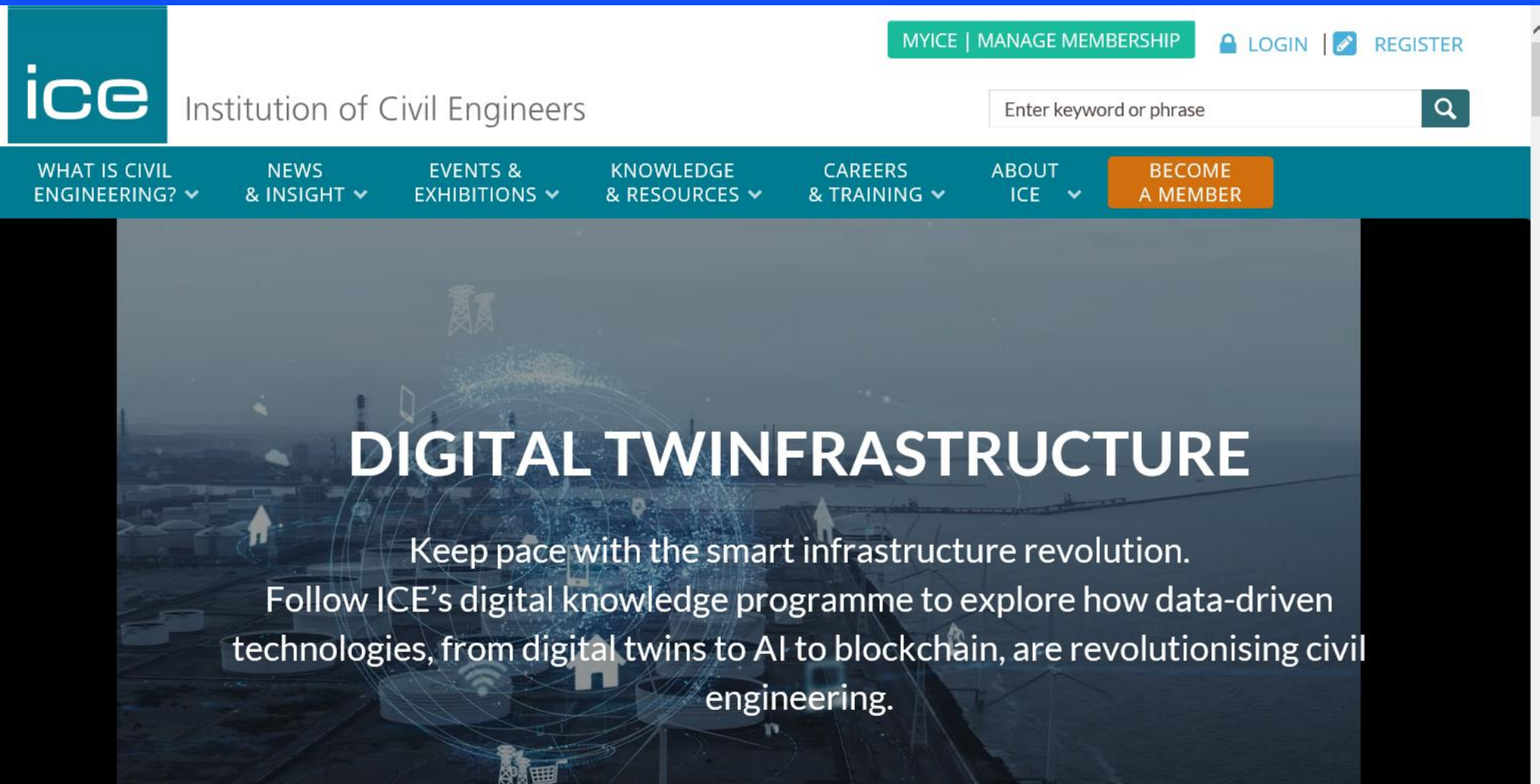
Phoon, K. K., Ching, J., and Wang Y. (2019). Managing risk in geotechnical engineering – from data to digitalization. Proceedings, 7th International Symposium on Geotechnical Safety and Risk (ISGSR 2019), Taipei, Taiwan, 13-34. http://rpsonline.com.sg/proceedings/isgsr2019/index.html

GEO 4.0 – 7 Es

1. **E**SSENCE – *REAL* DATA FIRST METHOD SECOND
2. **E**CONOMIC VALUE – DECISION MAKING IN A ROUTINE PROJECT *AT A SPECIFIC SITE*
3. **E**XCHANGE – BIG INDIRECT DATA (D… LIMITED WORK …ACY)
4. **E**XTREMES – … LIMITED WORK …
5. **E**RRORS – UGLY DATA
6. **E**XTRAPOLATION – OVERFITTING
7. **E**XPLANATION – EX… LIMITED WORK …ILITY & HUMAN JUDGMENT

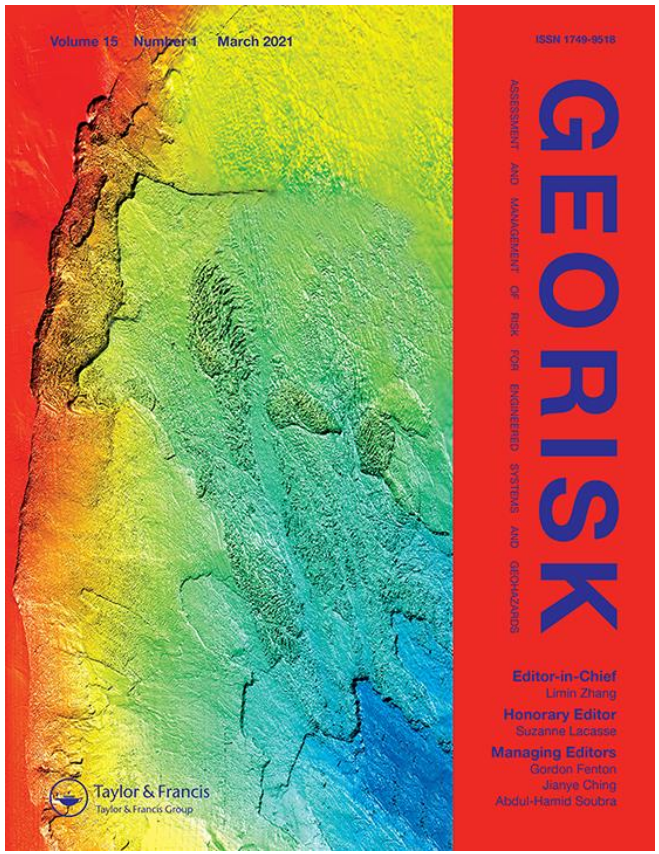
GEO 4.0

DATA-CENTRIC GEOTECHNICS



DATA-DRIVEN SITE CHARACTERIZATION (DDSC)

- **METHODOLOGY THAT RELIES SOLELY ON MEASURED DATA, BOTH SITE-SPECIFIC DATA COLLECTED FOR THE CURRENT PROJECT & EXISTING DATA OF ANY TYPE COLLECTED FROM PAST STAGES OF THE SAME PROJECT OR PAST PROJECTS AT THE SAME SITE, NEIGHBORING SITES, OR BEYOND**
  - SMALL DATA FROM ***ROUTINE*** PROJECTS
  - BIG INDIRECT DATA FROM ***"SIMILAR"*** PROJECTS
  - QUASI-SITE-SPECIFIC MODEL***TRAINED*** BY ***REAL*** DATA (BIG & SMALL)
  - COMPUTABLE IN ***3D***



GEORISK
https://doi.org/10.1080/17499518.2021.1896005

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Challenges in data-driven site characterization

Kok-Kwang Phoon [a], Jianye Ching [b] and Takayuki Shuku [c]

[a]Dept. of Civil and Environmental Engineering, National Univ. of Singapore, Singapore; [b]Dept. of Civil Engineering, National Taiwan University, Taipei, Taiwan; [c]Dept. of Environmental Management Engineering, Okayama Univ., Okayama, Japan

ABSTRACT

Site characterisation is a cornerstone of geotechnical and rock engineering. "Data-driven site characterisation" refers to any site characterisation methodology that relies solely on measured data, both site-specific data collected for the current project and existing data of any type collected from past stages of the same project or past projects at the same site, neighbouring sites, or beyond. It is an open question what data-driven site characterisation (DDSC) can achieve and how useful are the outcomes *for practice*, but this "value of data" question is of major interest given the rapid pace of digital transformation in many industries. The scientific aspects of this question are presented as three challenges in this paper: (1) ugly data, (2) site recognition, and (3) stratification. The practical aspect that cannot be ignored is how to scale any solution to a realistic 3D setting in terms of size and complexity at reasonable cost. No deployment in practice is possible otherwise. At this point, the practicing community at large has yet to be convinced what data, big or small, could do to transform current practice. The authors believe that we need a more purposeful agenda to hasten research in this direction that would include articulating clearer statements for the challenges, developing benchmarks to compare solutions, and bringing research to practice through software.

ARTICLE HISTORY
Received 31 October 2020
Accepted 23 February 2021

KEYWORDS
Data-driven site characterisation (DDSC); ugly data; MUSIC-3X; site recognition; stratification

Phoon, K. K., Ching, J., and Shuku, T. 2021. Challenges in data-driven site characterization. *Georisk: Assessment and Management of Risk for Engineered Systems and Geohazards*, online

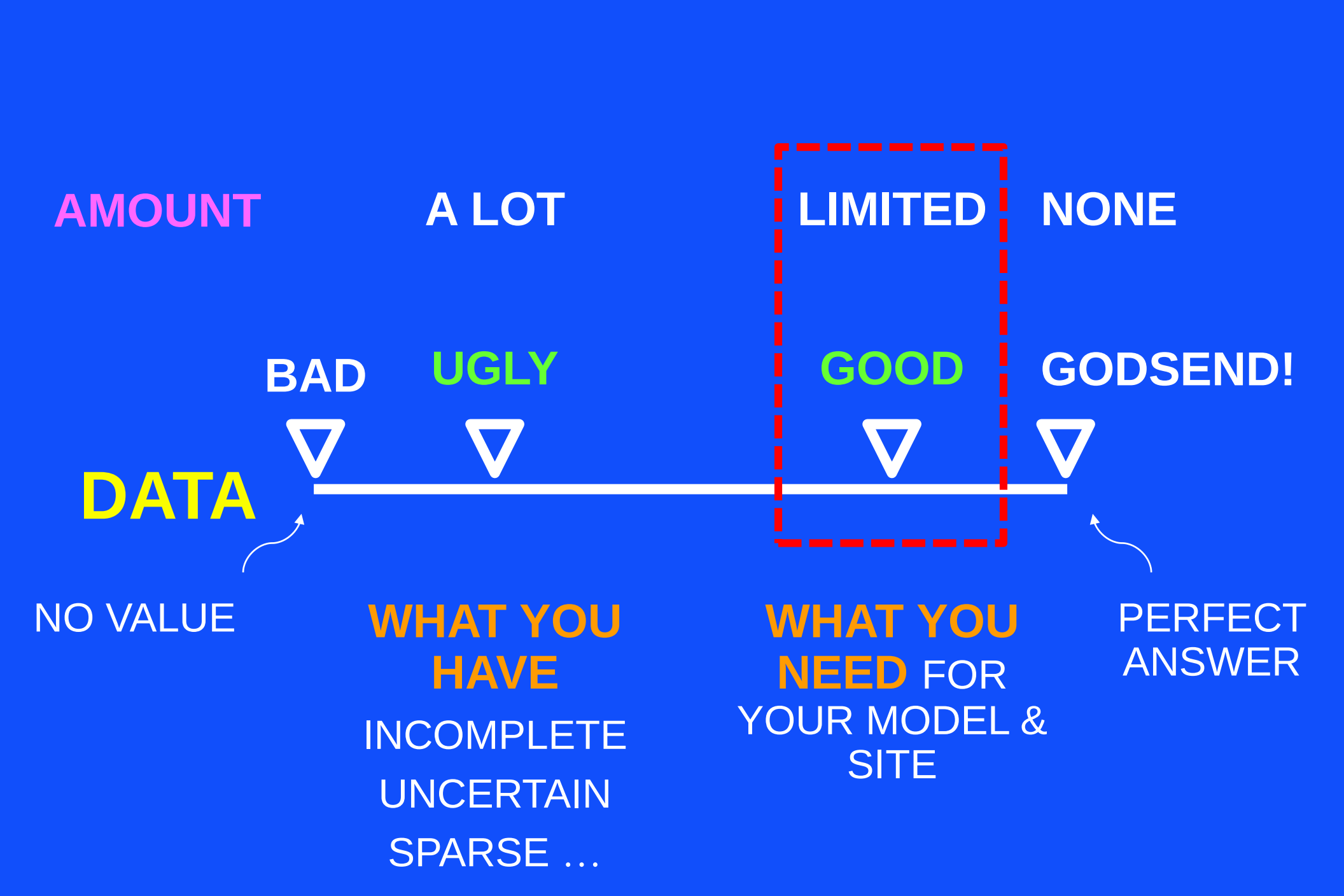
THREE CHALLENGES

1. **UGLY DATA**

2. **SITE RECOGNITION**

3. **STRATIFICATION**
   - BENCHMARKING

Phoon, K. K., Ching, J. and Shuku, T. 2021. Challenges in data-driven site characterization. Georisk: Assessment and Management of Risk for Engineered Systems and Geohazards, online


AMOUNT
A LOT
LIMITED
NONE
BAD
UGLY
GOOD
GODSEND!
DATA
NO VALUE
WHAT YOU HAVE
INCOMPLETE
UNCERTAIN
SPARSE …
WHAT YOU NEED FOR YOUR MODEL & SITE
PERFECT ANSWER

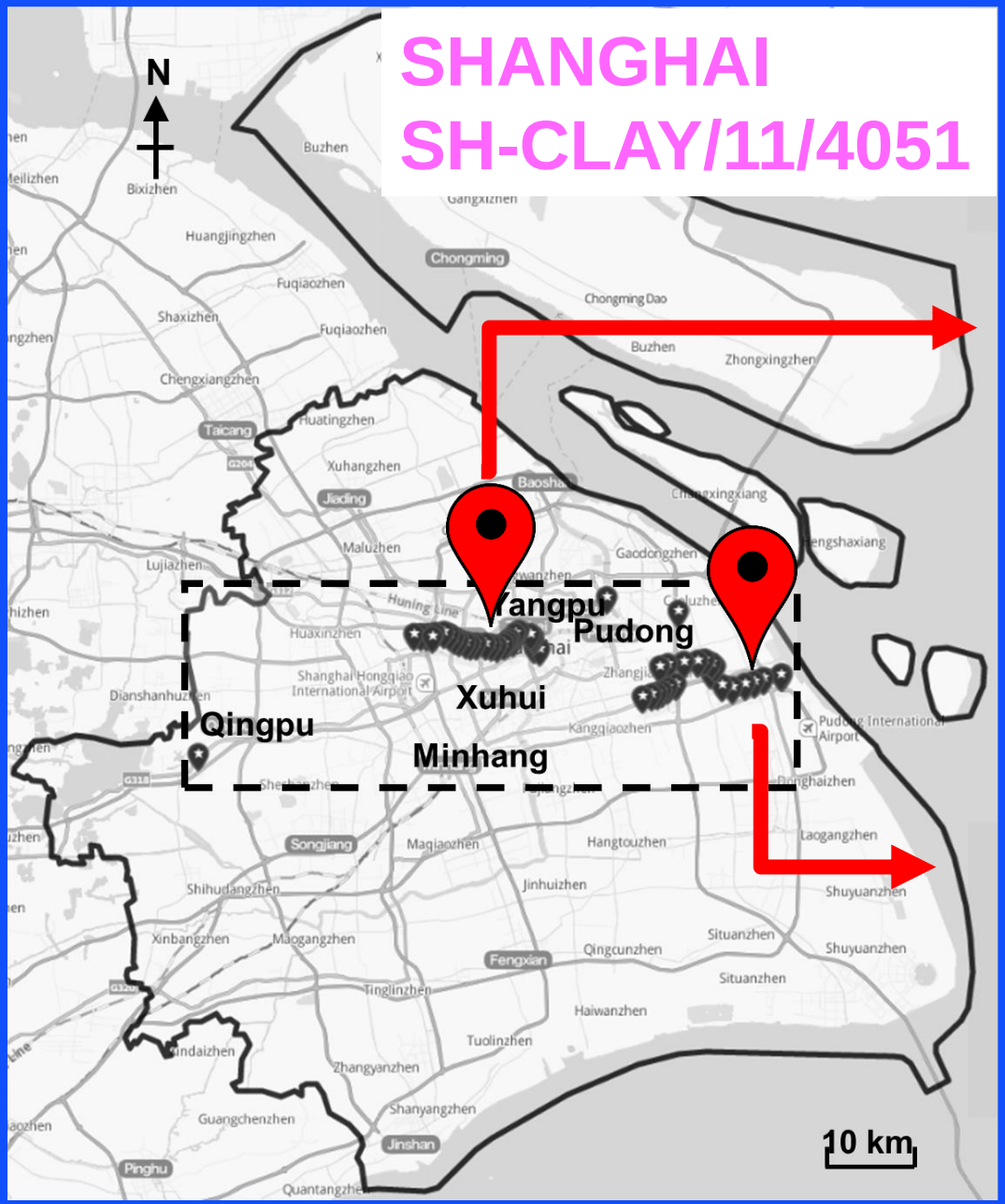
WHAT IS BAD DATA

LIMITED WORK

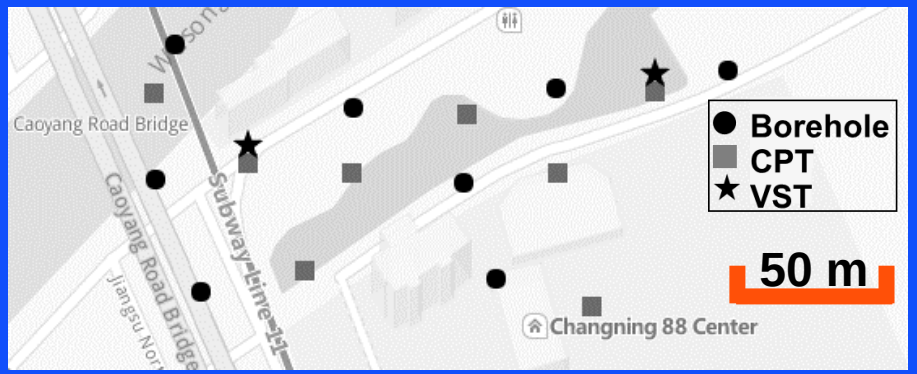
- BAD DATA IS WORSE THAN NO DATA
- BAD DECISION FROM BAD DATA
- GOOD DECISION FROM UGLY DATA

- UGLY DATA IS ***NOT*** BAD DATA
- UGLY DATA A LOT
- BAD DATA UNKNOWN

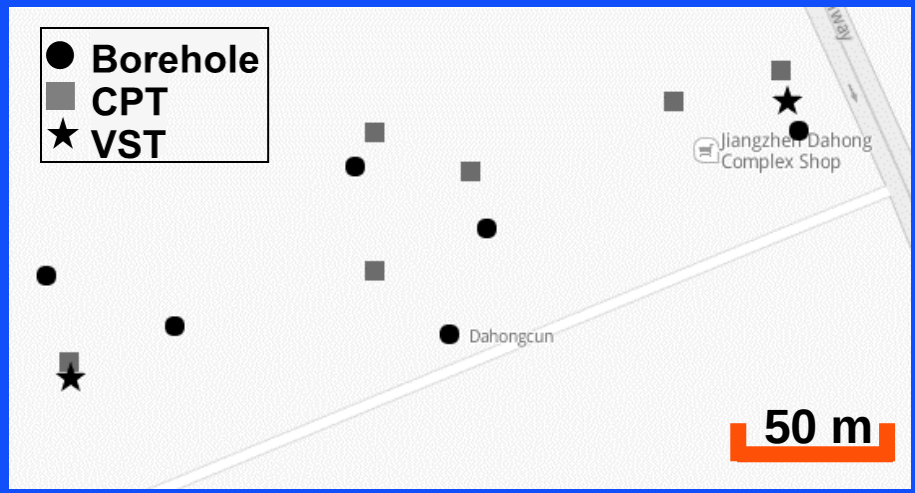
SHANGHAI
SH-CLAY/11/4051



SITE PLAN



METRO LINE 13, JINSHA JIANG ROAD STATION



METRO LINE 2, EAST CHUANSHA STATION

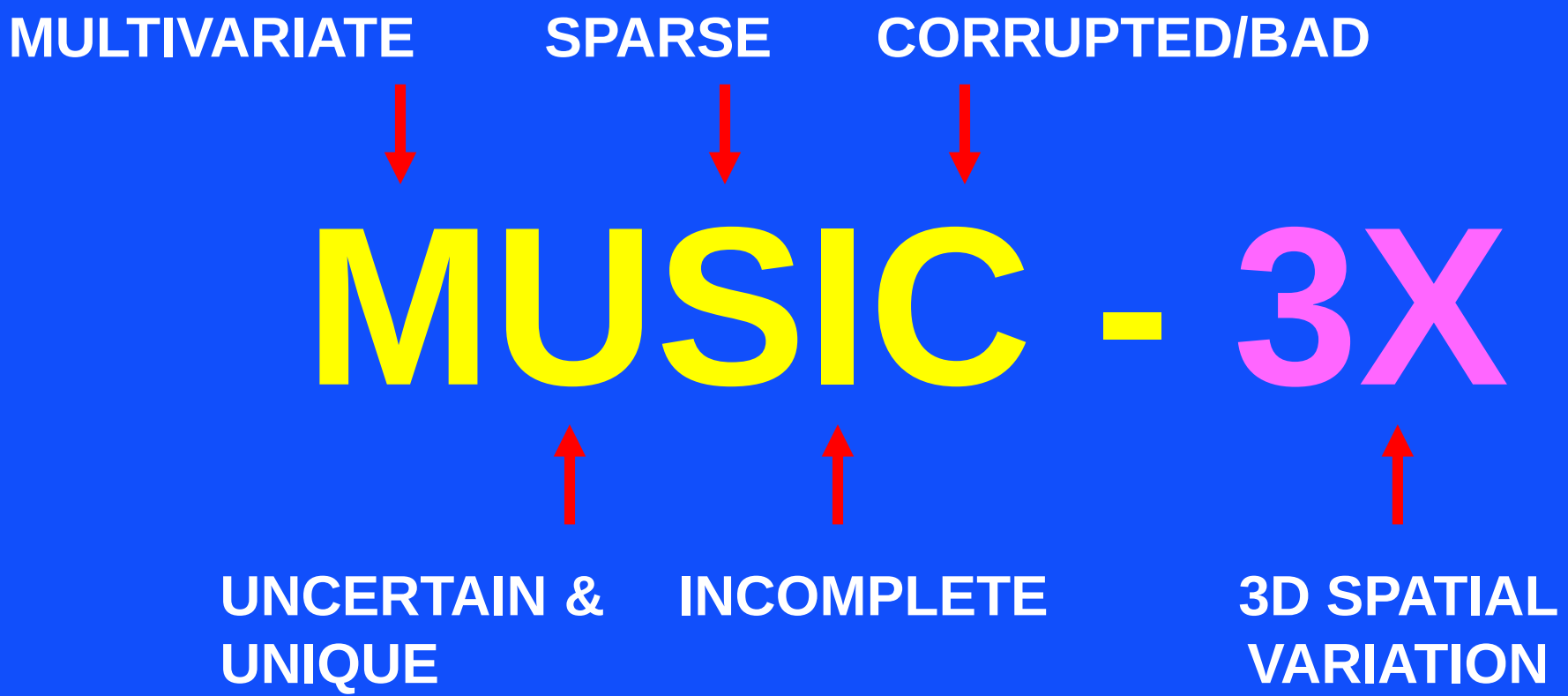
Zhang, D. M., Zhou, Y., Phoon, K. K. & Huang, H. W. 2020. Multivariate probability distribution of Shanghai clay properties. Engineering Geology, 273, 105675.

SITE-SPECIFIC DATA

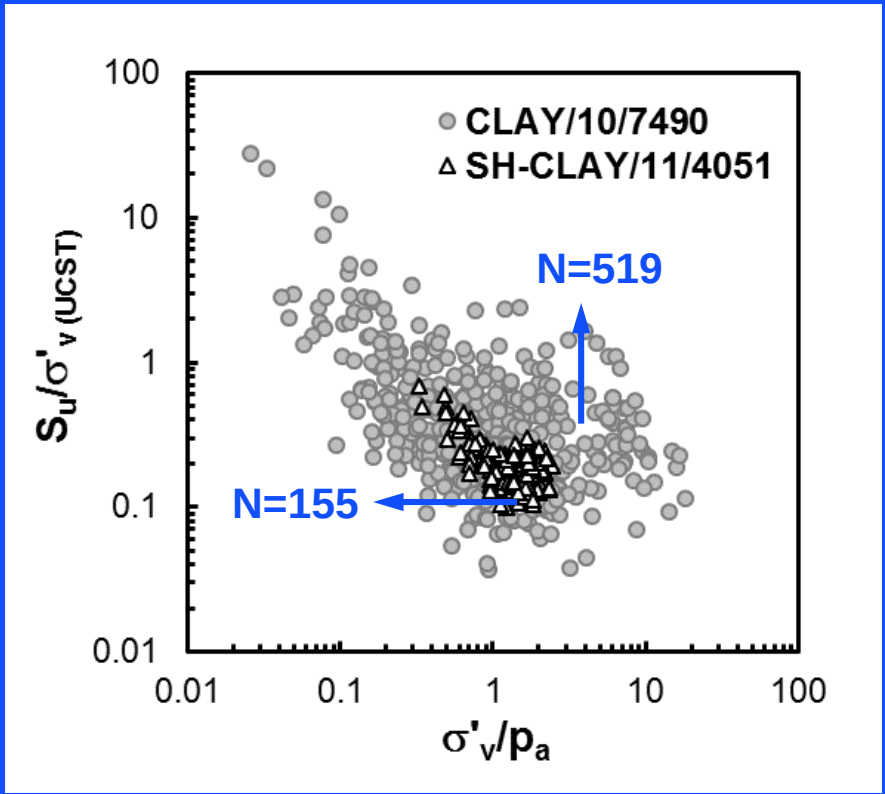
CPT

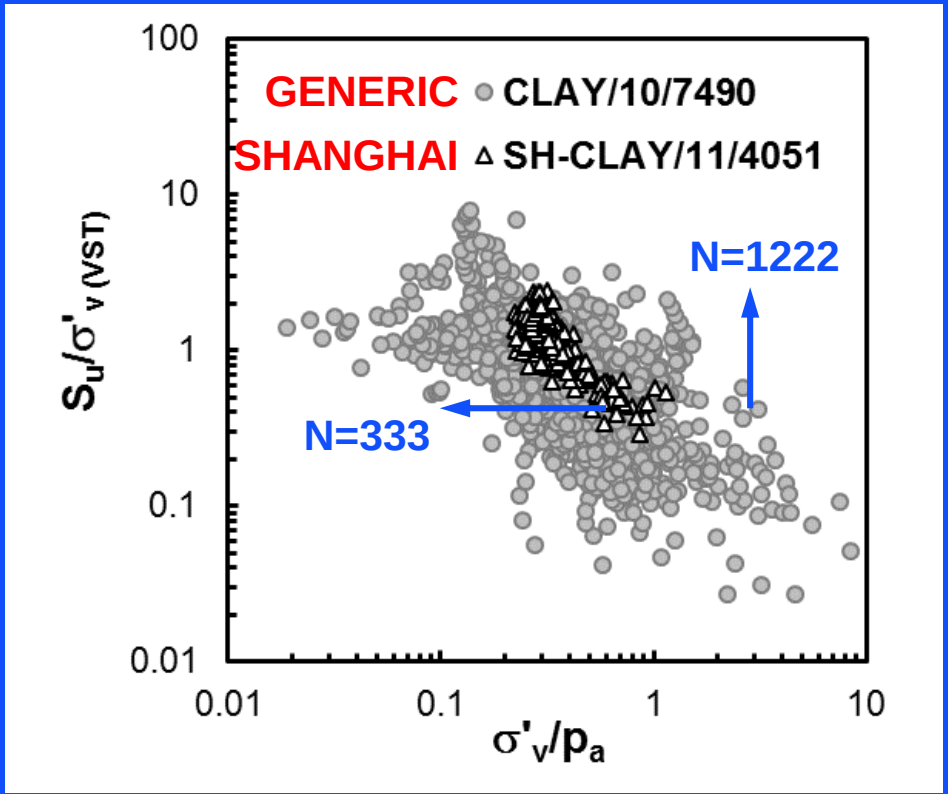
Site	Depth	LL	PI	LI	e	K_0	σ'_v	$S_{u(UCST)}$	$S_{t(UCST)}$	$S_{u(VST)}$	$S_{t(VST)}$	p_s
Metro Line 13 Jinsha-Jiang Road Station	10.5	33.5	13.4	1.20	1.013		90.09	42				1.54
	11	41.3	18.0	1.48	1.432		93.60			32.6	10.5	0.84
	11.5	45.7	20.1	1.14	1.388	0.54	97.19					0.68
	12	45.8	22.4	1.38	1.539		100.56	46		38.6	9.9	0.63
	12.5	43.6	21.3	1.24	1.407		104.13					0.63
	14.5	43.5	20.2	1.42	1.473		117.99			41.6	11.5	0.63
	16.5	41.9	20.3	1.05	1.260		133.17			51.8	12.2	0.73
	18	37.5	16.7	0.86	1.015	0.48	145.79					0.84
	18.5	37.3	16.8	0.98	1.044		149.94	111				0.84
	19	35.1	15.2	0.90	0.993		154.19					0.76
	19.5	33.8	13.2	1.02	0.981		158.44					0.79
	20	35.7	15.3	0.78	0.954		162.78					0.79

Zhang, D. M., Zhou, Y., Phoon, K. K. & Huang, H. W. 2020. Multivariate probability distribution of Shanghai clay properties. Engineering Geology, 273, 105675.


MULTIVARIATE
SPARSE
CORRUPTED/BAD
MUSIC - 3X
UNCERTAIN & UNIQUE
INCOMPLETE
3D SPATIAL VARIATION

UNIQUE





Zhang, D. M., Zhou, Y., Phoon, K. K. & Huang, H. W. 2020. Multivariate probability distribution of Shanghai clay properties. Engineering Geology, 273, 105675.

GOOD TO UGLIER

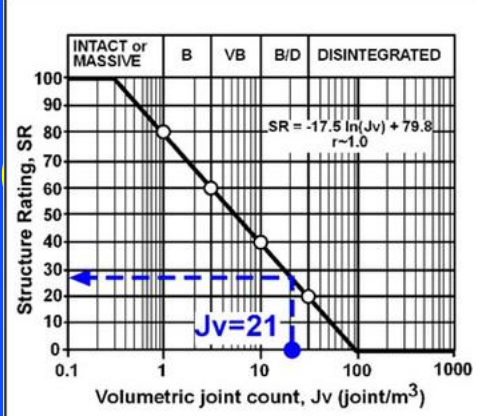
DETERMINISTIC	X = 5.0
PROBABILISTIC	MEAN = 5.0, STD = 1.0
IMPRECISE	MEAN = [4.0, 6.0], STD = [0.5, 1.5]
INTERVAL	X = [3.5, 6.5]
CENSORED	X > 5.0
TRUNCATED	N = 0 for X < 5.0
MISSING	N = 0

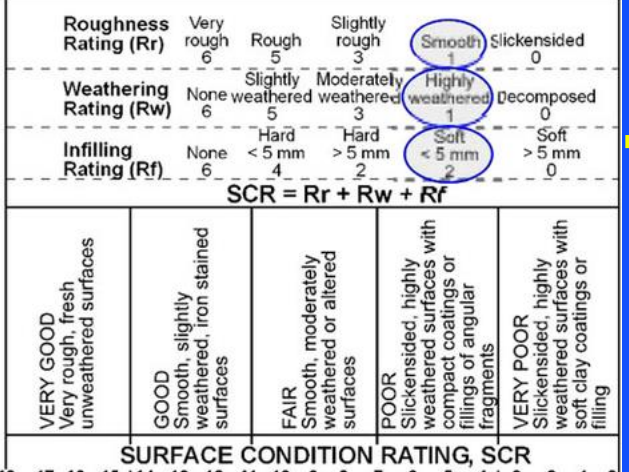
NOMINAL ORDINAL — CATEGORICAL

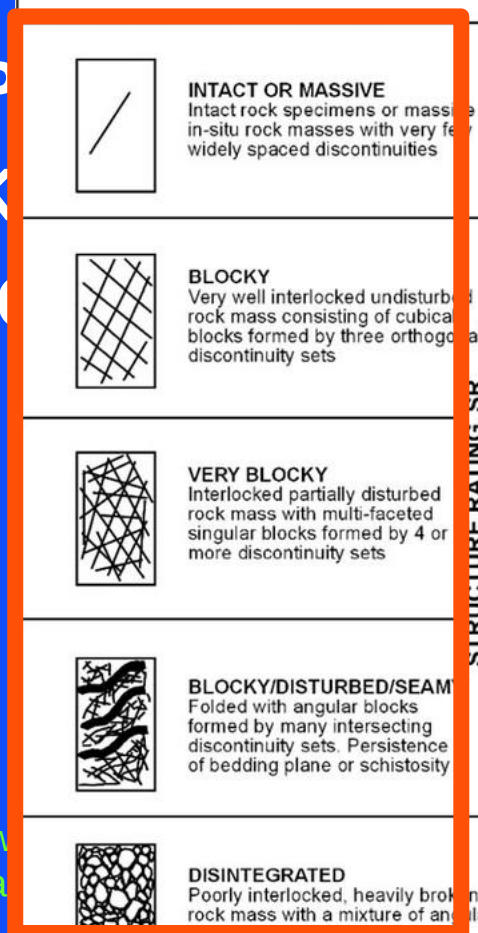
INTERVAL RATIO — NUMERICAL

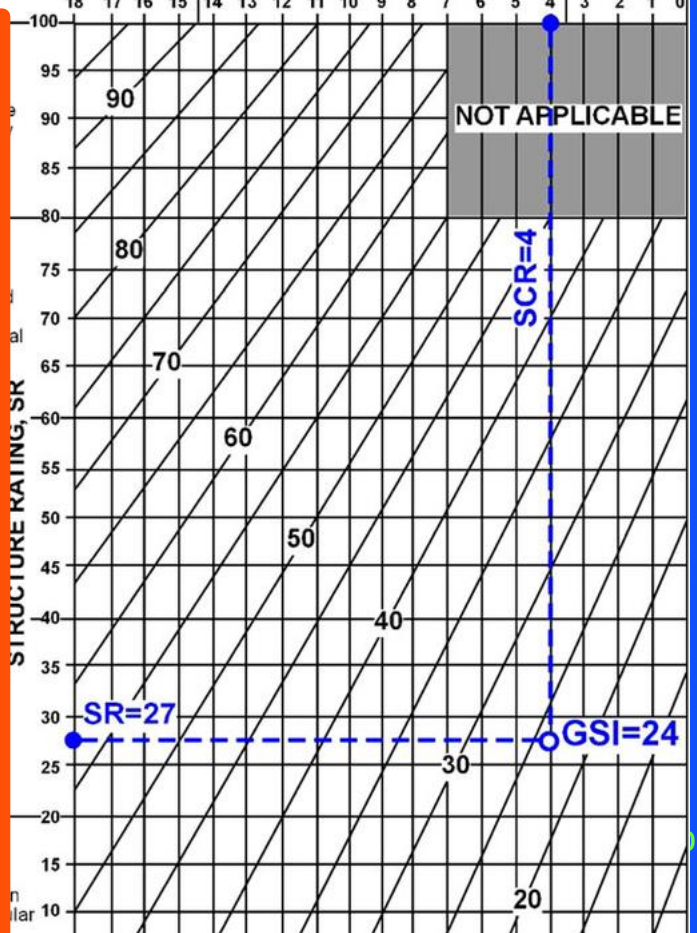
GE TH

- EXAMP
- BLOCK
- JOINT









Hoek, E. and Brow on. Journal of Rock Mechanics a

MOONSHOTS

STATE OF DDSC	SOME LITERATURE	LIMITED LITERATURE	NONE?
GEOMATERIALS	SOIL	ROCK	IMPROVED GROUND
DATA TYPES	GEOTECHNICAL INVESTIGATION	GEOPHYSICAL	EMERGING DATA: LASER SCANNING, PHOTOGRAMMETRY
UGLY DATA CHALLENGE	MUSIC-3X	CATEGORICAL DATA	FALSIFIED DATA
SITE RECOGNITION CHALLENGE	TRANSFORMATION MODELS	PERFORMANCE DATA: LOAD TESTS, OBSERVATIONS	HEALTH MONITORING, REMOTE SENSING
STRATIFICATION CHALLENGE	CPT SOIL BEHAVIOR TYPE	DISCONTINUITIES	ANOMALIES

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BIG INDIRECT DATA (BID)

ANY DATA THAT ARE POTENTIALLY USEFUL BUT NOT DIRECTLY APPLICABLE TO THE DECISION AT HAND

GENERIC PROPERTY DATABASES (1)

Database	Reference	Parameters of interest	# Data points	# Sites/ studies	Range of parameters		
					OCR	PI	S_t
CLAY/5/345	Ching and Phoon (2012)	LI, s_u, s_u^{re}, σ'_p, σ'_v	345	37 sites	– 4	—	Sensitive to quick clays
CLAY/6/535	Ching et al. (2014)	s_u/σ'_v, OCR, $(q_t-\sigma_v)/\sigma'_v$, $(q_t-u_2)/\sigma'_v$, $(u_2-u_0)/\sigma'_v$, B_q	535	40 sites	– 6	Low to very high plasticity	Insensitive to quick clays
CLAY/7/6310	Ching and Phoon (2013, 2015)	s_u from 7 different test procedures	6310	164 studies	– 10	Low to very high plasticity	Insensitive to quick clays
CLAY/10/7490	Ching and Phoon (2014)	LL, PI, LI, σ'_v/P_a, S_t, B_q, σ'_p/P_a, s_u/σ'_v, $(q_t-\sigma_v)/\sigma'_v$, $(q_t-u_2)/\sigma'_v$	7490	251 studies	– 10	Low to very high plasticity	Insensitive to quick clays
CLAY/9/249	D'Ignazio et al. (2019)	σ'_p/P_a, σ_v/P_a, σ'_v/P_a, q_t/P_a, u_2/P_a, u_0/P_a, PI, w_n, S	249	18 sites	– 10	Low to very high plasticity	Insensitive to quick clays
FG/KSAT/4/1358	Feng and Vardanega (2019)	e, LL, w_n/LL, $-\ln(k_{sat})$	1358	33 studies	–	Low to very high plasticity	—

Site (region)	LI	s_u	s_u^{re}	σ'_v	σ'_p	Reference
Ariake Bay (Japan) UC tests S_t = 2.0 ~ 43.4	1.28	2.58	0.22	9.56	7.94	Ohtsubo et al. (1995)
	1.27	4.74	0.16	12.82	29.41	
	1.45	5.42	0.39	16.44	17.14	
	1.20	5.82	0.59	20.06	27.63	
	1.26	6.97	0.65	24.04	23.37	
	1.36	6.83	0.44	27.30	26.53	
	1.29	11.08	0.44	31.65	34.10	
	1.24	10.36	0.52	34.54	29.30	
	1.24	13.10	0.39	38.53	40.84	
	1.31	15.88	0.63	41.79	42.82	

Database	Reference	Parameters of interest	# Data points	# Sites/ studies	Range of parameters		
					OCR	PI	S_t
CLAY/5/345	Ching and Phoon (2012)	LI, s_u, s_u^{re}, σ'_p, σ'_v	**345**	**37 sites**	1 – 4	—	Sensitive to quick clays

	0.89	49.35	2.94	73.65	181.98	
Gosport (U.K) UC tests S_t = 2.4 ~ 3.1	0.59	8.93	3.67	39.01	29.61	Skempton (1948)
	0.38	34.55	13.67	130.66	128.31	
	0.55	9.87	3.22	35.72	31.49	
	0.42	20.68	6.75	110.45	88.36	
	0.46	12.22	4.13	33.37	46.06	
Åsrum (Canada) UC tests	2.02	10.56	0.14	7.70	29.98	Parry and Wroth (1981)

Ching, J. Y. & Phoon, K. K. 2012. Modeling parameters of structured clays as a multivariate normal distribution. Canadian Geotechnical Journal, 49(5), 522-545

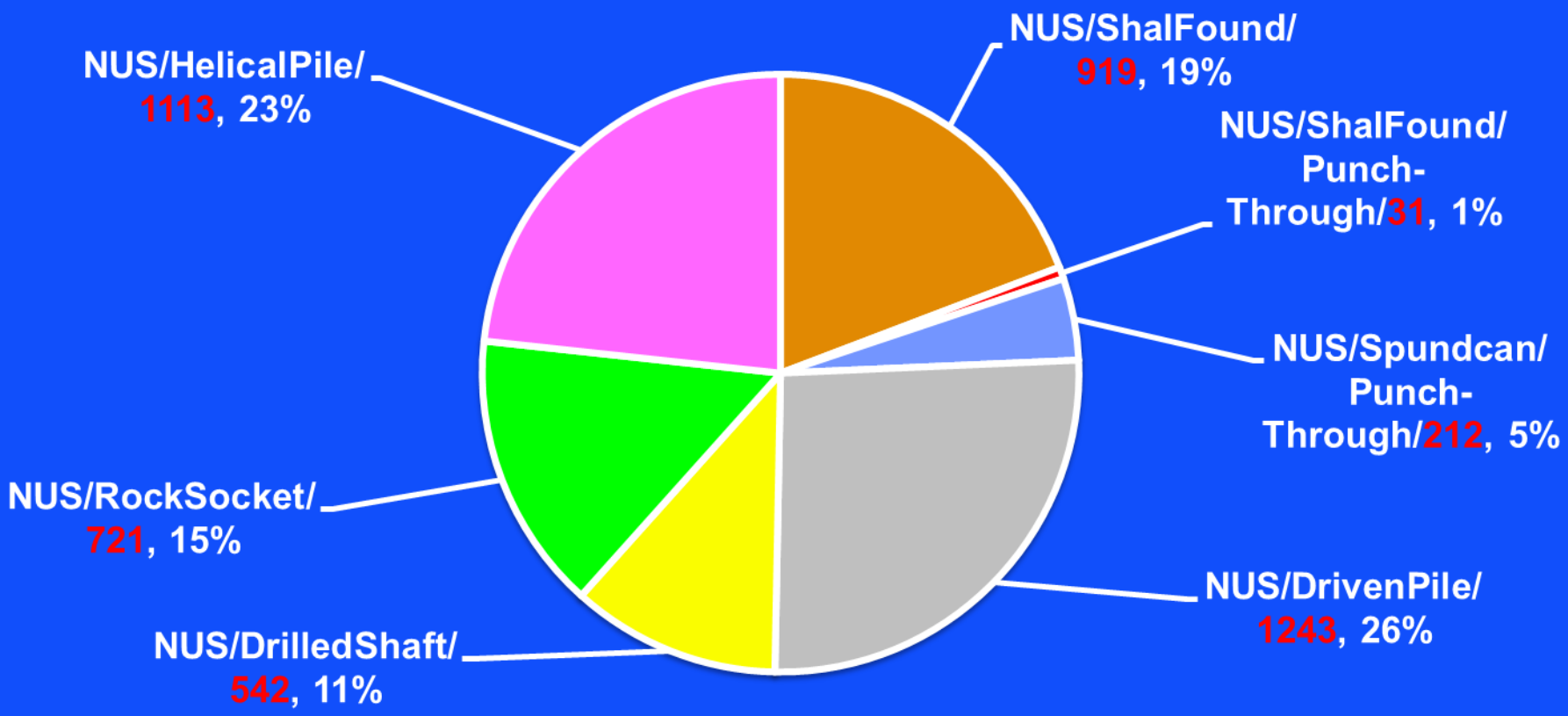
GENERIC PROPERTY DATABASES (2)

Database	Reference	Parameters of interest	# Data points	# Sites/ studies	Range of parameters		
					OCR	PI	S_t
FI-CLAY/7/216	D'Ignazio et al. (2016)	s_u^{FV}, σ'_v, σ'_p, w_n, LL, PL, S_t	216	24 sites	– 7.5	Low to very high plasticity	Insensitive to quick clays
JS-Clay/5/124	Liu et al. (2016)	M_r, q_c, f_s, w_n, γ_d	124	16	Soft to stiff clayey soils and silty clay soils with high variability of the strength and stiffness characteristics M_r = 12.54 – 95.82 MPa, q_c = 0.22 – 3.93 MPa, f_s = 0.03 – 0.14 MPa, w_n (%) = 6.91 – 78.11, γ_d=10.47 – 19.92 kN/m^3		
RFG/TXCU-278	Beesley and Vardanega (2019)	s_u/σ'_v, $\gamma_{50\ CIU}$, OCR, $\gamma_{50\ CKU}$	278	21 studies	– 32	Low to medium-high plasticity	
SE-CLAY/4/499	Hov et al. (2019)	s_u^{FV}, s_u^{DSS}, σ_p', LL	499	Sweden	σ_p' = 13 – 505 kPa; s_u^{FC} = 5 – 201 kPa; s_u^{DSS} = 6 – 53 kPa; LL = 22 – 145%		10 – 20
SH-CLAY/11/4051	Zhang et al. (2019)	LL, PI, LI, e, K_0, σ'_v/p_a, $s_u/\sigma'_{v(UCS)}$, $S_{t(UCST)}$, $s_u/s'_{v(VST)}$, $S_{t(VST)}$, p_s/s'_v	4051	50 sites (Shanghai)	Normal consolidated to slightly over-consolidated clay; Very soft clay (LI = 0.49 – 2.19) with slight to medium plasticity (PI = 10.4 – 26.5) and with medium to high sensitivity (S_t = 2.7 – 7.8)		
FI-CLAY/14/856	Löfman and Korkiala-Tanttu (2021)	w_n, e, LL, F, PL, γ, Org, Cl, s_u, S_t, σ'_p, OCR, C_c, C_s	856	33 sites (Finland)	w_n = 31~162%, LL = 49~113%, PL = 23~42%, Org = 0~6%, Cl =22~81%, s_u = 10~35 kPa, S_t =6~43, OCR = 0.3~41, C_c = 0.11~4.22, C_s =0.02~0.18 (65% clays and 35% various fine-grained soils)		

GENERIC PROPERTY DATABASES (3)

Database	Reference	Parameters of interest	# Data points	# Sites/ studies	Range of parameters		
					OCR	PI	S_t
SAND/7/2794	Ching et al. (2017)	D_{50}, C_u, D_r, σ'_v/P[illegible]a, ϕ', q_{t1}, $(N_1)_{60}$	2794	176 studies	1 – 15	D_{50} = 0.1 – 40 mm, C_u = 1 – 1000+ D_r = -0.1 – 117%	
ROCK/9/4069	Ching et al. (2018)	n, γ, R_L, S_h, σ_{bt}, I_{s50}, V_p, σ_c, E	4069	184 studies	γ = 15 – 35 kN/m^3, n = 0.01 – 55% σ_c = 0.7 – 380 MPa, E = 0.03 – 120 GPa		
ROCKMass/9/ 5876	Ching et al. (2021)	RQD, RMR, Q, GSI, E_m, E_{em}, E_{dm}, E σ_{ci}	5876	225 studies	RMR = 0~97, Q = 0.001~1000, GSI = 8~100, and E_m = 0.0011~104 GPa (17% igneous, 37% sedimentary, 26% metamorphic, and 20% unknown)		

GENERIC LOAD TEST DATABASES



Tang, C. and Phoon, K. K. 2021. Model Uncertainties in Foundation Design. CRC Press, Boca Raton and London.

GENERIC LOAD TEST DATABASES (1)

Database/Reference	Limit state	Soil type	N	Pile geometry B (m)	D/B	Soil parameter
NUS/ShalFound/919	Bearing	Clay	56	0.3–5	0–5.7	s_u=9–200 kPa
(Tang et al. 2020a)		Sand	427	0.25–7	0–6.1	ϕ=26–53˚
	Tension	Clay	123	0.31–3.05	0.8–13.2	s_u=15–300 kPa
		Sand	313	0.1–2.5	0.5–14.5	ϕ=30–49˚
NUS/ShalFound/Punch-Through/31	Punch-through	Sand-over-clay	31	0.3–3	0.5–3	ϕ_{cv}=32˚ , D_r=88%
(Tang and Phoon 2019a)						s_u=8.7–85.9 kPa
NUS/Spudcan/Punch-Through/212	Punch-through	Multi-layer clay	140	3–20	0.16–1.17	ϕ_{cv}=31–34˚ , D_r=44–99%
(Tang and Phoon 2019a)		with sand				s_u=7.2–44.8 kPa
		Multi-layer clay	72	3–12		s_u=3–50 kPa
		with stiff layer				ρ=0–2.6 kPa/m
NUS/DrilledShaft/542	Bearing	Clay	64	0.32–1.52	1.6–56	s_u=41–256 kPa
(Tang et al. 2019)		Sand	44	0.35–2	5.1–59	ϕ=30–41˚
		Grave;	41	0.59–1.5	6.2–30	ϕ=37–47˚
	Tension	Clay	32	0.36–1.8	3.4–55	s_u=21–250 kPa
		Sand	30	0.3–1.31	2.5–43	ϕ=30–45˚
		Gravel	109	0.43–2.26	1.77–17.3	ϕ=42–48˚
NUS/DrivenPile/1243 (H section)	Bearing	Clay	47	0.28–0.41	16–95	N_{SPT}=5–50
(Tang and Phoon 2018a;		Sand	52	0.28–0.42	22–110	N_{SPT}=7–40
Phoon and Tang 2019)		Mixed	50	0.28–0.42	17–85	N_{SPT}=4–29

GENERIC LOAD TEST DATABASES (2)

Database/Reference	Limit state	Soil type	N	Pile geometry B (m)	D/B	Soil parameter
NUS/DrivenPile/1243 (Tube/box section) (Tang and Phoon 2019b)	Bearing	Clay	175	0.1–0.81	7.9–200	PI=11%–160% OCR=1–43.2, S_t=1–17
	Tension		64	0.1–0.81	12–110	PI=12%–110% OCR=1–43.2, S_t=1–8.3
NUS/DrivenPile/1243 (Tube/box section) (Tang and Phoon 2018b)	Bearing	Sand	134	0.14–0.76	13–251	ϕ=30–42° D_r=15%– 93%
	Tension		28	0.25–0.76	19–84	ϕ=30–42° D_r=31%– 97%
NUS/RockSocket/721 (Tang et al. 2020a)	End bearing	Rock	270	0.1–2.5	1–31.3	σ_c=0.5–99 MPa E_m=7.82–75113 MPa GSI=7.5–95 RQD=20–100%
NUS/RockSocket/721 (Tang et al. 2020b)	Shaft shearing	Rock	544	0.2–3.2	0–19.5	σ_c=0.4–99 MPa E_m=24–19844 MPa GSI=50–70 RQD=0–100%
NUS/HelicalPile/1113 (Tang and Phoon 2018c, 2020)	Bearing	Clay	270	0.21–1.02	6–74	s_u≤305 kPa
		Sand	181	0.21–1.02	6–110	ϕ=30–45°
	Tension	Clay	165	0.21–0.91	12–48	s_u≤300 kPa
		Sand	121	0.21–0.91	10–62	ϕ=30–45°

Model Uncertainties in Foundation Design

Chong Tang
Kok-Kwang Phoon

CRC Press
Taylor & Francis Group

Tang, C. and Phoon, K. K. 2021. Model Uncertainties in Foundation Design. CRC Press, Boca Raton and London.

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304dB TC304 databases

One key finding from the recently concluded ISSMGE 2017 SOA/SOP Survey is that publically-available databases that include information available for benchmarking studies of inherent profession. Thus, compiling geotechnical databases represents one of the key missions of the current TC304. We present the current databases below (nickname: **304dB**), and we encourage profession; we also invite you to contact the task force leaders below if you are willing to contribute databases to this effort. 304 dB was initiated by Prof Kok-Kwang Phoon (immediate past

Acknowledgments

For those interested in using any of 304dB, please download the data and feel free to use it subject to the constraints described in the Disclaimer and Restrictions, shown at the bottom of this dissertation, conference paper, journal paper, engineering report, etc.) requires the Acknowledgement of this TC304 effort and the citations of the database reference(s), indicated in the last appropriate (e.g., in the Front Matter of a dissertation, or in an Acknowledgement section of a journal paper, typically presented after the Conclusions and before the References): **The autho Practice of Risk Assessment & Management of the International Society of Soil Mechanics and Geotechnical Engineering for developing the database 304dB used in this stu name of Database Owner> for contributing this database to the TC304 compendium of databases.**

CPT databases
Leader: Armin Stuedlein
These databases are mostly CPT clusters, i.e., multiple CPTs are conducted in a local site.
The names of the databases are in the format of A/B/C:
A: Type of in-situ test (CPT or CPTU)
B: number of soundings
C: rough size of sounding area
Please contact Armin armin.stuedlein@oregonstate.edu if you want to contribute databases.

Database	Sounding details	File format			Database owner	Database referenc
		Text	Excel	Matlab		
A-CPT/232/2500m^2 Adelaide, Australia Stiff, OC alluvial clay (CH)	Total depths = 3.5 ~ 5.6 m Horizontal spacing = 0.2 m ~ 71 m Site Map	Link	Link	Link	M Jaksa mark.jaksa@adelaide.edu.au	1. Jaksa, M. (1995). The Influence of Spatial V Design Properties of a Stiff, Overconsolidat University of Adelaide, Australia. Research 2. Jaksa, M., Kaggwa, W.S., and Brooker, P.I. evaluation of the scale of fluctuation of a s 8th International Conference on Applicatio A.A. Balkema, Rotterdam, 415-422. Resea
A-CPT/1/horizontal Adelaide, Australia Stiff, OC alluvial clay (CH)	Horizontal sounding in embankment Horizontal extent = 7.62 m	Link	Link	Link	M Jaksa mark.jaksa@adelaide.edu.au	1. Jaksa, M. (1995). The Influence of Spatial V Design Properties of a Stiff, Overconsolidat University of Adelaide, Australia. Research 2. Jaksa, M., Kaggwa, W.S., and Brooker, P.I. evaluation of the scale of fluctuation of a s 8th International Conference on Applicatio A.A. Balkema, Rotterdam, 415-422. Resea
						1. Bong, T. and Stuedlein, A.W. (2017). Effect Conditioning on Random Field Model Param Variability on Liquefaction-induced Differer

THREE CHALLENGES

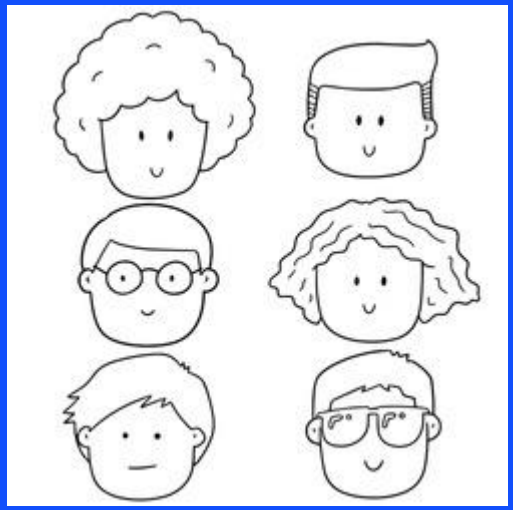
1. **UGLY DATA**

2. **SITE RECOGNITION**

3. **STRATIFICATION**
   - BENCHMARKING

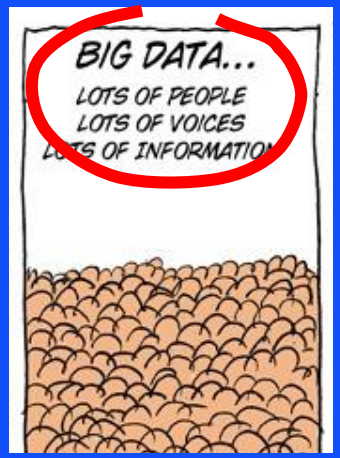
Phoon, K. K., Ching, J. and Shuku, T. 2021. Challenges in data-driven site characterization. Georisk: Assessment and Management of Risk for Engineered Systems and Geohazards, online

SITE RECOGNITION



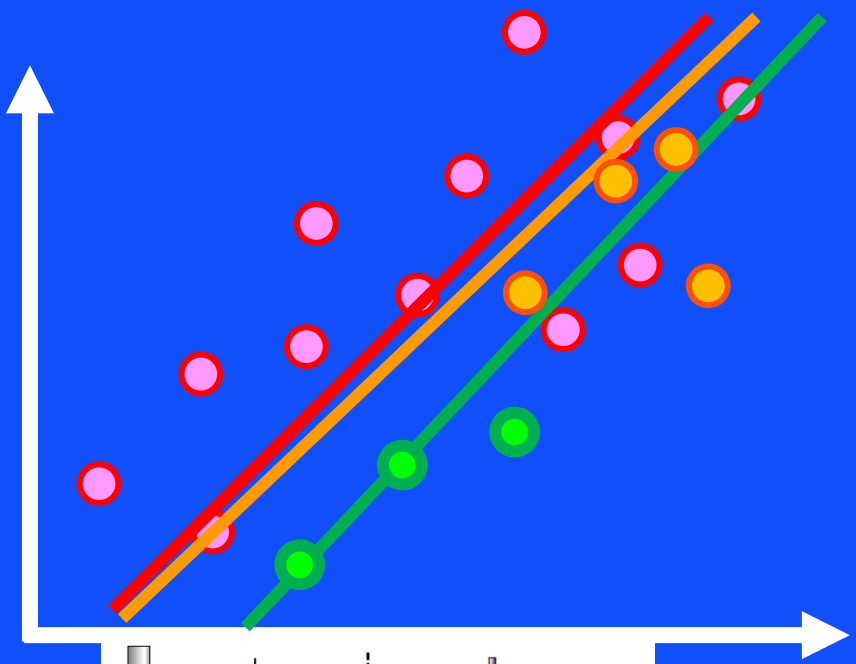
HOW TO COMBINE SMALL DATA (SITE-SPECIFIC) WITH BIG INDIRECT DATA?

BIG DATA SMALL DATA



SMALL + BIG DATA

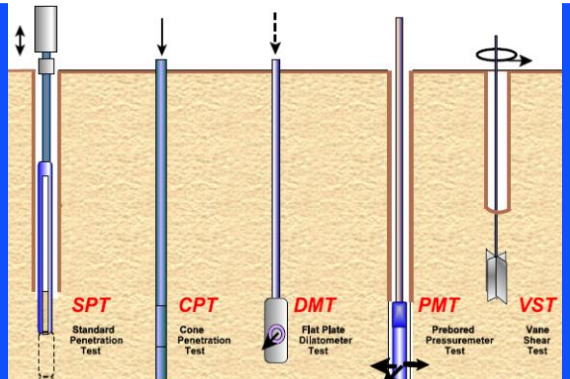
Y = DESIGN PARAMETER



BIG DATA

SMALL DATA

SIMILAR DATA



X = FIELD TEST

SITE-SPECIFIC DATA

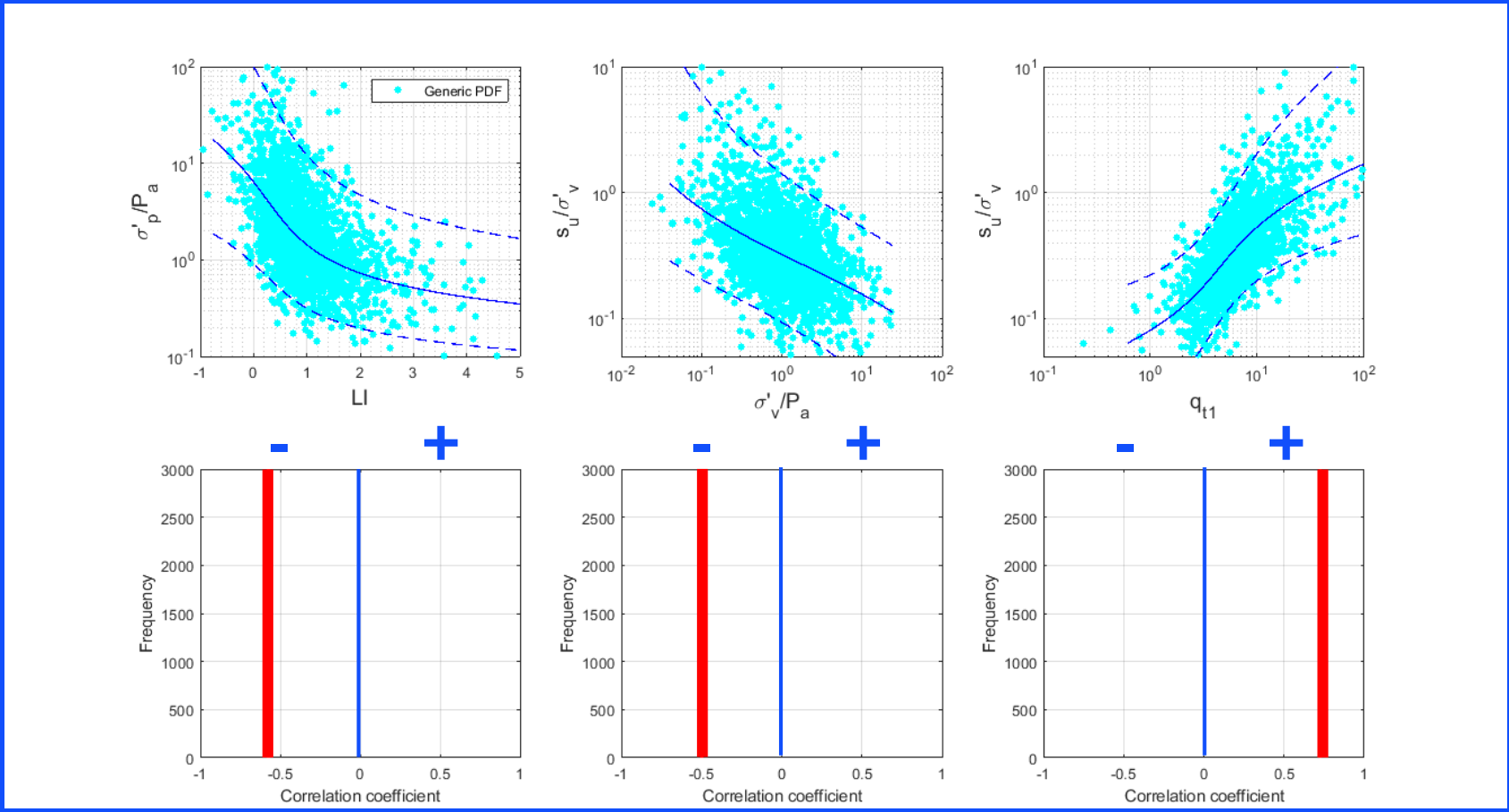
- **TAIPEI (TAIWAN)**

CPT

	Depth (m)	PI	PL	LL	w	σ'_v (kPa)	σ'_p (kPa)	S_u (kPa)	q_c (MPa)
1	12.8	9	21	30	32	127.9	127.7	55.2	0.89
2	14.8	13	20	33	38	144.9			0.88
3	16.1	15	22	36	40	155.6		61.9	0.93
4	17.8	19	23	42	40	169.9	181.9	54.2	1.01
5	18.3				41	174.5			1.25
6	20.2	17	21	38	33	190.0		73.1	1.23
7	22.7	16	21	37	30	210.9			1.42
8	24.0	16	22	38	34	221.7	221.7	82.2	1.57
9	26.6	14	21	35	32	243.7		98.1	1.78

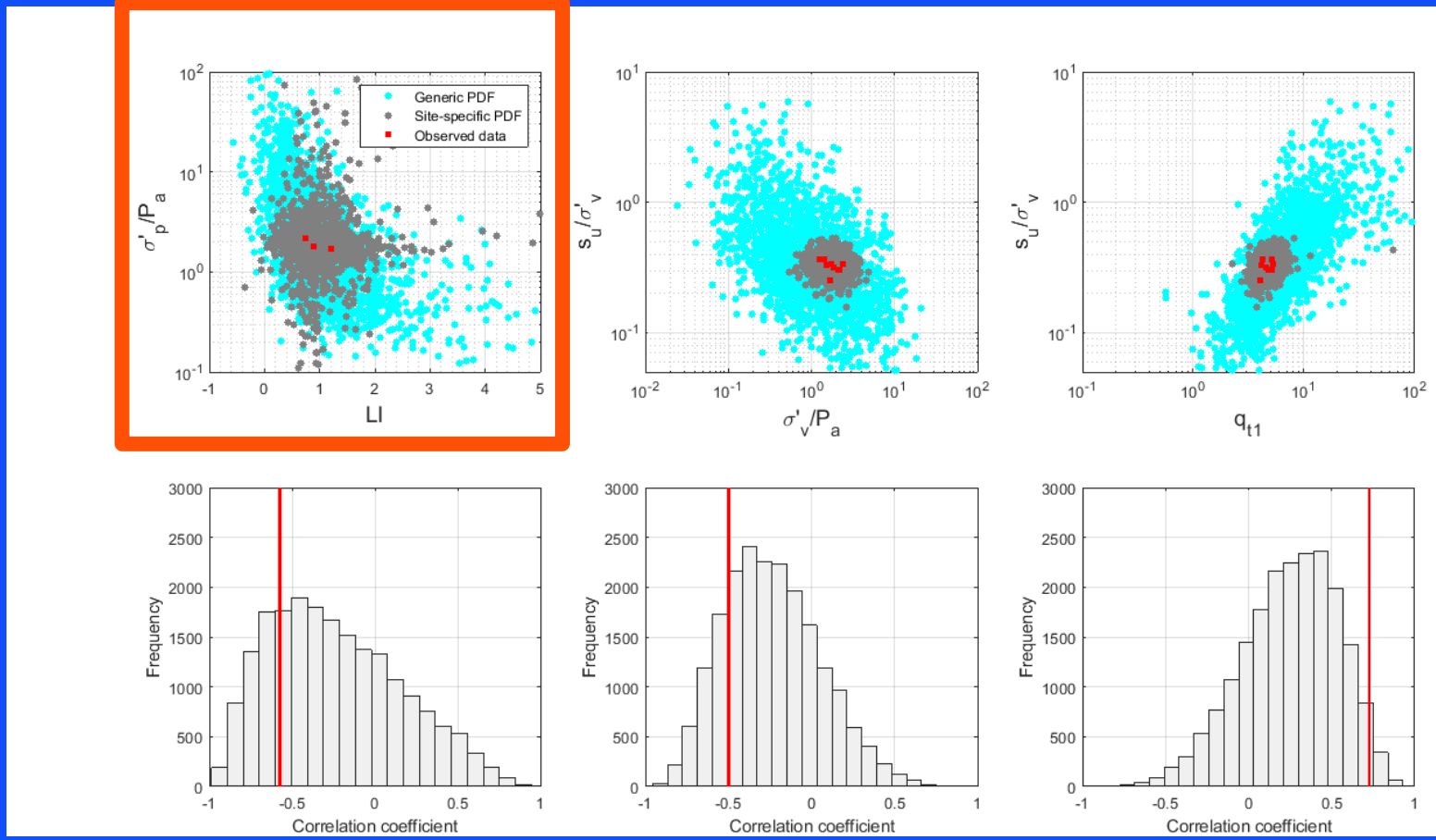
Ching, J. Y. & Phoon, K. K. 2019. Constructing site-specific probabilistic transformation model by Bayesian machine learning. Journal of Engineering Mechanics, ASCE, 145(1), 04018126

GENERIC DATA *CLAY/10/7490*

- 

Ching, J. Y., Li, D. Q., and Phoon, K. K. 2016. Statistical characterization of multivariate geotechnical data. Chapter 4, Reliability of Geotechnical Structures in ISO2394, CRC Press/Balkema, 89-126

GAUSSIAN PROCESS REGRESSION (GPR-MUSIC)



Ching, J. Y. & Phoon, K. K. 2019. Constructing site-specific probabilistic transformation model by Bayesian machine learning. Journal of Engineering Mechanics, ASCE, 145(1), 04018126

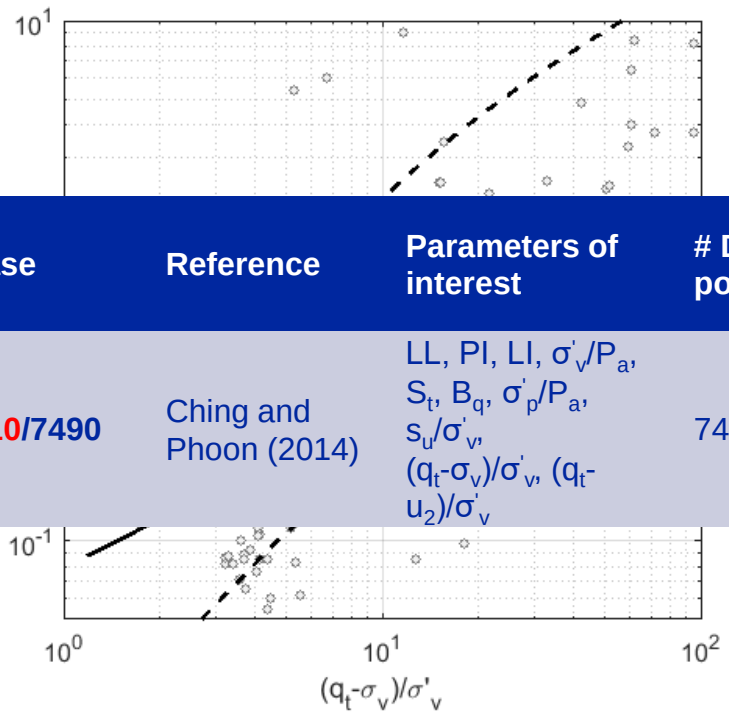
HIERARCHICAL BAYESIAN MODEL (HBM-MUSIC)

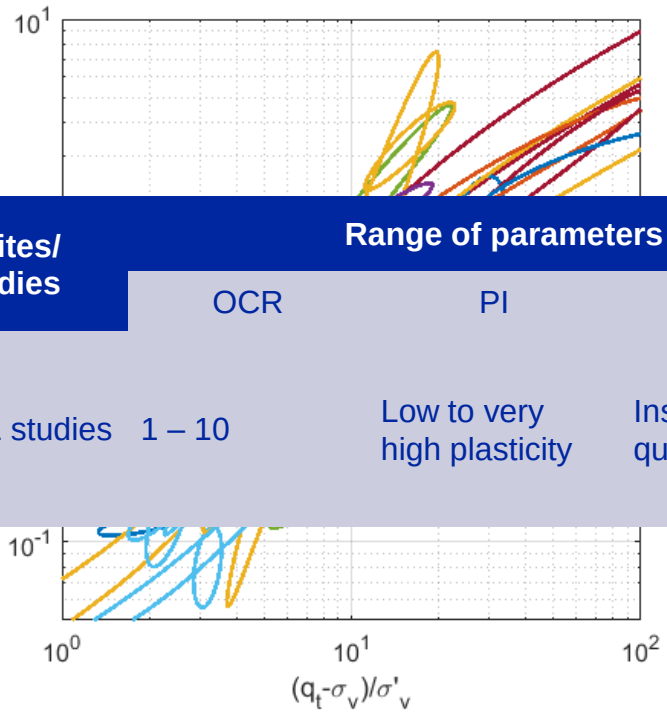
INTER-SITE VARIABILITY

INTRA-SITE VARIABILITY

Ching, J. Y., Wu, S., and Phoon, K. K. 2021. Constructing quasi-site-specific multivariate probability distribution using hierarchical Bayesian model. Journal of Engineering Mechanics, ASCE, 147 (10), 04021069

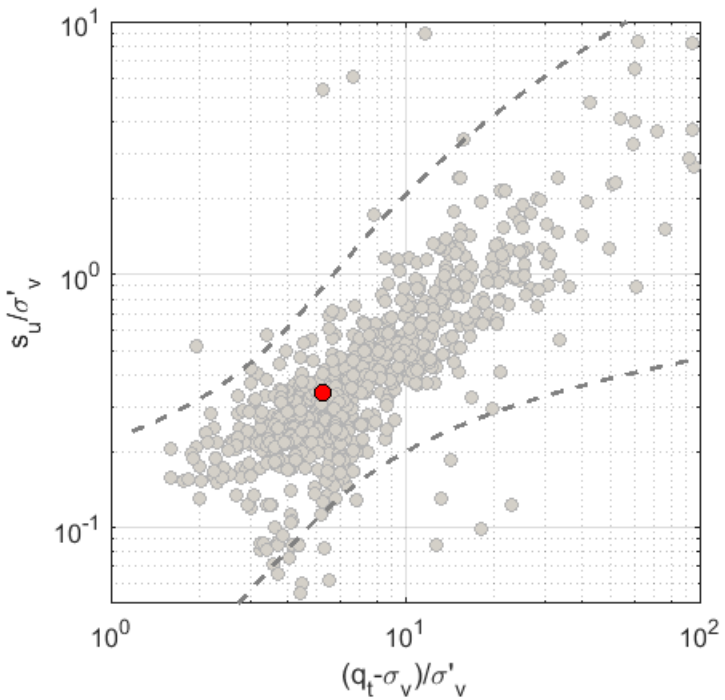
HBM LEARNING FROM BID

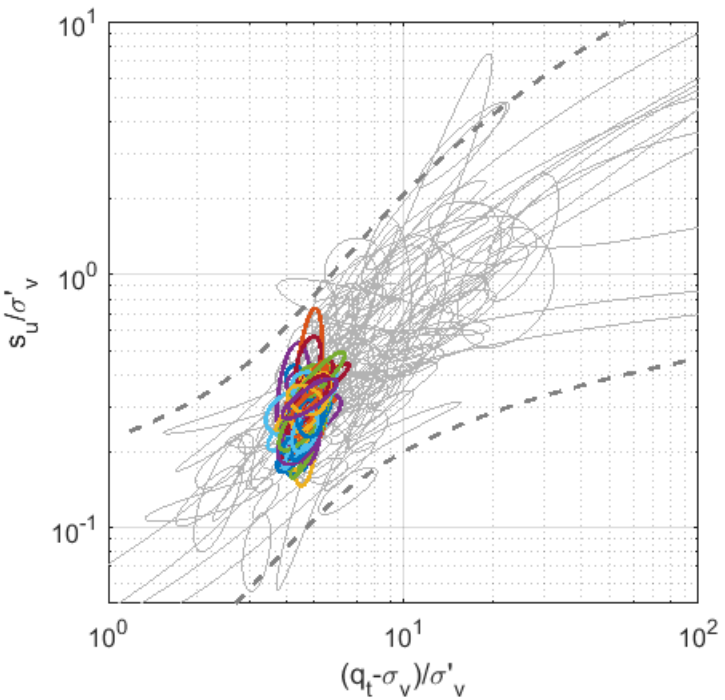




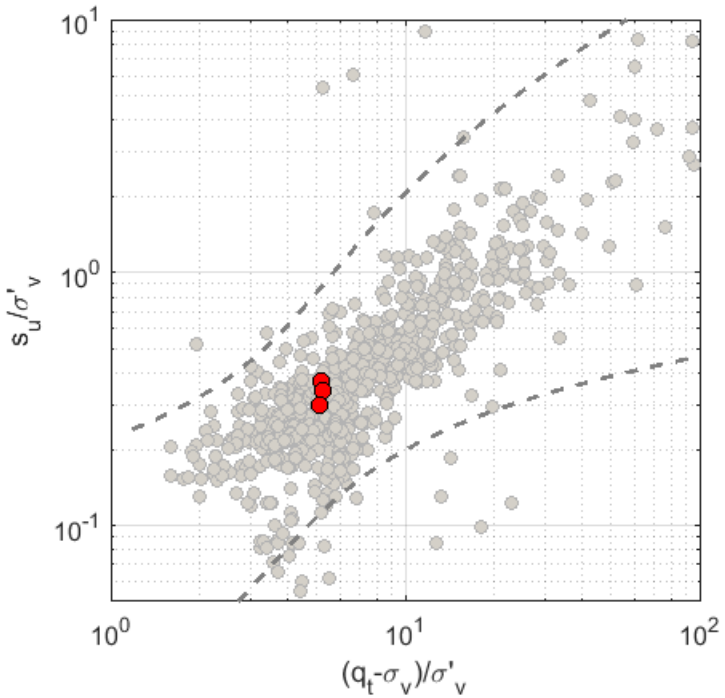
Database	Reference	Parameters of interest	# Data points	# Sites/ studies	Range of parameters		
					OCR	PI	S_t
CLAY/10/7490	Ching and Phoon (2014)	LL, PI, LI, σ'_v/P_a, S_t, B_q, σ'_p/P_a, s_u/σ'_v, $(q_t-\sigma_v)/\sigma'_v$, $(q_t-u_2)/\sigma'_v$	7490	251 studies	1 – 10	Low to very high plasticity	Insensitive to quick clays

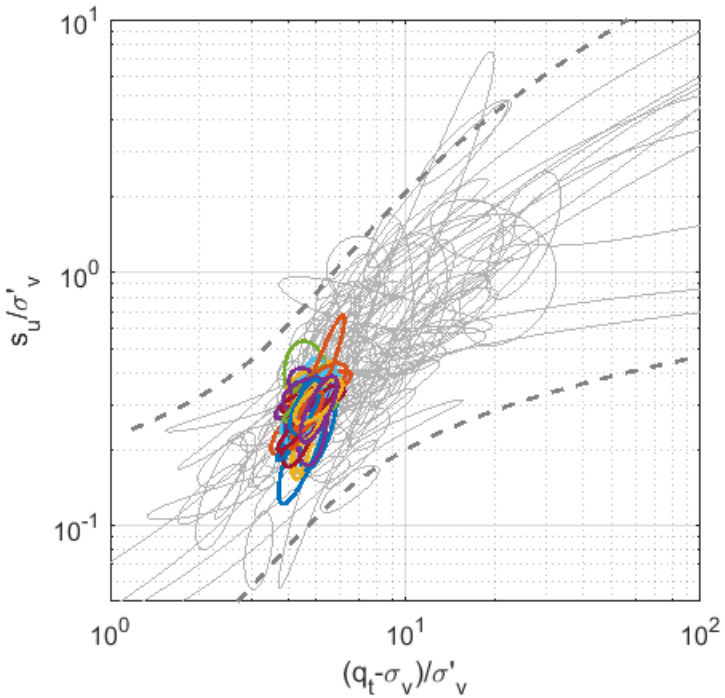
HBM INFERENCE FOR NEW SITE (1 DATA POINT)



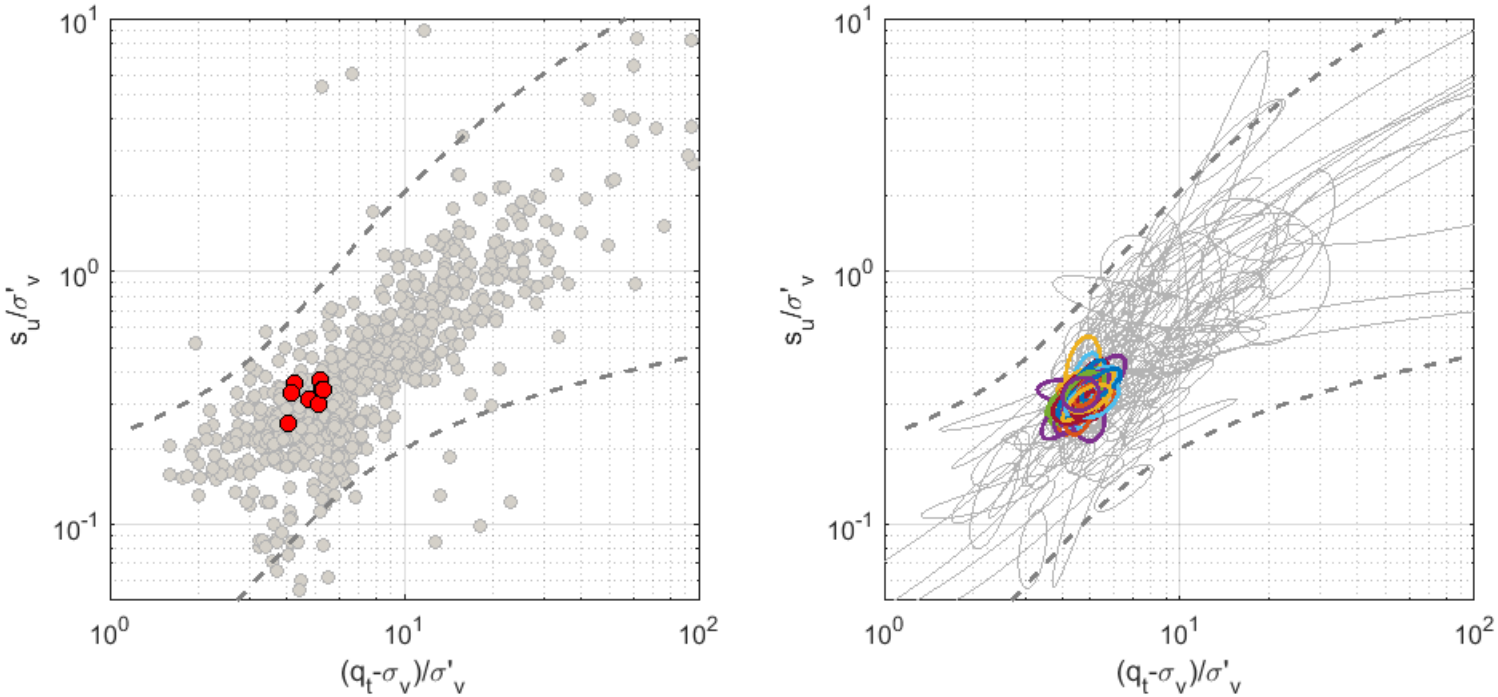


HBM INFERENCE FOR NEW SITE (3 DATA POINTS)

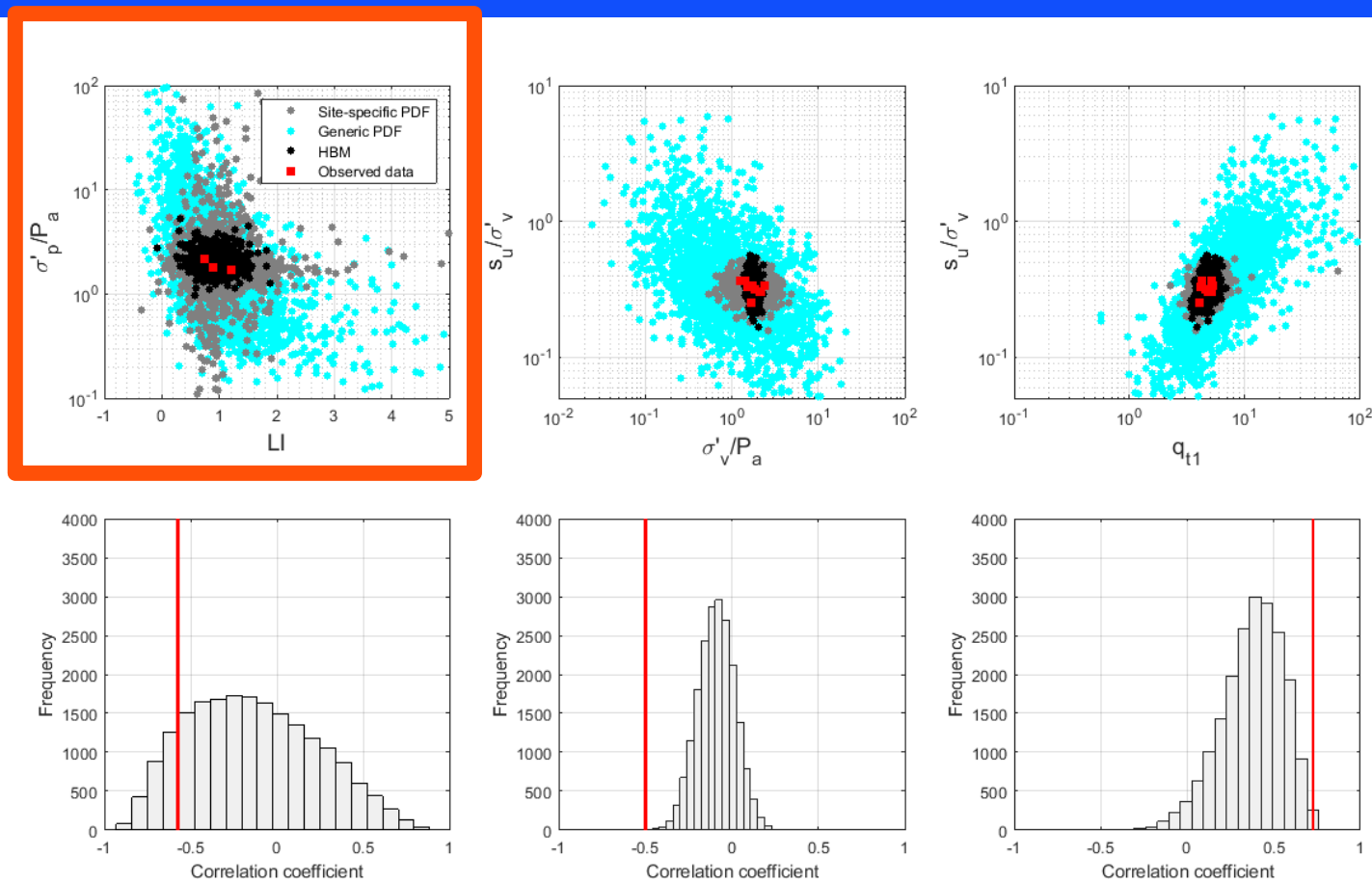




HBM INFERENCE FOR NEW SITE (8 DATA POINTS)



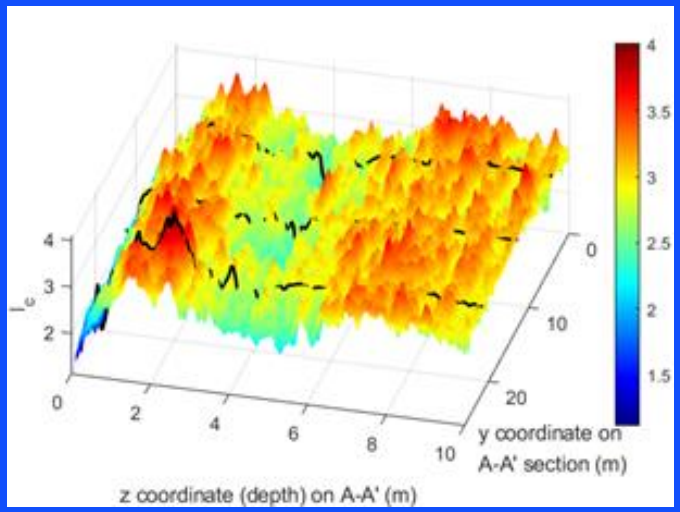
HIERARCHICAL BAYESIAN MODEL (HBM-MUSIC)

- 

Ching, J. Y., Wu, S., and Phoon, K. K. 2021. Constructing quasi-site-specific multivariate probability distribution using hierarchical Bayesian model. Journal of Engineering Mechanics, ASCE, 147 (10), 04021069

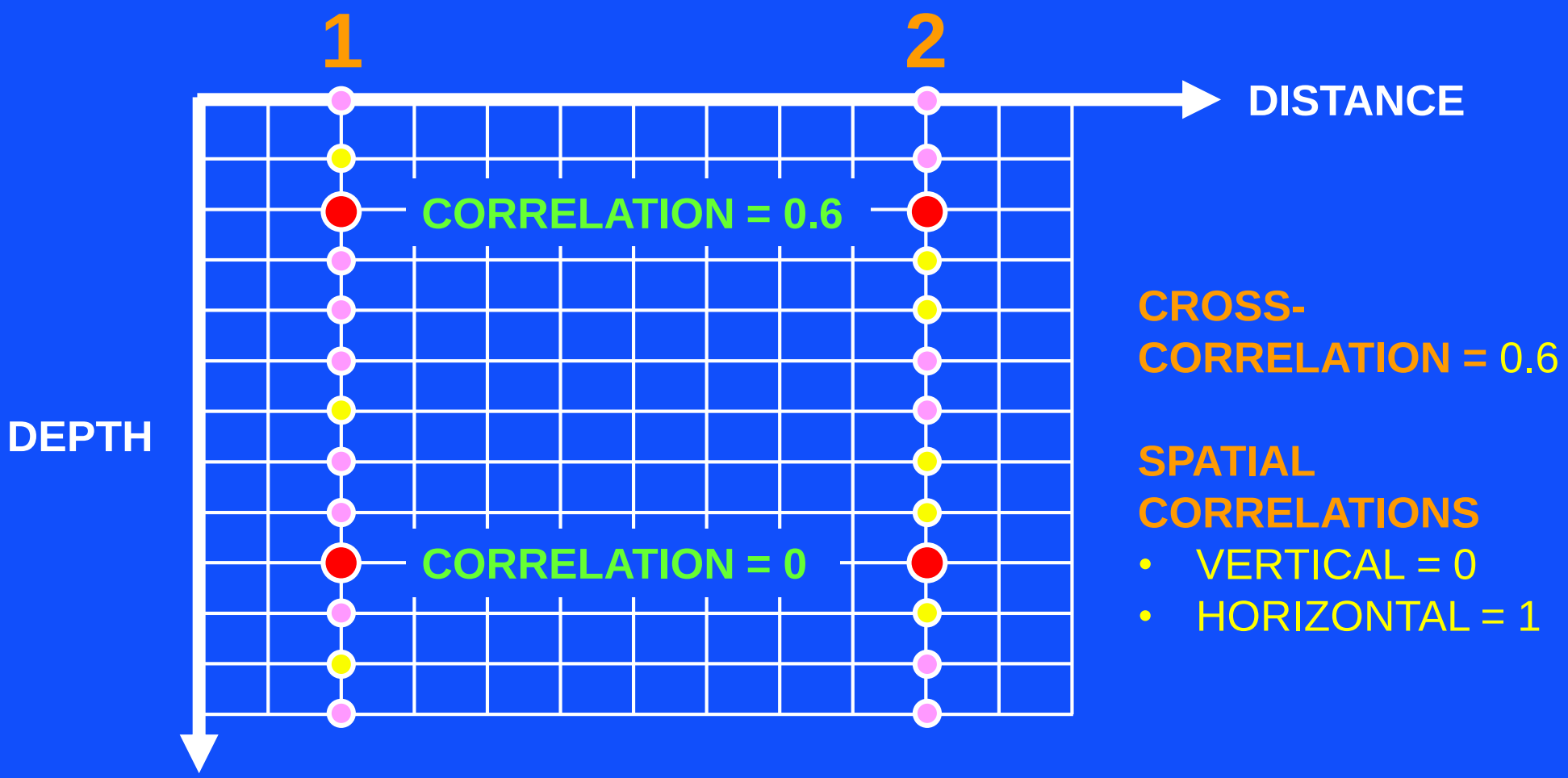
Method	No. of parameters	Spatial variability		Use generic database?	Other limitations	Reference
		Trend	Auto-correlation			
Sparse Bayesian Learning (SBL)	Single	Yes	1X	No	Stationary autocorrelation	Ching and Phoon (2017)
Sparse Bayesian Learning (3D SBL)	Single	Yes	3X	No	Stationary separable autocorrelation; vertically dense; lattice	Ching et al. (2020)
Sparse Bayesian Learning (3D SBL)	Single	Yes	3X	No	Stationary separable autocorrelation; vertically dense	Ching et al. (2021d)
Gaussian Process Regression (GPR-MUSIC)	Multiple	-	-	No	No vertical auto correlation; perfect horizontal autocorrelation	Ching and Phoon (2019)
Gaussian Process Regression (GPR-MUSIC-X)	Multiple	No	1X	No	Prescribed stationary vertical autocorrelation; perfect horizontal autocorrelation	Ching and Phoon (2020a)
Gaussian Process Regression (GPR-MUSIC-3X)	Multiple	No	3X	No	Prescribed stationary separable autocorrelation	Ching et al. (2021a)
Gaussian Process Regression + Hierarchical Bayesian Model (HBM-MUSIC)	Multiple	-	-	Yes	No vertical auto correlation; perfect horizontal autocorrelation	Ching et al. (2021b, 2021c)
Gaussian Process Regression + Hierarchical Bayesian Model (HBM-MUSIC-3X)	Multiple	No	3X	Yes	Prescribed stationary separable autocorrelation	Ching et al. (2021a)
Full Gaussian Process Regression (FGPR-MUSIC-3X)	Multiple	Yes	3X	No	Stationary separable autocorrelation	In progress

HBM-MUSIC-3X



HOW TO COMBINE ***SPATIALLY VARIABLE*** SMALL DATA (SITE-SPECIFIC) WITH BIG INDIRECT DATA?

