Imperial College London

Detecting Flood Embankment Deterioration and Future Projection

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lpdp

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Outline

Source
E.g. Rainfall, Wind, Waves, Excessive runoff, upstream release

Pathway
E.g. Overtopping, overflow, breach, flood plain inundation

Receptor
E.g. People, Environment, Assets

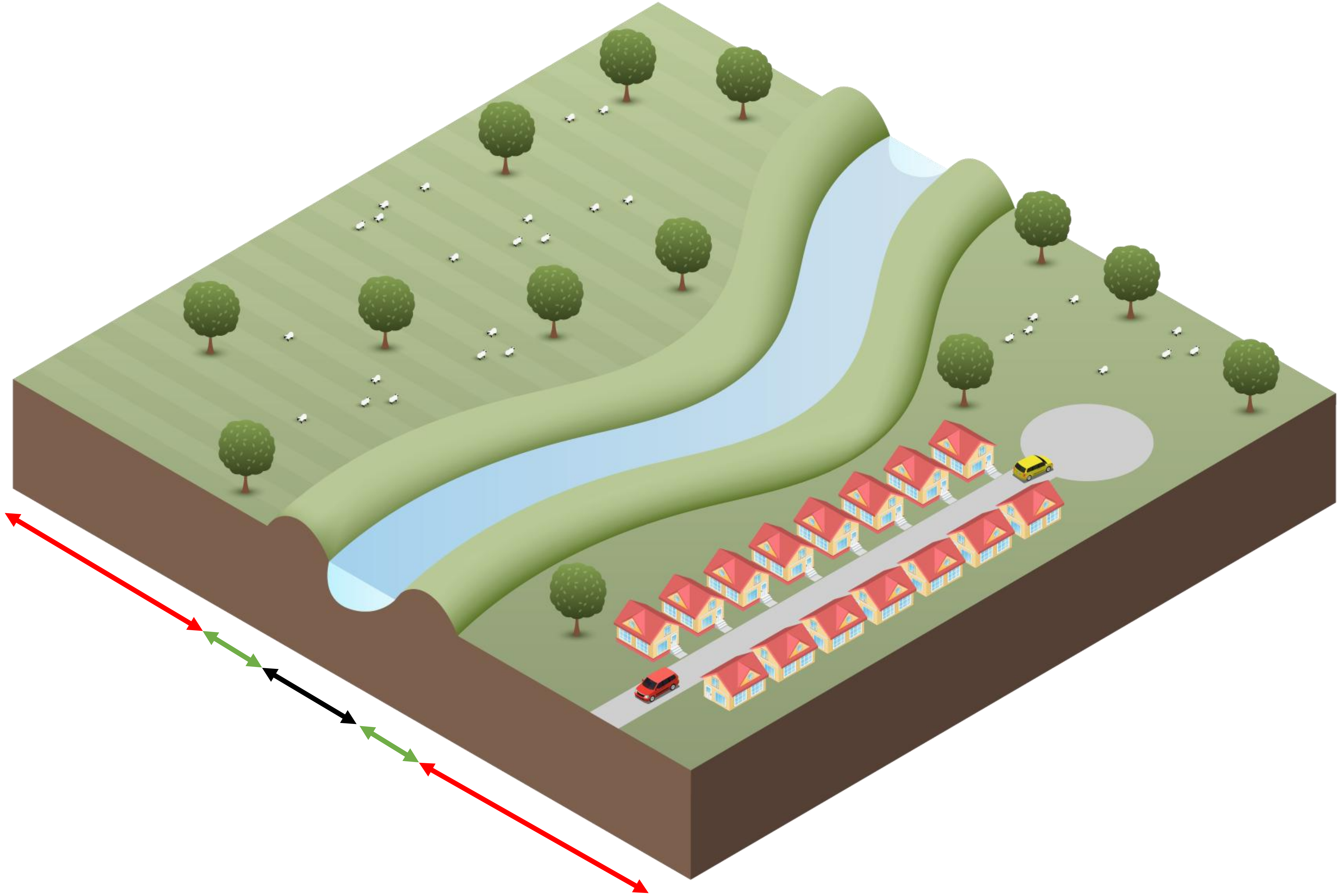
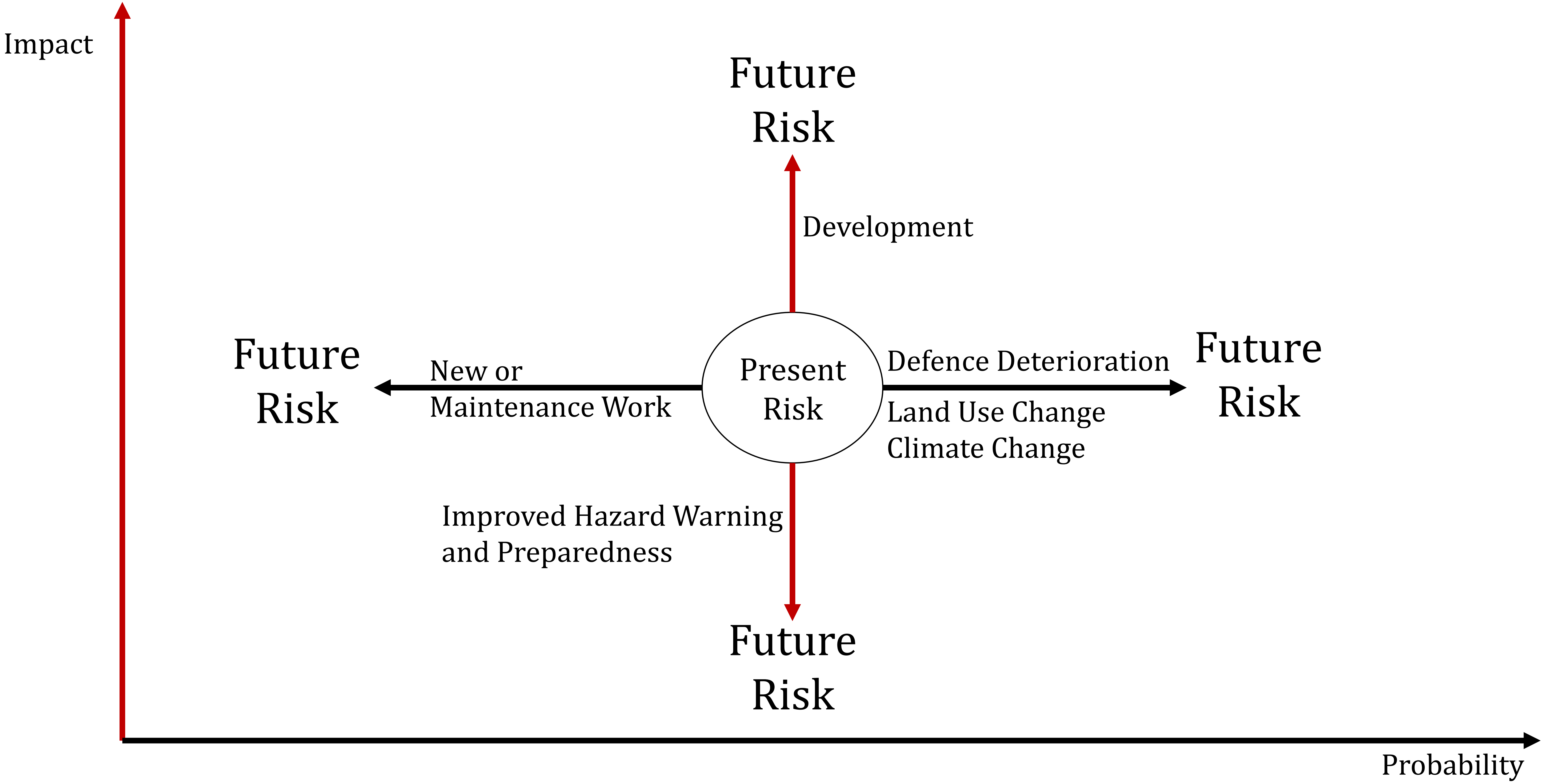


Figure: The Flooding System

Source: The International Levee Handbook

Outline



Source: The International Levee Handbook

Flood Disaster

Flooding is defined as the temporary presence of surface water, on or near an embankment, and as the most frequent and widespread natural disaster in the world and typically destructive (1).

Key Point

"Globally, during 2000 – 2019, ***rapid urbanisation*** *increased potential of disaster susceptibility, and extreme weather events have caused thousands reported disasters,* ***many of fatalities****, and continue to cause billions of dollars of direct* ***economic loss****. And under the background of global warming, such losses will continue to increase in the future."*

Flood Data (2000 – 2019) compared to other types of disasters

1st Floods are the most common type of disasters, accounted for around 3254 (44%) of total events.

1st The type of disasters that affecting 1.6 billion people worldwide or around 41% of total affected population.

3rd It accounted around 636 billion US$ (21%) economic losses.

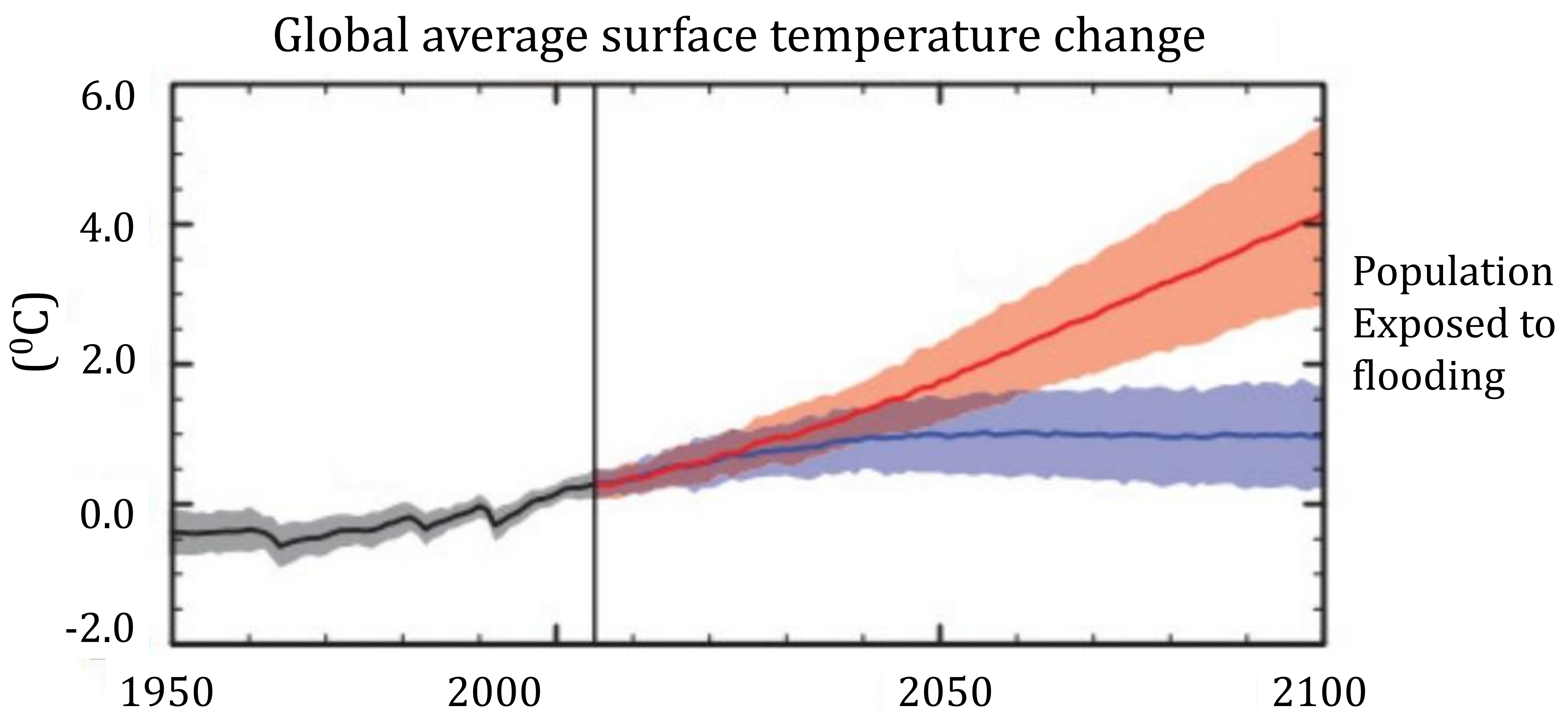
4th One of the deadliest disasters with at around 104.614 fatalities.

Source:
[1] Iqbal et al. (2021), [2] Centre for Research on the Epidemiology of Disasters (CRED), United Nations Office for Disaster Risk Reduction

Flood under Climate Scenario

Key Point

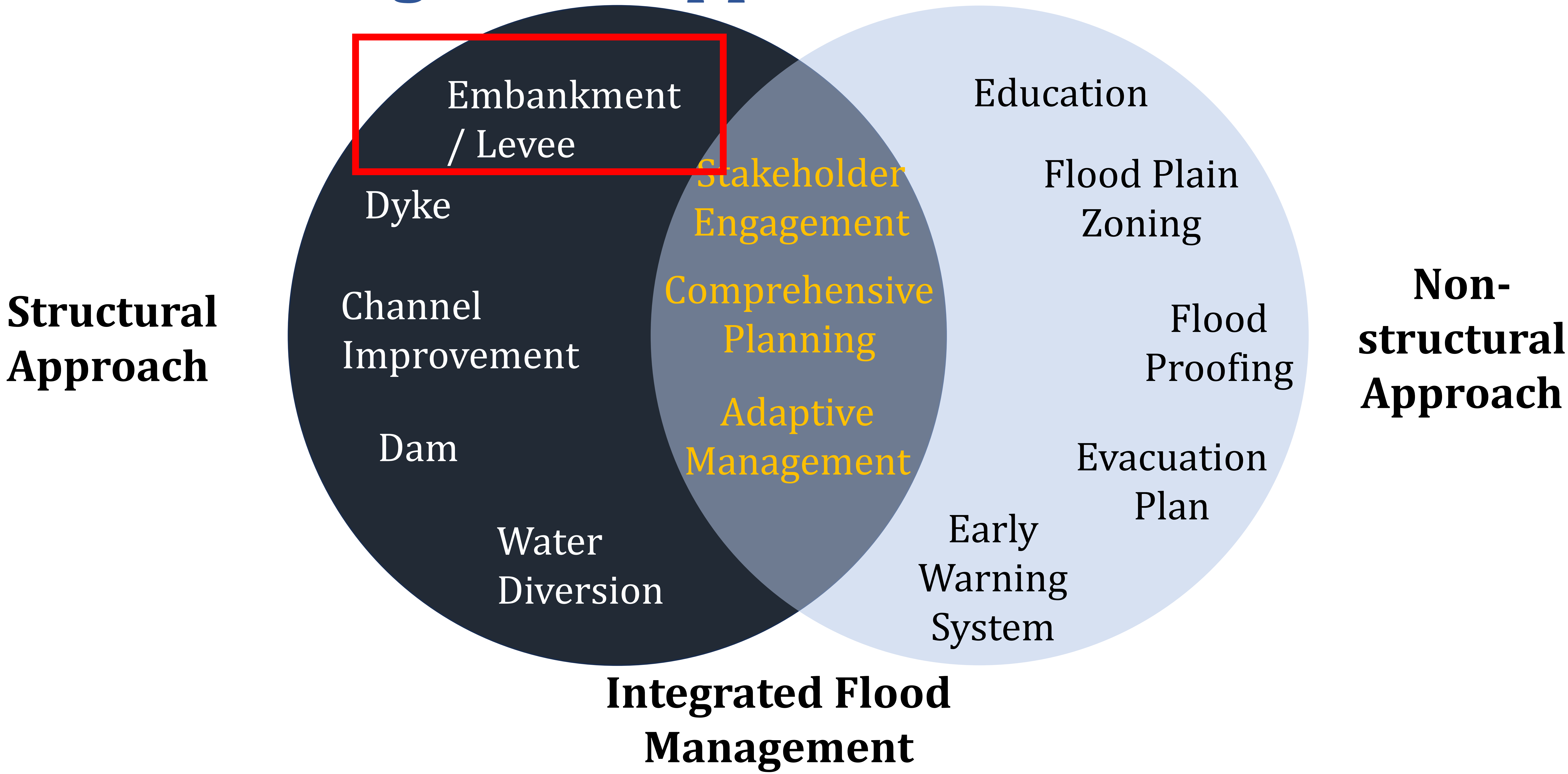
Better flood control, including prediction and monitoring, *is one of the possible solutions in DRR policy terms since affordable and effective technologies already exist. The priority should be given to* ***cost-effective measures*** *in poor regions at high risk of recurrent flooding.*



- People living in **coastal cities and riverine areas** are considered among the most vulnerable to sea level rise, storm surges, and coastal flooding.
- **Global warming** is estimated to increase the frequency of potentially high impact natural hazard events across the world.