MUSIC

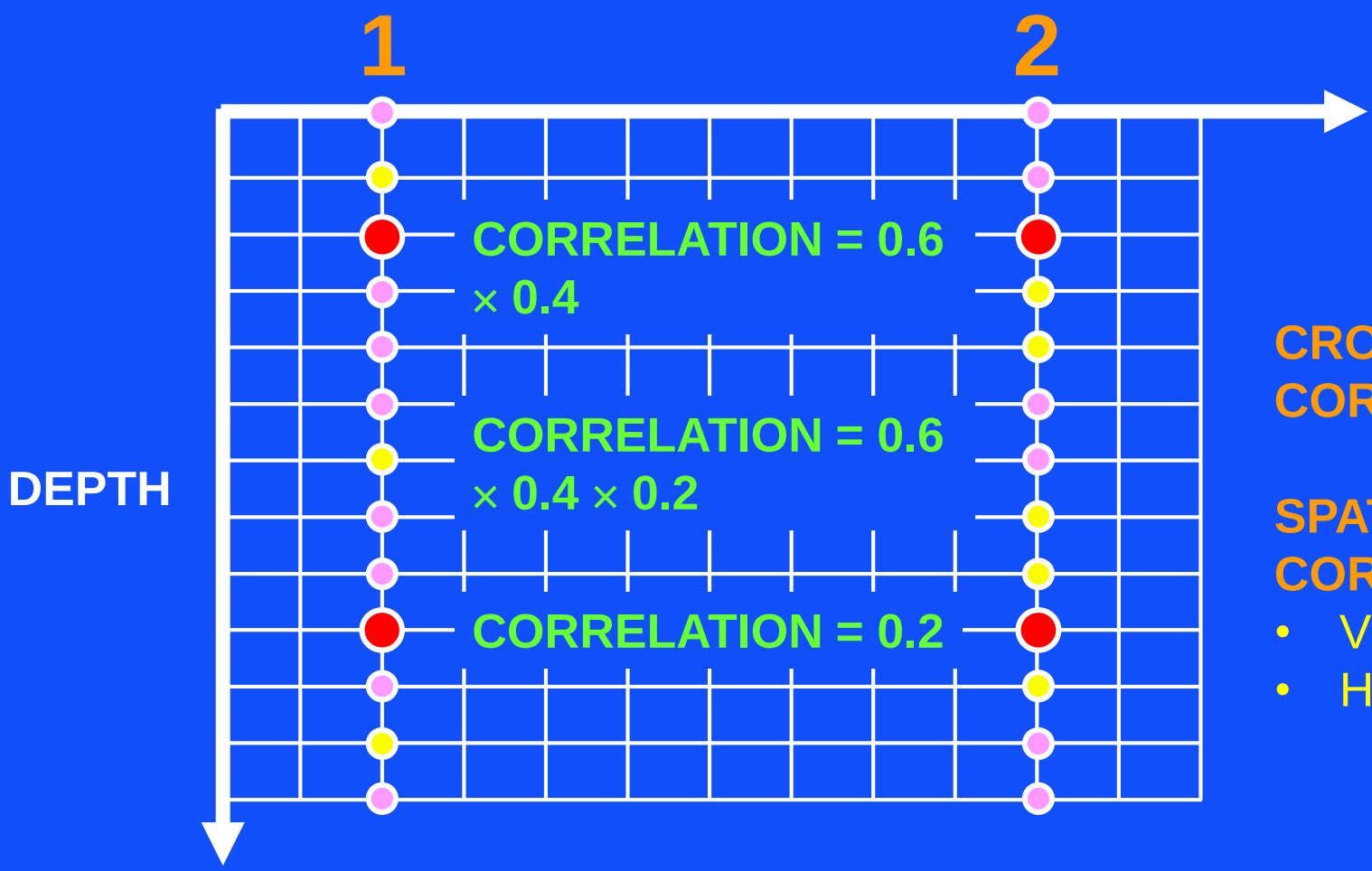


CROSS-CORRELATION = 0.6

SPATIAL CORRELATIONS

- VERTICAL = 0
- HORIZONTAL = 1

MUSIC-3X



CROSS-CORRELATION = 0.6

SPATIAL CORRELATIONS

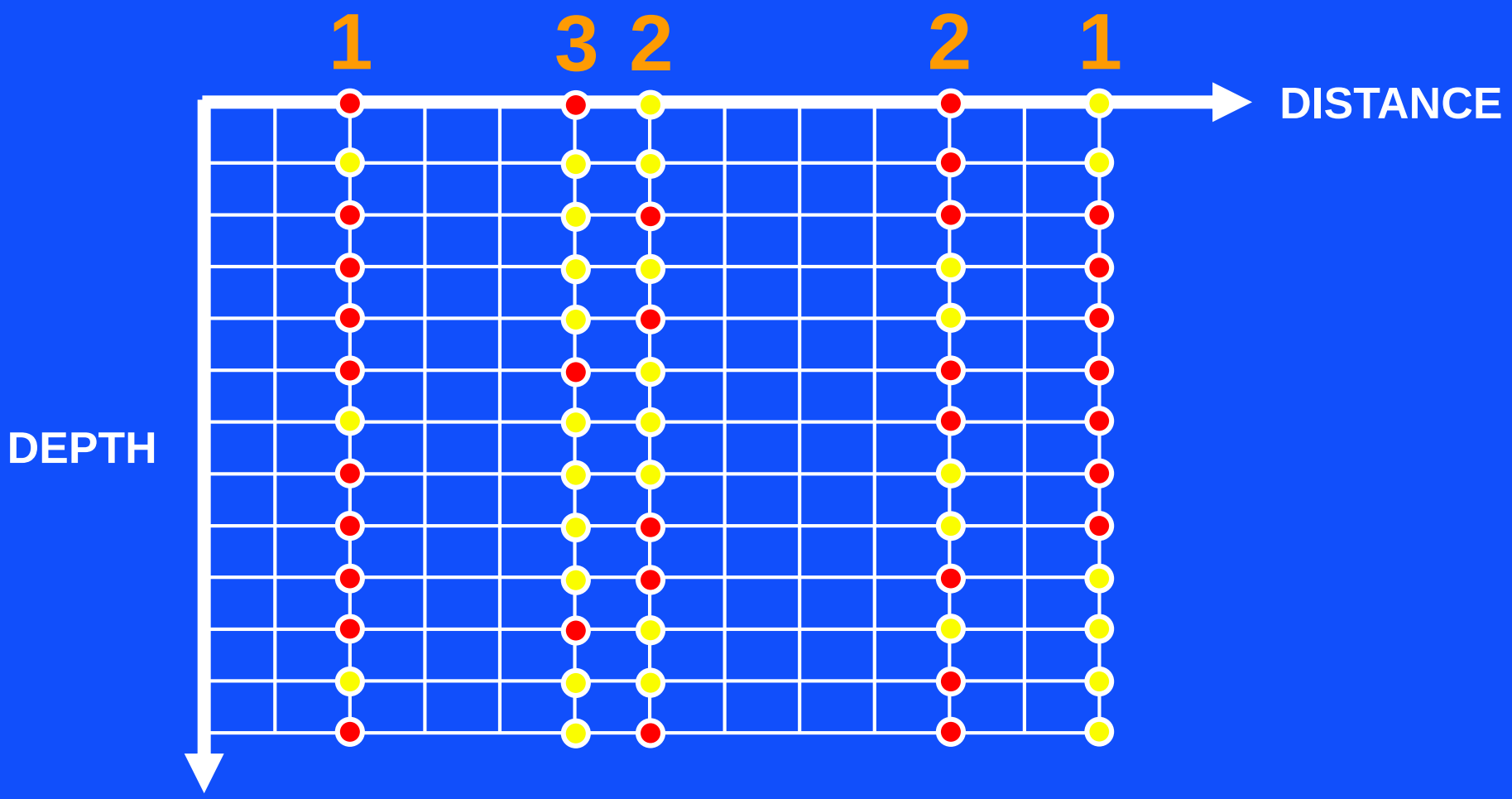
- VERTICAL = 0.2
- HORIZONTAL = 0.4

AMAZON'S ALGORITHM

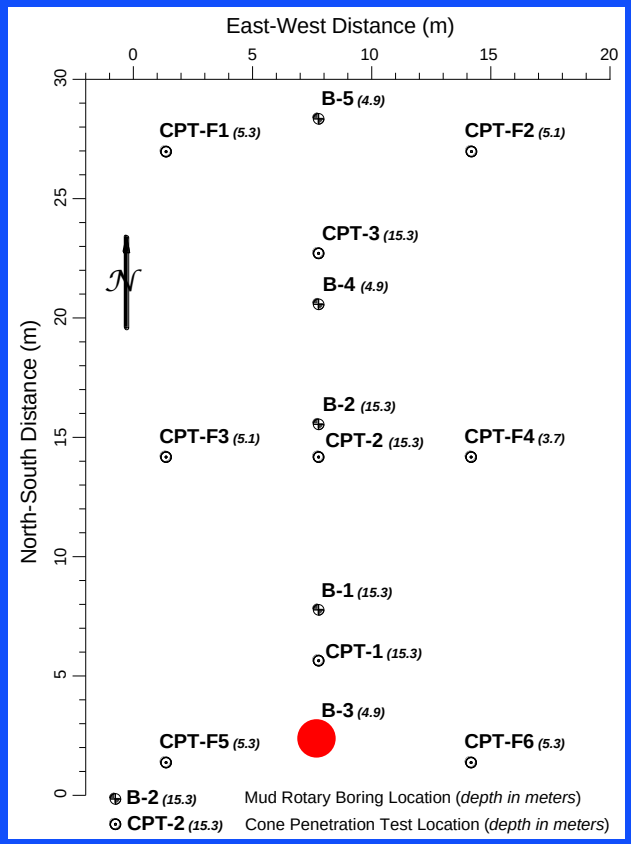
- THAT NOTION OF RELATEDNESS IS STILL DERIVED FROM CUSTOMERS' PURCHASE HISTORIES: ITEM B IS RELATED TO ITEM A IF CUSTOMERS WHO BUY A ARE USUALLY LIKELY TO BUY B AS WELL.
- BUT AMAZON'S PERSONALIZATION TEAM FOUND, EMPIRICALLY, THAT ANALYZING PURCHASE HISTORIES AT THE ITEM LEVEL YIELDED BETTER RECOMMENDATIONS THAN ANALYZING THEM AT THE CUSTOMER LEVEL.

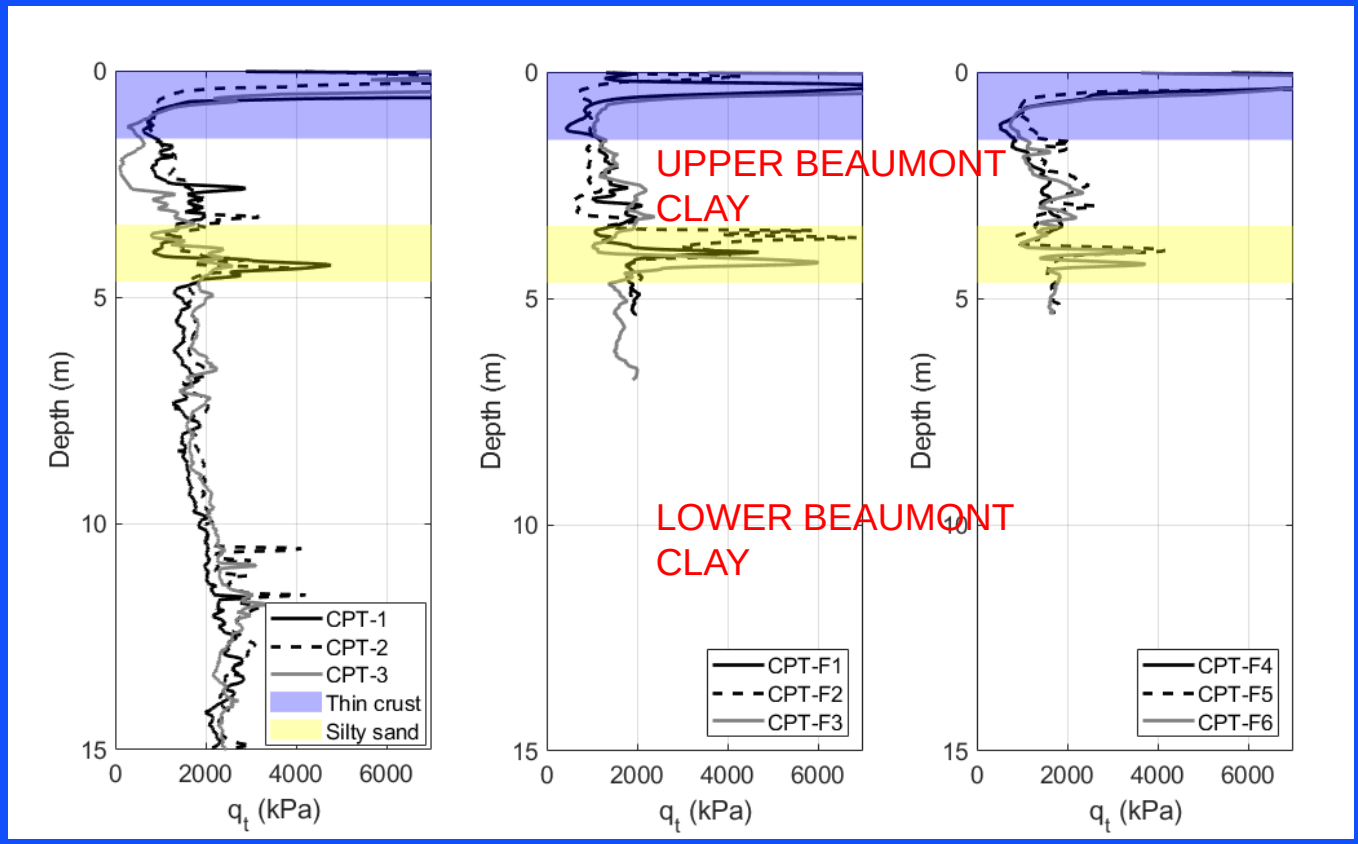
https://www.amazon.science/the-history-of-amazons-recommendation-algorithm

MUSIC-3X



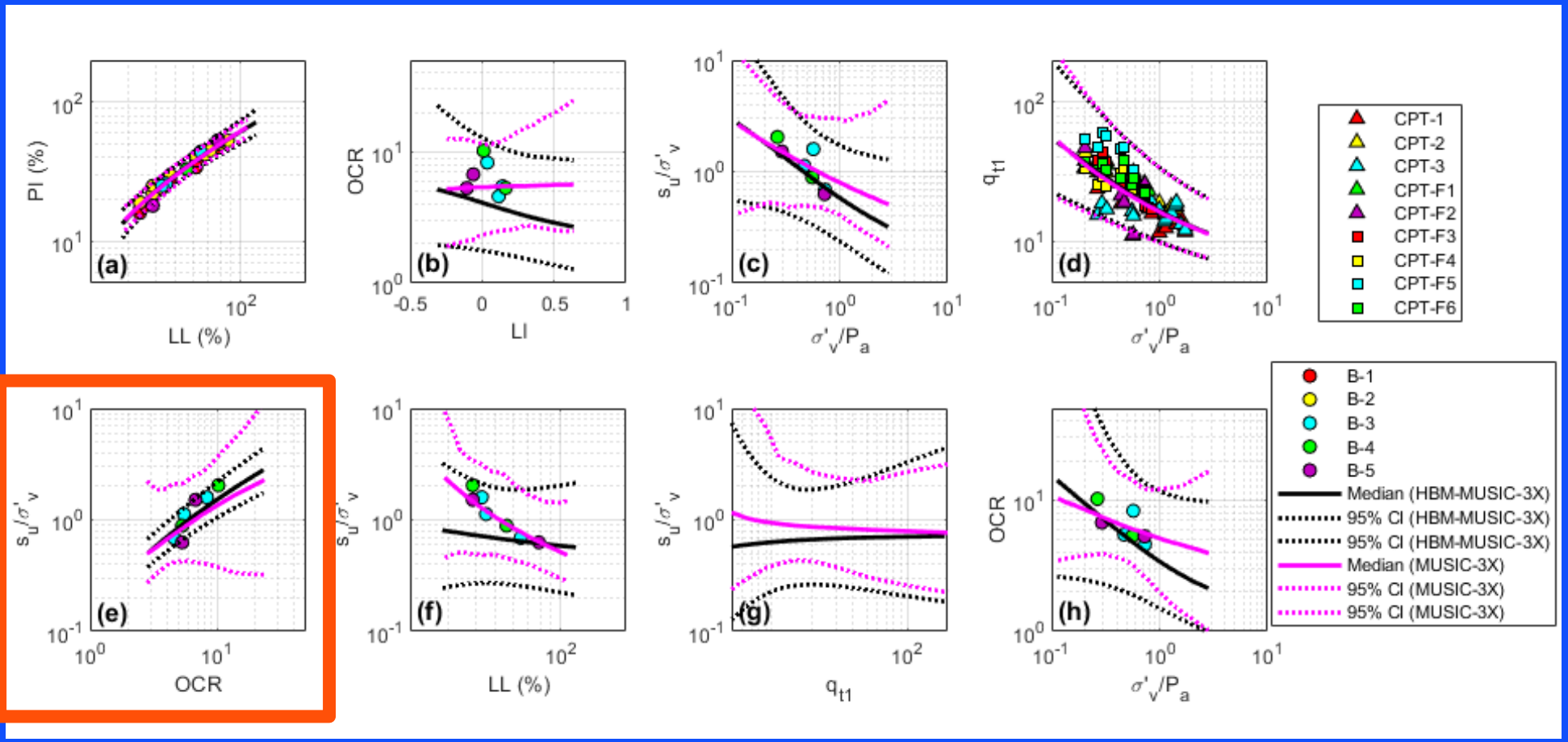
BAYTOWN, TEXAS





Ching, J., Phoon, K. K., Yang, Z., and Stuedlein, A. W. (2021). Constructing a quasi-site-specific multivariate probability distribution model for soil properties using sparse, incomplete, and three-dimensional (MUSIC-3X) data. Georisk, in press

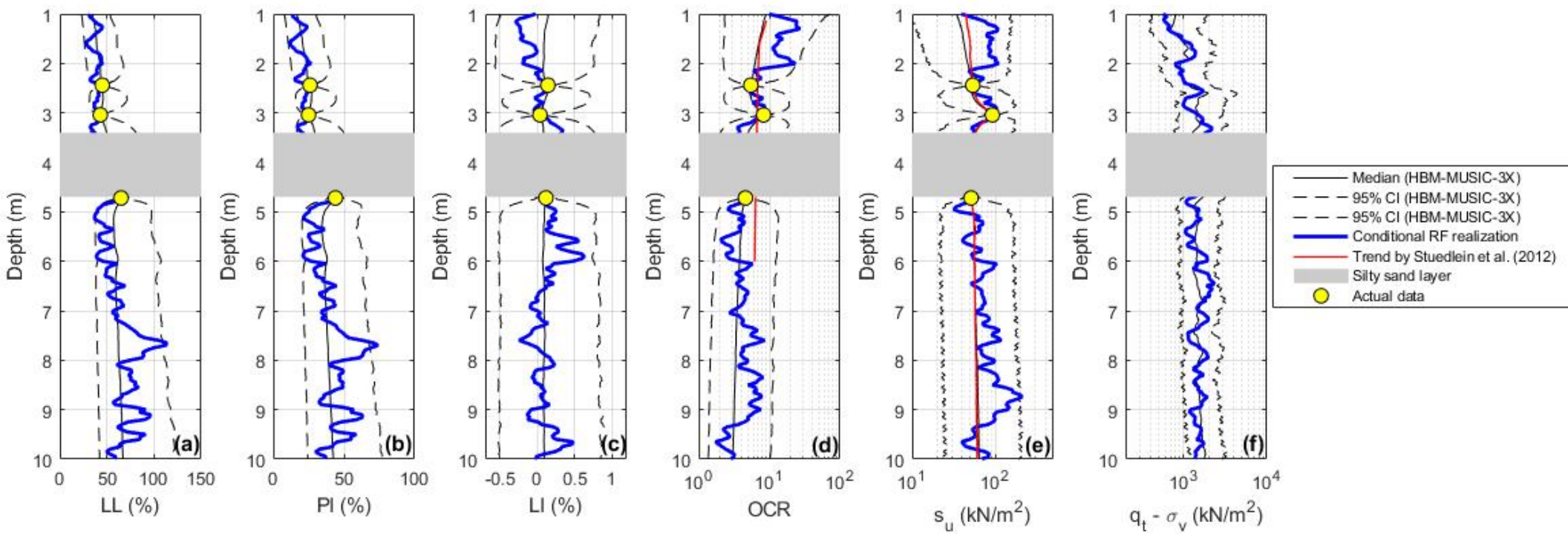
CROSS-CORRELATIONS



SPATIAL VARIABILITY

SPATIAL VARIABILITY

- CHARACTERISTIC VALUE
- *3D* (RANDOM) FINITE ELEMENT



CONCLUSIONS

- DATA-CENTRIC GEOTECHNICS MUST DEAL WITH UGLY DATA
- 3 CHALLENGES IN DATA-DRIVEN SITE CHARACTERIZATION (DDSC)
- UGLY DATA CHALLENGE IN DDSC IS MUSIC-3X
- BAYESIAN MACHINE LEARNING IS PROMISING
- BEST WE HAVE NOW IS HBM-MUSIC-3X

SINGAPORE UNIVERSITY OF
TECHNOLOGY AND DESIGN

THANK YOU

Wait, we've had big data this whole time?
Nobody has ever asked.
freshspectrum

Symposium on Digital Geosciences and Geotechnology, Hong Kong
16 September 2021

同济大学 TONGJI UNIVERSITY | 土木工程学院 COLLEGE OF CIVIL ENGINEERING

Long-term deformation monitoring and analysis of shield tunnel by smart sensing

HUANG Hongwei

Tongji University

Email: huanghw@tongji.edu.cn

Sept. 16, 2021

Research Team Members

Prof. Hongwei HUANG

Prof. Bin HE

Dr. Yan WU
From Wisen

Prof. Dongming ZHANG

Dr. Jingkang SHI

Mr. Jingjian HU

Mr. Mingqiao CHEN

Outline

1 Background

2 Present deformation monitoring technology

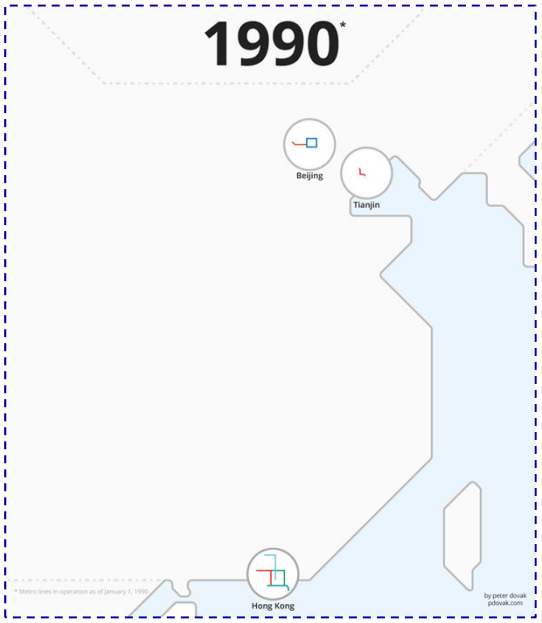
3 Smart sensing technology

4 Case study of long-term deformation monitoring

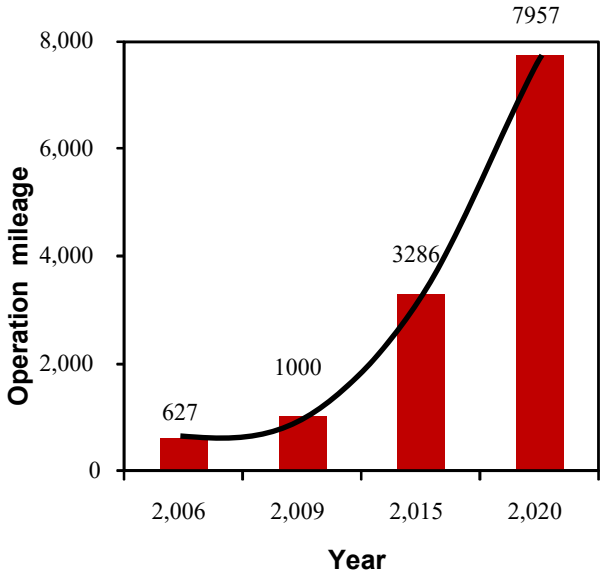
5 Conclusions

1. Background

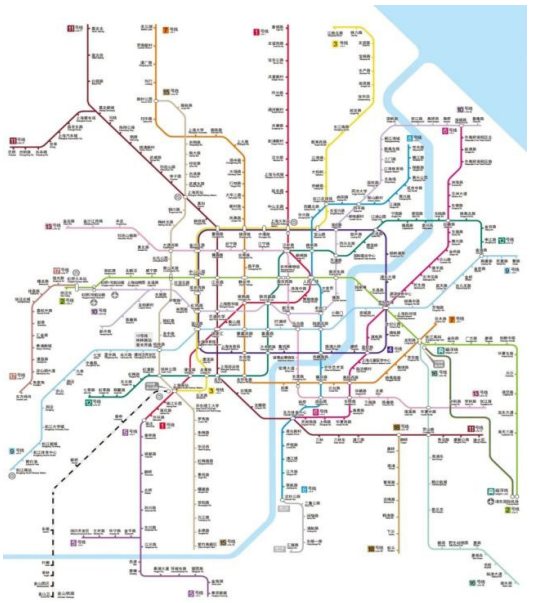
- Rapid development of Urban Rail Transit
- Exponential growth of shield tunnel mileage



Urban Rail Transit development:
47 cities, 245 lines, 7957km
(China mainland, June, 2021)



Exponential growth of operation mileage



Shanghai Metro (2021)
772km in operation

2/3 lines underground, and constructed mainly by the shield tunneling;
Great need --- The maintenance of shield tunnels !

1. Background

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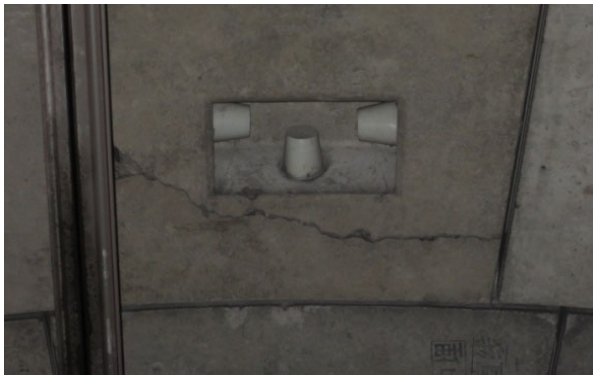
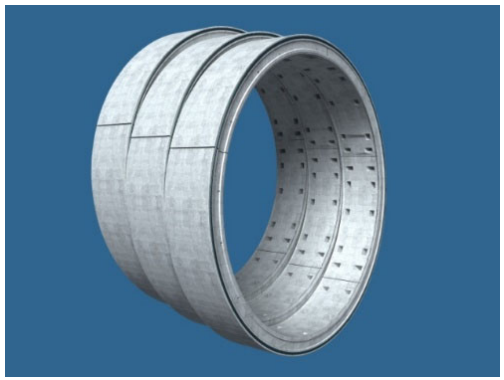
- **Main lining structure defects**

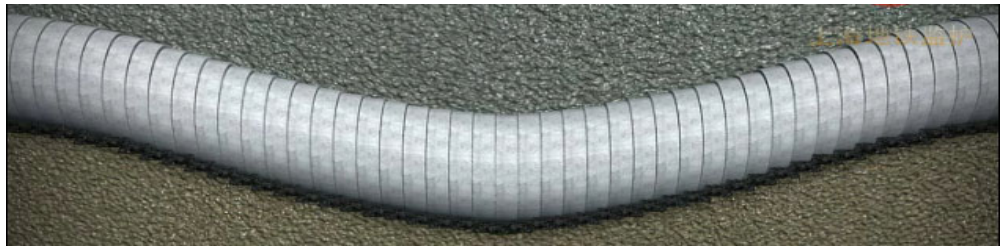
Leakage



Cracks



Dislocation



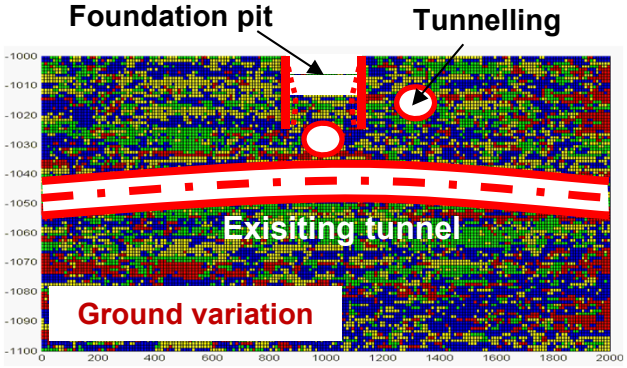
Settlement and difference settlement

Large convergence deformation and joint opening

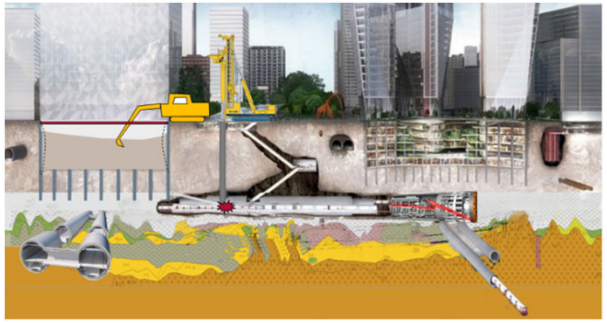
Monitoring and other maintenance of tunnels --- 2-3 hours in midnight
Working time is very tight

1. Background

- **Main reasons causing tunnel defects**

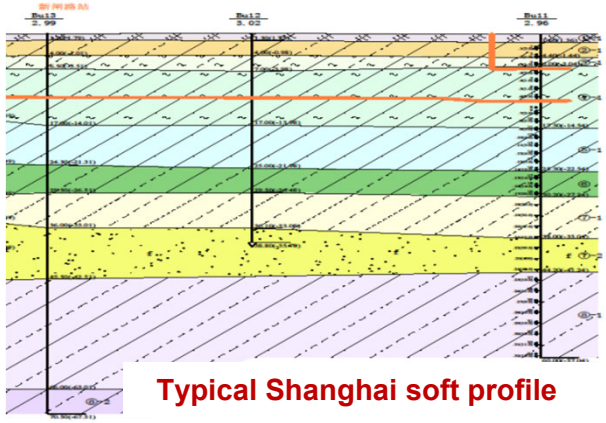


Ground uncertainty

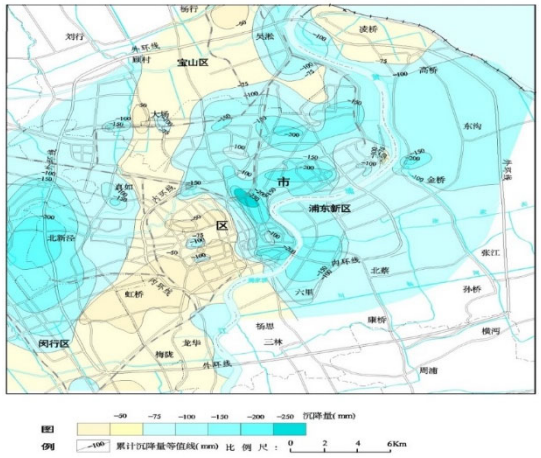


Closer engineering disturbance

Poor workmanship



High sensitivity and low strength soft clay ground



Ground difference settlement

1. Background

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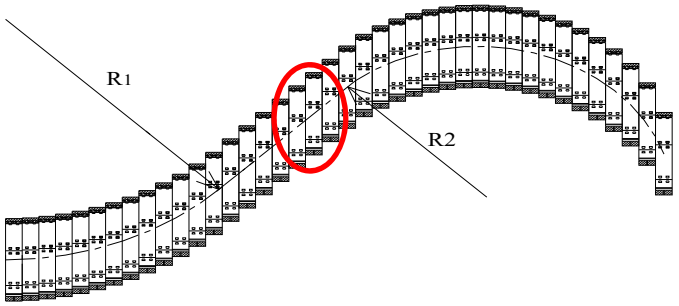
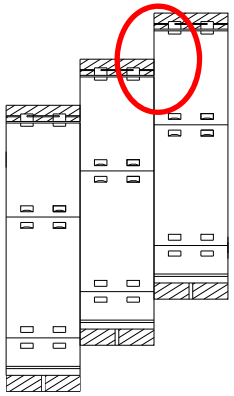
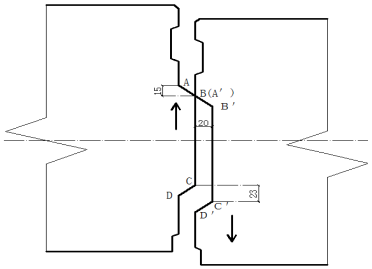
- **The correlation of tunnel deformation and other defects**

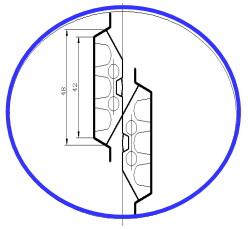




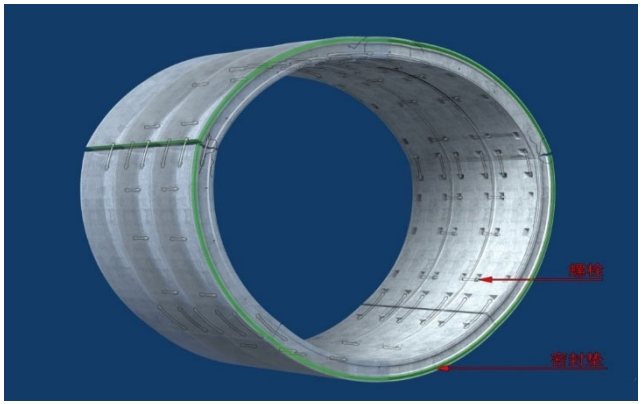
Dislocation ⇔ Difference settlement



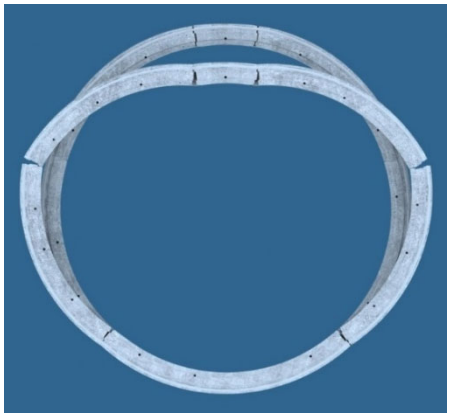
Large dislocation causes leakage



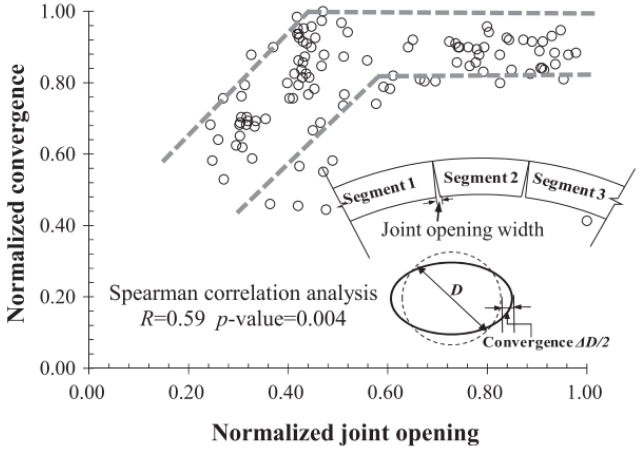
Waterproof gasket failure



Large convergence for consecutive rings



Large convergence for single ring



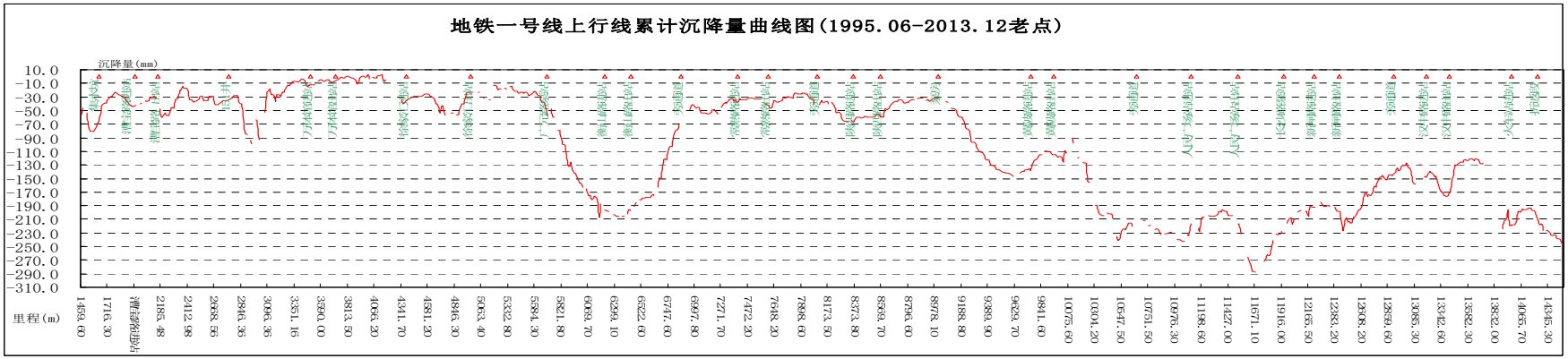
Tunnel defects highly correlated to deformation

Large convergence ⇒ Large joint opening ⇒ Leakage

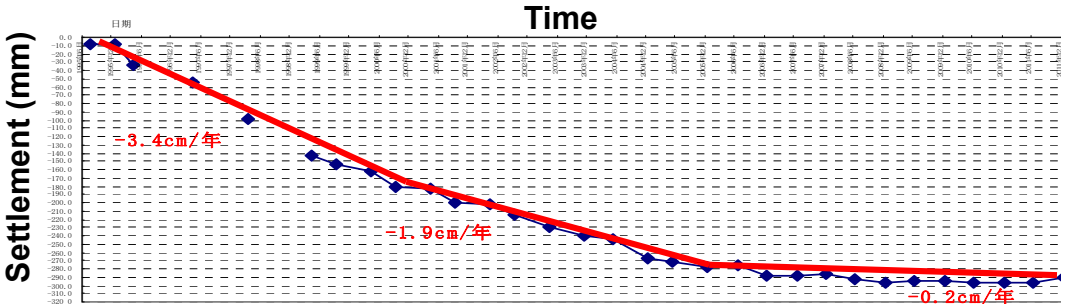
The *DEFORMATION* of tunnel structure --- the main defect and also the reasons of other defects

1. Background

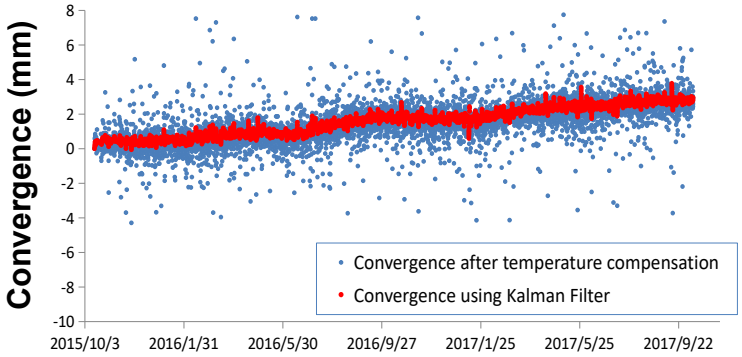
- **Long-term deformation of Shanghai Metro tunnel**



Accumulative settlement distribution of Shanghai Metro L1



Settlement time history curve



Horizontal convergence time history curve

- The maximum settlement of tunnel is about 30cm, 75% is induced by ground settlement
- Settlement increase speed: 2~3cm/year in the 1st 5 years; 0.9~1.2cm/year in the 2nd 5 years; 0.2cm/year in the 3rd 5 years
- Horizontal convergence: 2mm/1.5year

Long-term deformation monitoring --- crucial for tunnel safety

Outline

1 Background

2 Present deformation monitoring technology

3 Smart sensing technology

4 Case study of long-term deformation monitoring

5 Conclusions

2. Present monitoring technique

● Present deformation monitoring technique

□ Settlement monitoring

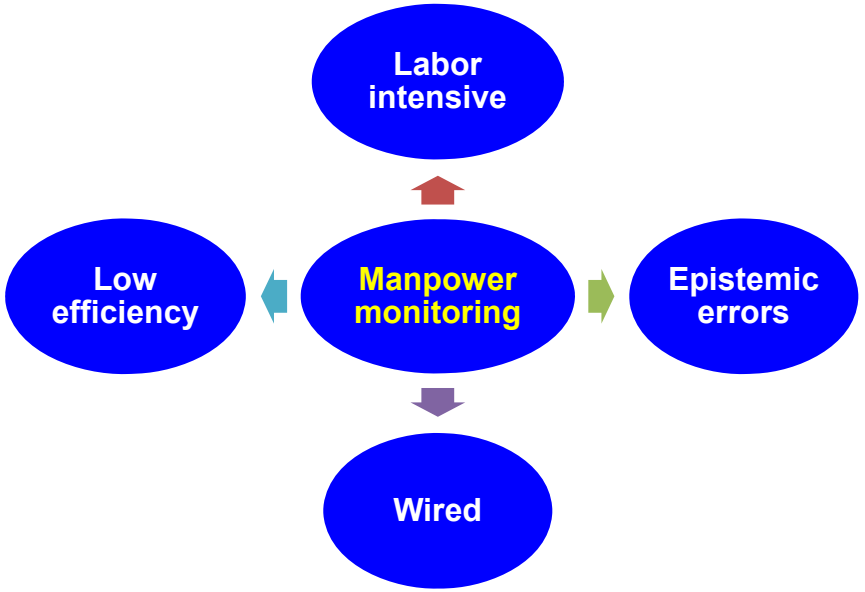
Hydrostatic leveling

Electronic leveling

Total station

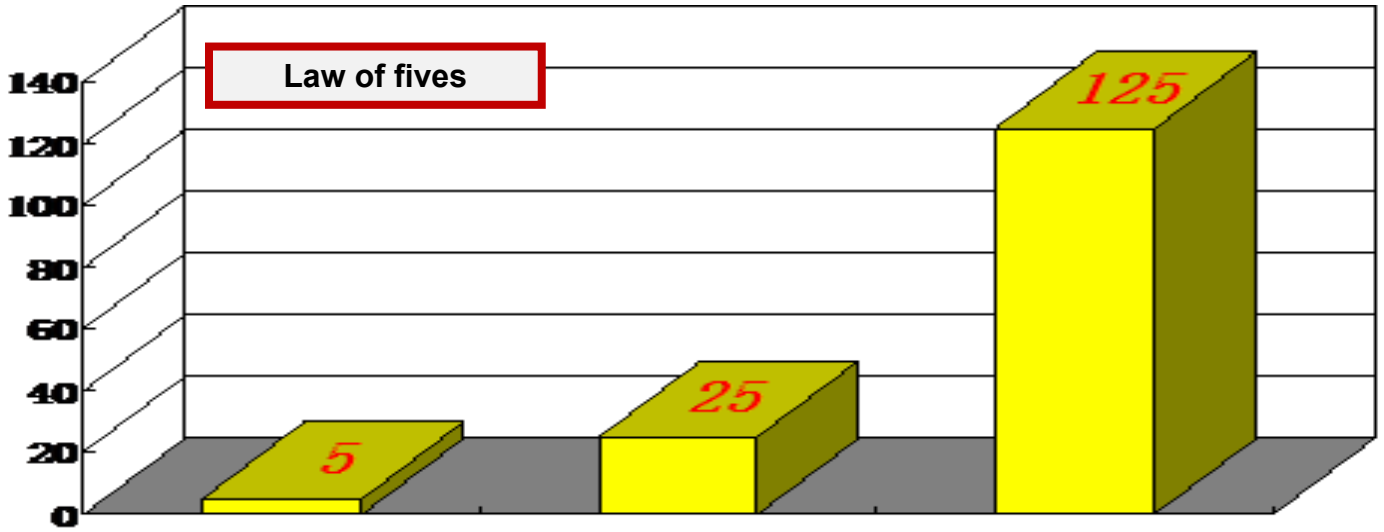
□ Convergence monitoring

Total station



2. Present monitoring technique

De Sitter (1984) proposed "Law of fives":



Quite similar ---- "Law of fives" for the monitoring of infrastructures

Manual monitoring: **250,000** RMB/km

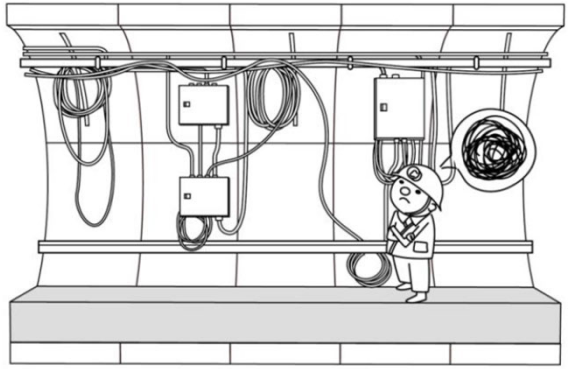
Manual monitoring with iPad: **50,000** RMB/km

Real time wireless monitoring: **10,000** RMB/km

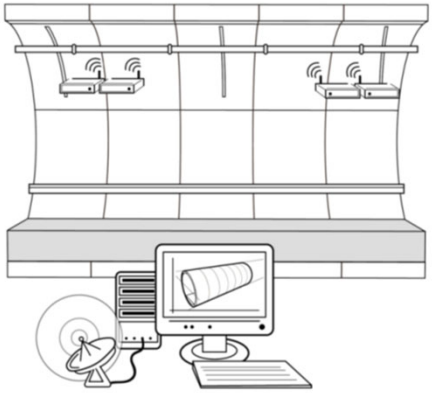
Preventive maintenance（Monitoring/Inspection）essential and low cost

2. Present monitoring technique

Settlement monitoring of Shanghai Dalin Road Tunnel (20201112)



Wired monitoring system



Wireless monitoring system

Outline

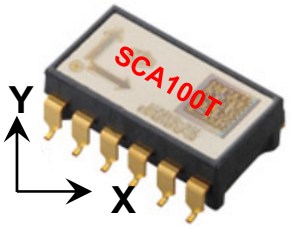
1. Background
2. Present deformation monitoring technology
3. **Smart sensing technology**
4. Case study of long-term deformation monitoring
5. Conclusions

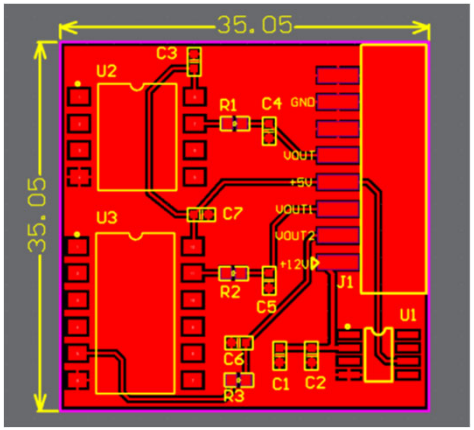
3. Smart sensing technology

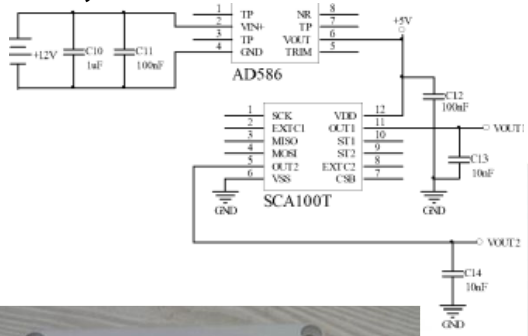
● Dual-Axis Tilt Sensor Node

- Operating Temperature(-40℃-85℃);
- High resolution (0.0001°);
- Decoupling calibration for each axis;
- Low power cost;
- Sleeping-listening Mechanism;
- Accuracy 0.002°;
- Small size 5 cm;
- Lifespan 10 years;
- Battery lifespan 5 years

11.31 x 5.08 x 15.58 mm







Chip circuit

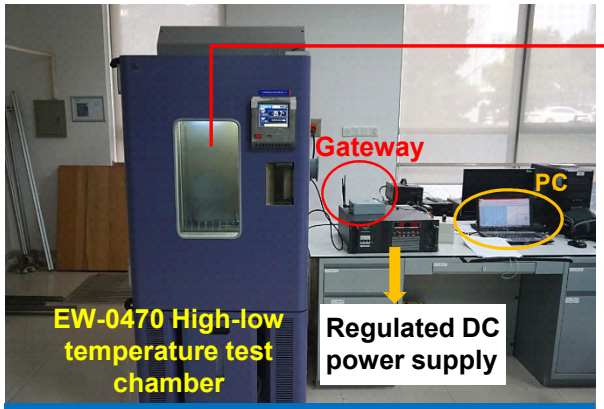
Smaller size，higher accuracy，Industrialization

Hongwei Huang et al, (2013). *International Journal of Architecture, Engineering and Construction*, 2(1), 25-34.

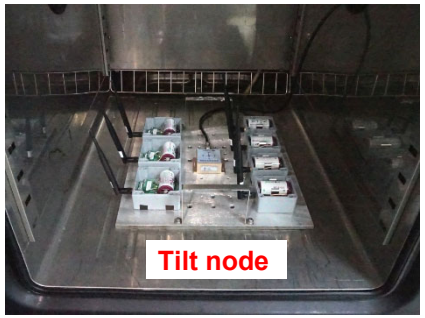
3. Smart sensing technology

● Temperature compensation for tilt node

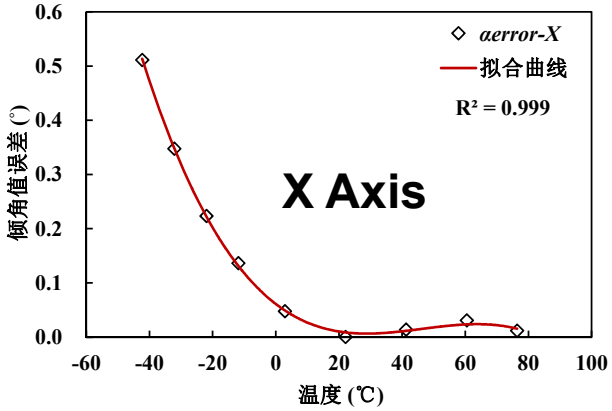
Indoor test using thermal invasion method

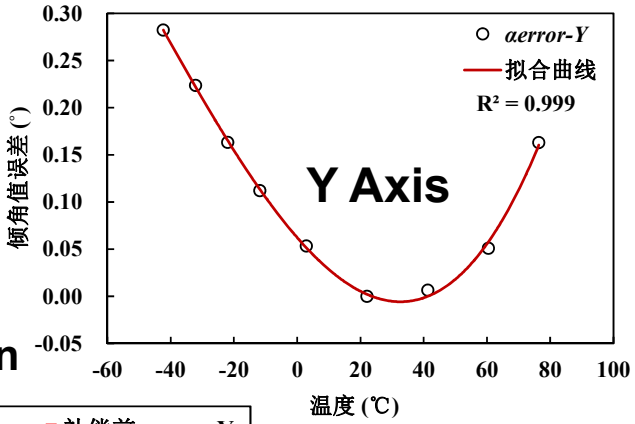


Shanghai Institute of measurement and testing technology

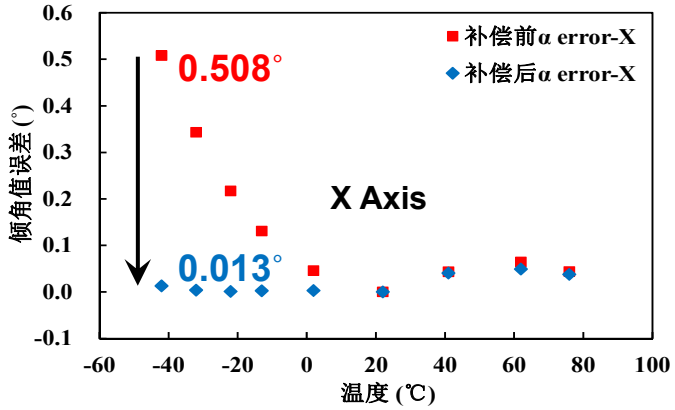


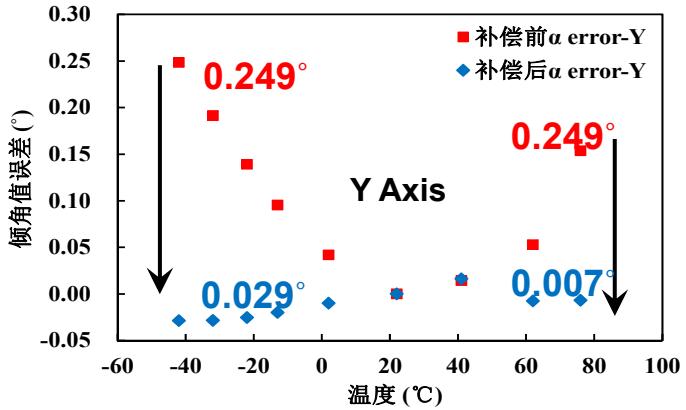
Temperature compensation model based on polynomial fitting





Validation test for the effect of temperature compensation





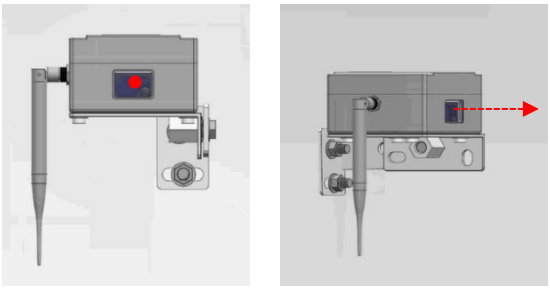
***Patent*：ZL201811125487. Fei Du**, et al.（2017）, *WSN-based health monitoring of highway tunnel lining in seasonal cold region[C]. Proceedings of the 2017 World Congress on ASEM17.*

3. Smart sensing technology

同济大学 TONGJI UNIVERSITY | 土木工程学院 COLLEGE OF CIVIL ENGINEERING

● Laser Tilt & Distance Sensor Node

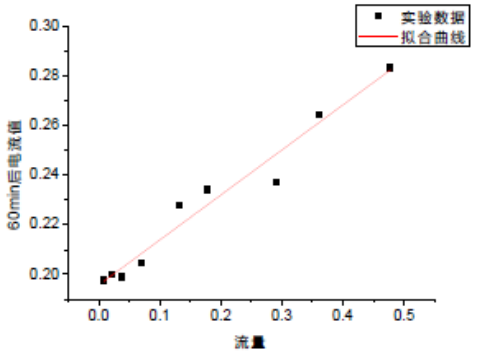
Laser distance sensor module + **Dual-axis tilt sensor module** → **Laser Tilt & Distance Sensor Node**



Sketch

On-site installation

● Interface water leakage sensor node based on electrode



Calibration function: Seepage discharge vs. current variation

Indoor test

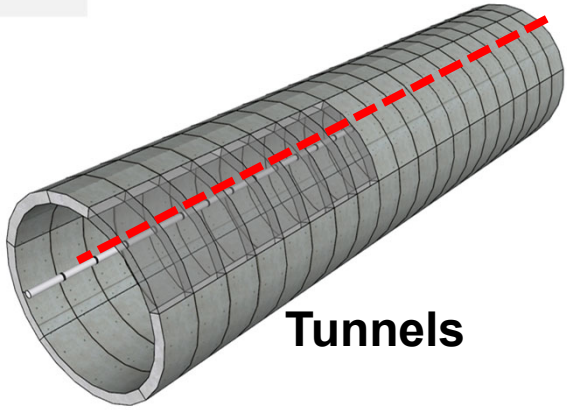
*(**Patents：** ZL201310229686.7, ZL201310231689.4.*
*Chen SF and **Huang HW**, Chinese Journal of underground space and Engineering, 2014)*

3. Smart sensing technology

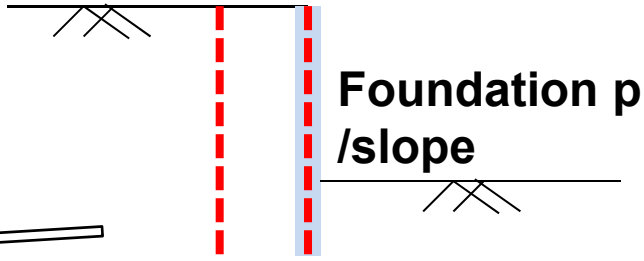
● Wisen Smart Shape (WSS) based on tilt node

An array of tilt nodes make up the longitudinal deformation sensor node, and can be used to monitor:

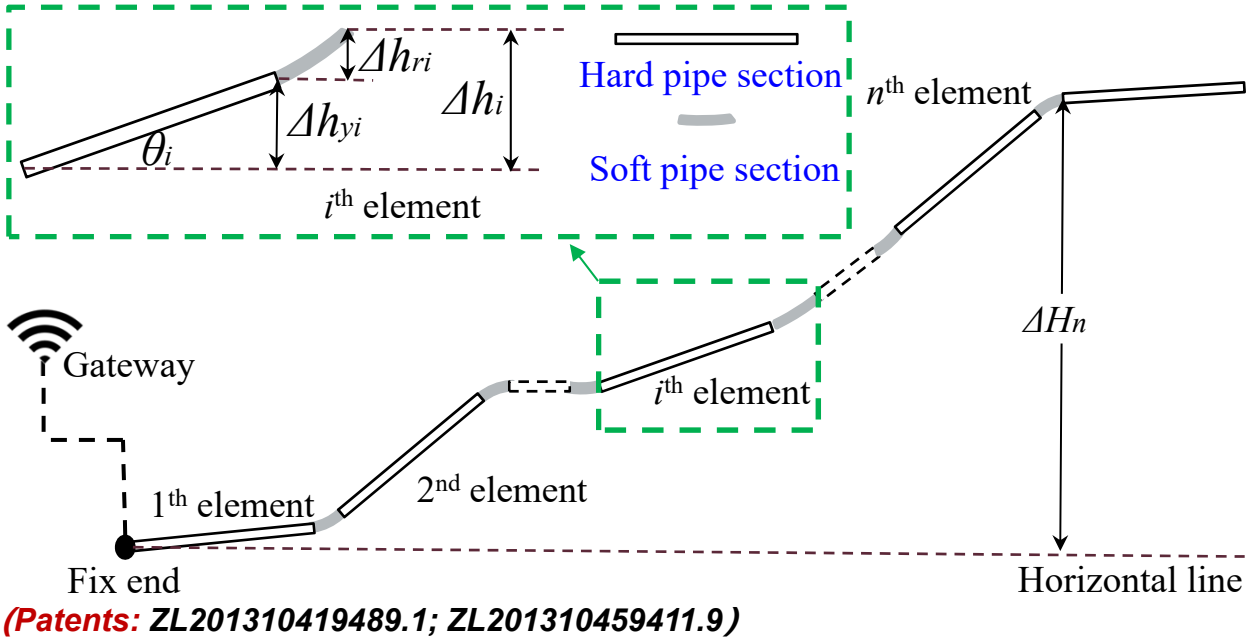
- **Tunnel longitudinal difference settlement;**
- **Horizontal displacement of retaining wall of foundation pit ;**
- **Subsurface horizontal and vertical ground displacement ;**
- **3D displacement for any other linear-shape structure;**



Tunnels



Foundation pit /slope



$$\Delta h_i = \Delta h_{yi} + \Delta h_{ri}$$

$$\Delta h_{yi} = L \times \sin\theta_i$$

$$\Delta H_n = \sum_{i=1}^{n} \Delta h_i$$

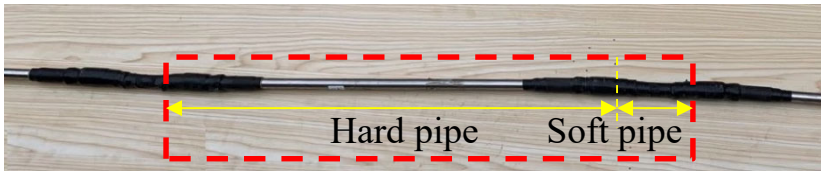
Δhi : elevation difference of ith element
Δhyi : elevation difference of hard pipe
Δhri : elevation difference of soft pipe
ΔHn : relative vertical displacement
L : length of hard pipe

(Patents: ZL201310419489.1; ZL201310459411.9)

3. Smart sensing technology

- **New products of WSS**

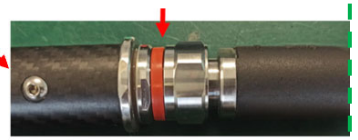
1st Generation devices

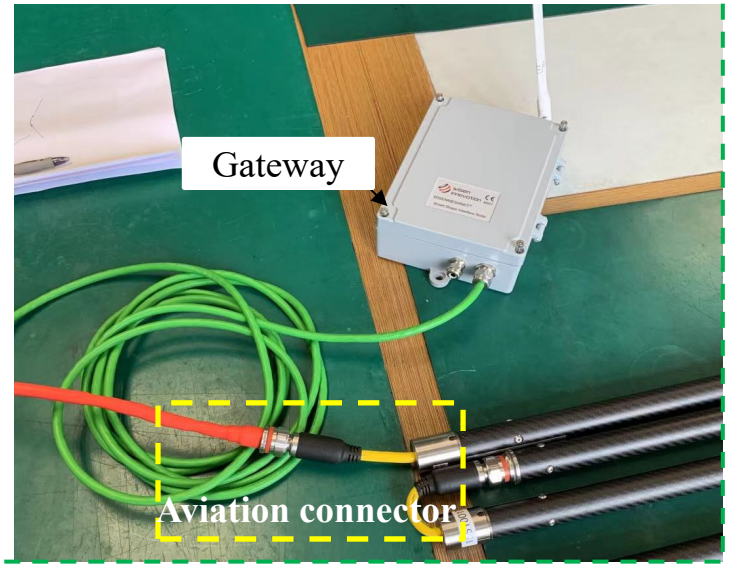


2nd Generation devices

Anti daze interface

Waterproof rubber ring



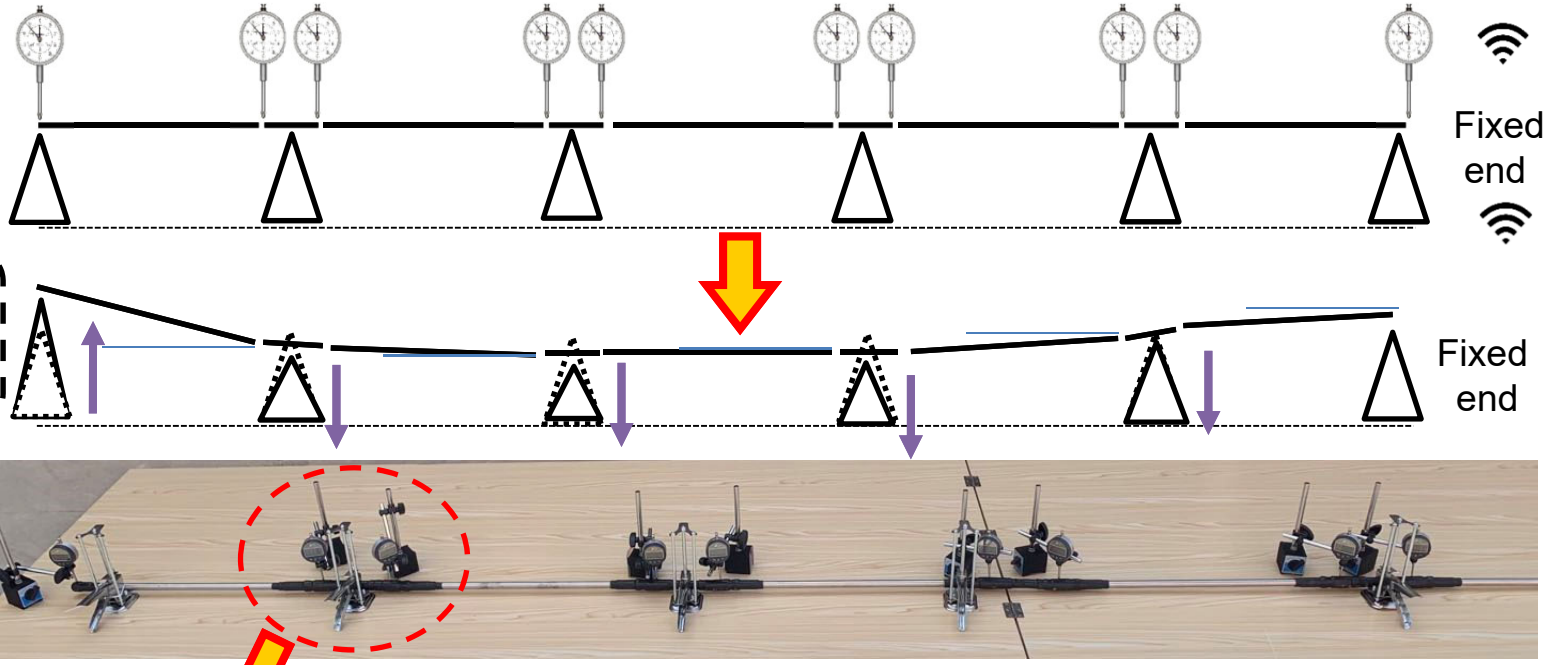


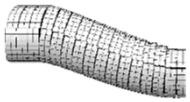
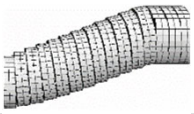
3. Smart sensing technology

● Error calibration laboratory test

Step 1: initialize the testing system

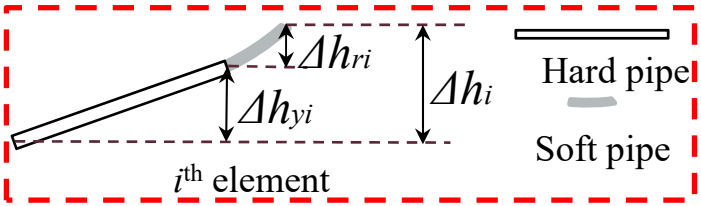
Step 2: change the elevation of some points and record the data



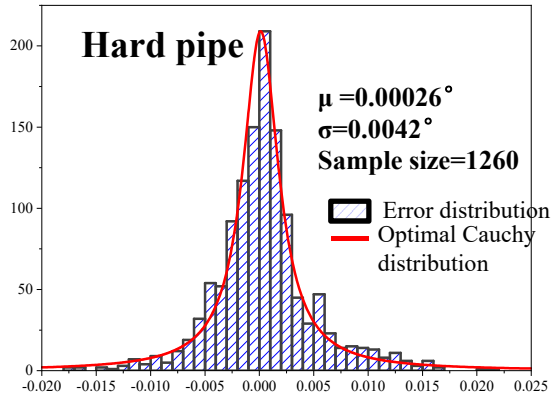
Settlement mode	Posture	Testing groups	Settlement mode	Posture	Testing groups
	Downward	66		Convex	38
	Upward	20		Crisscross	67
	Concave	61		Total	252

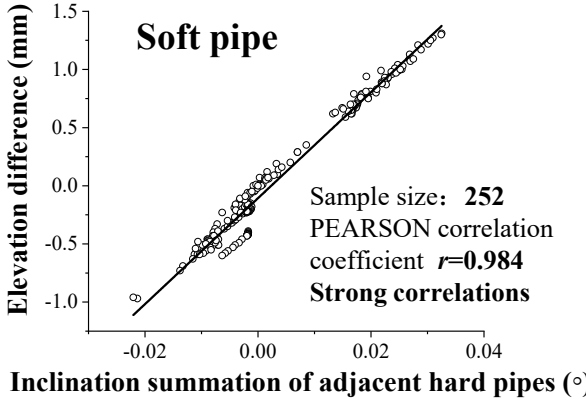
3. Smart sensing technology

● Error analysis of the whole system

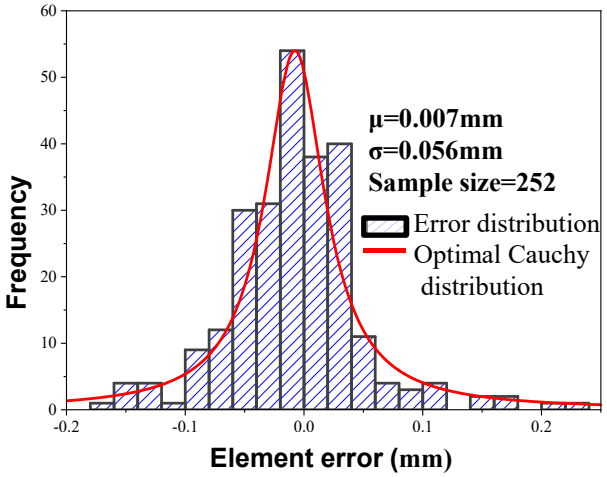


$$\begin{cases} T = atan(\dfrac{\Delta h_{yi}}{\Delta y_i}) \\ E_a = \Delta\theta_i - T \end{cases}$$

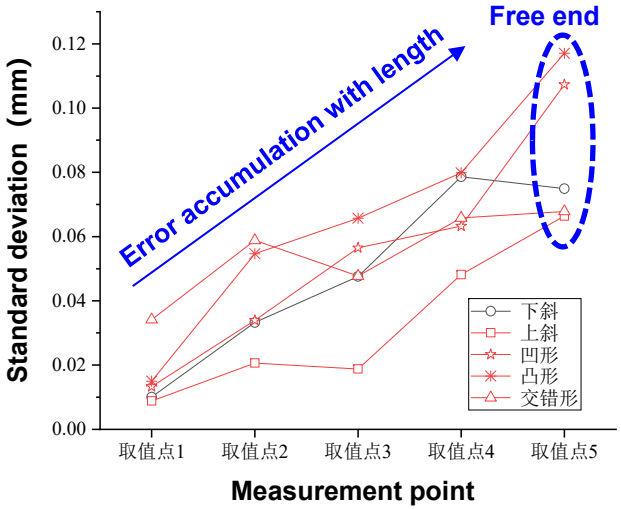




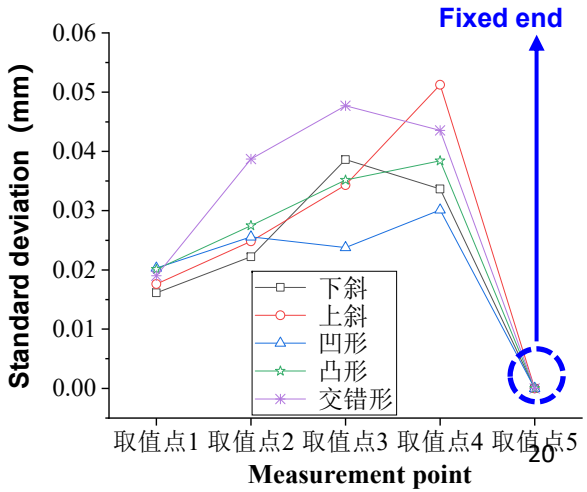
➢**Typical element error:**
element precision set as the two times of standard deviation, **0.11mm/element**



➢**System error with free end:** the measurement point as the middle of element, three times of average standard deviation **0.053mm / element**

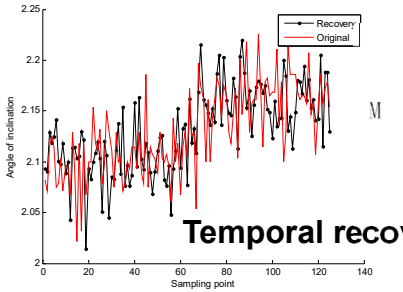


➢**System error with fixed end:**
end error is averaged to each measurement point, three times of the average standard deviation **0.021mm/element**。

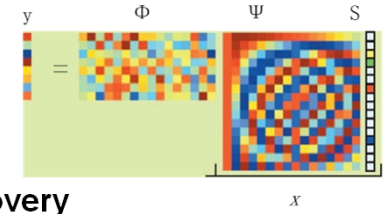


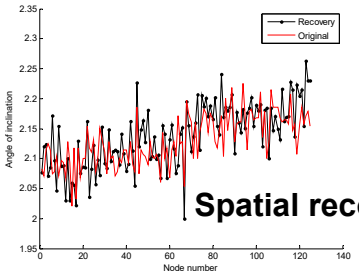
3. Smart sensing technology

- **Considering the spatial characteristic of tunnel, propose spatial-temporal data compression and recovery algorithm, uneven clustering routing algorithm, deep sleeping mechanism for the wireless network communication.**



Temporal recovery

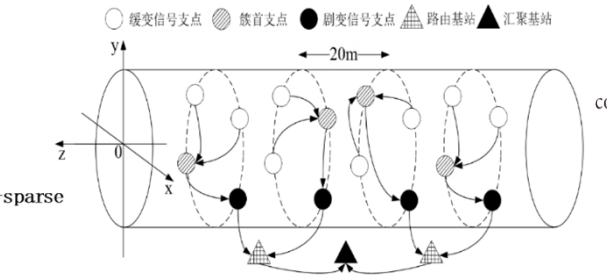




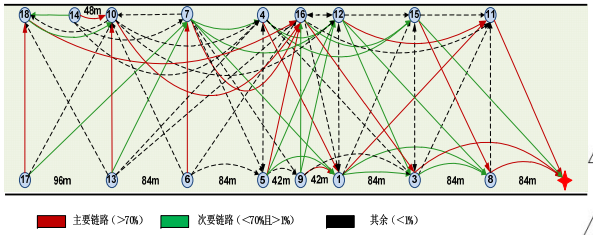
Spatial recovery

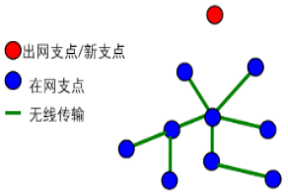
$$\begin{cases} \gamma = \dfrac{\|X(:,j)-U(:,j)\|_2}{\|X(:,j)\|_2} \\ \beta = \dfrac{\|X(i,:)-U(i,:)\|_2}{\|X(i,:)\|_2} \end{cases}$$

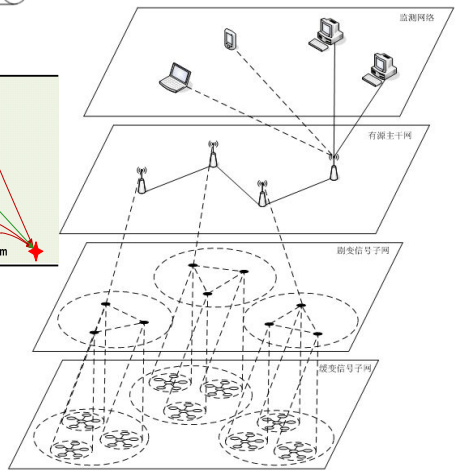
Recovery error< 2%



$$\text{cost}(i,j) = \begin{cases} a\dfrac{E_n(n_i)}{E_C(n_j)} + b\dfrac{N_c(n_j)}{N_n(n_i)} + c\dfrac{d_{ij}^2 + d_{jS}^2}{d_{iS}^2} + dL_{ij}, \\ \quad i \neq j \\ +\infty, \\ \quad i = j,\ d_{iS} > D_{MAX} \\ 0, \\ \quad i = j,\ d_{iS} < D_{MIN}, \end{cases}$$





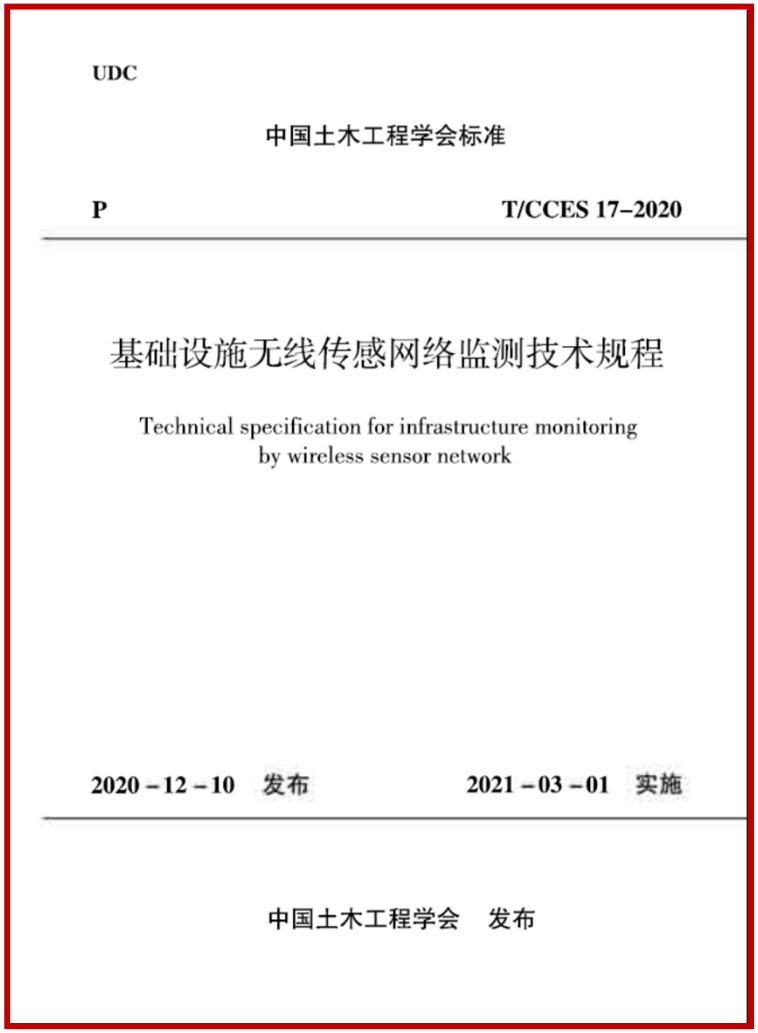


Network stability

Patents ***ZL201410110917.7; ZL201010571192.3; ZL201010571223.5; ZL201611111551.0;***

He, et al.(2014); Wu, et al.(2009,); Li, et al.(2016), etc

3. Smart sensing technology



UDC

中国土木工程学会标准

P T/CCES 17–2020

基础设施无线传感网络监测技术规程

Technical specification for infrastructure monitoring by wireless sensor network

2020 – 12 – 10 发布 2021 – 03 – 01 实施

中国土木工程学会 发布

The first Chinese technical code for infrastructure smart sensing

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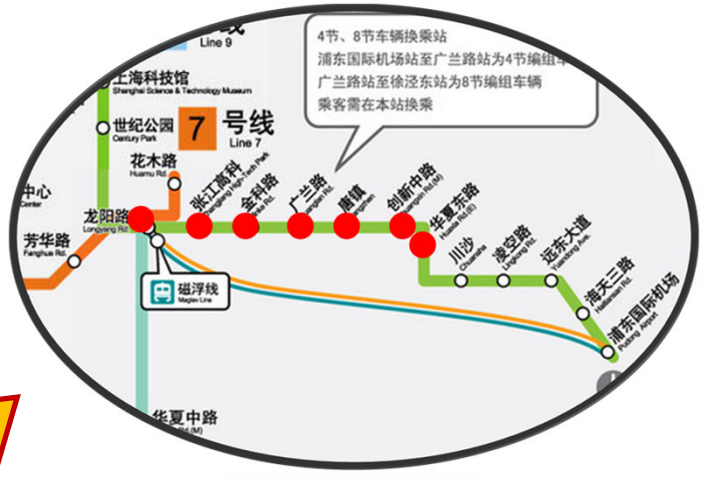
Outline

1. Background
2. Present deformation monitoring technology
3. Smart sensing technology
4. Case study of long-term deformation monitoring
5. Conclusions

4. Case study-Case 1

- Smart sensing of metro tunnel—20.4km Shanghai Line 2 (2010)



259 Monitoring sections;

518 Tilt nodes;

20 Gateways;

6 Station intervals 12 Tunnels;

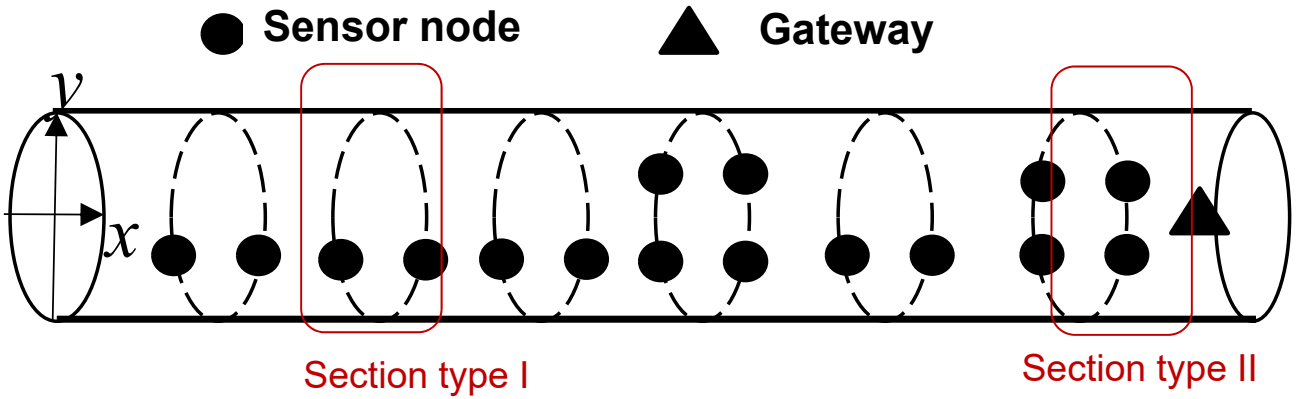
20.4km Tunnel length;

6 years Routine monitoring(2015.08-)

The first long-term and long distance application of WSN in tunnels

4. Case study-Case 1

- **Smart sensing of metro tunnel—monitoring sections deployment**



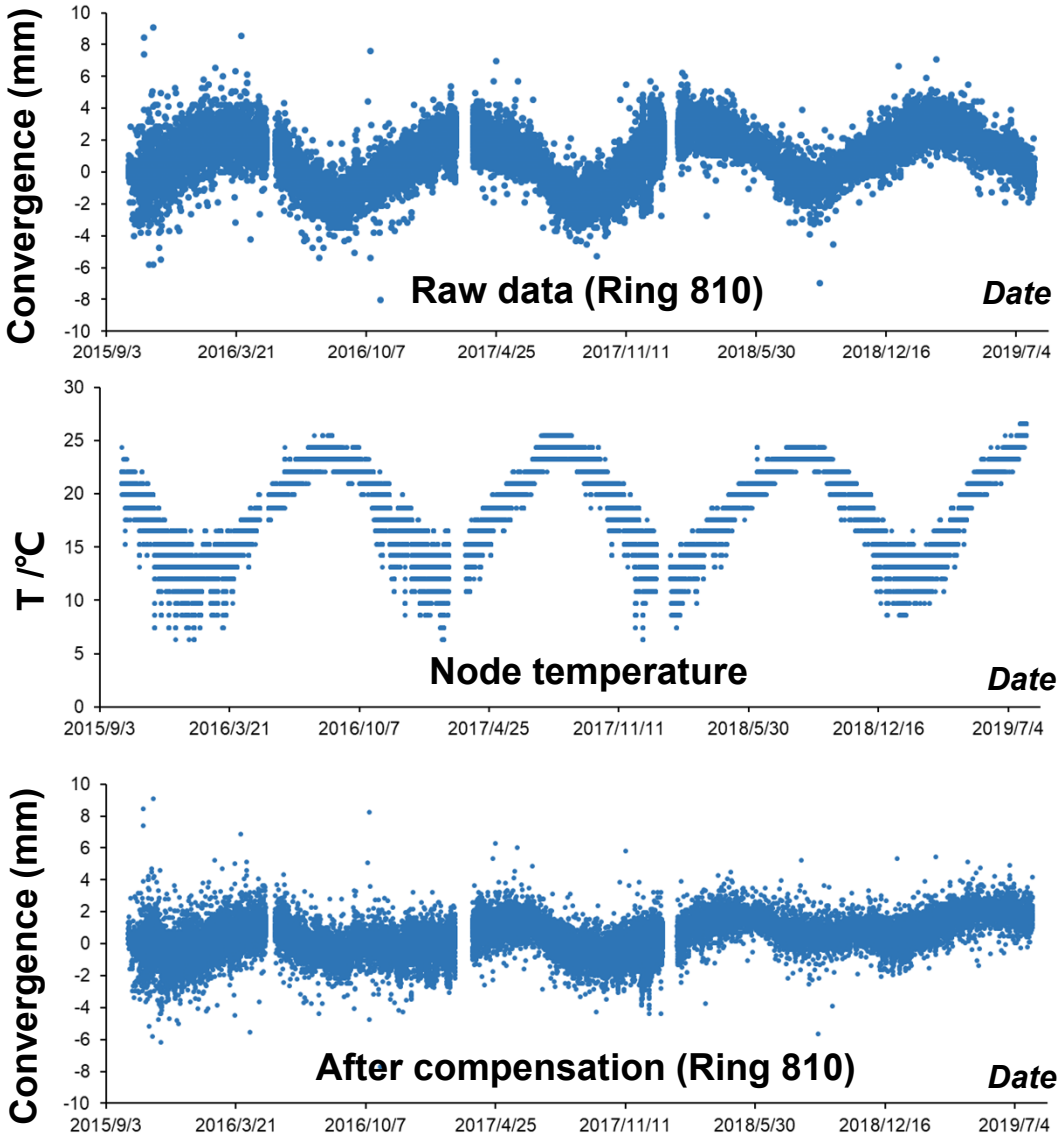
Gateway

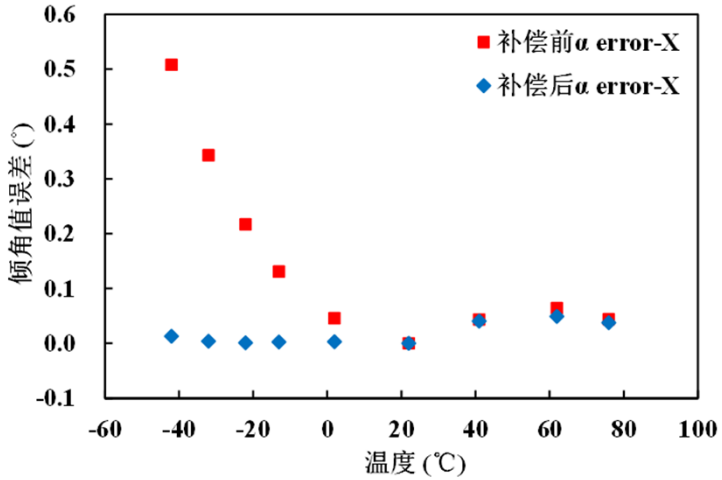
Tilt node

Tilt node

4. Case study-Case 1

- **Smart sensing of metro tunnel—effect of temperature**



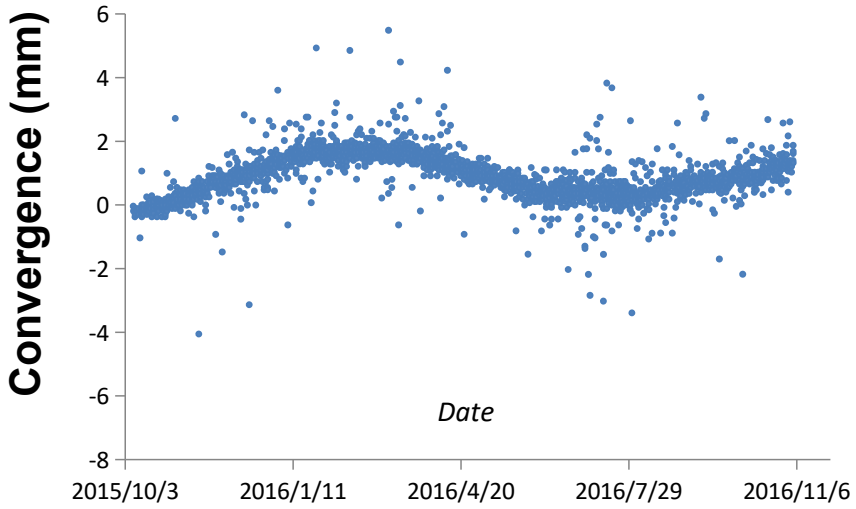


Temperature compensation

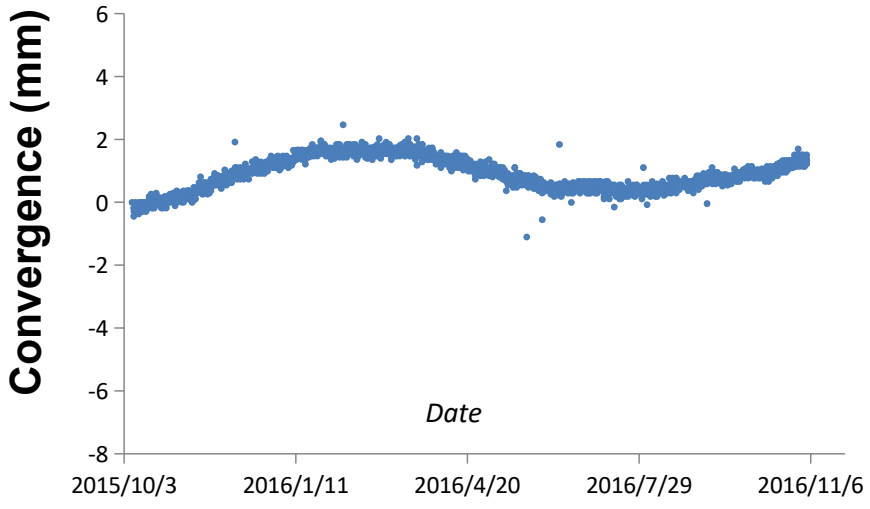
(Fei du, Master Thesis, Tongji Univeristy, 2018)

4. Case study-Case 1

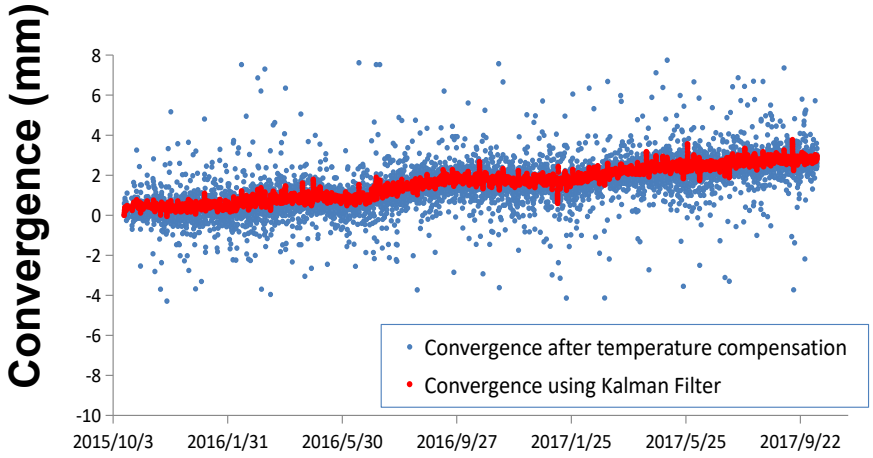
- **Smart sensing of metro tunnel—effect of train induced vibration**



(Morning rush hour 6AM - 9AM)



(Midnight 00AM - 3AM)

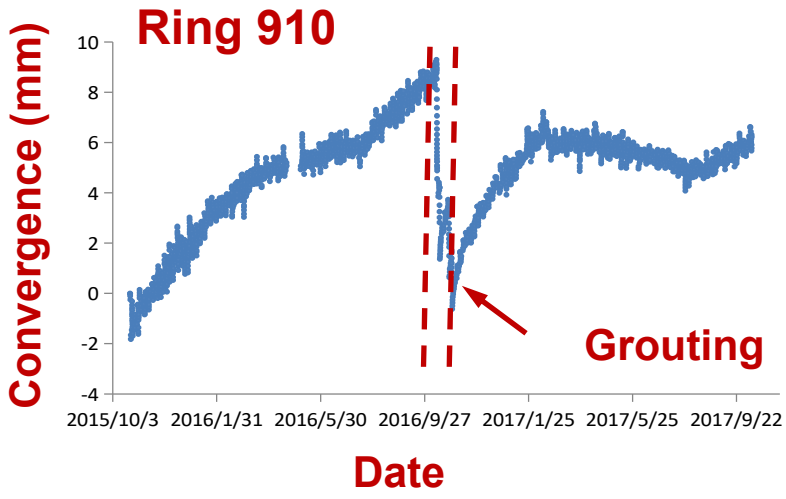


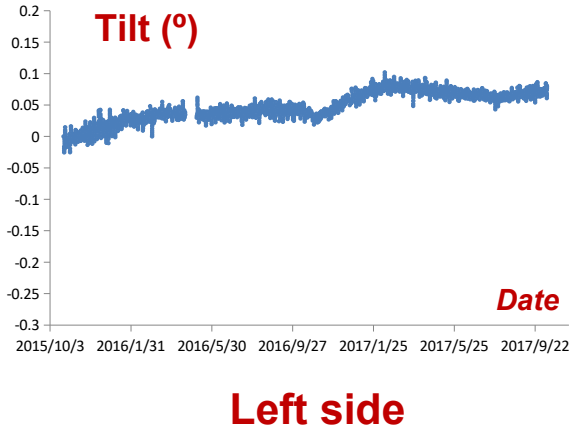
Kalman Filter

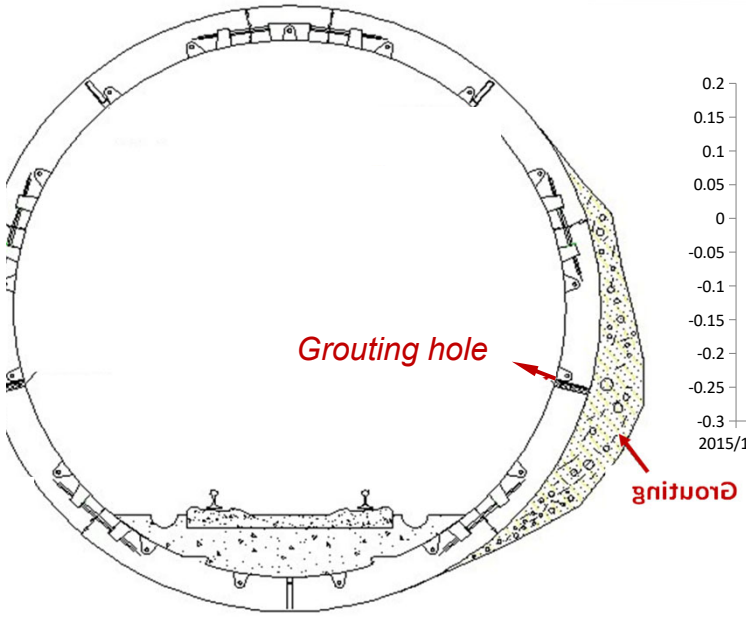
- **Static problem**: vibration data is not needed (Filtering)
- **Dynamic problem**: vibration data is needed

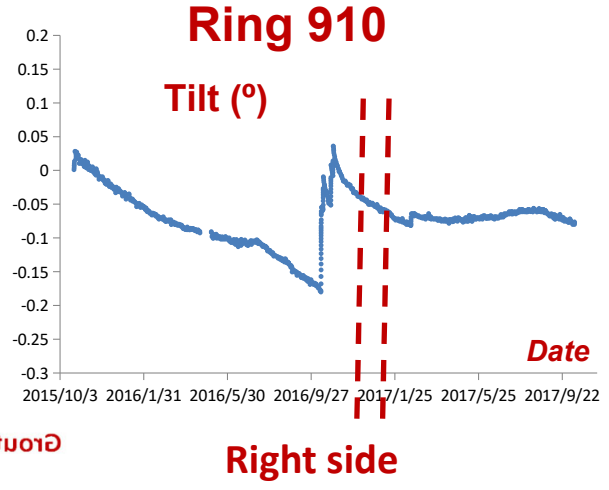
4. Case study-Case 1

- Smart sensing of metro tunnel—effect of grouting



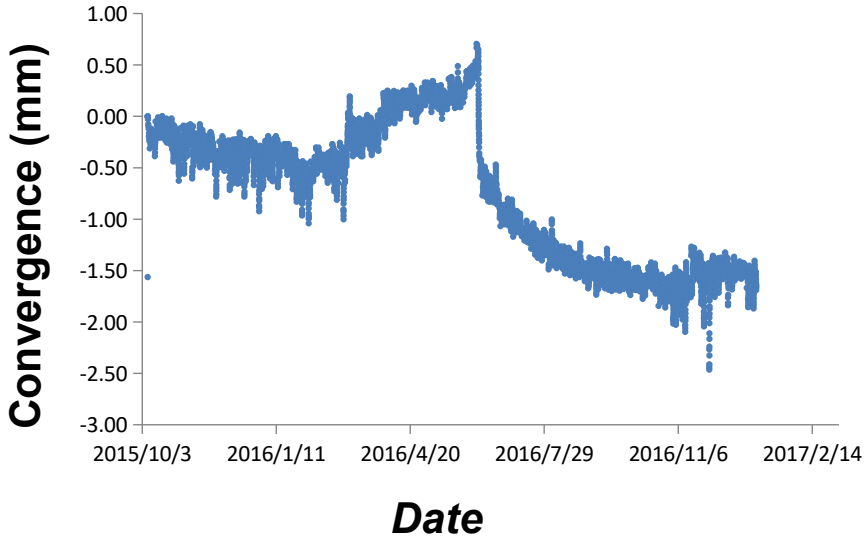


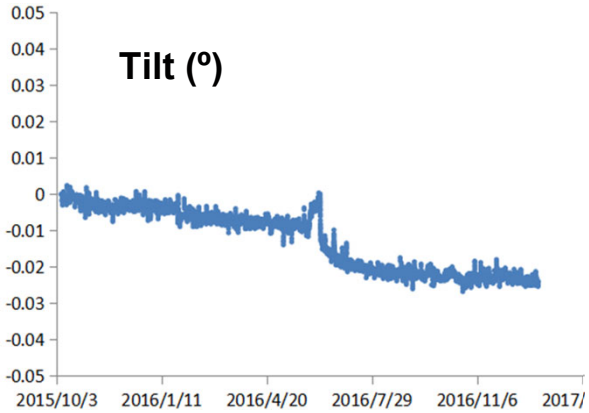




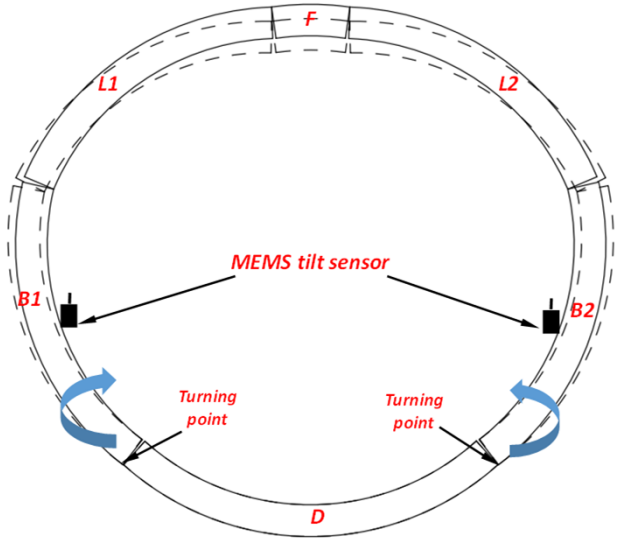
4. Case study-Case 1

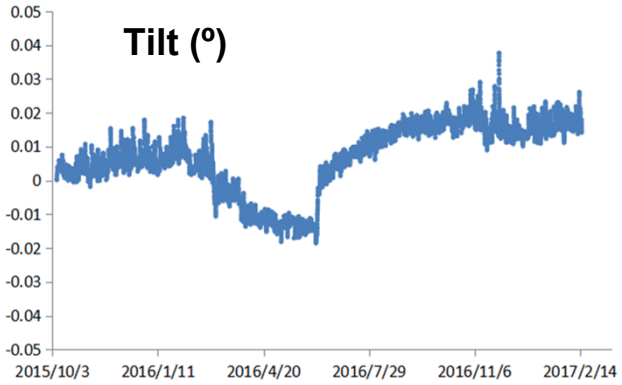
- **Smart sensing of metro tunnel—effect of adjacent excavation**





Ring 280





Ring 280

Huang H, Xie X, Zhang D, Liu Z, Lacasse S. Multi-sensor data fusion based assessment on shield tunnel safety. ***Smart Structures and Systems****, 2019, 24(6): 693-707*

4. Case study-Case 2

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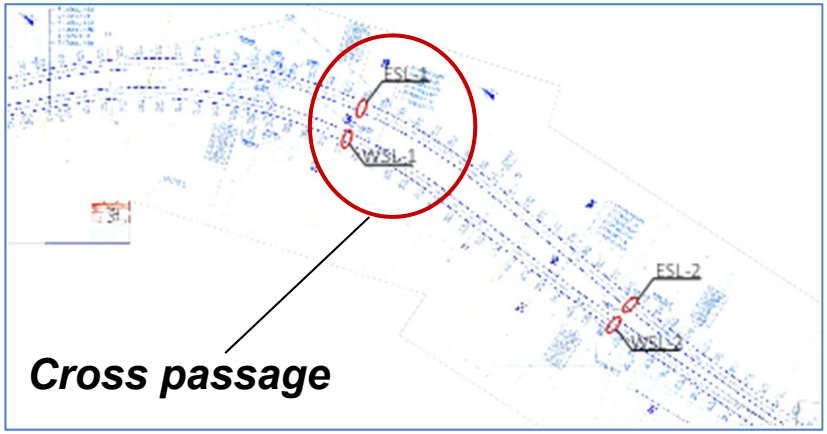
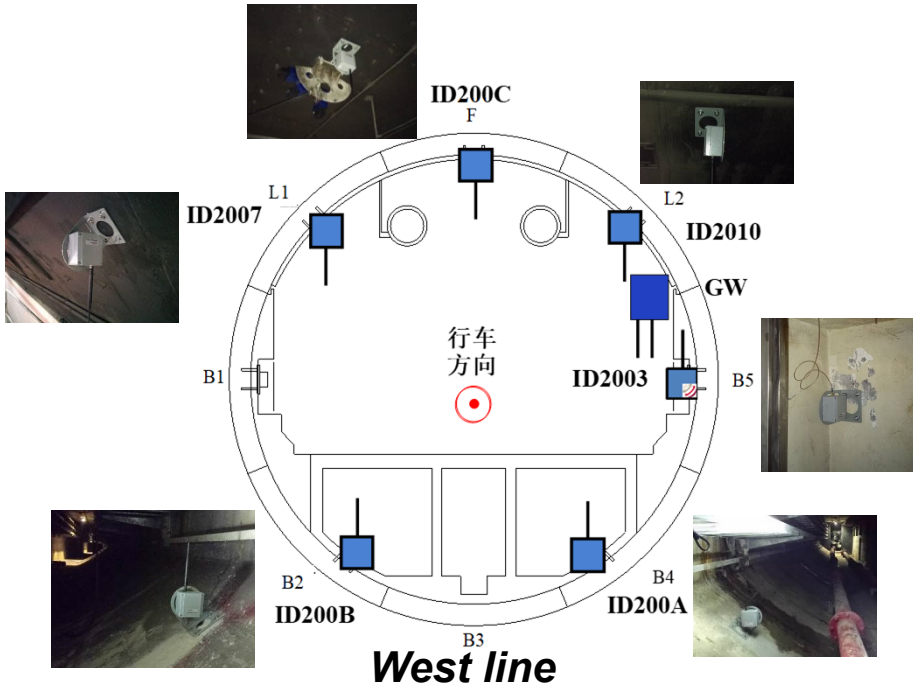
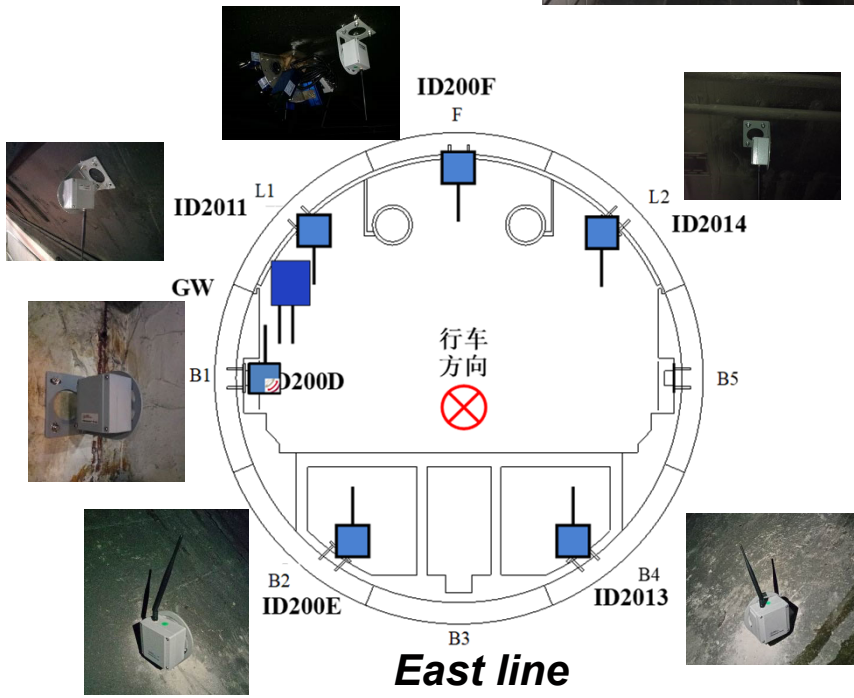
- **Smart sensing of road tunnel- Shanghai Dalian Road tunnel (2003)**

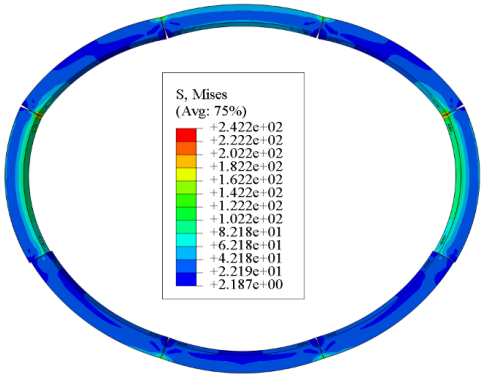




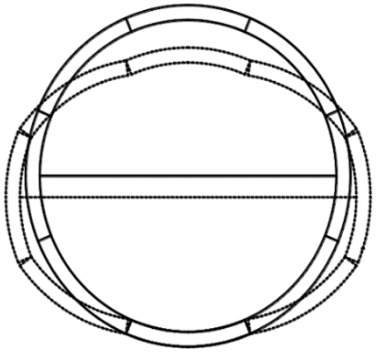


4. Case study-Case 2

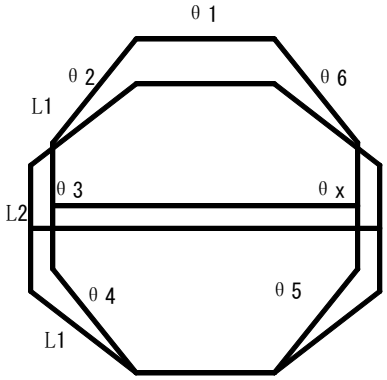
● Calculation of tunnel convergence from inclination of segments



Numerical simulation of tunnel deformation



Typical deformation mode



Simplification of segmental shield tunnels

Horizontal convergence

$$\Delta DH = \Delta D_{left} + \Delta D_{right}$$

$$= 2L_1 \sin(51° - \Delta\theta_5/2)\sin(\Delta\theta_5/2) - \frac{1}{2}L_2 \sin\sum_{i=1}^{6}\Delta\theta_i$$

$$- 2L_1 \sin(51° + \Delta\theta_4/2)\sin(\Delta\theta_4/2) - \frac{1}{2}L_2 \sin\Delta\theta_3$$

Assumptions:

- Segments are rigid body
- Deformation are symmetric
- No slide for joints

Vertical convergence

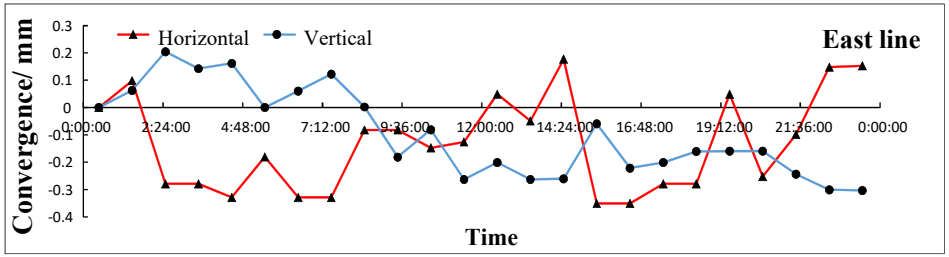
$$\Delta DV_1 = L_1\left[\sin(51° - (-\Delta\theta_4)) - \sin 51°\right] + L_1\left[\sin(51° - \Delta\theta_2) - \sin 51°\right] - L_3 \sin\Delta\theta_1$$

$$= 2L_1 \cos(51° + \Delta\theta_4/2)\sin(\Delta\theta_4/2) + 2L_1 \cos(51° - \Delta\theta_2/2)\sin(\Delta\theta_2/2)$$

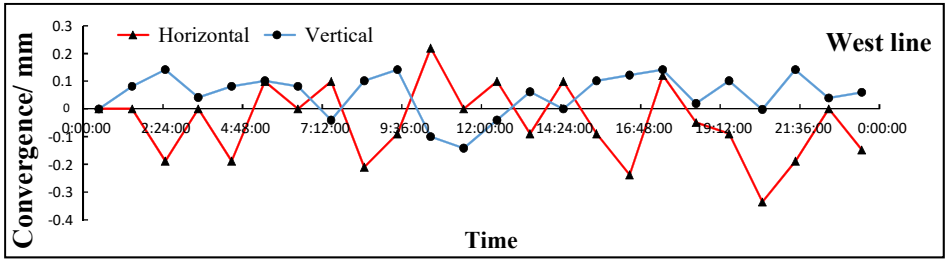
$$- \frac{1}{2}L_3 \sin\Delta\theta_1$$

4. Case study-Case 2

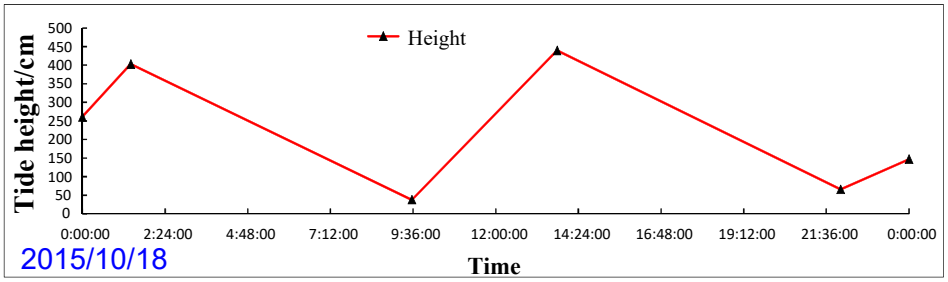
Monitoring data in one day



Convergence for East line

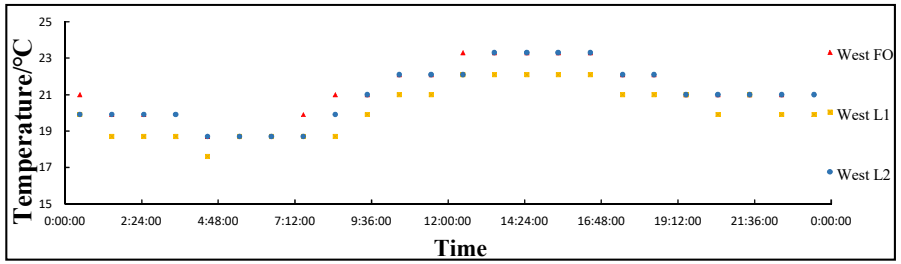


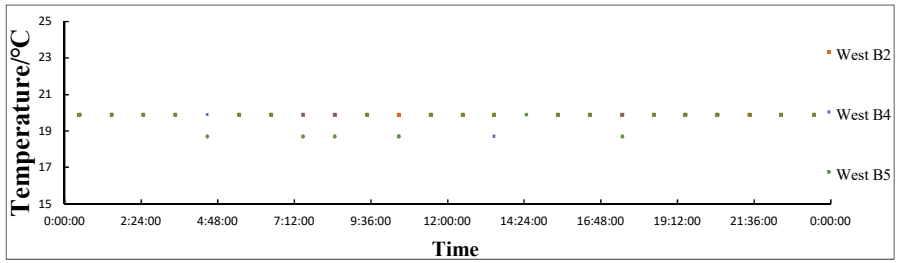
Convergence for West line



Tide height for Huangpu River

Monitoring frequency:1time/h





Temperature monitoring

- The convergence is fluctuated in one day. The maximum variation is 0.63mm for horizontal convergence, 0.51mm for vertical convergence
- The fluctuation is possibly caused by ***temperature variation*** and ***tide height change*** for Huangpu River

4. Case study-Case 2

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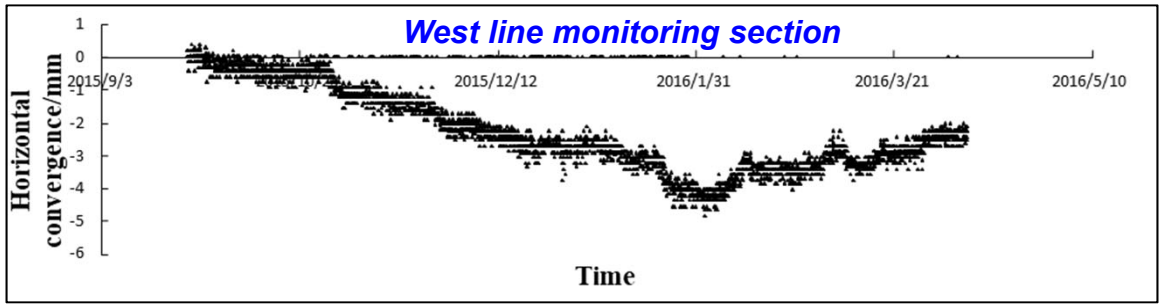
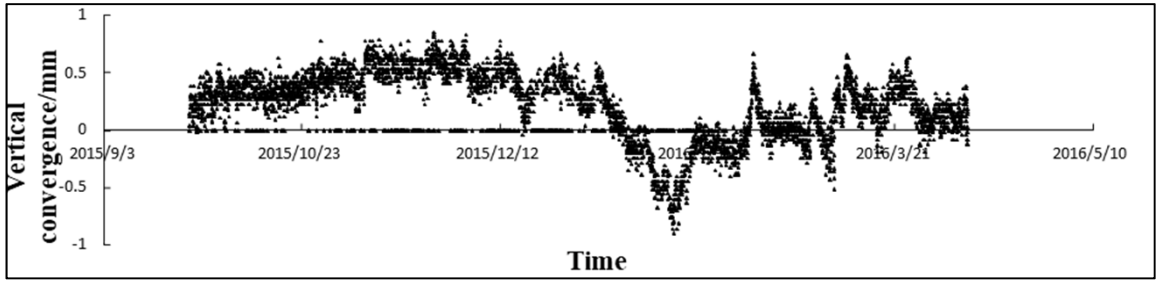
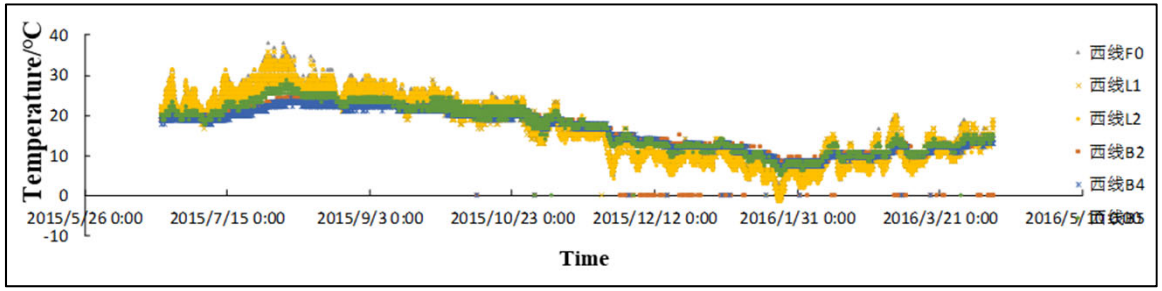
● Long-term deformation monitoring results



Horizontal convergence



Vertical convergence



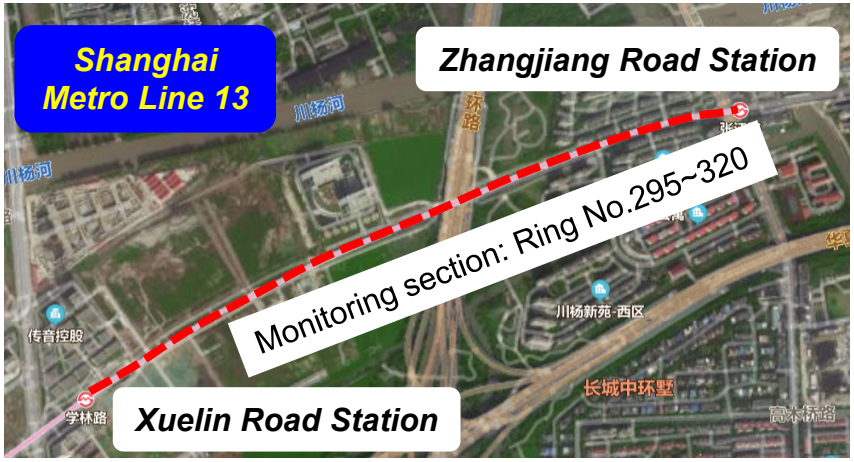
Temperature

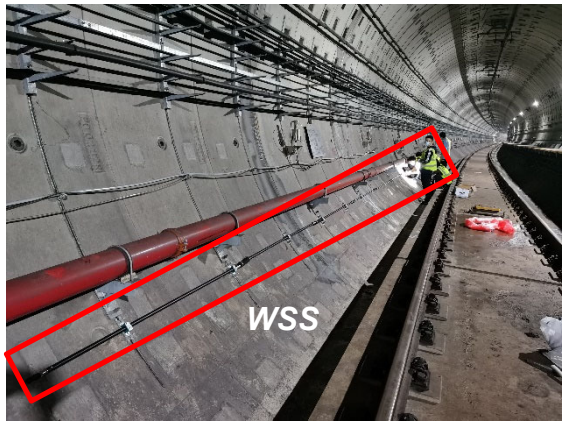
- Horizontal convergence has a maximum variation of 5mm. The horizontal convergence is highly correlated to seasonal changed temperature
- Vertical convergence has a very limited change which is under 1mm. The fluctuation of vertical convergence is possible caused by tide height fluctuation of Huangpu River

Wireless tilt sensors can not only monitor the segment inclination, but also can monitor the long-term horizontal and vertical convergence by reasonable installation

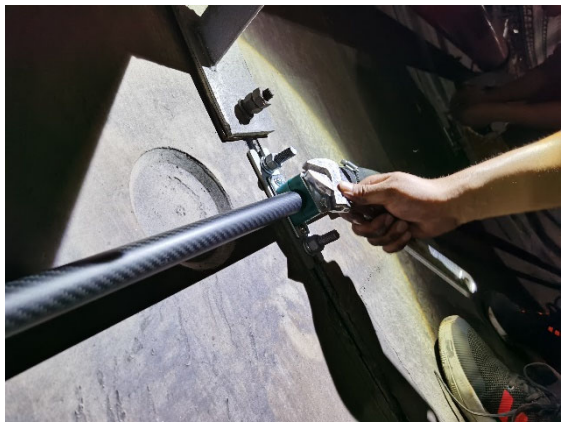
4. Case study-Case 3

- **Tunnel difference settlement monitoring using WSS**

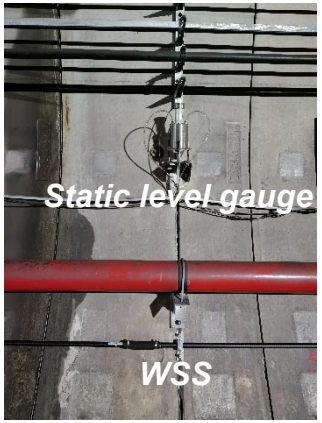




On site installation of WSS system



WSS element installation



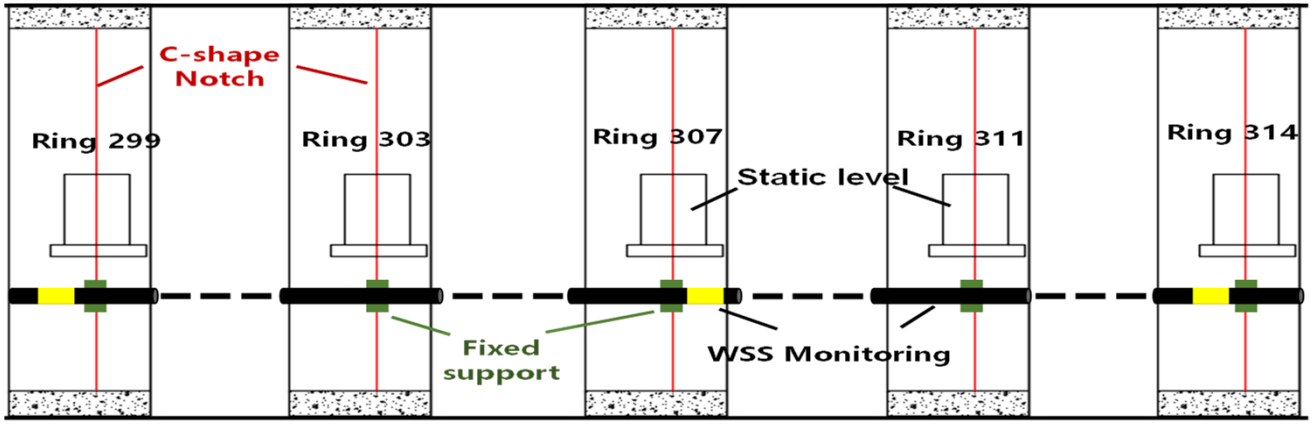
Comparison of WSS and static level gauge

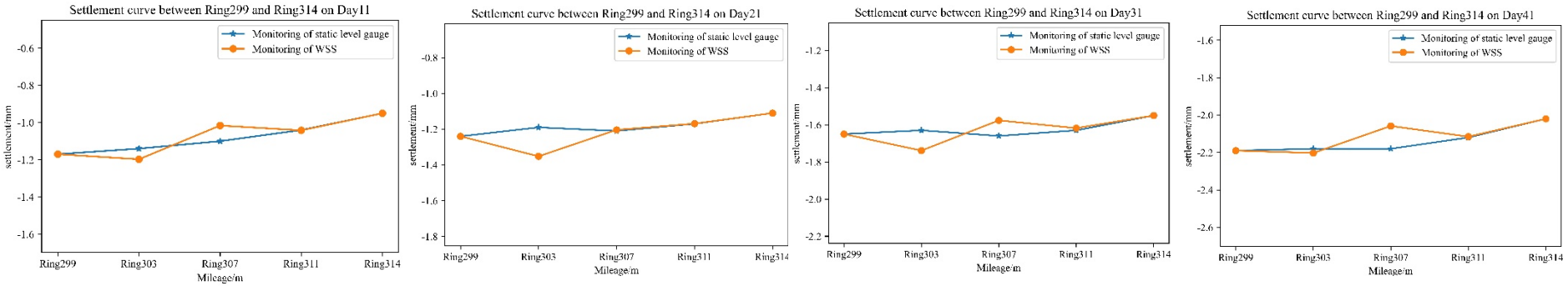
4. Case study-Case 3

- **Tunnel difference deformation monitoring results**

☐ Validation

WSS v.s. Traditional Static Level (2021 Jun 3rd – Jul 19th)





11th Day **21st Day** **31st Day** **41st Day**

WSS can monitor the tunnel difference settlement. The results of WSS well agrees with the measurements of conventional static level gauge within a maximum discrepancy of 0.1 mm.

Outline

1 Background

2 Present deformation monitoring technology

3 Smart sensing technology

4 Case study of long-term deformation monitoring

5 Conclusions

5. Conclusions

- Smart city should have huge data without ignoring capture short-lived and important behavior. WSN real time monitoring can play this key role.
- Smart sensing technologies are developed to monitor the long-term deformation of shield tunnels, and can reflect other defects indirectly .
- Our goal is 10 years long term settlement monitoring. 4 years later we can share the results again.

Acknowledgements

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Acknowledgements: some data of this presentation is provided by Rulu Wang and Jingya Yan from Shanghai Metro.

上海地铁 Shanghai Metro

Rulu Wang

Jingya Yan

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Thank You!

Joint Technical Symposium on Digital Geosciences & Geotechnology,
16 September 2021, Hong Kong

Machine Learning and Landslide Studies

Zhongqiang Liu

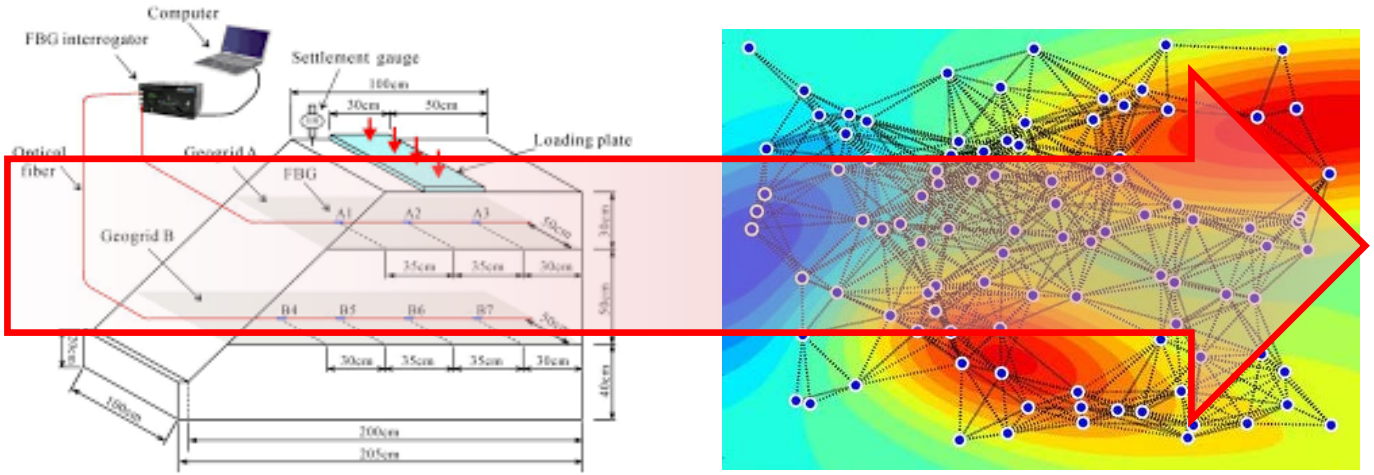
(with contributions from Dr Suzanne Lacasse, Dr Beibei Yang Prof. Jinhui Li and PhDs/MScs)

Norwegian Geotechnical Institute (NGI)

Contents

1 **A glimpse of technological opportunities**
   - Sensing technology, big data and machine learning
2 **State-of-the-Art of ML in landslide study**
3 **Recent developments of ML in landslide study**
   - Rainfall-induced landslide mapping in Kvam, Norway
   - Displacements in Three Gorges Dam reservoir, China
4 **Conclusion and perspective**

Sensors: paradigm shift



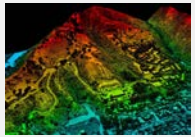
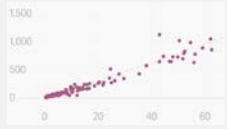
Few sensors, specific for purpose

- Dedicated monitoring systems
- High quality electronics
- High accuracy measurements

Vast quantity of sensors (internet of things, IoT)

- Ad hoc, impromptu systems
- Low quality, cheap, low accuracy but many data
- Sophisticated processing and interpretation tools based on statistics, machine learning, and artificial intelligence (AI)

Big data

Technology shift:

From dedicated, high quality sensors and small scale systems

To large, distributed systems with vast numbers of measurements and data

Paradigm shift:

From designing specific sensors at specific locations

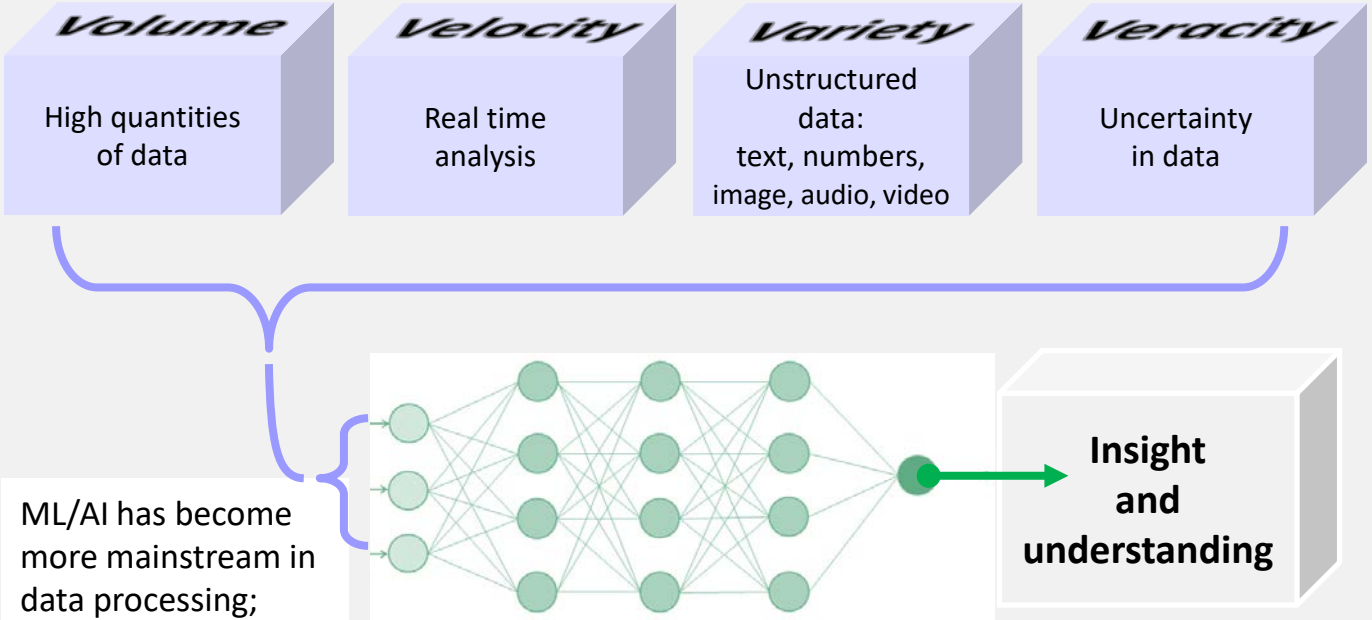
To observing a response (e.g. streams of direct/indirect relationships)

New tools and techniques:

- Cost-effective and innovative forms of processing that enable enhanced insight, help decision making, and have higher level of automation.
- Data management and system architecture

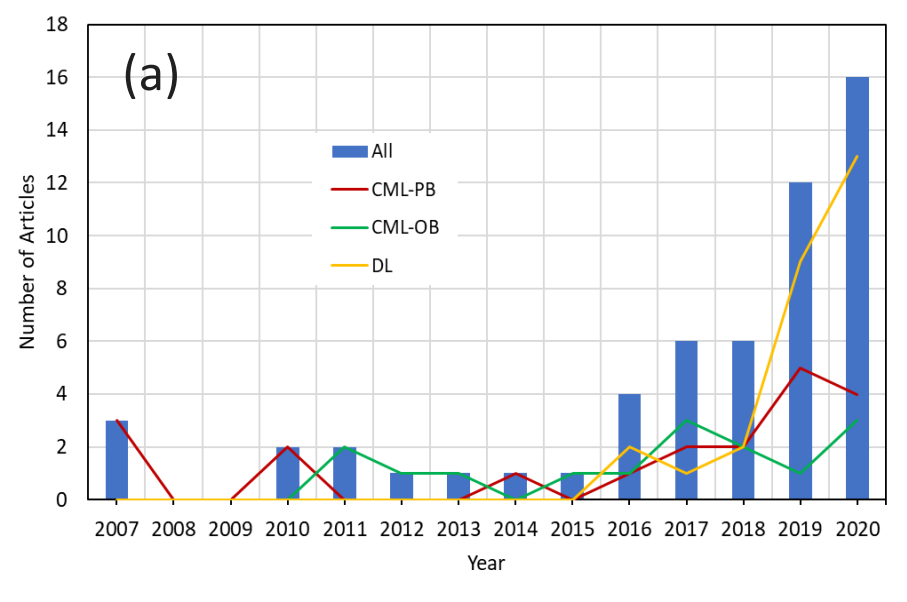
Appealing for an engineer/scientist

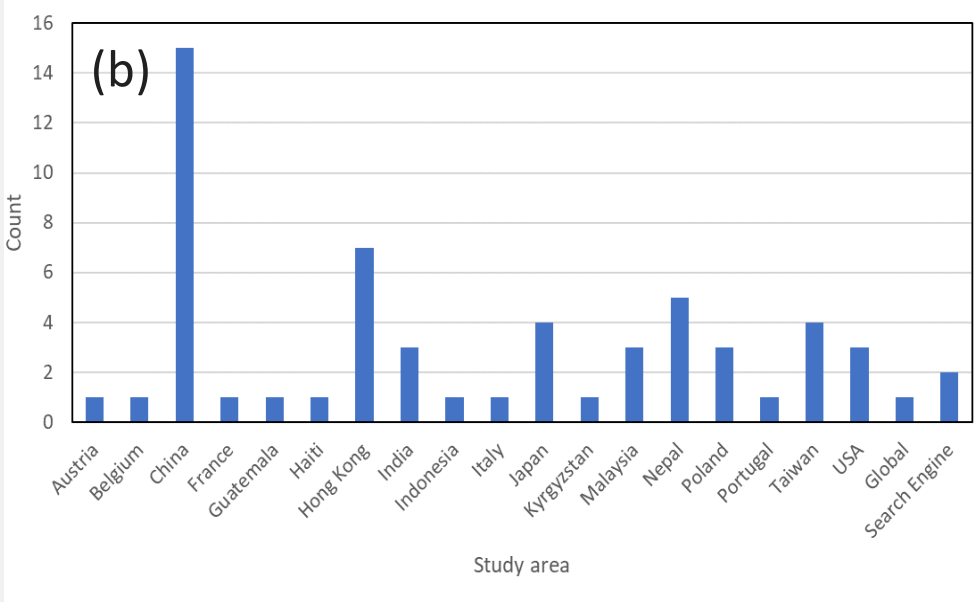
Machine learning



ML/AI has become more mainstream in data processing; will be embedded services in monitoring systems and solutions.

SOA of ML – detection and mapping



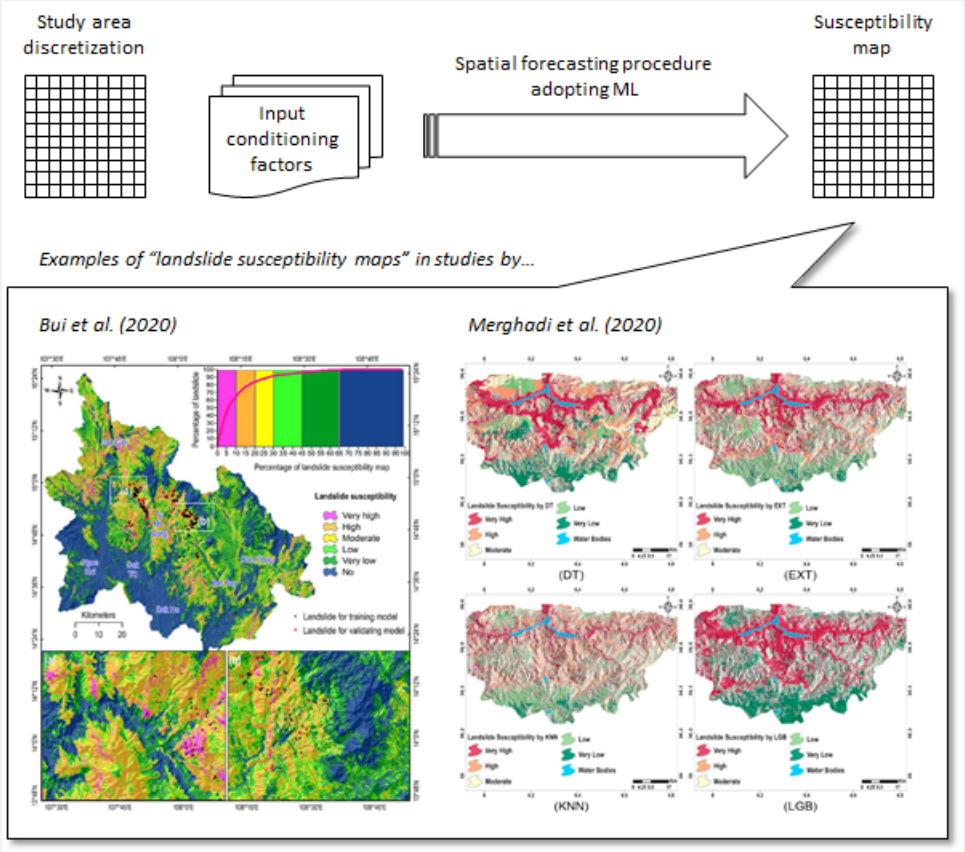


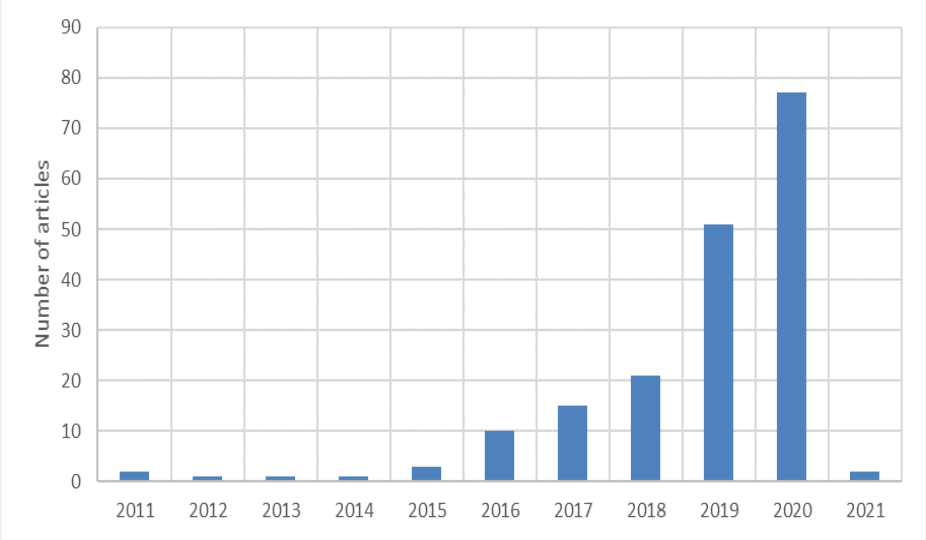
Trend in application of ML algorithms in landslide detection studies:

(a) use of conventional ML in pixel-based methods (CML-PB), conventional ML in object-based methods (CML-OB) and DL methods,

(b) case study areas for ML-related landslide detection studies.

SOA of ML – Suceptibility Mapping





Number of published journal articles dealing with ML studies for landslide susceptibility modeling (source: Scopus database, accessed 16/11/2020)

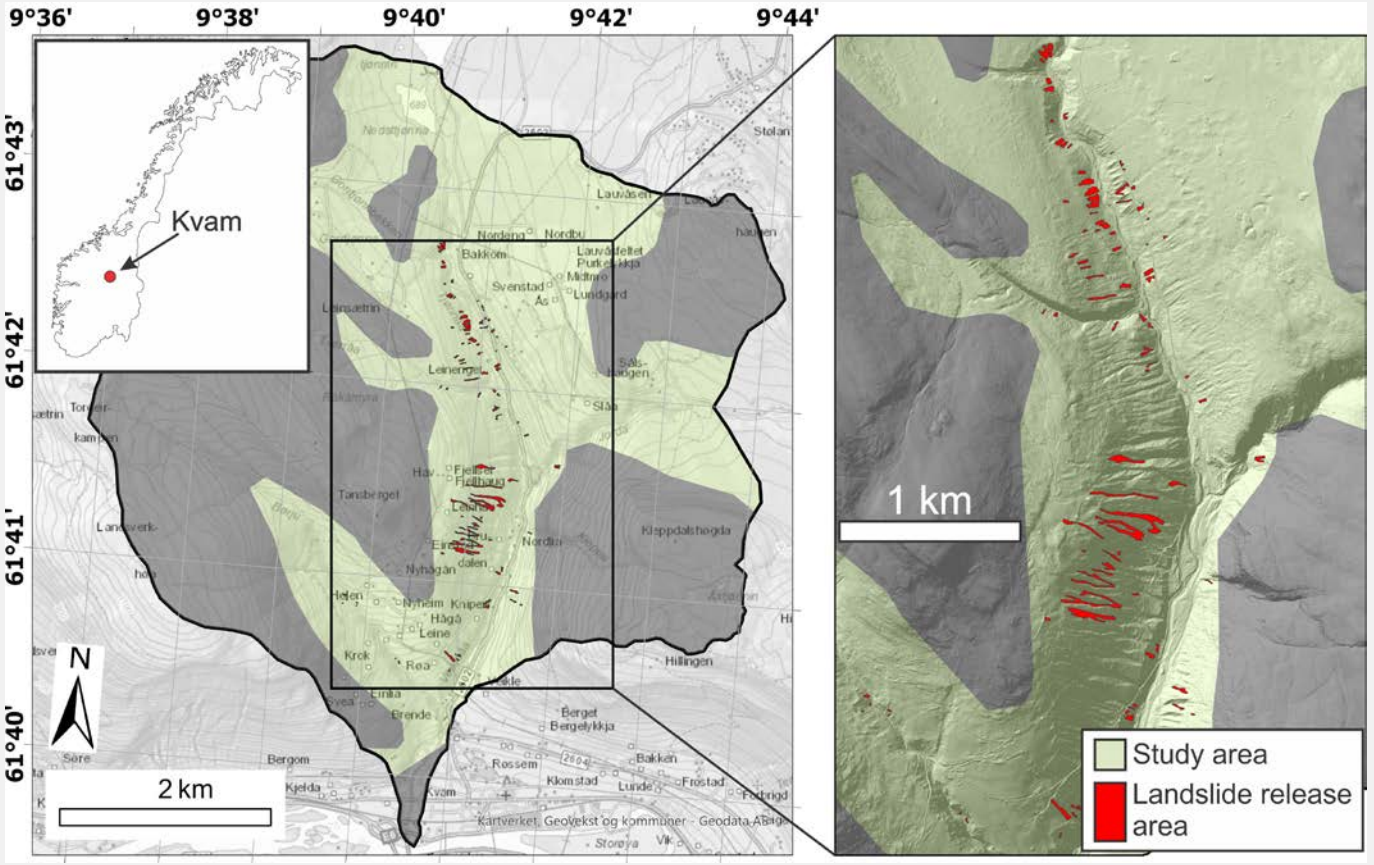
SOA of ML –Temporal Forecasting:

Comparison of best prediction performance of ML methods for predicted periodic displacement for the Baishuihe landslide

Study	ML (or hybrid ML) algorithms*	performance metrics **				
		MAPE/%	MAE/mm	RMSE/mm	MSE/mm	R
Li et al. (2020)	DBN	5.05	2.78	3.48	-	-
Liu et al. (2020)	LSTM	5.0	-	7.5	-	-
Liu et al. (2020)	Hybrid SVR-K-means-LSTM	-	3.86	6.76	-	-
Li et al. (2019)	ELM	-	-	17.41	-	0.968
Yang et al. (2019)	LSTM	10.43	-	7.11	-	-
Li et al. (2018)	Hybrid LASSO-ELM	1.30	26.44	35.63	2.28	-
Zhou et al. (2018)	Hybrid PSO-KELM	0.083	18.104	-	-	0.983

Kvam landslides (2011, 86 release zones)

- Inventory from field surveys and high-resolution aerial photographs the weeks following the 2011 intense rainfall
- Landslides are expected as a consequence of increased rainfall intensity and snowmelt



Kvam area

- Valley 32 km^2 (69% forested).
- Subarctic climate with cold winters and warm summers.
- Mean annual temperature in Kvam is about 3° C (1981–2010).
- “Normal”: 500 mm/year of precipitation (40% as snow).
- Primarily glaciofluvial or fluvial sediments, with accumulations of colluvium at the base of bedrock cliffs.
- Till of variable thickness on the slopes.
- 2011: 60 mm rain in one day.

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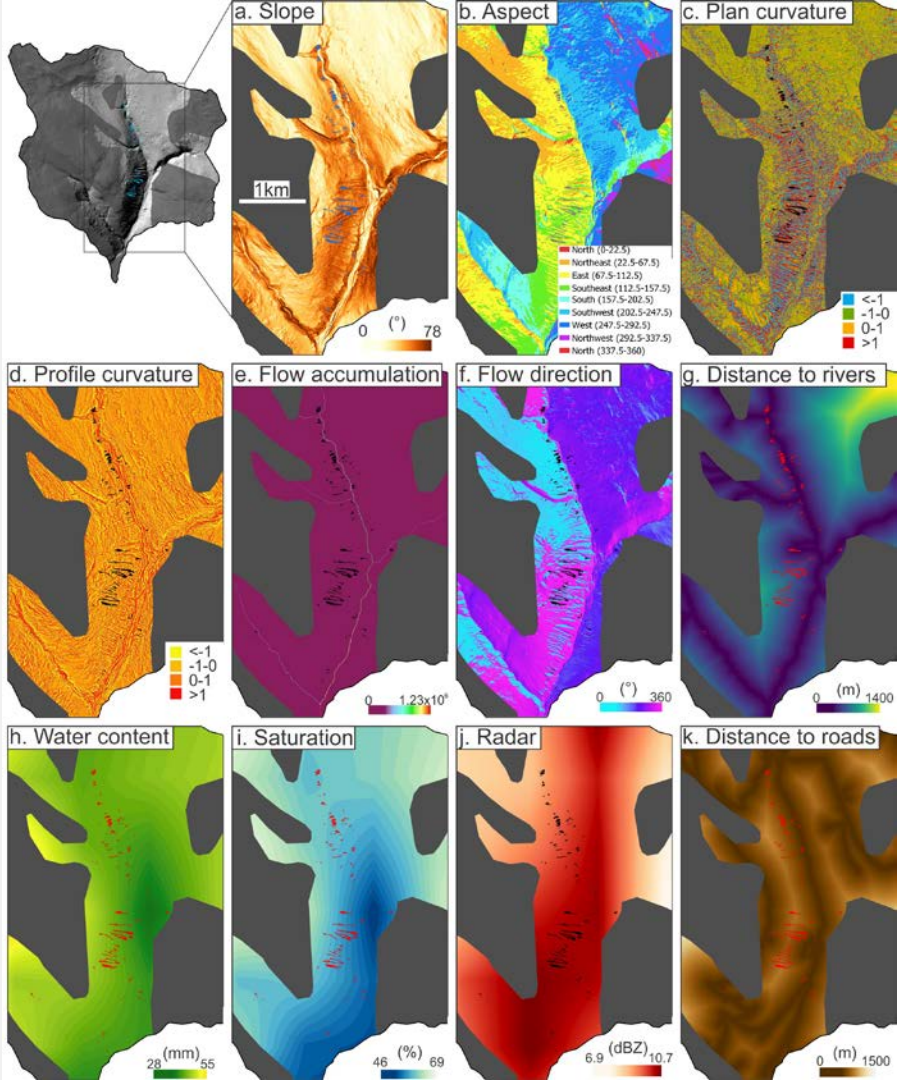
Controlling factors

- 1-m DEM was resampled to reduce the spatial resolution to 5 m
- The water content of the soil column (h) and the percentage of soil saturation (i) were daily values modelled and interpolated on a 1 km^2 grid



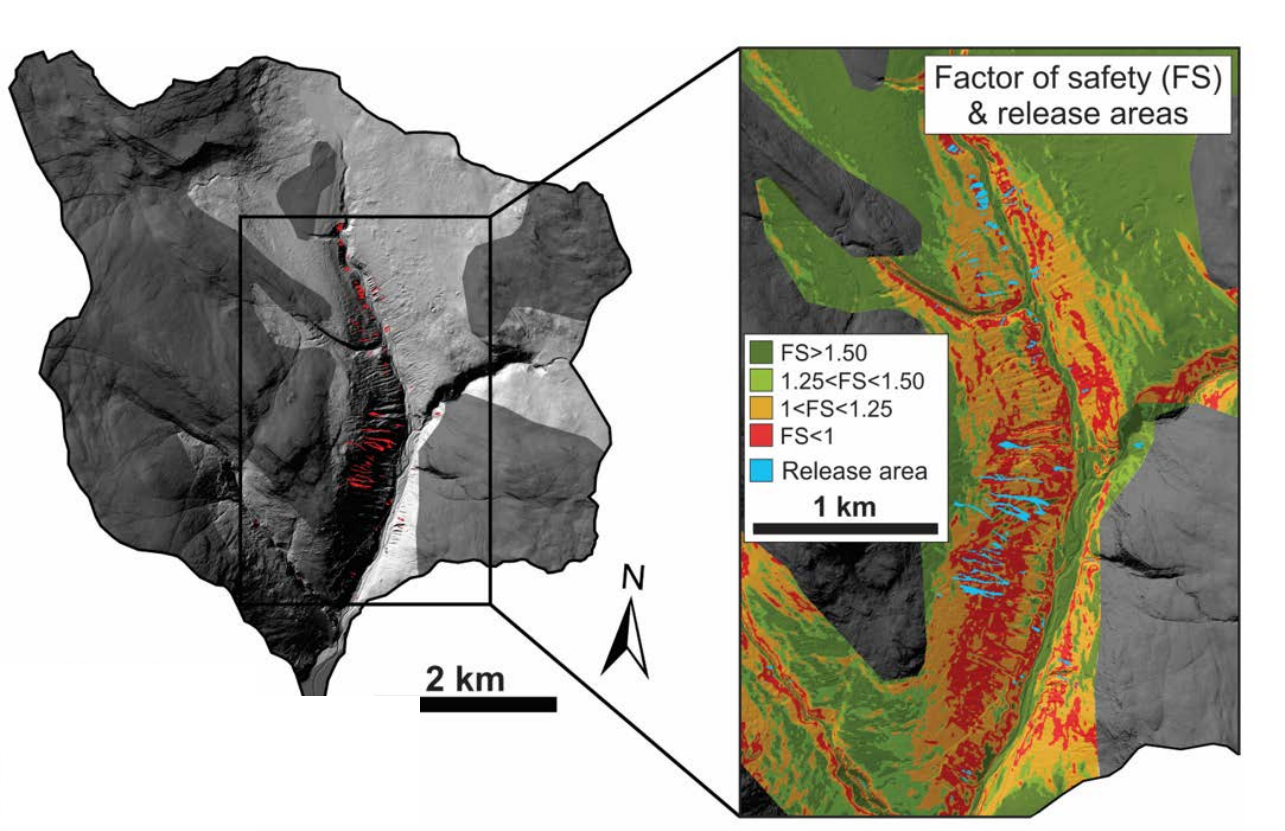
Controlling factors

Class	Conditioning and triggering factor	Variable importance indicator, VI
Conditioning factors	Slope angle	0.29
	Plan curvature	0.1
	Aspect	0.08
	Distance to rivers	0.06
	Distance to roads	0.06
	Flow accumulation	0.05
	Flow direction	0.04
	Profile curvature	0.03
Triggering factors	Degree of saturation	0.11
	Rainfall	0.11
	Water content	0.08

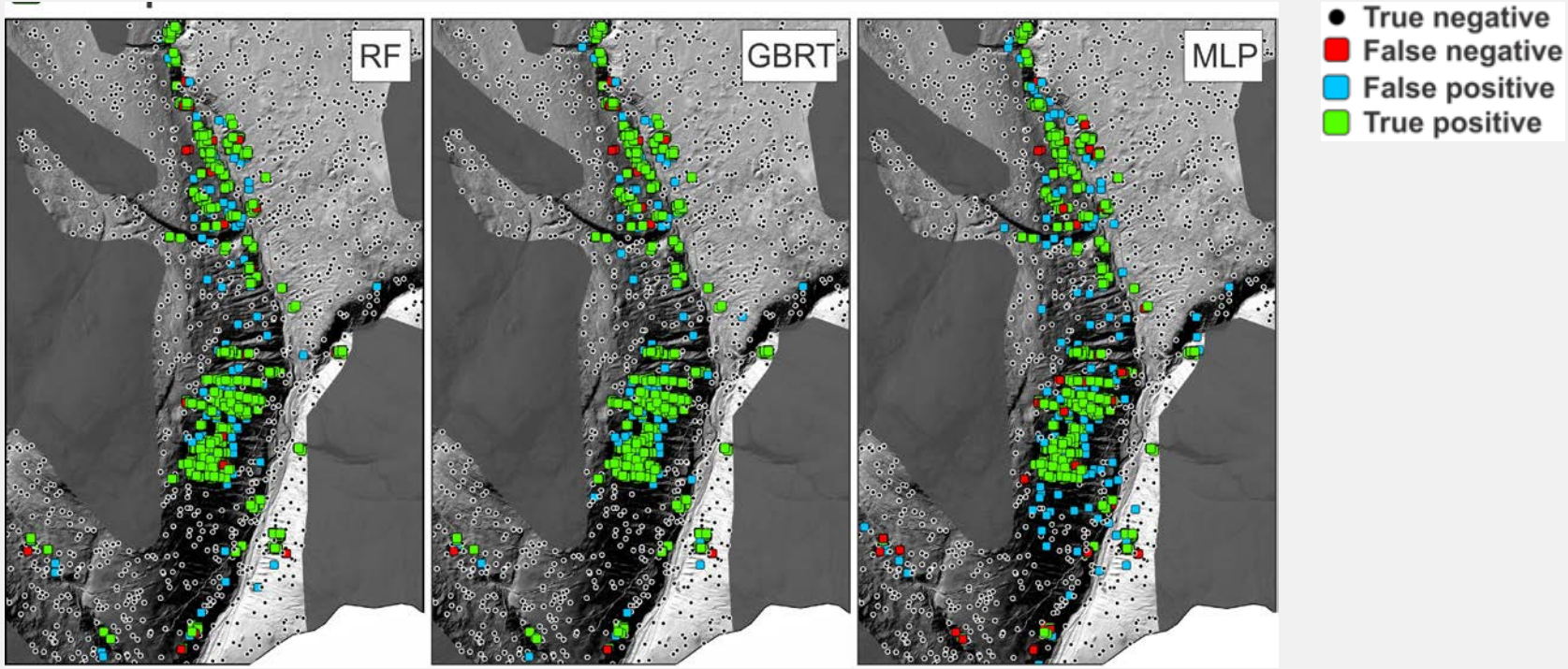
ML algorithms

RF	Random Forest
GBRT	Gradient Boosted Regression Tree
MLP	Multilayer perceptron ANN
TRIGRS	Numerical model (infiltration and limit-equilibrium analysis software)

Geo-mechanical model



ML models

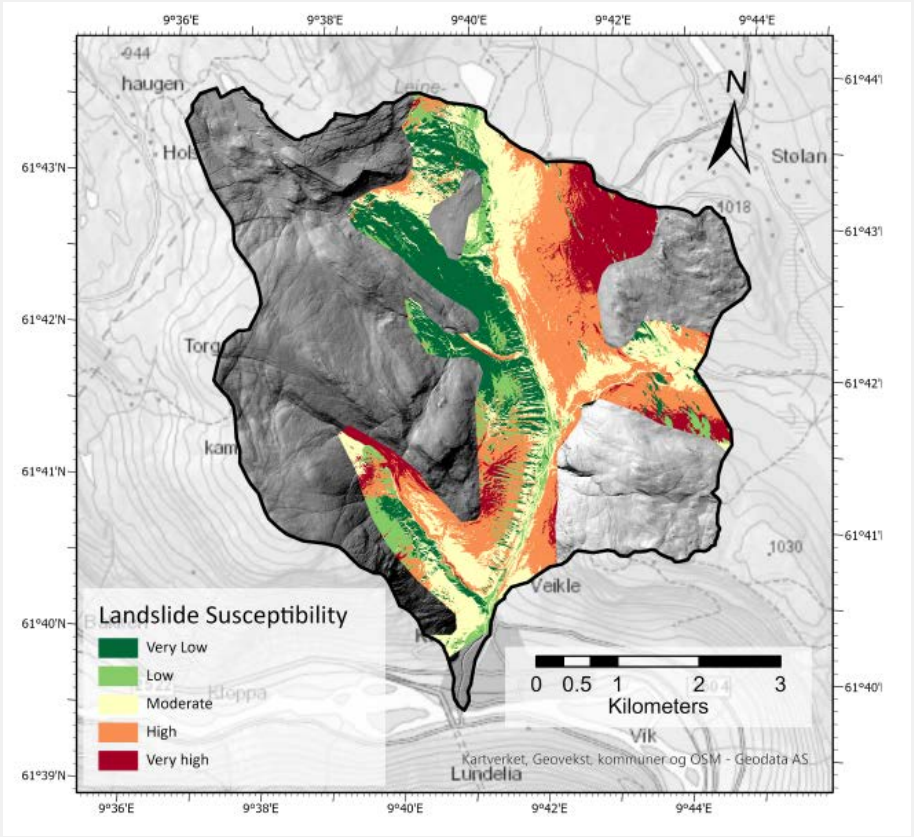

RF
GBRT
MLP
True negative
False negative
False positive
True positive

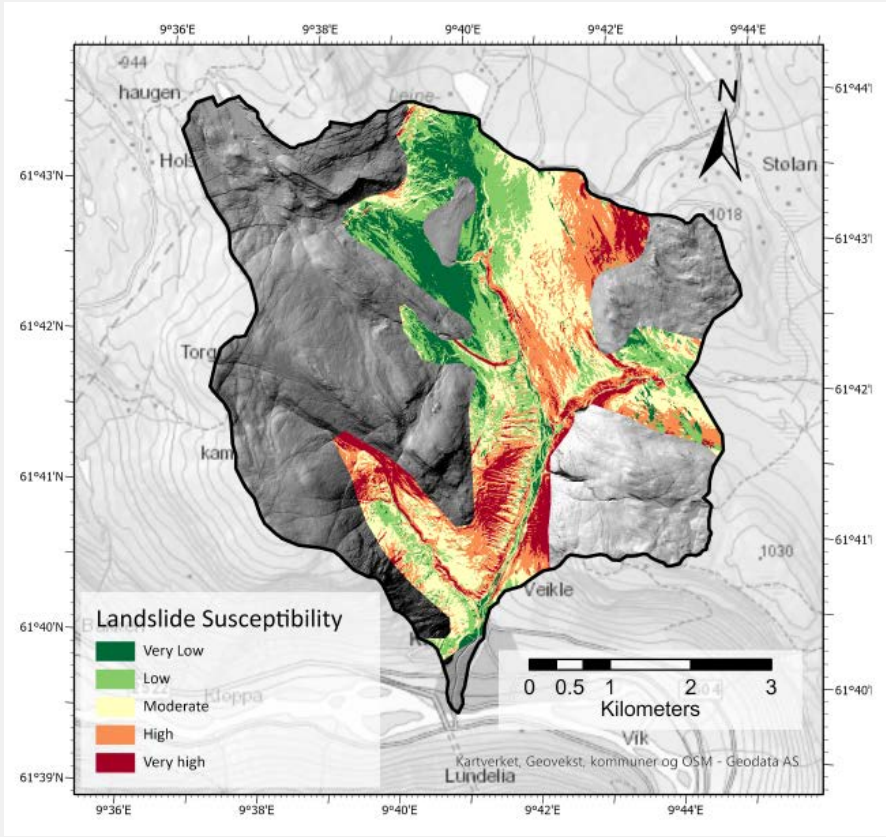
Predictions

ML model Parameters	RF	GBRT	MLP	TRIGRS
ACC (%)	94.7	95.4	92.1	81.6
POD (%)	93.5	94.9	90.7	68.3
POFD (%)	4.7	4.4	7.2	9.2
EI (%)	85.5	87.3	79.3	60.3

ACC Accuracy
POD Probability of detection
POFD Probability of false detection
EI Efficiency index

Landslide susceptibility map – MLP and RF





Take-aways

- Unbalanced dataset: 535 839 location points, whereof
  - 3 399 were release areas
  - 6 798 non-landslide points, i.e. twice the number of release areas, were randomly selected.
- The selection of the controlling conditioning and triggering factors is a key requirement for successfully predicting landslide occurrence.
- All three ML models gave a greatly improved prediction of landslide occurrence than the geo-mechanical solution TRIGRS
- The RF and GBRT models gave the best results.

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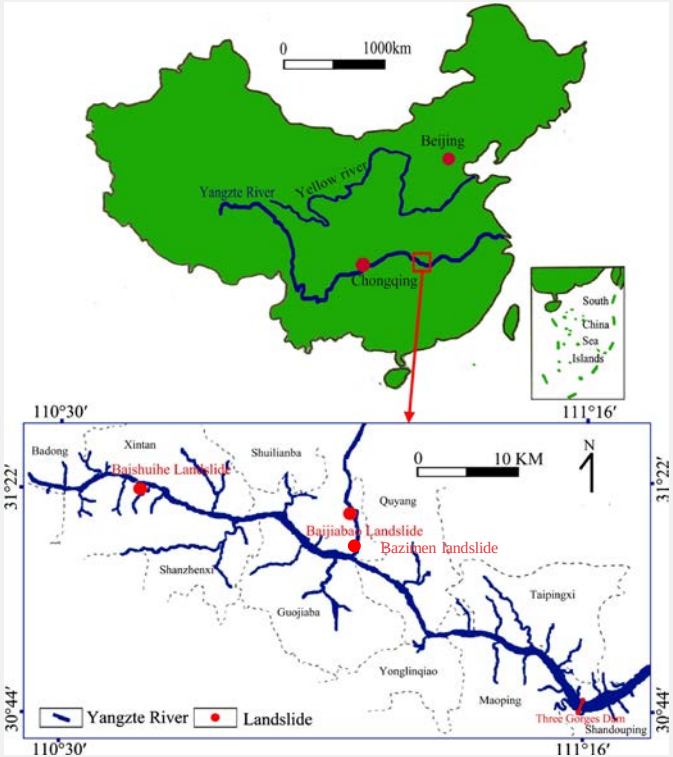
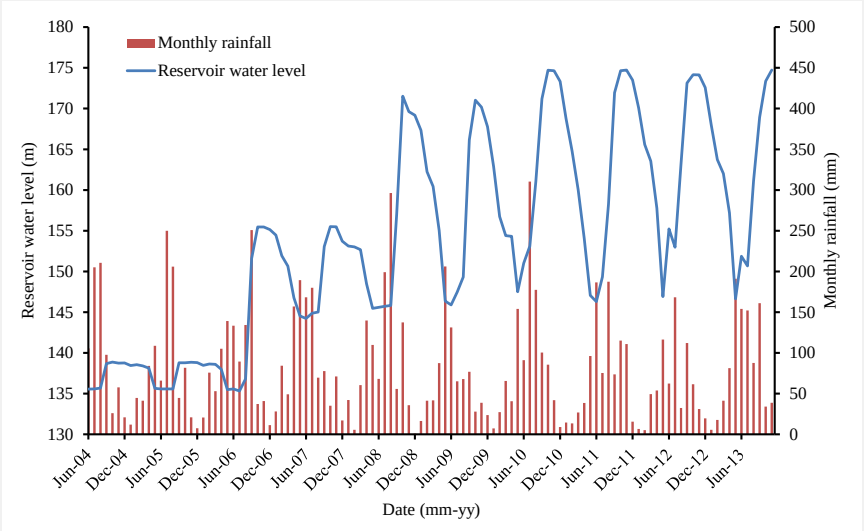
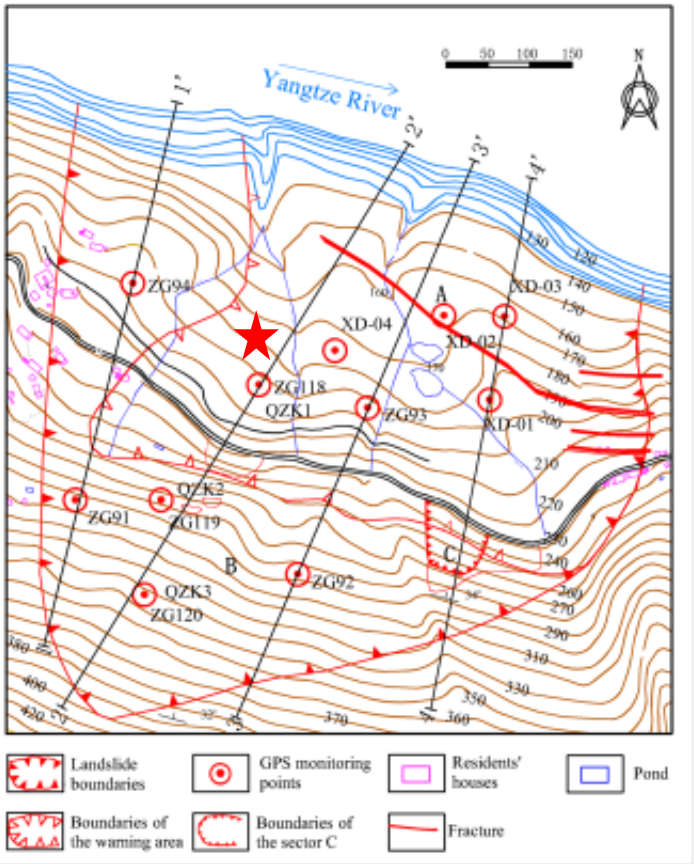
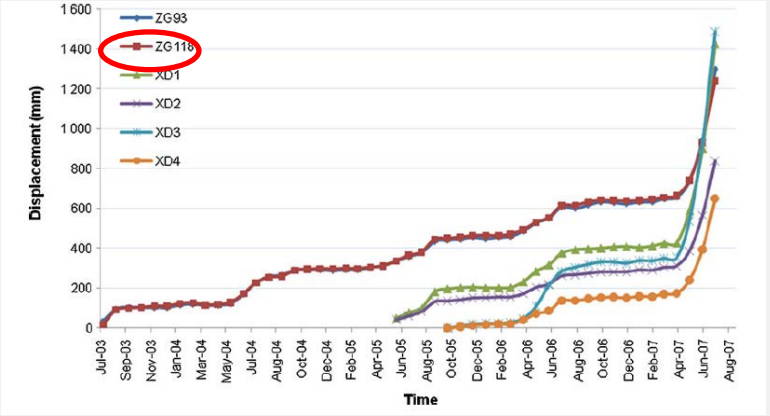
Landslide displacement prediction

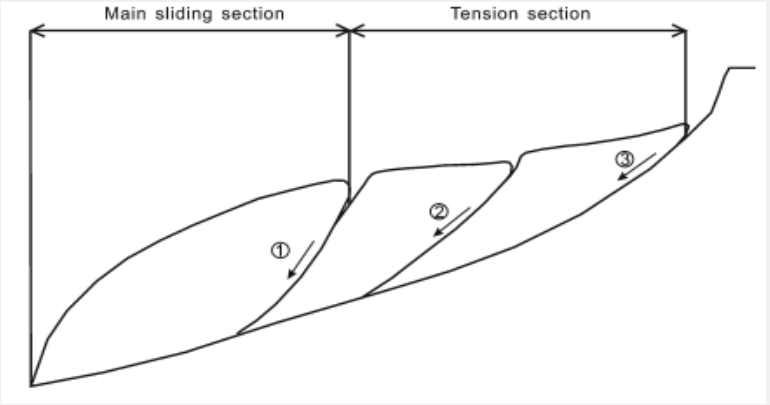




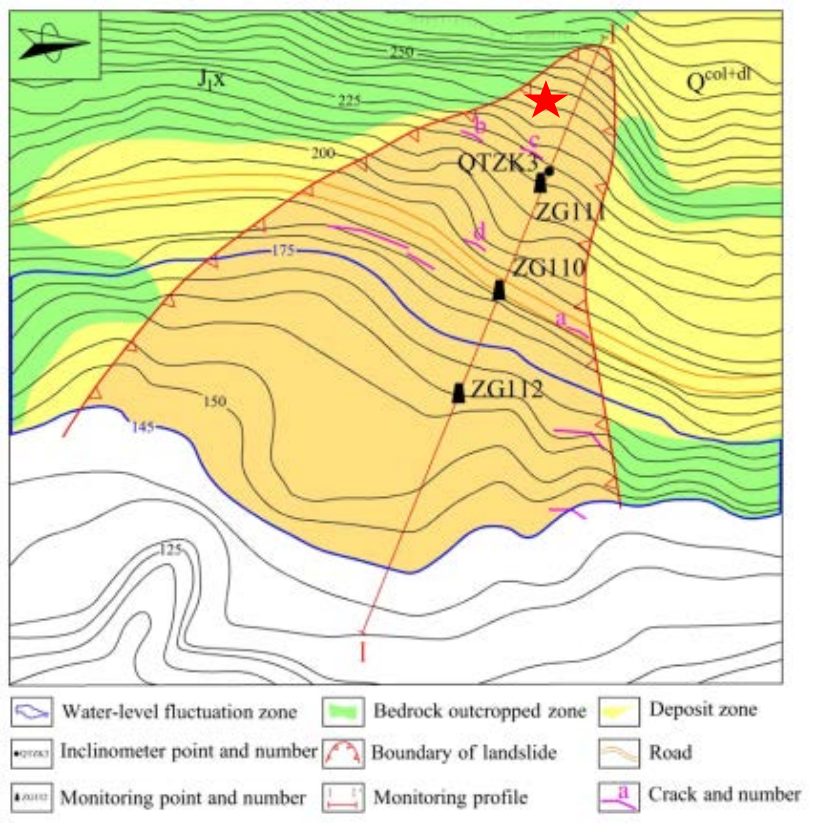
Monitoring system of the Baishuihe landslide (retrogressive landslide)

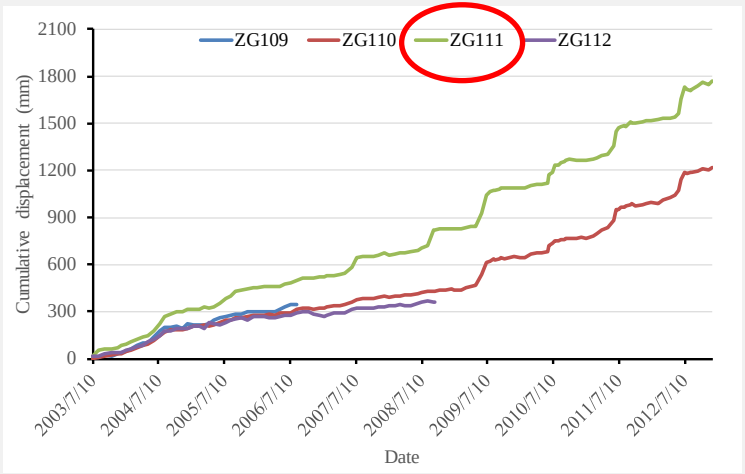


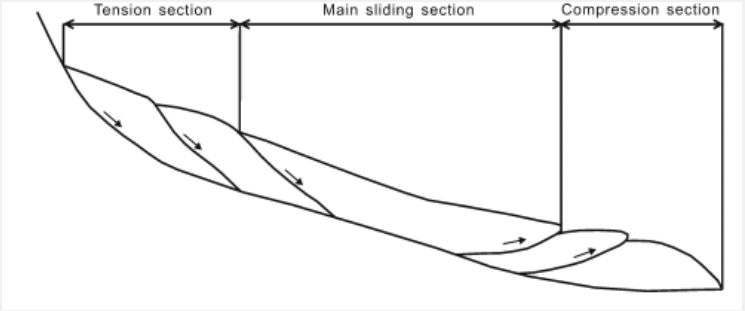




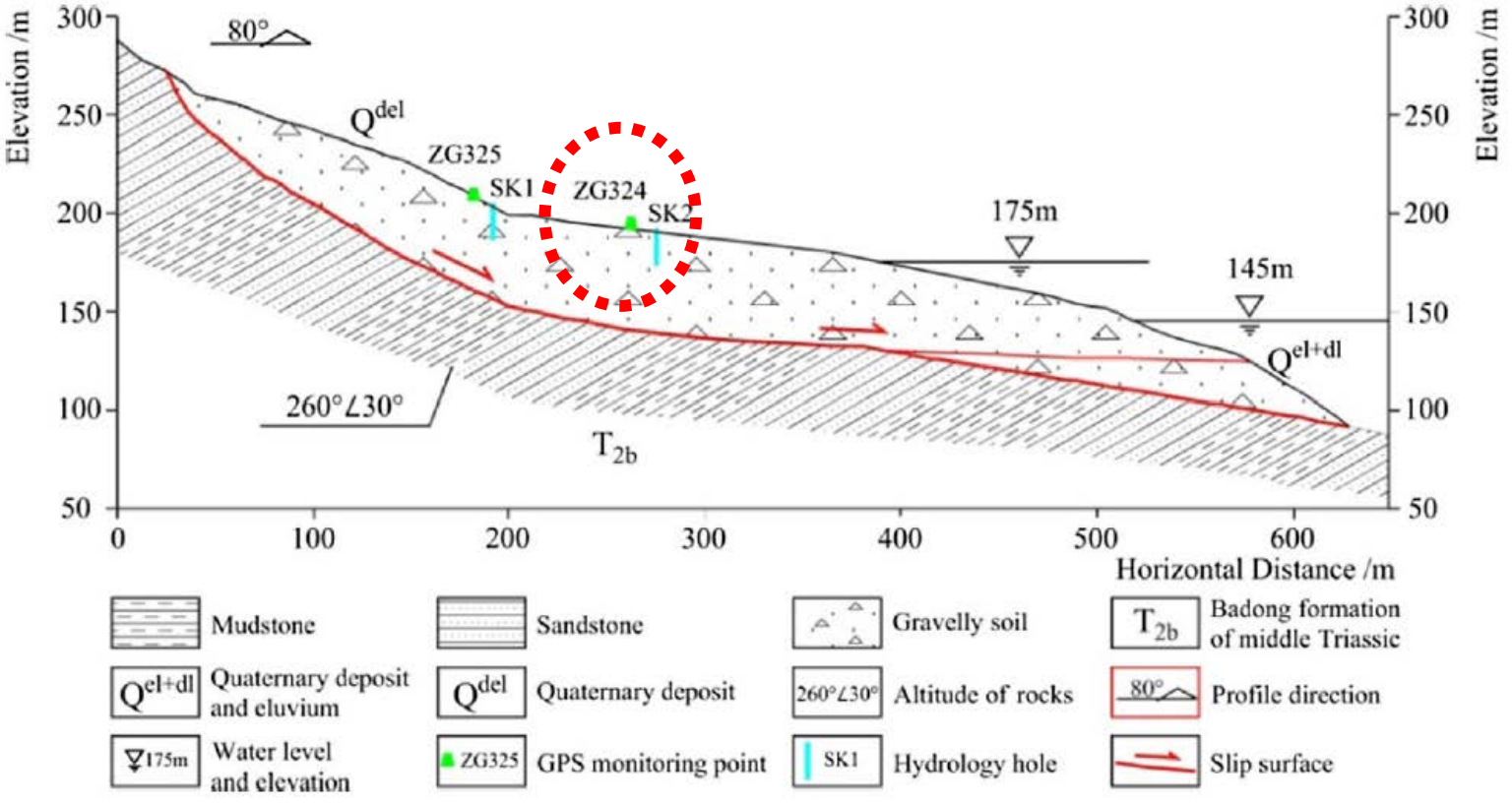
Monitoring system of the Bazimen landslide (advancing landslide)