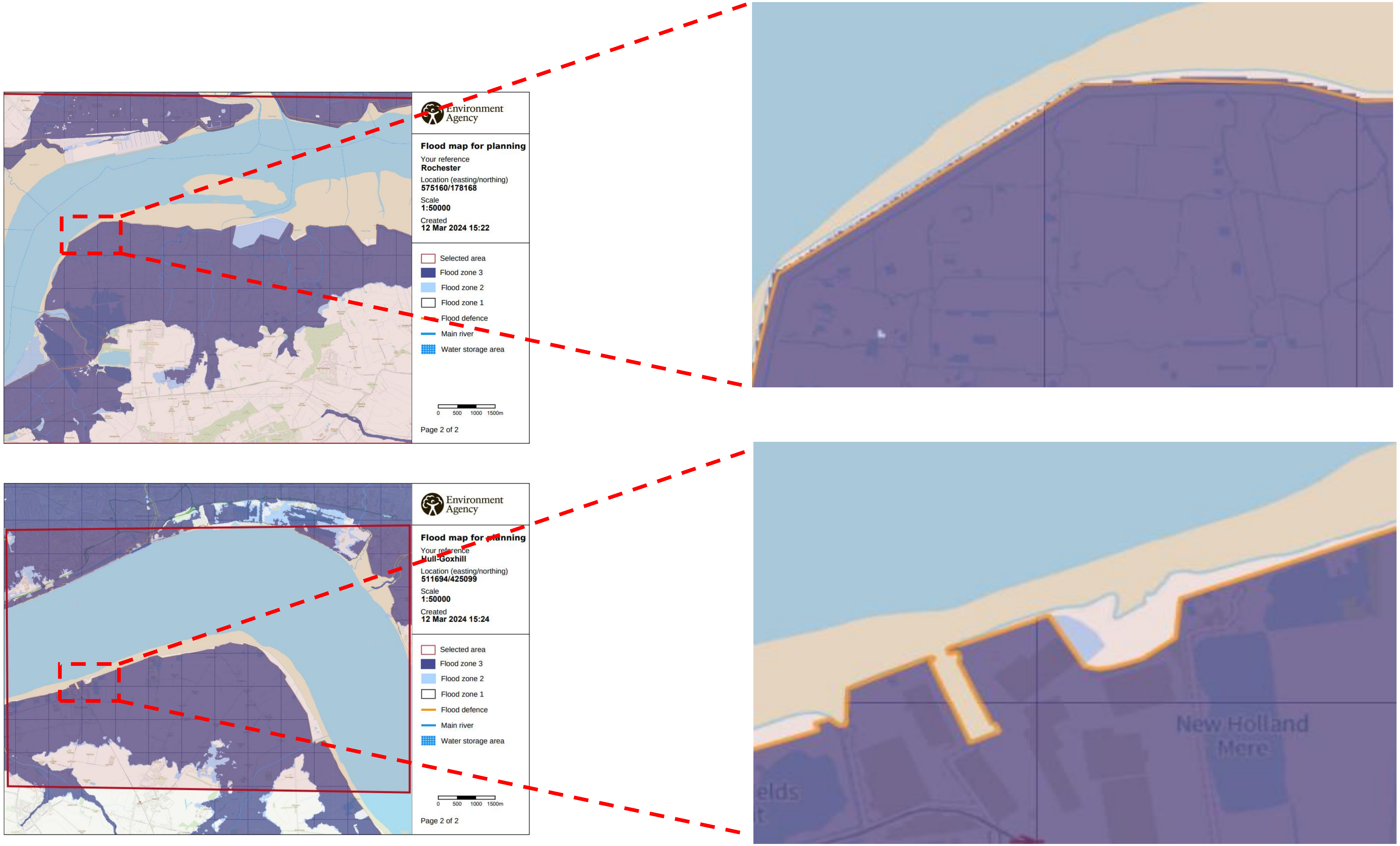
Source: Centre for Research on the Epidemiology of Disasters (CRED), United Nations Office for Disaster Risk Reduction

Flood Management Approach



Source: Allsop et al. (2009)

Flood Planning and Embakment System



Source: Environmental Agency

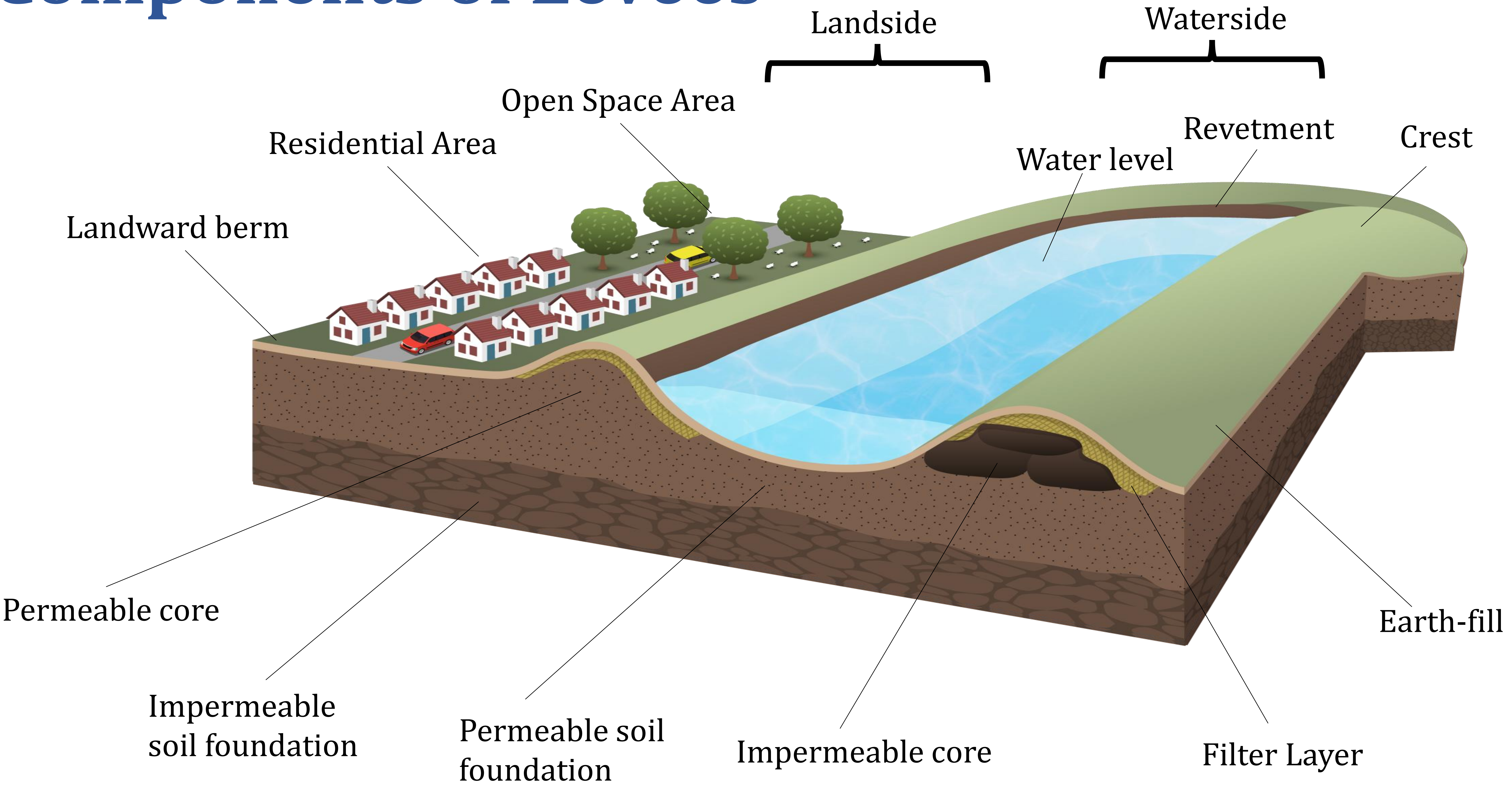
Structural Approach : Levee / Embankment

- Levees are raised, predominantly earth, structures that are not reshaped under normal conditions by the action of waves and currents.
- Primary objective is to provide **protection** against fluvial and coastal flood events along coasts, rivers and artificial waterways.
- Unlike engineered structures, levees can be **irregular in the standard** and nature of their construction and **can deteriorate** markedly over time if they are not well maintained.

Source: The International Levee Handbook

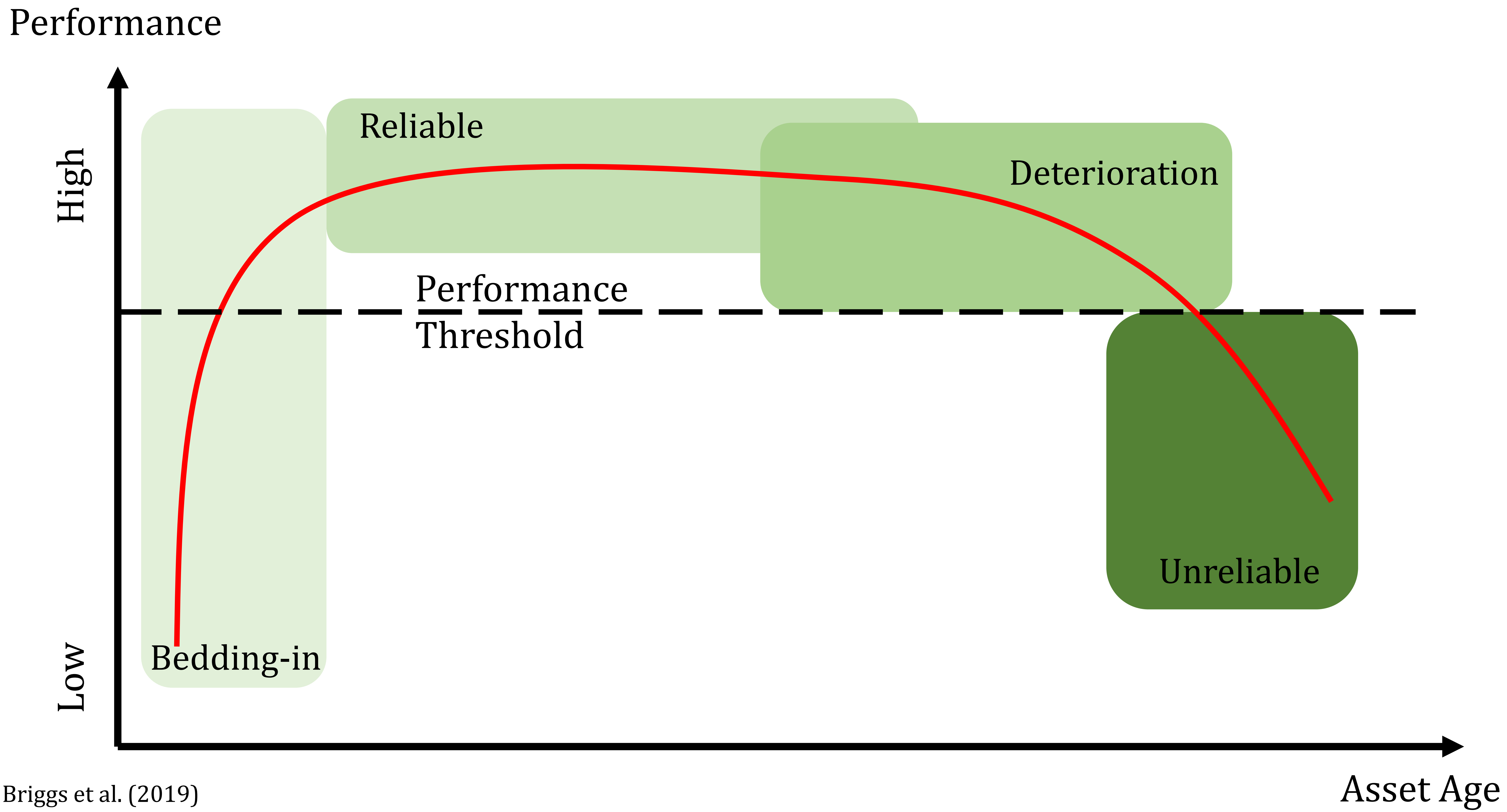
Source: adapted from nad.usace.army.mil

Main Components of Levees



Source: adapted from https://www.geoace.com/app/Riverbank-and-Channel-Protection/Levees-and-Dikes

Performance of an Asset Over Time

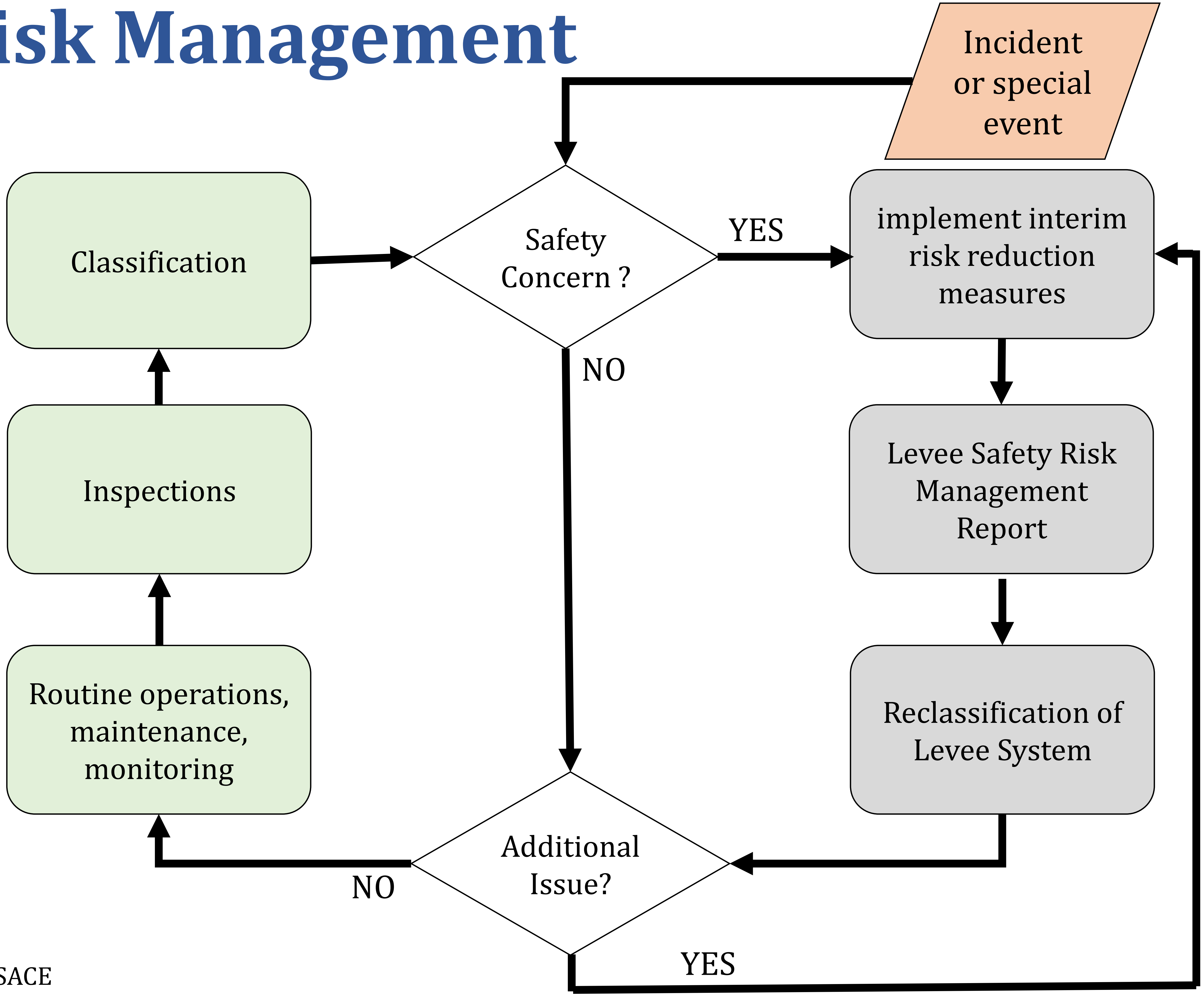


Source: Briggs et al. (2019)