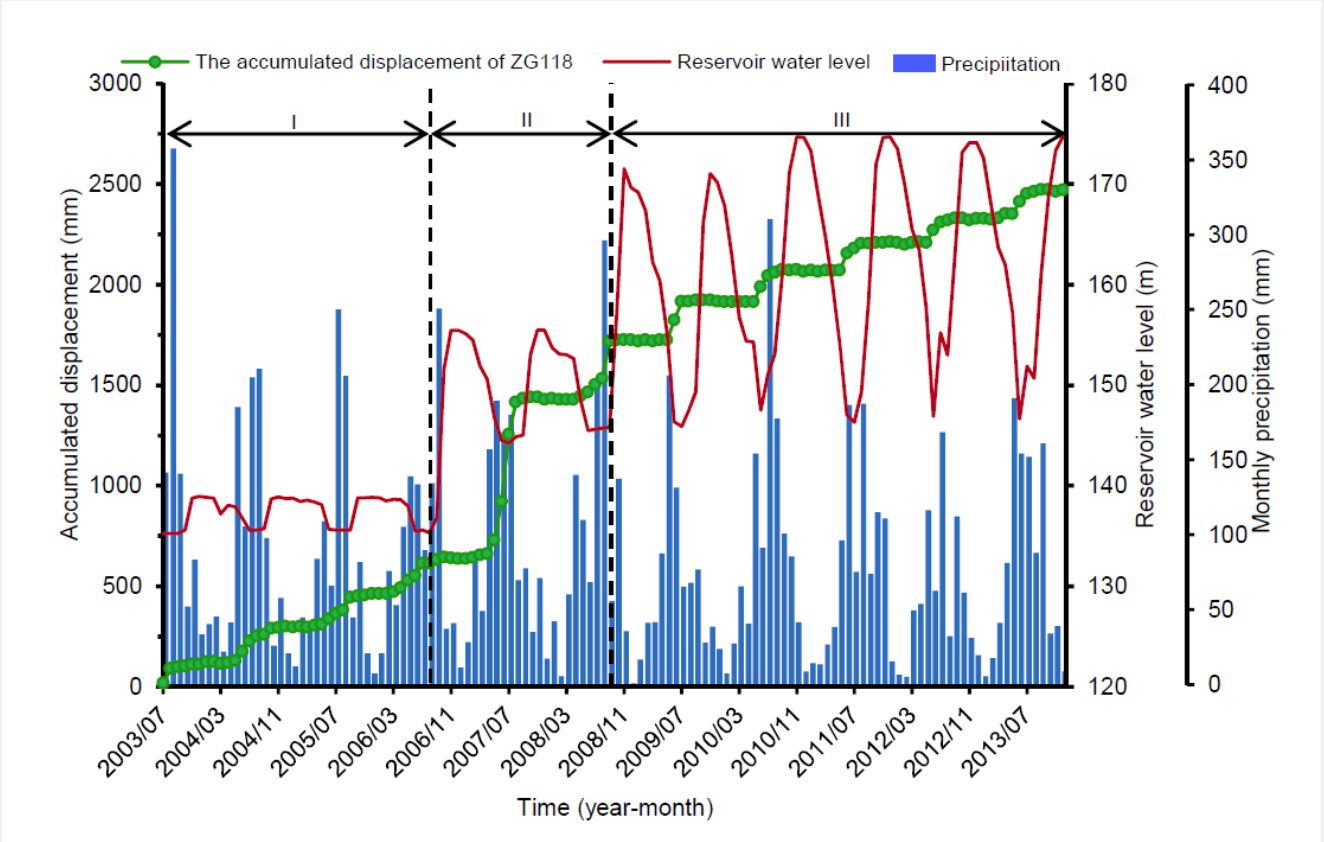




Monitoring system of the Baijiabao landslide (deformed as a whole)



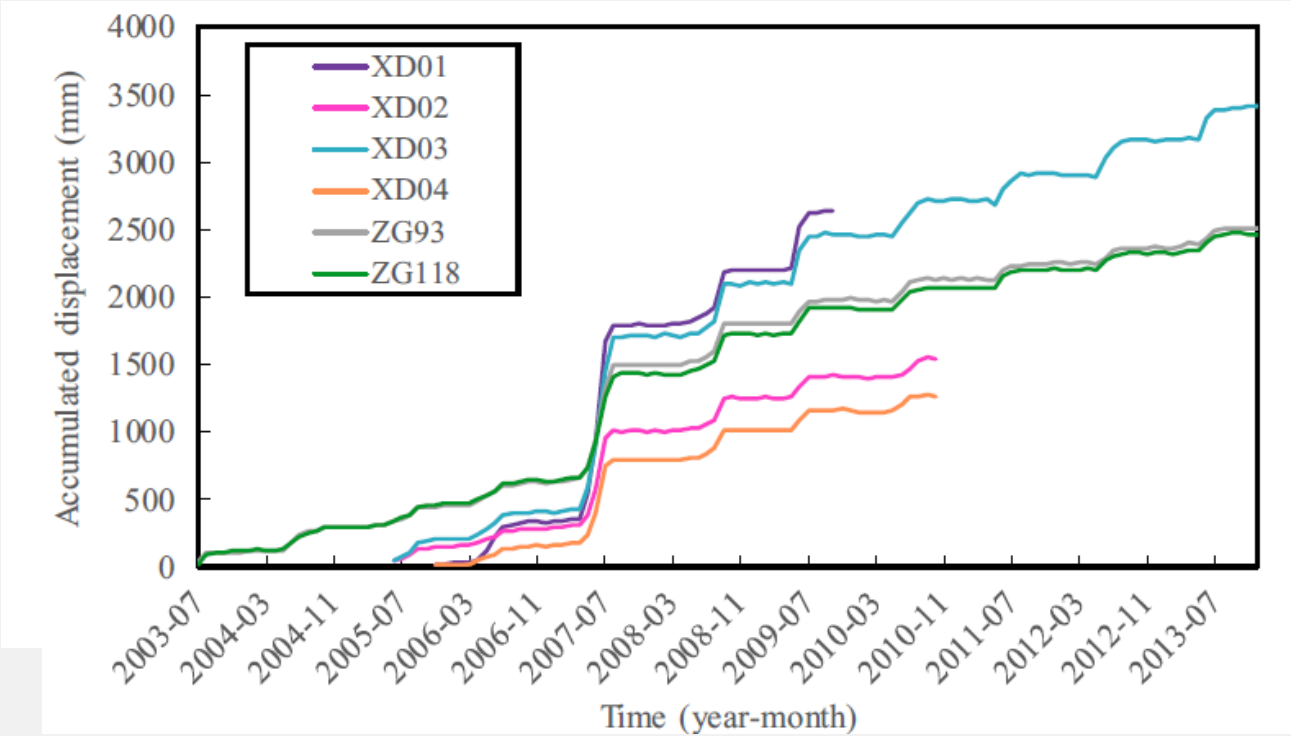
Rainfall, reservoir water level and displacement Baishuihe landslide



Accumulated displacement in the Baishuihe slide

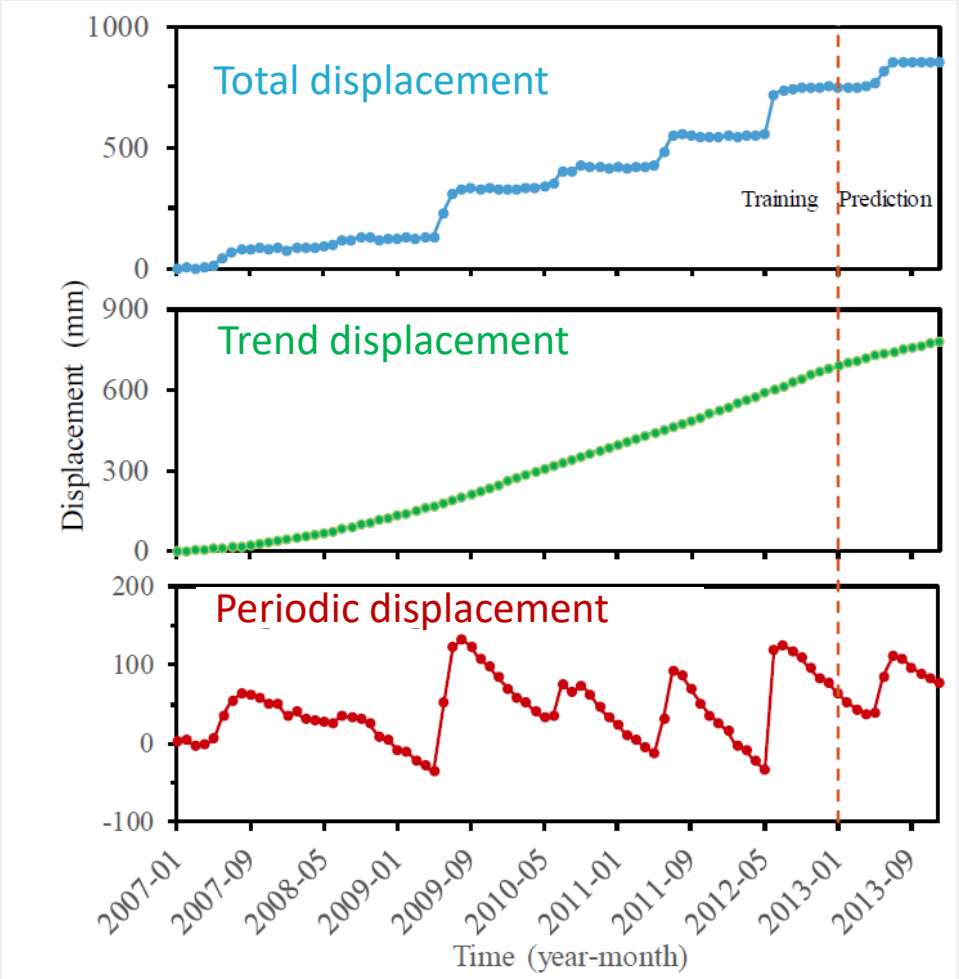
6 locations

(2003-2013)



Displacement decomposition, **Baijiabao landslide**

Trend and periodic displacement terms

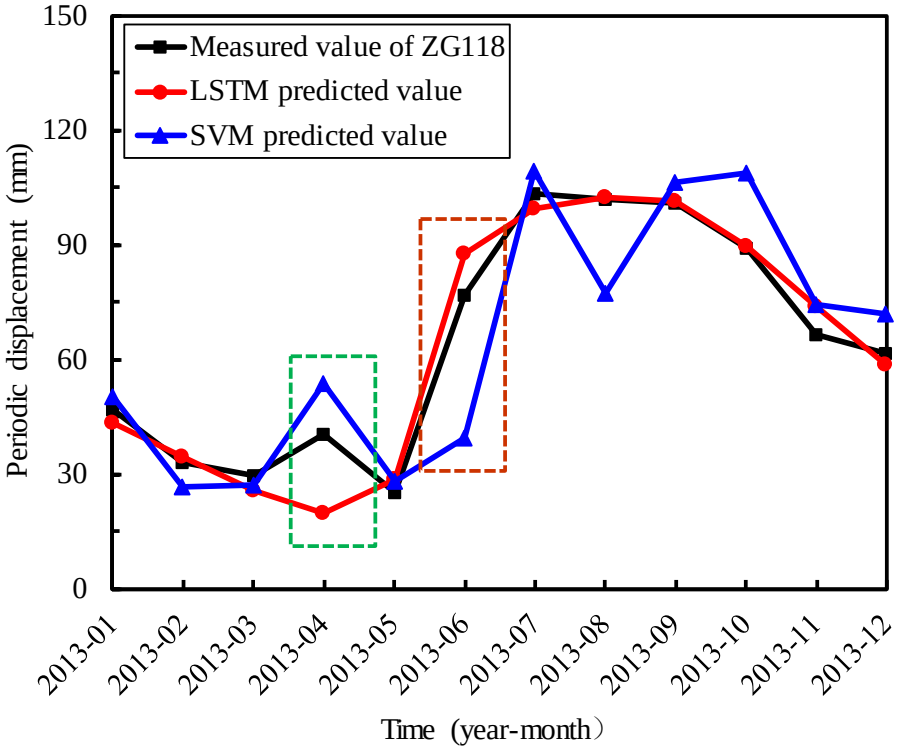


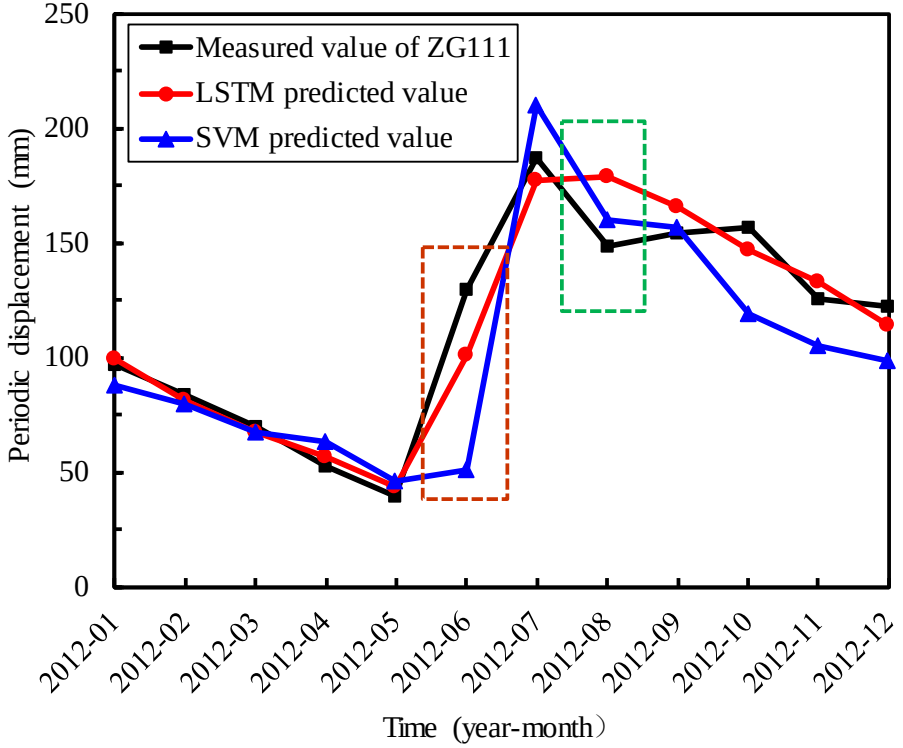
Models used in analysis of 3 step-wide landslides

Landslide	Statistical and ML Models	
	Trend term	Periodic displacement term
Baishuihe	3rd degree polynomial	- Multivariate Long Short-Term Memory neural networks - Multivariate Support Vector Machine model (SVM) - Random Forest (RF) - Gated Recurrent Unit (GRU)
Bazimen	3rd degree polynomial	- Multivariate Long Short-Term Memory neural network - Multivariate Support Vector Machine model - Random Forest (RF) - Gated Recurrent Unit (GRU)
Baijiabao	3rd degree polynomial	- Multivariate Long Short-Term Memory neural network - Random Forest (RF) - Gated Recurrent Unit (GRU)

Predicted and measured periodic displacements with the LSTM and SVM models, Baishuihe and Bazimen landslides

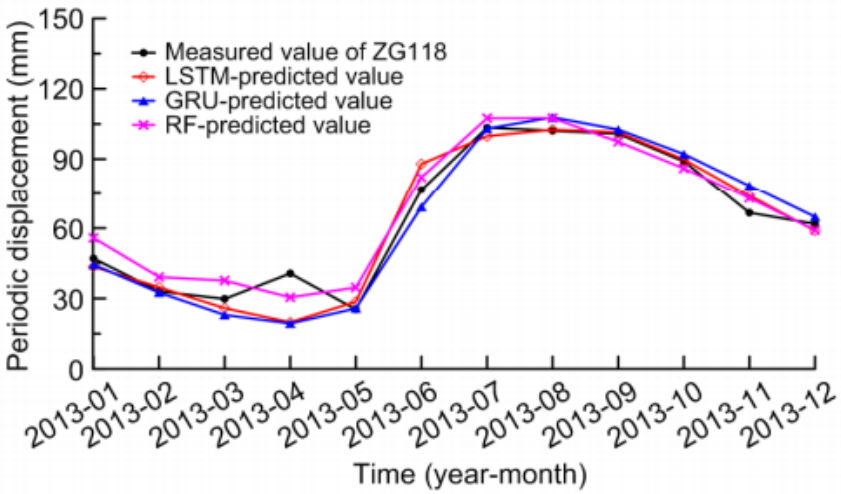
LSTM and SVM ML models

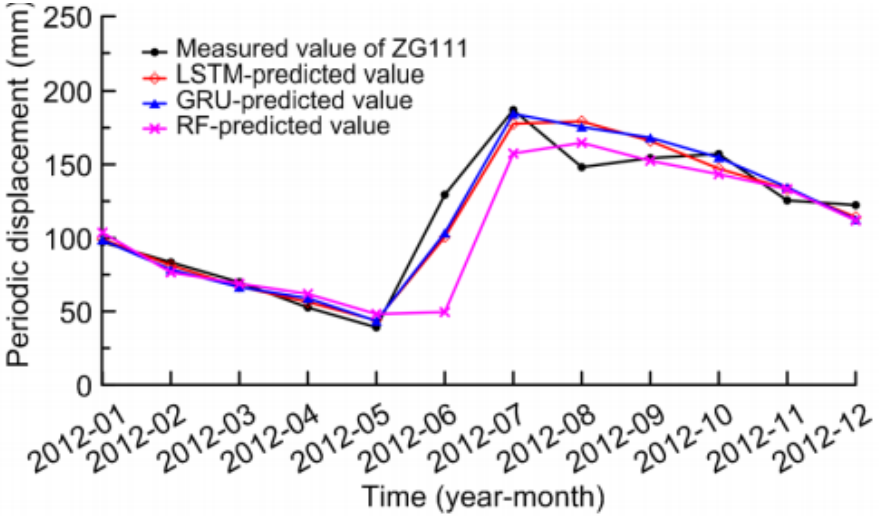




Predicted and measured periodic displacements with the LSTM and SVM models, Baishuihe and Bazimen landslides

LSTM, GRU and RF ML models





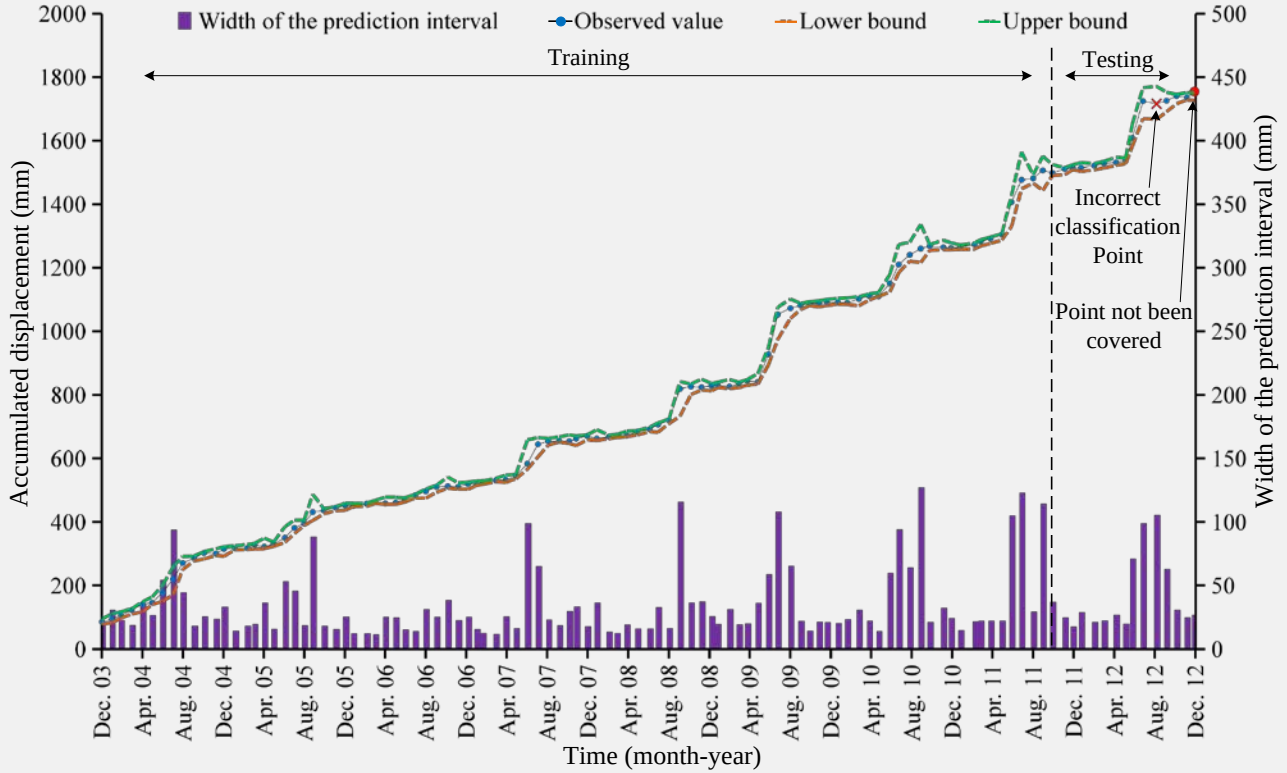
Predicted and measured periodic displacements with the LSTM and SVM models, Baishuihe and Bazimen landslides

LSTM, GRU and RF ML models

Table 5 Comparison of accuracy of predicted periodic displacement at location ZG111 with three machine learning algorithms (Bazimen landslide)

Time (year-month)	Measured displ. (mm)	LSTM model			GRU model			RF model		
		Displ. (mm)	Absolute error (mm)	Relative error (%)	Displ. (mm)	Absolute error (mm)	Relative error (%)	Displ. (mm)	Absolute error (mm)	Relative error (%)
2012-01	97.2	99.2	2.0	2.1	98.6	1.4	1.5	103.7	6.5	6.7
2012-02	83.4	81.3	2.1	2.5	78.5	4.9	5.9	76.5	6.9	8.3
2012-03	69.9	67.0	2.9	4.2	66.5	3.3	4.8	69.0	0.9	1.3
2012-04	52.6	56.4	3.8	7.1	58.9	6.3	12.0	61.9	9.3	17.6
2012-05	39.1	43.9	4.8	12.3	43.5	4.4	11.2	48.2	9.1	23.1
2012-06	129.4	100.7	28.7	22.2	103.4	26.0	20.1	49.5	79.8	61.7
2012-07	187.1	177.7	9.4	5.0	184.5	2.6	1.4	157.5	29.6	15.8
2012-08	148.2	179.3	31.1	21.0	175.5	27.3	18.4	164.7	16.6	11.2
2012-09	154.3	166.0	11.7	7.6	168.2	13.9	9.0	152.5	1.9	1.2
2012-10	157.1	147.2	10.0	6.3	154.7	2.4	1.5	143.3	13.8	8.8
2012-11	125.5	133.3	7.8	6.2	134.4	8.9	7.1	133.3	7.7	6.2
2012-12	122.3	114.2	8.2	6.7	112.4	9.9	8.1	111.9	10.4	8.5
Min. error	–	–	2.0	2.1	–	1.4	1.4	–	0.9	1.2
Max. error	–	–	31.1	22.2	–	27.3	20.1	–	79.8	61.7
MAPE (%)	–	–	10.2	8.6	–	9.3	8.4	–	16.0	14.2
RMSE (mm)	–	13.8	–	–	12.6	–	–	26.0	–	–

Interval prediction (96% confidence level)
Bazimen landslide



Take-aways

- The proposed dynamic modeling approach, based on time series analysis and LSTM, can achieve accurate prediction in case of the slow and step-wise deformation periods.
- GRUs with fewer tuning parameters, also did a good prediction.
- RFs, as a combination of binary decision trees are not able to predict time-series observations.

Conclusion and perspective

- ML is a vibrant field with expanding interest and rapid advancement.
- Landslide researchers don’t need follow the same pace of ML progress in implementing ML algorithms for landslide studies, as it can jeopardize the deep understanding of both processes and ML methods.
- The landslide community should however closely observe ML upgrades and get inspiration for implementing innovative data-driven methods in landslide studies.

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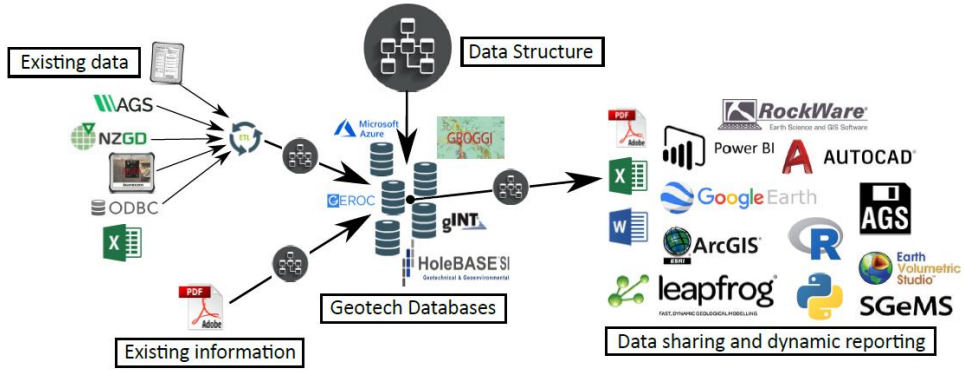
NORGES GEOTEKNISKE INSTITUTT
NGI.NO

3-D Ground Models in a World of Digital Twins

Philip Kirk
Technical Director - Geology
Aurecon New Zealand Ltd
philip.kirk@aurecongroup.com

Joint Technical Symposium on Digital Geosciences & Geotechnology
Hong Kong, 16 September 2021

3-D Ground Models in a World of Digital Twins

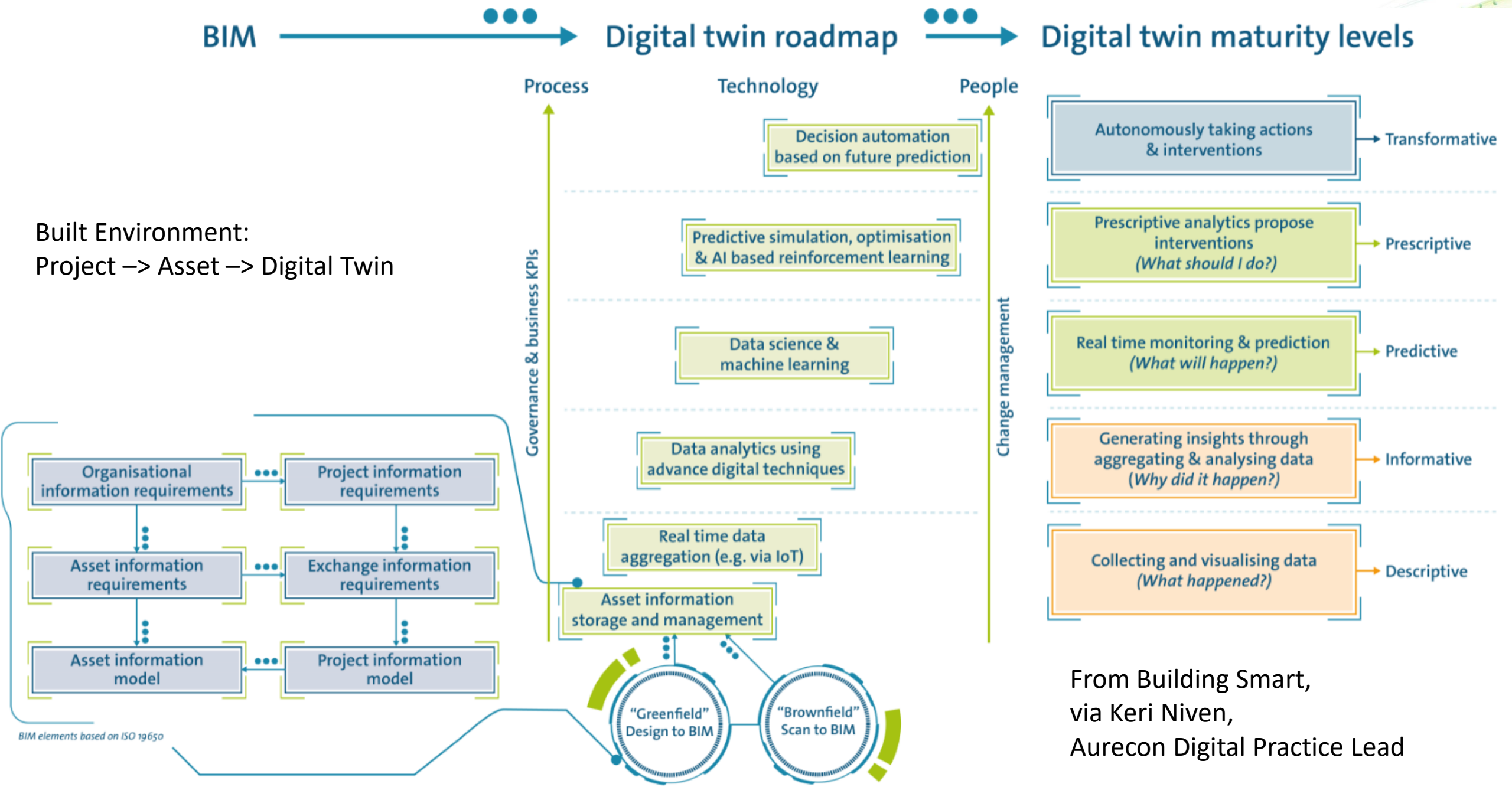


Talk outline:

- geology for linear infrastructure – using commercial software
- use of 3-D ground models to support BIM - and digital twin - approaches to data and information
- ISO19650 – BIM standard

- exploring the interface between a natural-world ground model and built-environment models
- suggestions for areas to improve current practice (and software)

Built Environment:
Project –> Asset –> Digital Twin



From Building Smart,
via Keri Niven,
Aurecon Digital Practice Lead

The Digital 3D Ground Model is just one of the many components of the wider “Engineering Geological Model”:

Sections, charts, tables, block diagrams, report text, images, etc … no precise definition of what a EGM comprises

- ground conditions
- nature of project)

No real consensus on the term “Engineering Geology Model”
Hearn (2021) lists 12 other terms that are widely used

Geological Society of London:
QJEGH Volume 54 (2021) Ground models in engineering geology and geomorphology collection

Fookes 1997 (“Geological Model”)
Norbury 2021 (“Ground Model”)

“

Table 1. *Range of published ground modelling references*

Model description* (in very approximate order according to project stage and with inevitable *imbrication*)	Authors† (not comprehensive)
Geological model‡	Fookes (1997), Fookes *et al.* (2000, 2001‡), Hutchinson (2001), Brunsden (2002), Knill (2003), Griffiths *et al.* (2004*a*)‡, Baynes *et al.* (2005), Culshaw (2005)‡, CEN (2007), GEO (2007), Baynes (2010), Loew *et al.* (2010), Sullivan (2010), Culshaw and Price (2011), Hencher (2012), Eggers (2016), Bar and Baczynski (2017), de Mello (2018), Fillion and Hadjigeorgiou (2019), Ting *et al.* (2020)‡
Landscape (evolution) and geomorphological landform model	Hansen (1984), Brunsden *et al.* (1981), Fookes *et al.* (1985, 2000, 2015), Griffiths and Stokes (2008), Hearn *et al.* (2012), Ruse *et al.* (2013), Hearn and Pettifer (2016)
Slope development model	Hutchinson (2001), Fookes and Baynes (2008)
Geomodel	Griffiths and Stokes (2008), Fookes *et al.* (2015), Hearn (2019*a*)
Engineering geomorphological model	Ruse *et al.* (2013)
Engineering geological model	Fell *et al.* (2000), Fookes *et al.* (2000), Griffiths *et al.* (2004*b*), Culshaw (2005), Fookes and Baynes (2008), Parry (2010), Parry *et al.* (2014, 2019), Eggers (2016), Quinta-Ferreira (2017), Baynes *et al.* (2020)
Engineering geological ground model	Griffiths (2016)
Engineering geology environment model	Fookes *et al.* (2001)
Conceptual site model	ASTM (2014), Quinta-Ferreira (2017), Privett (2019)
Ground model	Sellwood *et al.* (2000), Brunsden (2002), Knill (2003), GEO (2007), Griffiths and Stokes (2008), Loew *et al.* (2010), Hearn *et al.* (2012), Hencher (2012), Ruse *et al.* (2013), BSI (2015), Eggers (2016), Moore *et al.* (2017), Sweeney (2017), Hearn (2019*a*), de Freitas 2020, Norbury (2020), Ting *et al.* (2020)
Geotechnical model§	Fell *et al.* (2000), Hutchinson (2001), Knill (2003), Griffiths *et al.* (2004*a*), CEN (2007), Eggers (2016), Bar and Baczynski (2017), Fillion and Hadjigeorgiou (2019)
Design Model	GEO (2007)

*Includes only those model variants developed specifically for engineering projects. The list excludes generic modelling terms, e.g. theoretical, process-based, equilibrium, stochastic, statistical, digital, spatial, digital elevation/terrain, mathematical and analytical. It also excludes groundwater and hydrogeological models.
†Note that some authors describe modelling through the various phases of project development and use multiple terms according to project stage.
‡Includes geological/geomorphological model of Fookes *et al.* (2001) and Griffiths *et al.* (2004*a*), the 3D geological model of Culshaw (2005) and the Project Stratigraphic Model of Ting *et al.* (2020).
§Excludes 3D geotechnical database systems for GeoBIM-type applications (e.g. Tawelian and Mickovski 2016; Tonni *et al.* 2019; Valeria *et al.* 2019). BIM, building information modelling.

Considerable agreement about the purpose of Engineering Geological Models:

- Ground characterisation
- Identification of Ground Risk
- etc

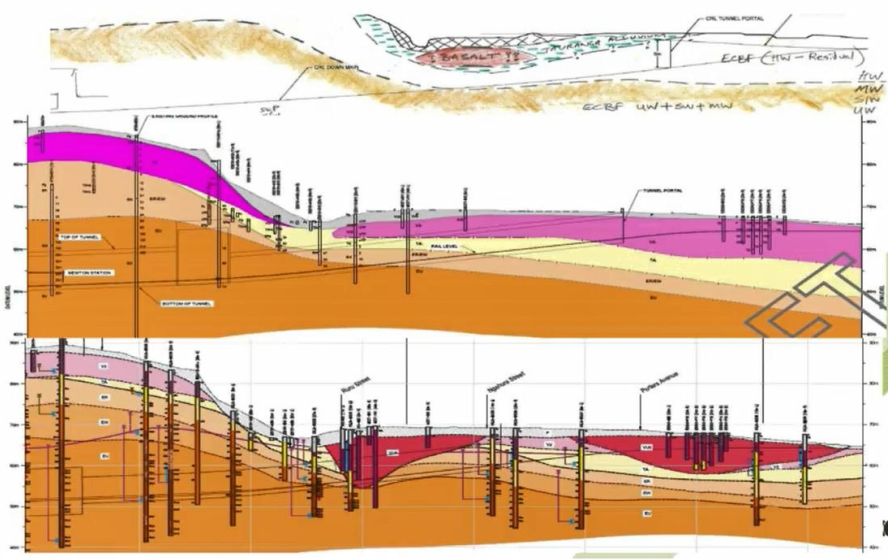
Characteristics of engineering geological models …

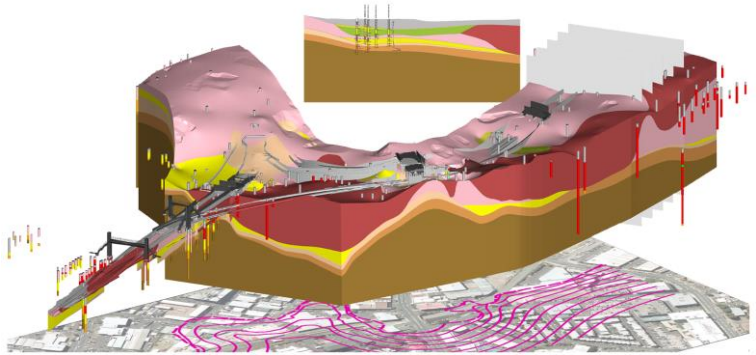
- Sparse data
- Variable quality inputs
- Time and budget constraints
- Inherent uncertainty due to complexity/variation
- Uncertainty due to limited investigation

- DIGITAL GROUND MODELS are NOT DIGITAL TWINS

- Importance of iterative development of the model
- Contrast of visual language – 2D vs 3D

Iterative development ….

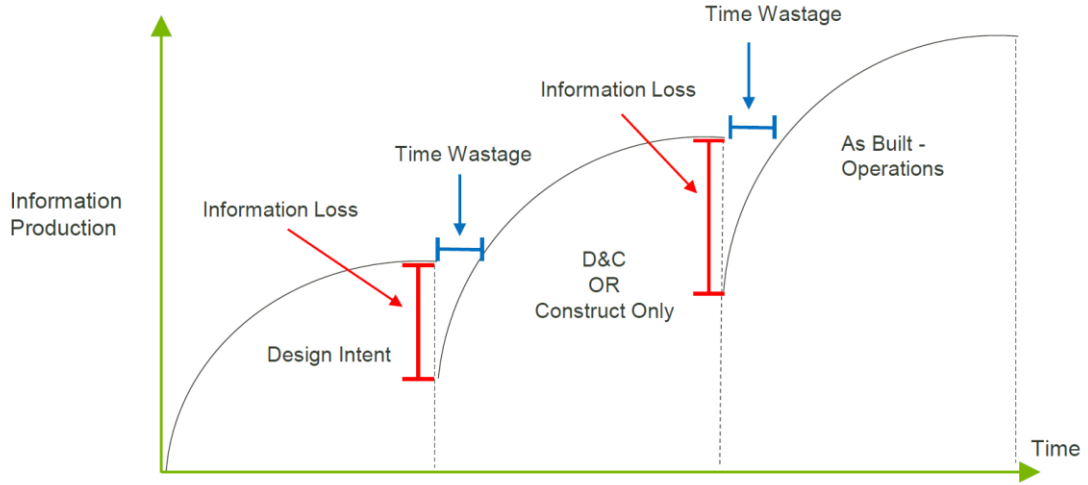


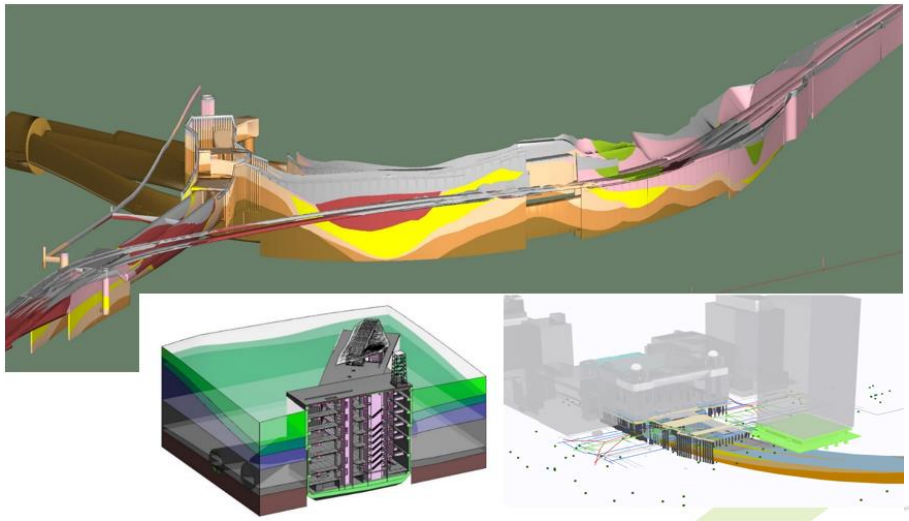


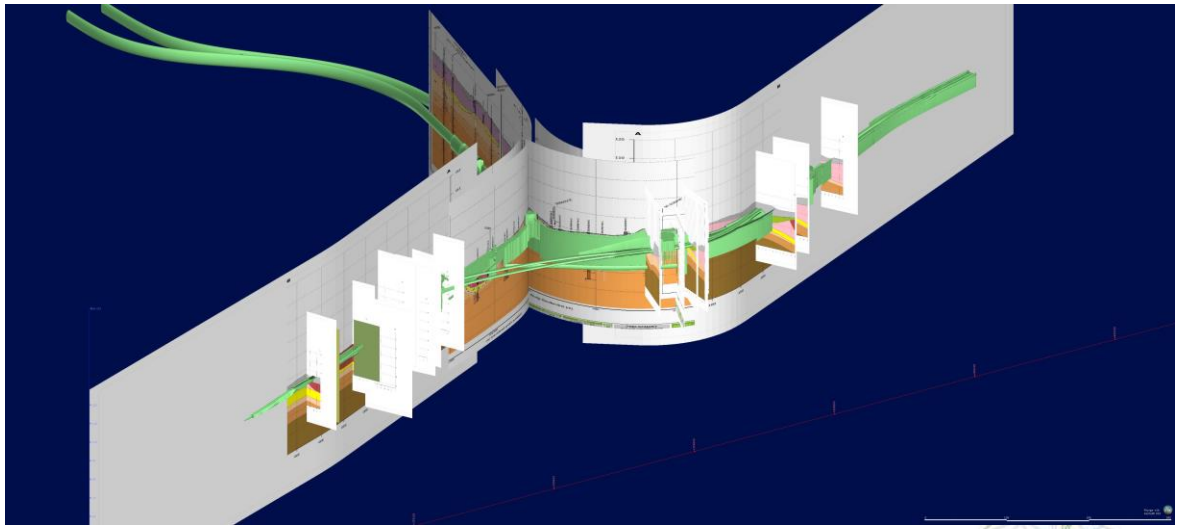
3-D ground models in the project life cycle –

Visualisation, big picture – Concept Design, Reference Design
Procurement packages (tenders)

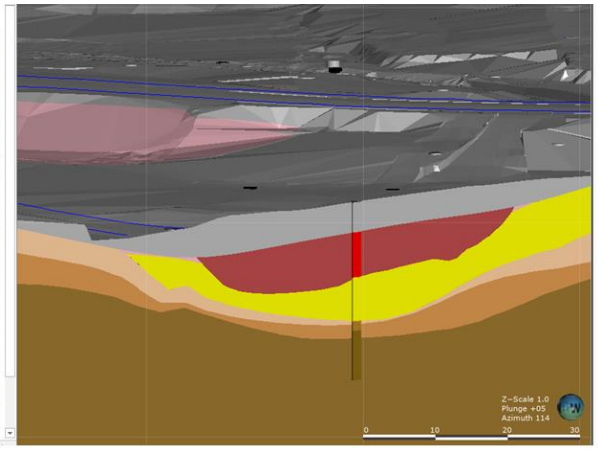
But we have usage issues:
Models used beyond specified purpose
Minimisation of uncertainties
User preference for 3d (over more accurate 2d representations)
Miscommunication (visual cues better than text specification)

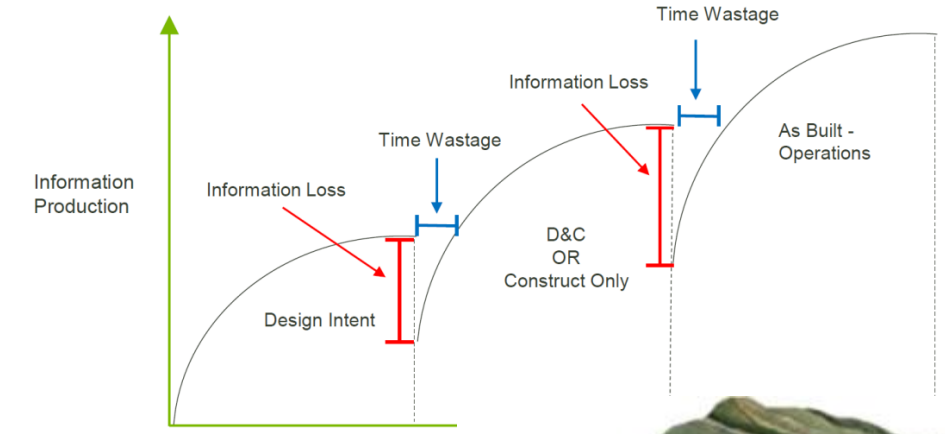


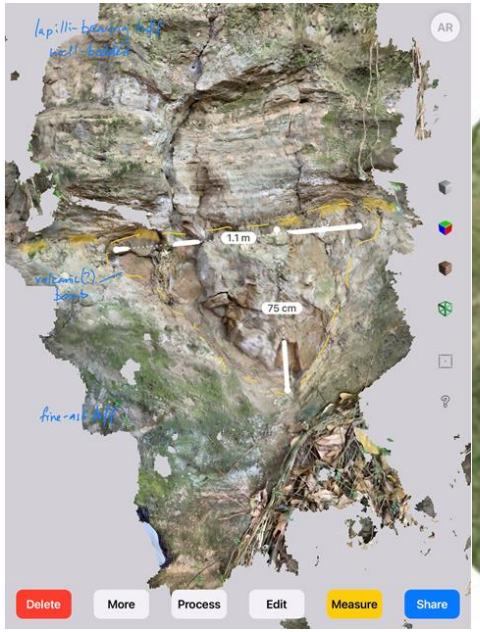




Construction Phase Observations





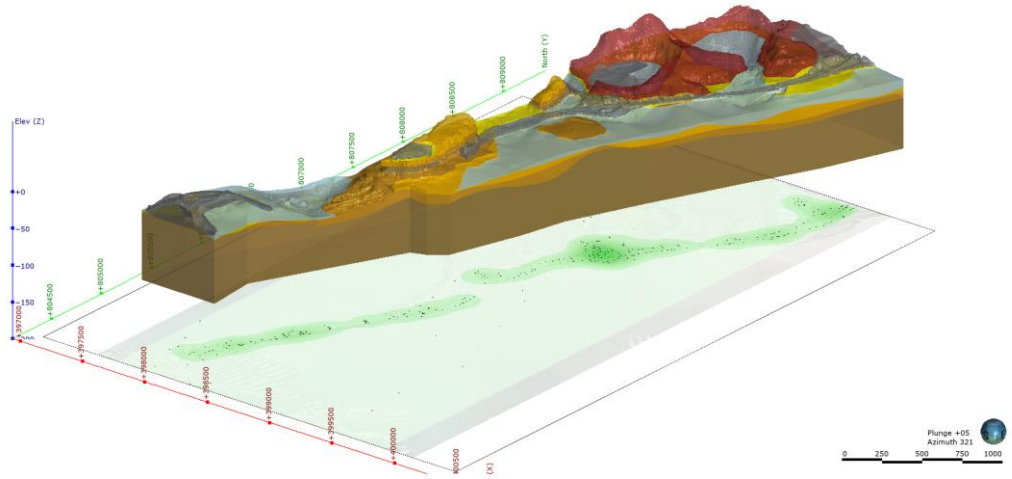


3D ground models much less popular at construction:

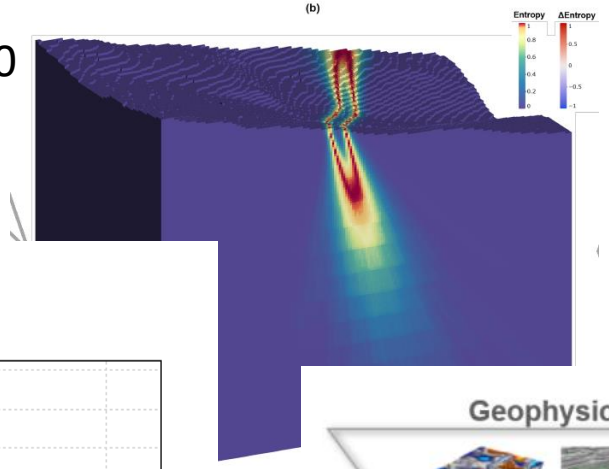
- Massive increase in ground data available
- Few geologically-trained observers
- 3D Ground models too generalised
- Ground materials not recognised
- Data is collected - but in diverse formats
- Relatively little gets in to the model …

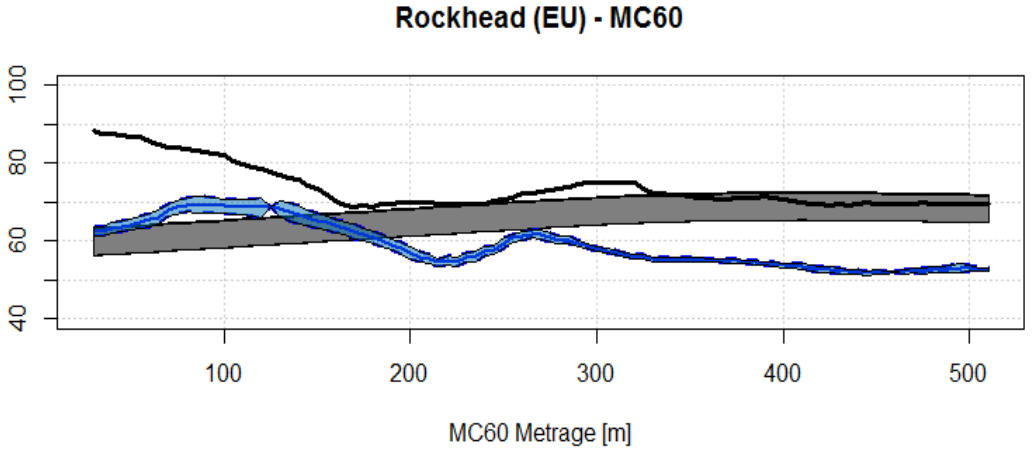
Uncertainty / Level Of Development

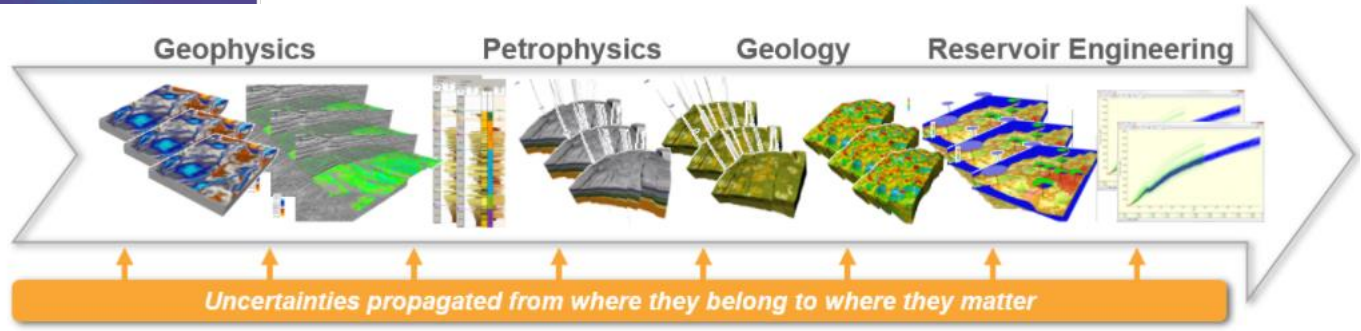
Traditional: Heat maps, reliability diagrams, model status
Other ground industries further down the track (petroleum, mining)
Uncertainty enabled 3D Geological models – prediction tools



Krajnovich et al 2020



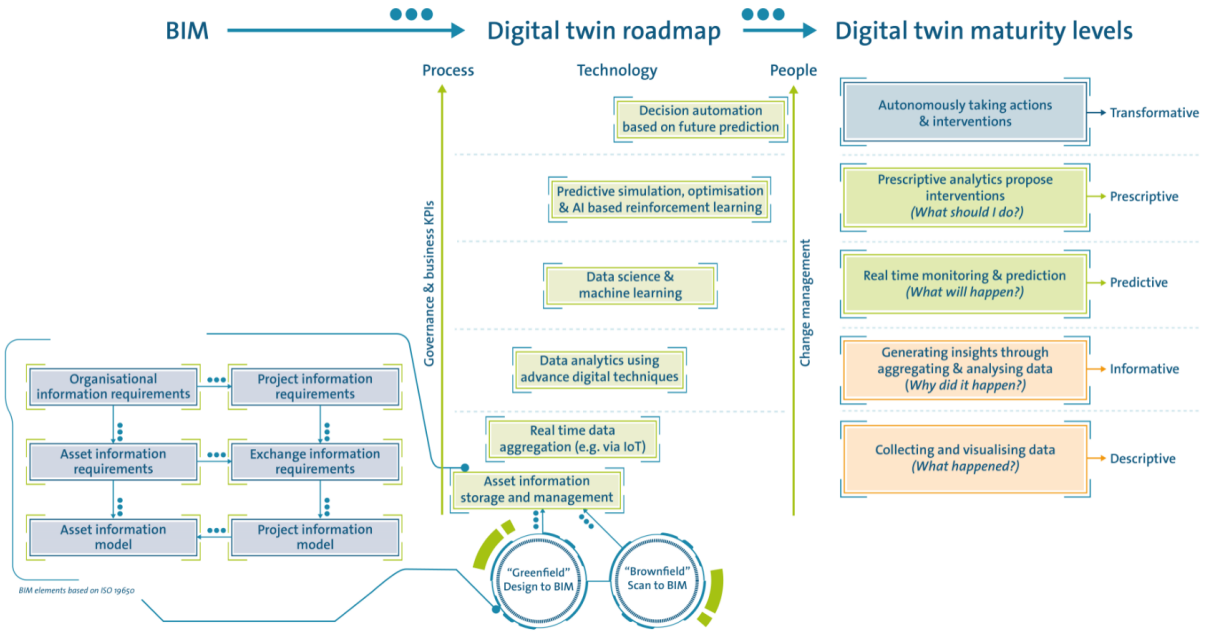




Conclusions

Opportunity for Improvements:

- Better use ground models (ISO19650 compliance)
- Develop more flexible construction-side tools
- Uncertainty-enabled ground models offer time and cost savings, and improved resilience



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Total Digital Architecture

Embedding digital throughout geotechnical designs

Stuart Millis

16 September 2021

The Key Speech

Delivered by Sir Ove Arup on 9 July 1970

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"We are led to seek overall quality, fitness for purpose, as well as satisfying, or significant, forms and economy of construction. To this must be added harmony with the surroundings and the overall plan. We are then led to the ideal of **Total Architecture**

75 years

The term **Total Architecture** implies that all relevant design decisions have been considered together and have been integrated into a whole"

Total Digital Architecture

Modern day approaches to this philosophy

The philosophy is **equally applicable to the use of digital data and tools** throughout the investigation, design, construction and management of engineering assets, with the digital elements considered together and **integrated as a whole**

75 years

ARUP

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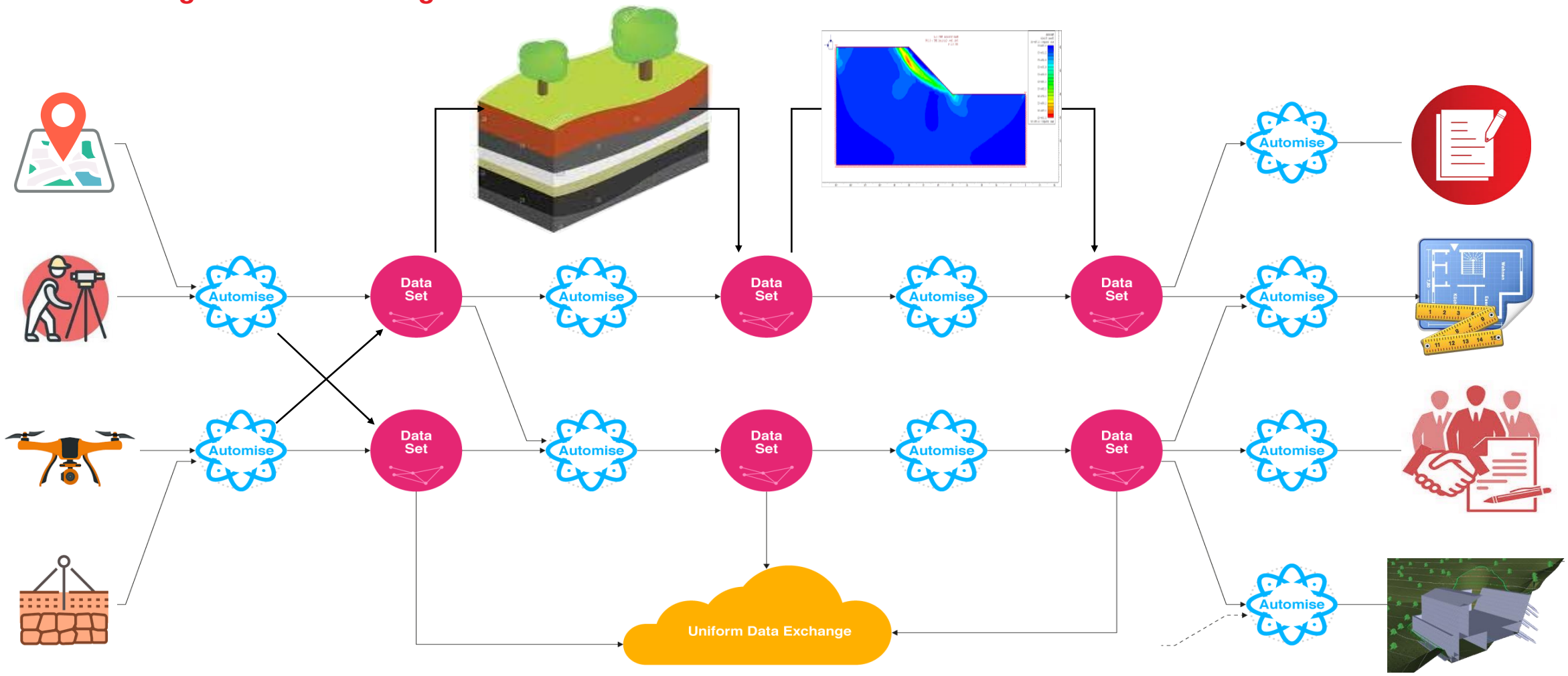
Geotechnical Design

data flow for geotechnical designs



Data Collection

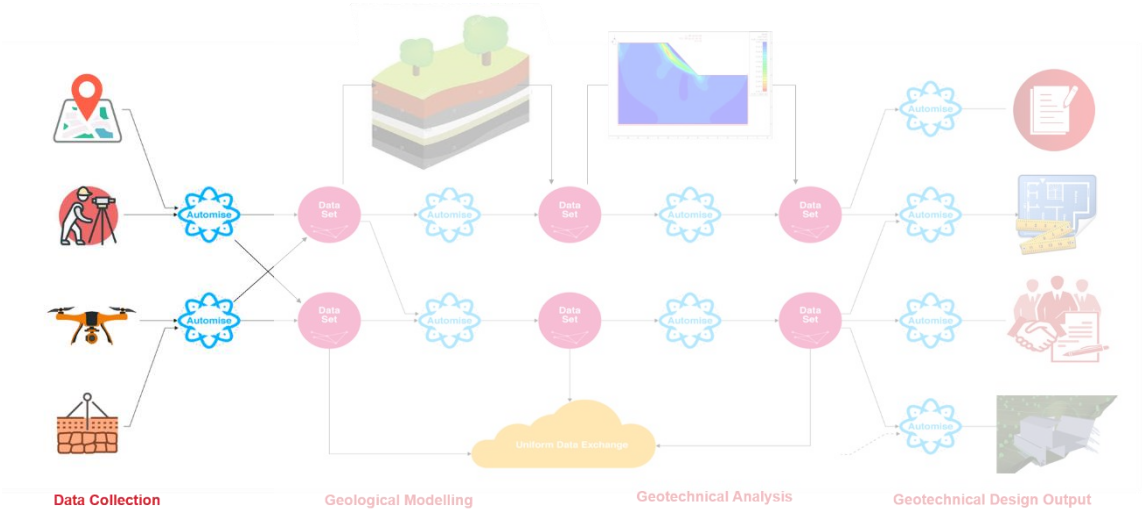
Geological Modelling

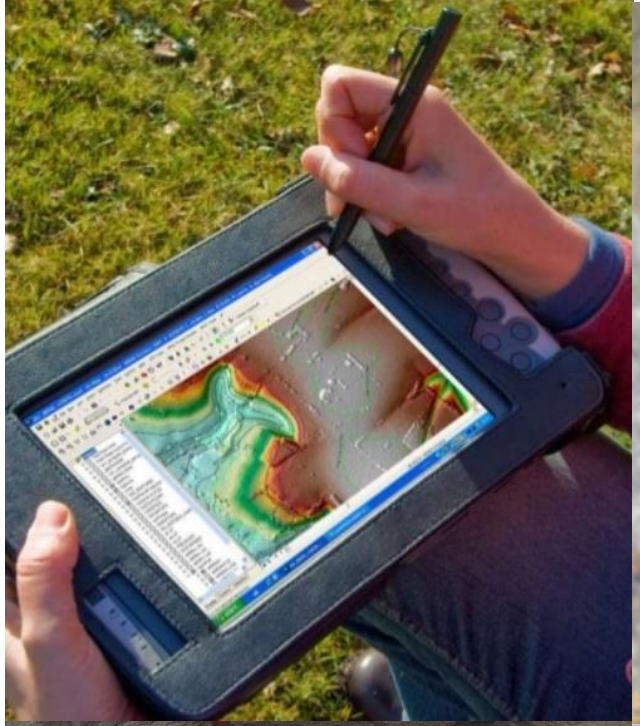
Geotechnical Analysis

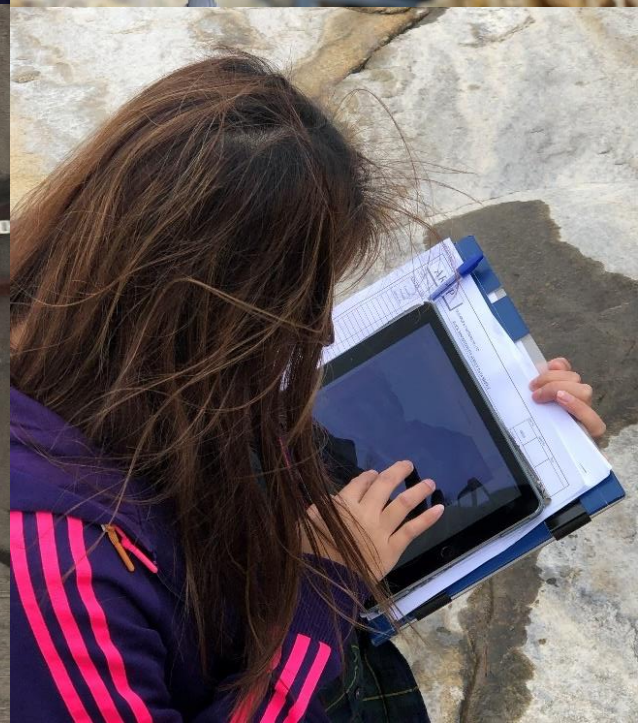
Geotechnical Design Output

Data Collection

gathering and collating existing information





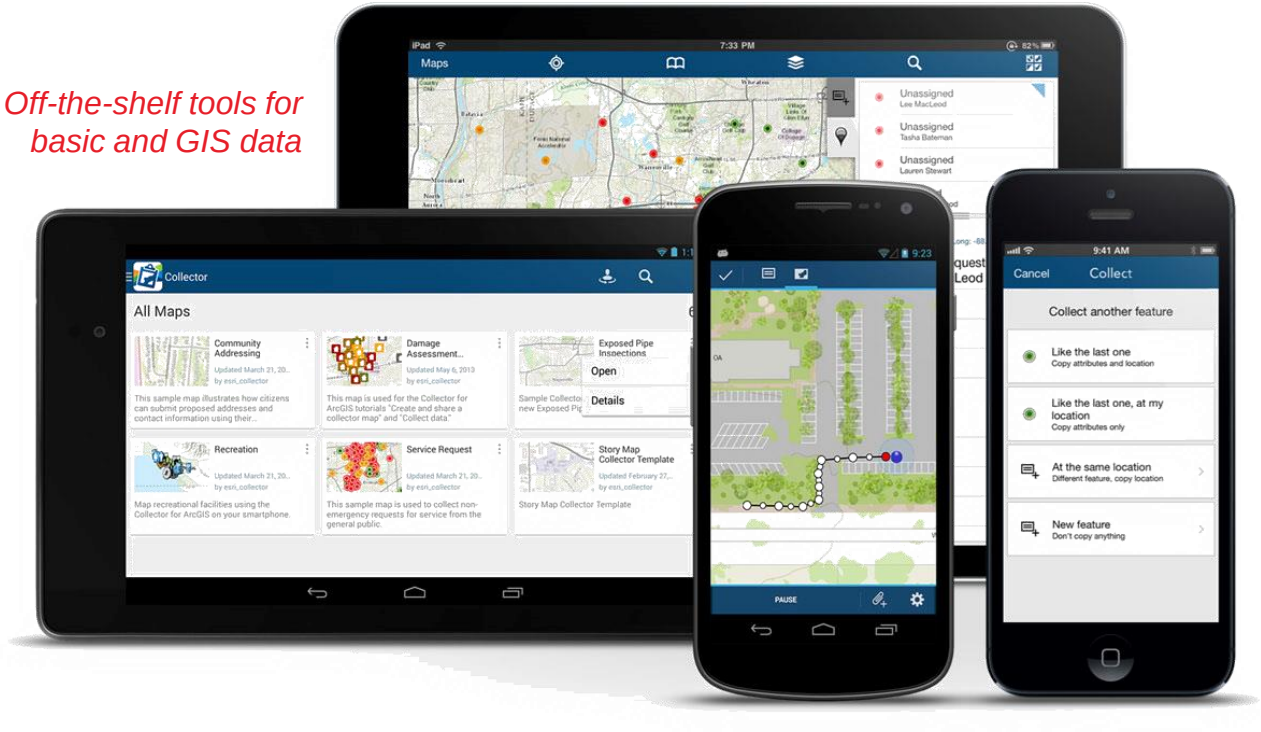


Field Data Collection

enhancing efficiency

ditching paper forms and
collecting data digitally
in the first place

Off-the-shelf tools for basic and GIS data

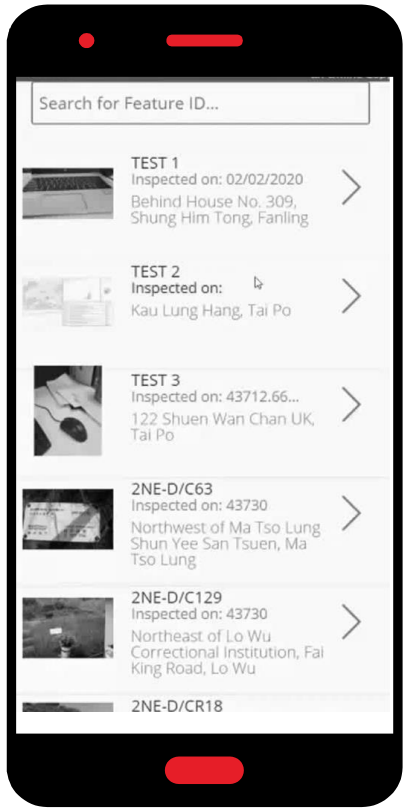


Adopt Adapt Invent

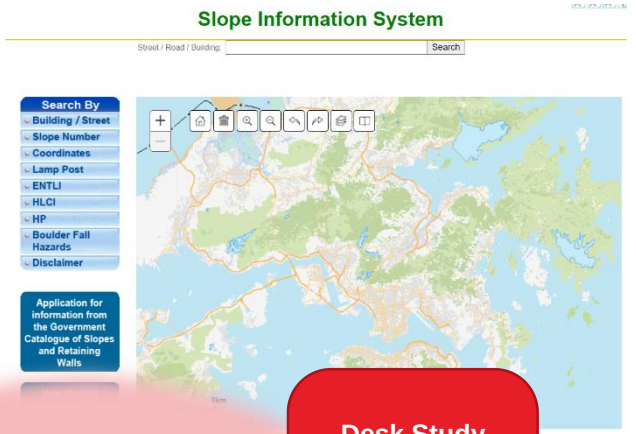
Field Data Collection

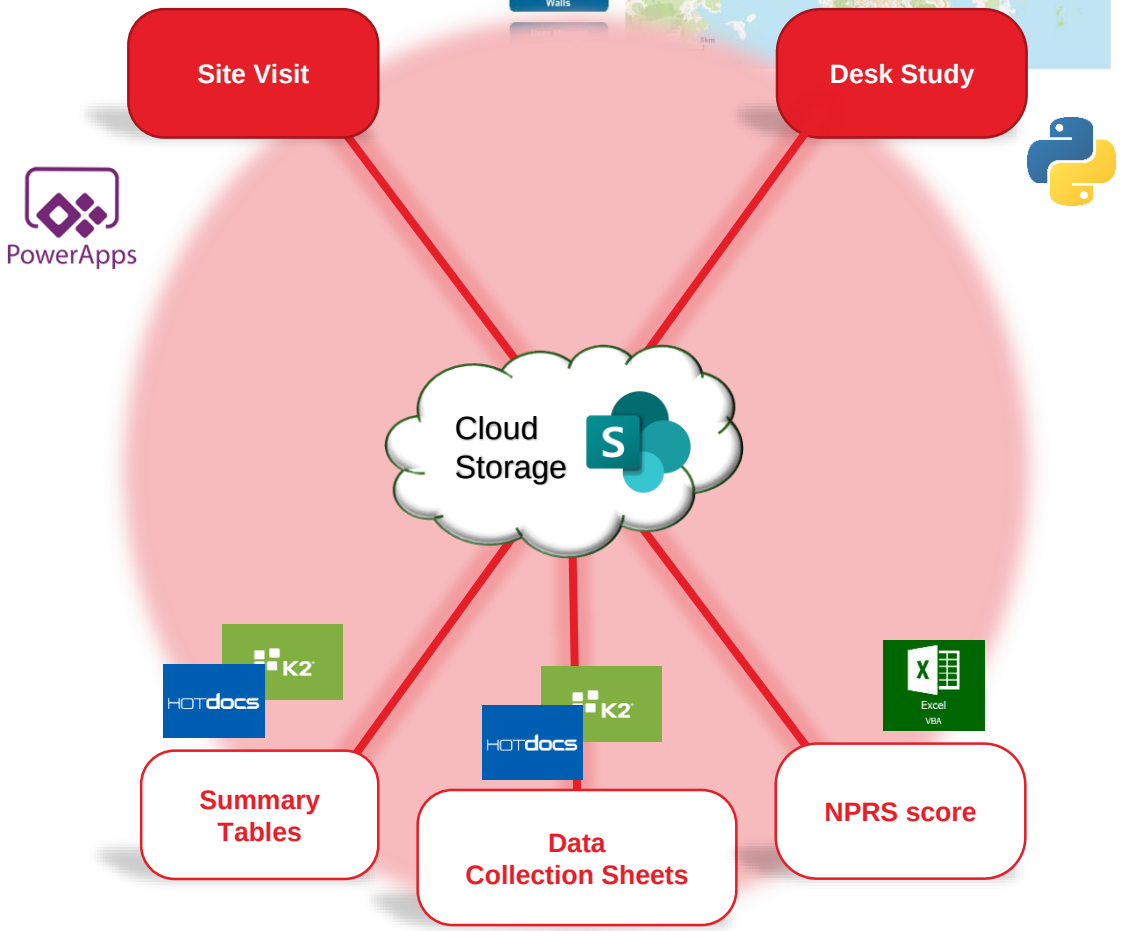
enhancing efficiency

to more bespoke tools developed for specific purposes



Slope Data Collection Works



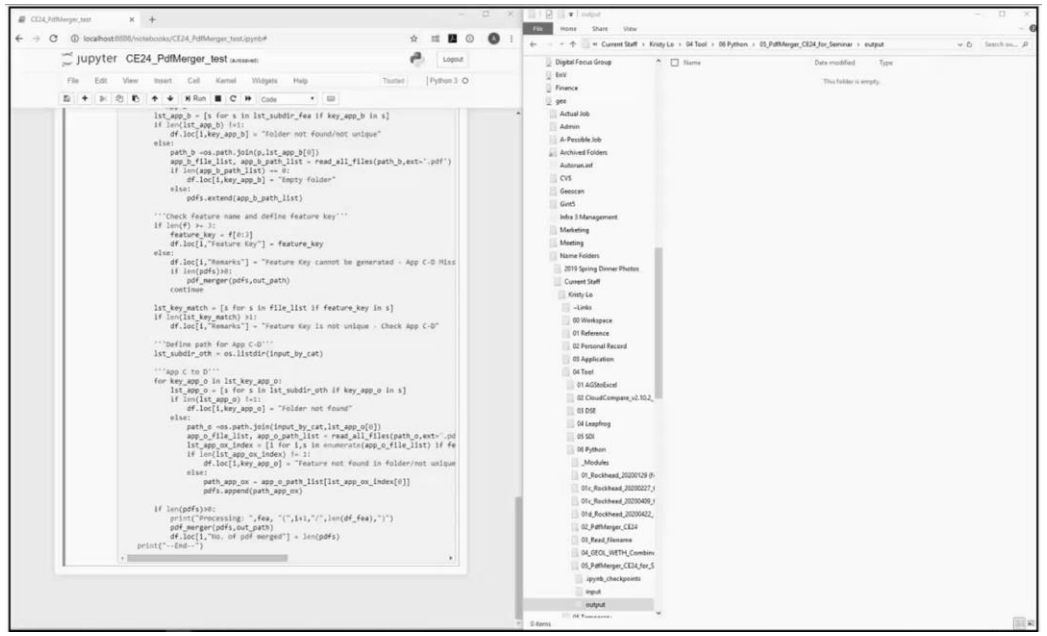


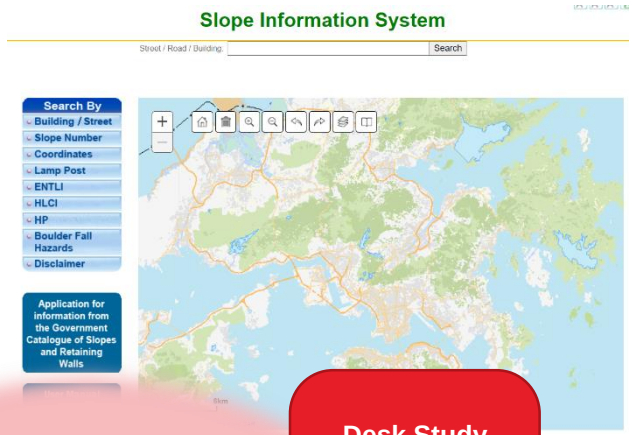
Adopt **Adapt** Invent

Field Data

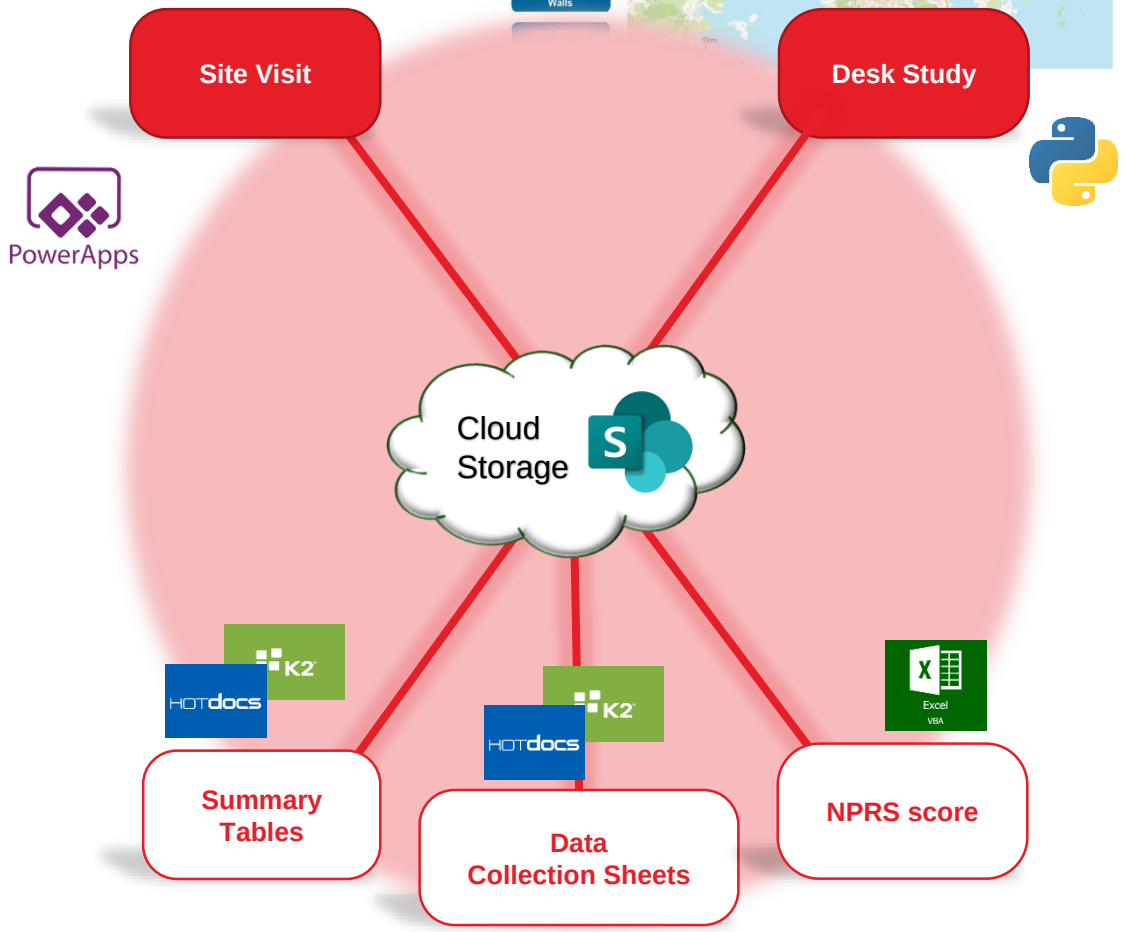
enhancing efficiency

and then use the collected data to systematically (auto)generate output





Slope Data Collection Works

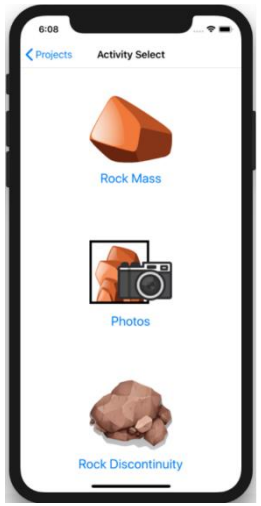


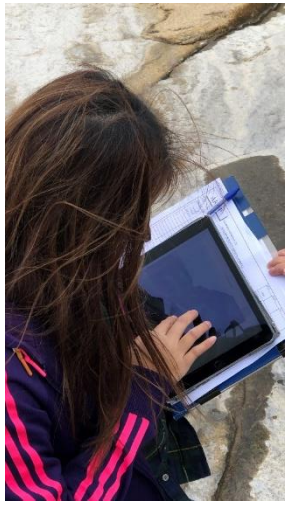
Adopt **Adapt** Invent

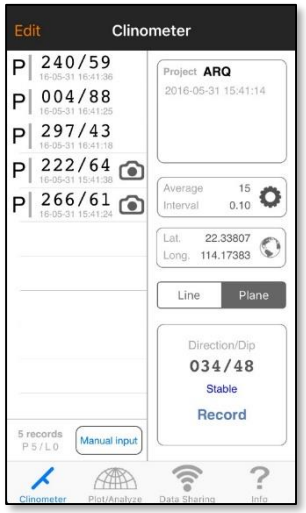
Field Data

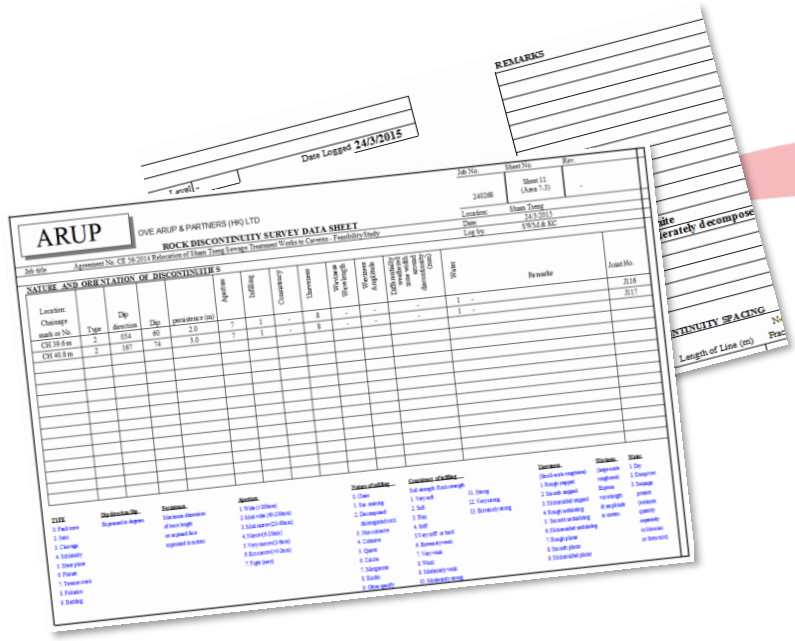
enhancing efficiency

and doing this for any aspect that collects site data in a standardized and consistent manner

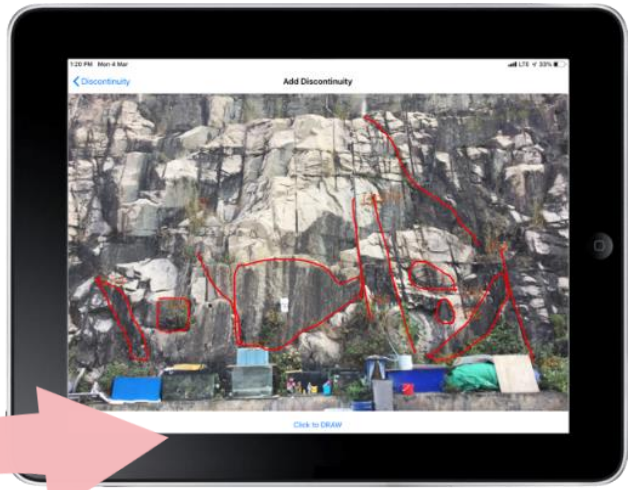


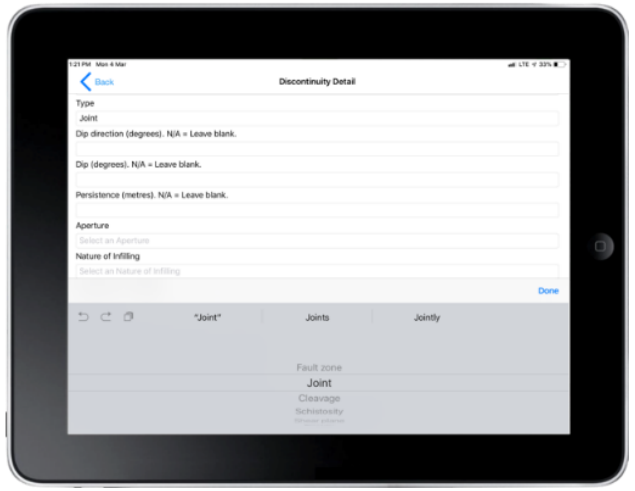






Discontinuity Mapping



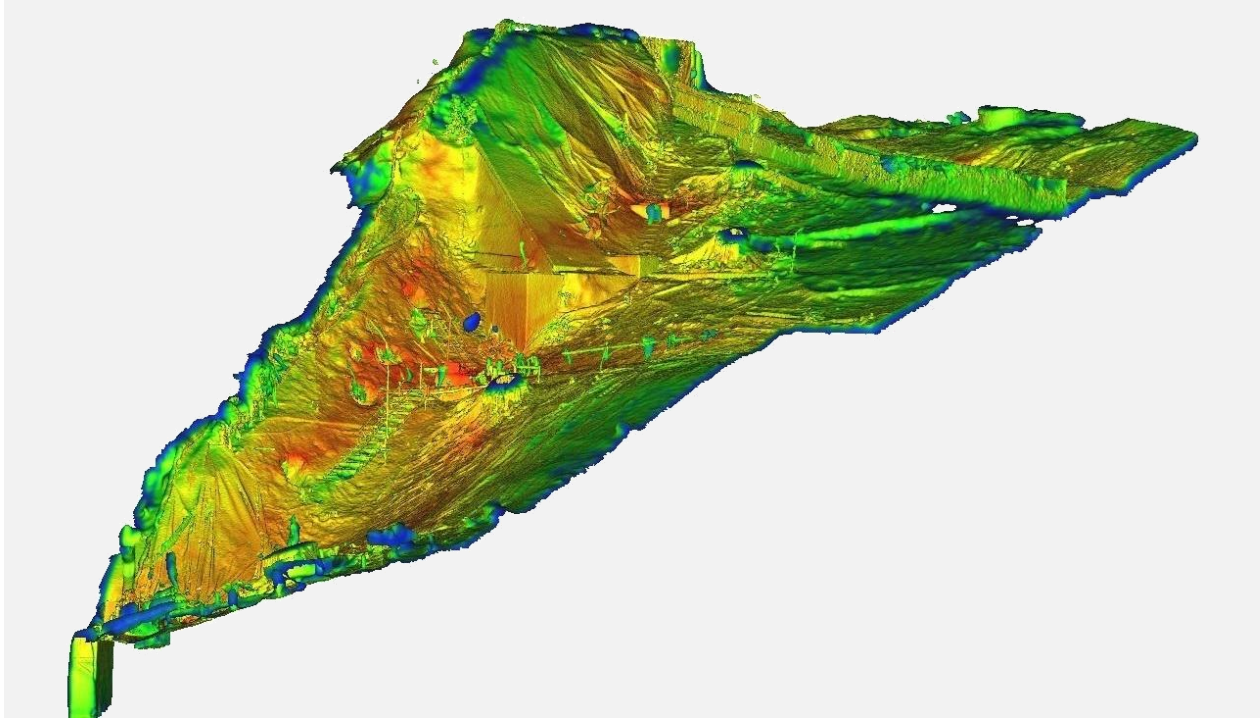


Adopt Adapt **Invent**

Site Conditions

laser scanning

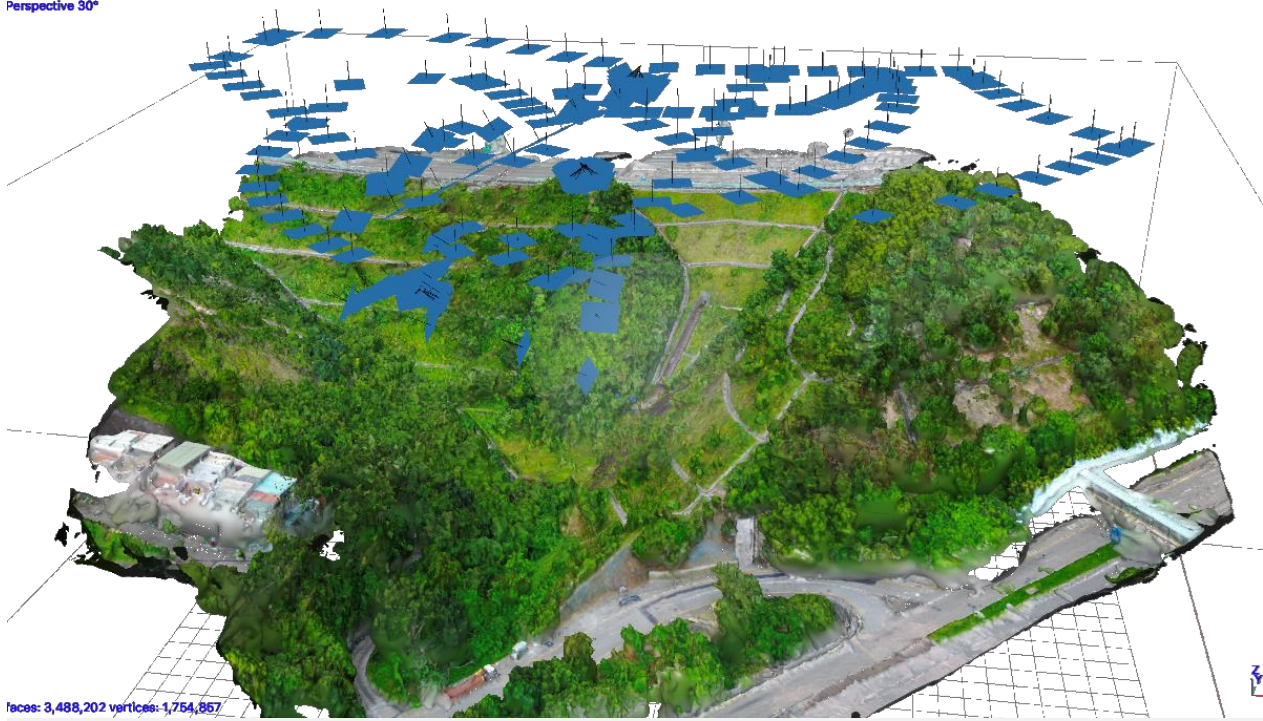
Terrestrial Laser Scanner and Mobile Laser Scanners to enable rapid generation of 3D Point Clouds

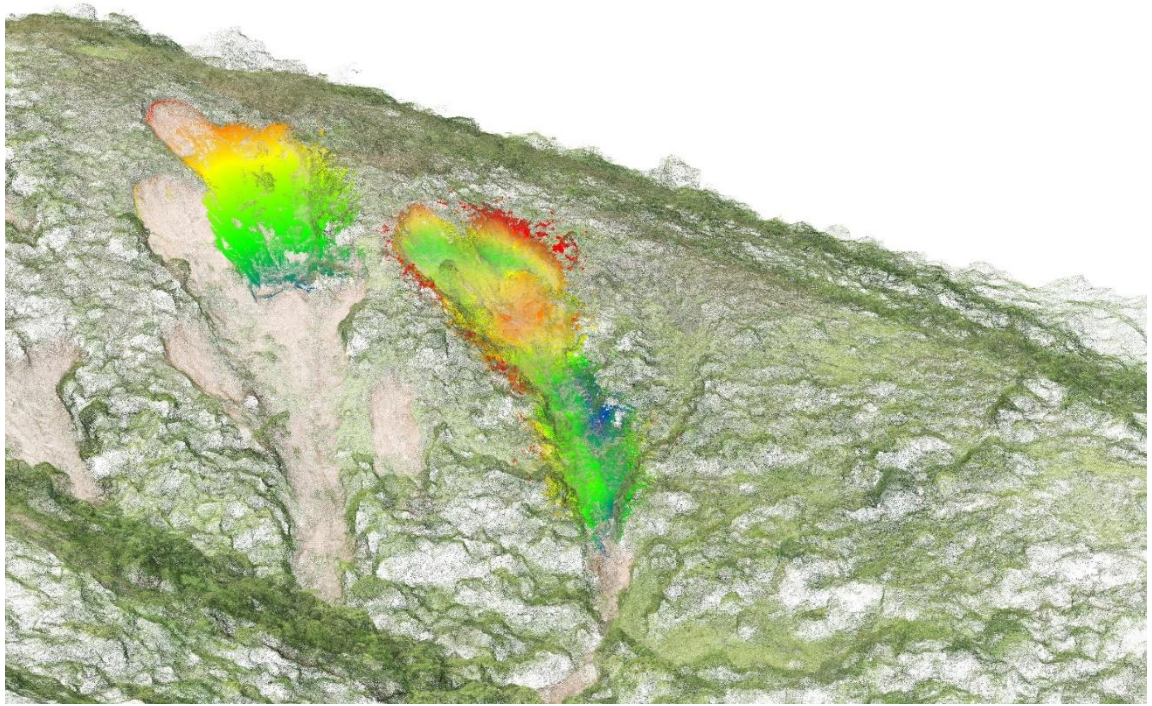


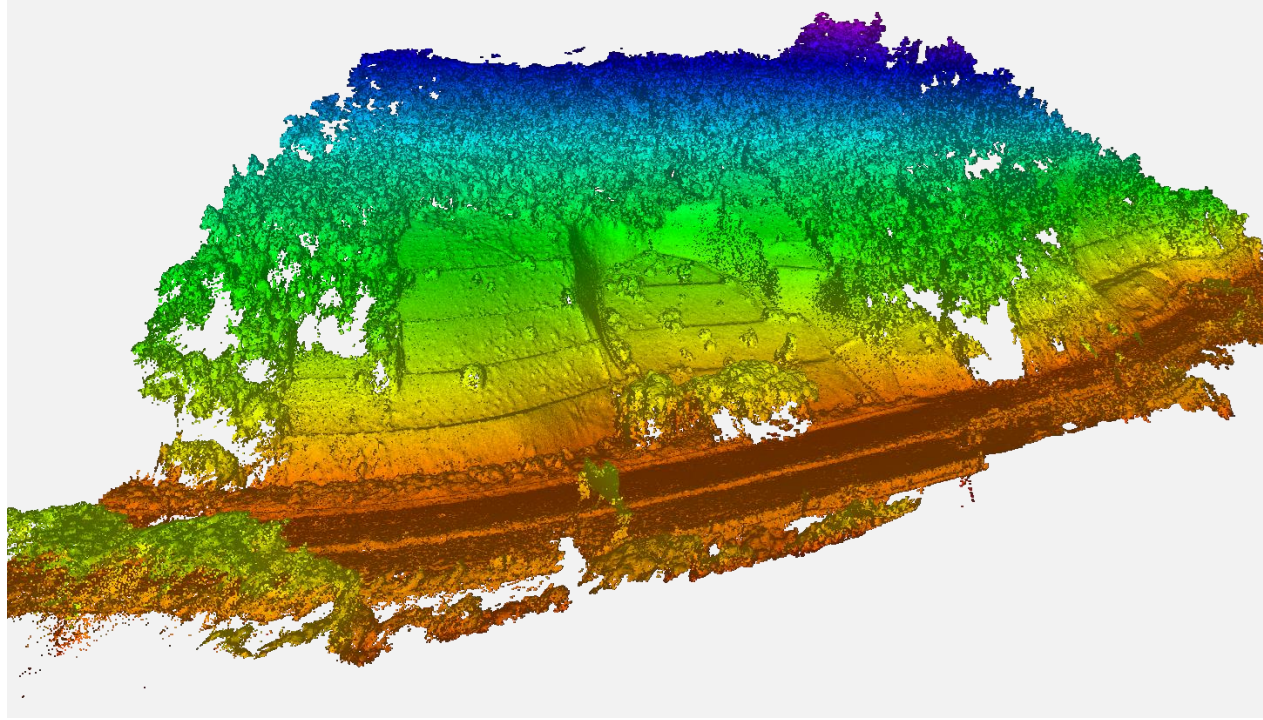
Site Conditions

digital photogrammetry

UAV surveys for rapid terrain modelling of large and inaccessible areas of interest







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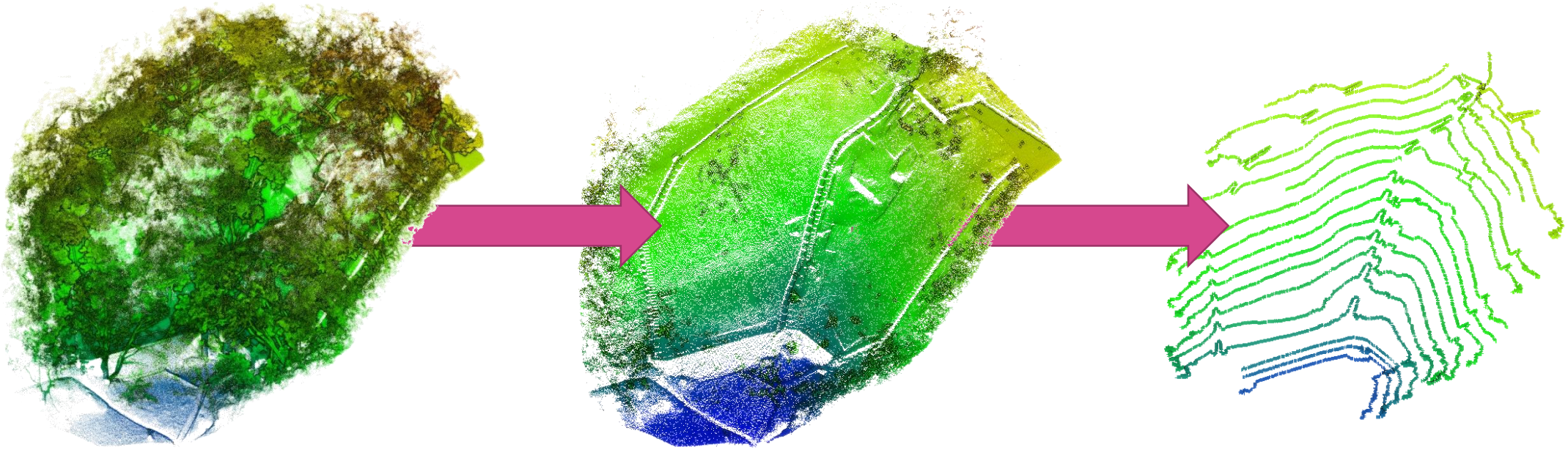
Site Conditions

topographic mapping in hours rather than weeks

rapid surface model generation



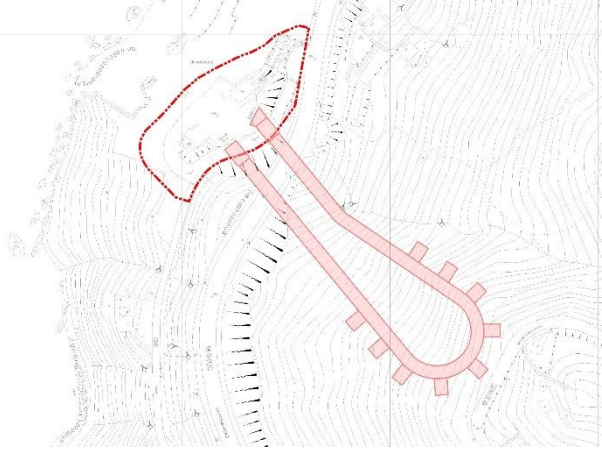
Scan Data

Post-processed Data

Contour Model

Site Conditions

condition survey recording

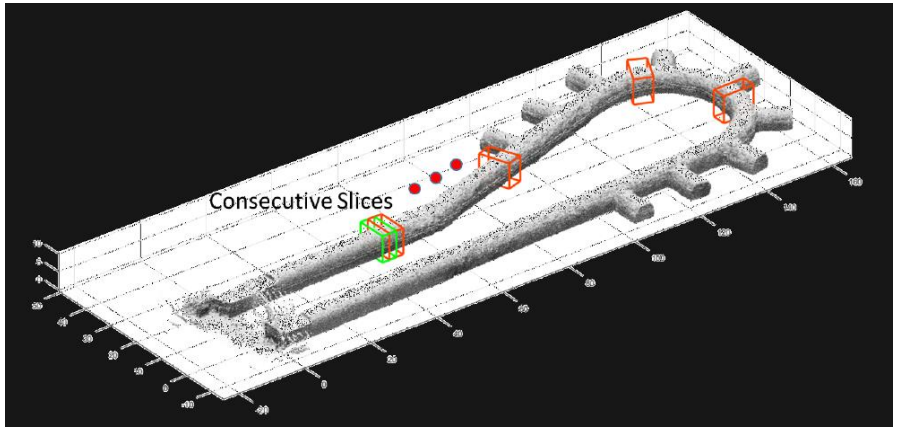


ARUP

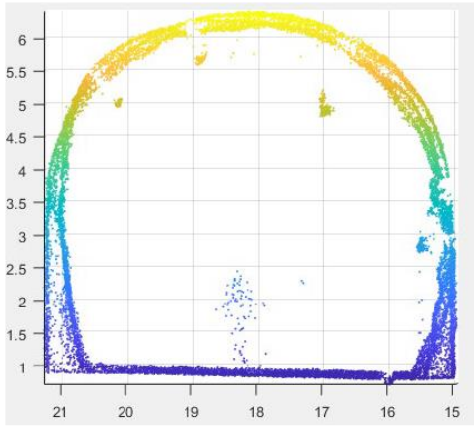
Site Conditions

condition survey recording

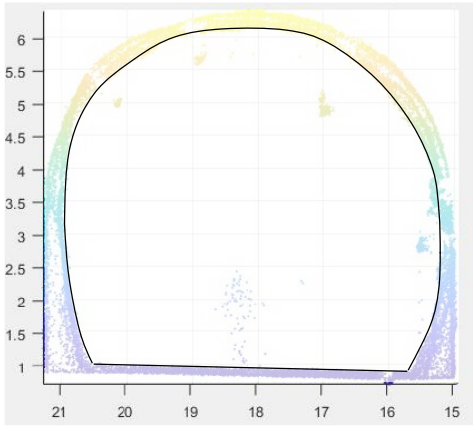
tunnel profile generation



Scan Data



Profile Extraction

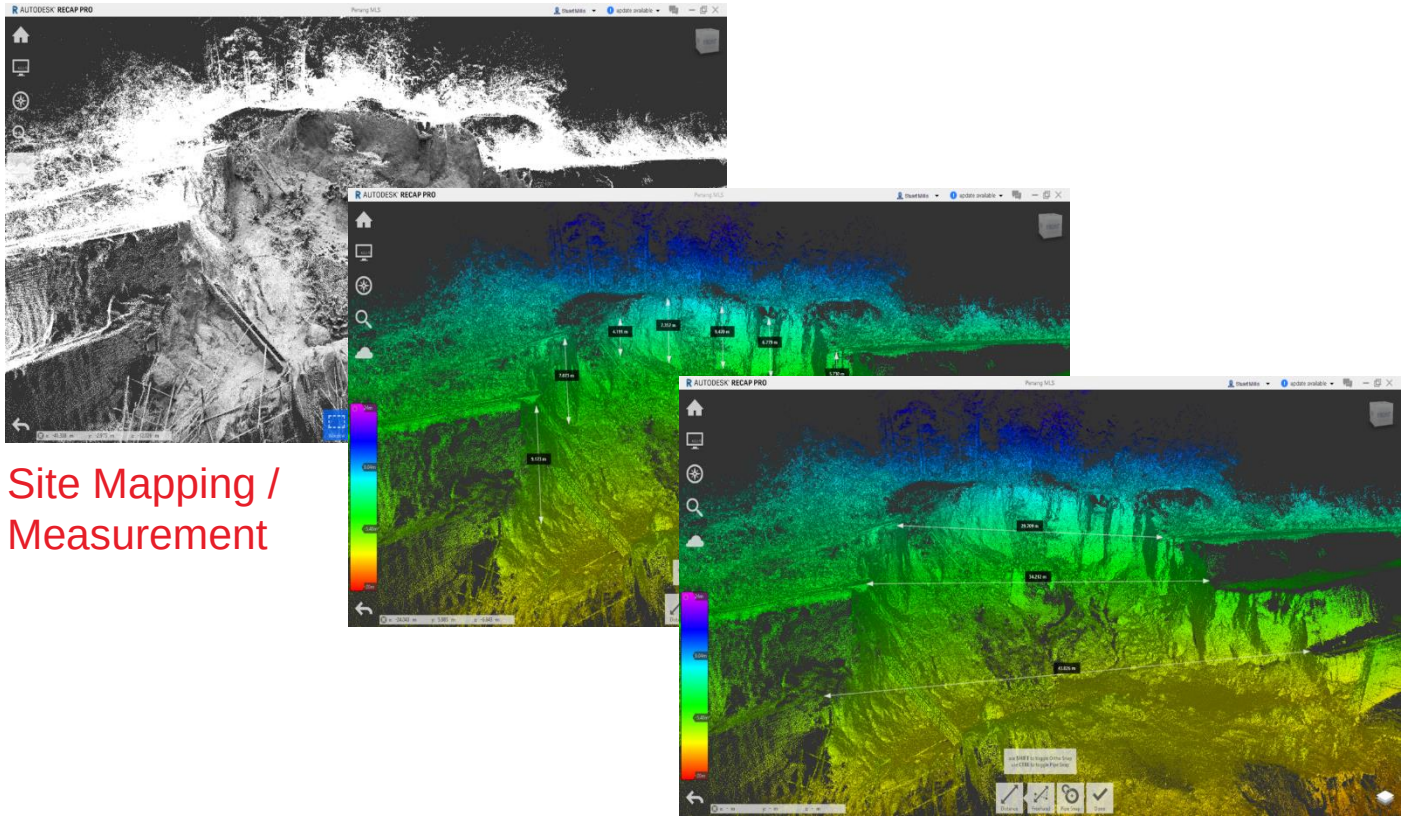


Geometry Extraction

Site Conditions

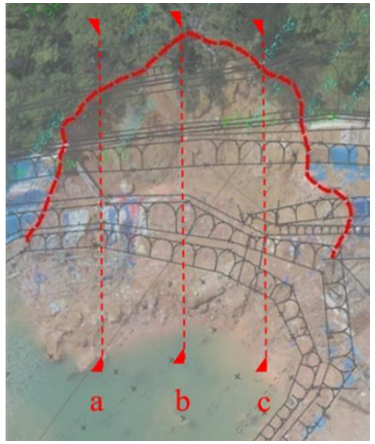
mapping and measurement of key features

accurate meaurement of key features



Site Mapping / Measurement

Section Generation

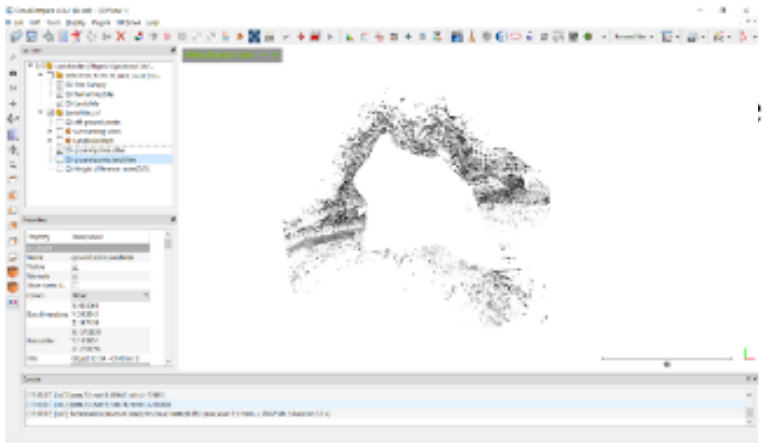


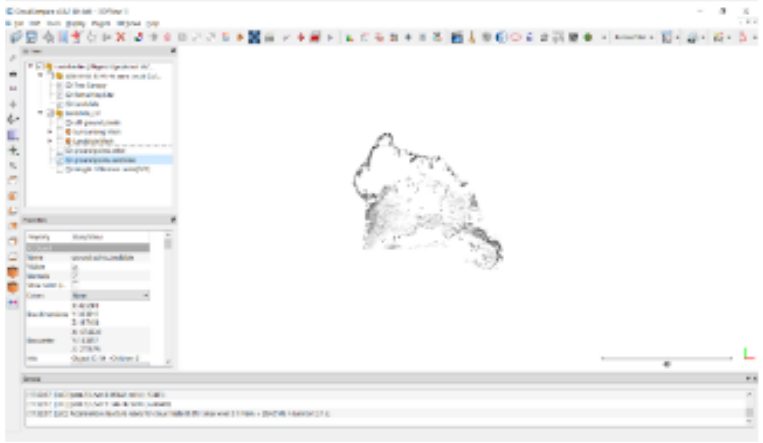
ARUP

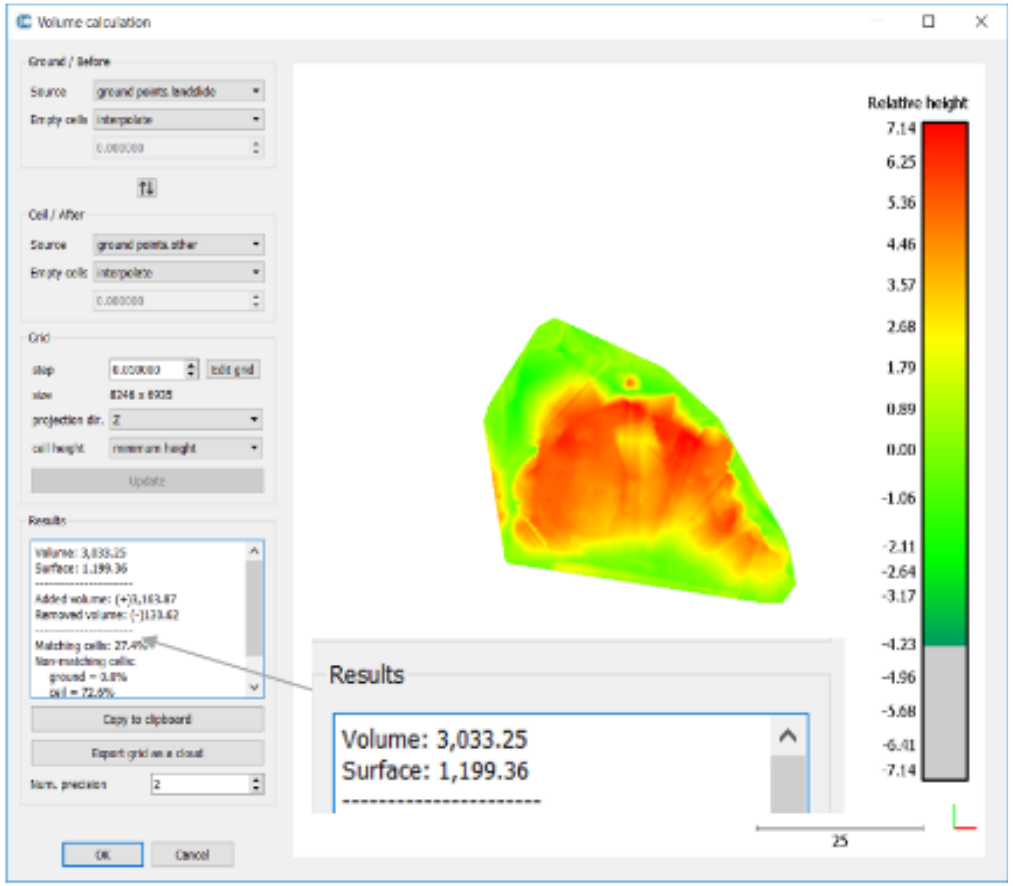
Site Conditions

mapping and measurement of key features

accurate meaurement of key features







Direct Volume Calculation for landslides / material stockpiles etc.

Digital Discontinuity Mapping

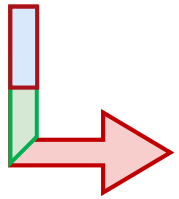
Site Conditions

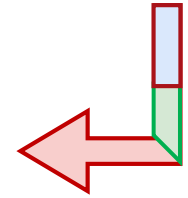
digital rock face mapping

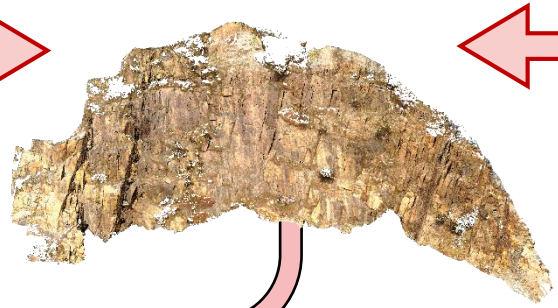
fully automated mapping of specific characteristics

TLS-derived Model

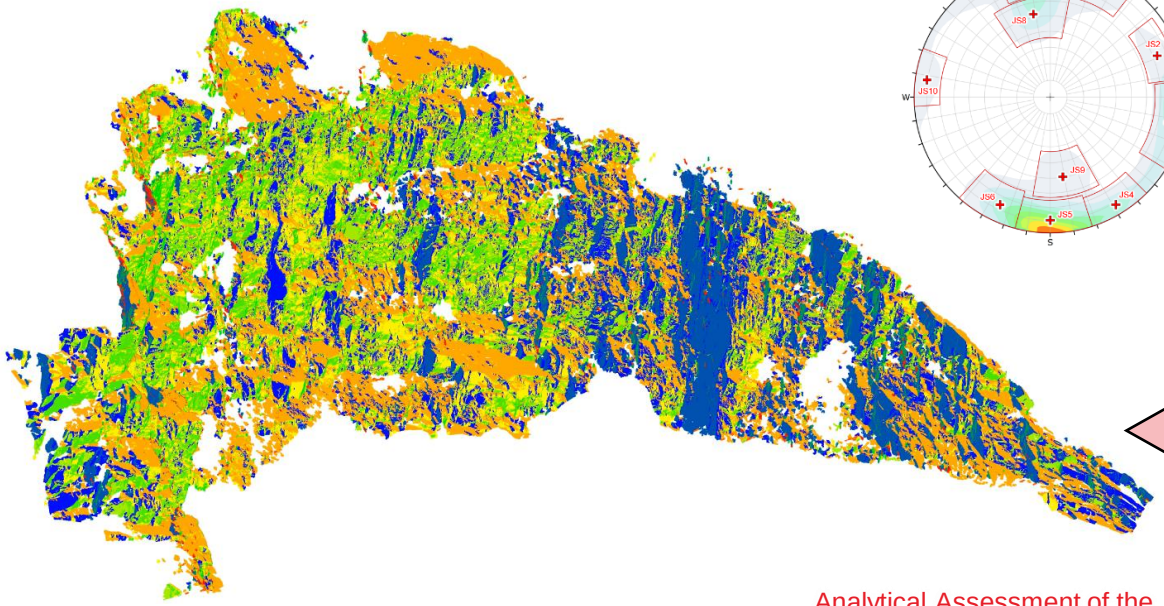
Photogrammetry-derived Model

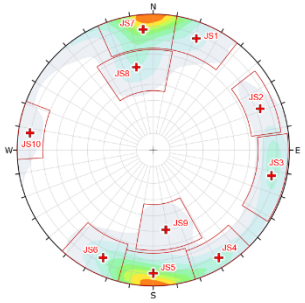






Combined Model



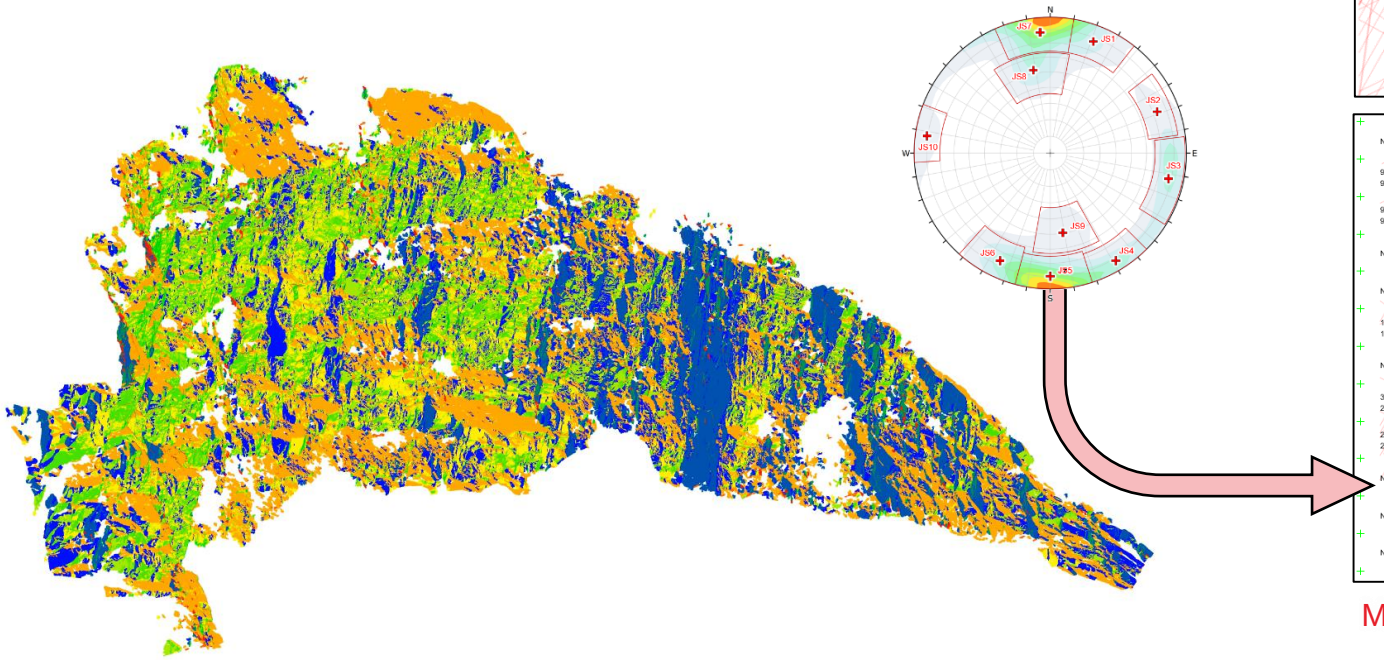


Analytical Assessment of the Entire Area of Interest

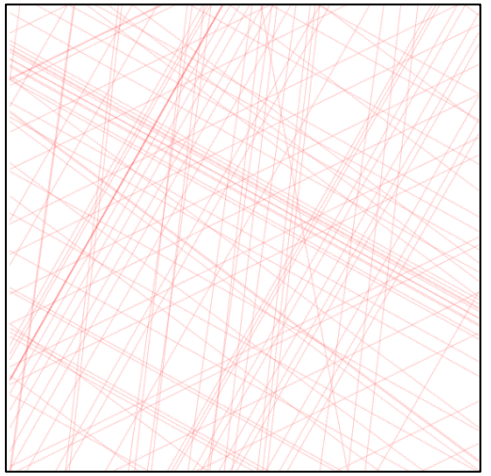
Site Conditions

digital rock face mapping

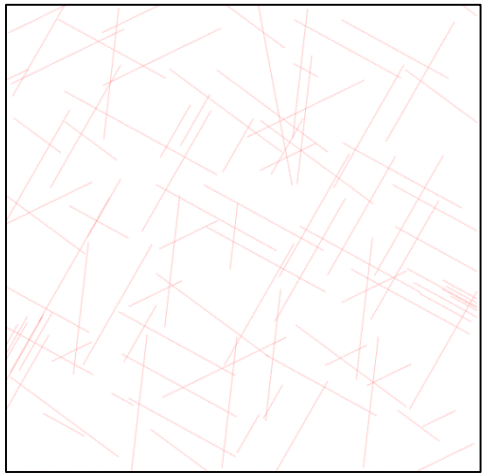
fully automated mapping of specific characteristics

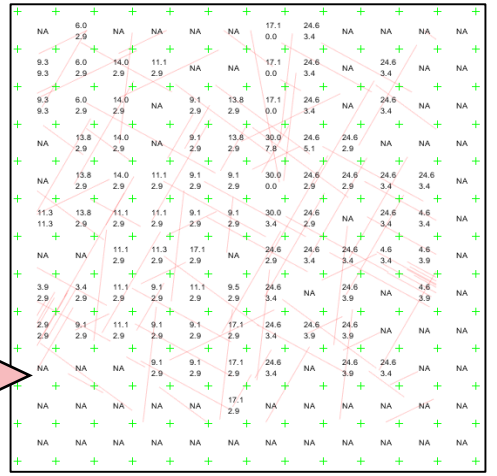


2D Discontinuity Map
(Infinite Persistence)

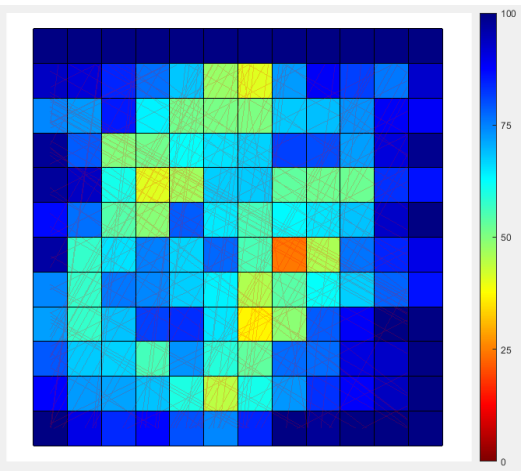


2D Discontinuity Map
(Derived Persistence)





Max. and Min. Vb

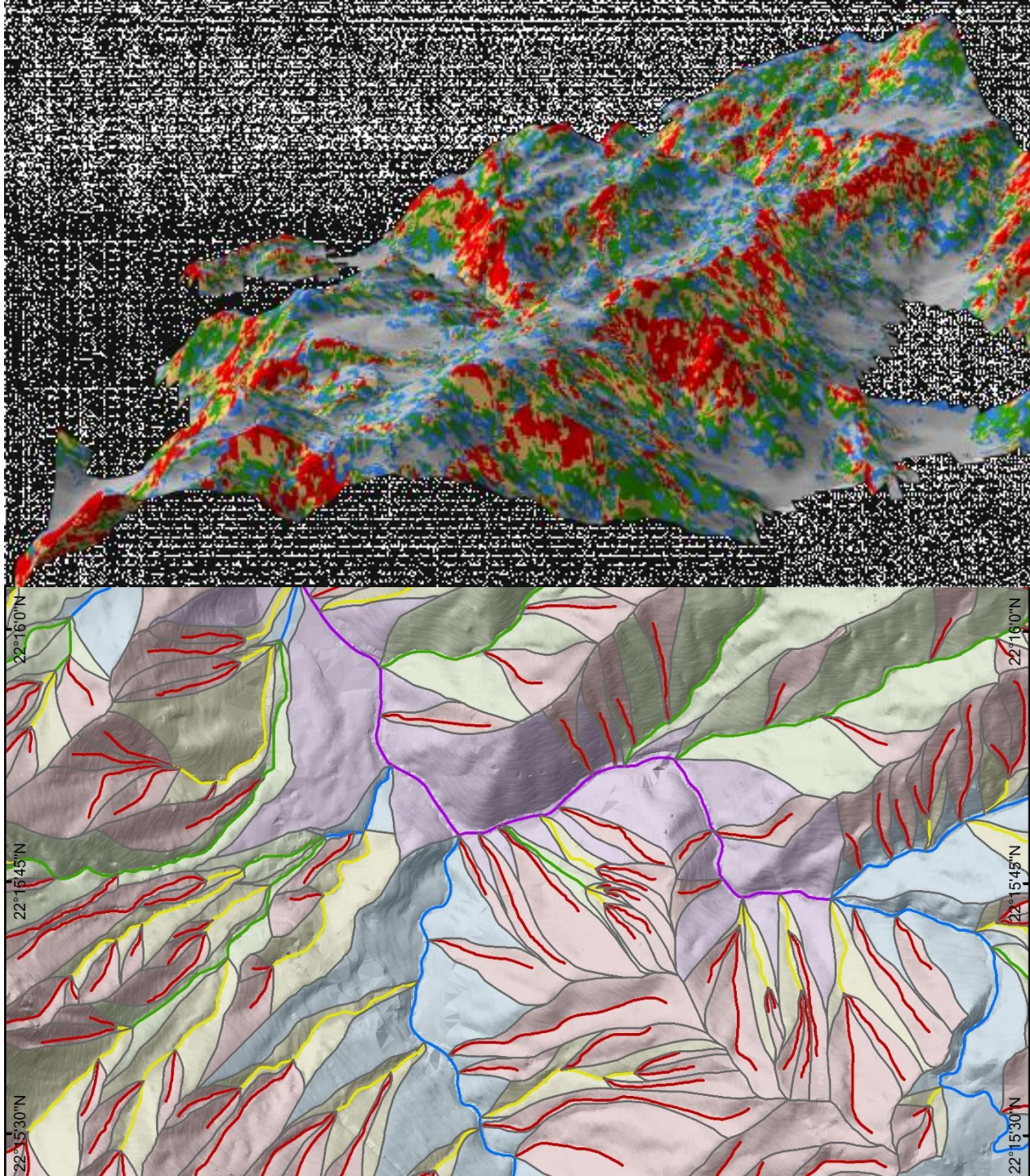


Heat Map of Jv / RQD

Remote Sensing

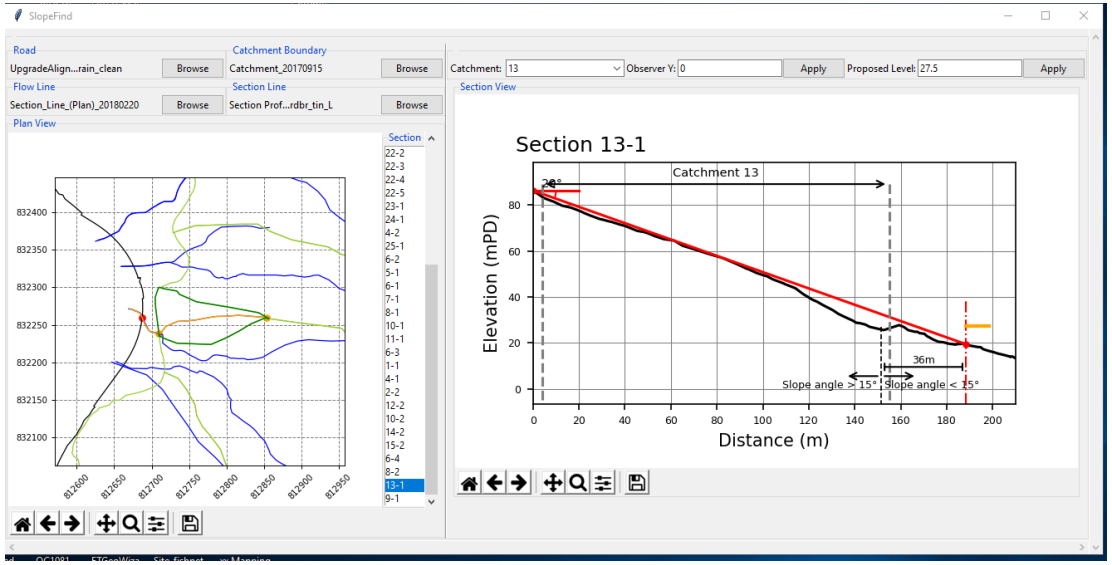
looking at the bigger picture

making use of remote sensing datasets such as LiDAR / IfSAR / InSAR etc.

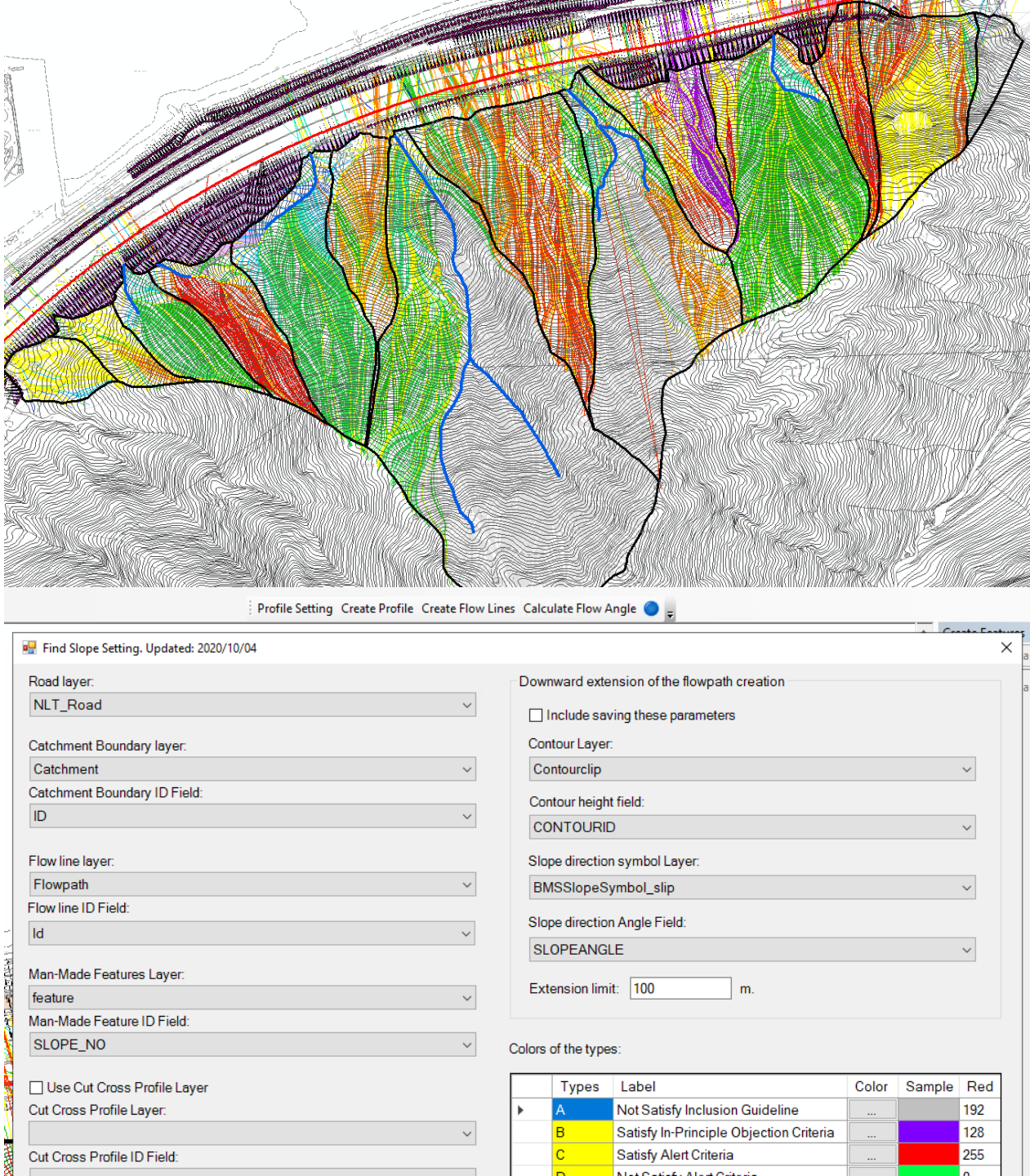


Remote Sensing

terrain analysis and catchment screening



ArcGIS



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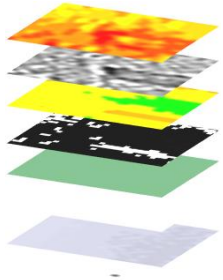
Remote Sensing

AI-driven landslide identification and mapping

Processed LiDAR
+
Processed Geological data



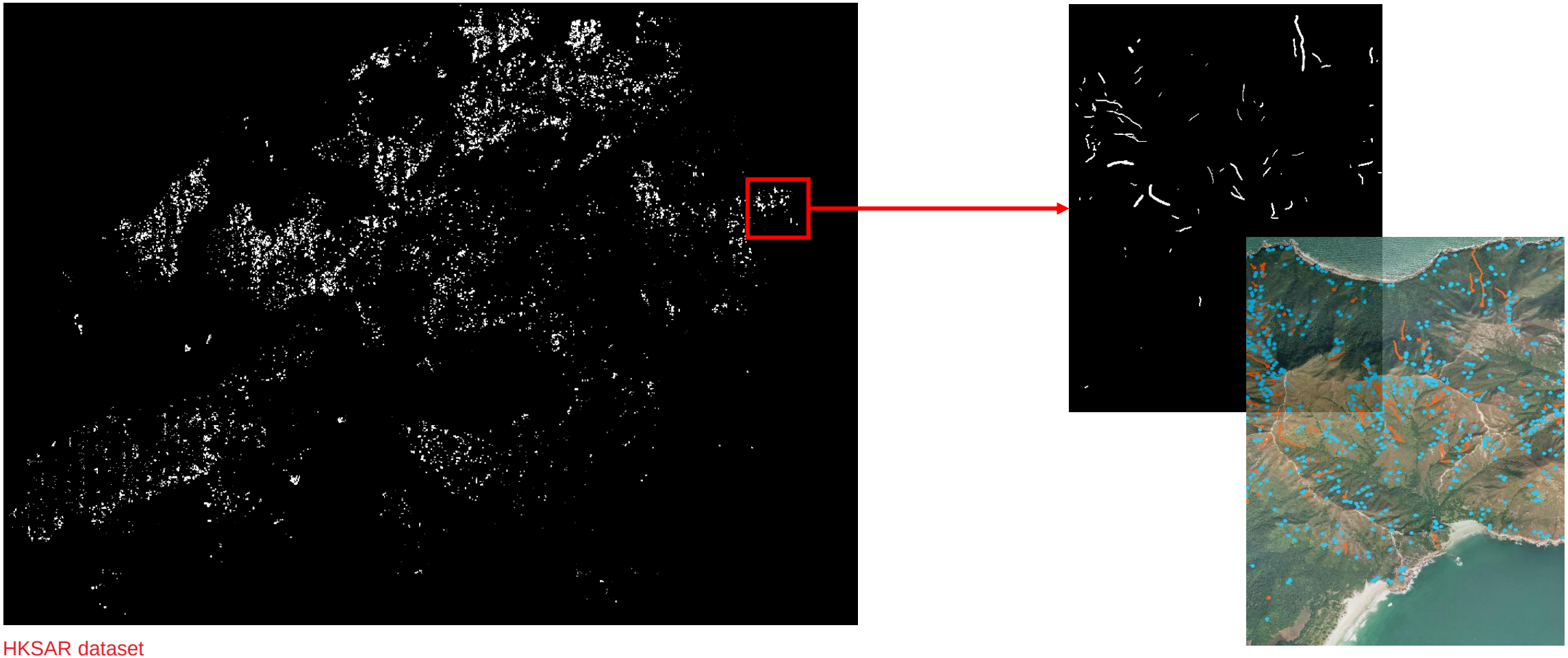
ENTLI

Samples

Training the ML model

Remote Sensing

AI-driven landslide mapping from DTM's



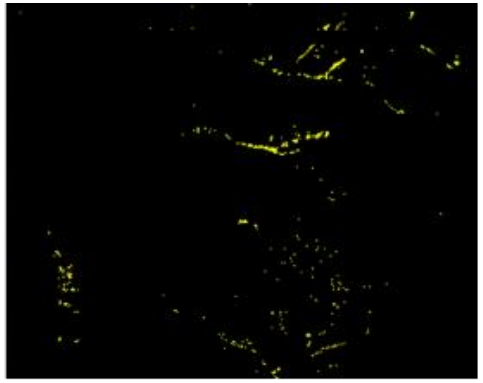
HKSAR dataset

ARUP

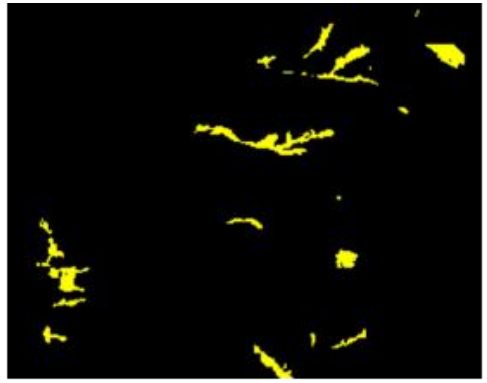
Remote Sensing

AI-driven landslide mapping from Digital Aerial Photos

Original Image

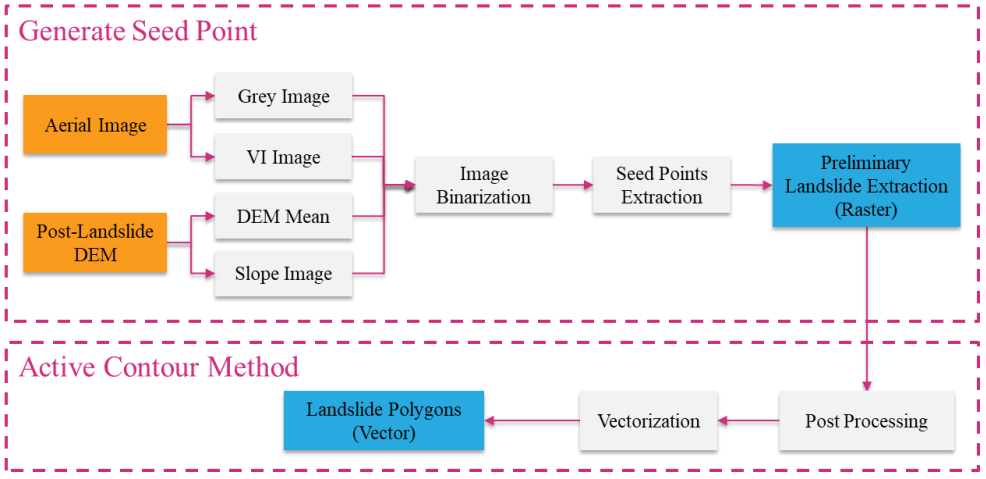


Seed Point Extraction



Active Contour Result

Landslide Polygon Generation

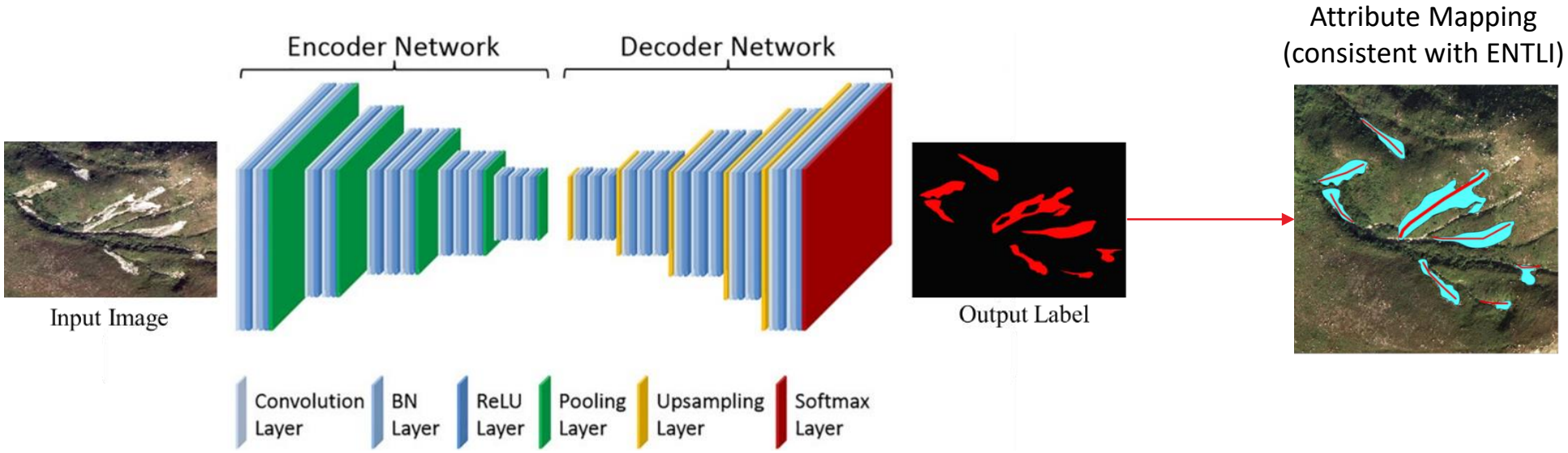


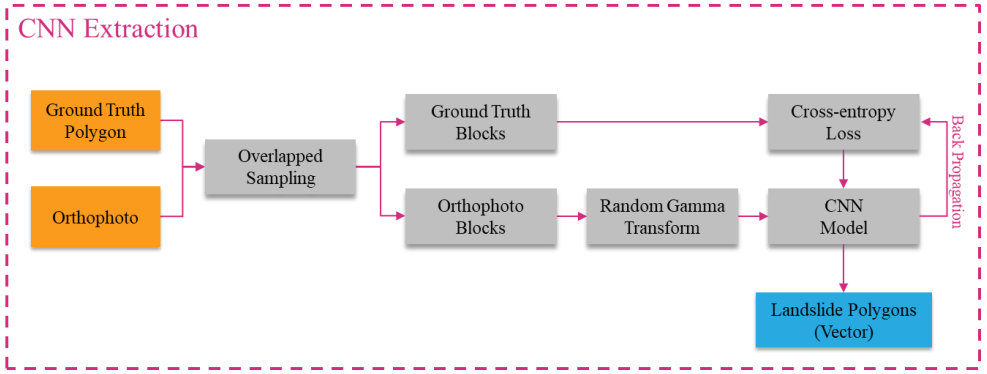
Feature-based Extraction Workflow

ARUP

Remote Sensing

AI-driven landslide mapping from Digital Aerial Photos





Deep Learning Workflow

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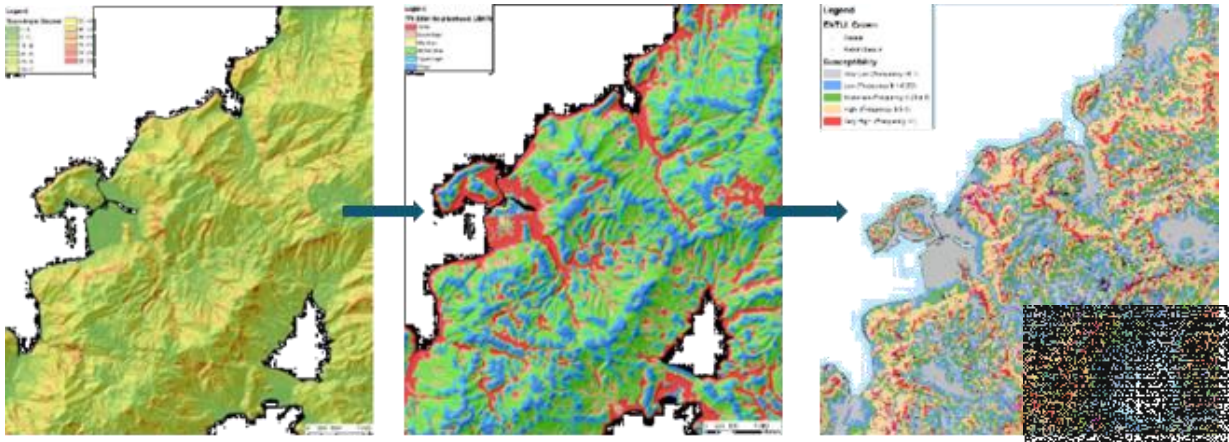
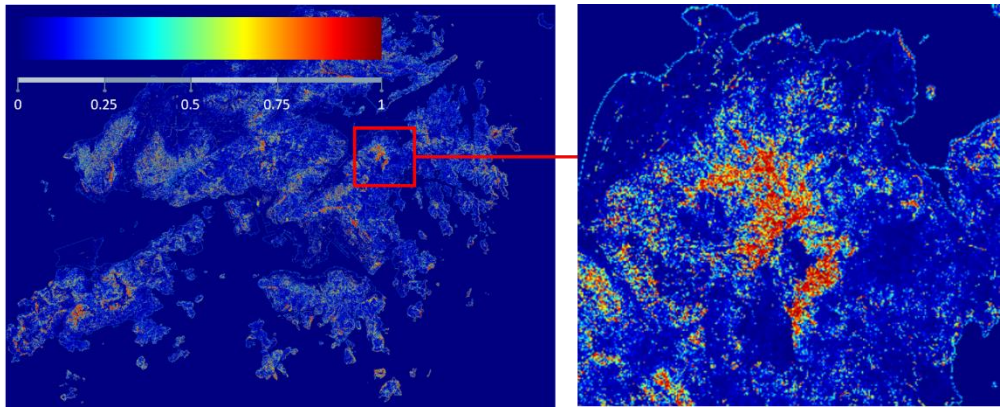
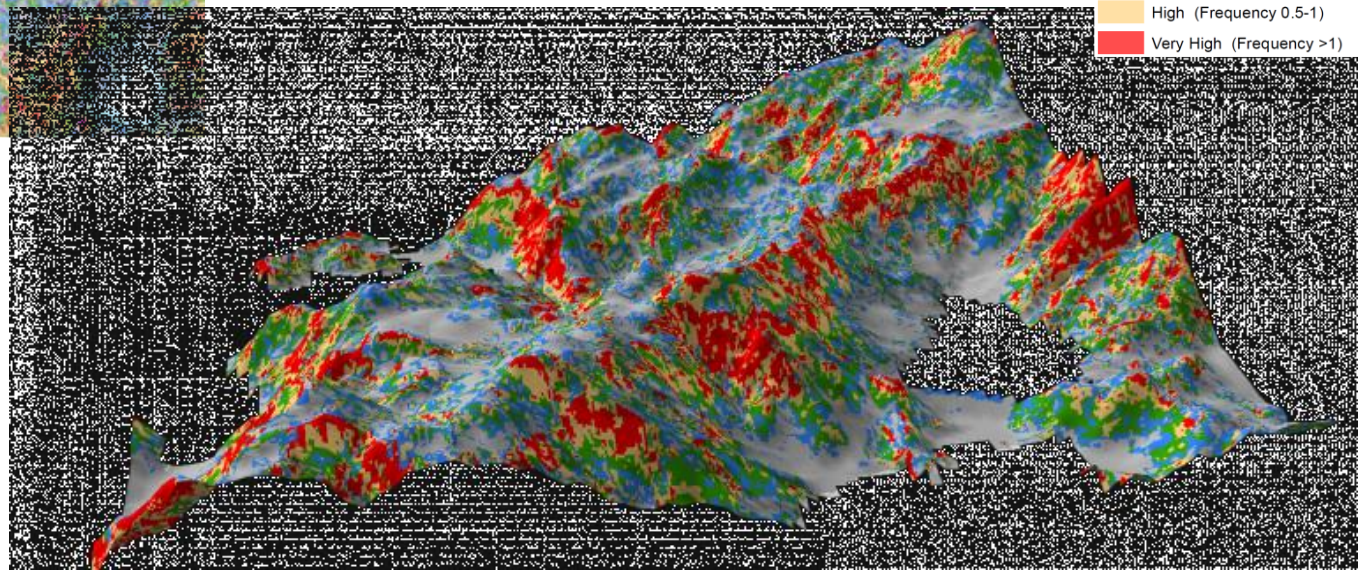
Remote Sensing

AI-driven susceptibility mapping from DTM's

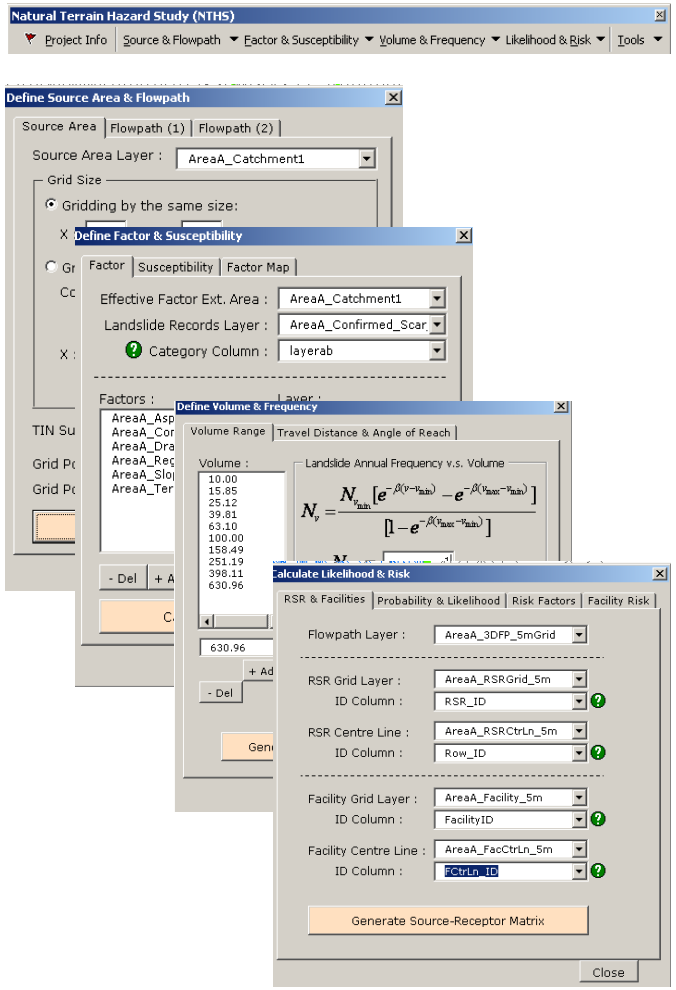


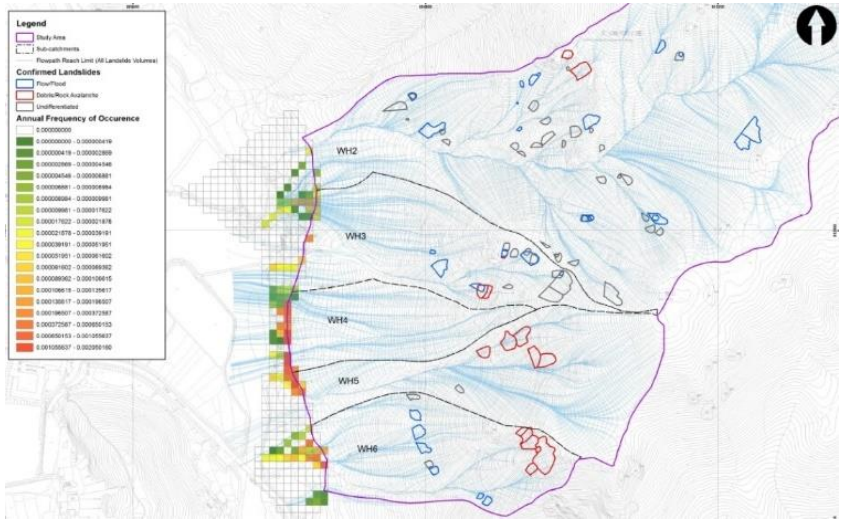


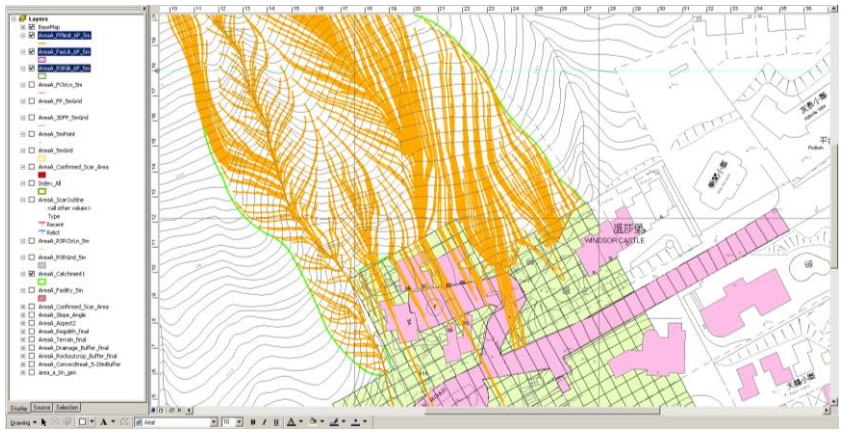


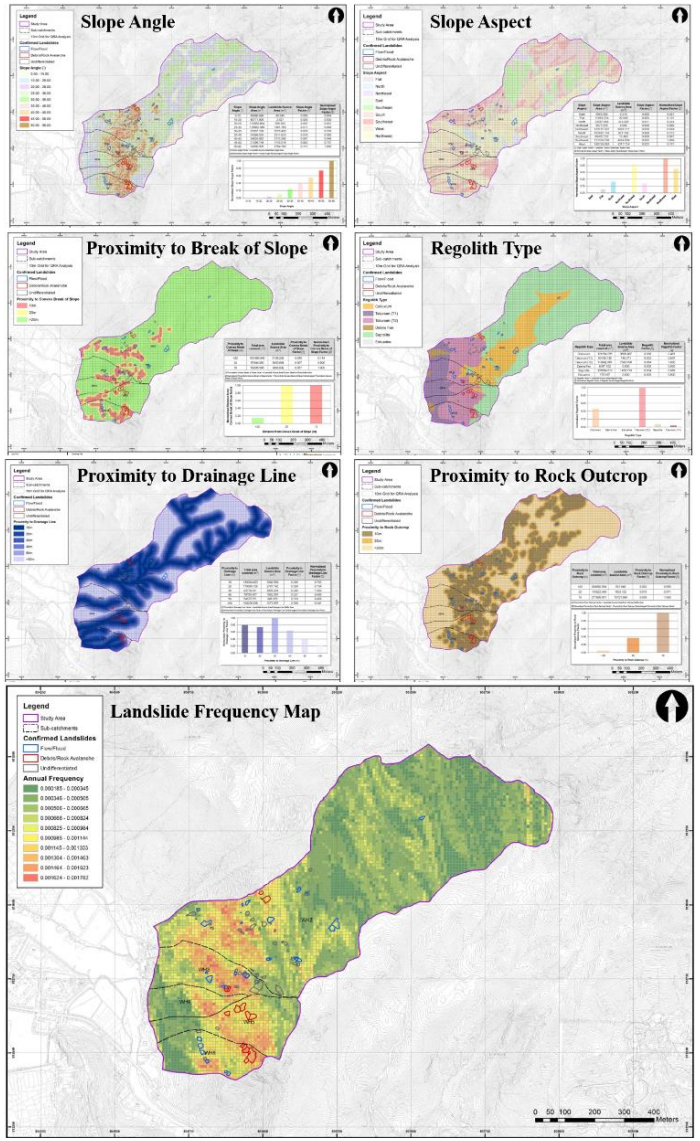
Remote Sensing

even enabling semi-automated risk assessment



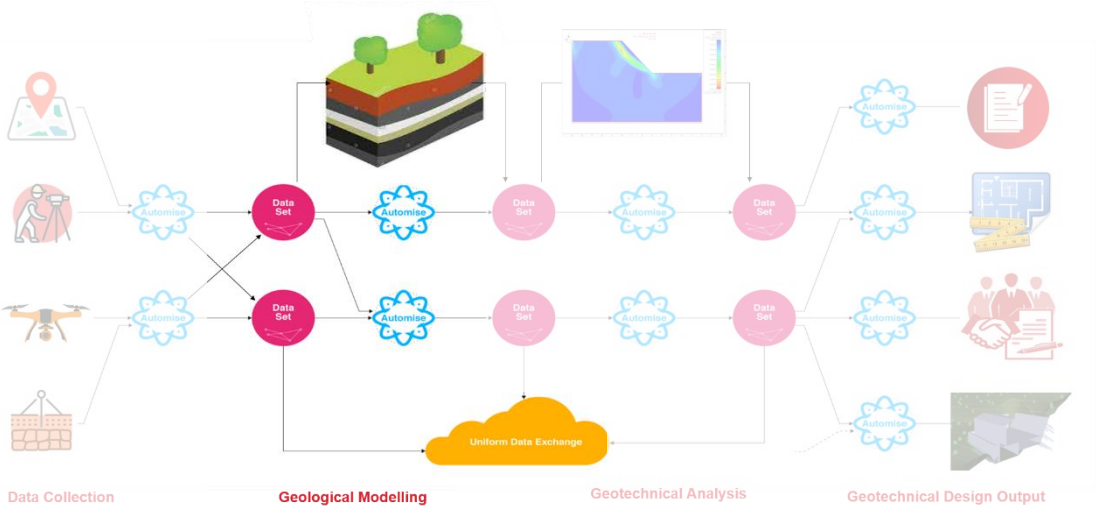


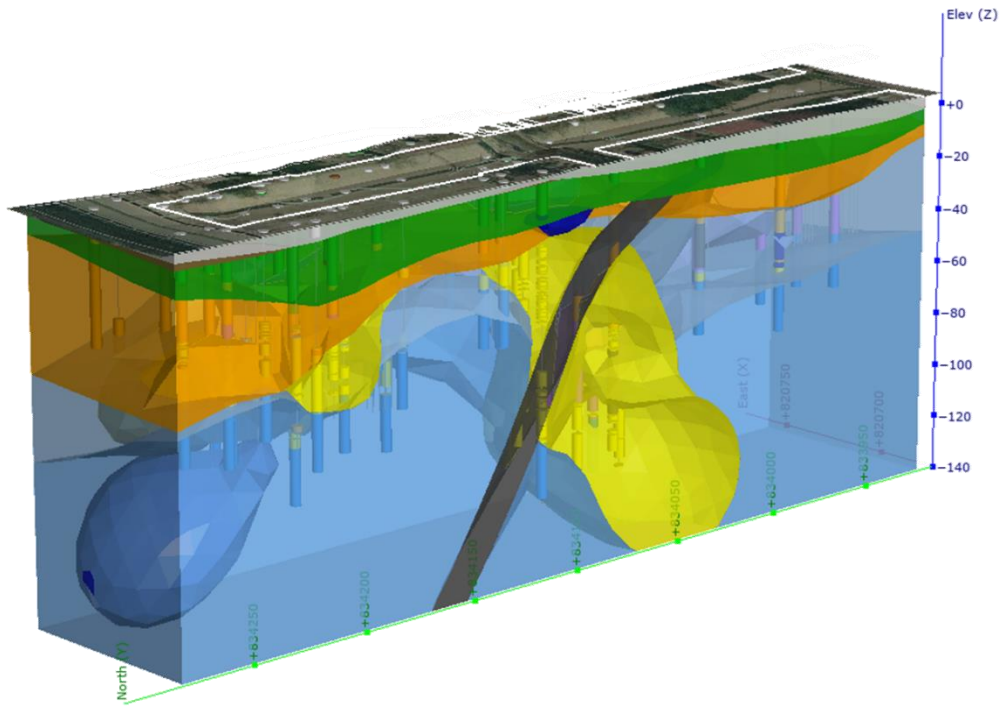


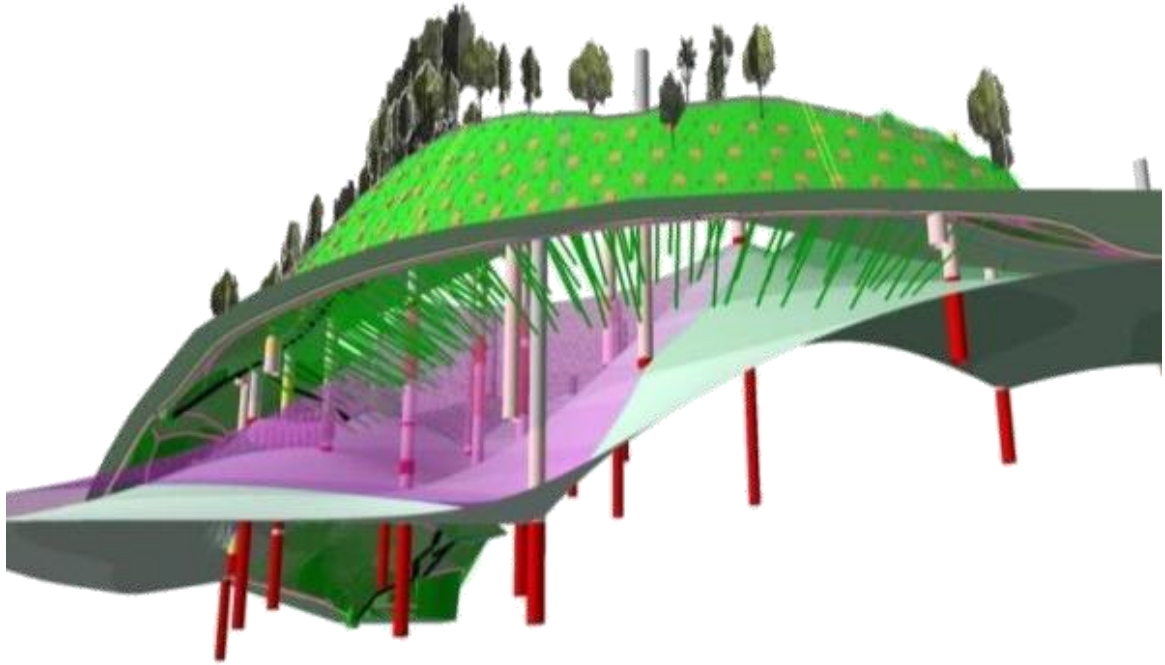


Geological Modelling

avoiding anything unforeseen





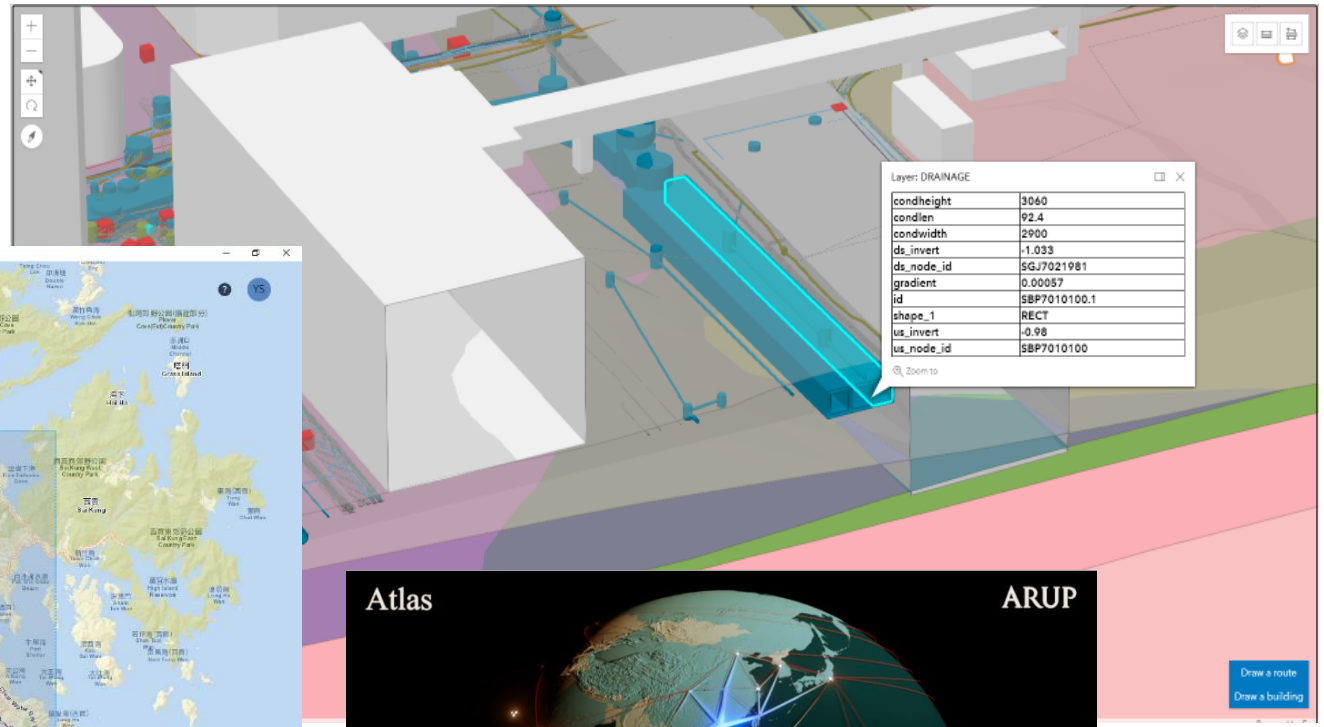


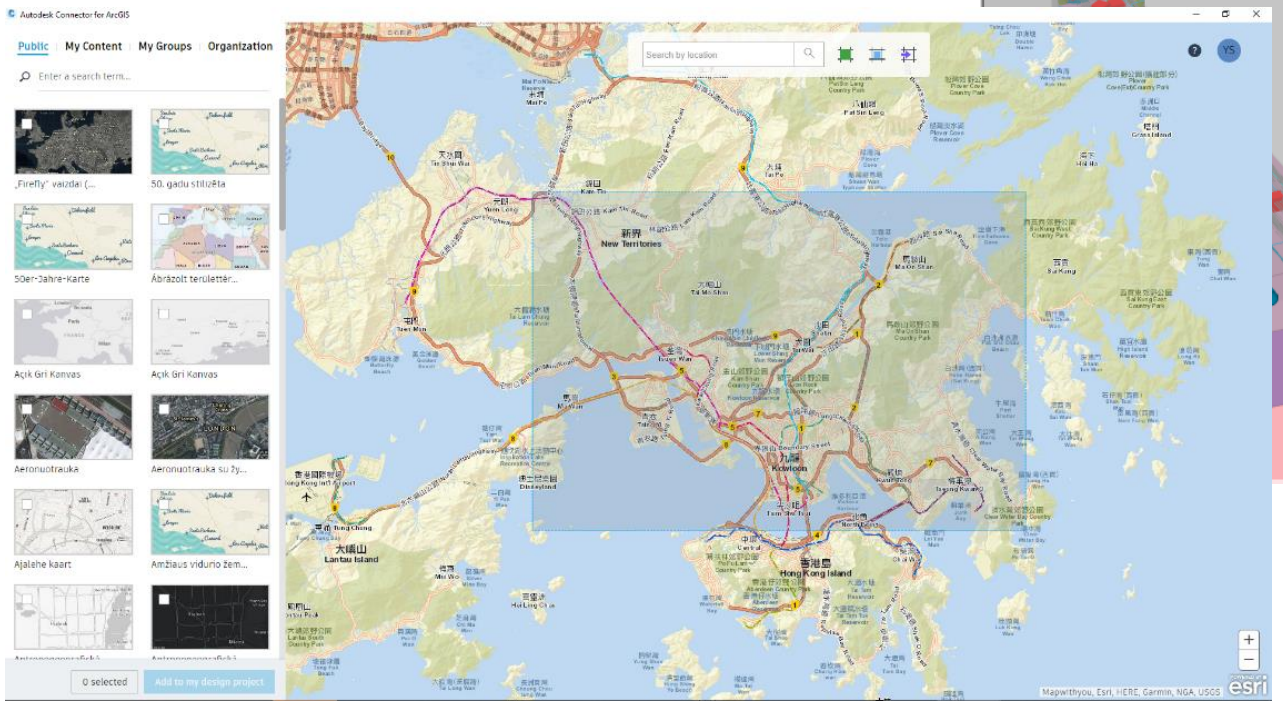
Data Management

existing mapped datasets

collating, managing and visualizing existing data

Atlas GIS Management of Datasets



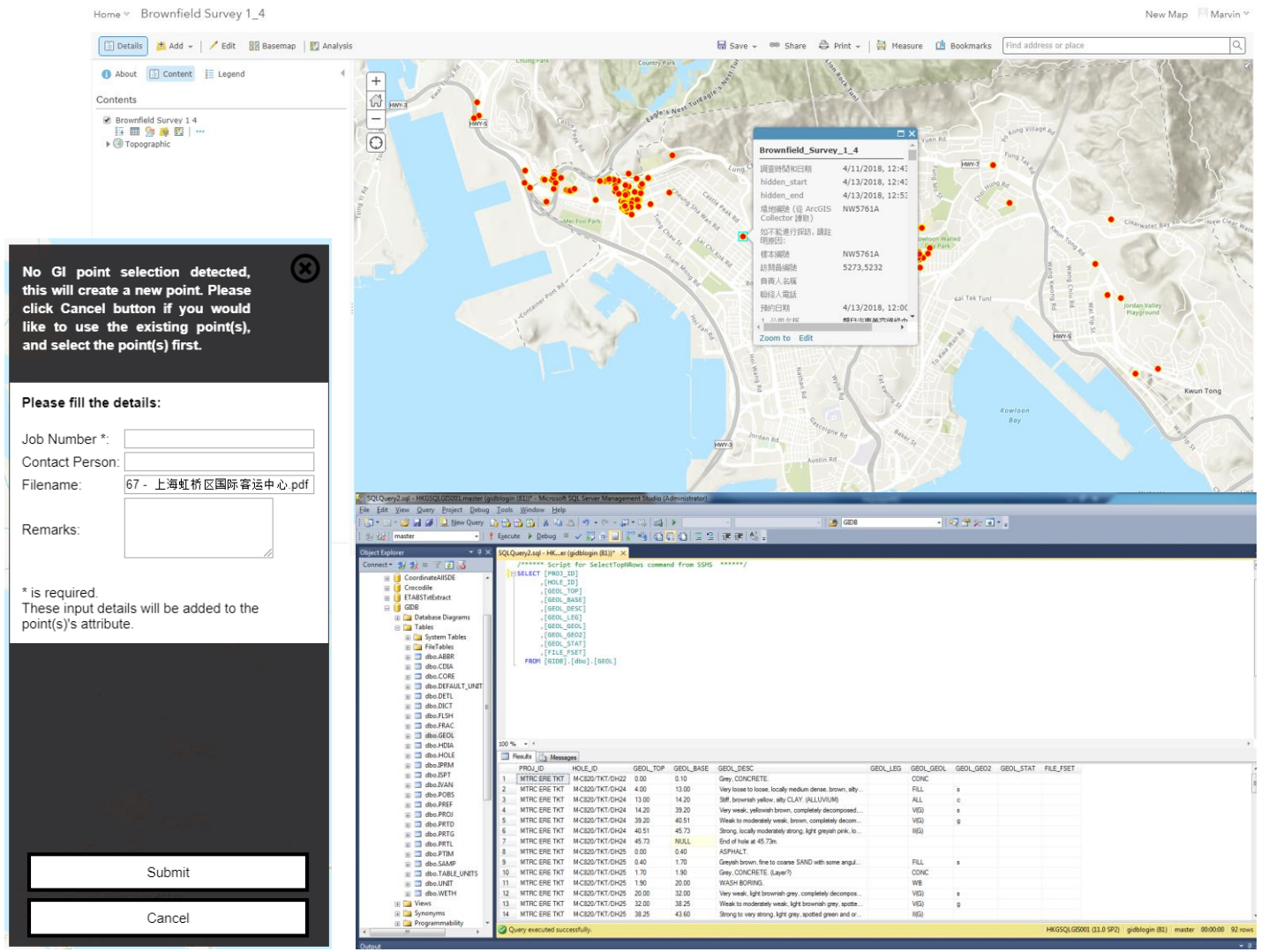


Data Management

site investigation data

standard data taxonomy and storage locations

In-house Spatial Data Infrastructure for AGS Records



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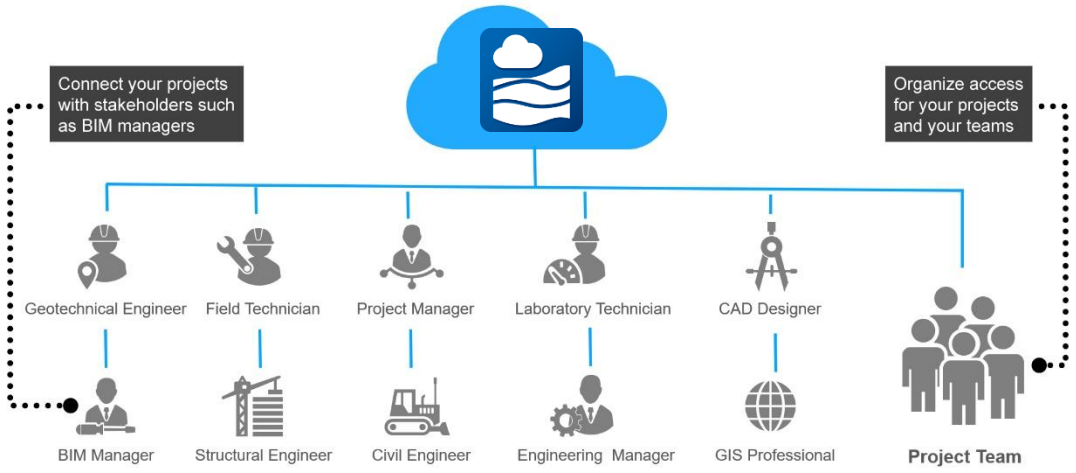
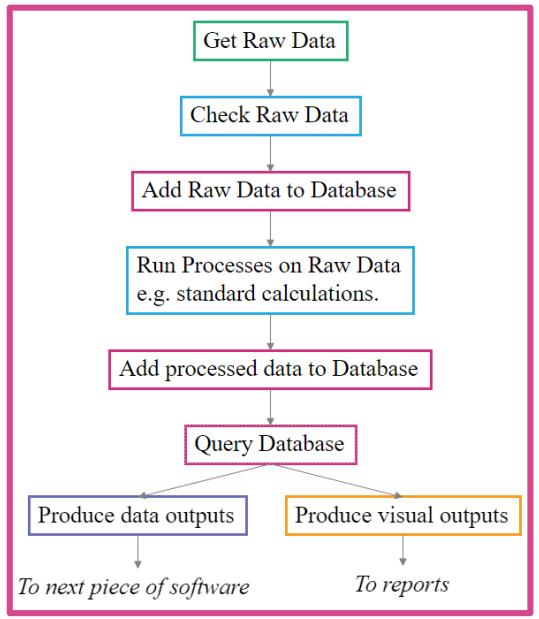
Data Management

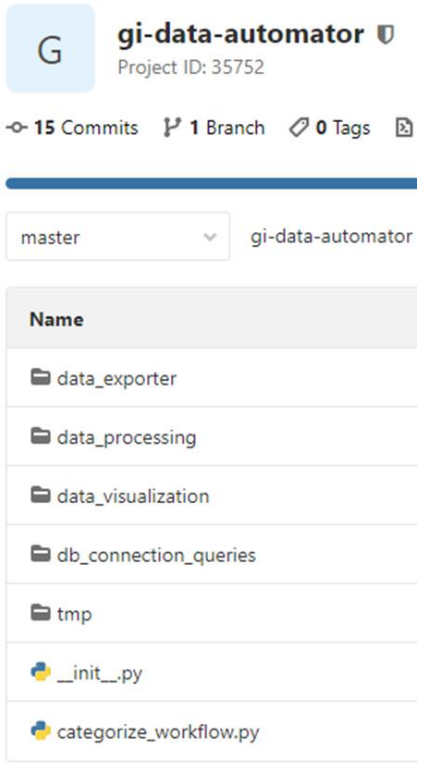
consistency is key

to enable consistent processing, retrieval, interrogation and linkage between platforms



Automated processing of AGS data





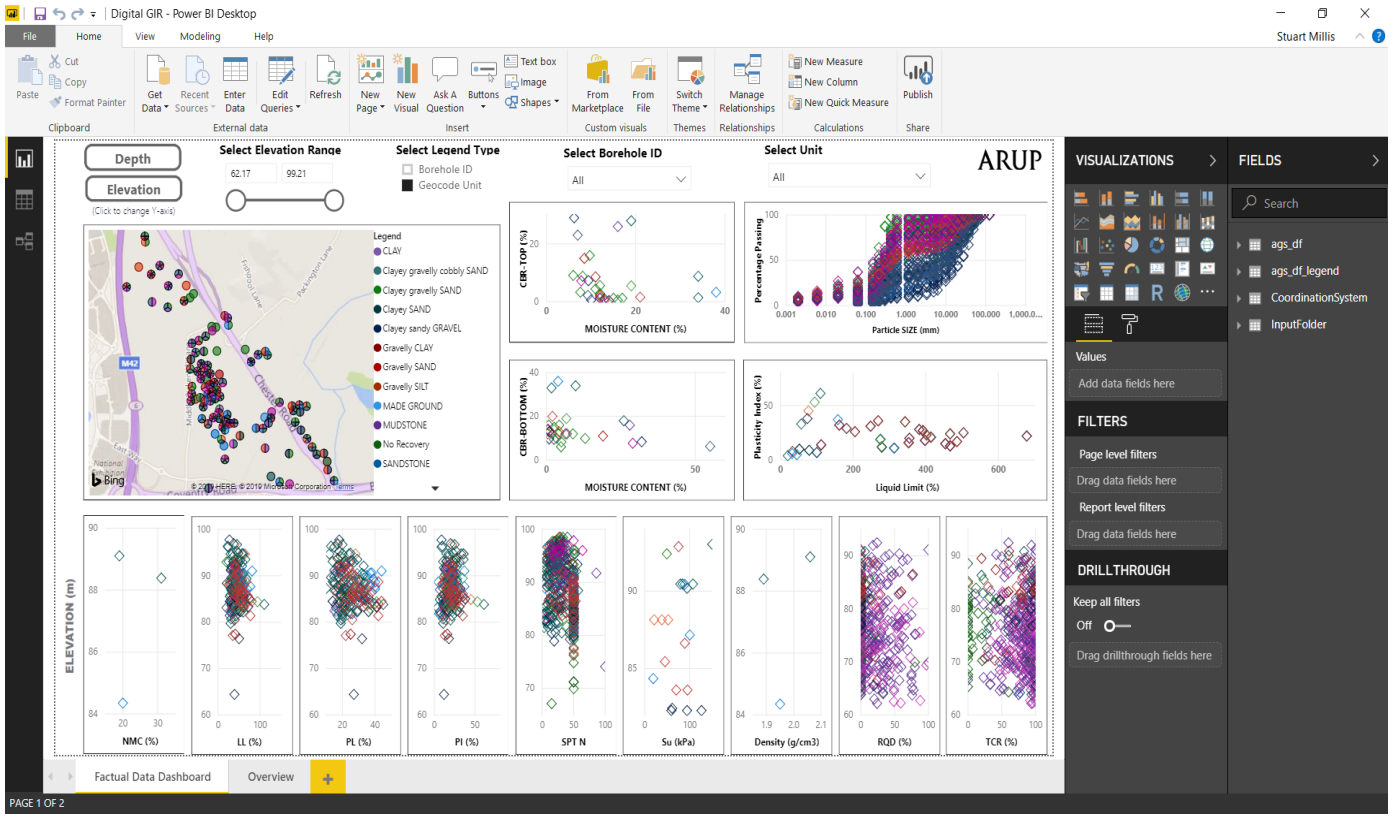
Data Management

consistency is key

to enable consistent retrieval and interrogation (and sharing)