Levee Safety Risk Management

Key Point

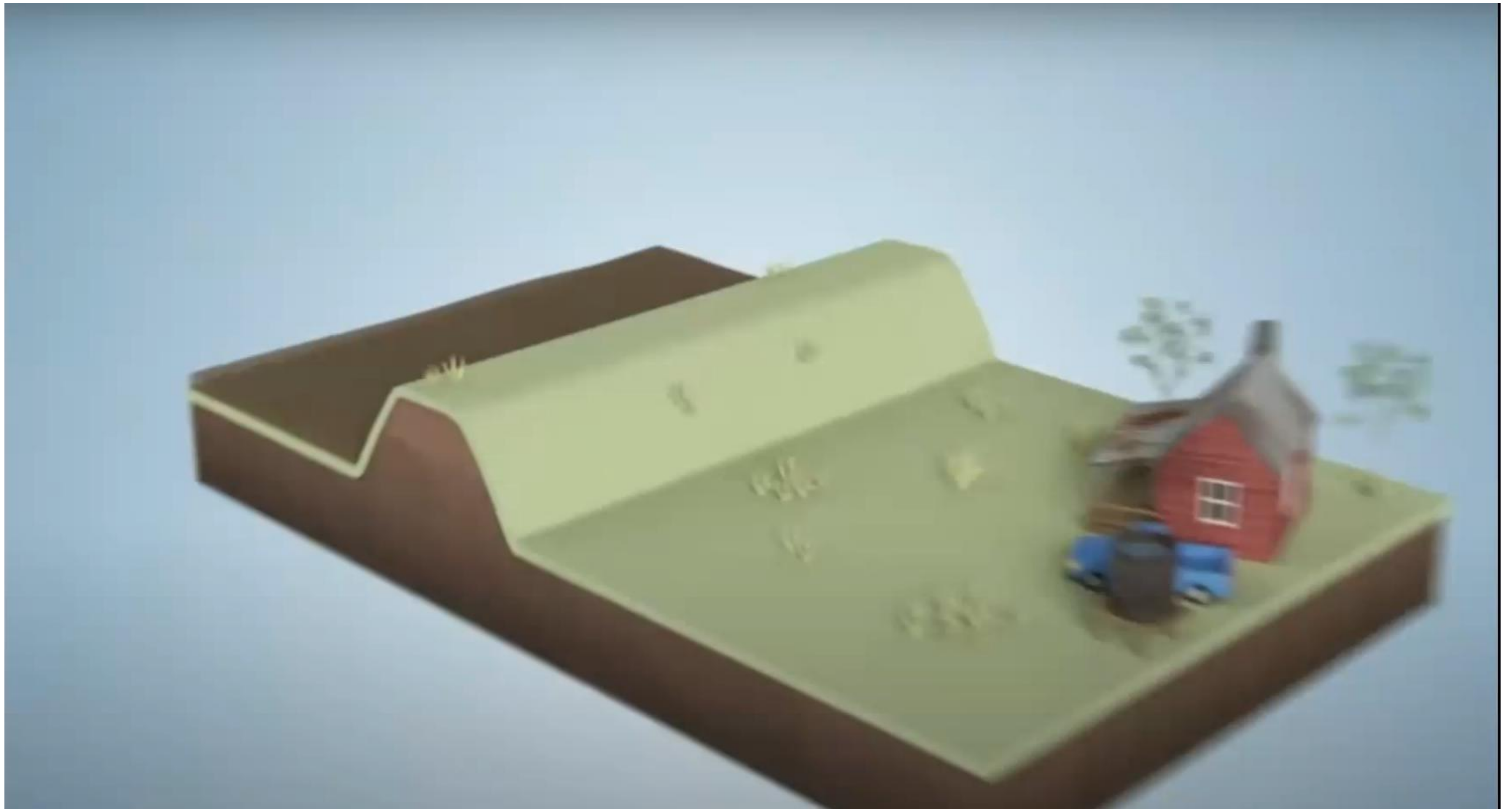
Typical routine activities are combination between ***field inspections*** *and* ***screenings****. It must be remembered that although* ***flood risk may be reduced*** *by such an approach,* ***it can never be removed completely****.*



Source: Recommended framework adapted from USACE (The International Levee Handbook)

Disaster Potential of Embankment System

1. Overtopping
2. Cracking
3. Piping, Tree, Weather, and Animal/Human Activities



Courtesy : YouTube NSW SES accessed at 14/03/2023

Disaster Potential of Embankment System

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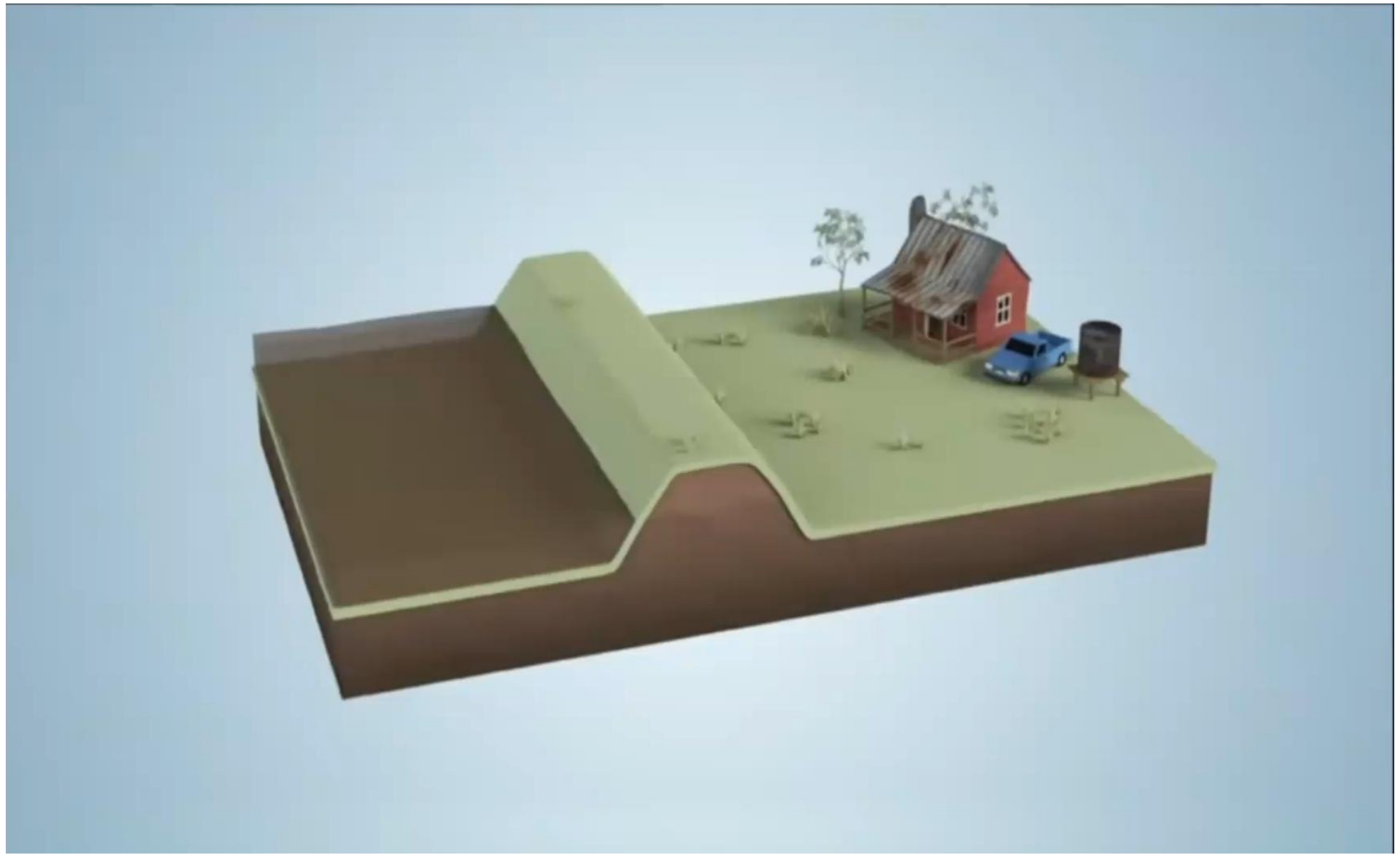

Courtesy : YouTube NSW SES accessed at 14/03/2023

Source : Best 20 aerial shots of flooding along the Thames - Mirror Online accessed at 21/03/2023

Disaster Potential of Embankment System

1. Overtopping

2. Cracking

3. Piping, Tree, Weather, and Animal/Human Activities

Courtesy : YouTube NSW SES accessed at 14/03/2023

Source : https://blogs.agu.org/landslideblog/2020/05/22/edenville-dam-breach/ accessed at 21/03/2023

Disaster Potential of Embankment System

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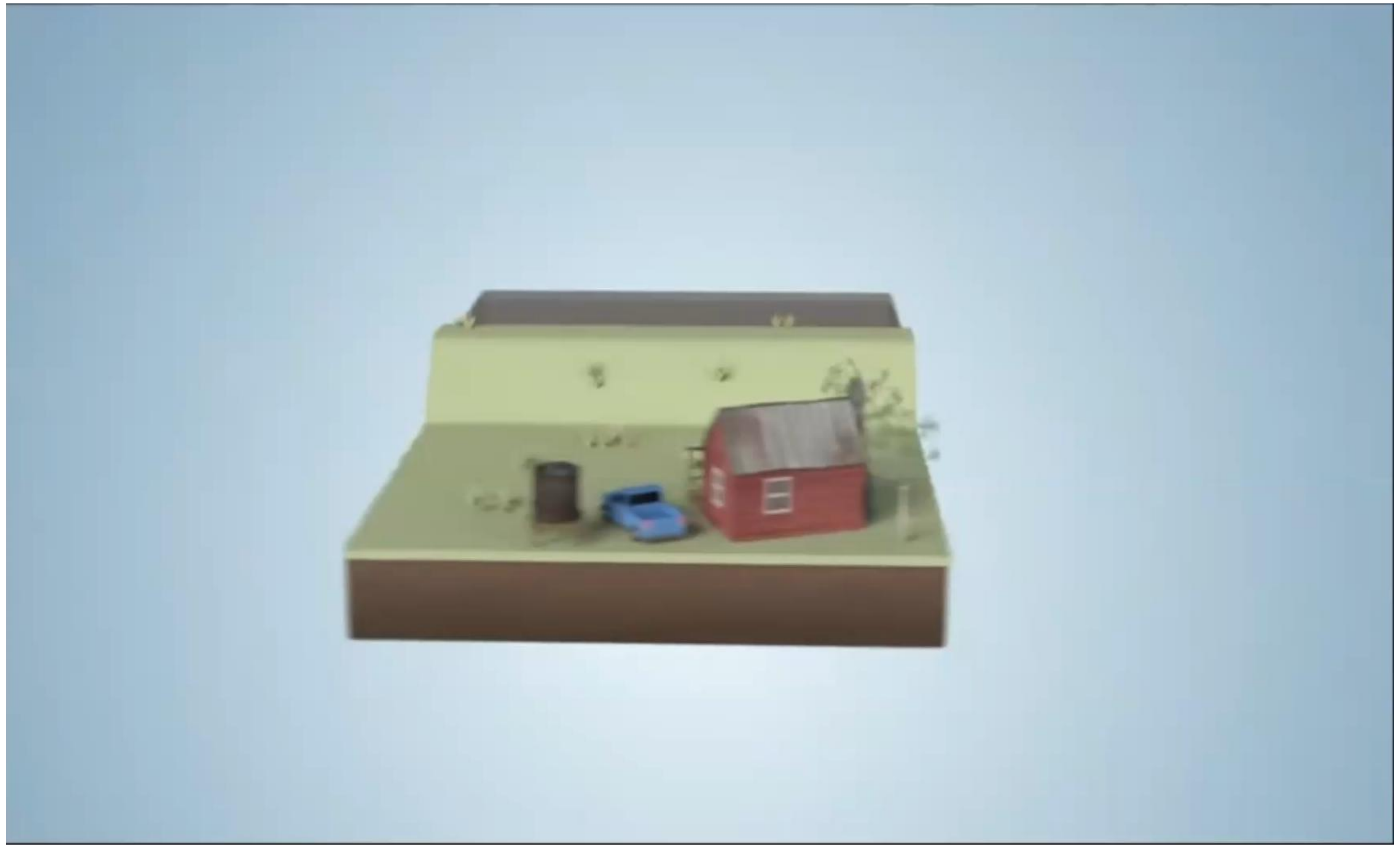


Courtesy : YouTube NSW SES accessed at 14/03/2023

Source : https://www.pinterest.com/pin/543457880009317934/ accessed at 21/03/2023

Main Challenge in the Embankment System

Key Point

It is essential for mitigating flood embankment before extreme flood events and ensuring sustainable flood and coastal defence [1].

+ The rate of deterioration can be detected in high accuracy through long-term observation and inspection.

− The traditional inspection methods by visual monitoring are inefficient and can be inaccurate or operator dependent.

? The use of algorithms and techniques based on remote sensing can help local government to identify vulnerable levee sections and repair them rapidly with lower costs [2].

Source: Morris et al., 2007 (1), Mahrooghy et al., 2015 (2)

Goal and Objective

Key Point

*"The structure and components of the embankment should be in a **sustainable design**, consider the effect of **water loading**, and understanding **climate variability**." (1)*

Goal

This research aims to calculate the robust deterioration rate of soil embankment, particularly along the Thames and Humber Rivers, and predict future potential failure.