Power BI

Dashboard for Data Assessment



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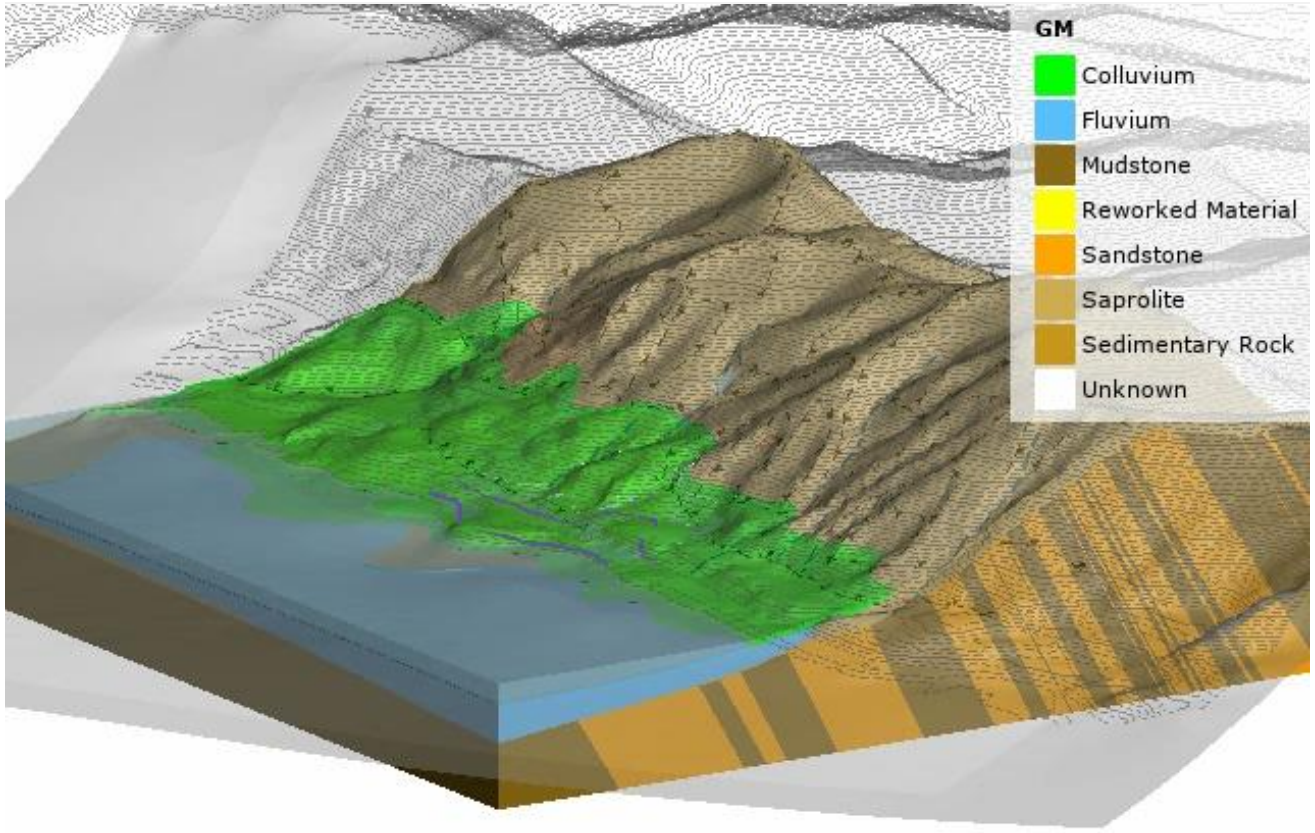
Geological Modelling

working in three-dimensions

and easy integration with modelling packages

Leapfrog Modelling



leapfrog®
FAST, DYNAMIC GEOLOGICAL MODELLING

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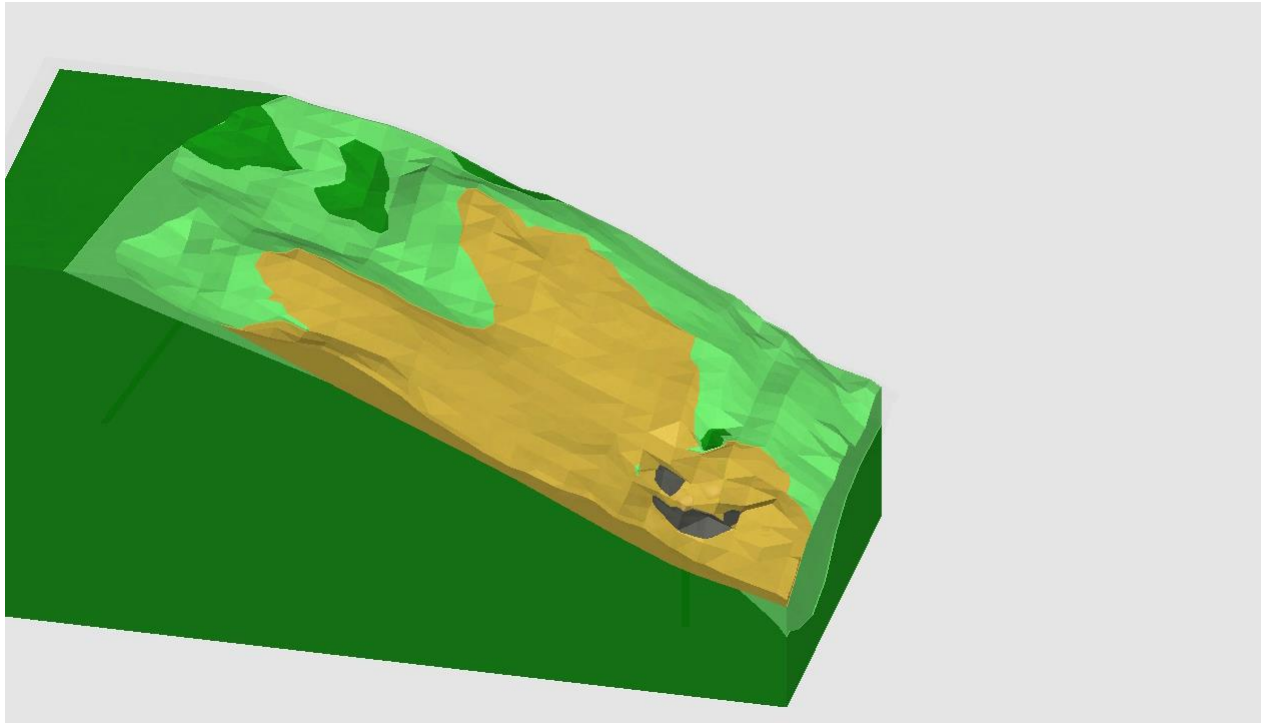
Geological Modelling

working in three-dimensions

preferably also integrating BIM models for the engineering works too

Leapfrog Modelling

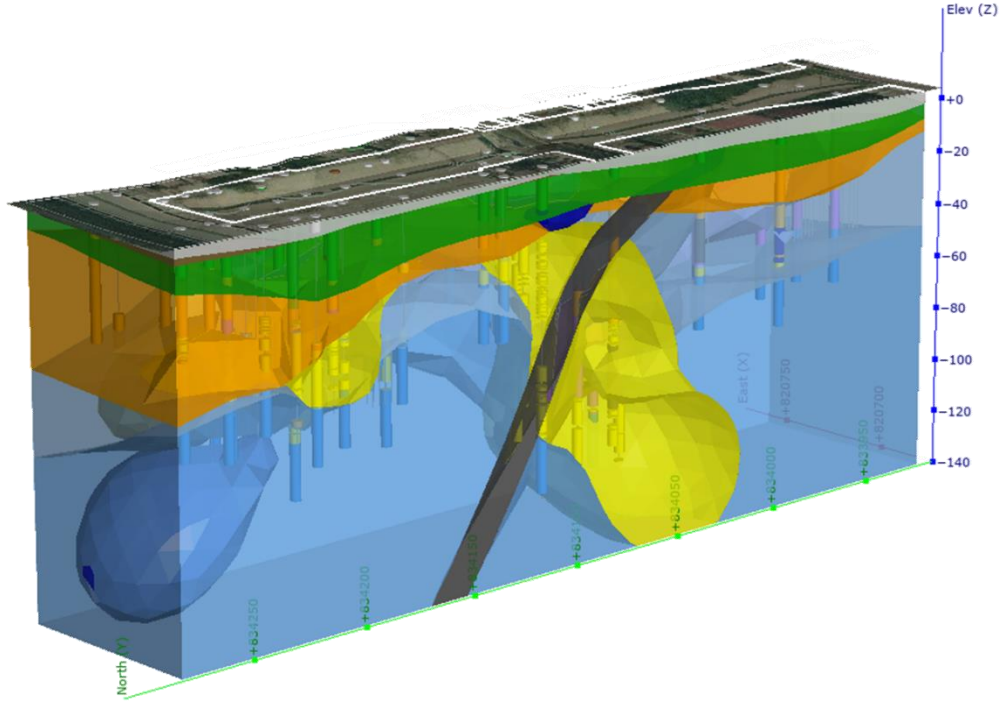


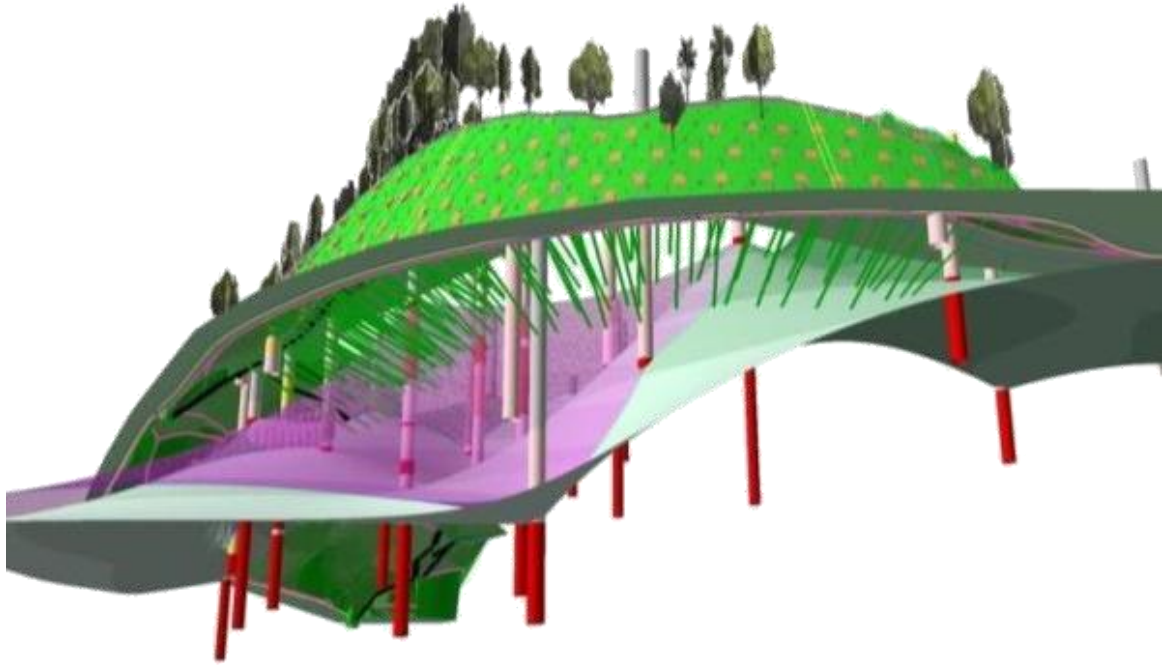
leapfrog®
FAST, DYNAMIC GEOLOGICAL MODELLING

Geological Modelling

avoiding anything unforeseen

and communicating ground conditions and ground related risks in easily digestible formats





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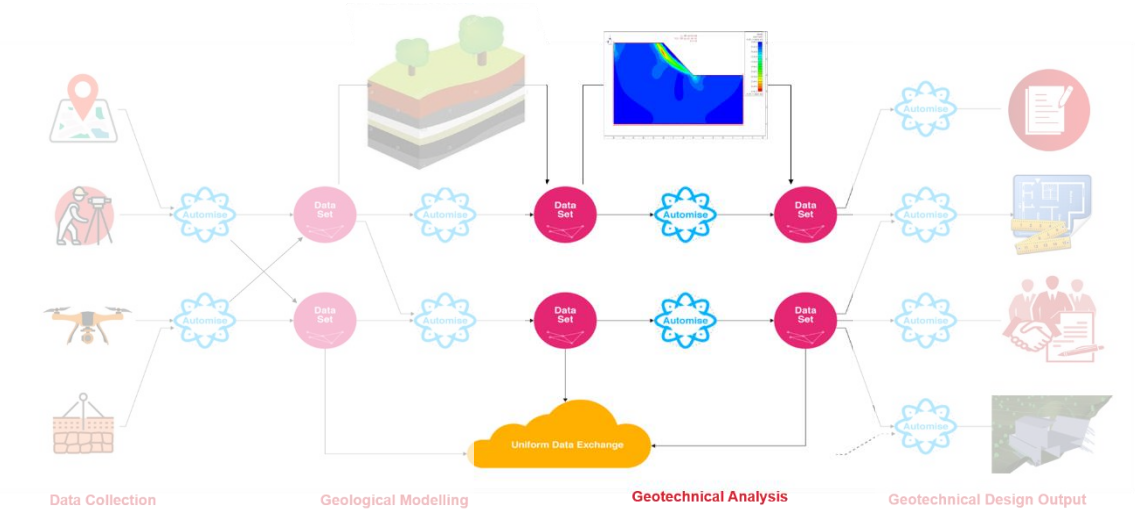
Geological Modelling

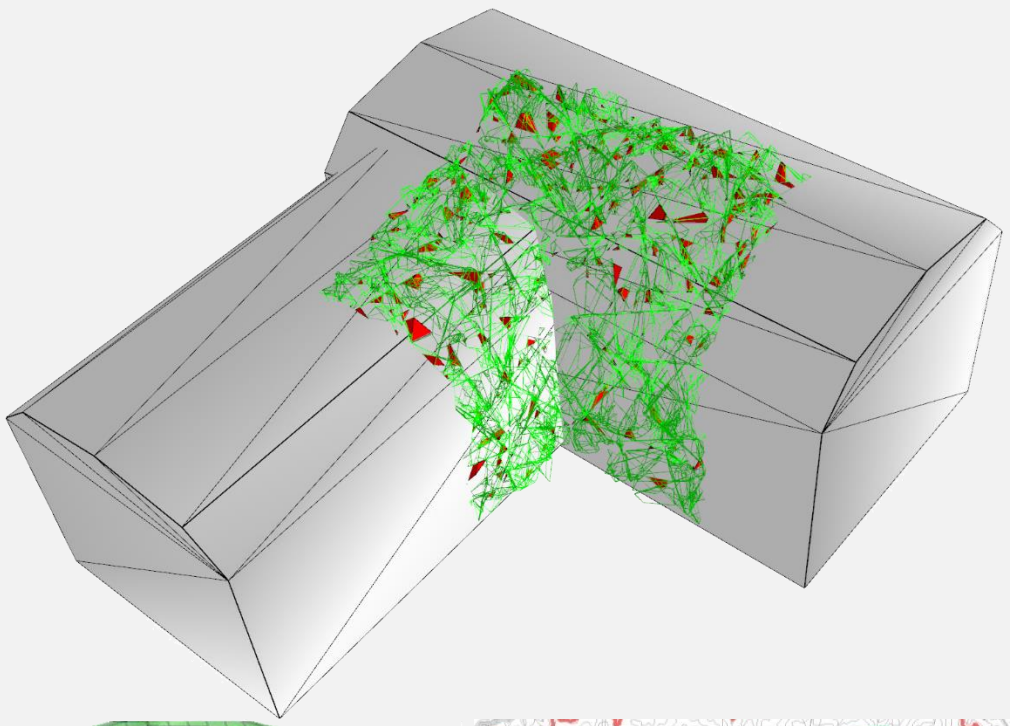
working in three-dimensions

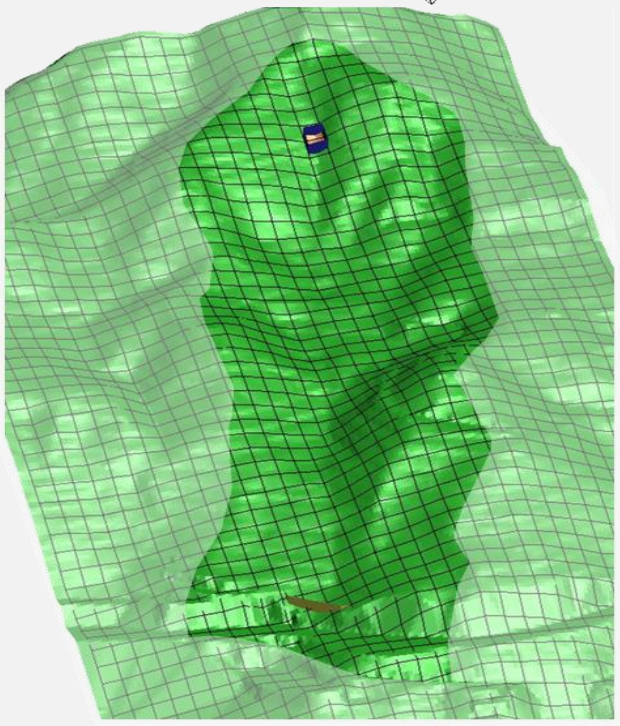
but never forgetting the
need for specialist input
from engineering geologists

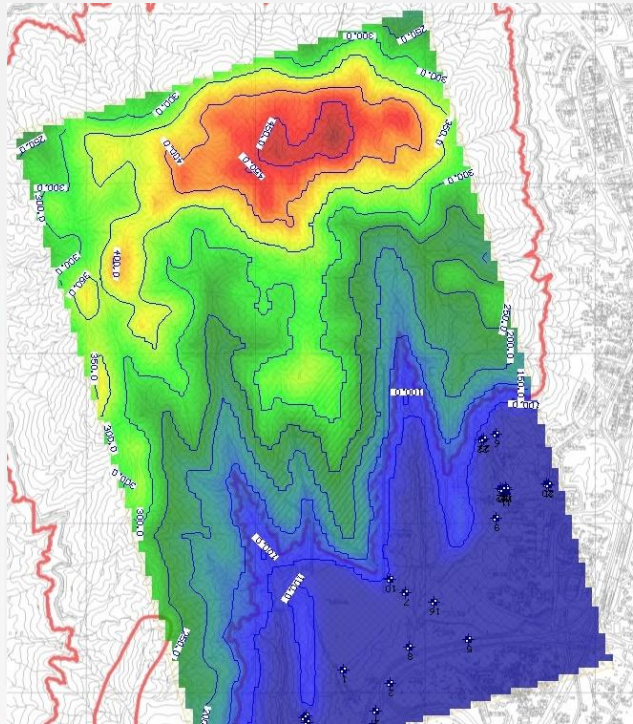
Geotechnical Analysis

making relieable predictions





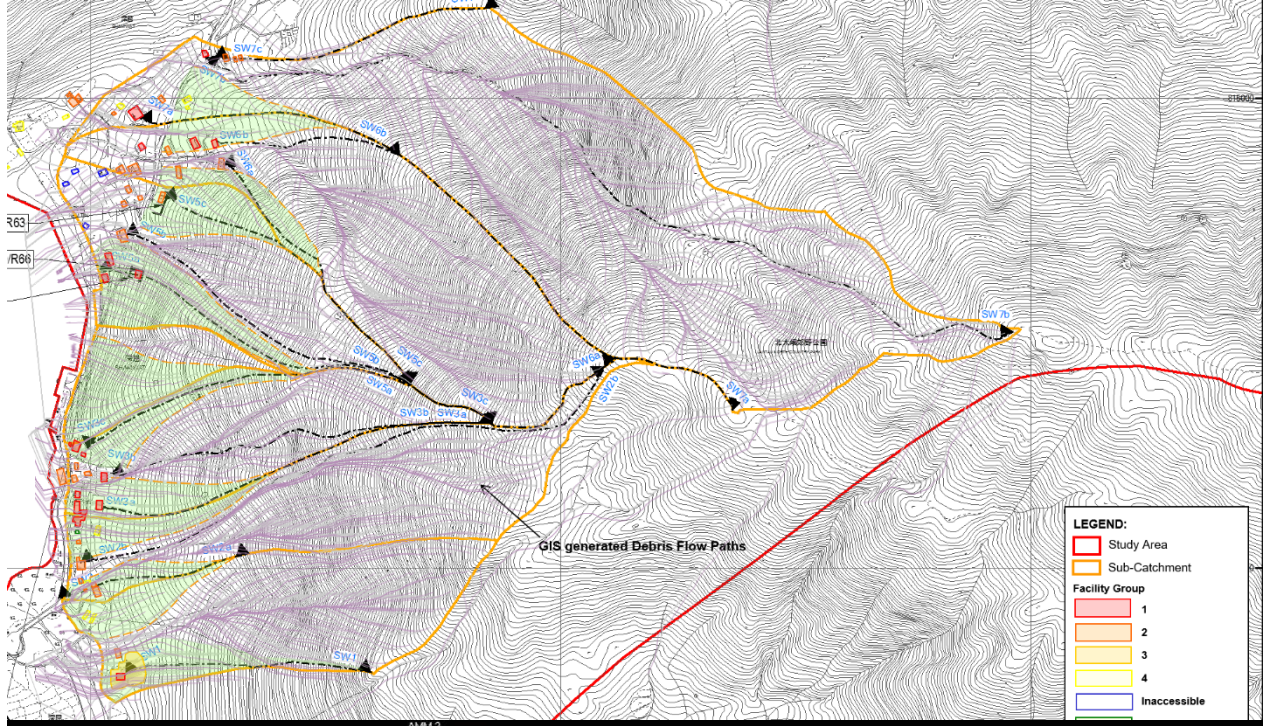


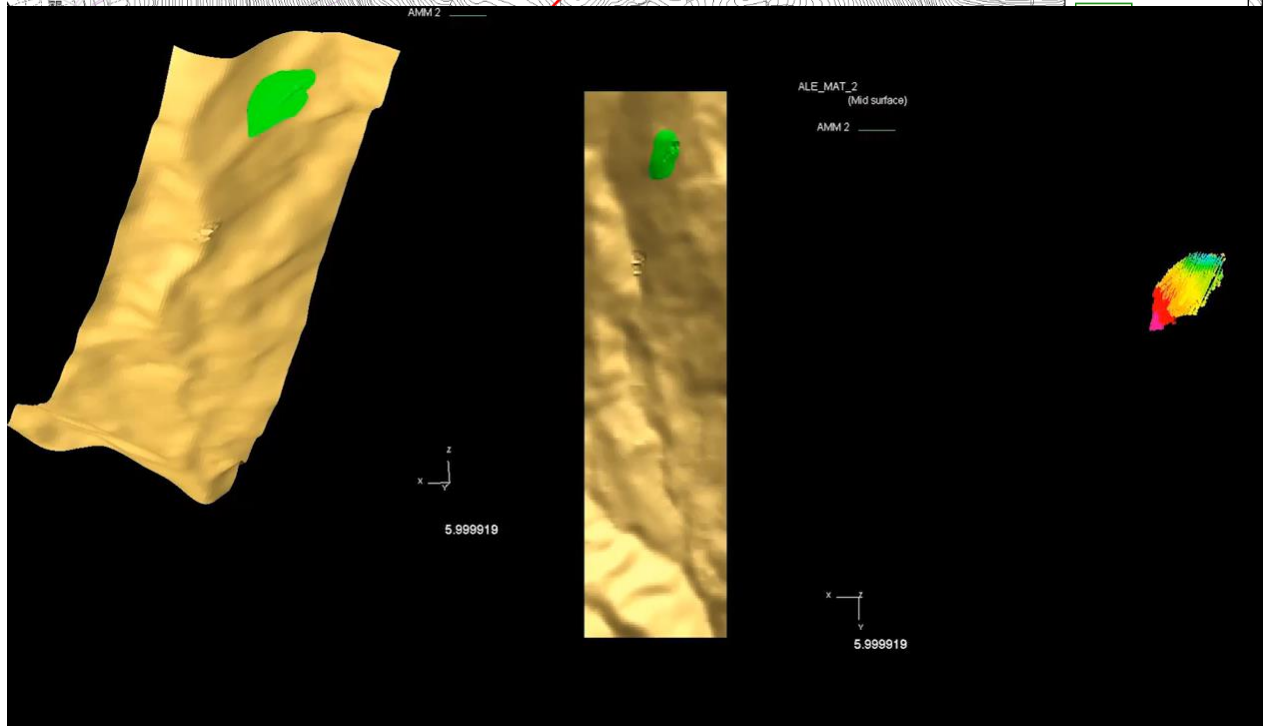


Complex Modelling

integrating our tools

making good use of the datasets that have been collected





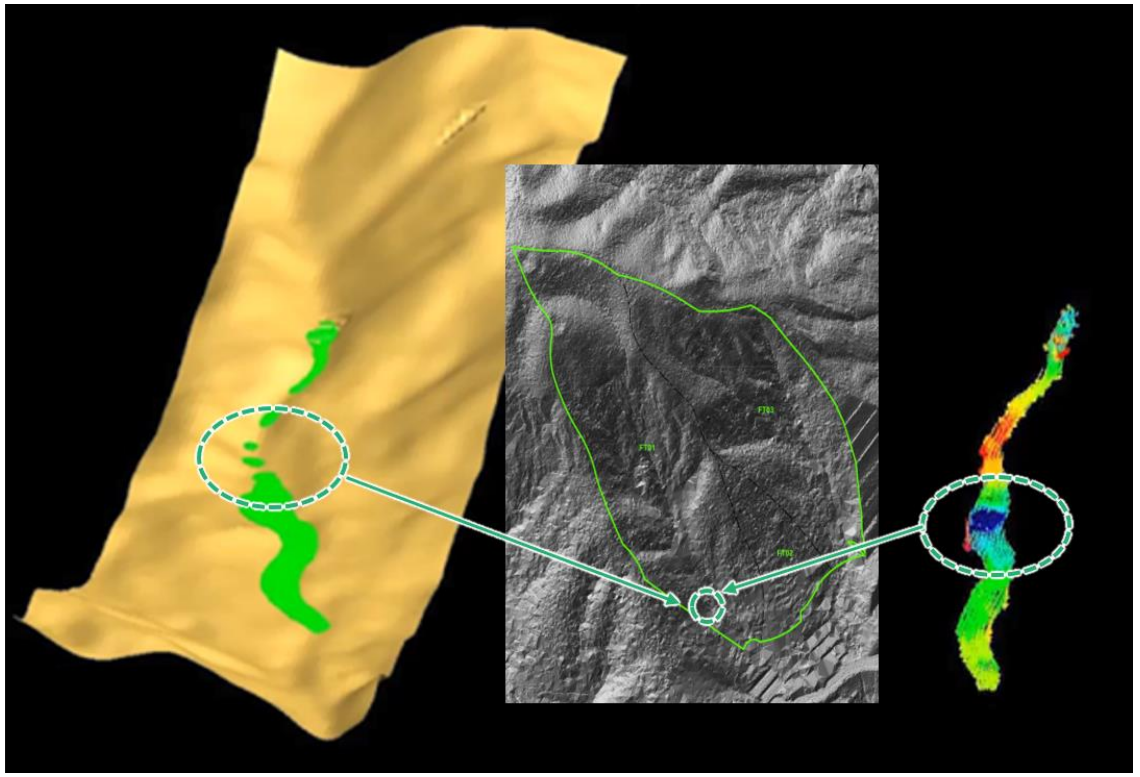
Complex Modelling

integrating our tools

to facilitate informed
decision making

LS-DYNA

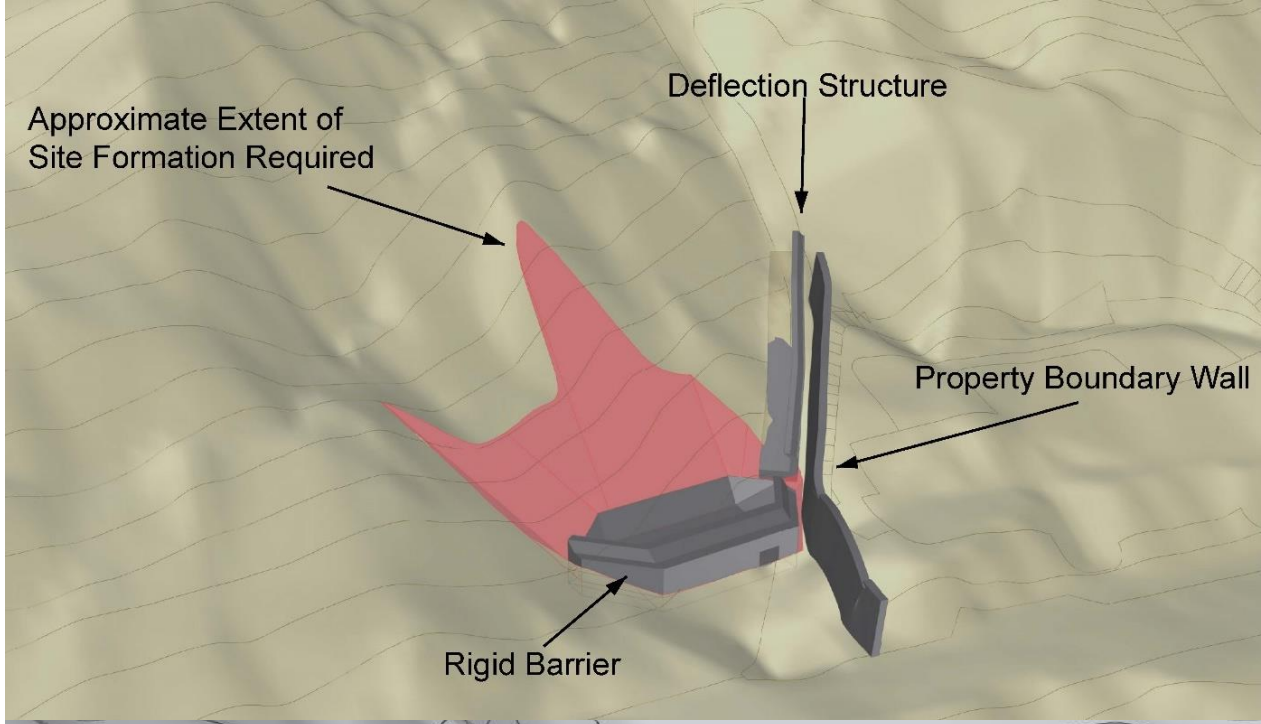
Optimal Barrier Positioning

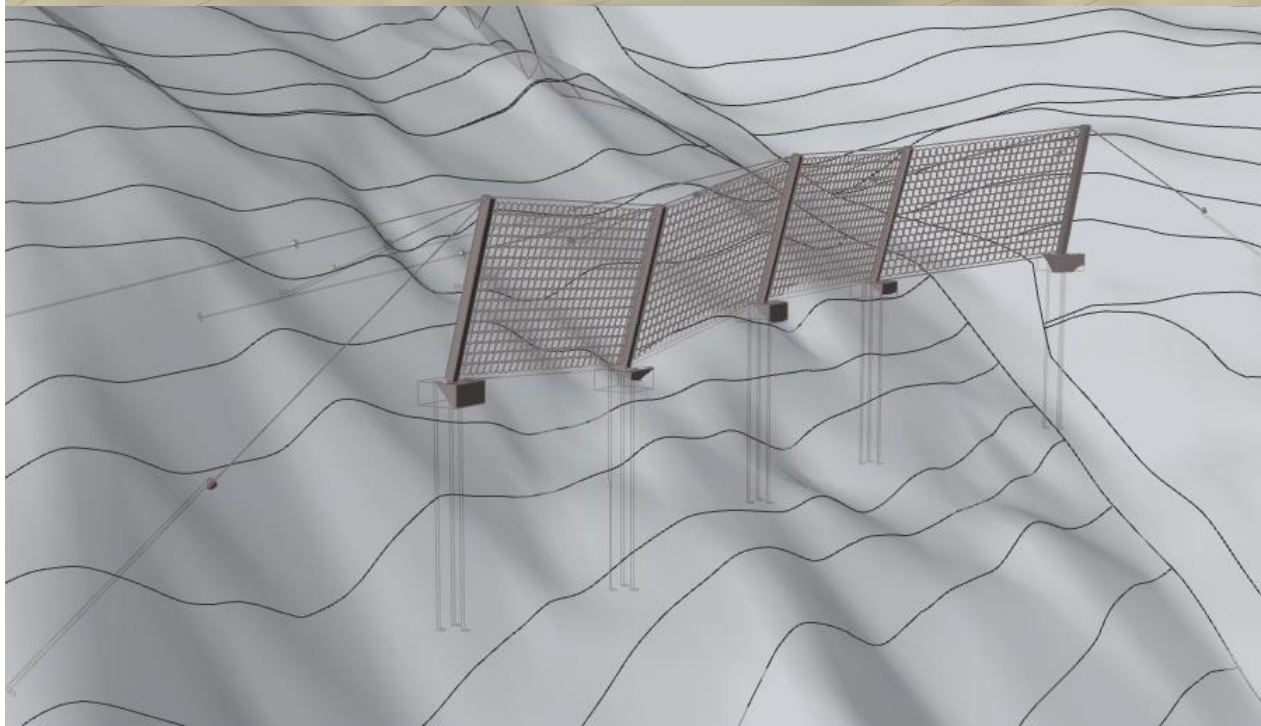


Complex Modelling

integrating our tools

and linking them with easy-to-use tools that facilitate rapid and visual designs





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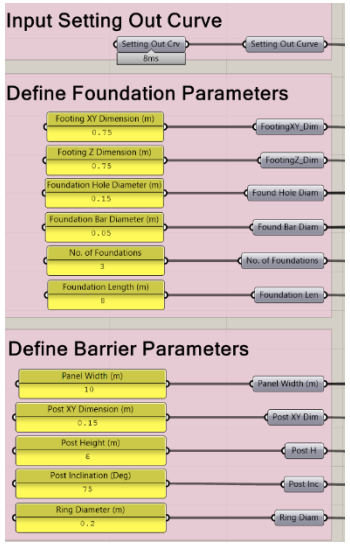
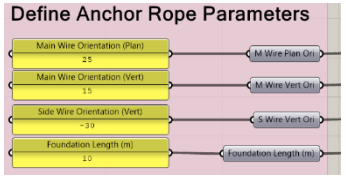
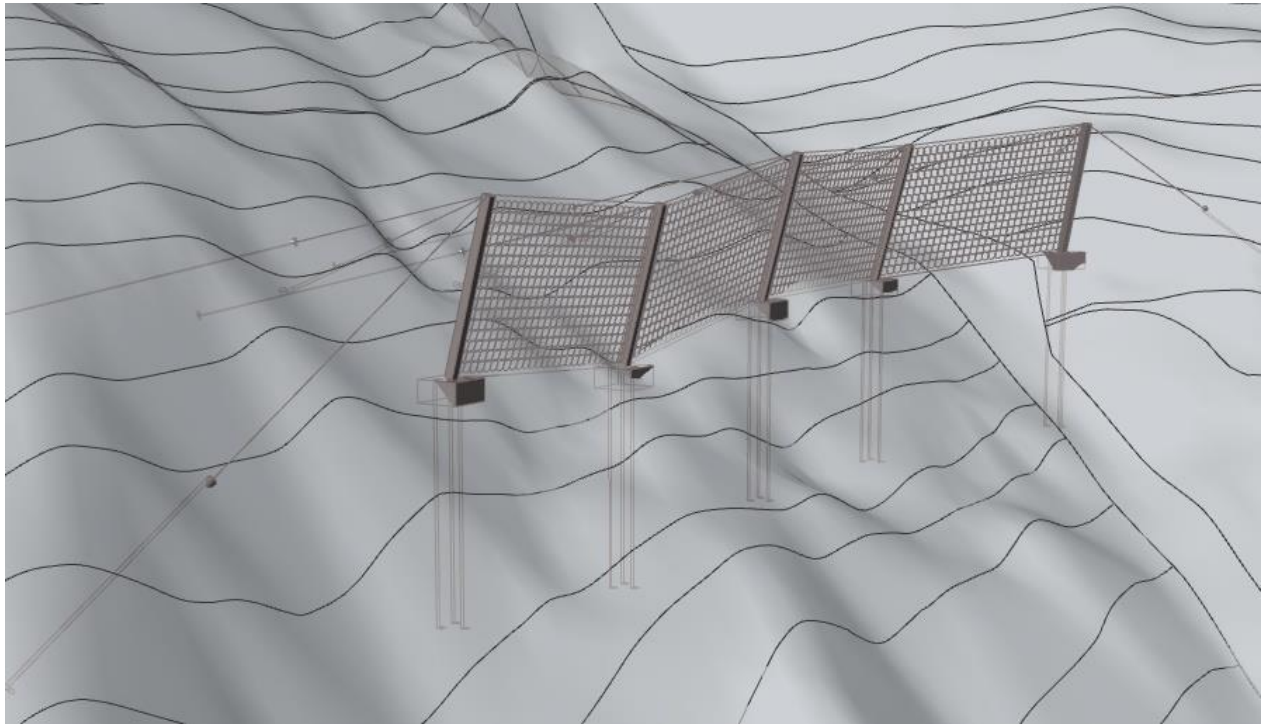
Complex Modelling

integrating our tools

that allow us to design within the actual site settings



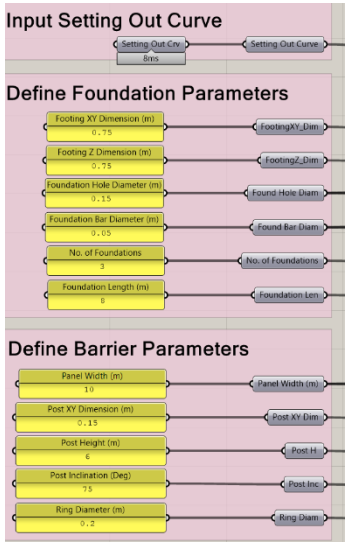


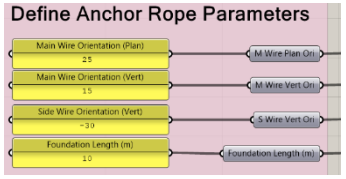


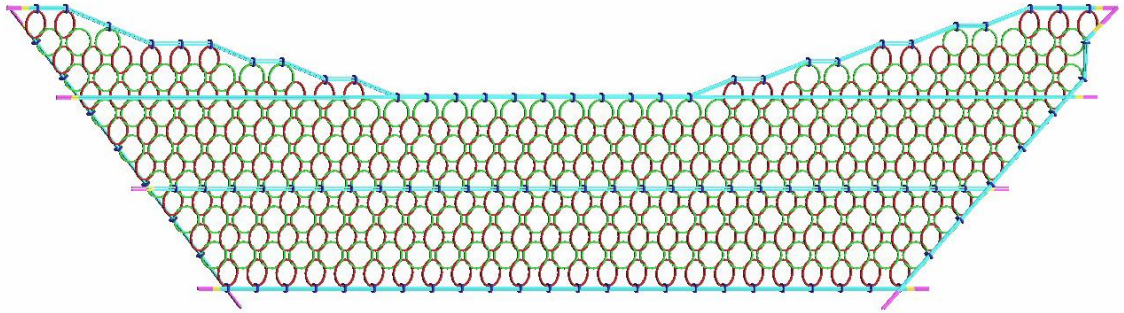
Complex Modelling

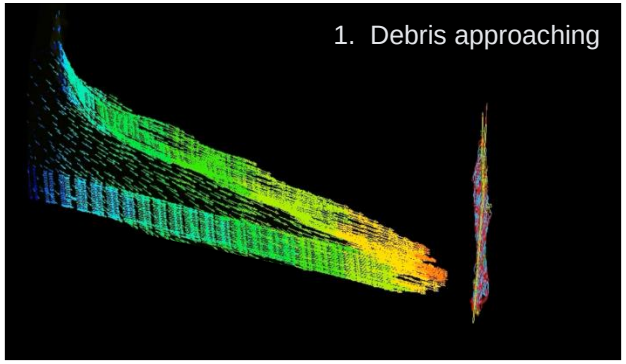
integrating our tools

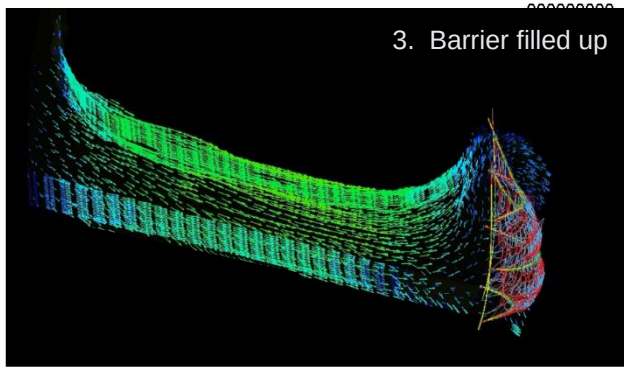
and then quickly and easily check the adequacy of the designs

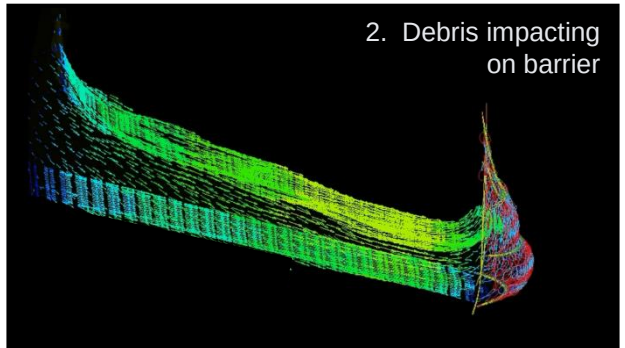


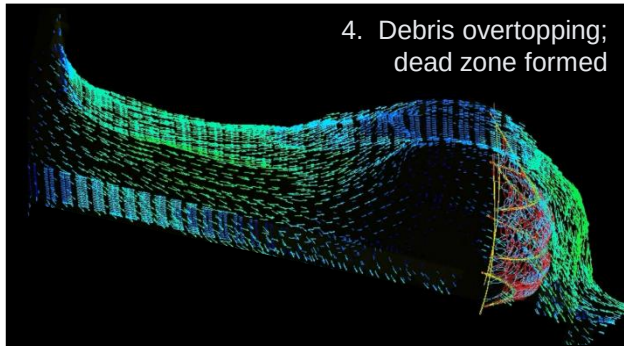








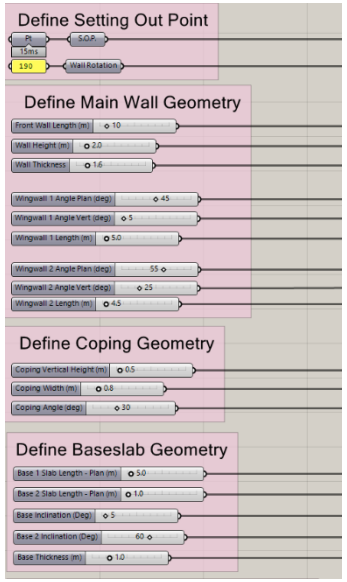


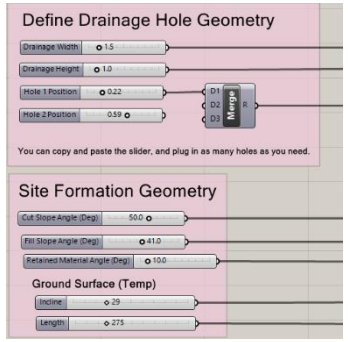


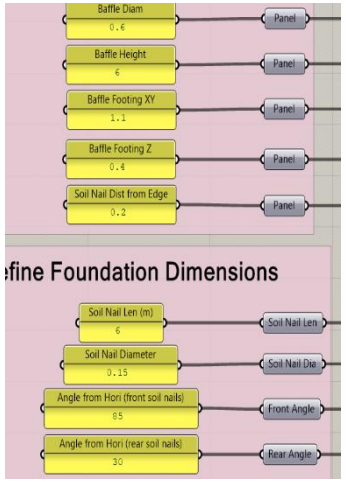
Complex Modelling

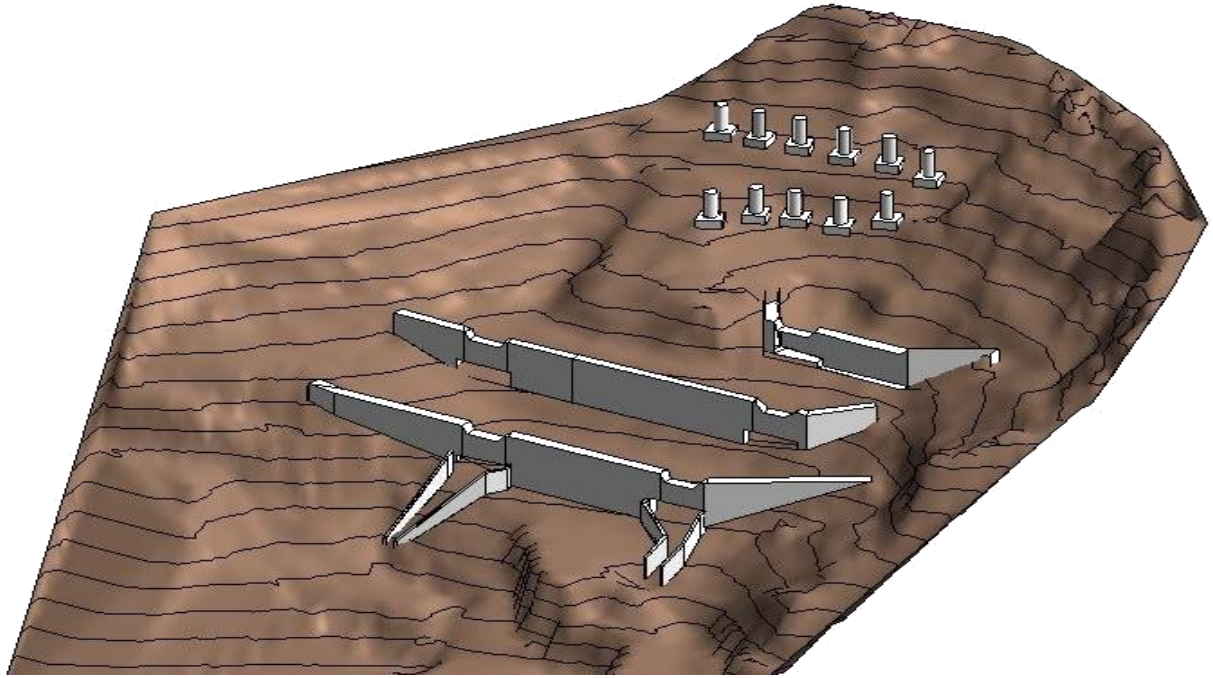
integrating our tools

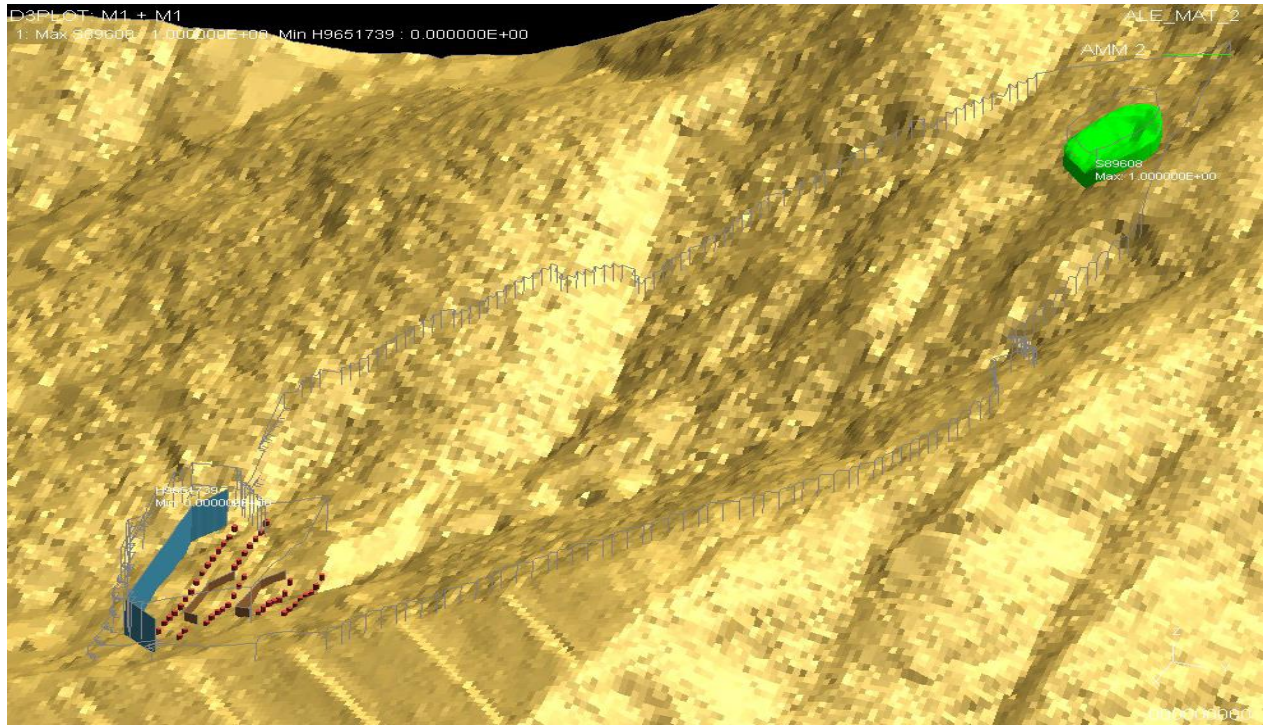
also enabling quick and easy refinement, where necessary









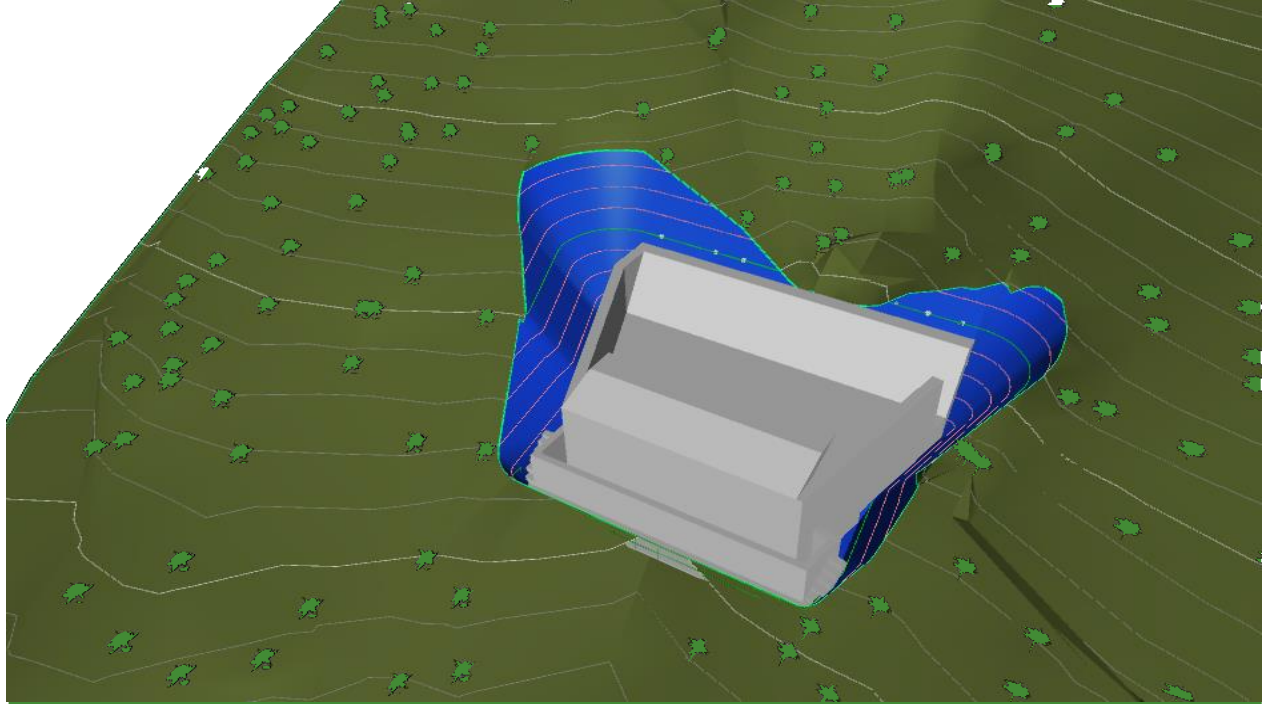


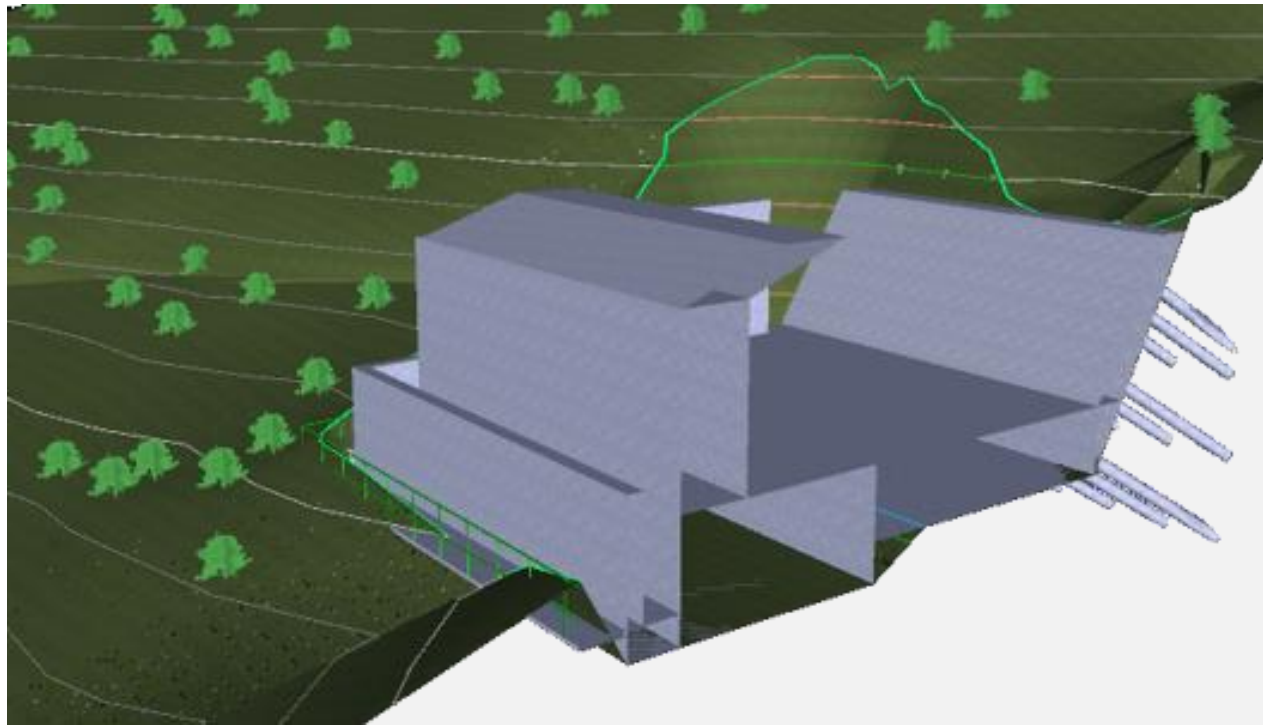
Complex Modelling

integrating our tools

and enabling transfer to
common model platforms

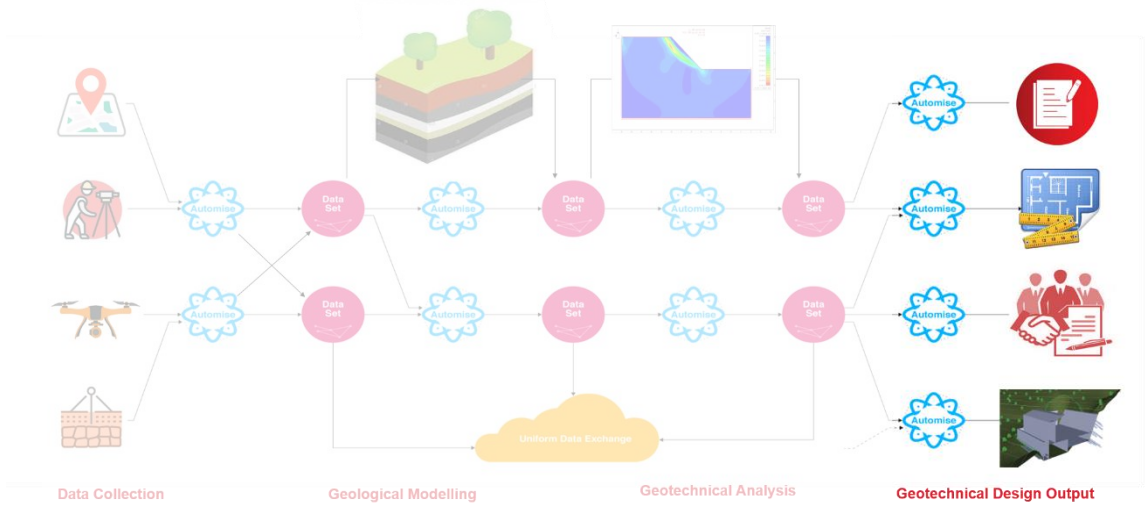
Rhino.Inside®.Revit

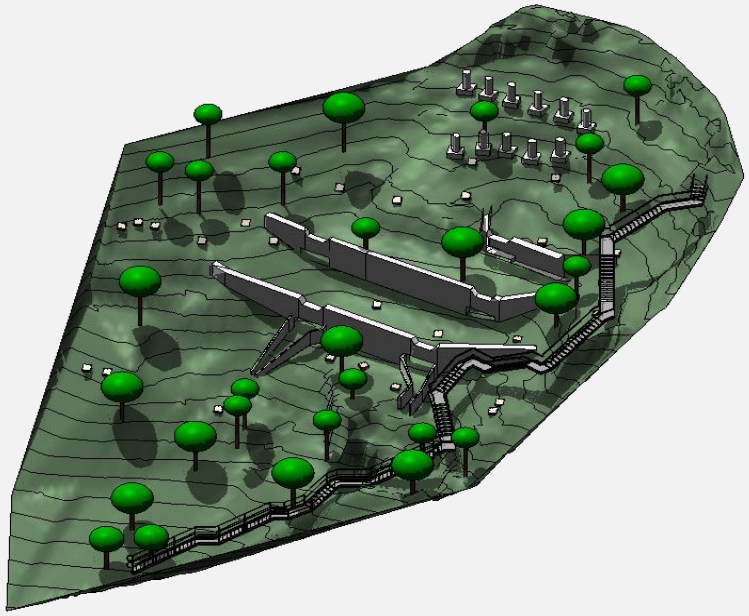


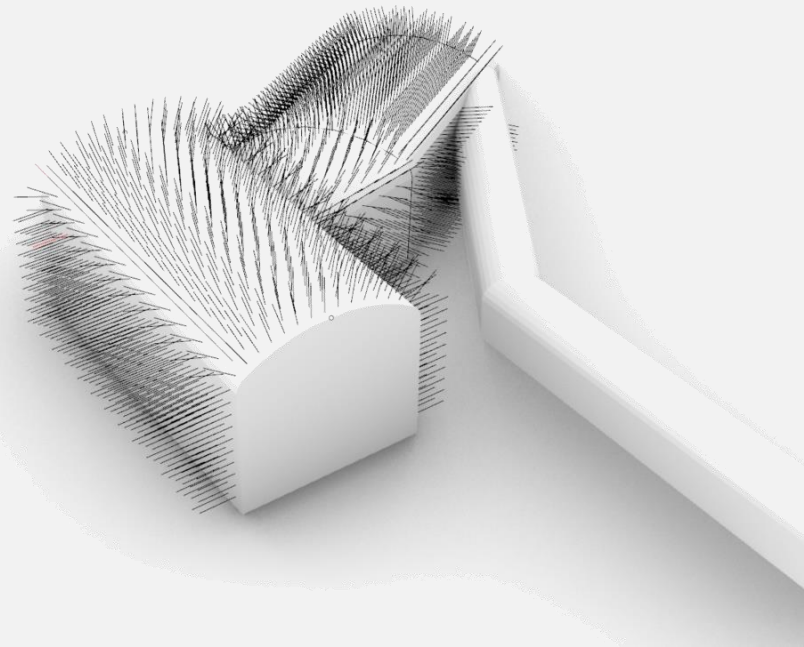


Geotechnical Design

connecting the dots



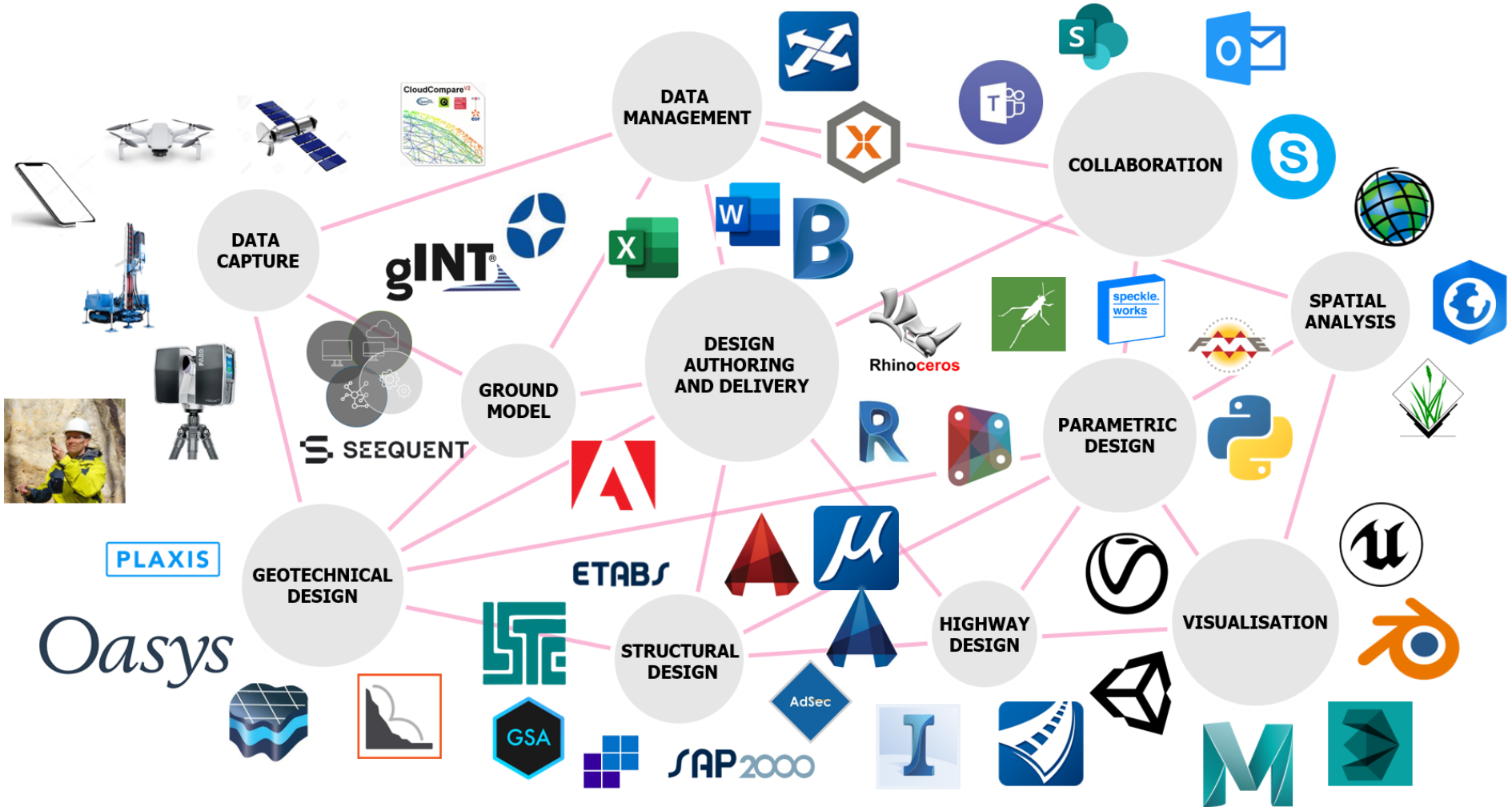




ARUP

Data Integration

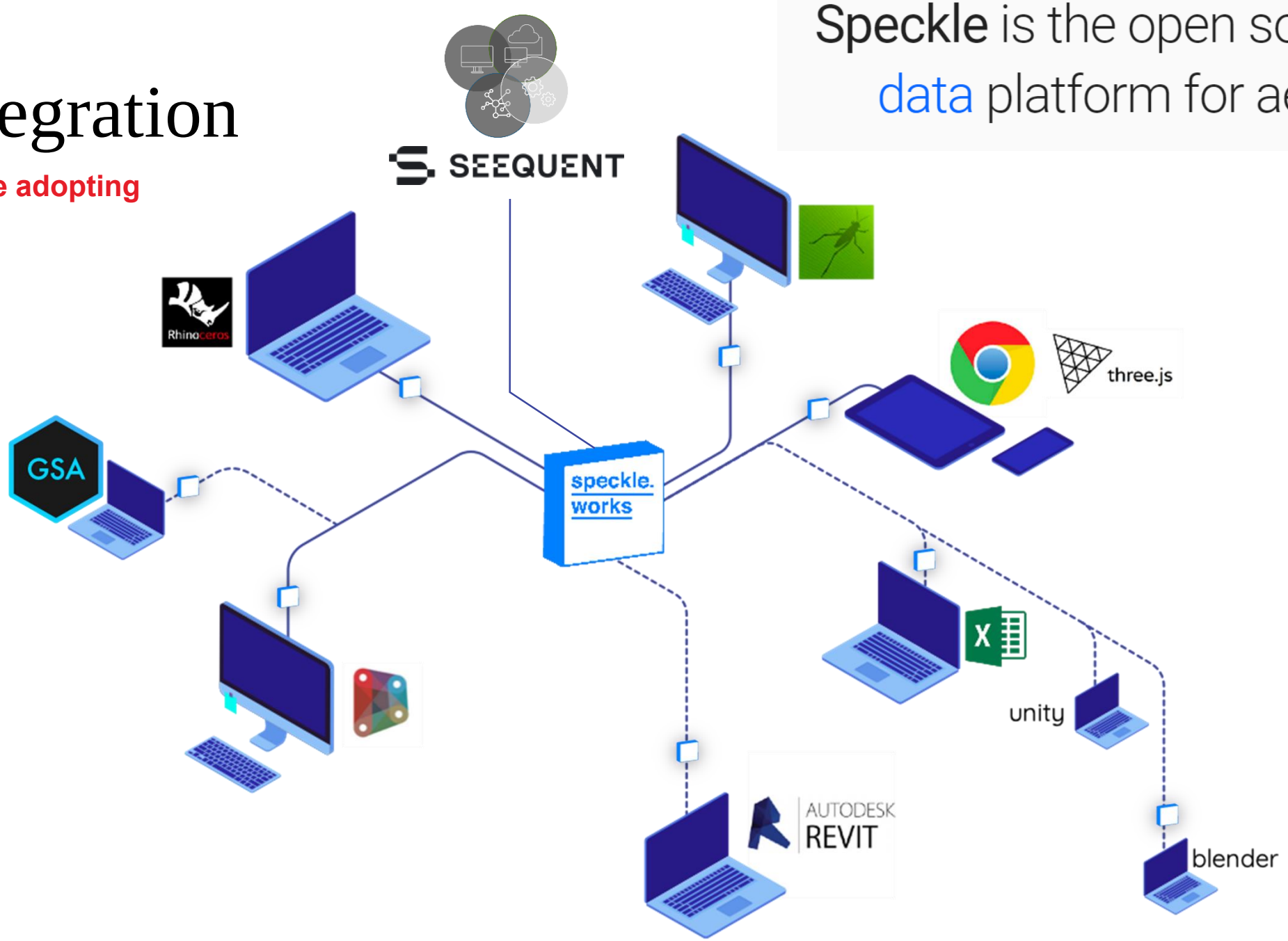
the situation we've all been facing



Data Integration

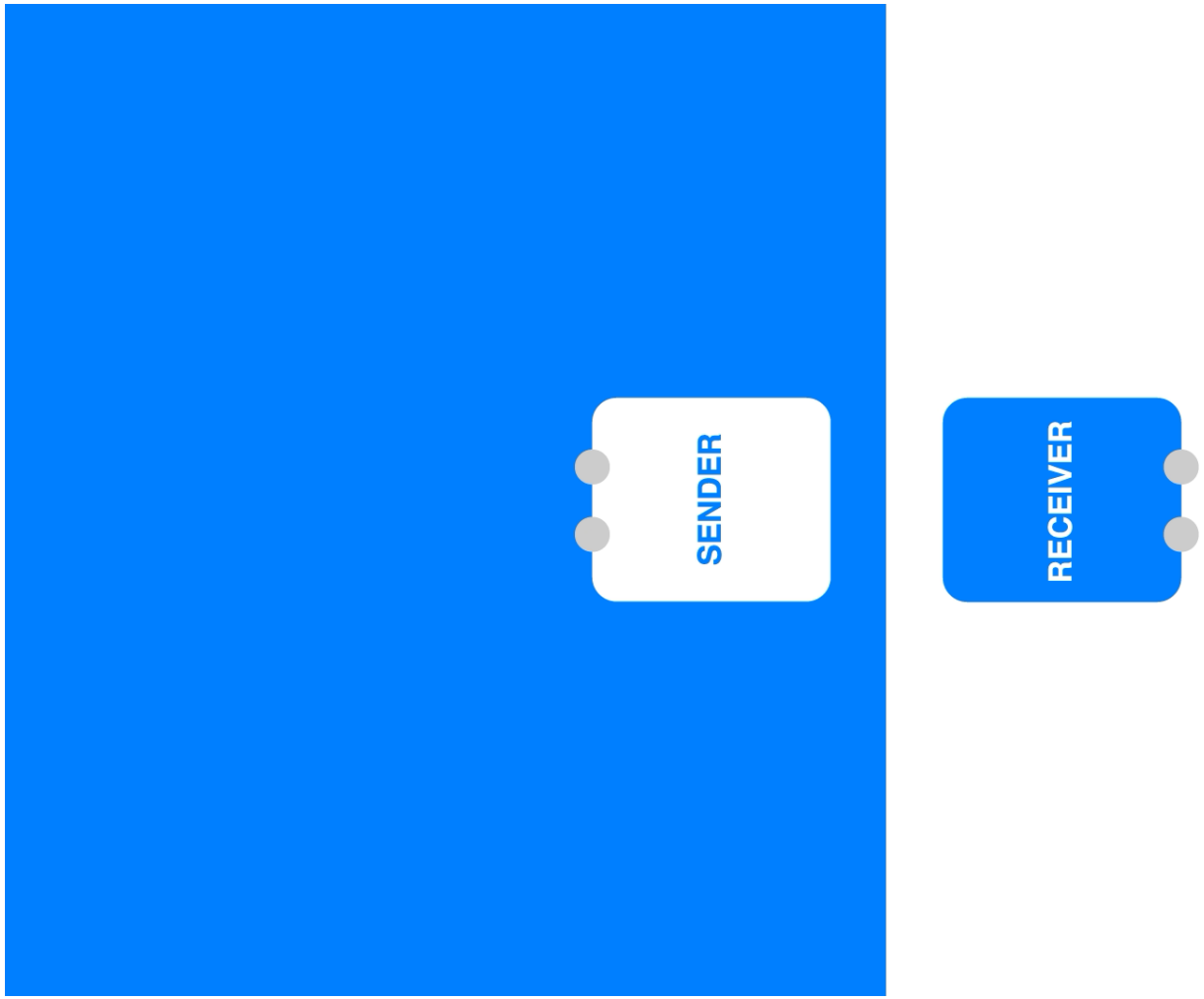
the solution we're adopting

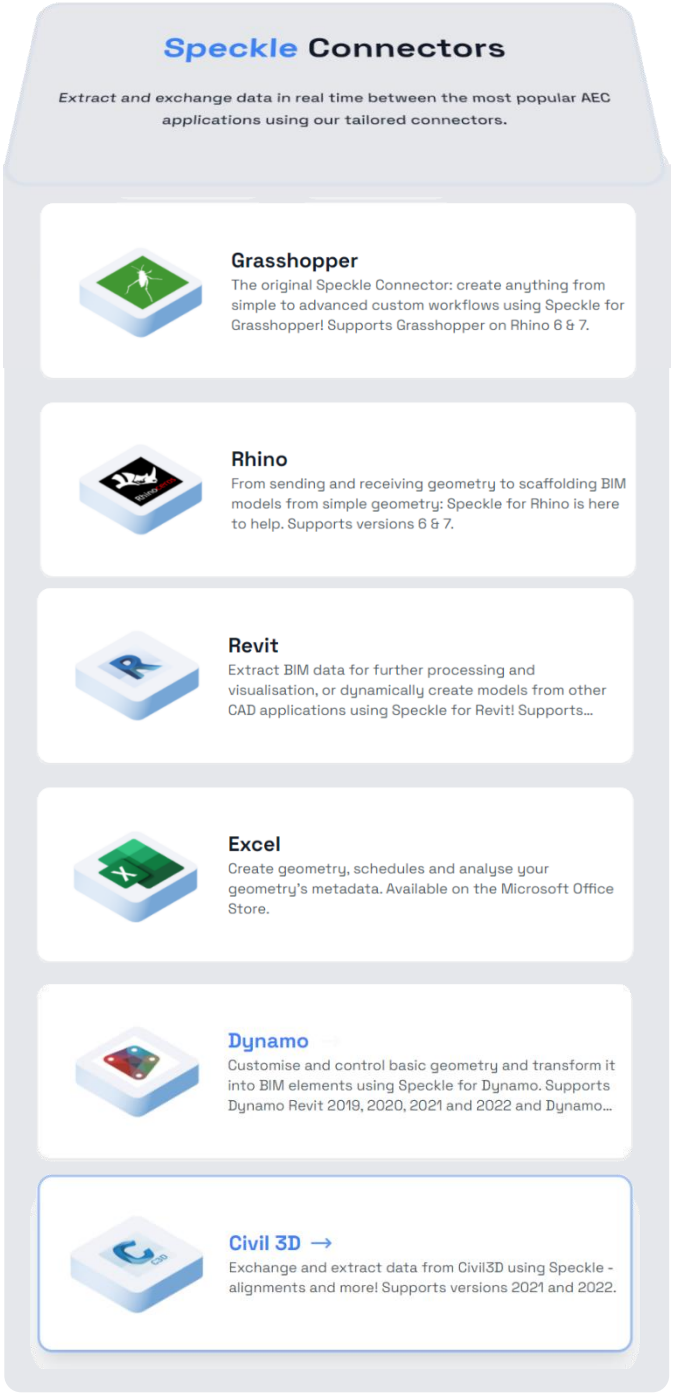
Speckle is the open source data platform for aec



Data Integration

connecting the dots

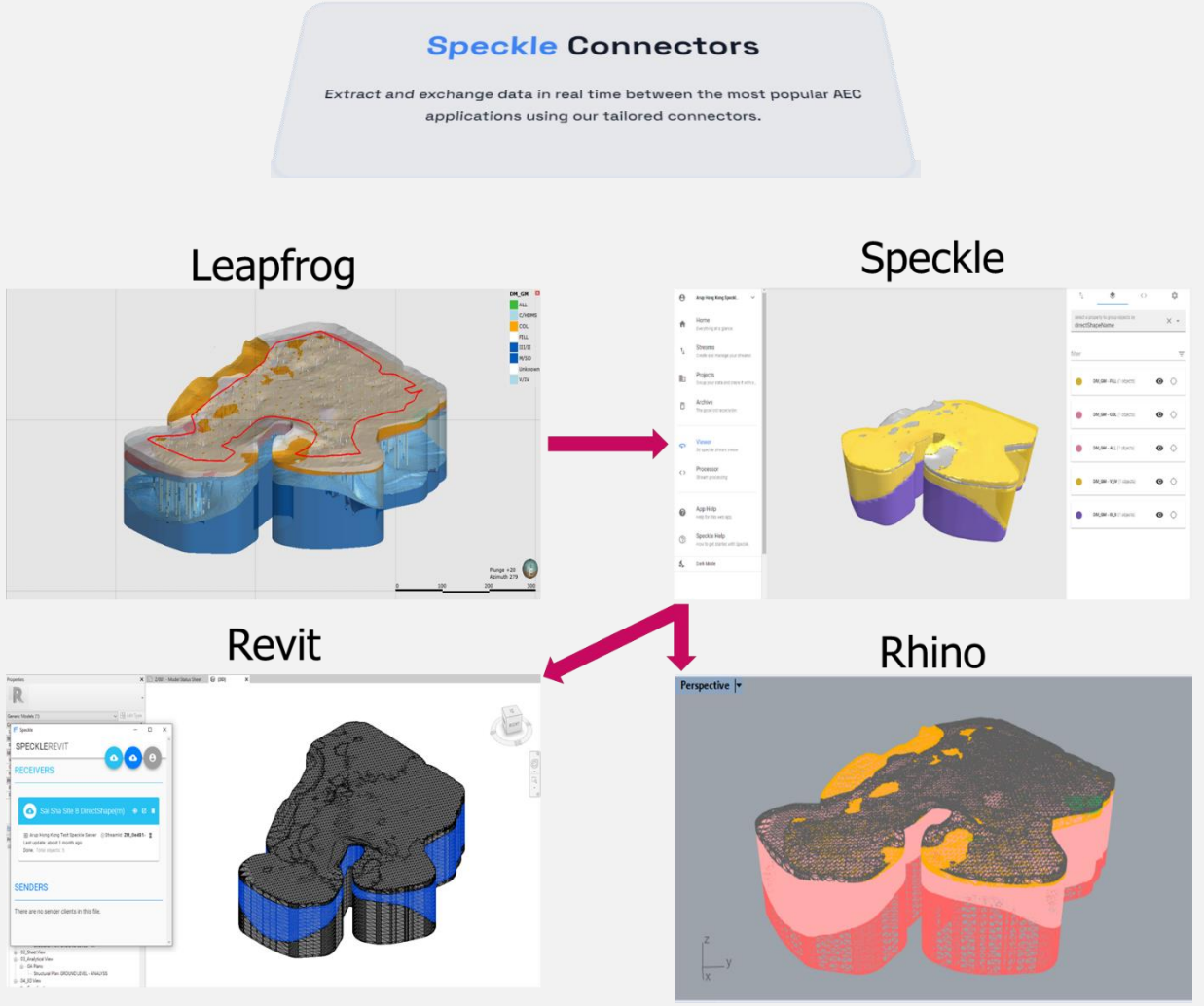




Data Integration

and streaming the lines created

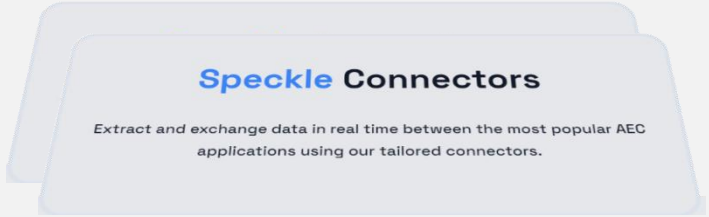
seamlessly push model updates throughout a whole suite of interconnected software packages

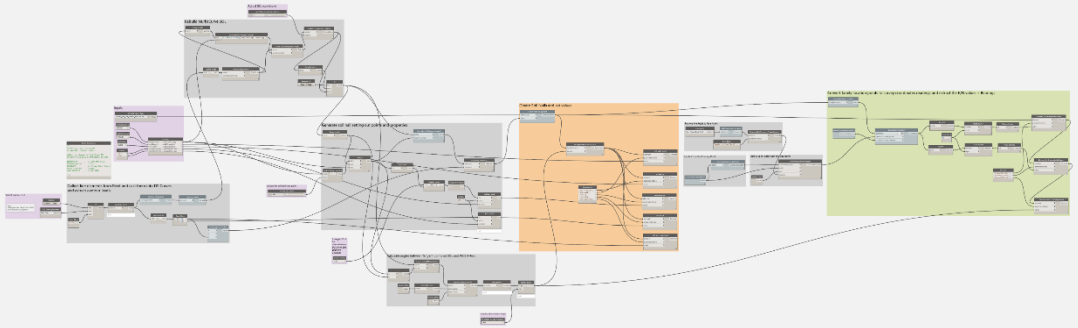


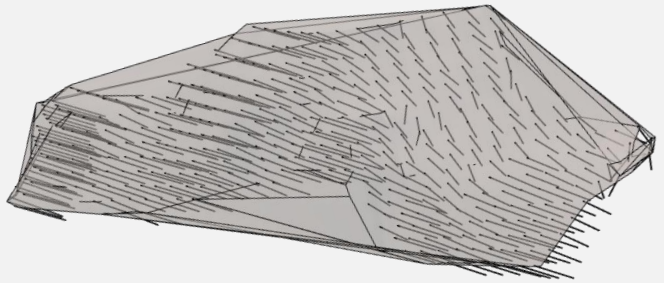
Data Integration

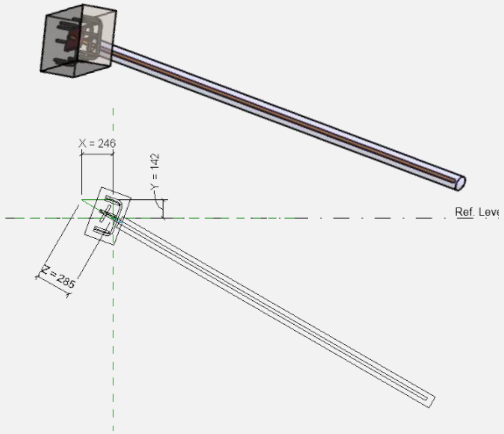
and streaming the lines created

allowing subsequent automated workflows to activate and take account of model updates









SOIL NAIL SCHEDULE (+101.000)

ROW NAME	MARK	HEAD LEVEL (mPD)	BAR DIA. (mm)	BAR LENGTH (mm)	INCLINATION TO HORI	ANGLE TO NORTH	EASTING (m)	NORTHING (m)	COUNT
ROW_101	SN1	+101.000	100	7500	30.00°	124.37°	834370.898	815096472	1
ROW_101	SN2	+101.000	100	7500	30.00°	126.66°	834372.690	815098950	1
ROW_101	SN3	+101.000	100	7500	30.00°	145.44°	834374.571	815101275	1
ROW_101	SN4	+101.000	100	7500	30.00°	172.08°	834377.201	815102610	1
ROW_101	SN5	+101.000	100	7500	30.00°	159.58°	834380.134	815103212	1
ROW_101	SN6	+101.000	100	7500	30.00°	151.27°	834382.863	815104443	1
ROW_101	SN7	+101.000	100	7500	30.00°	167.90°	834385.627	815105574	1
ROW_101	SN8	+101.000	100	7500	30.00°	171.50°	834388.587	815106049	1
ROW_101	SN9	+101.000	100	7500	30.00°	147.79°	834391.390	815107039	1
ROW_101	SN10	+101.000	100	7500	30.00°	136.38°	834393.721	815108916	1
ROW_101	SN11	+101.000	100	7500	30.00°	143.58°	834396.030	815110828	1
ROW_101	SN12	+101.000	100	7500	30.00°	148.27°	834398.505	815112522	1
ROW_101	SN13	+101.000	100	7500	30.00°	161.89°	834401.246	815113721	1
ROW_101	SN14	+101.000	100	7500	30.00°	163.67°	834404.125	815114564	1
ROW_101	SN15	+101.000	100	7500	30.00°	150.13°	834406.814	815115879	1
ROW_101	SN16	+101.000	100	7500	30.00°	176.95°	834423.279	815116648	1
ROW_101	SN17	+101.000	100	7500	30.00°	167.14°	834426.267	815116899	1
ROW_101	SN18	+101.000	100	7500	30.00°	167.14°	834429.201	815117522	1
ROW_101	SN19	+101.000	100	7500	30.00°	166.87°	834432.125	815118193	1
ROW_101	SN20	+101.000	100	7500	30.00°	185.51°	834435.084	815118622	1
ROW_101	SN21	+101.000	100	7500	30.00°	180.12°	834438.072	815118382	1
ROW_101	SN22	+101.000	100	7500	30.00°	178.92°	834441.071	815118436	1
ROW_101	SN23	+101.000	100	7500	30.00°	185.80°	834444.068	815118353	1
ROW_101	SN24	+101.000	100	7500	30.00°	183.48°	834447.048	815118028	1
ROW_101	SN25	+101.000	100	7500	30.00°	177.16°	834450.047	815118088	1
ROW_101	SN26	+101.000	100	7500	30.00°	177.92°	834453.041	815118254	1
ROW_101	SN27	+101.000	100	7500	30.00°	178.30°	834456.039	815118305	1
ROW_101	SN28	+101.000	100	7500	30.00°	175.91°	834459.030	815118541	1
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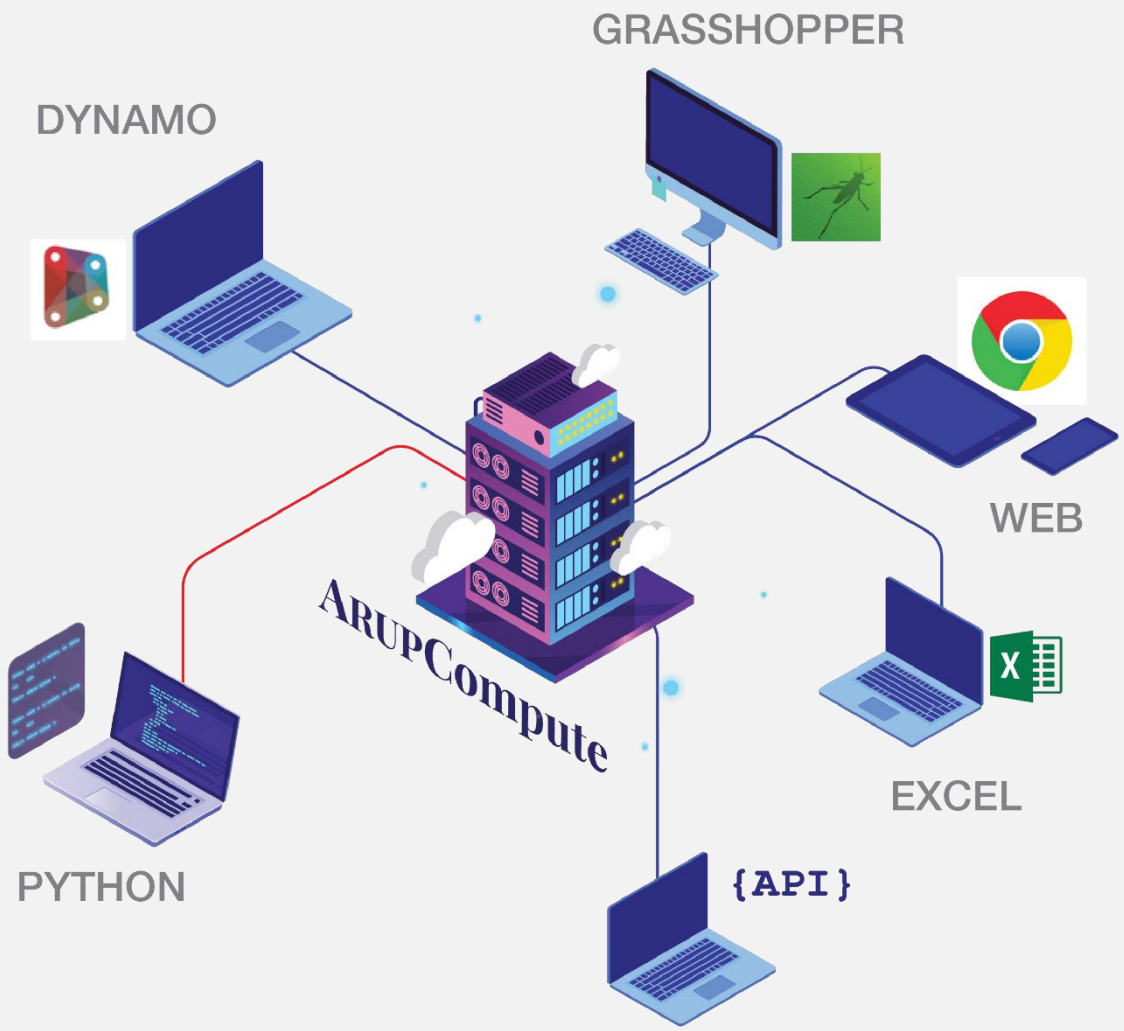
ROW_101	SN31	+101.000	100	7500	30.00°	231.44°	834474.316	815113271	1
ROW_101	SN32	+101.000	100	7500	30.00°	233.87°	834476.053	815110837	1
ROW_101	SN33	+101.000	100	7500	30.00°	231.98°	834477.899	815108463	1