Objective

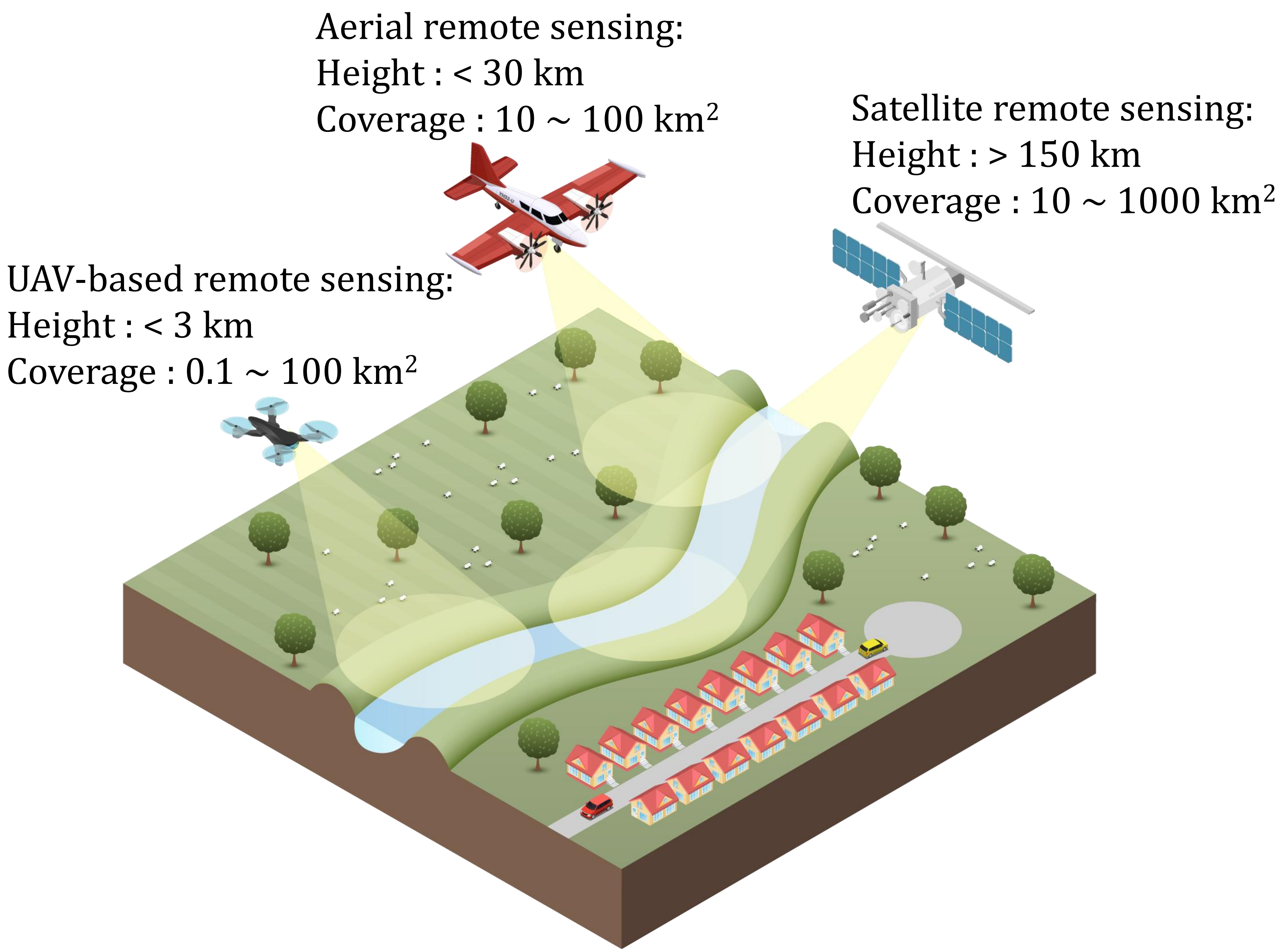
- To calculate deterioration rate of the embankment by identifying the sign of failure (subsidence, crack, or others)
- To project future potential of the embankment structure considering climate change approach

Source: Defra and Environment Agency (2007)

Unmanned Aerial Vehicle (UAV)

Advancements in sensor and UAV technologies have facilitated :

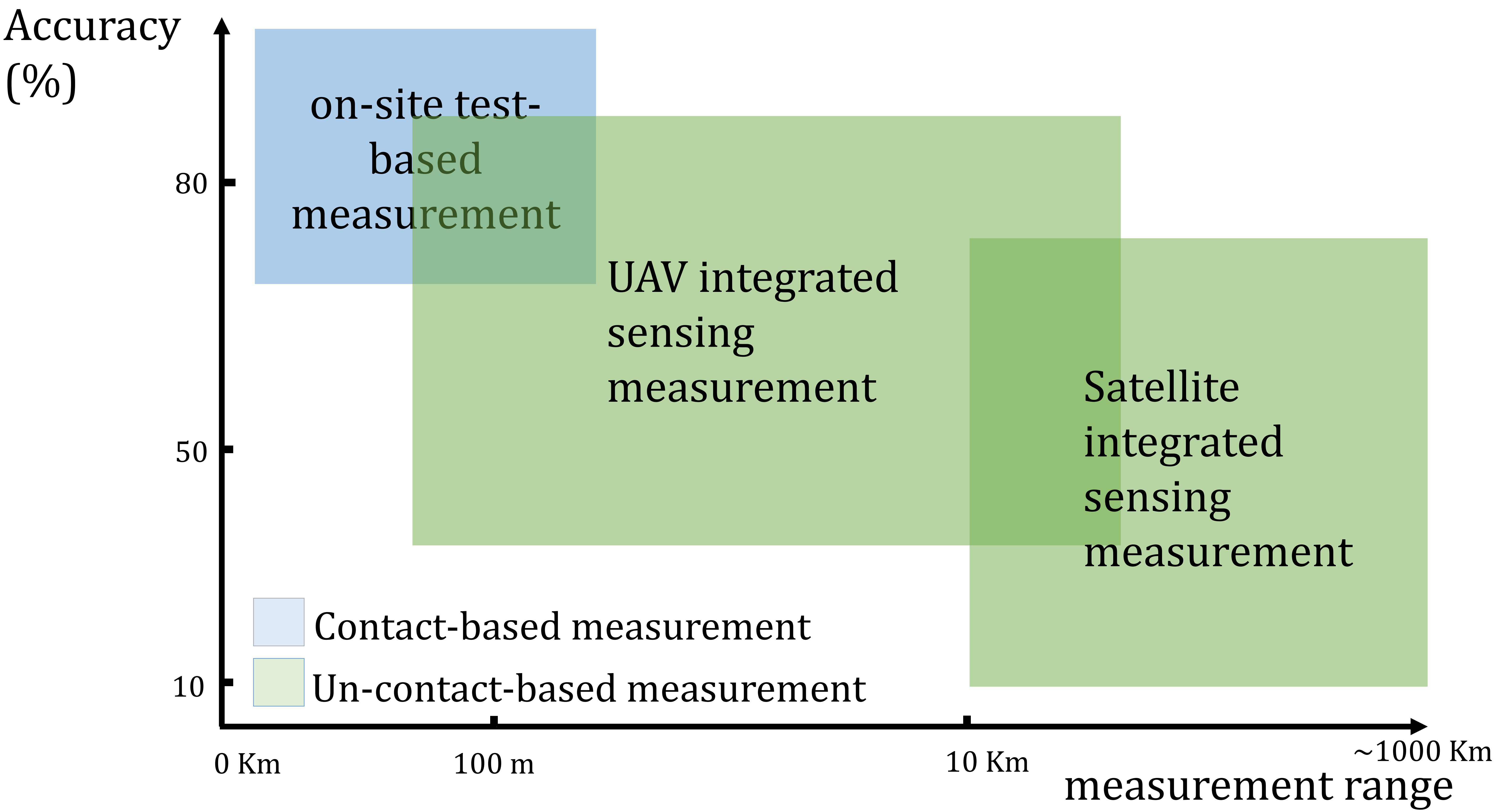
- more **intelligent monitoring** and inspection of sites prone to failure.
- provide both **on site and satellite measurements** with sufficient accuracy.
- **fewer spatiotemporal constraints** and **offer superior resolution** with reduced data gaps compared to satellite-based measurements.



Source: Mahrooghy et al., 2015

Source: Xiang et al., 2018

Comparison of UAVs Sensing Measurement



Source: Kim et al., 2023, Colomina et al., 2014 (UAV), Lillesand et al., 2015 (On-site Test), Congalton et al., 2009 (Satellite)

Type of sensors used on UAVs

UAVs Sensor

Cameras

- ⊕ Optical and High-Resolution Imaging
- ⊕ Inexpensive for mapping / inspection

- ⊖ Depend on lightning condition, weather, poor quality during night, foggy or rain

Infrared

- ⊕ Ideal for night-time, detect heat
- ⊕ Useful for search and rescue, wildlife monitoring

- ⊖ Cannot work properly during the day
- ⊖ Can be affected by environmental factors like water vapor and temperature changes

Chemical Sensors

- ⊕ Measuring chemical substance in the atmosphere (pollution, hazardous substance)

- ⊖ Limited range of detection
- ⊖ Can be sensitive to cross-contamination from other chemicals in the environment

RADAR (Radio Detection and Ranging

- ⊕ Can scan object through adverse weather condition during day and night
- ⊕ Useful for long-range detection and collision avoidance

- ⊖ Lower resolution compared to cameras and LiDAR

LiDAR (Light Detection and Ranging)

- ⊕ High precision of 3D mapping
- ⊕ Excellent for topographical surveys and urban planning
- ⊕ Can penetrate vegetation to capture ground-level details

- ⊖ It is generally heavier and more expensive than other sensors
- ⊖ Can be affected by weather or reflective surface

Source: Fahlstrom et al., 2012

Previous Research

3D point cloud data derived from LiDAR is widely used in the sector of autonomous driving, satellite remote sensing, and spatial mapping

Key Point

LiDAR output will contain noise and non-target information due to the complex and changeable environment (weather, interference or other types of obstacles)

Note

Airborne/spaceborne LiDAR commonly uses scanning or array detection to obtain 3D point information. It is commonly resulting in low density and poor-quality point cloud data acquisition after scanning due to volume and weight data.

Solution

A variety of pre-processing processes after acquisition is important, such as point cloud segmentation, denoising, background point cloud removal, sparse/ missing point cloud completion.

Source: Zhao et al., 2023 (1)

Previous Research

Key Point

LiDAR Enable 3D landslide analysis by using a narrow laser beam to scan a certain object [1]

LiDAR can be used to monitor landslides, rockfalls, and debris flows by generating an accurate slope map [1], calculating instability signs of landslide [2], and understanding the landslide processes and reducing related losses [3]

Note

Main factor of the quality of the application results of the LiDAR is **spatial resolution**, including sensor equipment performance, measurement distance, vegetation canopy density, and the **filtering algorithm** effect of the point cloud. [1]

Solution

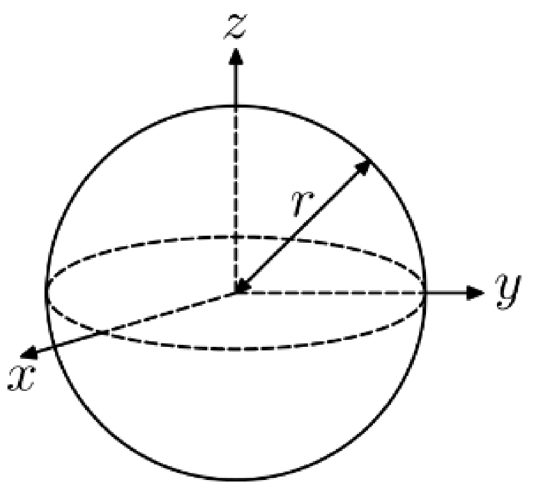
- Develop mathematical calculation as an input in computational methods that enable to identify potential failure on embankment system
- Develop a statistical approach to project future potential disaster under climate change consideration

Source: Casagli et al., 2023 (1), Zhong et al., 2020 (2), Mora et al., 2015 (3)

LiDAR

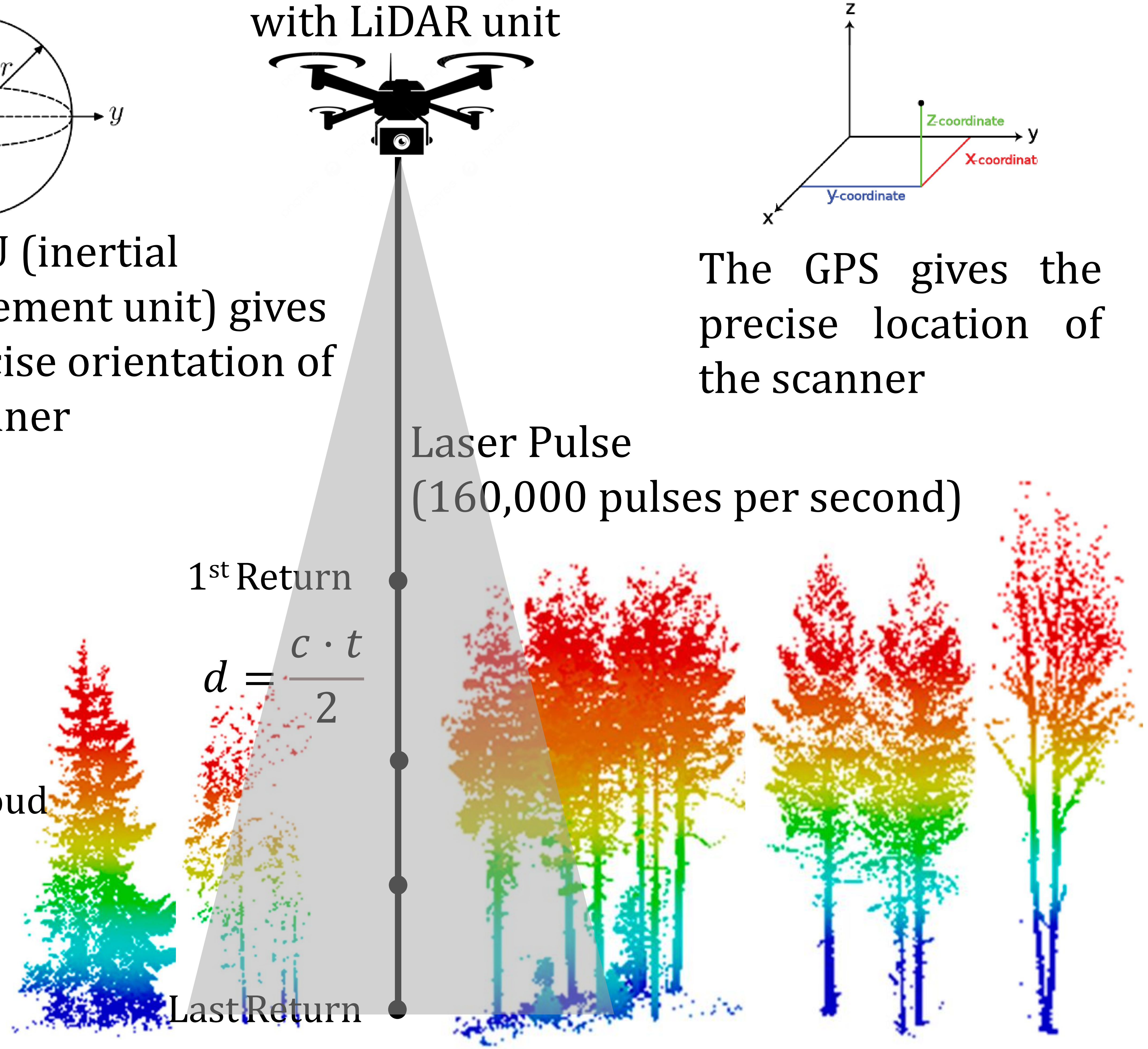
Key Point

LiDAR excels in capturing data with both **high spatial** and **spectral resolutions**, facilitating the generation of **precise classifications**, detection of surface alterations, environmental monitoring, and various other applications.



The IMU (inertial measurement unit) gives the precise orientation of the scanner

Drone equipped with LiDAR unit

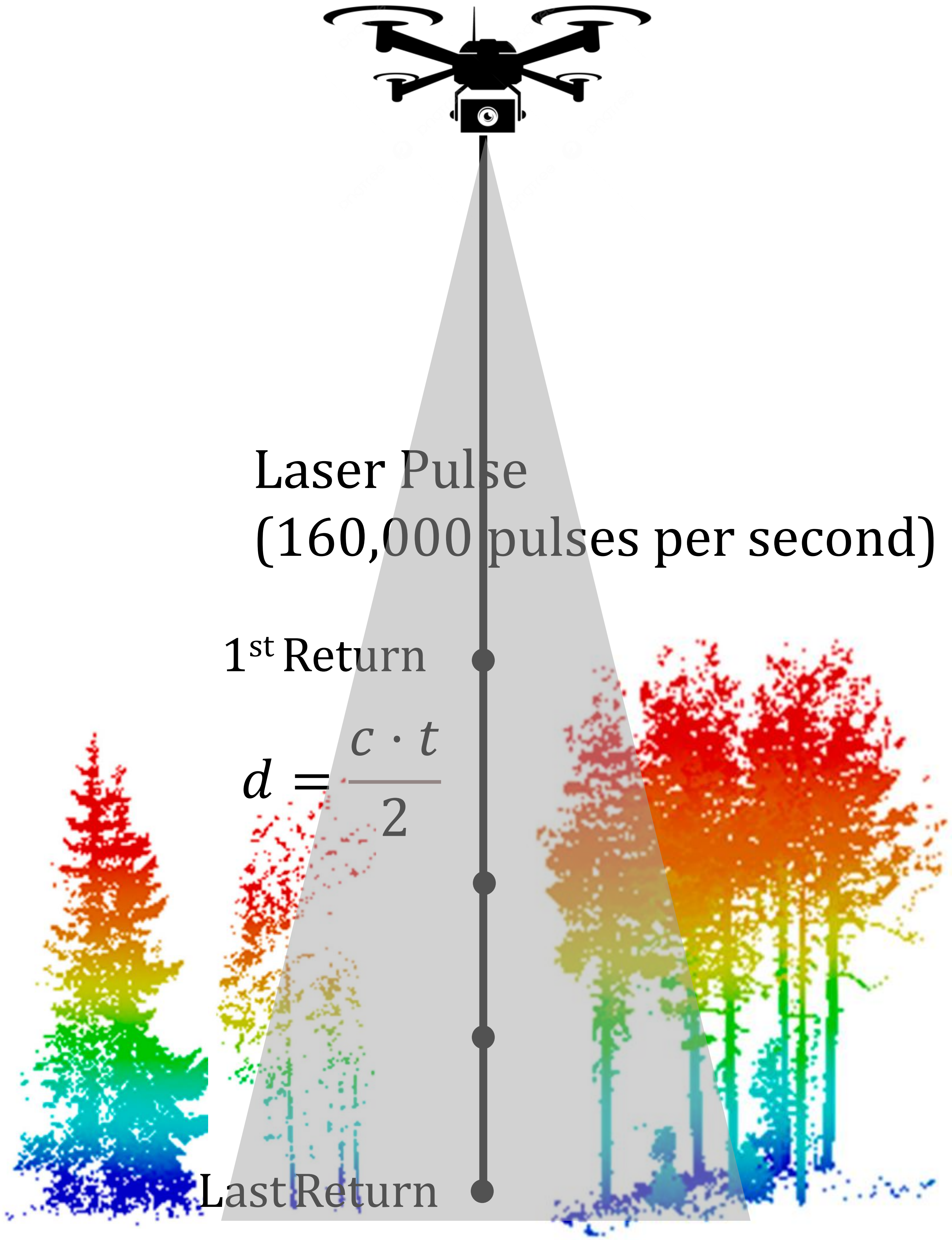


The GPS gives the precise location of the scanner

Source: Kahraman et al., 2021

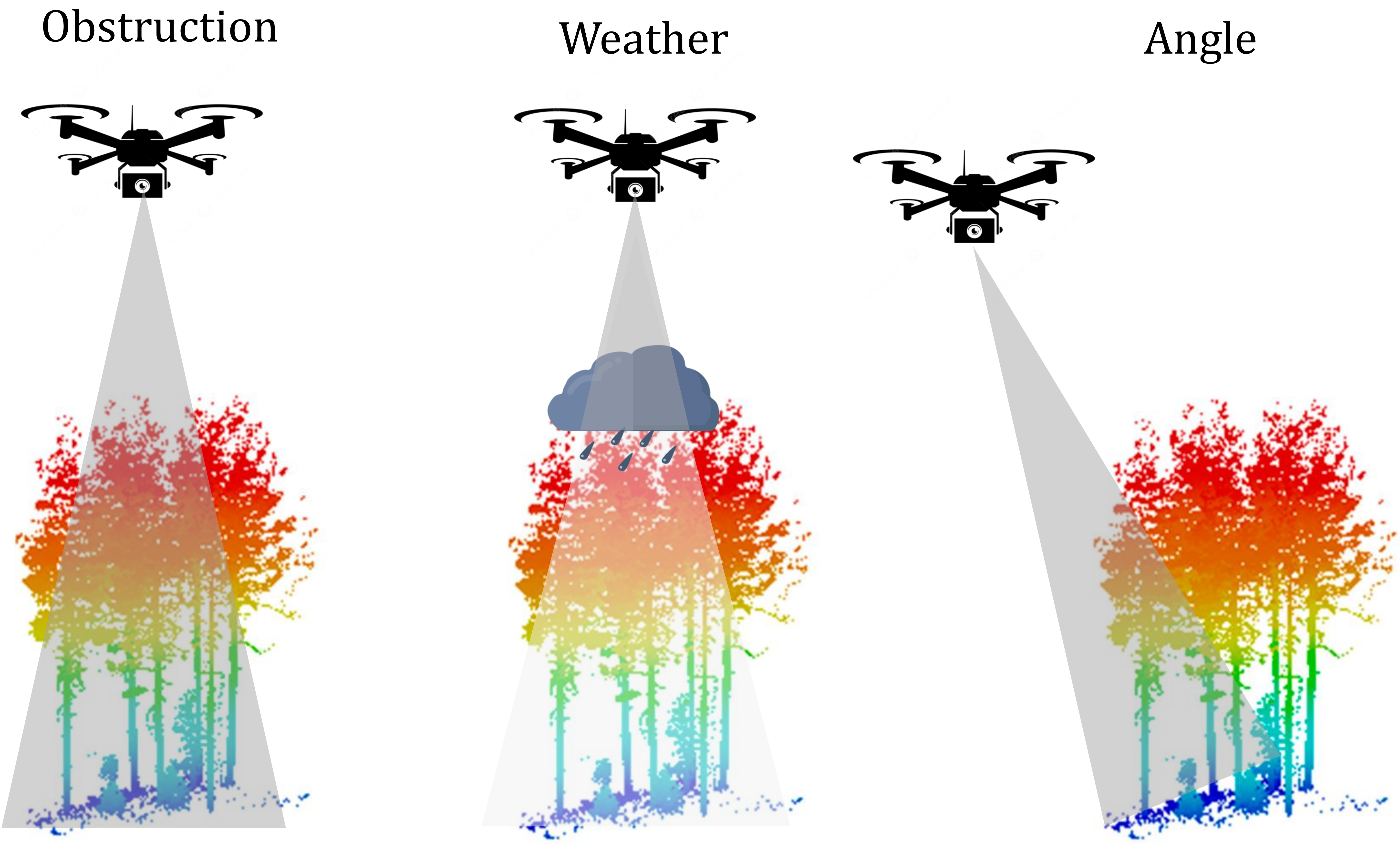
LiDAR

- One pulse may record 1-5 return pulses
- The returned pulses is classified into one or more discrete returns X, Y, Z intensity
- Optical frequency is between Green and near Infra-Red (wavelengths from 532 to 1064 nm)
- Spatial resolution is a function of the altitude and flight speed ranging from a few cm for altitudes of about 250 m to a few decimetres for higher than 1000m
- Can operate both day and night, some limitations may occur



Source: Kahraman et al., 2021

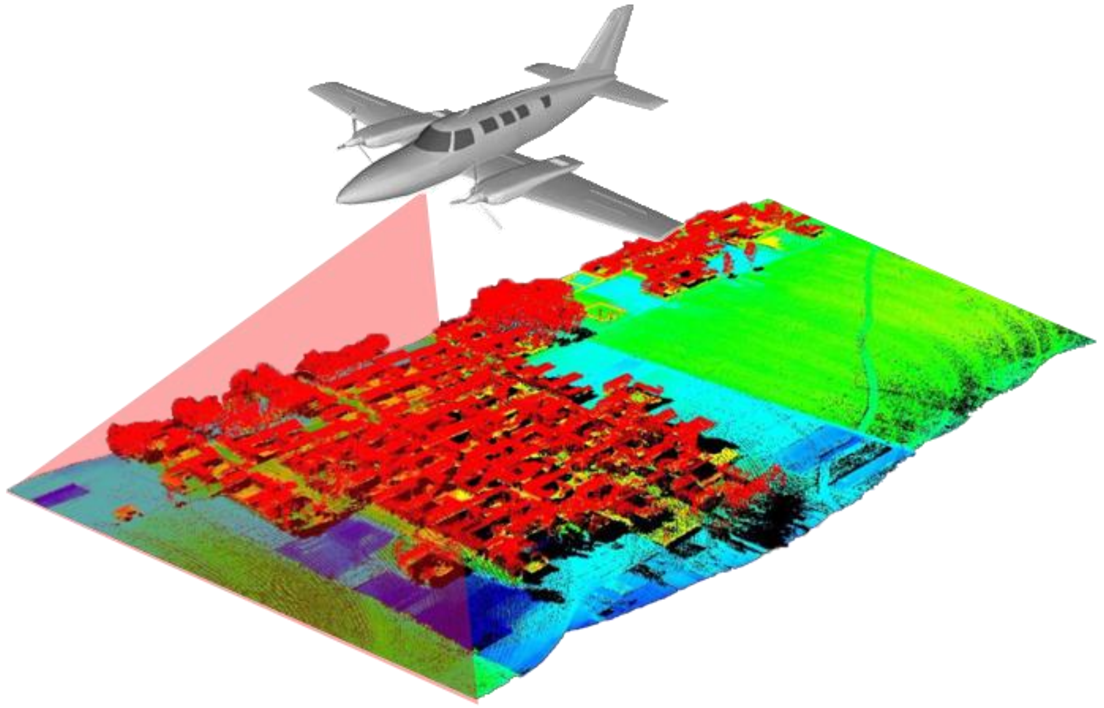
LiDAR Limitation



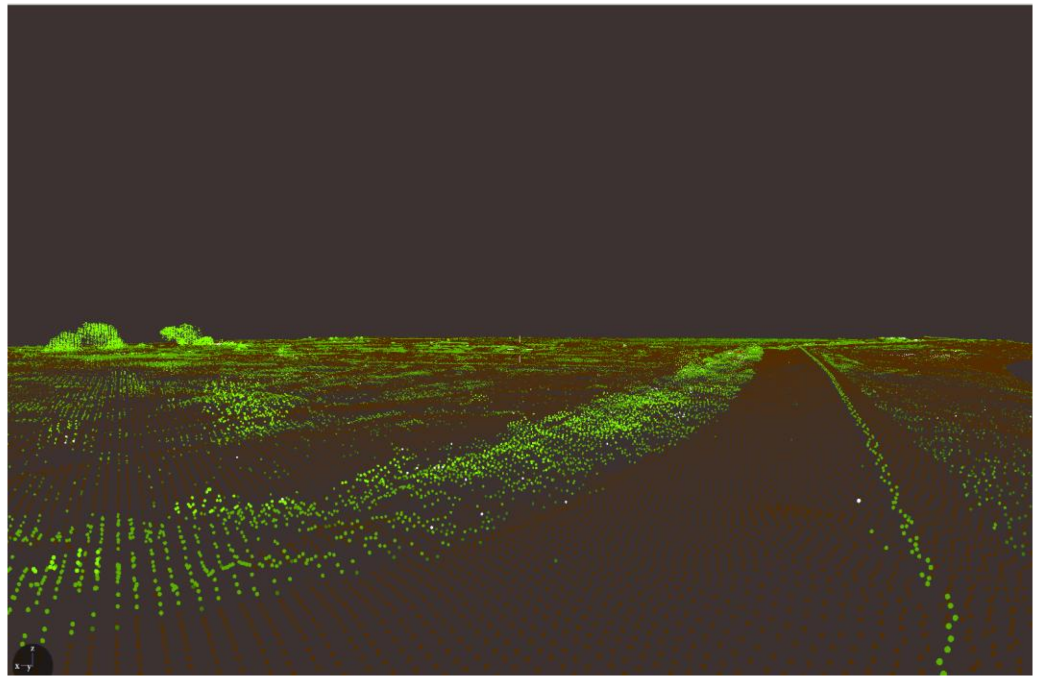
Source: Kahraman et al., 2021

Milestone of Methodology

Lidar Data Acquisition and Pre-processing	Segmentation and deterioration analysis	Predicting and Analysing Future Potential
Gathering the data sources and comprehend the data typology.	To isolate specific research areas and identify key features from the segmented data relevant to assessing the health and stability of flood embankments.	To project the embankment deterioration rate by applying real-world scenarios to inform decision-making processes in civil engineering.



Source: LIDAR - lidar.co.id



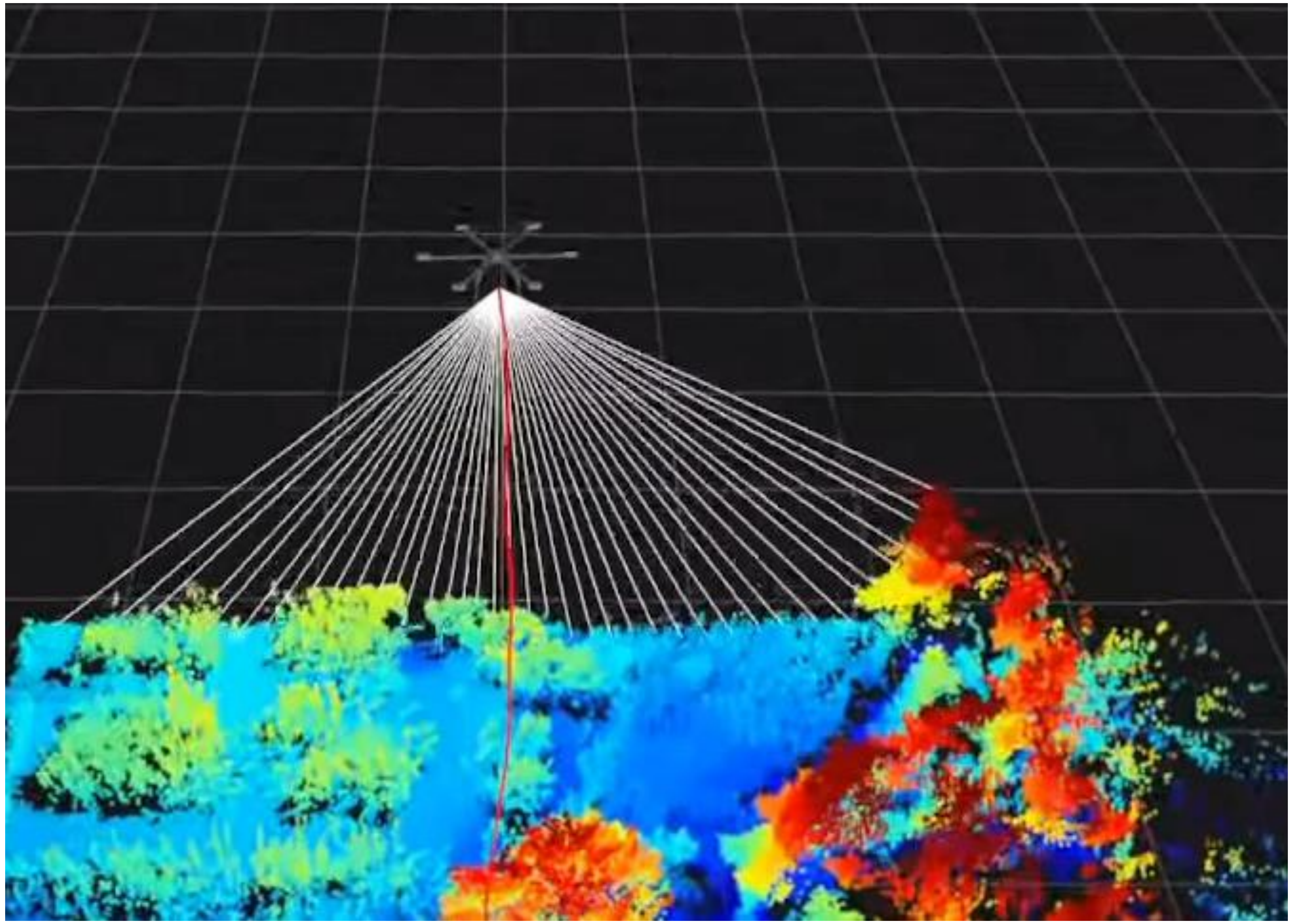
Source : LiDAR Data DEFRA
Tool : Displaz
Location : Lower Hope Point - Rochester

Source : Google Street View
Location : Lower Hope Point - Rochester

Lidar Data Acquisition and Pre-processing

Steps:

1. Project Planning and Preparation
2. Sensor selection and configuration
3. Platform deployment (aircraft / ground vehicle / tripod-mounted, or else)
4. Data acquisition
5. Quality control and assurance
6. Data processing



Source : [GNSS-LiDAR: Drone 3D Mapping]

Segmentation and Deterioration Analysis

Key Point

A segment-based approach offers a systematic and effective methodology for analysing scalar field data representing surface features to detect embankment cracks

NOTE

Divided into segments or regions of interest based on geometric properties, such as curvature, normal vectors, or point density.

Application

Identifying and analysing specific object recognition, scene understanding, and semantic segmentation.