ArupCompute

integrating our tools

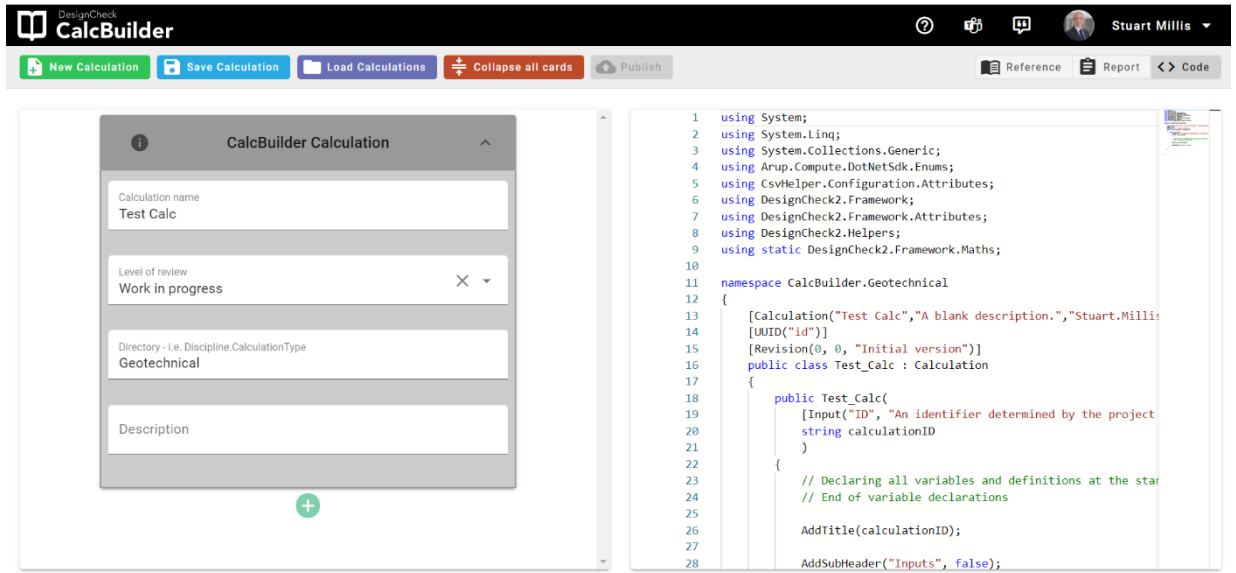
linking standardised and code-based analysis with visual programming and report generation packages



CalcBuilder

ditching Excel

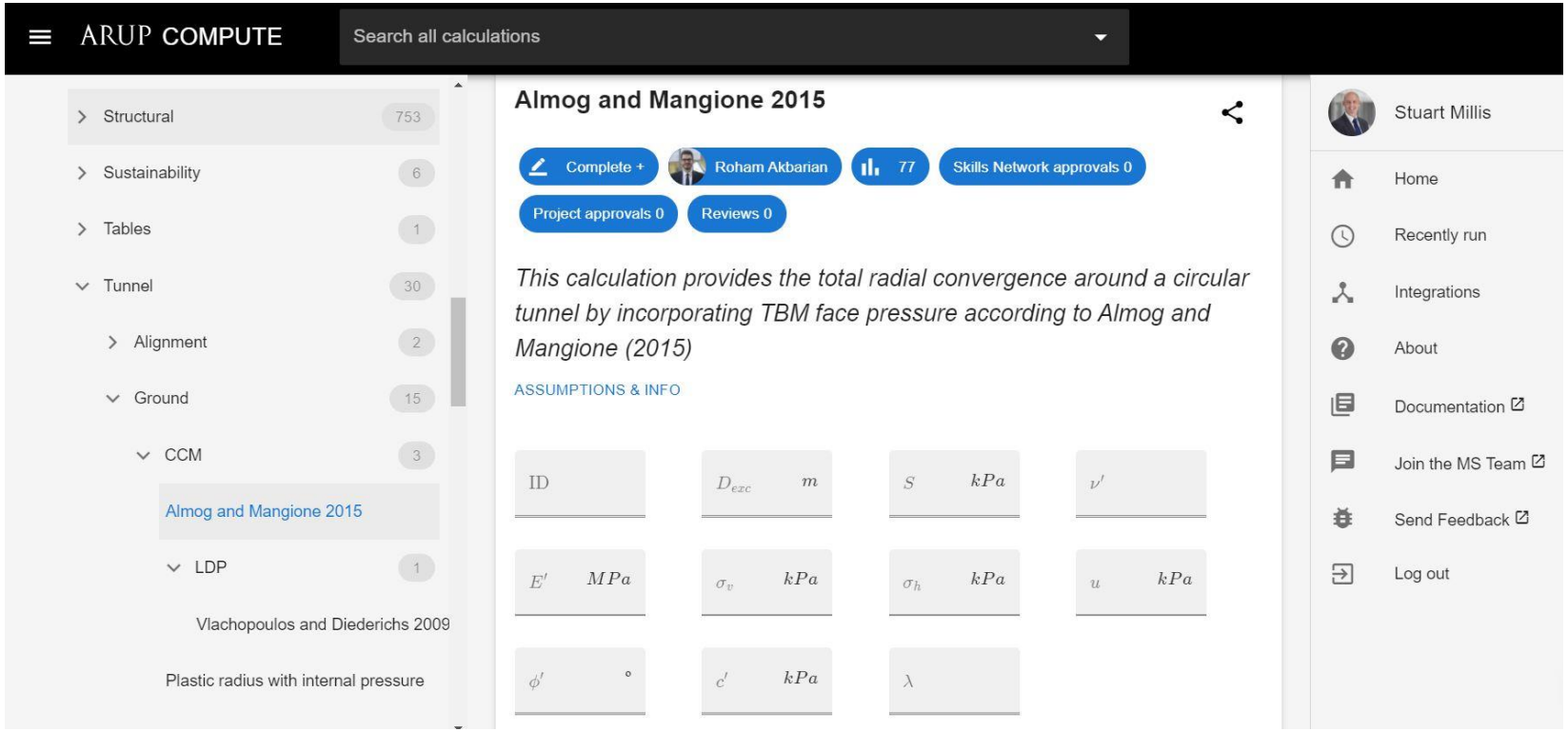
platforms for quick and easy scripting of design calculations, linking with Excel, Python, Grasshopper, Dynamo, etc. in an integrated online platform



DesignCheck

ensuring code compliance

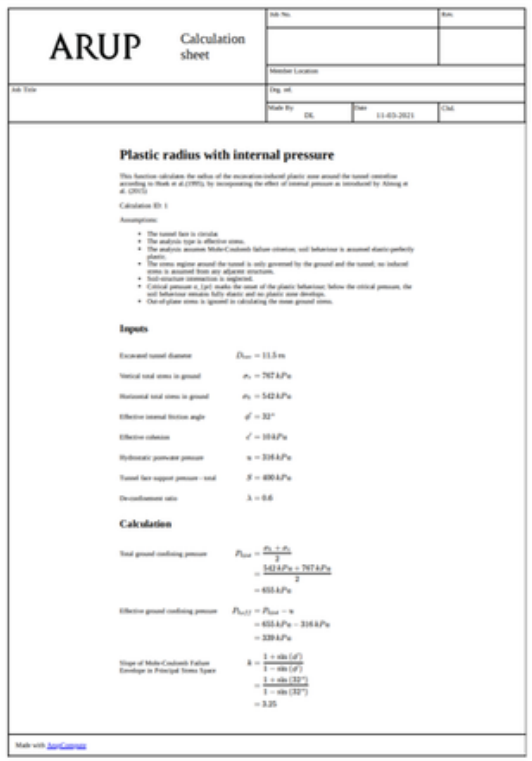
online quality assured platform for technical calculations



DesignCheck

ensuring code compliance

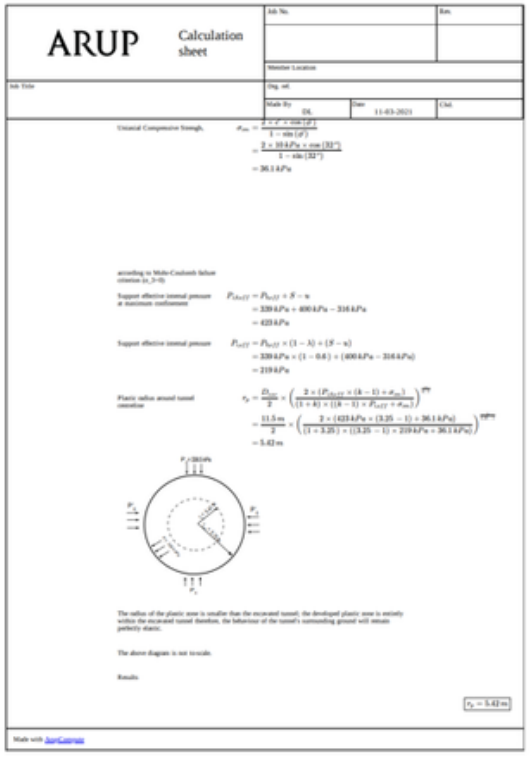
and automated report generation of the calculation output

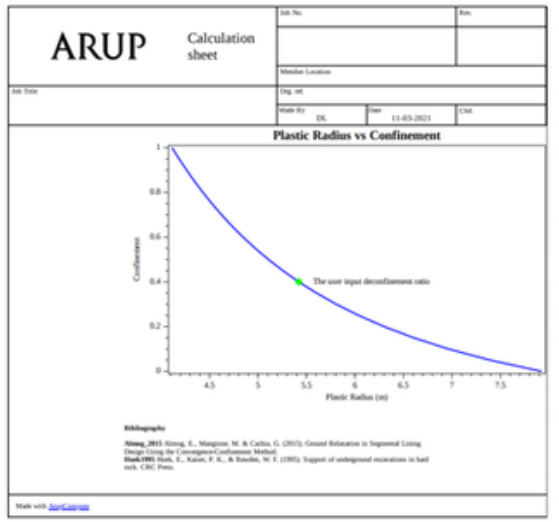

ARUP Calculation sheet

Plastic radius with internal pressure

Inputs

Calculation


ARUP Calculation sheet


ARUP Calculation sheet

Plastic Radius vs Confinement

The user input deconfinement ratio

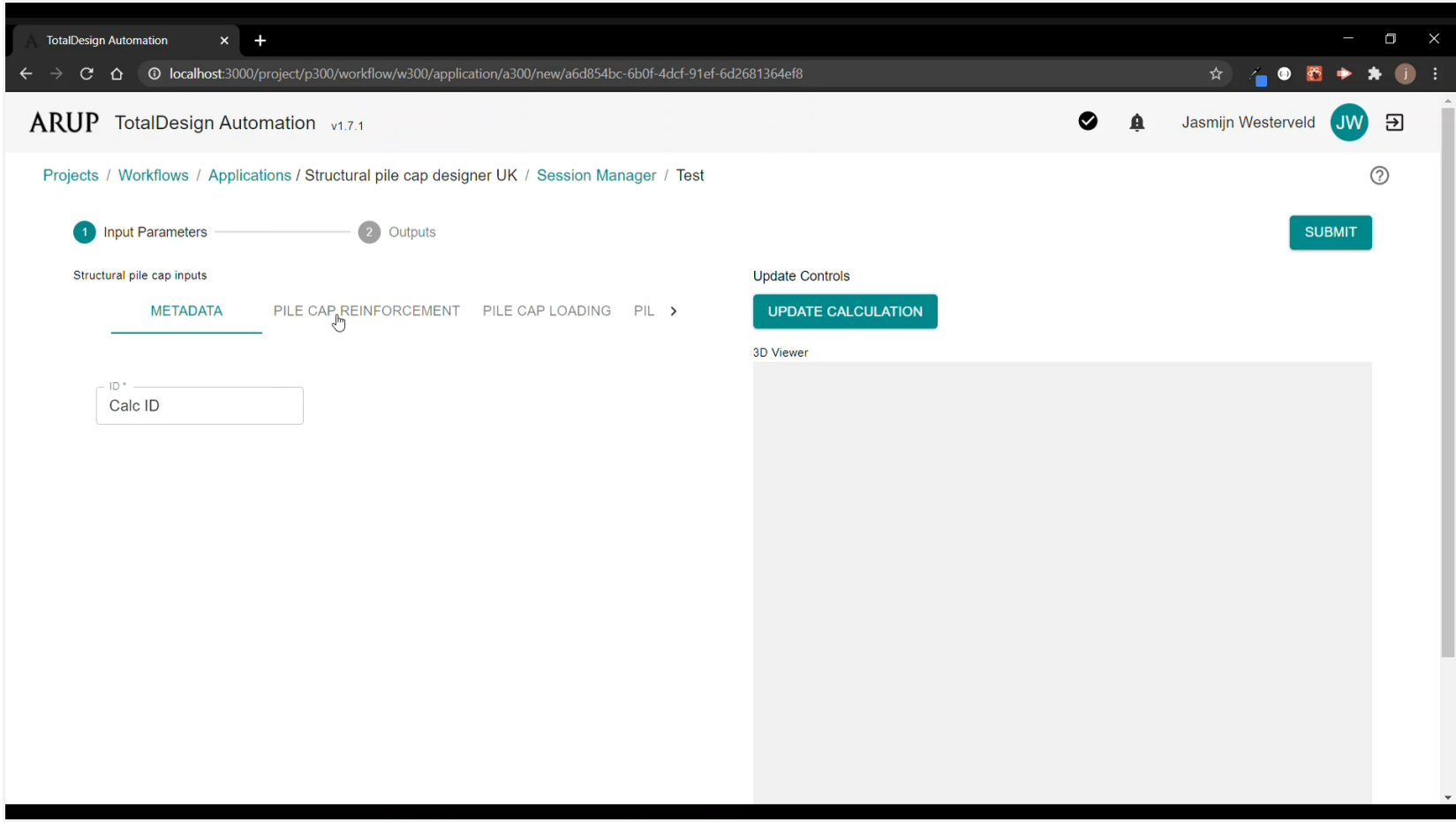
Confinement

Plastic Radius (m)

TotalDesign Automation

ensuring code compliance

that even links the designs to automated 3D visualisations



interconnected series of tools facilitating integrated digital data use throughout the project life cycle

the End Result

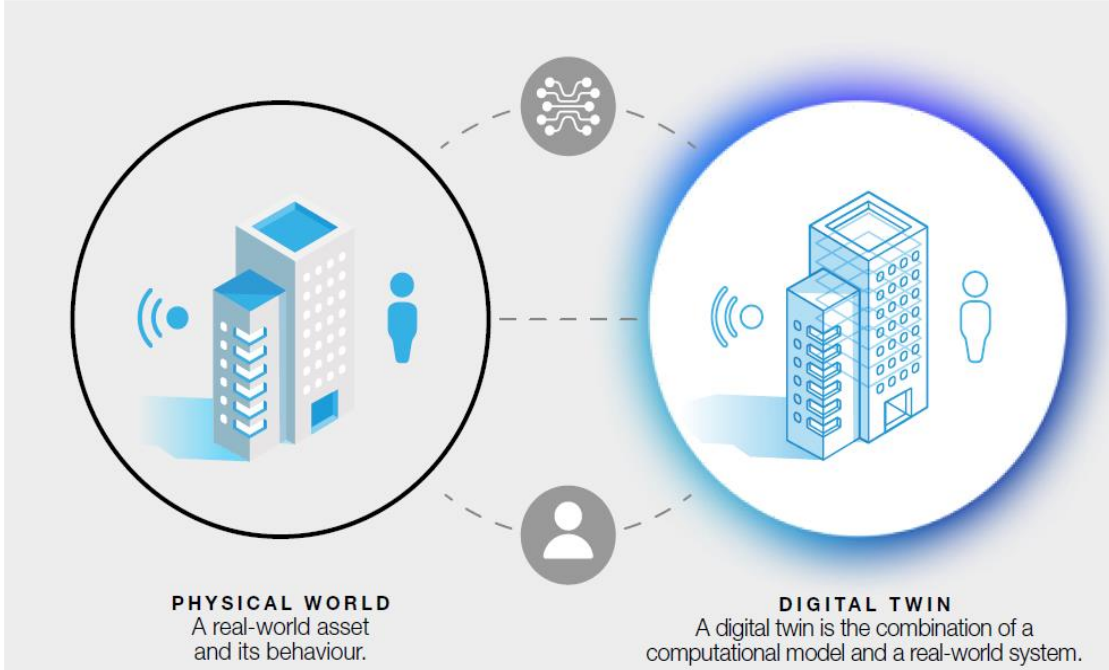
ARUP

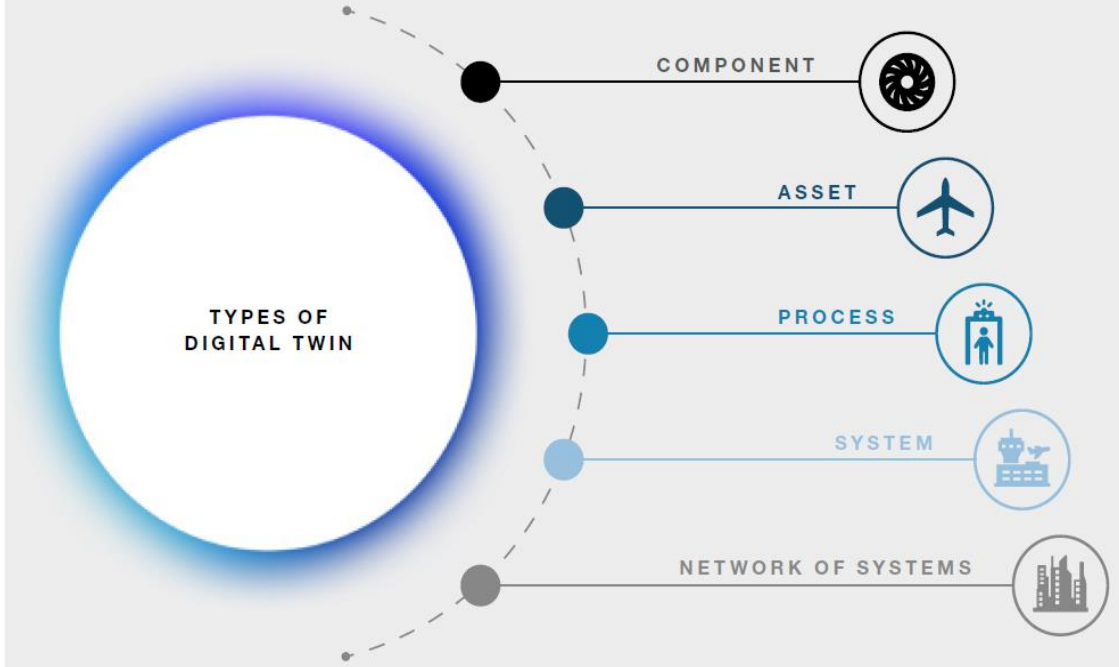
But we don’t need to stop at design…

Asset Management

maintaining and checking our designs

we can also link the design to long-term asset management through Digital Twins



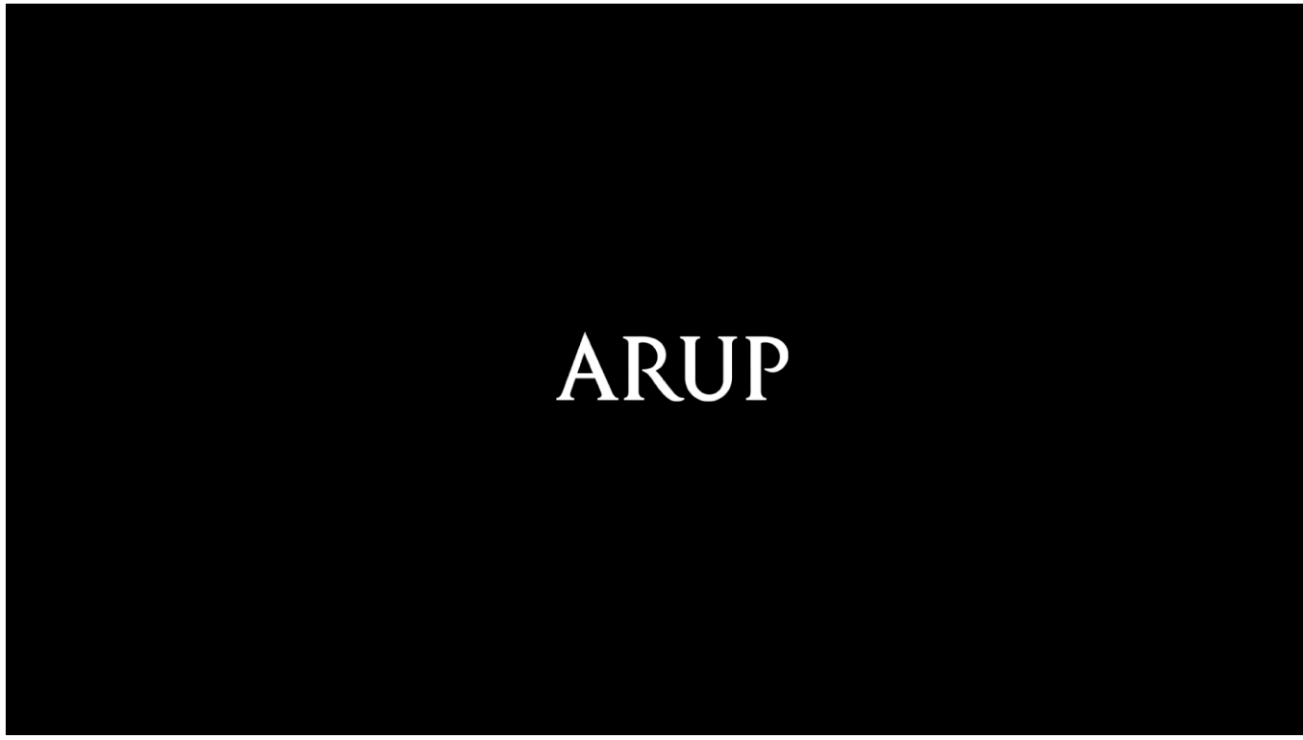


ARUP

Asset Management

from enhancing maintenance inspections

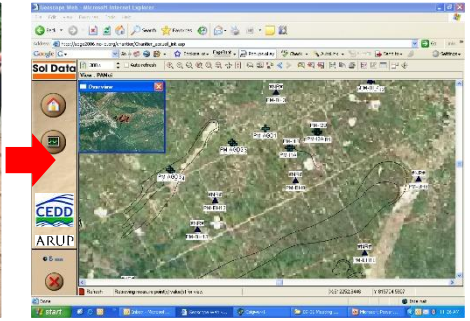
tablet enabled digital twin for maintenance inspection works

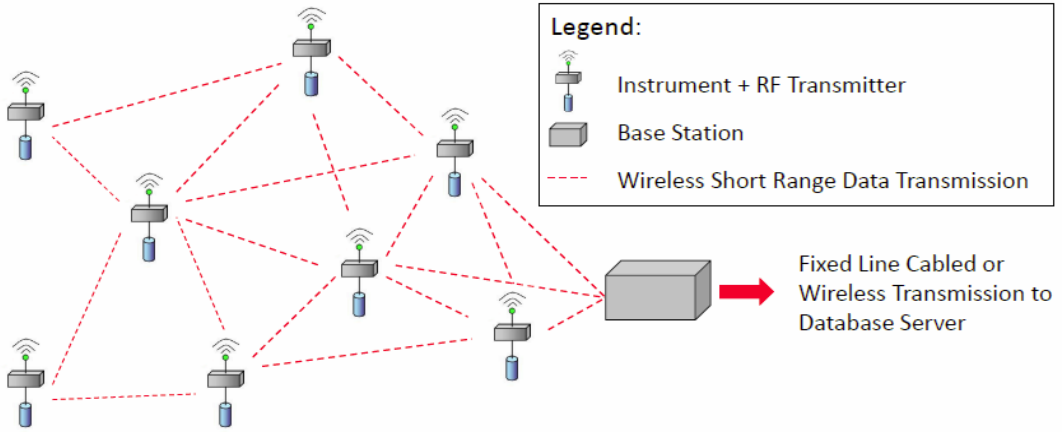


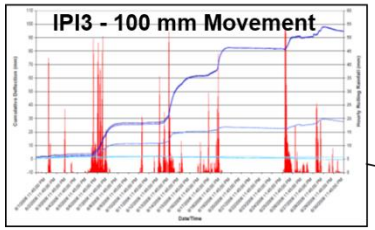
Asset Management

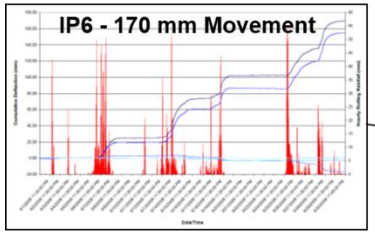
to maintaining and checking our designs

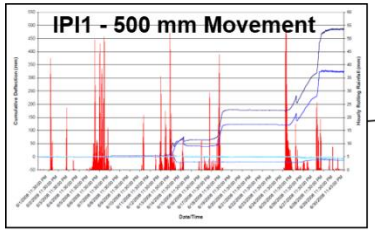
to monitor site performance
remotely and in real-time

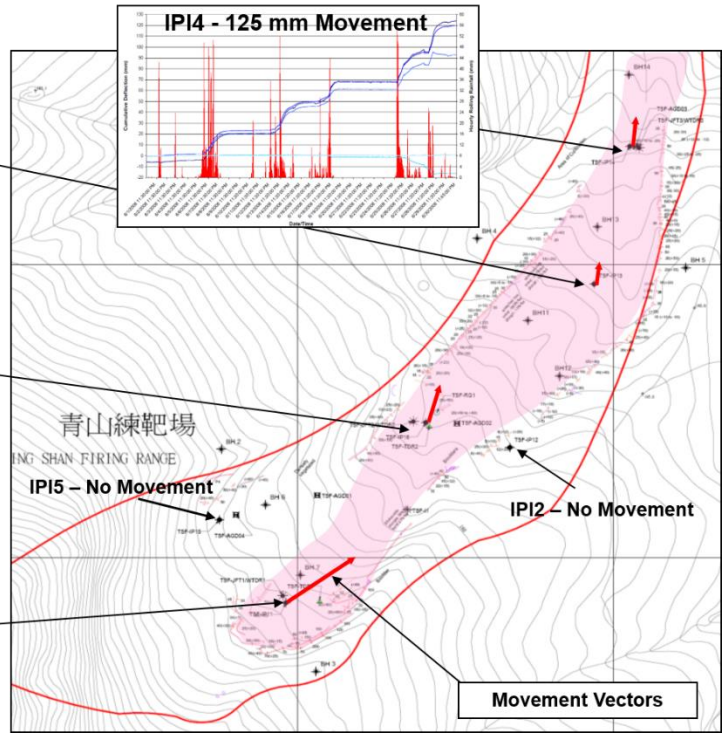








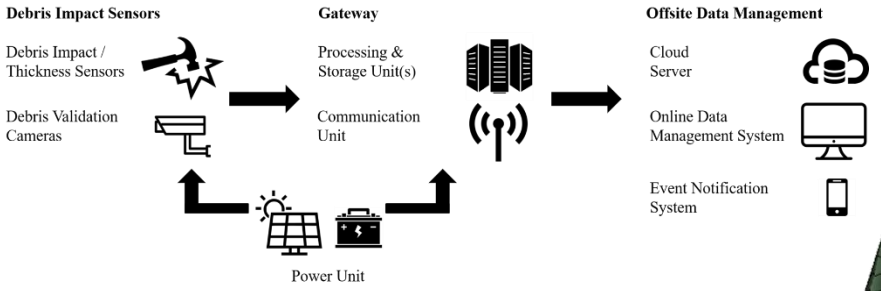


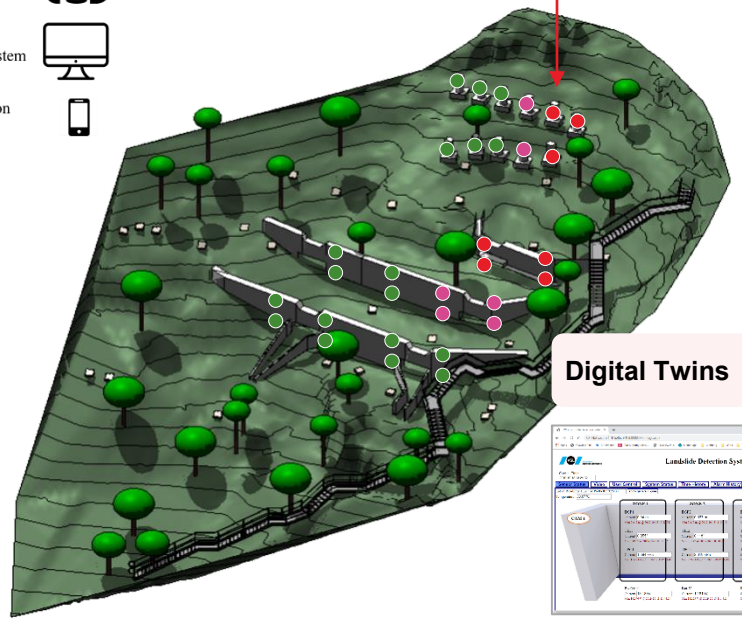


Asset Management

and responding to incidents when they do occur

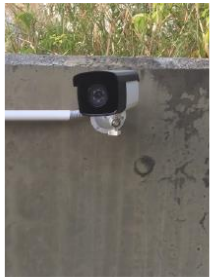
or trigger incident alarms and collect data on design performance when something happens





Impact Switch

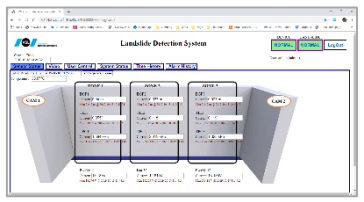
Validation Camera

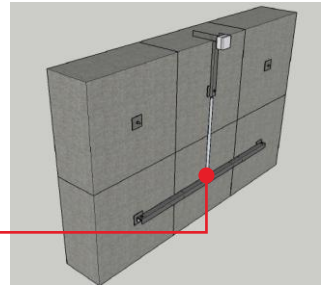


Laser Depth Gauge

Gateway

Digital Twins

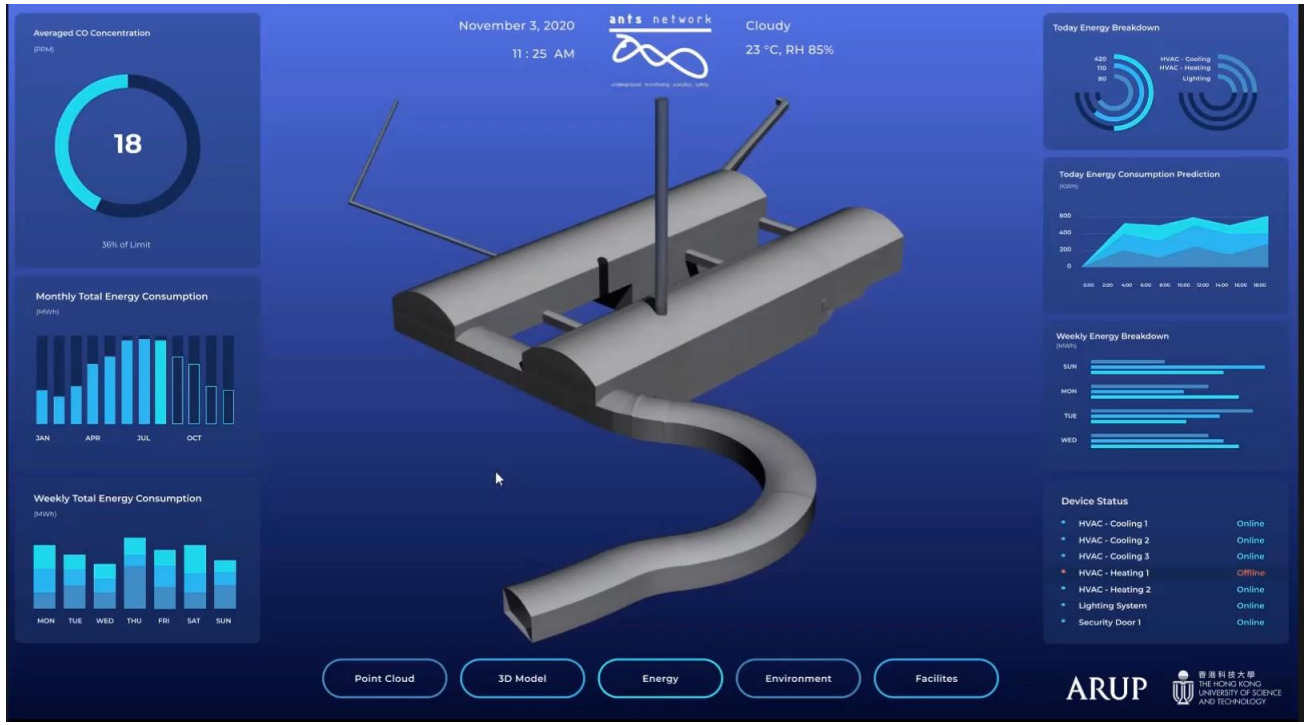




Asset Management

or even actively managing our sites

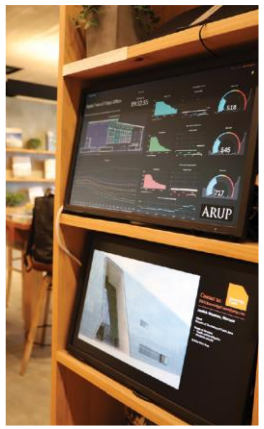
or even actively maintain aspects of the facility operation through interactive dashboards that make use of the models we've generated

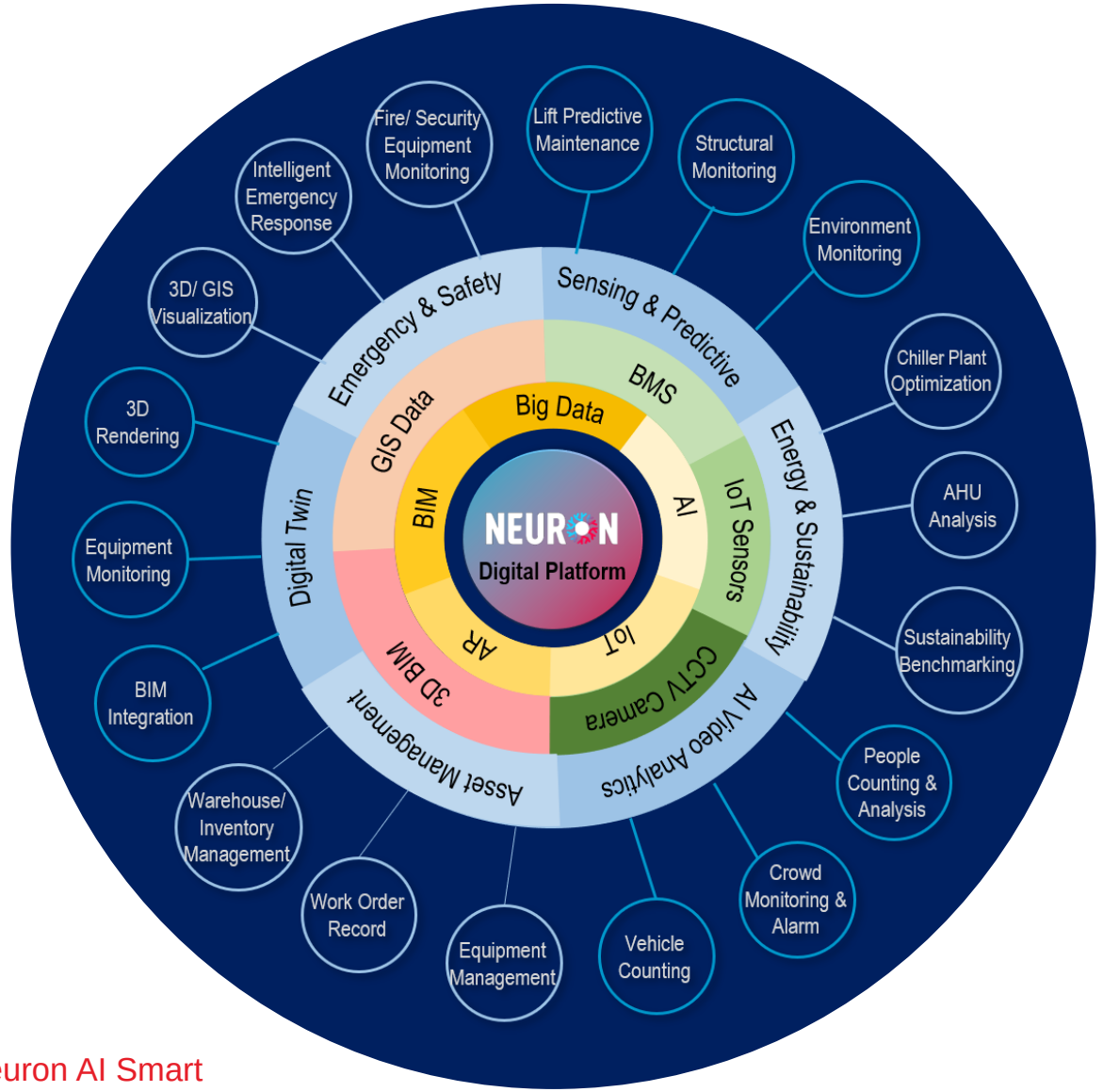


Asset Management

implementing AI in the process of doing so

we're already doing it for buildings, so why not our geotechnical works too?

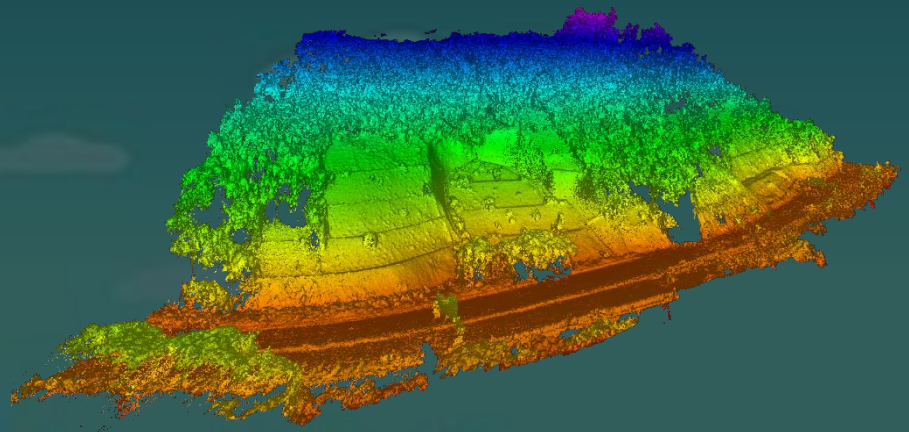


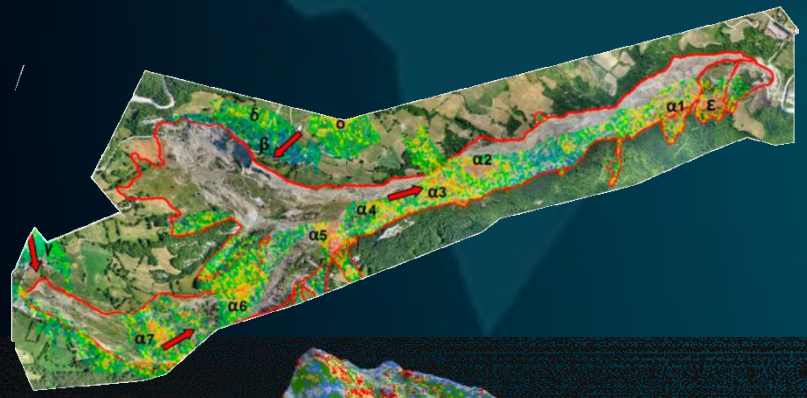


Arup Neuron AI Smart Building Management

The Future

we’re currently only at the tip of the iceberg in terms of what’s possible…





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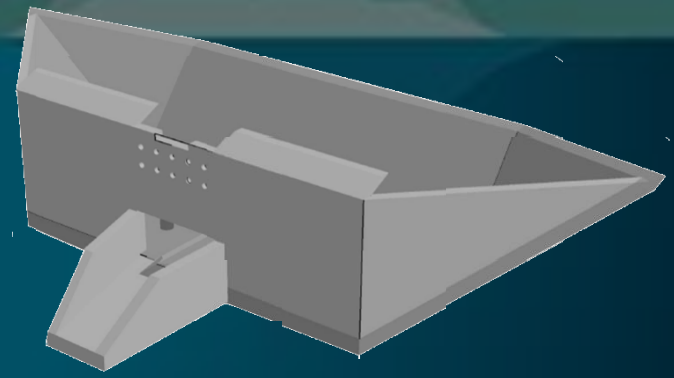

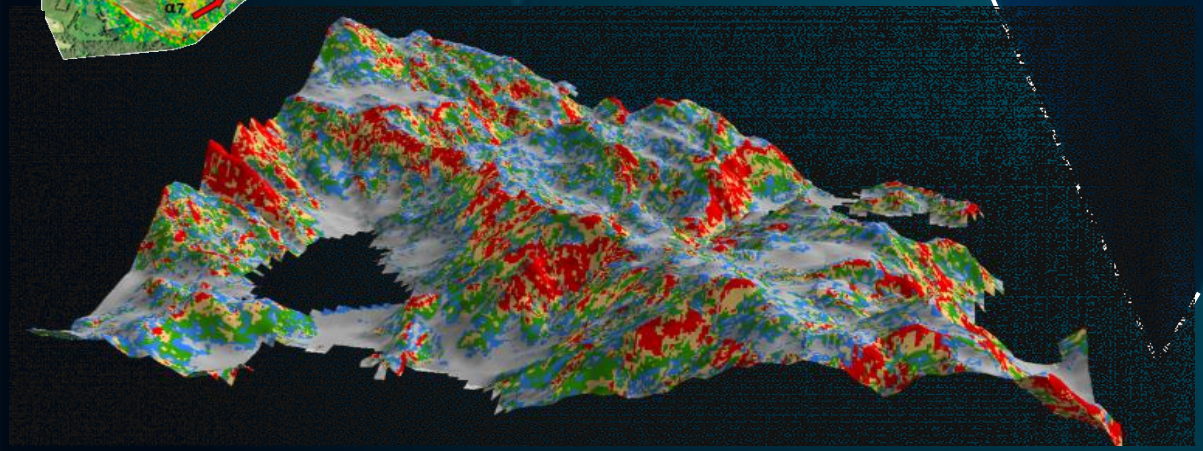

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Digital Journey to Improve Blasting

Joint Technical Symposium on Digital Geosciences & Geotechnology

Ir. Simon LEUNG

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Summary

1. Project Introduction
2. Prediction of Overbreak with AI
3. Live Monitoring while Blast Hole Drilling
4. Robotic Cum Photogrammetry Scanning
5. RSS Self-Developed Apps

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Project Background

Project Overview

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Prediction of Overbreak with AI

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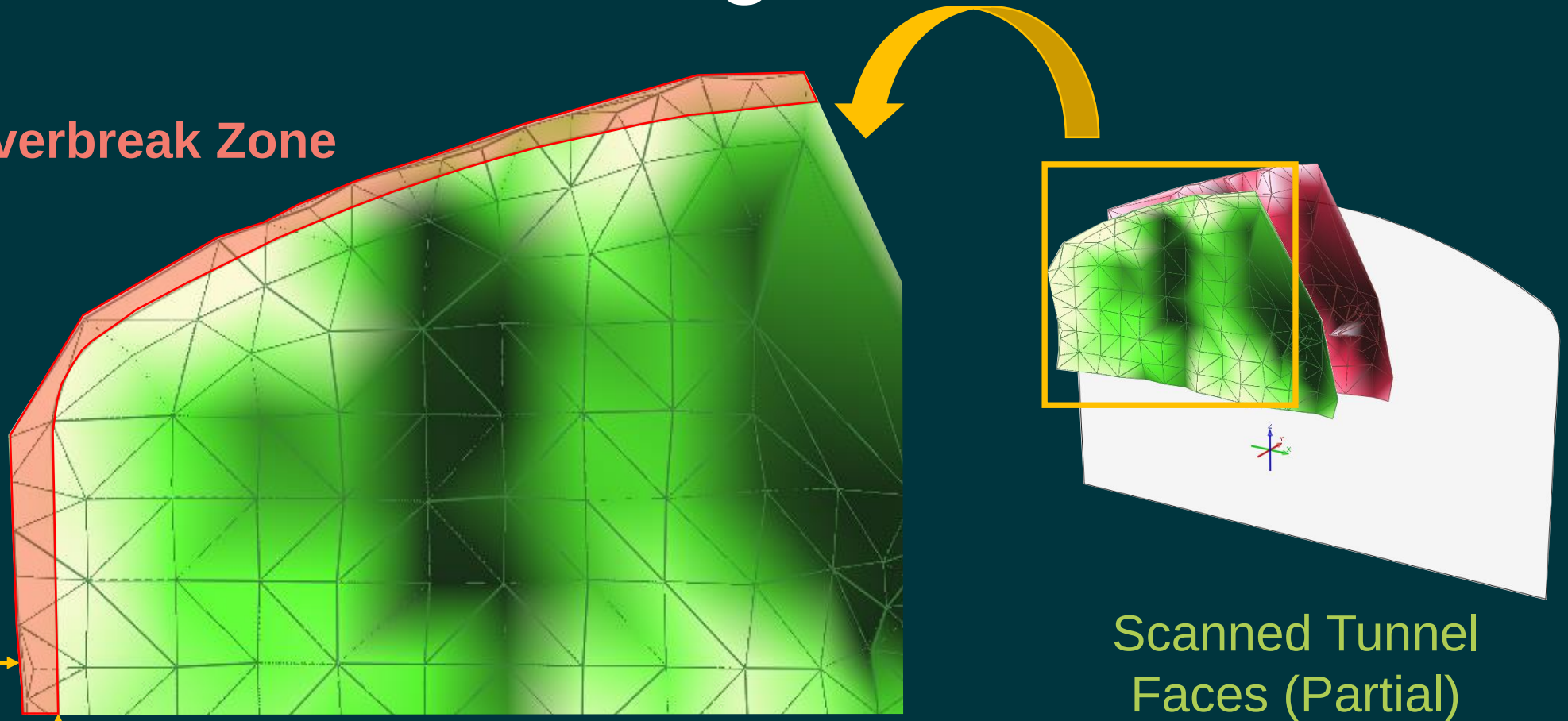
Overbreak in Tunneling



Problems from Overbreak

More blast induced damaged zone created

More mucking out volume and time induced

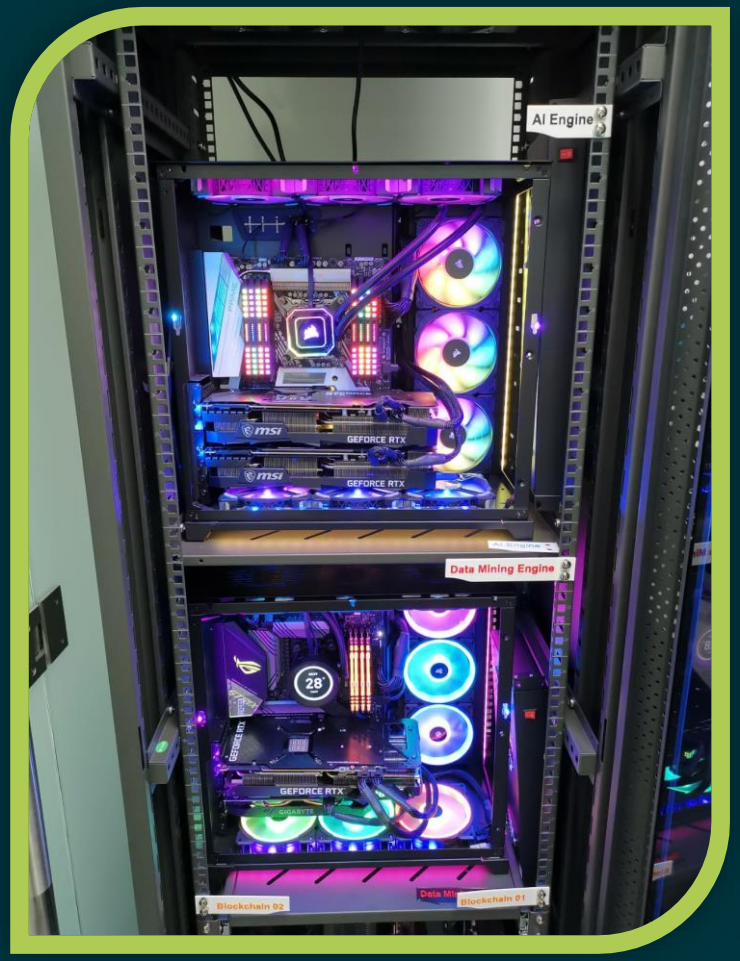
More permanent support required

Longer Construction Time

Higher Construction Cost

Less Construction Safety

Innovative Solution – Prediction with AI



Data Mining Engine &
AI Engine

AI System Overview

Big Data Database

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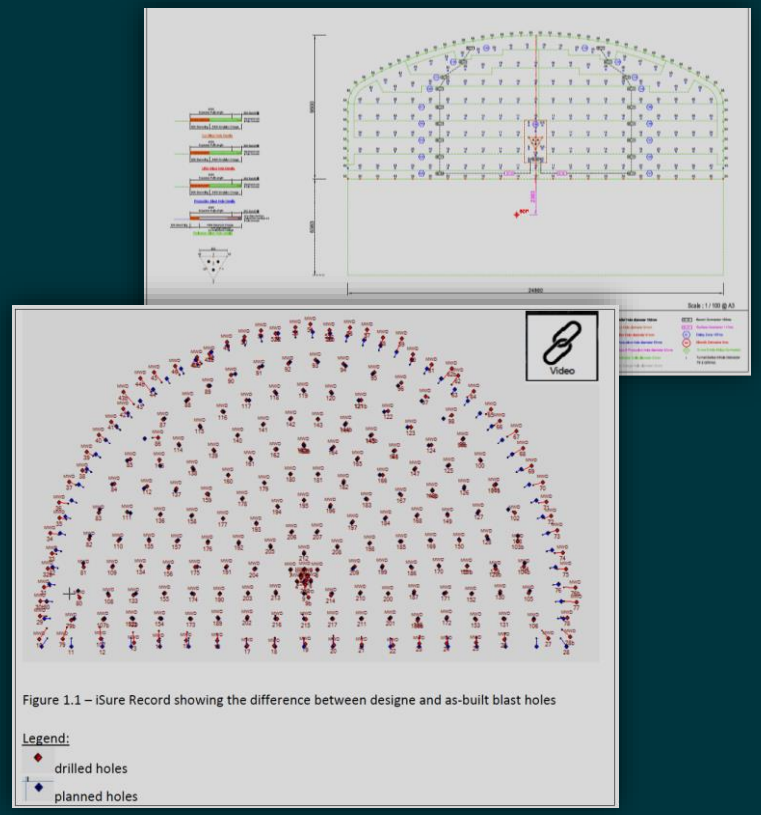
Prediction of Overbreak with AI

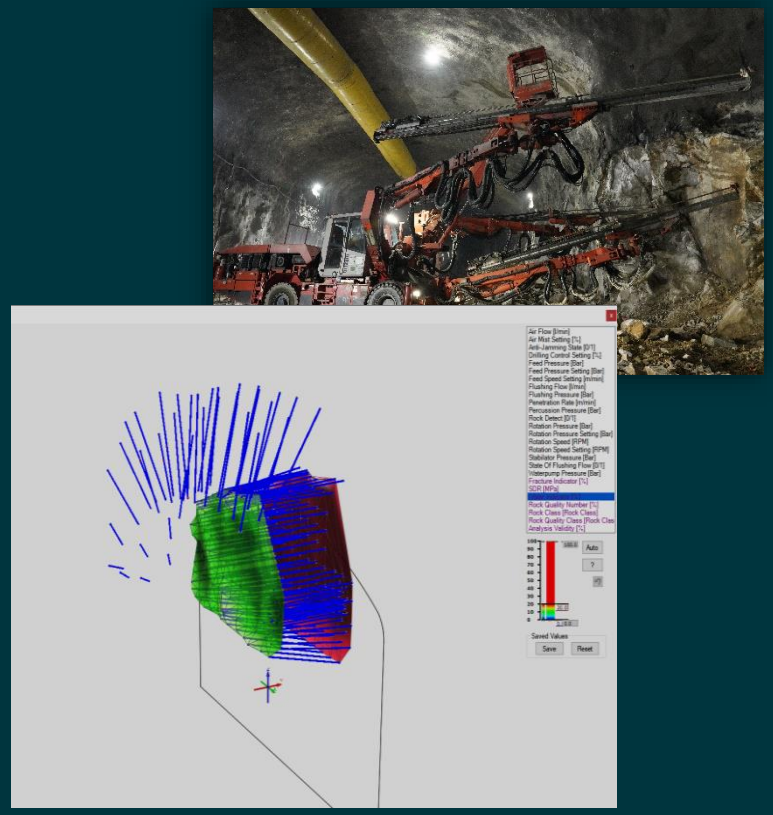
- Data Collection

Before Blasting



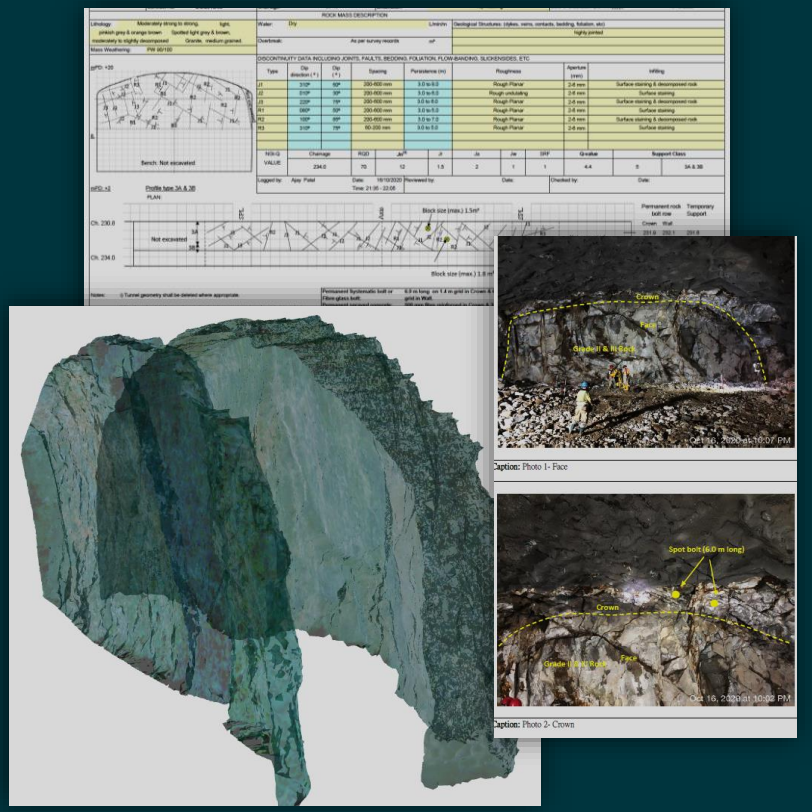
Blast Design Data

During Blasting



Measure While Drilling Data

After Blasting



Mapping and Point Cloud Data

Prediction of Overbreak with AI

- Data Pre-processing

Blasting Parameters

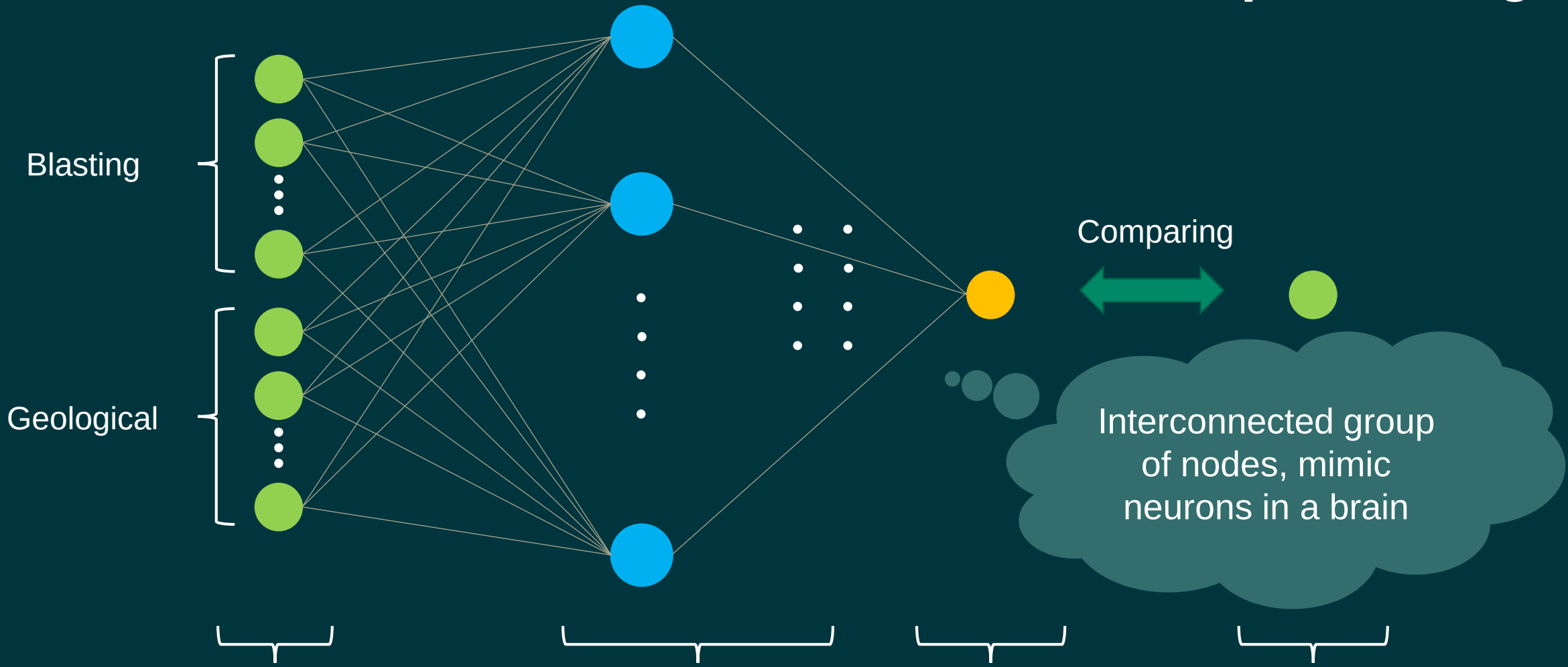
- Powder Factor
- Perimeter Powder Factor
- MIC
- Blast Holes Dimension (Pull Length, Blast Hole Depth)
- Confinement Factor (Blast Hole Depth / Tunnel Section Area)

Geological Parameters

- Q Value
- RMR
- Jointing (Orientation, Spacing, Infilling)
- Intact Rock Strength
- Ground Stress Effect
- Groundwater

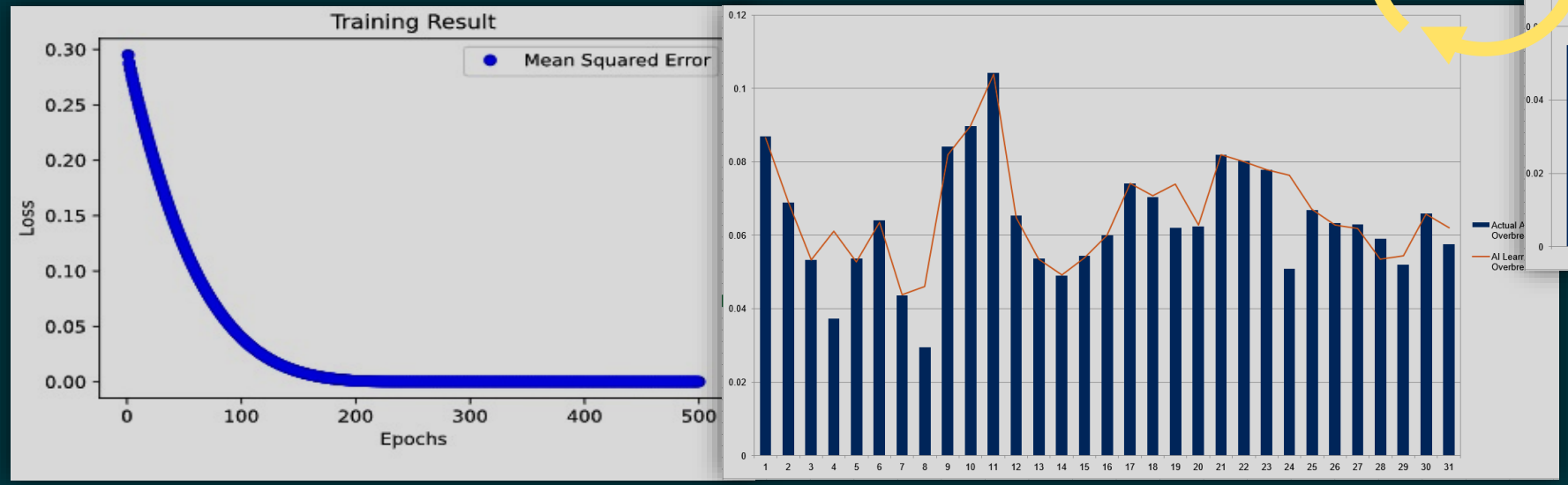
Prediction of Overbreak with AI

- Our Artificial Neural Network Model for Deep Learning

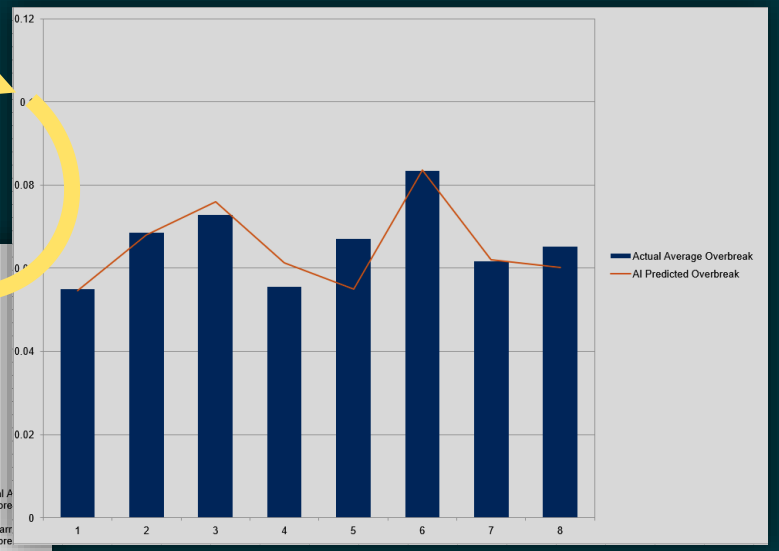


Prediction of Overbreak with AI

- Our AI Model Training and Inference Cycling Approach



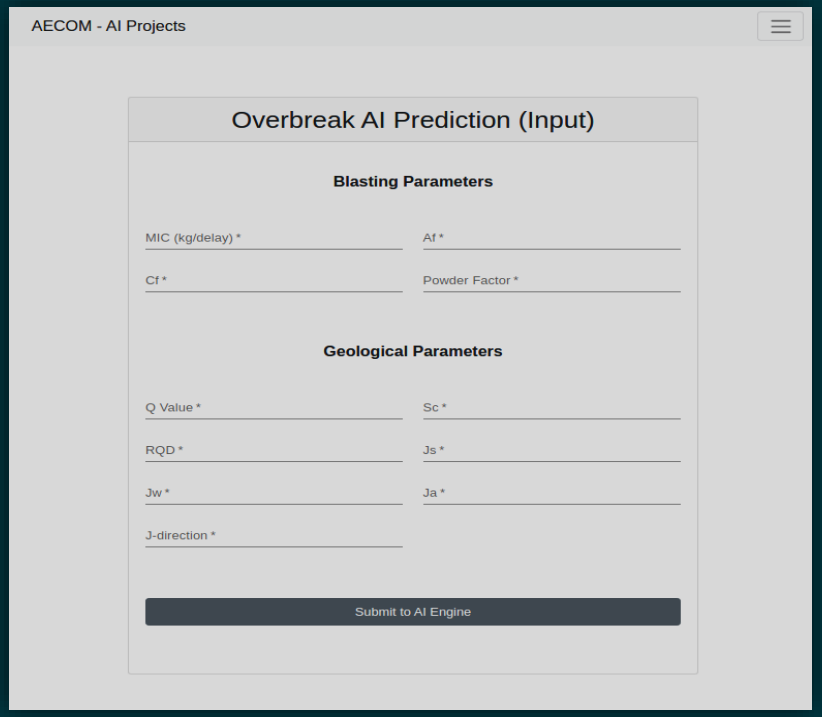
Monitoring of convergence of the error during training



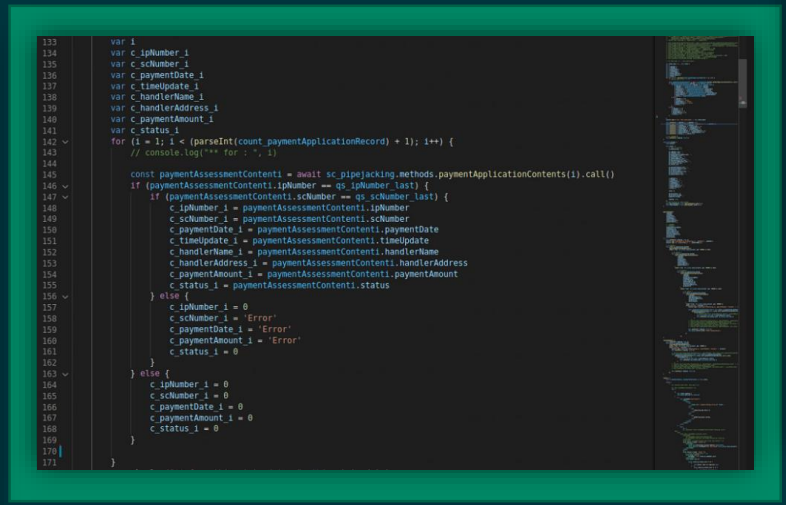
AI Prediction

Prediction of Overbreak with AI

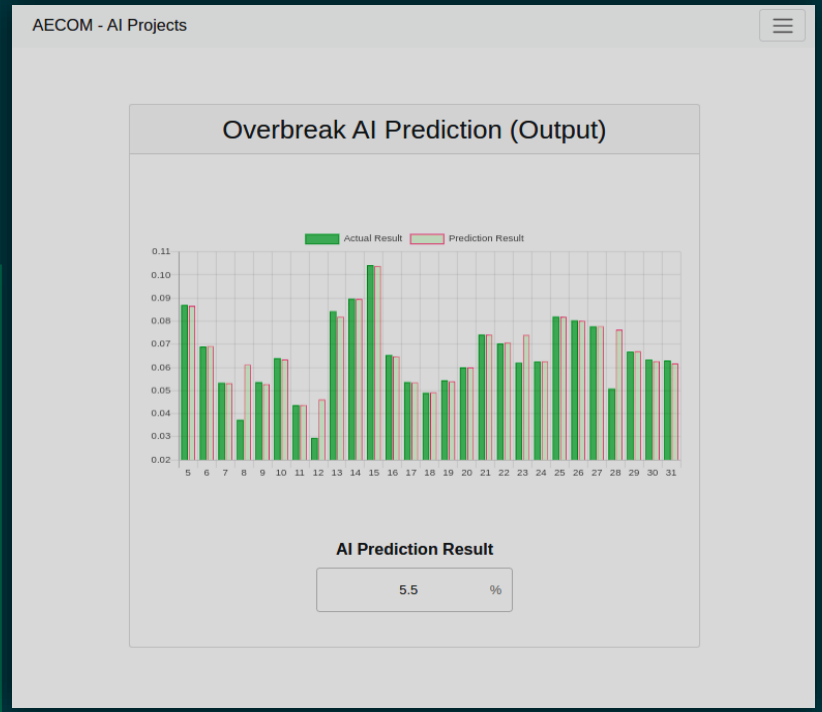
- Our Platform for AI Overbreak Prediction



Data Input



AI Engine



Result Output

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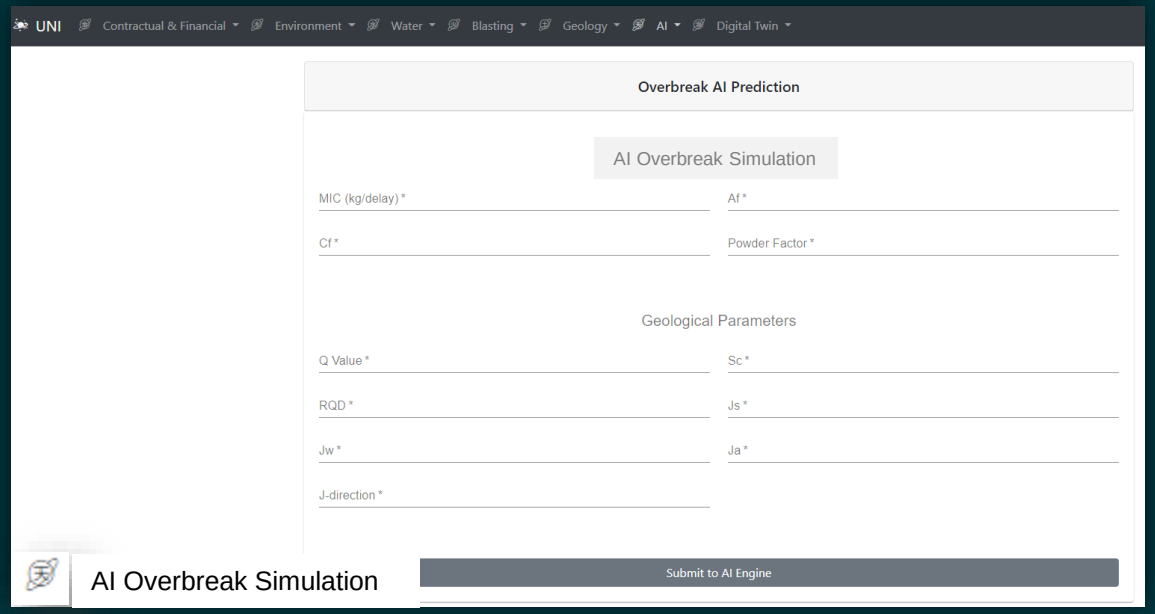
Prediction of Overbreak with AI

- Future Development

- ✓ Simulate the overbreak performance with designed geological and blasting environment
- ✓ Digital twin model



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Live Monitoring while Blast Hole Drilling

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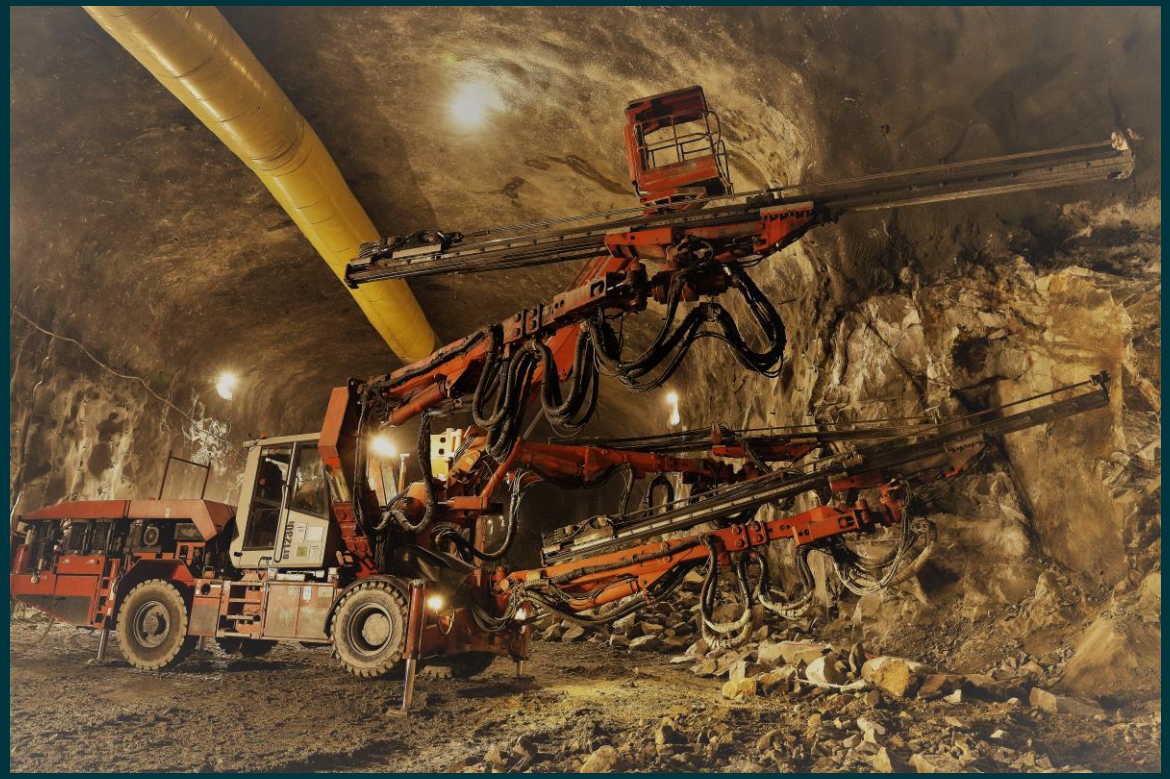
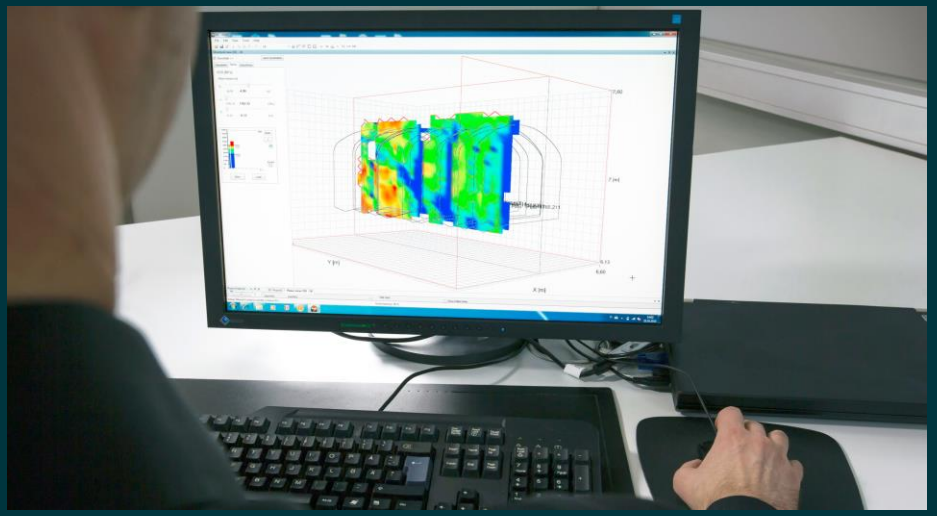
Live Monitoring System





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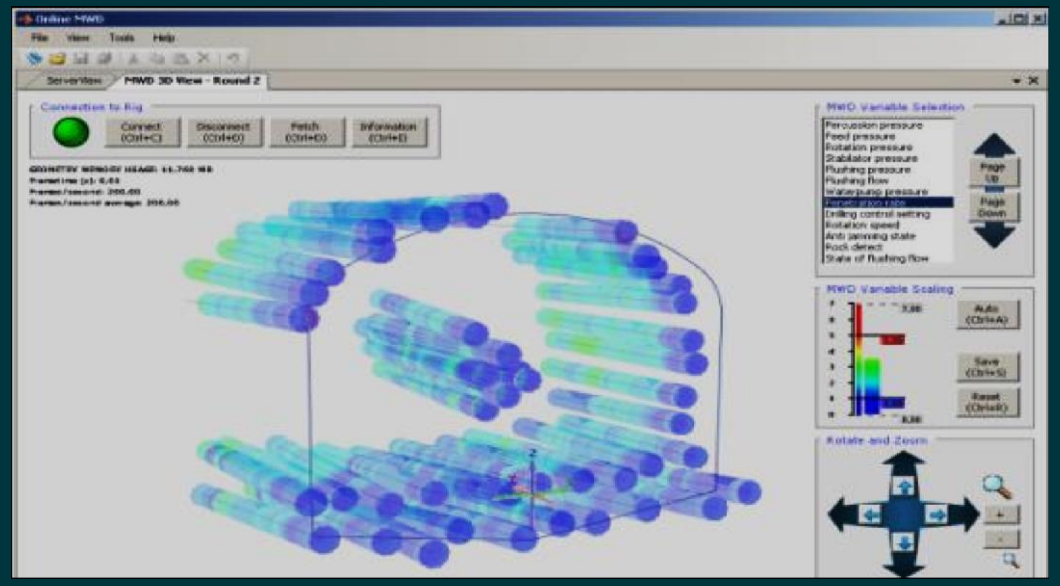
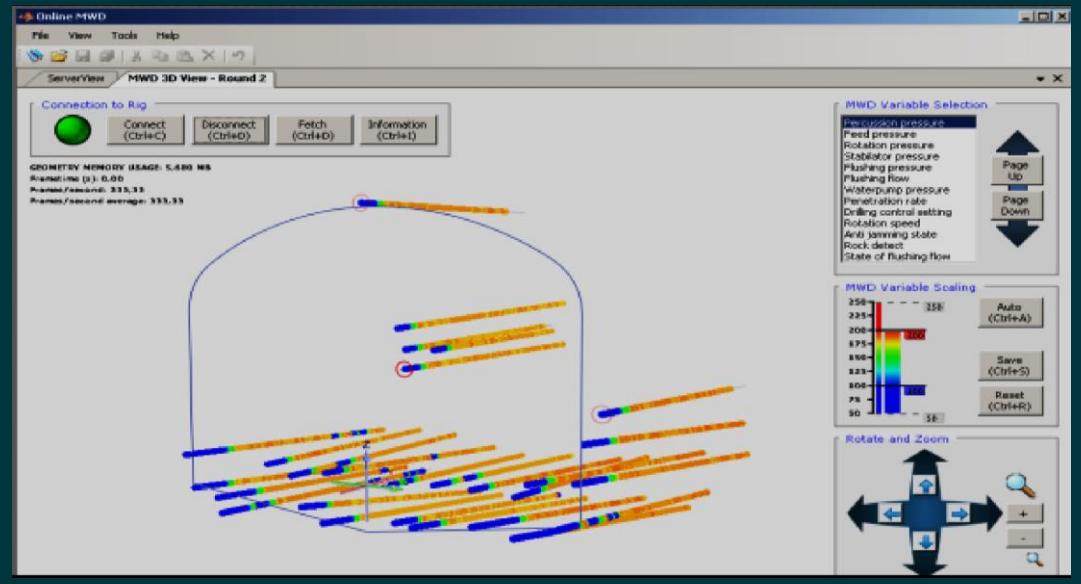
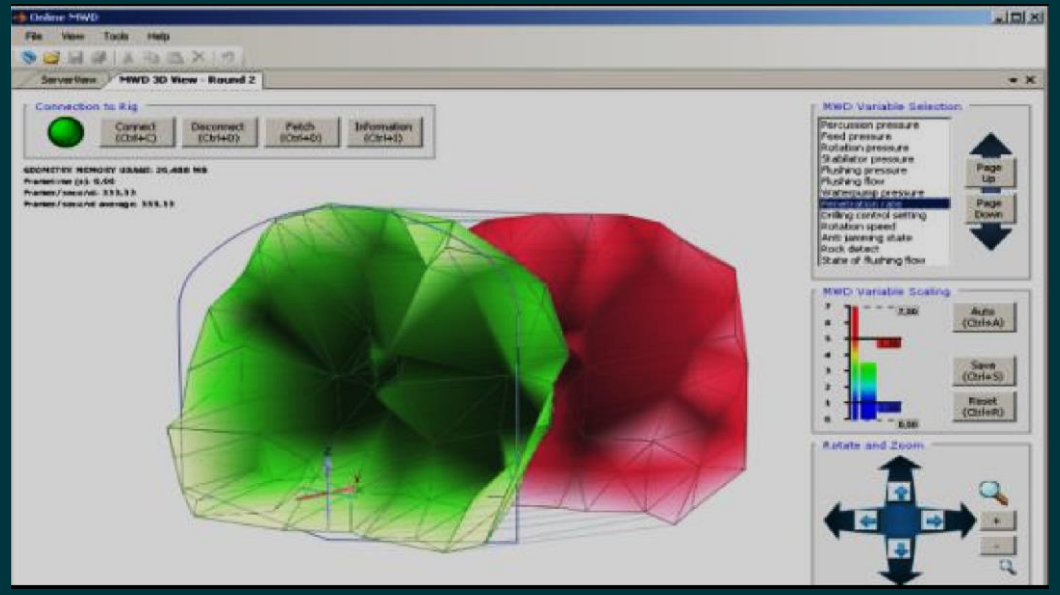
Key Function (1)

- 100% Live Checking of Blast Hole in 3D
- Live Progress Monitoring

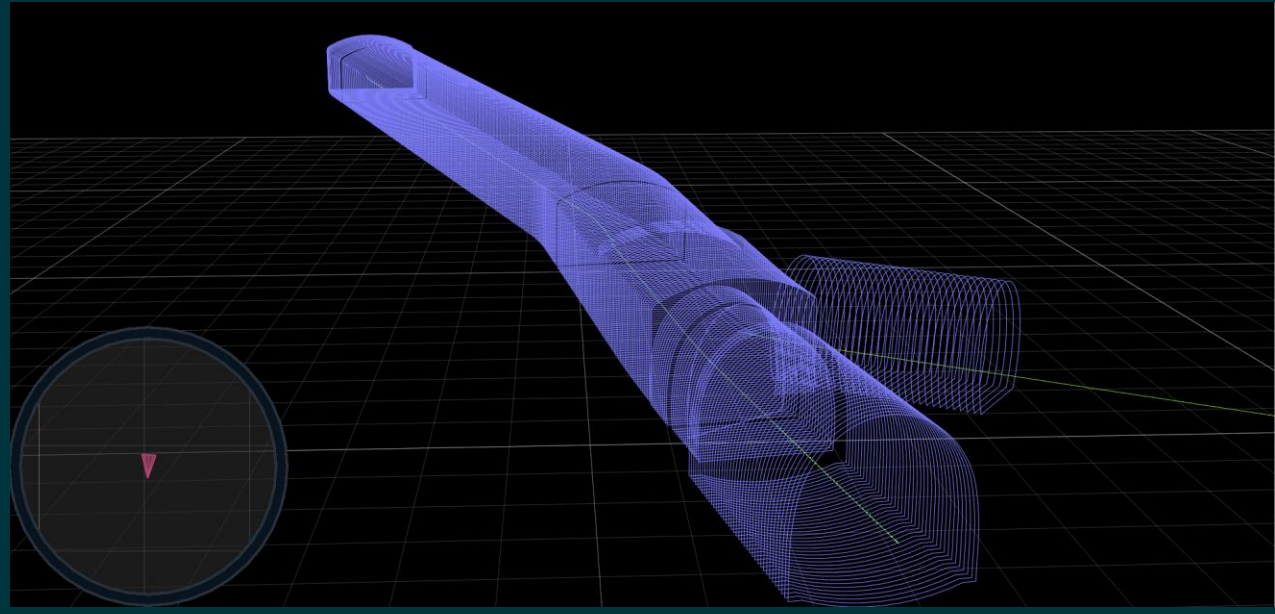


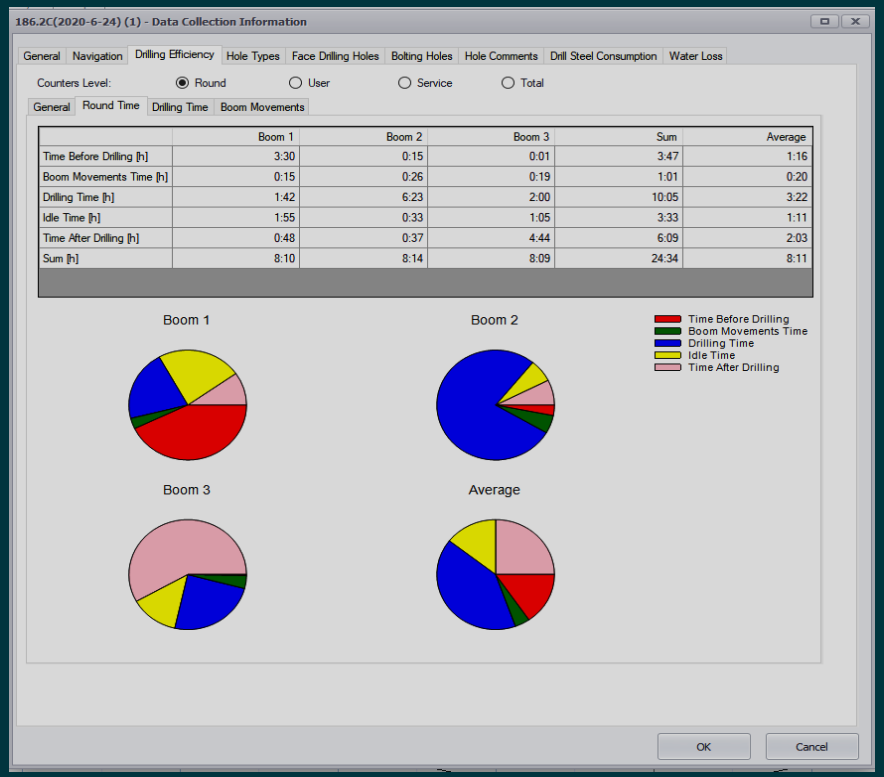


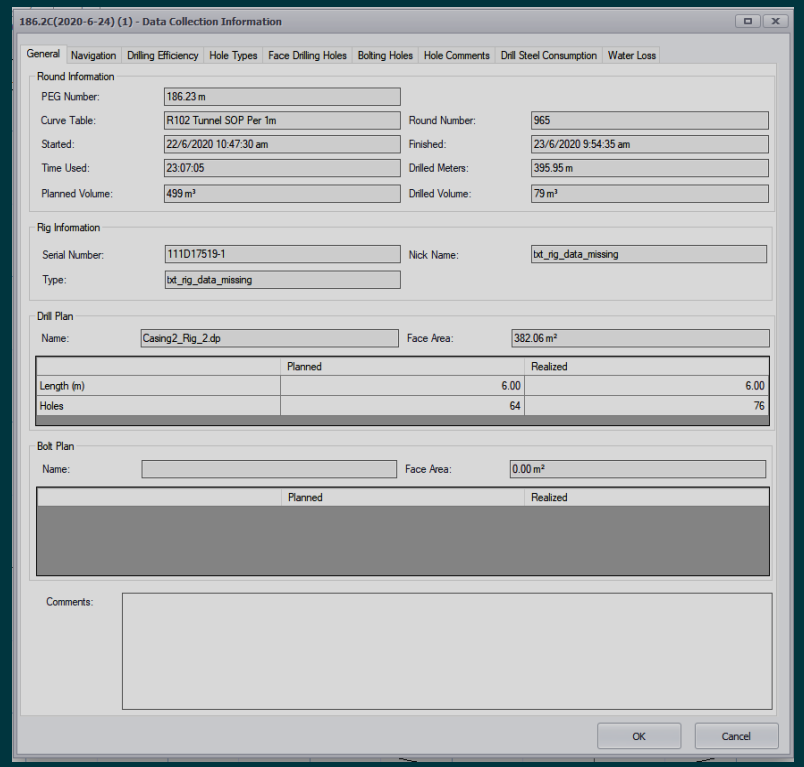


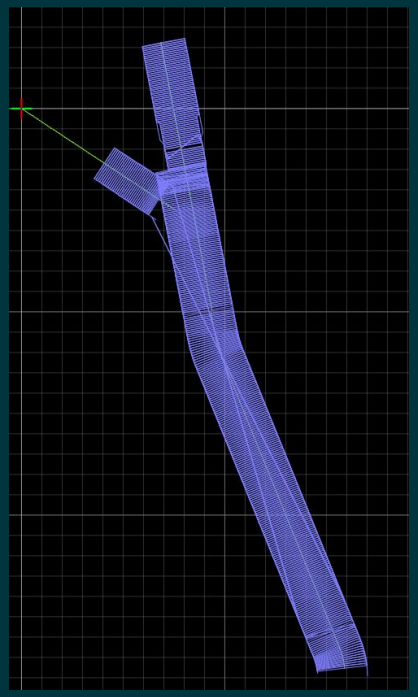
Key Function (2)