Advantage

Localised analysis, flexible, and interpretable

Drawback

Segmentation sensitivity, over-segmentation, and computational complexity

Source: Cheng et al., 2018

Segmentation Usage

2017
- PointNet
- PointNet++

2018
- PointCNN
- PU-Net

2019
- KPConv
- RSNet
- DGCNN
- OctreeNet
- Pseudo-LiDAR++

2020
- PointASNL
- SPH3D-GCN
- PF-Net
- PV-RCNN

2021
- RandLA-Net (4)
- Point Transformer (5)
- Orientation-Encoding (OE)

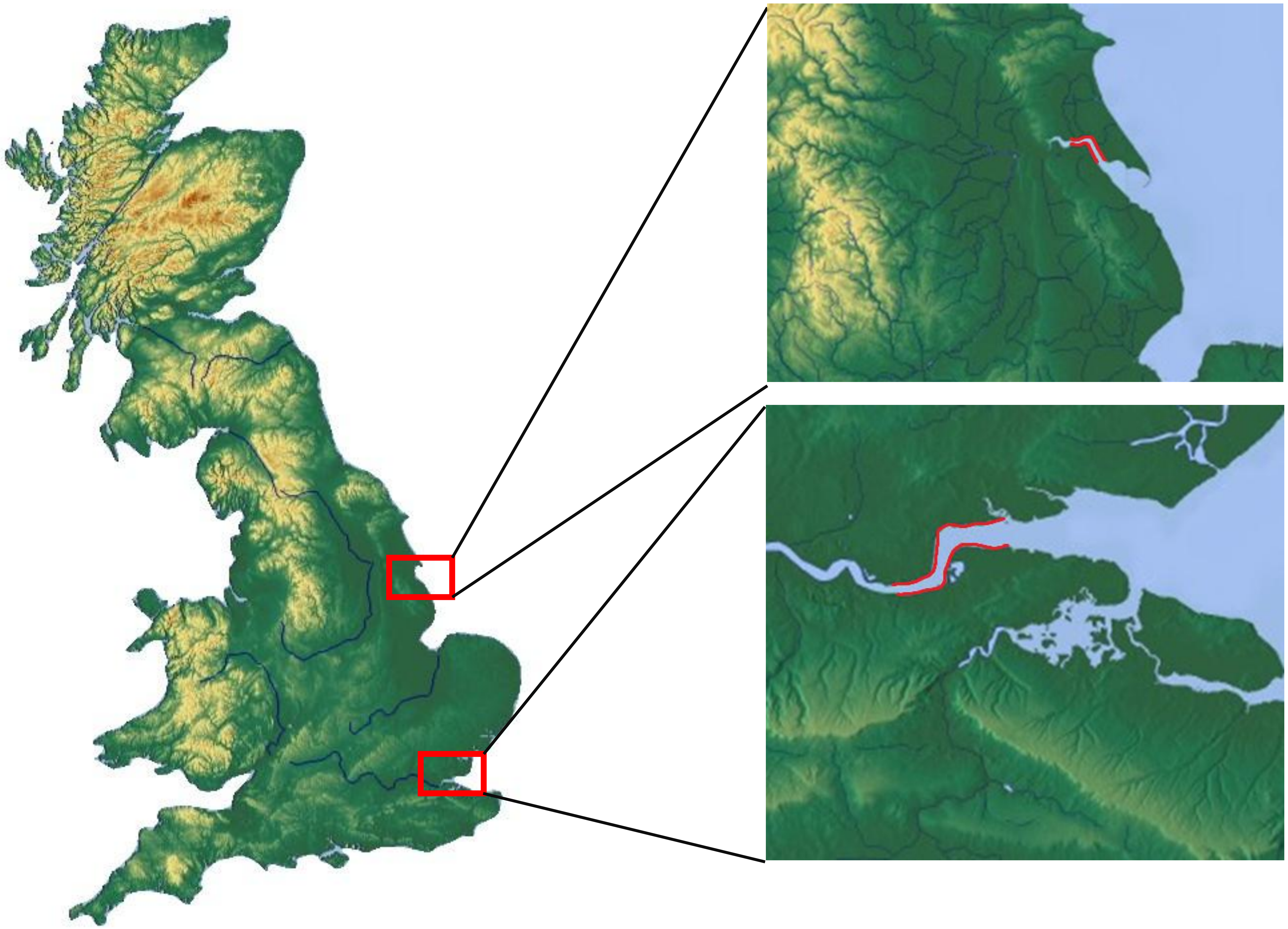
2022
- PAConv
(Point Aggregation Convolution)

Study Area

Levee or embankment system along River Thames and River Humber, England

Levee or embankment system along Railway in Folkestone – Warren Segment, England

Study Area (1)



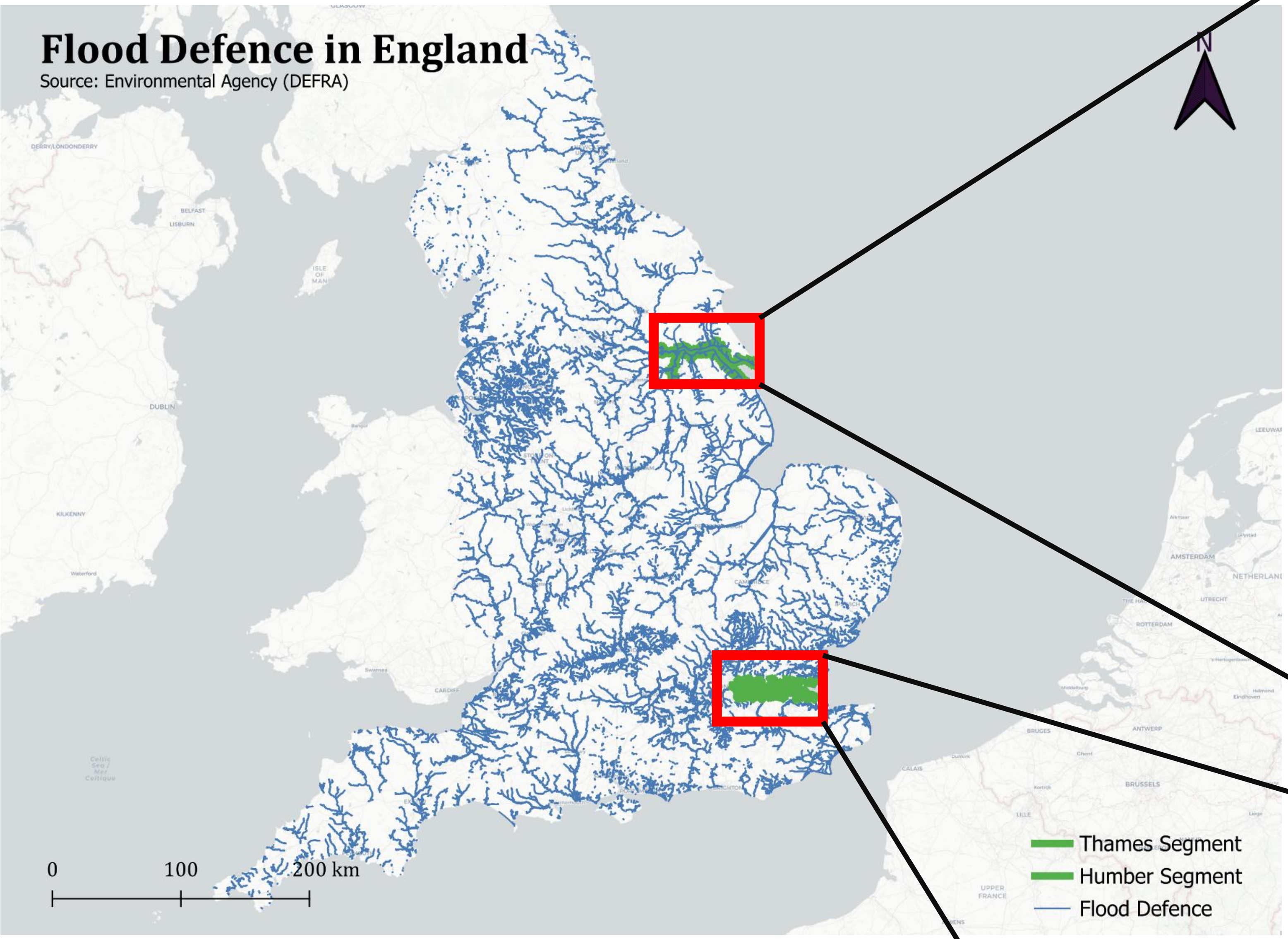
River Humber

The Humber is about 64 km long, the River is lined by the major ports of Kingston upon Hull, Grimsby, and Immingham.

River Thames

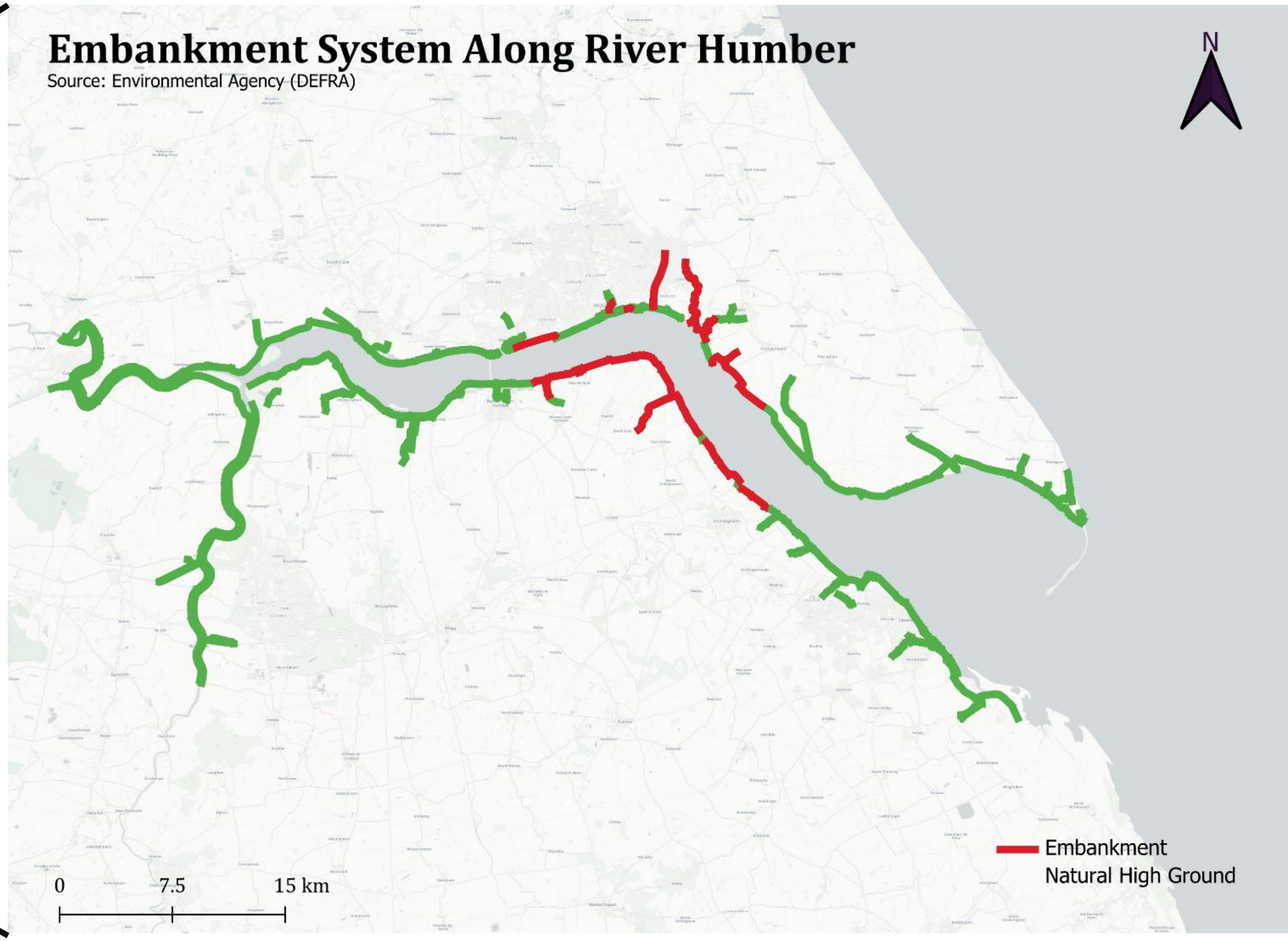
The Thames is the largest river in England, with a total length of 354km, housing a fifth of the UK population, including London.

Study Area (1)

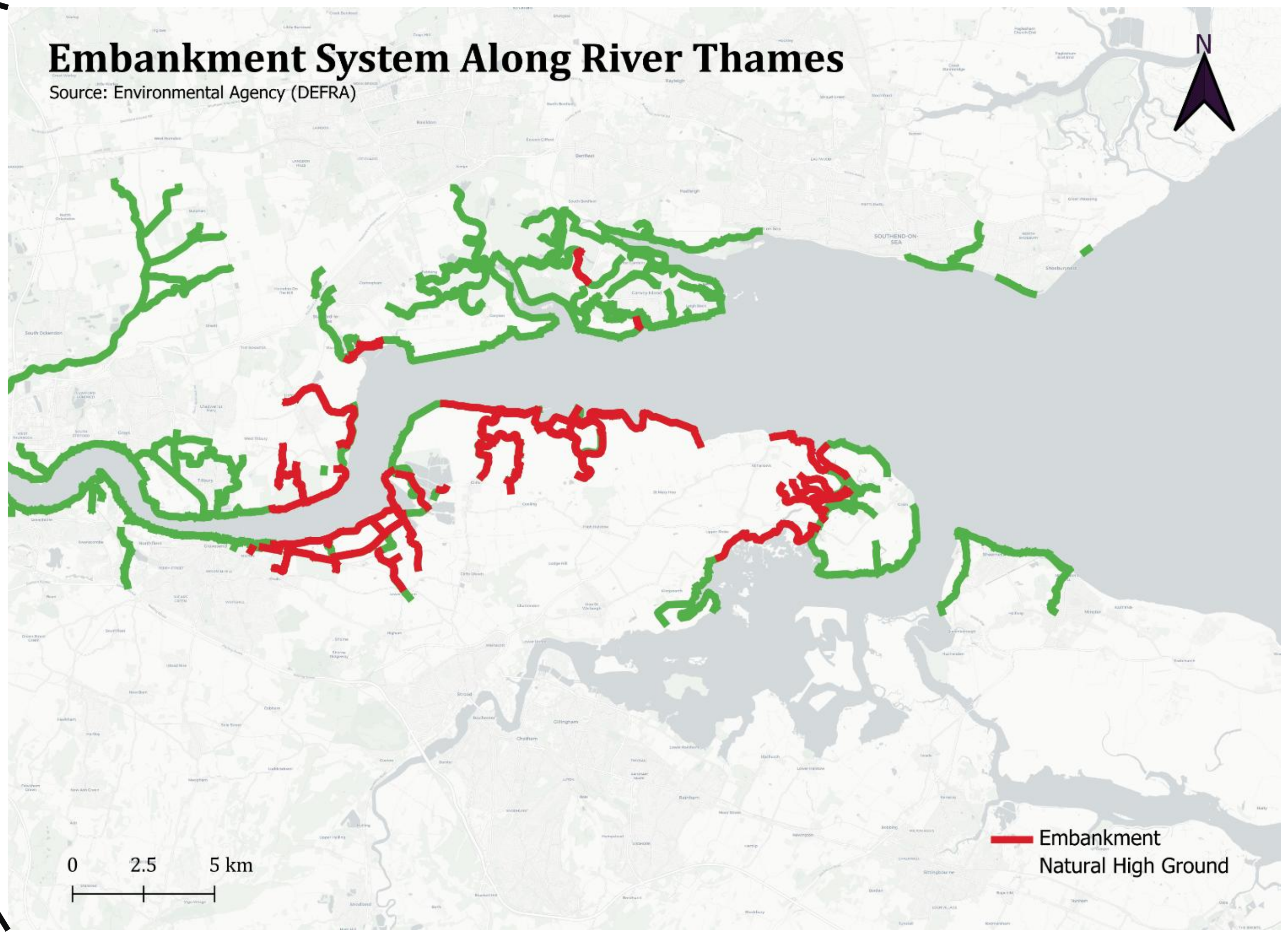


Total length of 19,506 kilometres (km) and it is divided into 8 regions:

- Southeast (2741 km)
- Northwest (2335 km)
- Anglian (2279 km)
- Southwest 1941 km)
- Thames (1558 km)
- Midlands (1395 km)
- Yorkshire (1143 km)
- Northeast (314 km).



- 240 km of embankments, walls, and other flood defence structures.
- 1953 North Sea significant flooding around the Humber estuary, killing 38 people.
- In 2013, a tidal surge overpowered the defensive structures, flooding over 600 homes and inflicting.



- 370 kilometres of flood walls, embankments, and other structures.
- 1953, North Sea flood triggered by a storm surge flooded the Thames estuary, killing 307 people.
- 2014, the Thames Barrier was closed 50 times to protect London from tidal surges.

Study Area (2)

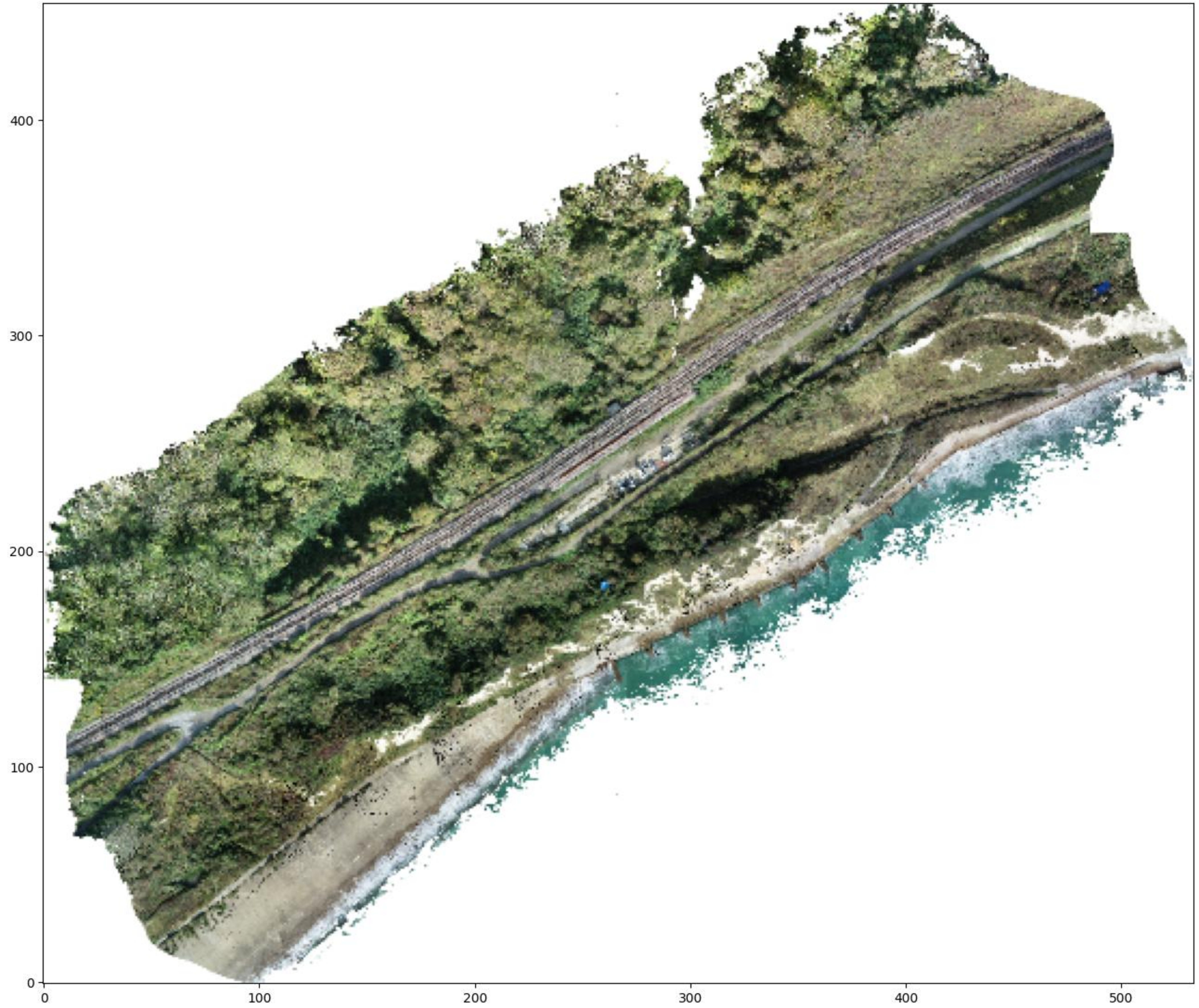
Coordinates :

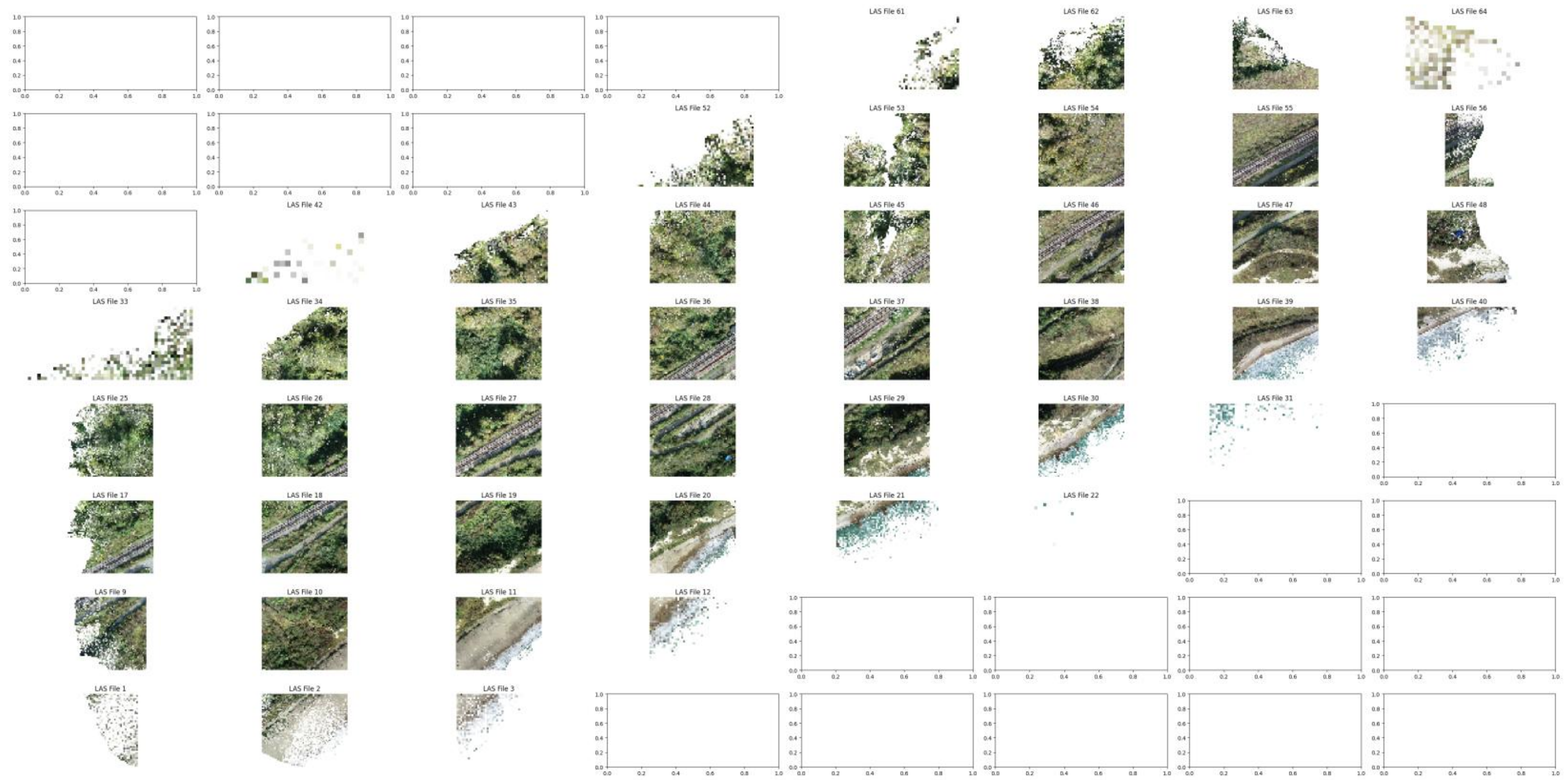
West : 1.20078W 51.09351N
South : 1.20421W 51.09141N
East : 1.23910W 51.10054N
North : 1.23798W 51.10161N