- Drilling Information
- Efficiency of Drilling Rigs









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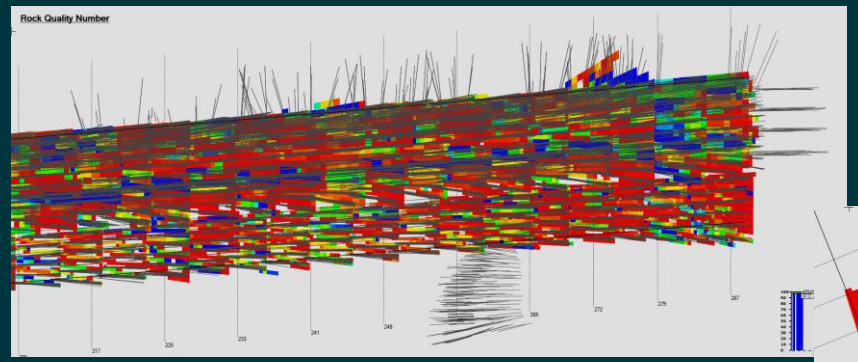
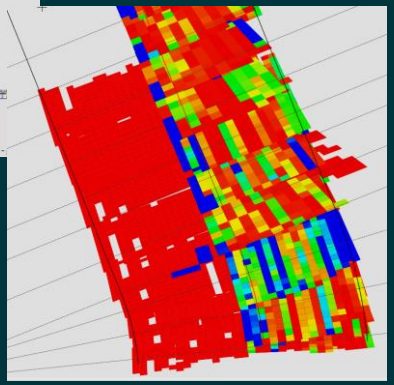
Key Function (3)

- Collection of Geo-Mechanical Data
- Carry out Rock Mass Analysis



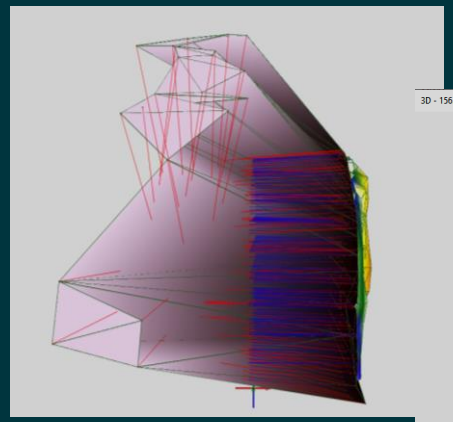


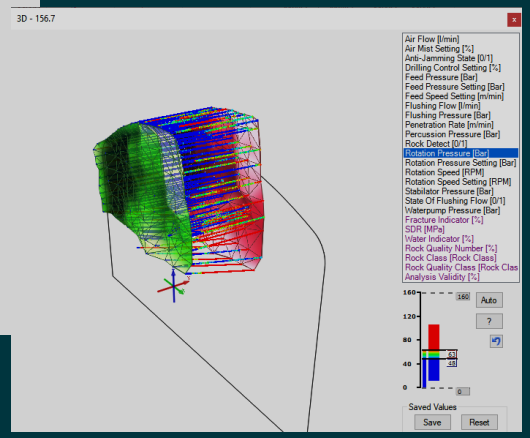
- ✓ Penetration Rate
- ✓ Percussive Pressure
- ✓ Rotation Pressure
- ✓ Flushing Pressure
- ✓ Feed Pressure

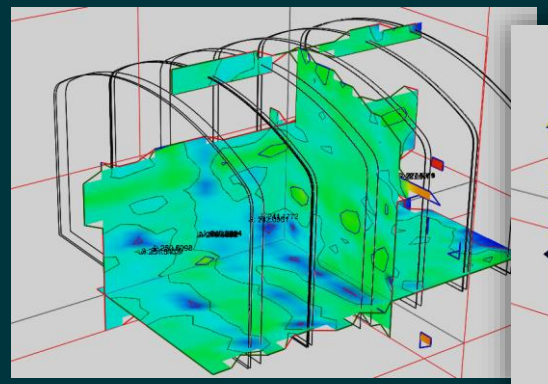
Geo-Mechanical Data

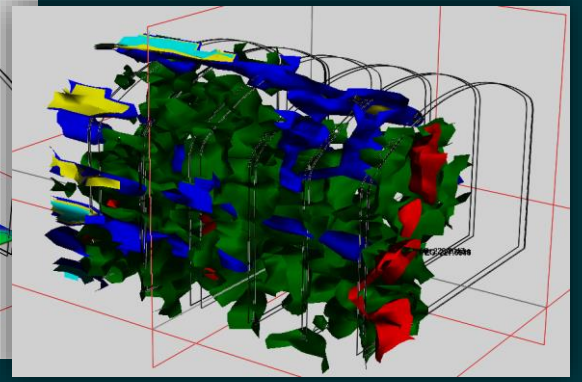
Rock Mass Analysis

- ✓ Fracture Index
- ✓ Rock Strength
- ✓ Water Indicator
- ✓ Rock Quality Number









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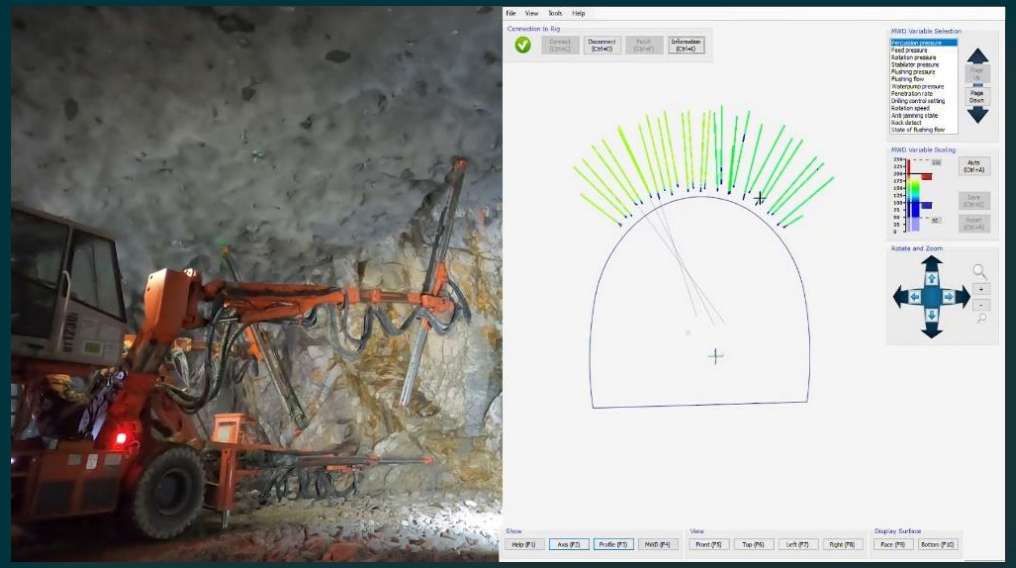
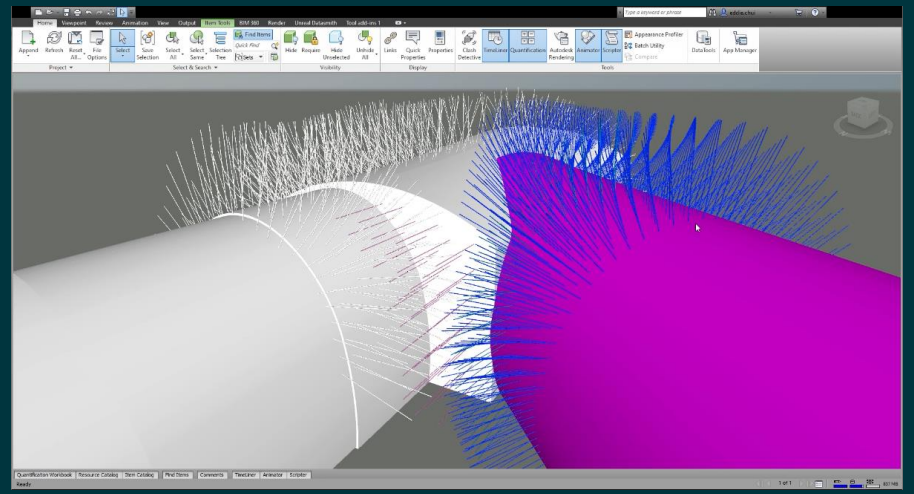
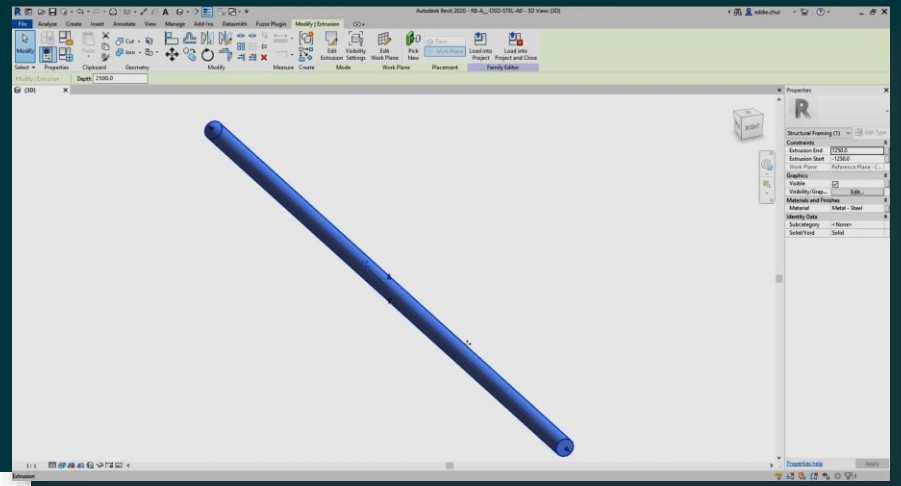
Key Function (4)

- Drill-to-BIM







Drilling with real-time data collection

Drill-to-BIM approach allows construction, operation and asset information modelling to occur simultaneously

Real-time modelling

Key Function (5)

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Robotic Cum Photogrammetry Scanning

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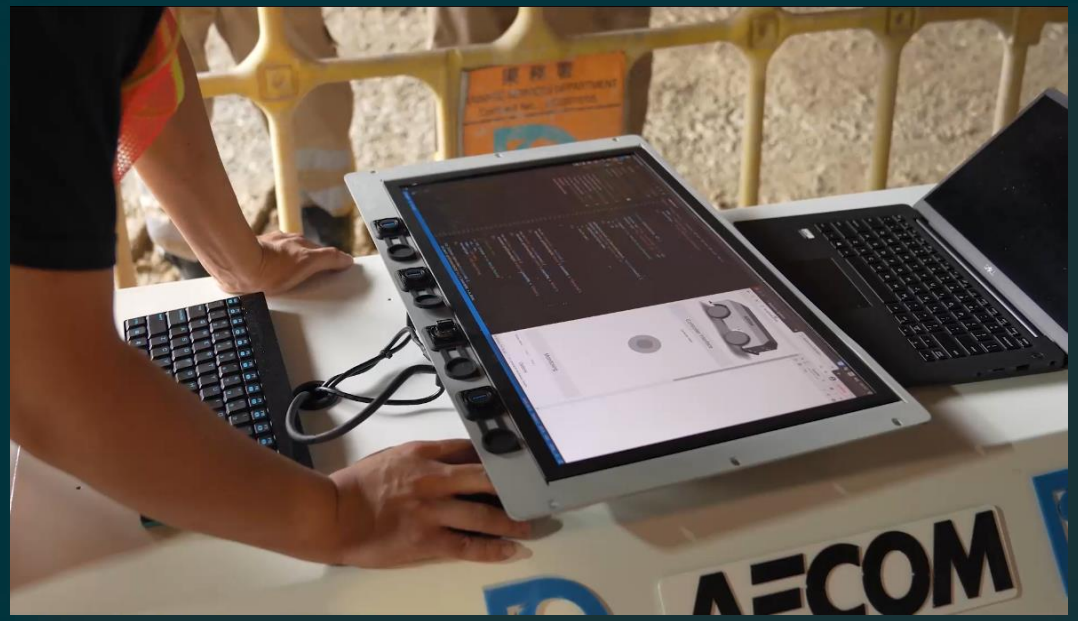
Robotic Cum Photogrammetry Scanning

- 3D Scanner Mounted Robot

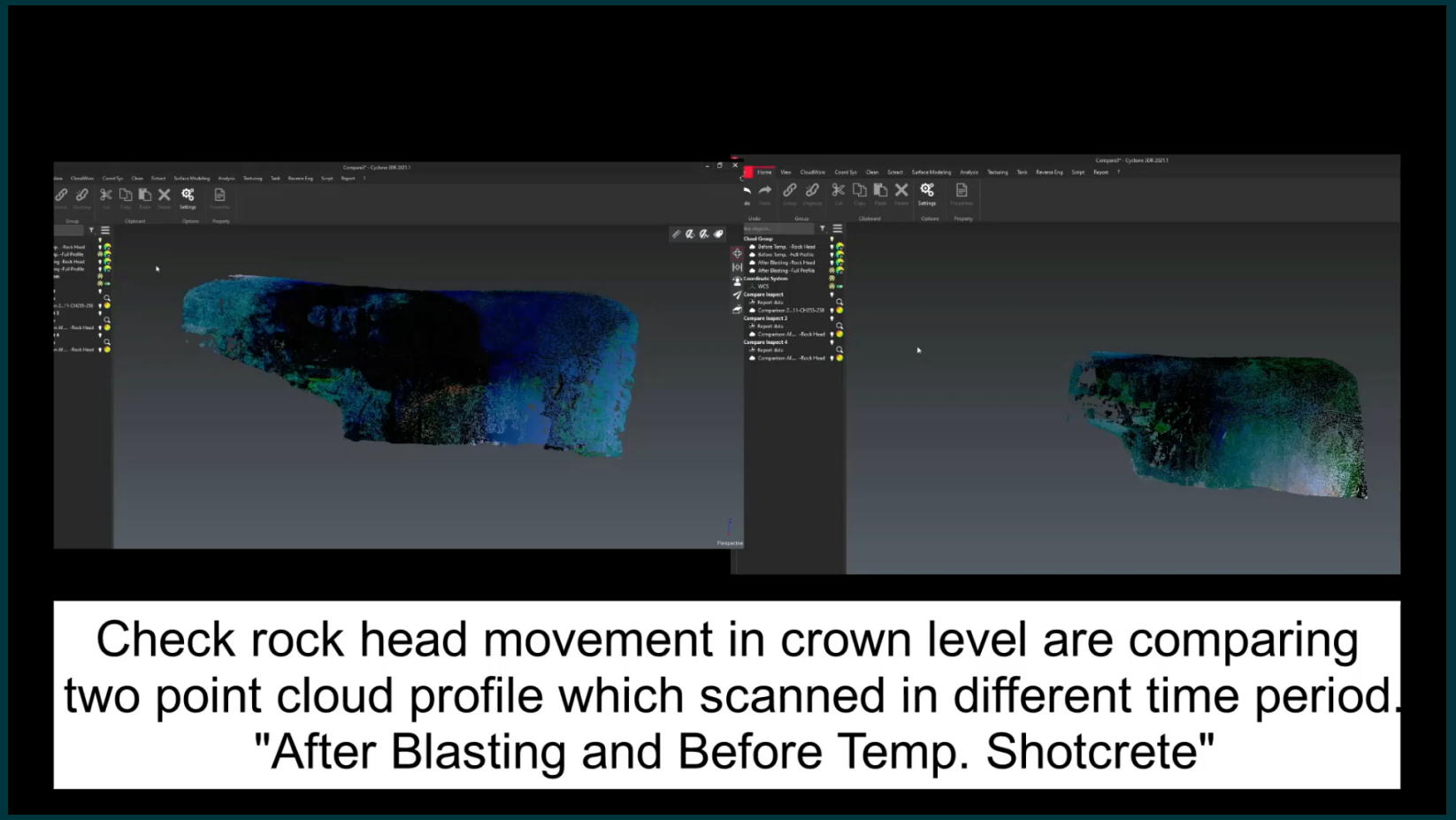


Robotic Cum Photogrammetry Scanning

- 3D Scanner Mounted Robot

Robotic Cum Photogrammetry Scanning

- Detecting Wedge Collapse Risk



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RSS Self-Developed Apps

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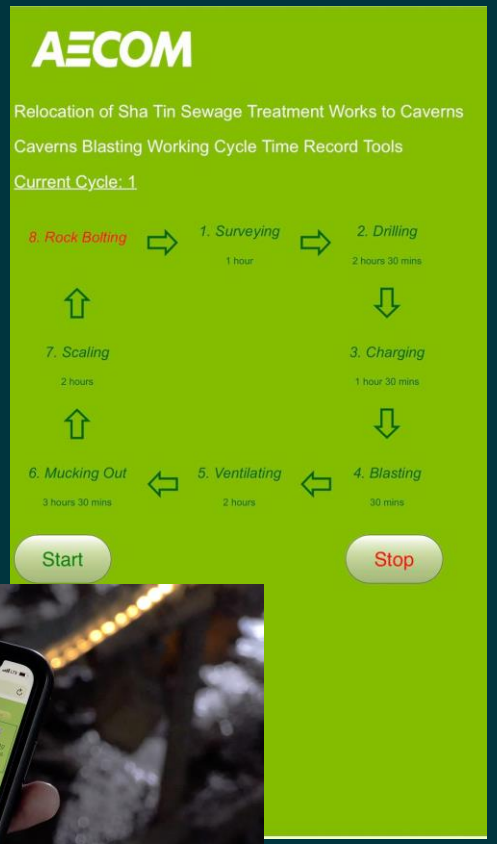
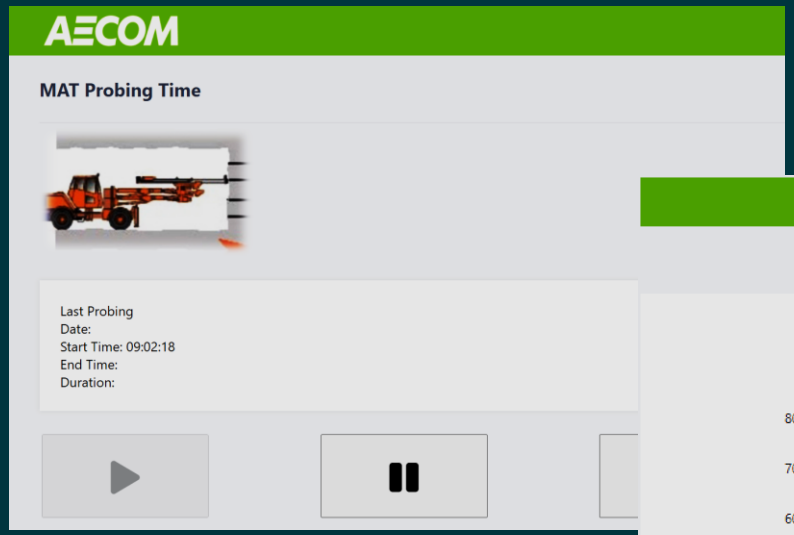
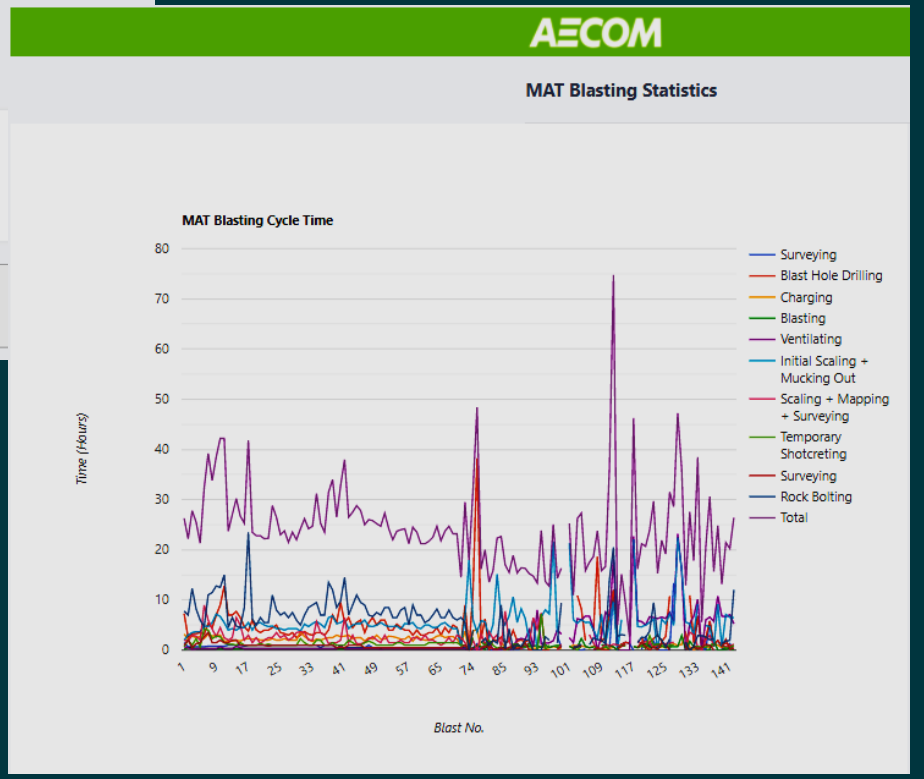
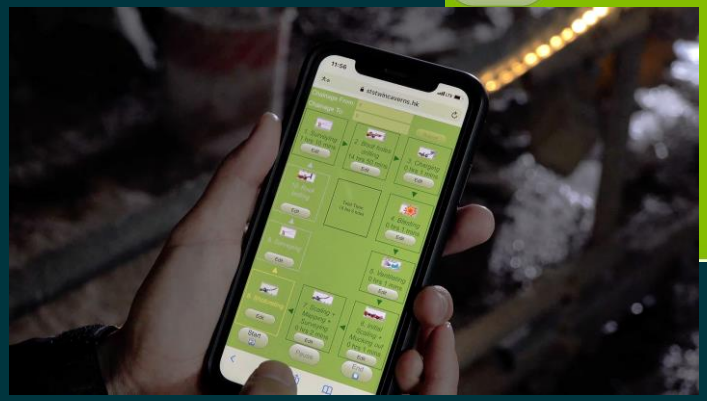
Blast Cycle Monitoring







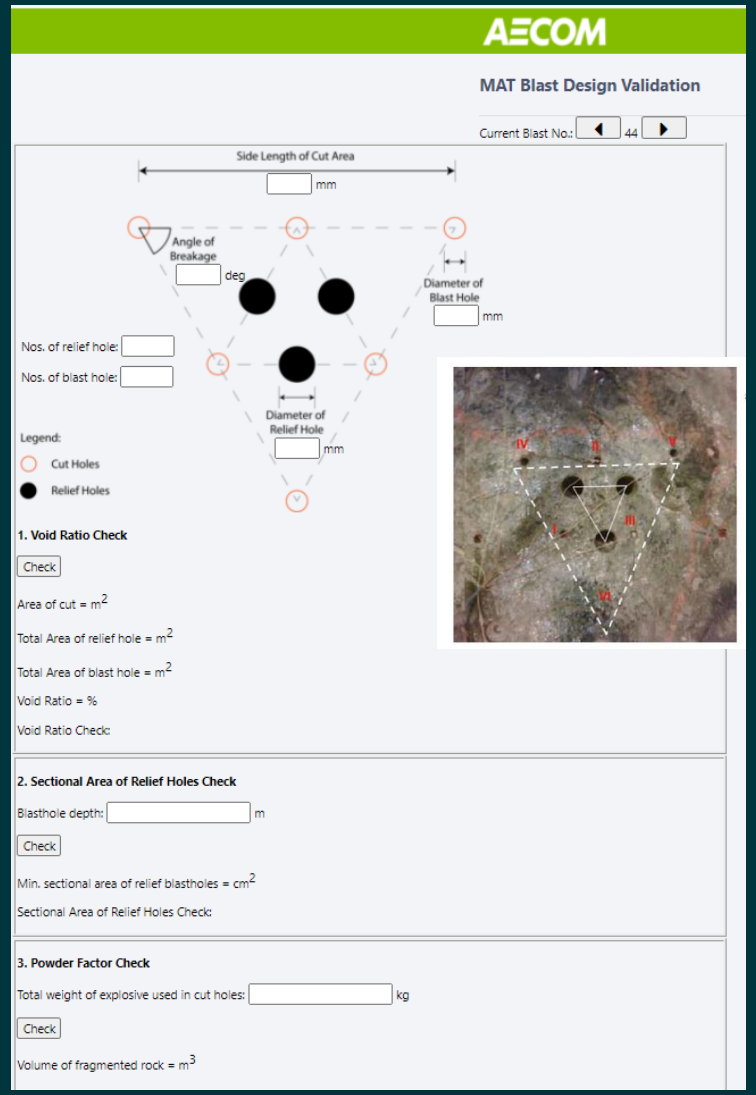


Blast Cycle Monitoring

Blast Design Validity Check

- Quick Check of Burn Cut Design

  - ✓ Void Ratio Check
  - ✓ Sectional Area of Relief Holes Check
  - ✓ Powder Factor Check
  - ✓ Breakage Angle Check
  - ✓ Delay Separation Check



Conclusion

- Various Technologies regarding Digital Geoscience and Geotechnology were Successfully Applied.

- Benefit:
  - ✓ Uphold the Supervision
  - ✓ Efficient and Cost Effective
  - ✓ Enhance the Site Safety

- Potential Value Added for Upcoming Main Cavern Project

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Thank you.

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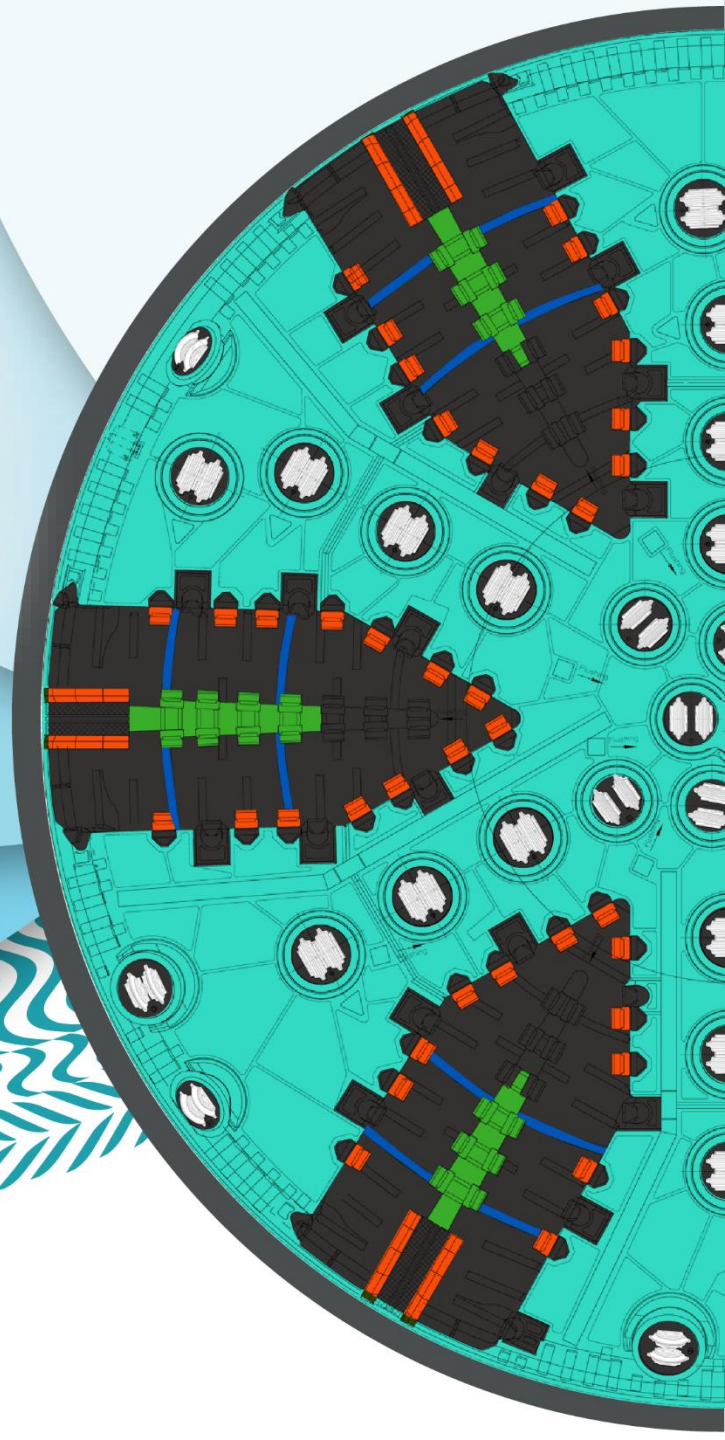
New Digital Paradigm for Geotechnical Works under Trunk Road T2 and Cha Kwo Ling Tunnel

Ir Stephen MAK
FHKIE FHKIHT FiStructE

T2主幹路及茶果嶺隧道
TRUNK ROAD T2 AND CHA KWO LING TUNNEL

土木工程拓展署
Civil Engineering and Development Department

Hyder - Meinhardt JV



T2 Project Background

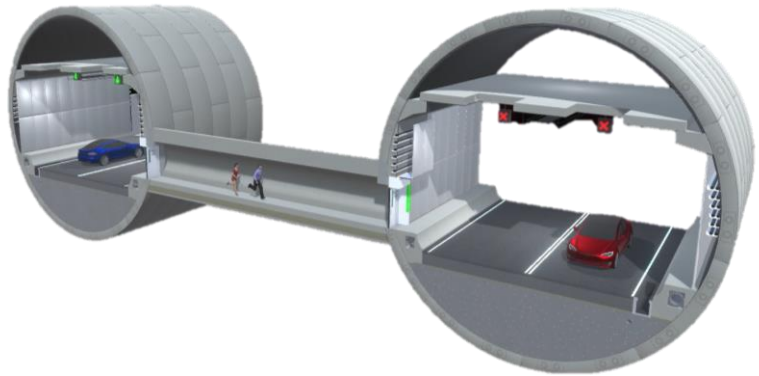
- 3.4km long dual two-lane trunk road with 3.1km in the form of tunnels
- Traffic control and surveillance systems
- Two ventilation buildings
- Associated civil, electrical and mechanical and landscaping works

Journey time during peak hours from Kai Tak to Lam Tin Interchange is greatly reduced from 15 to 3 minutes

Project Introduction

Commencement Date:	14 November 2019
Anticipated Completion Date:	2026
Contract Sum:	HK$ 16 billion
Client:	Civil Engineering and Development Department
Consultant:	**Hyder-Meinhardt Joint Venture**
Contractor:	Bouygues Travaux Publics

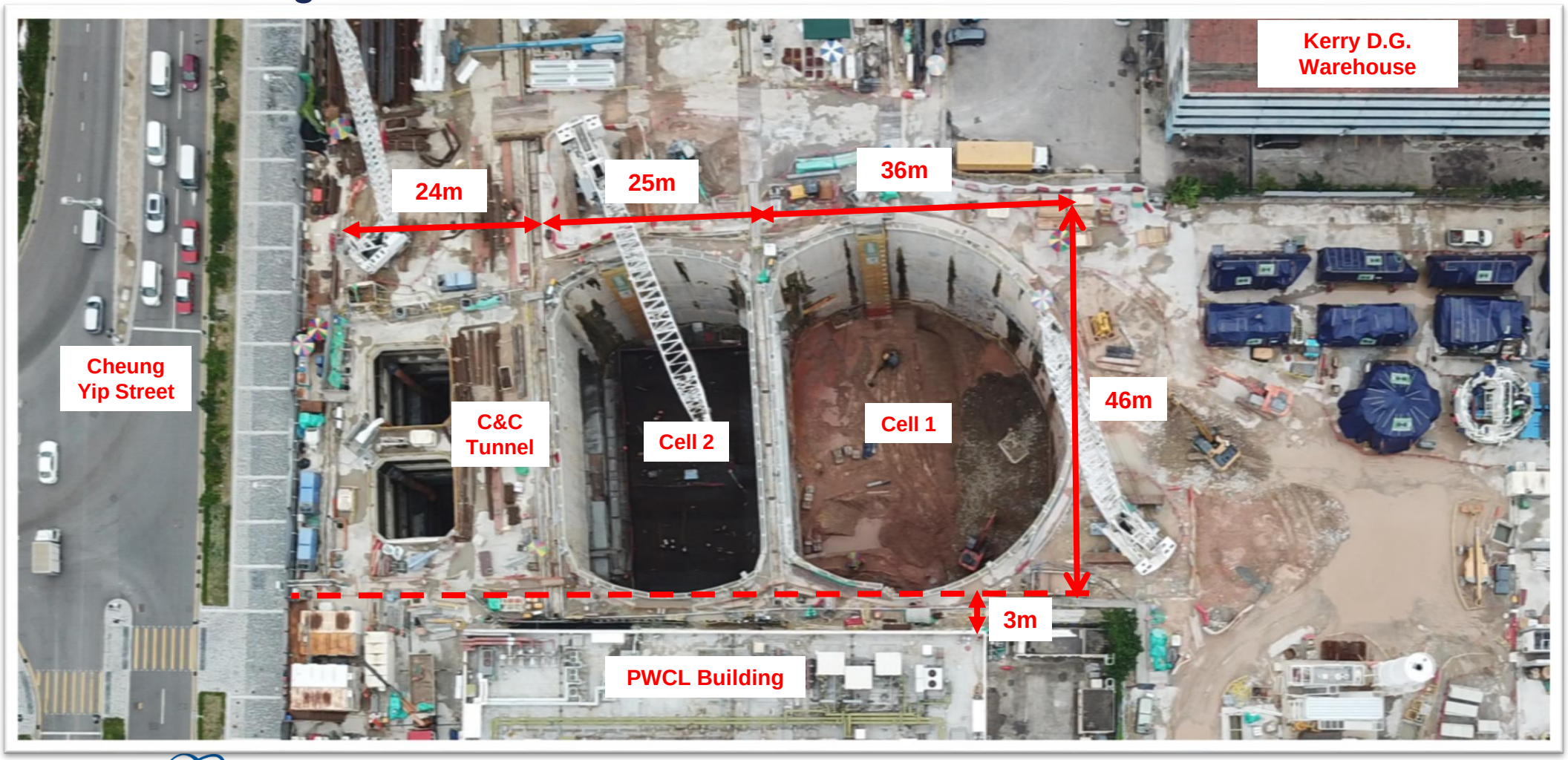
Hyder MEINHARDT
Hyder-Meinhardt JV



Innovative Technique Employed on Monitoring in the T2 Project

1	• Global Navigation Satellite System (GNSS)
2	• Handheld LiDAR Scanning for 3D Site Image
3	• Distributed Fibre Optic Sensing for monitoring in-situ strain behaviour
4	• InSAR Technology for monitoring ground movements

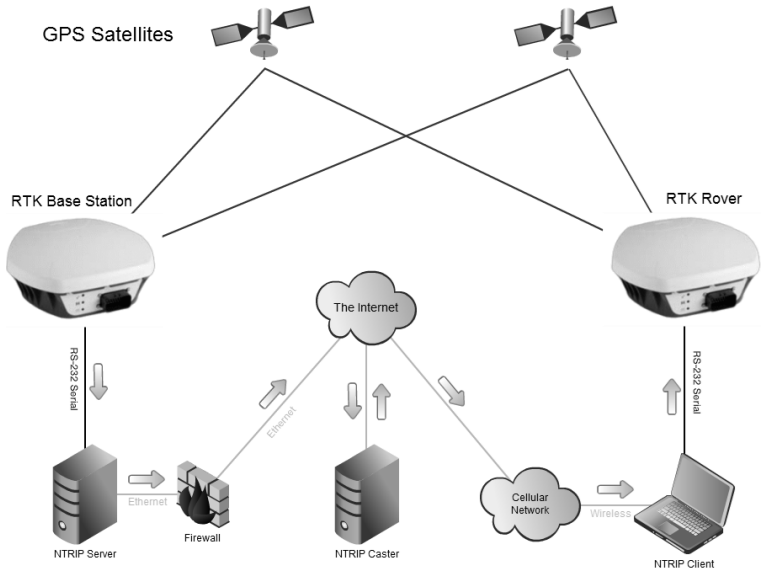
Layout Plan of Launching Shaft and C&C Tunnel Portion

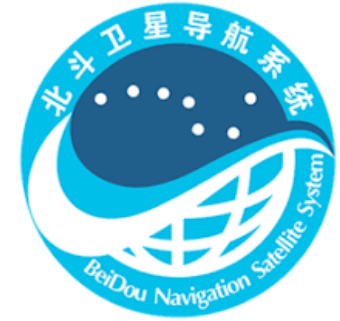


Final Excavation Depth: 38.3m (Cell 1), 37.7m (Cell 2), 33.7m (C&C Tunnel)

1. Global Navigation Satellite System (GNSS) monitoring

- Real time 3D monitoring at PWCL, South Apron seawall, Kwun Tong breakwater and Cha Kwo Ling seawall for TBM passing;
- Improve accuracy and reliability with the addition of **BeiDou Satellite (BDS) system**;
- Accuracy: ± 1mm (horizontal) and ± 2mm (vertical) in par with conventional survey;
- Automatic issue of alert Short Message Service (SMS) and/or e-mail to subscribers whenever the AAA limits are reached;
- Apply solar panel as power source for remote area.





Operating satellites above HK:

BeiDou (China):	16 nos.
GPS (US):	7 nos.
Galileo (Europe):	5 nos.
Glonass (Russia):	5 nos.
Total:	33 nos.

Limitations / constraints:

- Rover stations within 3km from base station;
- 70° open sky view for rover stations to receive satellite signals;
- Multi-path of satellite signals due to reflection at glass façades of high-rise buildings;
- Interference from other radio signals with similar frequency (~1.5 GHz).

May impair accuracy of GNSS

CEDD 土木工程拓展署 Civil Engineering and Development Department

Hyder MEINHARDT Hyder - Meinhardt JV

1. Global Navigation Satellite System (GNSS) monitoring

- Phase 1 for PWCL and South Apron seawall
- Phase 2 for breakwater and Cha Kwo Ling seawall
- Reuse same setup at different locations for cost saving

Phase 1 monitoring at PWCL & South Apron seawall

Phase 2 monitoring at breakwater

Phase 2 monitoring at CKL Seawall

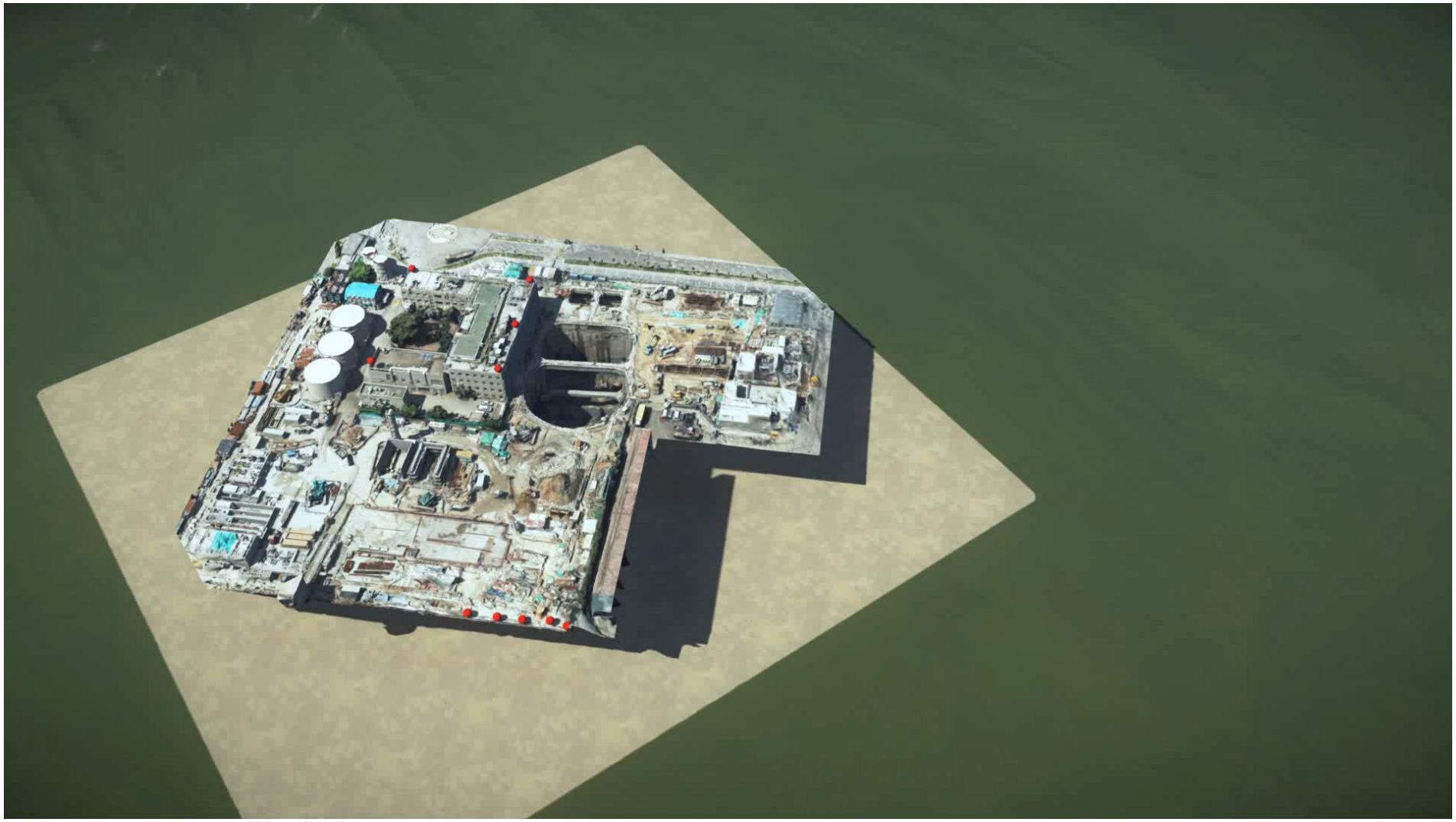
1. Global Navigation Satellite System (GNSS) monitoring

Typical setting up of GNSS rover station at roof of PWCL

Normal rover station

Rover station with choke ring for minimizing multi-path signals

1. Global Navigation Satellite System (GNSS) monitoring



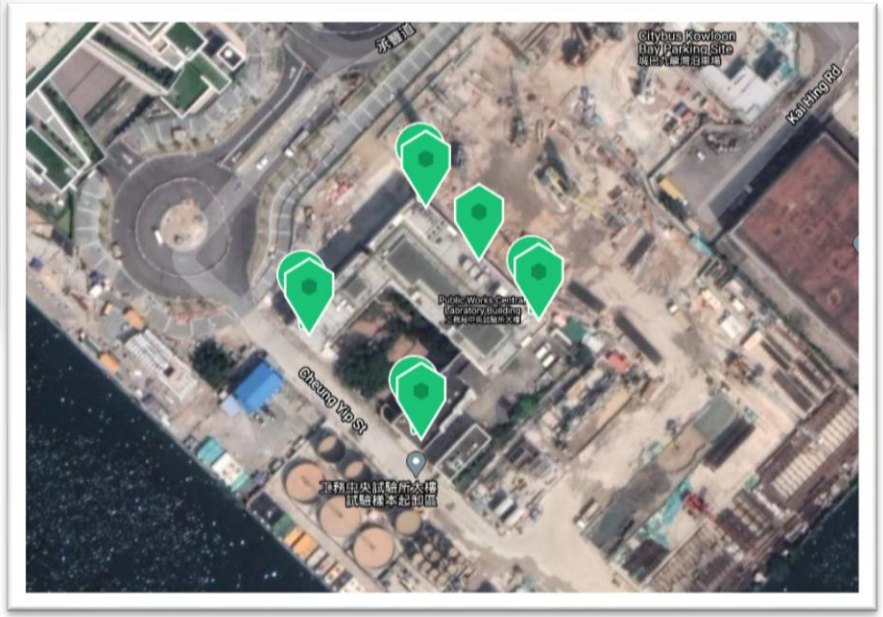
Phase 1 Monitoring at PWCL & South Apron seawall

1. Global Navigation Satellite System (GNSS) monitoring

Dedicated Web portal for real time reporting of monitoring data

Sensors

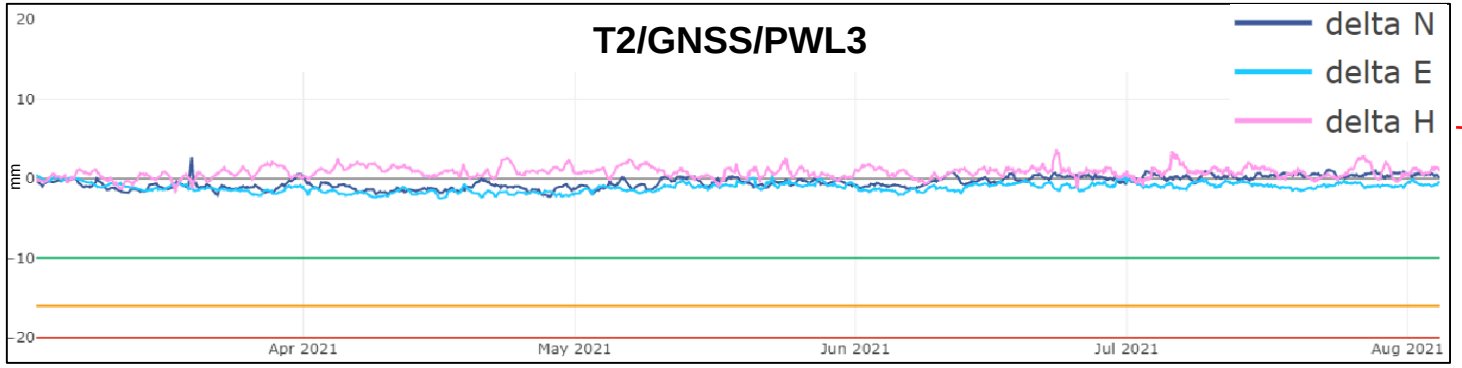
Name	Mac	Type	Status	Updated	Value
TS1	5b1c83	TILT	Normal	2021-01-18 08:03:13	Pitch = **0.0096**, Roll = **-0.017** (degree)
TS2	5b1a56	TILT	Normal	2021-01-18 08:30:25	Pitch = **0.0077**, Roll = **-0.0133** (degree)
TS3	5b1a3e	TILT	Normal	2021-01-18 07:23:22	Pitch = **-0.0103**, Roll = **0.0038** (degree)
TS4	5b1a61	TILT	Normal	2021-01-18 06:46:22	Pitch = **-0.0043**, Roll = **-0.0231** (degree)
PWL1	d051f2	GPS	Normal	2021-01-18 09:00:00	delta N = 0.87, delta E = 1.14, delta H = **-1.94** (mm)
PWL2	d05232	GPS	Normal	2021-01-18 09:00:00	delta N = 0.74, delta E = 0.96, delta H = **-1.73** (mm)
PWL3	d05239	GPS	Normal	2021-01-18 09:00:00	delta N = 0.42, delta E = 0.98, delta H = **-1.51** (mm)
PWL4	d0523a	GPS	Normal	2021-01-18 09:00:00	delta N = 0.26, delta E = 0.9, delta H = **-1.22** (mm)
PWL5	d051f6	GPS	Normal	2021-01-18 09:00:00	delta N = 0.52, delta E = 1.18, delta H = **-2.04** (mm)

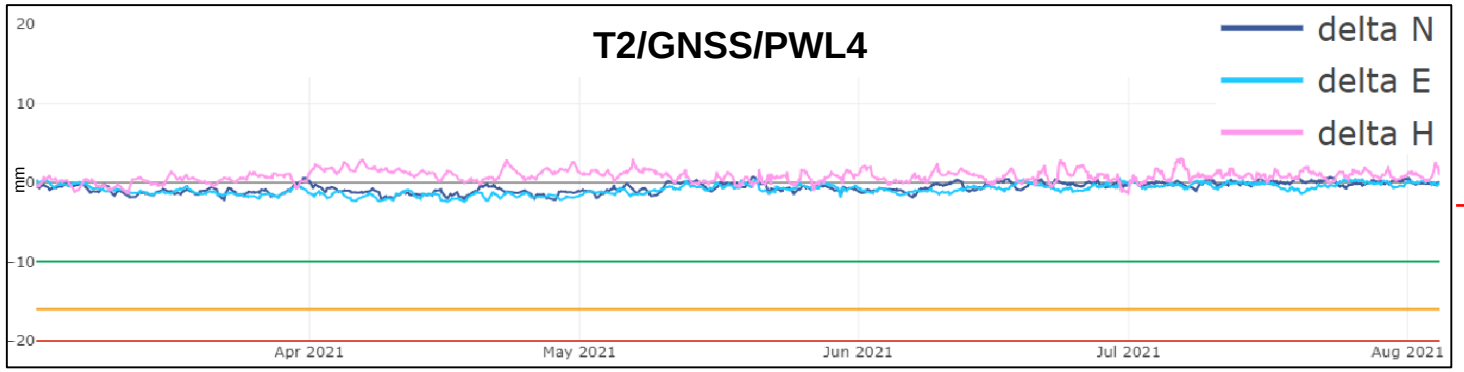


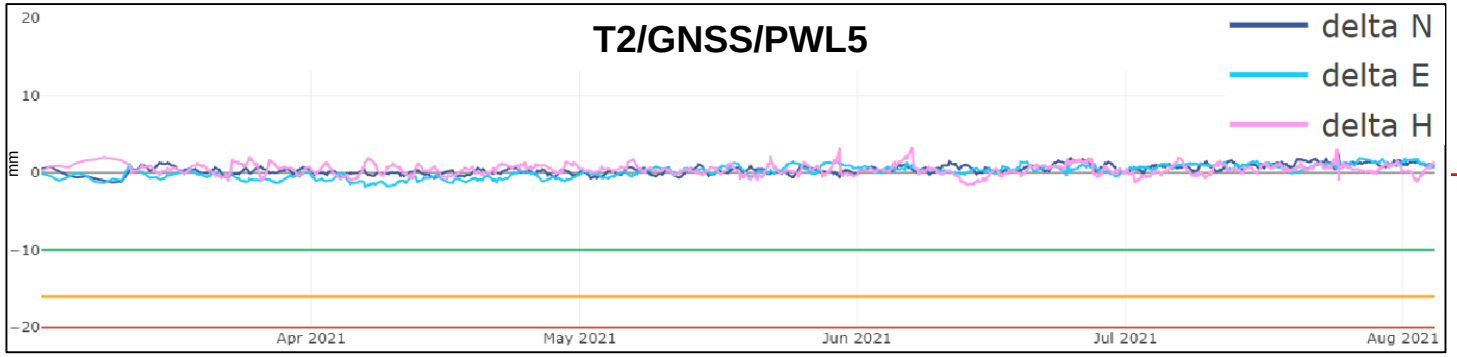
Location Plan of Rover Stations at PWCL Building

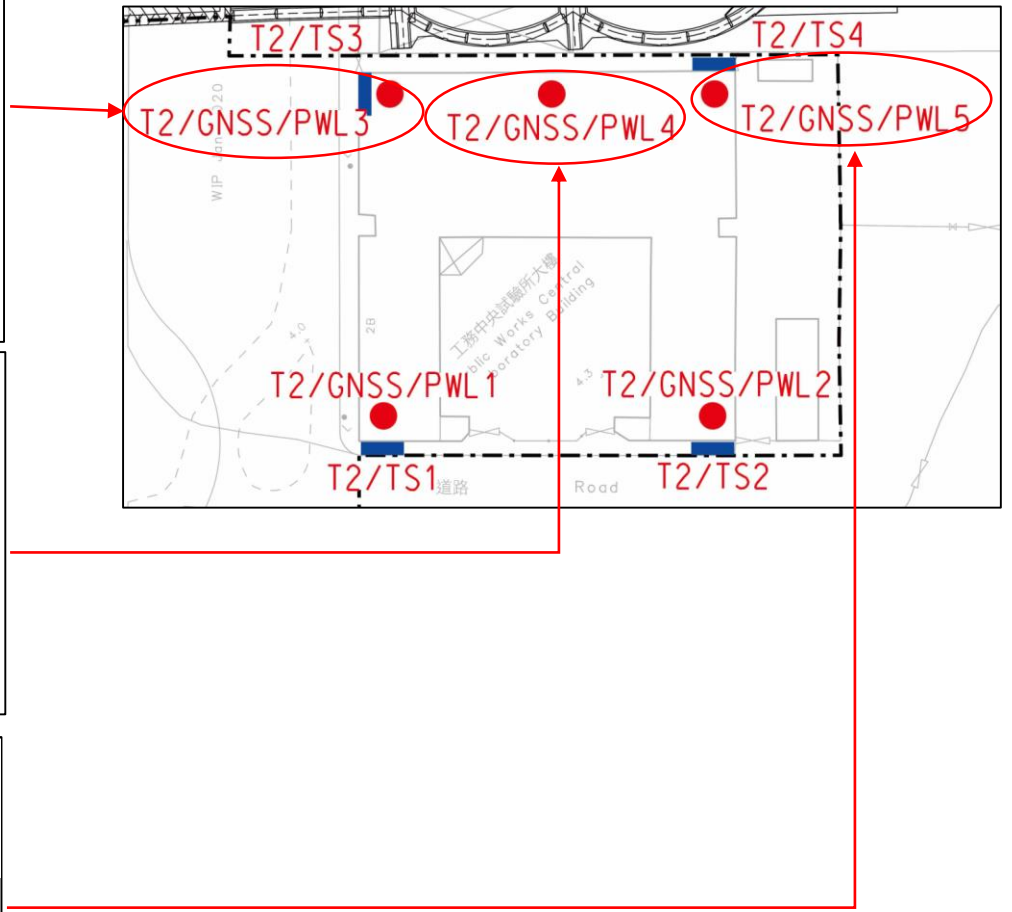
1. Global Navigation Satellite System (GNSS) monitoring

Monitoring Data at roof of PWCL from March 2021 to July 2021



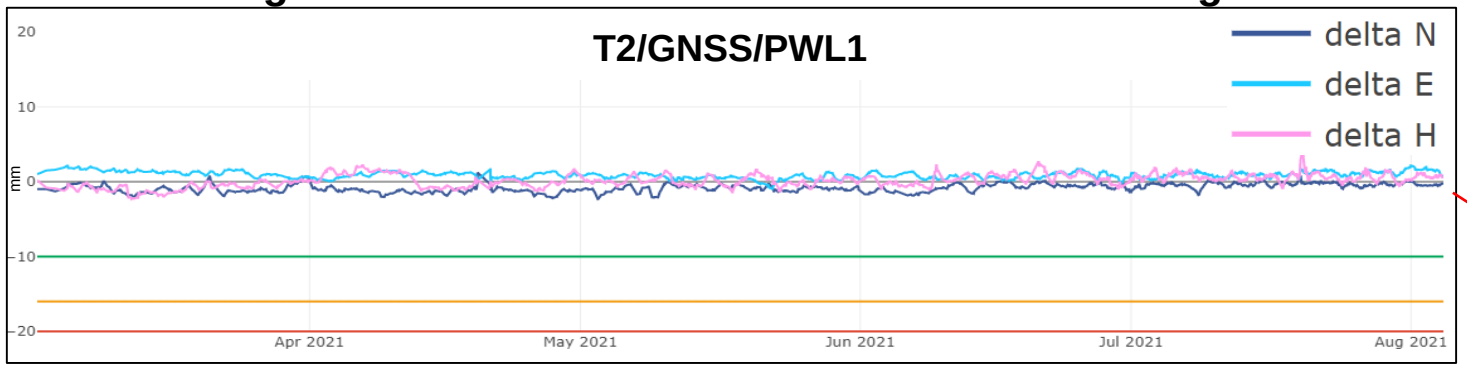


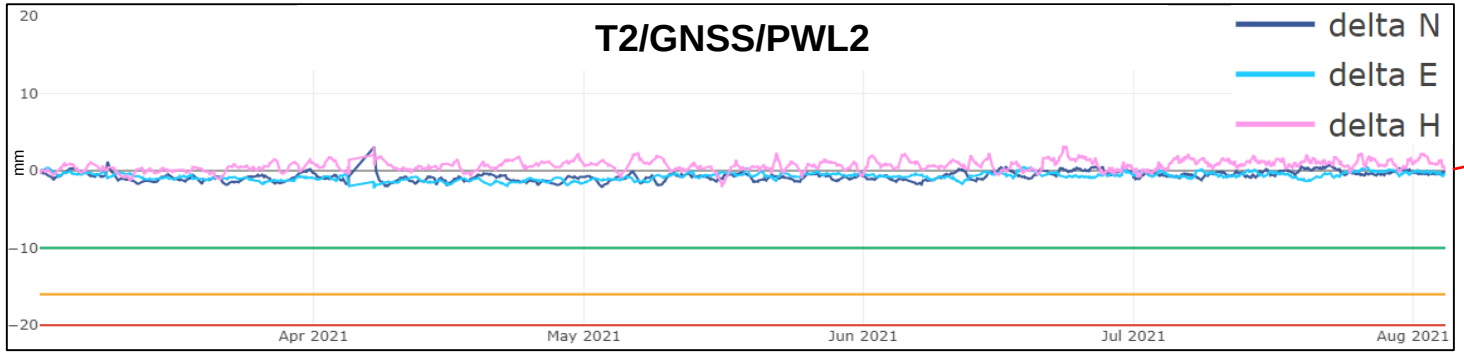


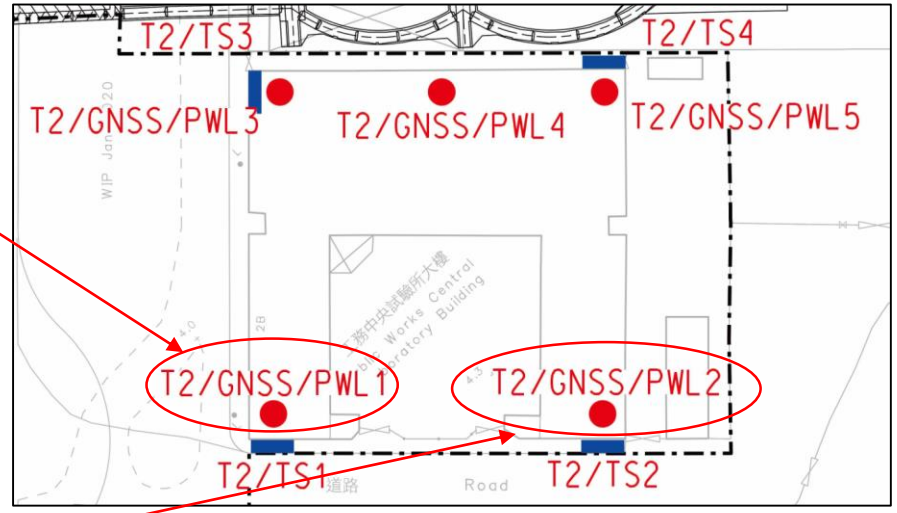


1. Global Navigation Satellite System (GNSS) monitoring

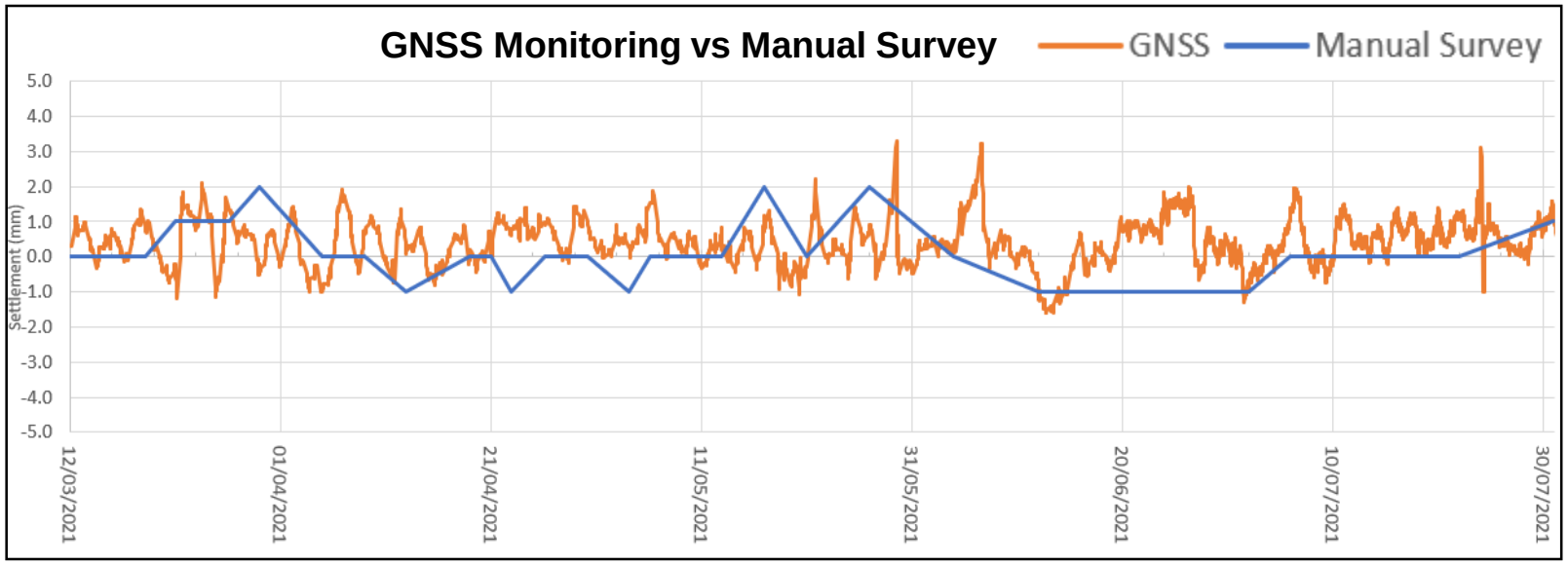
Monitoring Data at roof of PWCL from March 2021 to August 2021







1. Global Navigation Satellite System (GNSS) monitoring



Comparison of GNSS and Manual Survey

Monitoring Frequency

Every 15 mins
Fully autonomous
(using GNSS)

Vs

Daily
(using manual survey)

2. Handheld LiDAR Scanning for 3D Site Image

- Use of handheld LiDAR (Light Detection and Ranging) technique for scanning of 3D site image
- Regular record of excavation profile, for estimation of bulk excavation volume and to facilitate GEO's analysis of the performance of the ELS system
- Quick acquisition of large number of detected points using LiDAR technique (~20M points from a 5-min scan) than conventional survey (e.g. around 1hr walk to scan LSCC, much faster than traditional surveying method which may take 1 – 2 days)
- Approximately 1 – 2 hrs processing time from raw data to 3D models
- Accuracy: 3 to 5 cm

(Co-organised with GEO/S&T)

LiDAR scanning in progress

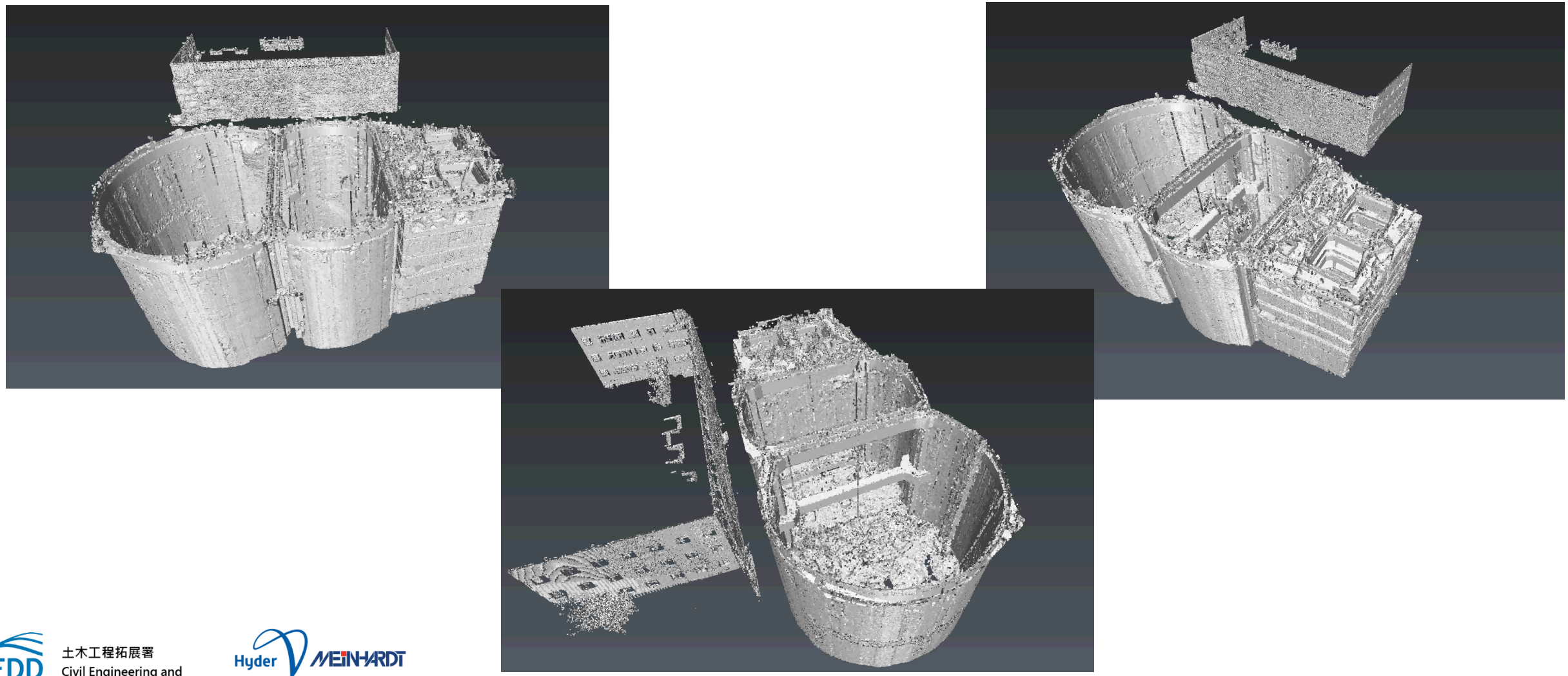
Scanner and Data Logger

Reference Point

2. Handheld LiDAR Scanning for 3D Site Image

Demonstration of LiDAR Scanning at LSCC

2. Handheld LiDAR Scanning for 3D Site Image



3D Point Cloud Images for LSCC

2. Handheld LiDAR Scanning for 3D Site Image

Animation of the 3D LSCC Point Cloud Image

3. Distributed Fibre Optic Sensing for monitoring in-situ strain behaviour of D-wall panels

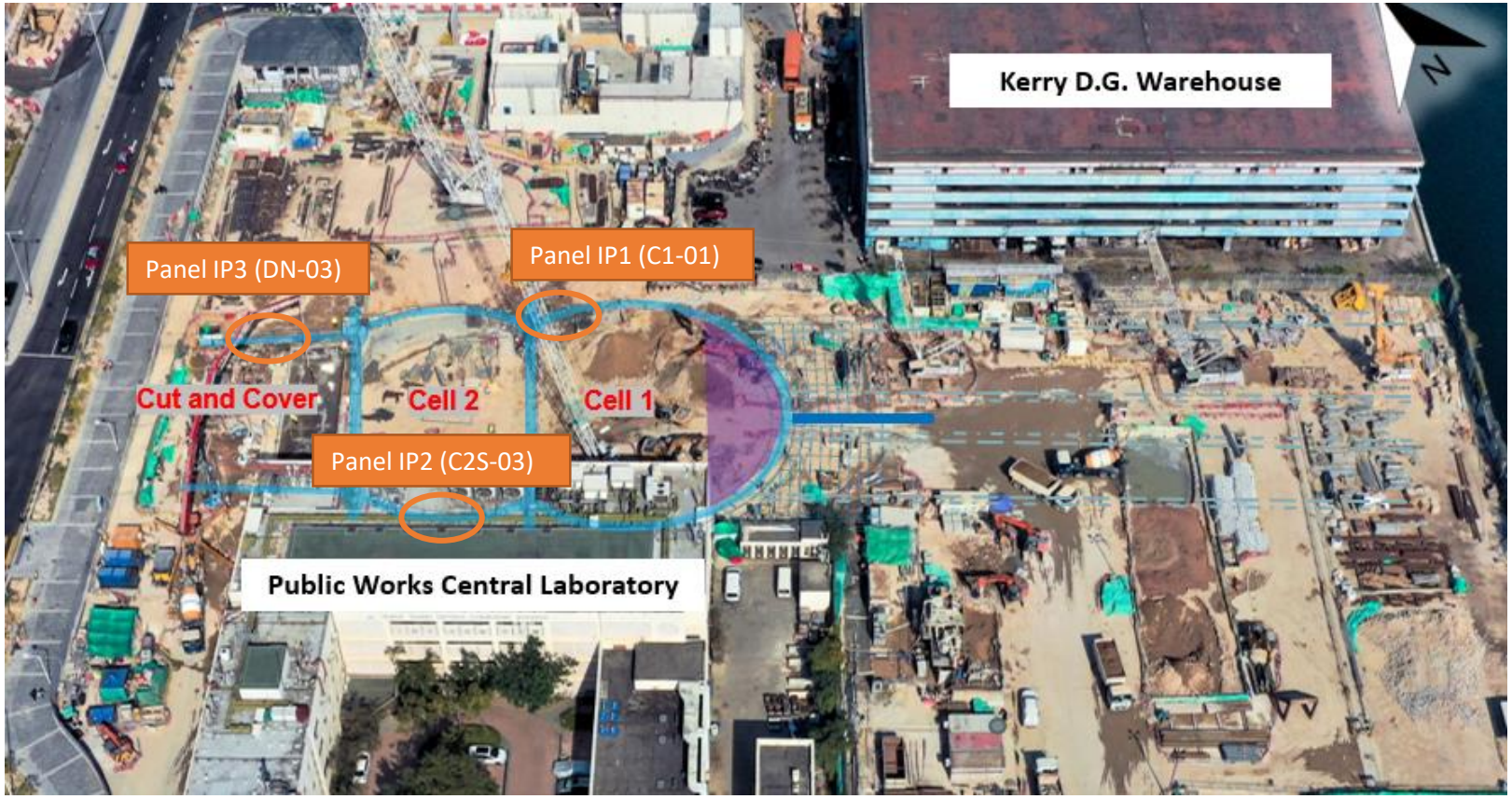
- Monitor the performance of the diaphragm wall panels
- Obtain continuous hoop and bending strain profiles along specific sections of the diaphragm wall panels (spatial resolution of 5cm is adopted for this project);
- Fibre optics as primary sensing technique, supplemented by strain gauges and earth pressure cells;
- Better understanding of the actual hoop behaviour of semi-circular ELS system to facilitate research and design review.

(Co-organised with GEO/S&T and PolyU)

Advantages of Fibre Optics :

- Continuous monitoring along fibre optics
- Not affected by E&M disturbance
- Long distance monitoring – less depletion of optical signal over long distance than other sensors

3. Distributed Fibre Optic Sensing for monitoring in-situ strain behaviour of D-wall panels



Installation of Fibre Optics in three D-wall panels:

- IP1 (in Cell 1) – Close to Y-panel for less hoop stress + large bending moment
- IP2 (in Cell 2) – Mid-span of two Y-panels for the largest hoop stress
- IP3 (in C&C) – Largest bending moment

3. Distributed Fibre Optic Sensing for monitoring in-situ strain behaviour of D-wall panels

Fibre Optic sensors

Fibre Optics installed on rebars

Lowering of steel cage in progress

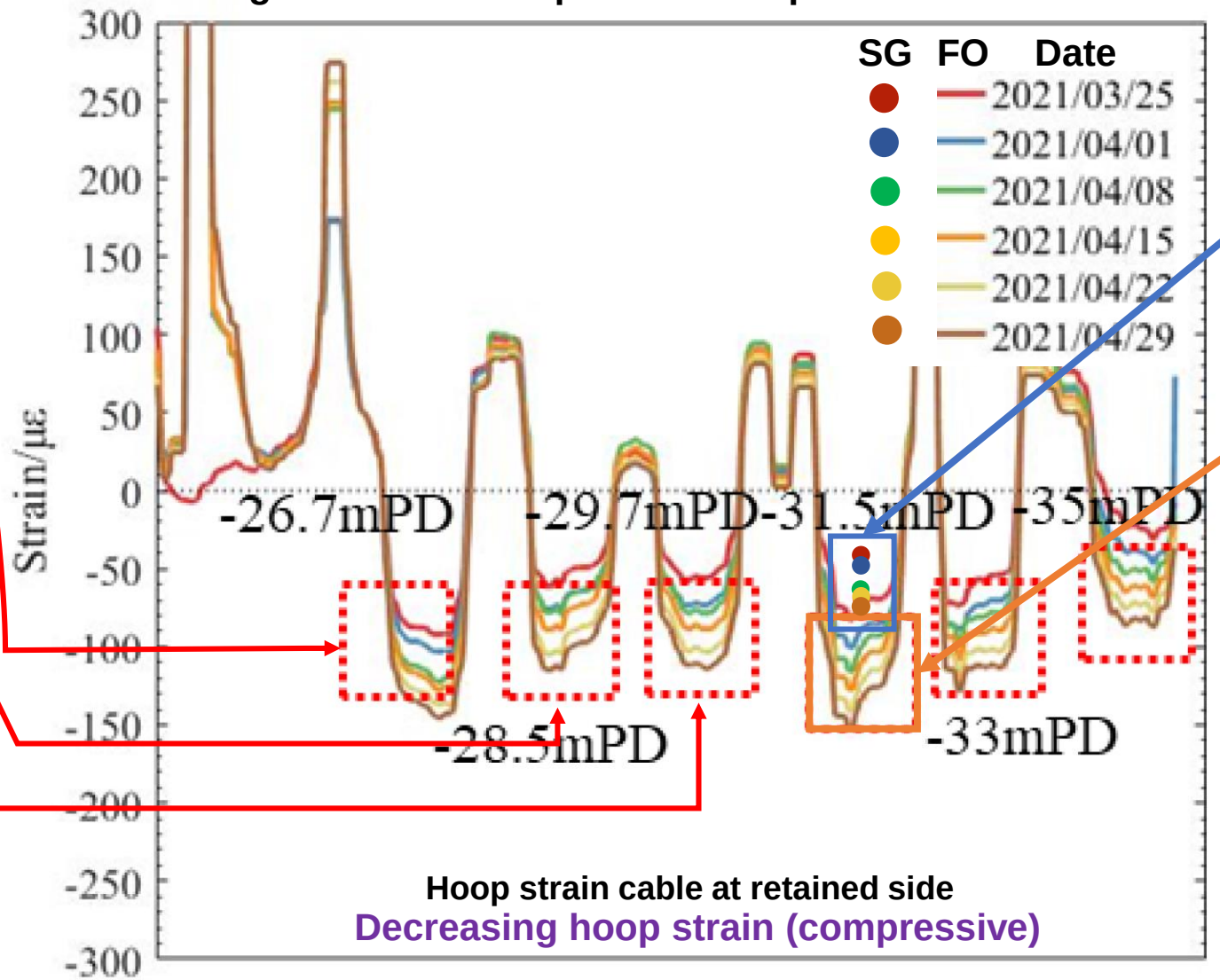
Testing of Fibre Optics after lowering of steel cage

3. Distributed Fibre Optic Sensing for monitoring in-situ strain behaviour of D-wall panels

Fixing of FO onto Steel Cage

3. Distributed Fibre Optic Sensing for monitoring in-situ strain behaviour of D-wall panels

Monitoring Data of Fibre Optics for Hoop Strain at Panel C2S-03



Hoop strain cable at retained side
Decreasing hoop strain (compressive)

Strain at a Discrete Point (using Strain Gauge)

Vs

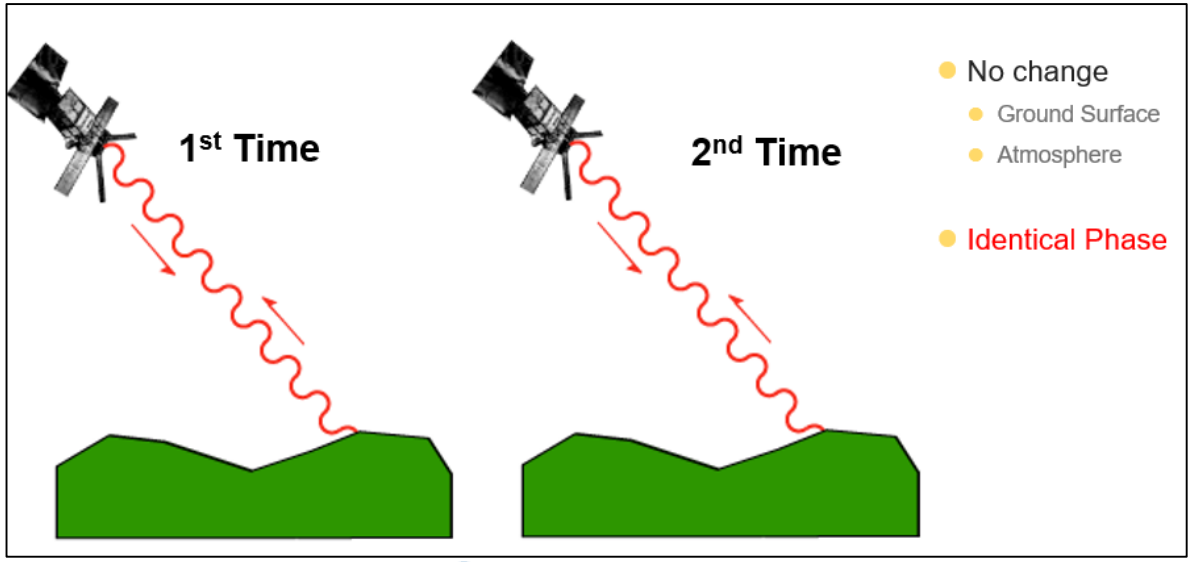
Continuous Strain Profile (using FO)

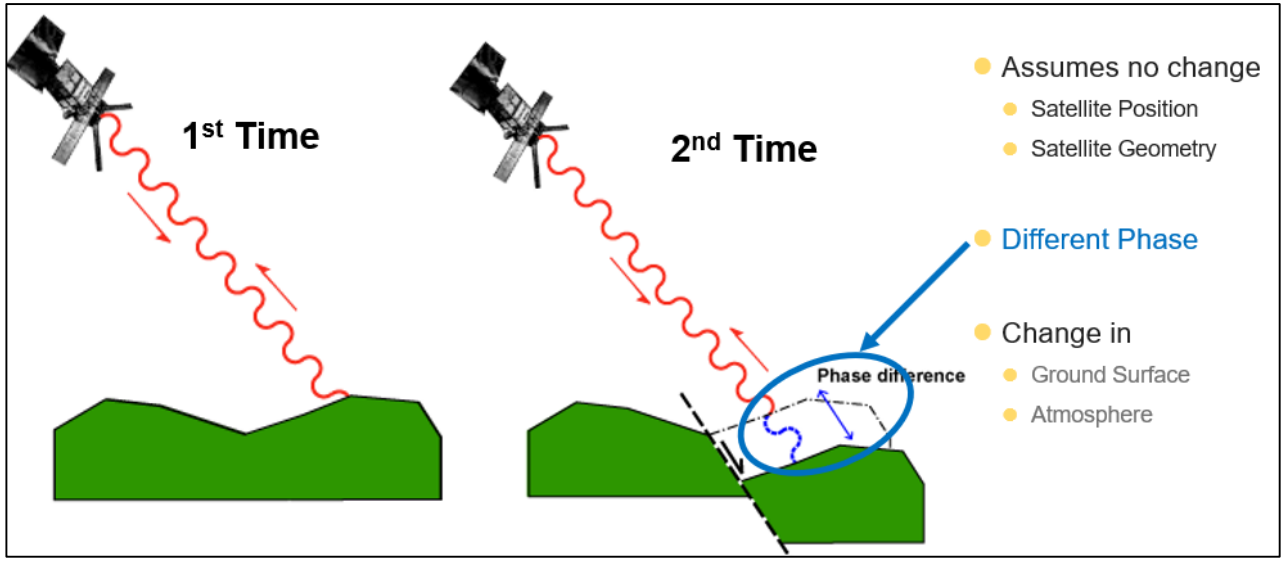
Strain change in D-wall generally tallies with design trend!
*Ongoing study by GEO/S&T and PolyU

CEDD 土木工程拓展署 Civil Engineering and Development Department
Hyder MEINHARDT Hyder - Meinhardt JV

4. InSAR Technology for monitoring ground movements at Cha Kwo Ling Village

- Use of InSAR (Interferometric Synthetic Aperture Radar) technology for mapping ground deformation using satellite radar images
- Radar image acquisition frequency: every 11 days (average orbiting cycle of satellite)
- Claimed accuracy: ± 2mm (vertical)
- Advantages of using InSAR monitoring:
  - ✓ Remote sensing technology, suitable for areas with restricted access (e.g. like Cha Kwo Ling Village due to COVID-19)
  - ✓ No disturbance to the residents of Cha Kwo Ling Village
  - ✓ Can retrieve historical monitoring data back from July 2017
  - ✓ Not affected by adverse weather conditions

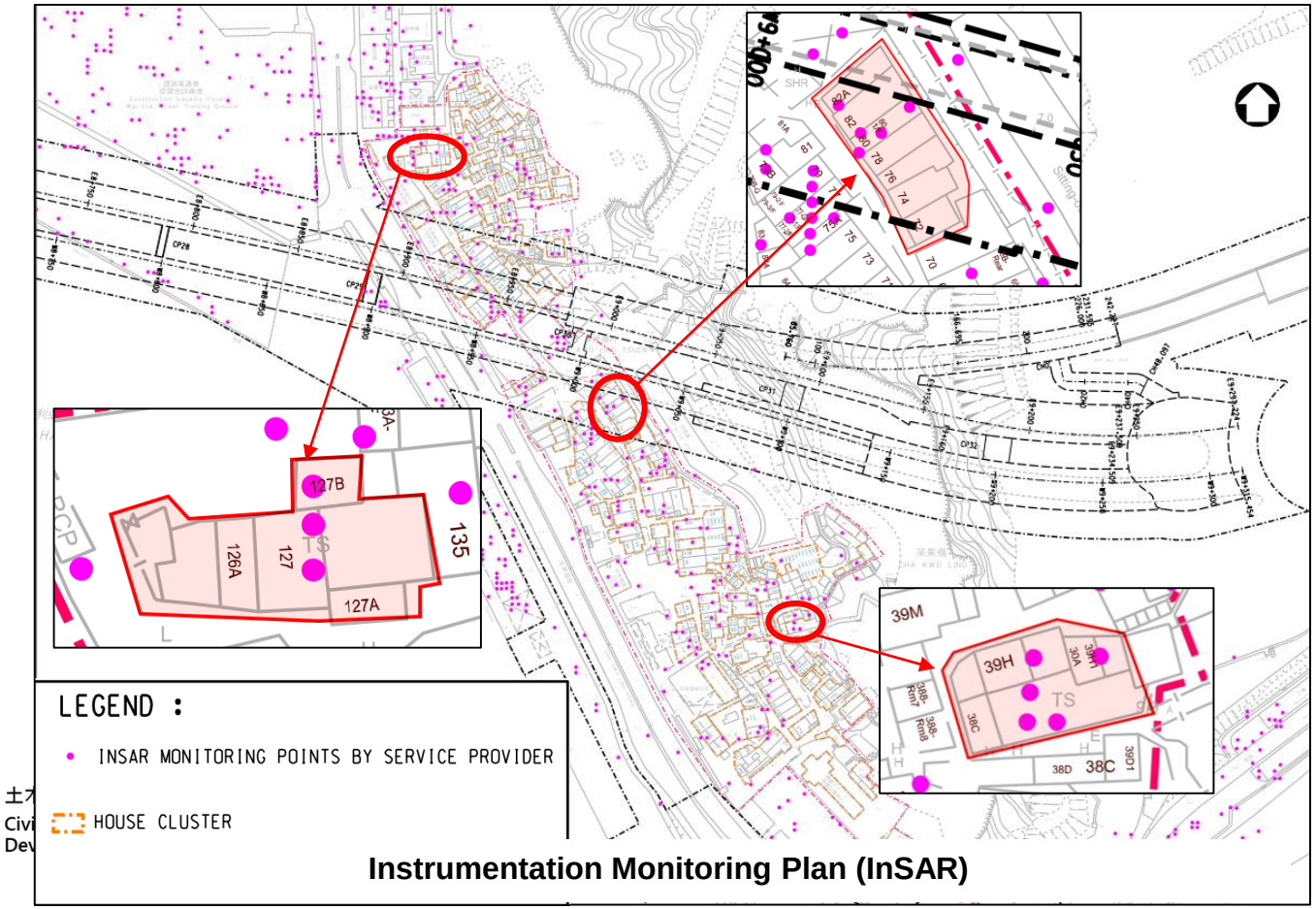




4. InSAR Technology for monitoring ground movements at Cha Kwo Ling Village

Potential Application in T2 Project:

- CKL Village closely clustered houses with narrow alleys, extremely difficult for manual survey; COVID-19 situation will also cause restricted access;
- Use InSAR monitoring for clusters of houses to supplement conventional survey;

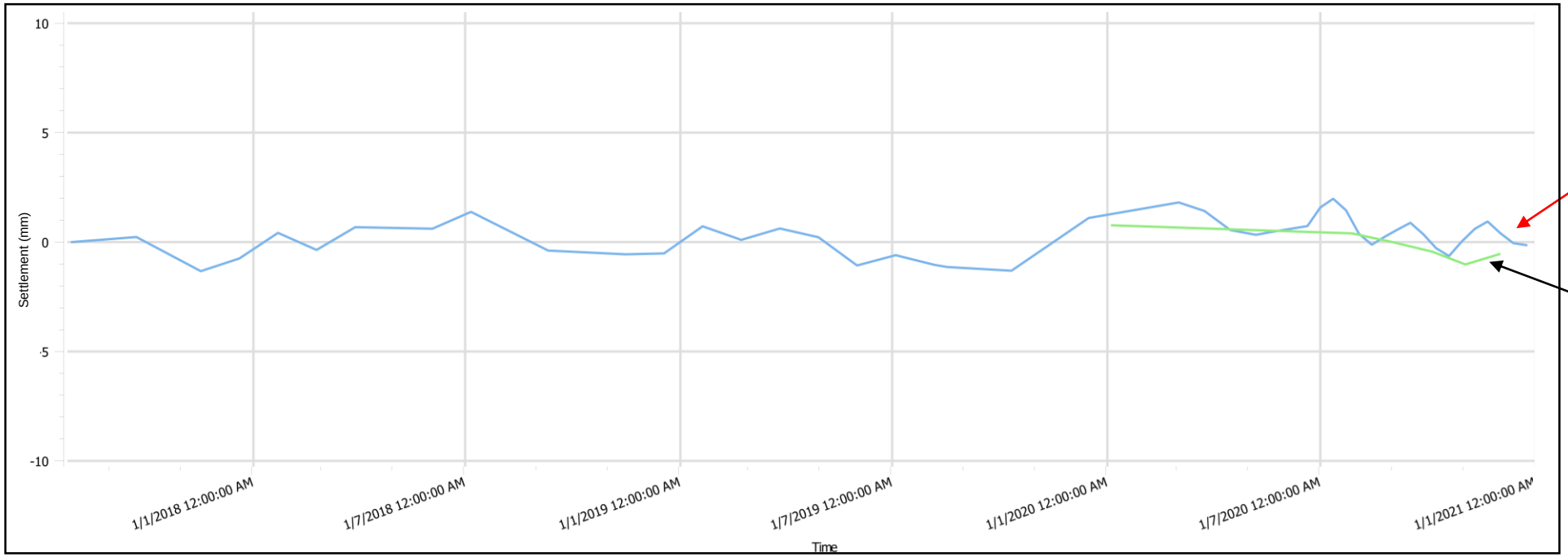


Instrumentation Monitoring Plan (InSAR)

House No.	No. of InSAR Point
Tin Hau Temple	0
44, 48C	3
41A, 41B, 42A, 43, 43B, 44A, 44C, 44D, 48, 48B2, TS2	6
39B, 39C, 39L, 42L, 39Q1, 39M388-Rm7, 388-Rm8	5
38C, 39H, 30A, 39H1	5
39B1, 39B2, 39C1, 39D, 39F, 39G, 39GG, 39MG, 39M1, 39Q, 39Q2, 39R, 42J, 42J1, 48B, 48D, 48E, 481, 48F2, 48V6, 48V7, 48V8, 48V11	5
48A, 48S, 48V	3
132	1
Cha Kwo Ling Public Toilet and Showroom	5
49, 50, 50B, Law's Manision (50B, 51, 51A), 58(58A2, 59A, 59A1, 59A2, 59A3), 58A(59B, 59E, 59H,63F),58B, 58C	7
53A, 54, 65A	3
90,55, 56, 57	3
89, 89D1	1
57A, 57B	3
59, 59D, 60, 61, 62, 63, 64, 65C	5
88, 88B, 88B1, 88B2, 88A, 88A-2/F, 65H, 65, 65C, 67, 69, 71, 73, 86, 75A, 77, 79, 79B, 81, 81A, 83, 84A, 84, 85, 86A,86, 87B	19
65B, 65D, 68, 68- Rear, 70, 68, 66	8
72, 74, 76, 78, 80, 80 1/F, 82, 82A	5
126A, 127, 127A, 127B,	3
135, 135B, 134C, 216G, 216, 133A, 133A-1/F	4
ESS	1
RCP	2
154	0

Grouping Different Houses into Clusters

4. InSAR Technology for monitoring ground movements at Cha Kwo Ling Village



Historical monitoring data of InSAR since July 2017

Manual survey data using conventional survey method since January 2020

Comparison of InSAR Monitoring and conventional manual survey

thank you

Hyder MEINHARDT

Hyder-Meinhardt JV