Point Cloud Data

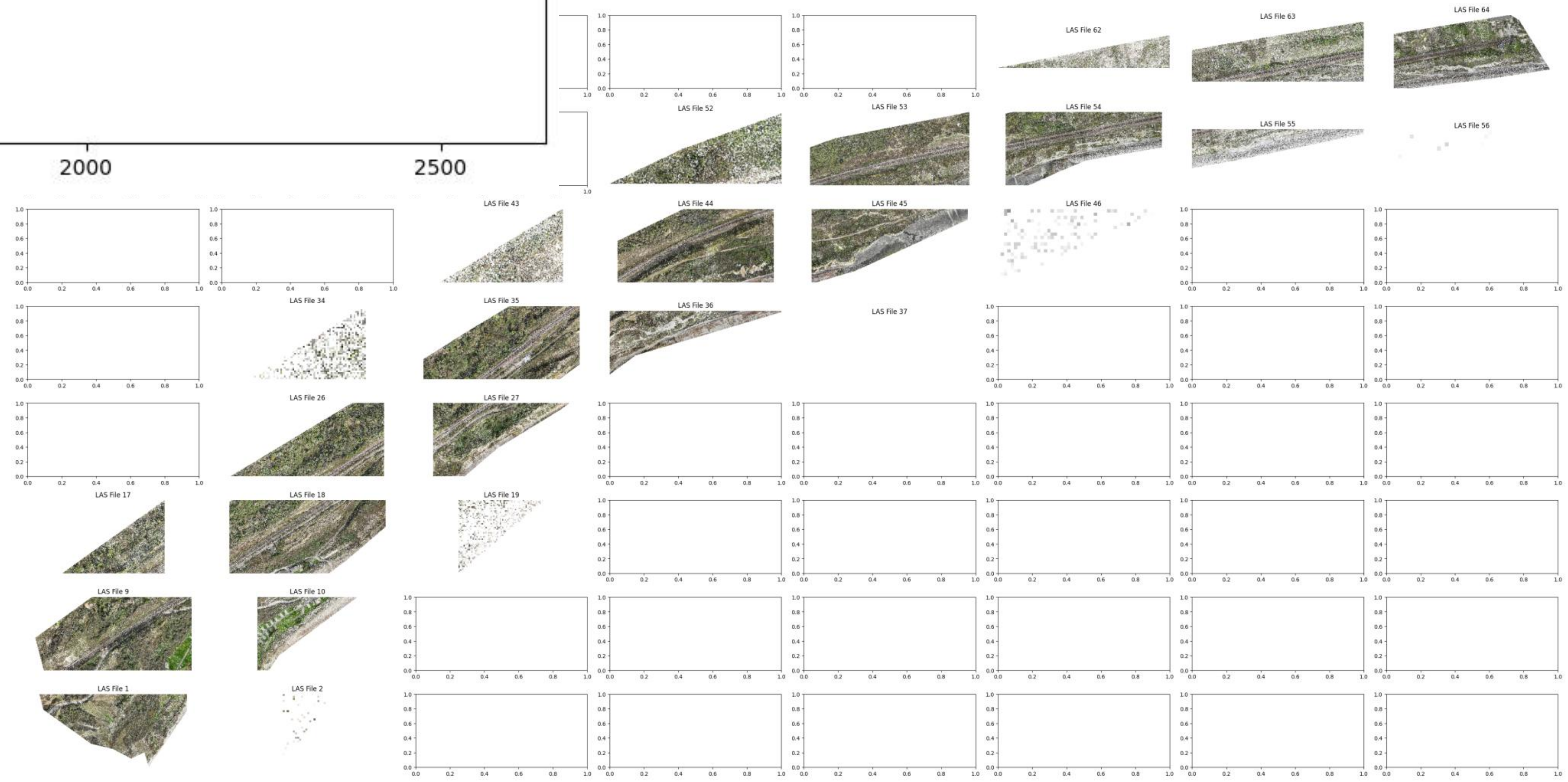
Number of Points : 267,231,656

Data LiDAR Point Cloud 2018





Data LiDAR Point Cloud 2024



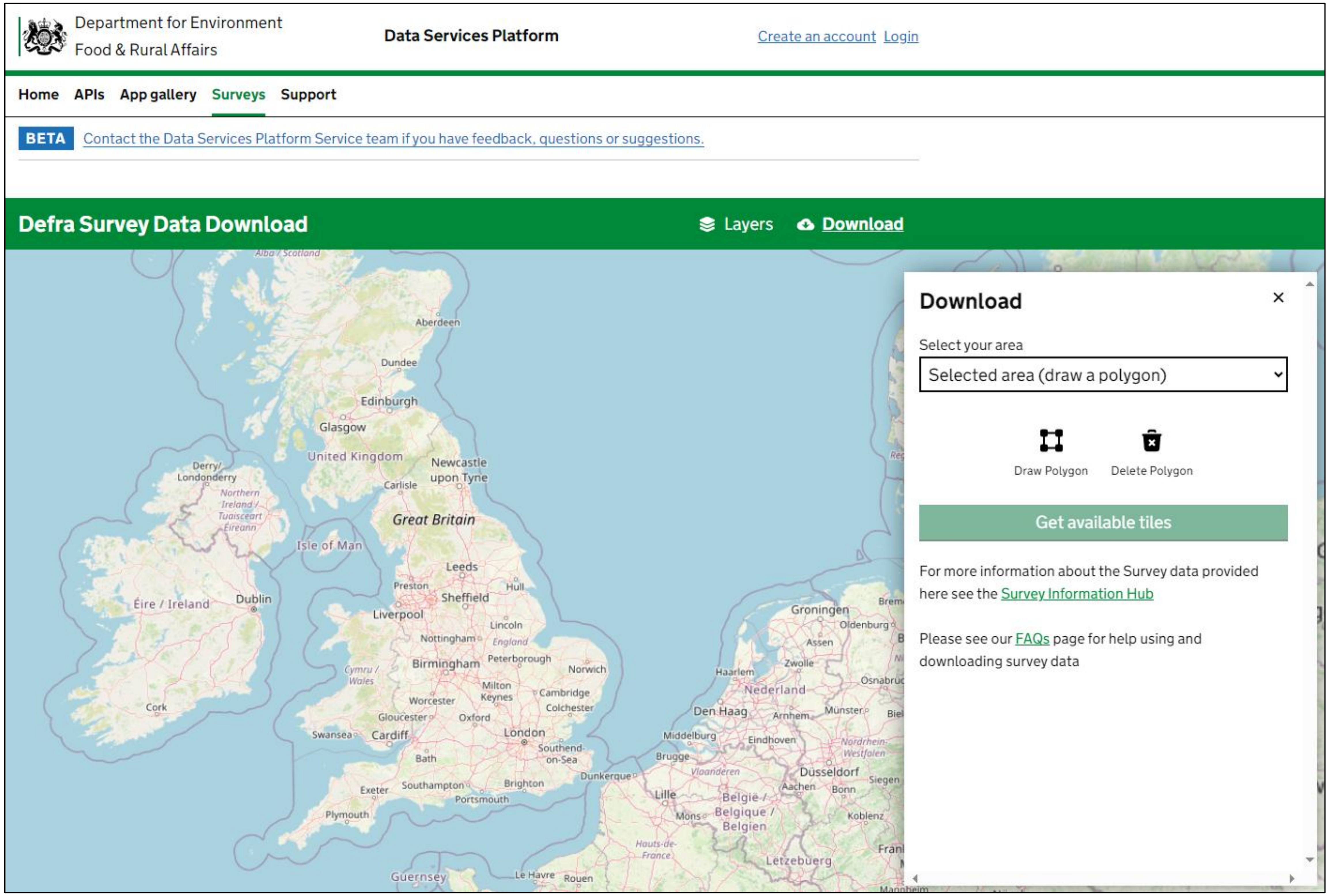
Background Data Folkestone Warren

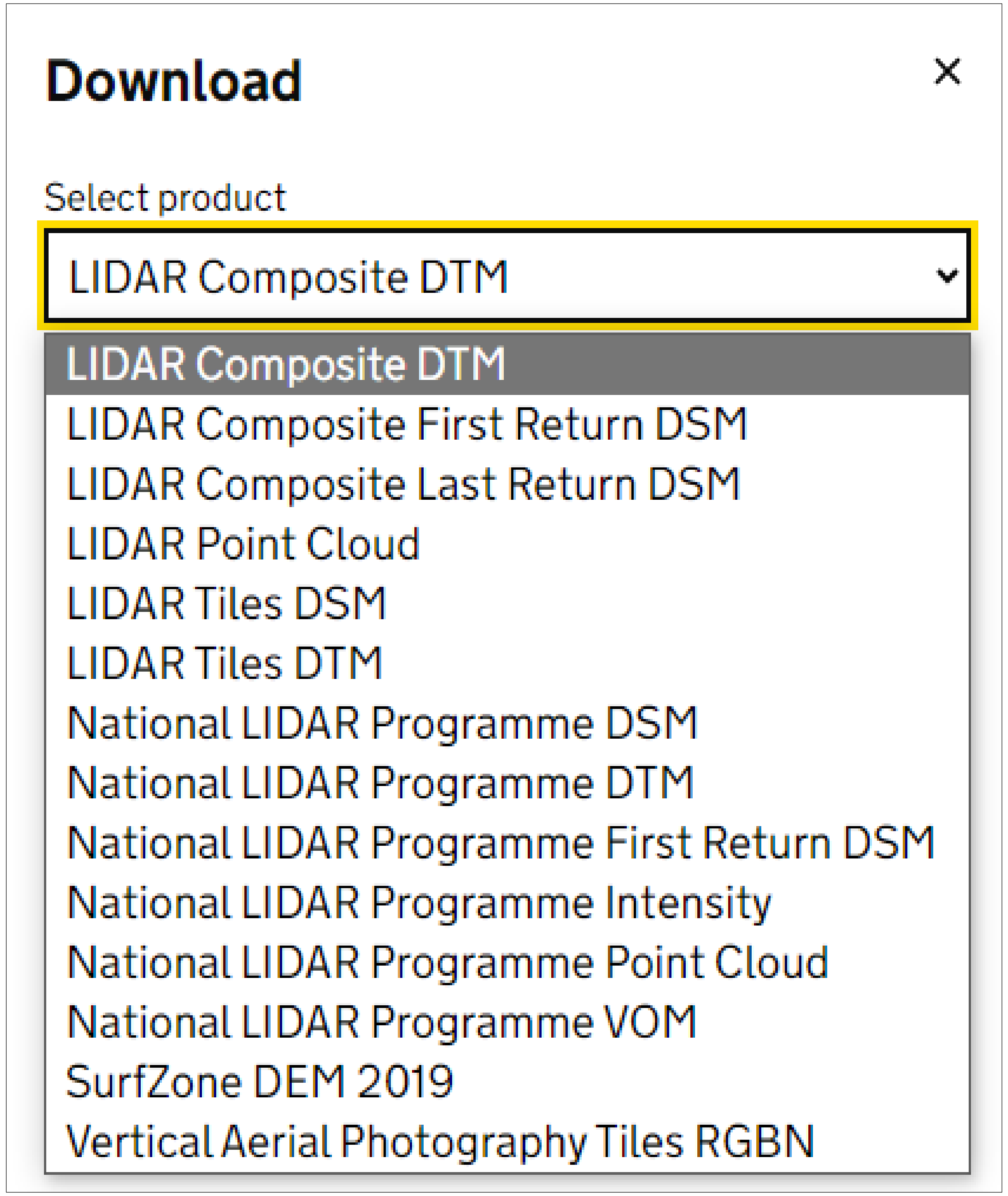
Data 2018					
Number of Grid	Number of Point	Average Point Density	Area per Point	Average Distance estimation (m)	Average Distance estimation (cm)
44	221751985	1336.699732	0.010446693	0.051922814	5.192281423

Data 2024					
Number of Grid	Number of Point	Average Point Density	Area per Point	Average Distance estimation (m)	Average Distance estimation (cm)
25	267231654	306.1451518	0.003986271	0.061535469	6.15354688

Area per point = 1 / average point density
Average distance estimation = It is assumed that the points are uniformly distributed

Training Data Source





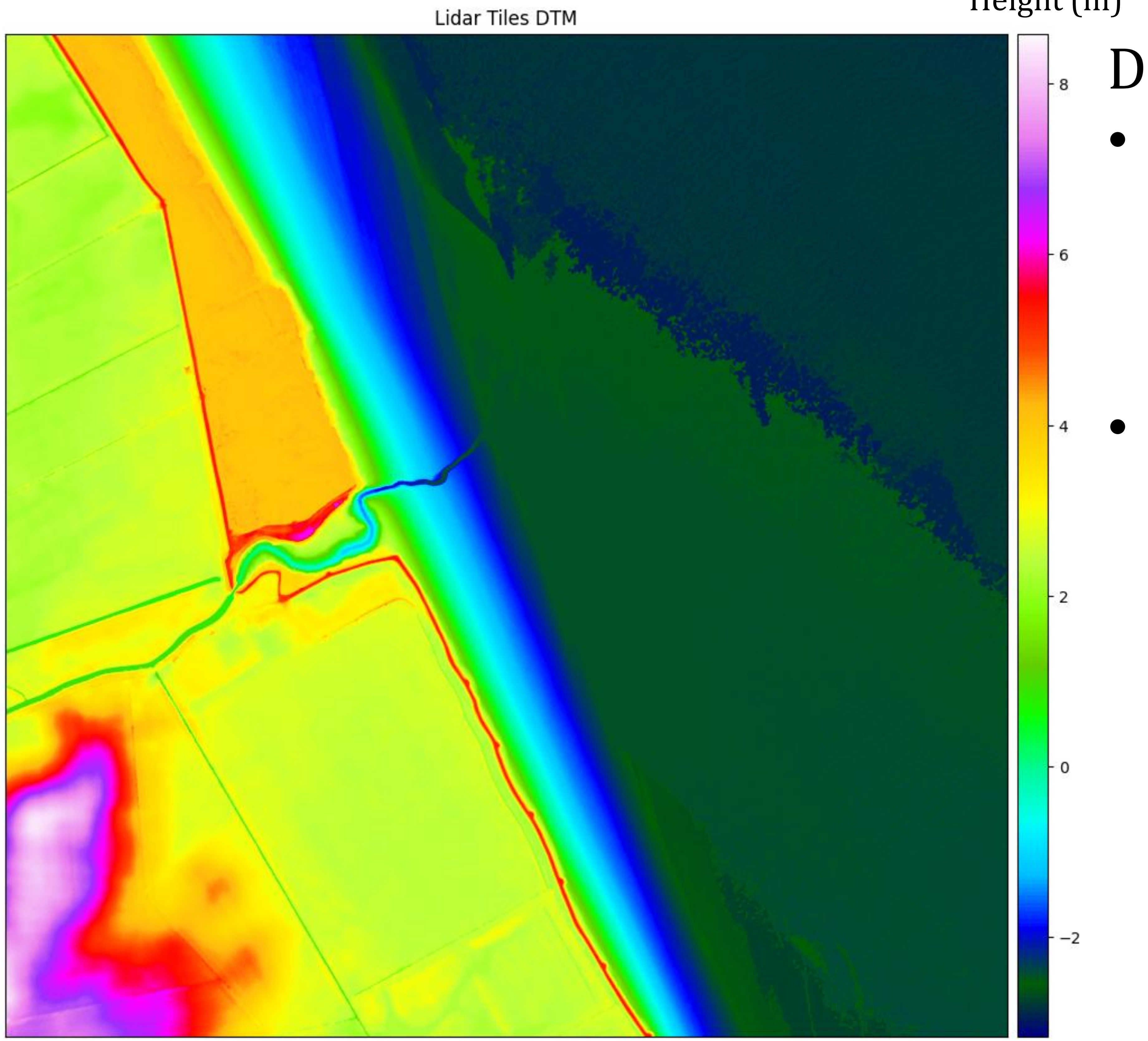
Link : Defra Survey Data Download

LiDAR DTM

1. LiDAR DTM

2. LiDAR DSM

3. LiDAR Point Cloud



Digital Terrain Model

- Represent the elevation or relief of the Earth's surface, **exclude** human-made features and Trees
- Resolution and accuracy depending on the sensor, but commonly lies between 1 meter to 20 meter.

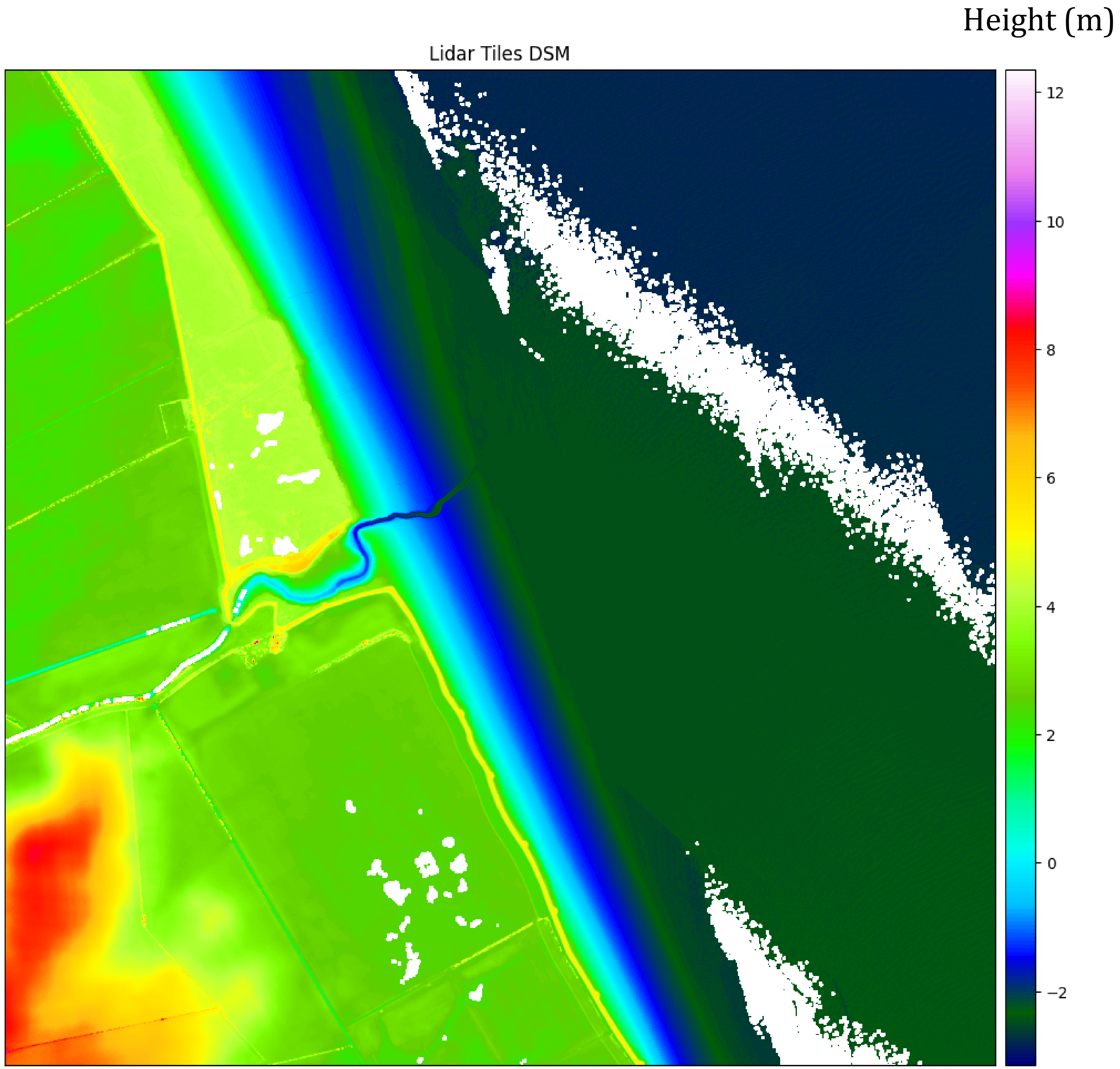
Source Data : DEFRA
Location : East Halton Skitter - Immingham
Tool : Google Colab - Python

LiDAR DSM

1. LiDAR DTM

2. LiDAR DSM

3. LiDAR Point Cloud



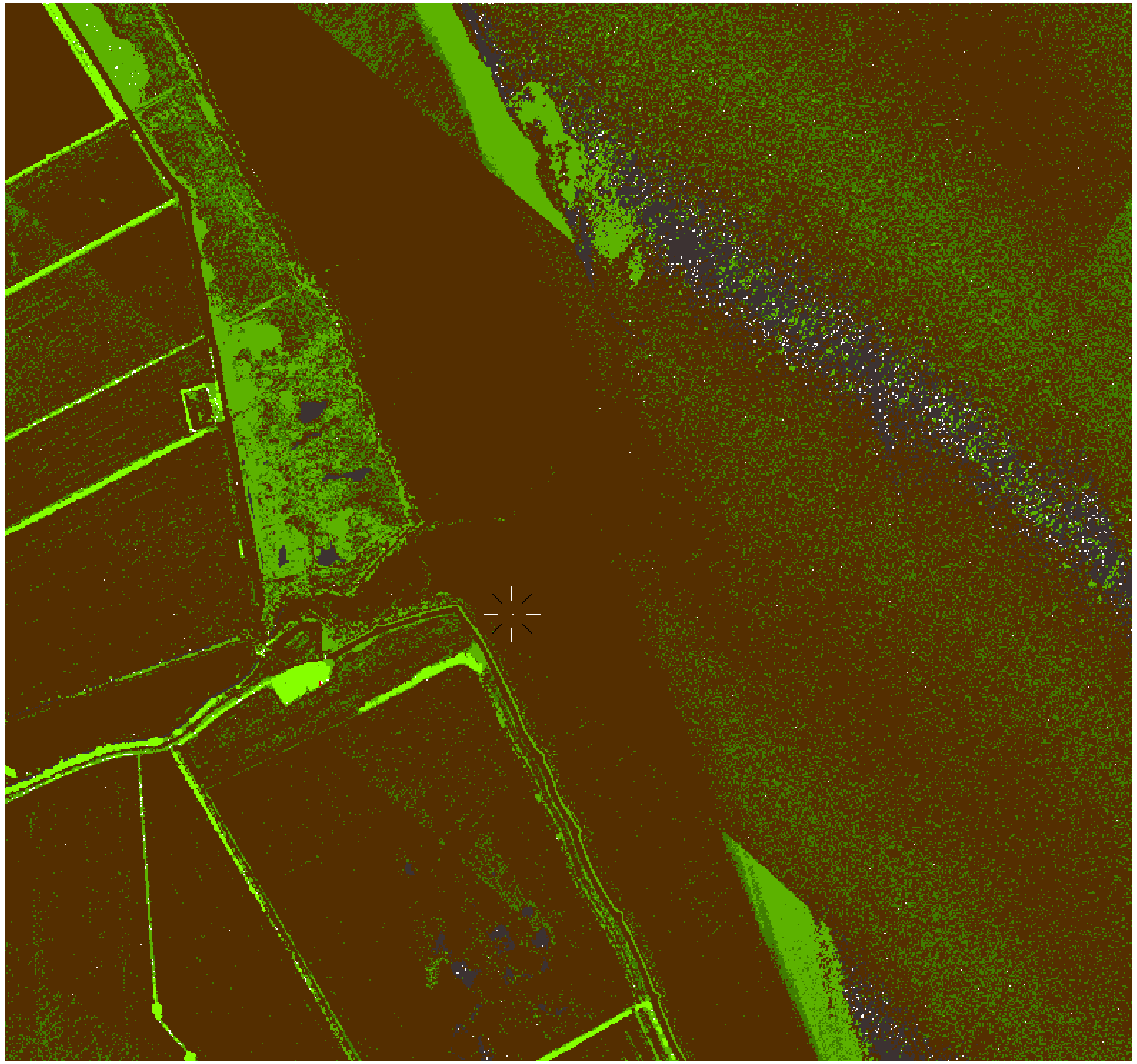
Digital Surface Model

- Represent the elevation or relief of the Earth's surface, **include** human-made features and surface features
- Resolution and accuracy depending on the sensor, but commonly lies between 1 meter to 20 meter

Source Data : DEFRA
Location : East Halton Skitter - Immingham
Tool : Google Colab - Python

LiDAR Point Cloud

1. LiDAR DTM
2. LiDAR DSM
3. **LiDAR Point Cloud**



Point Cloud

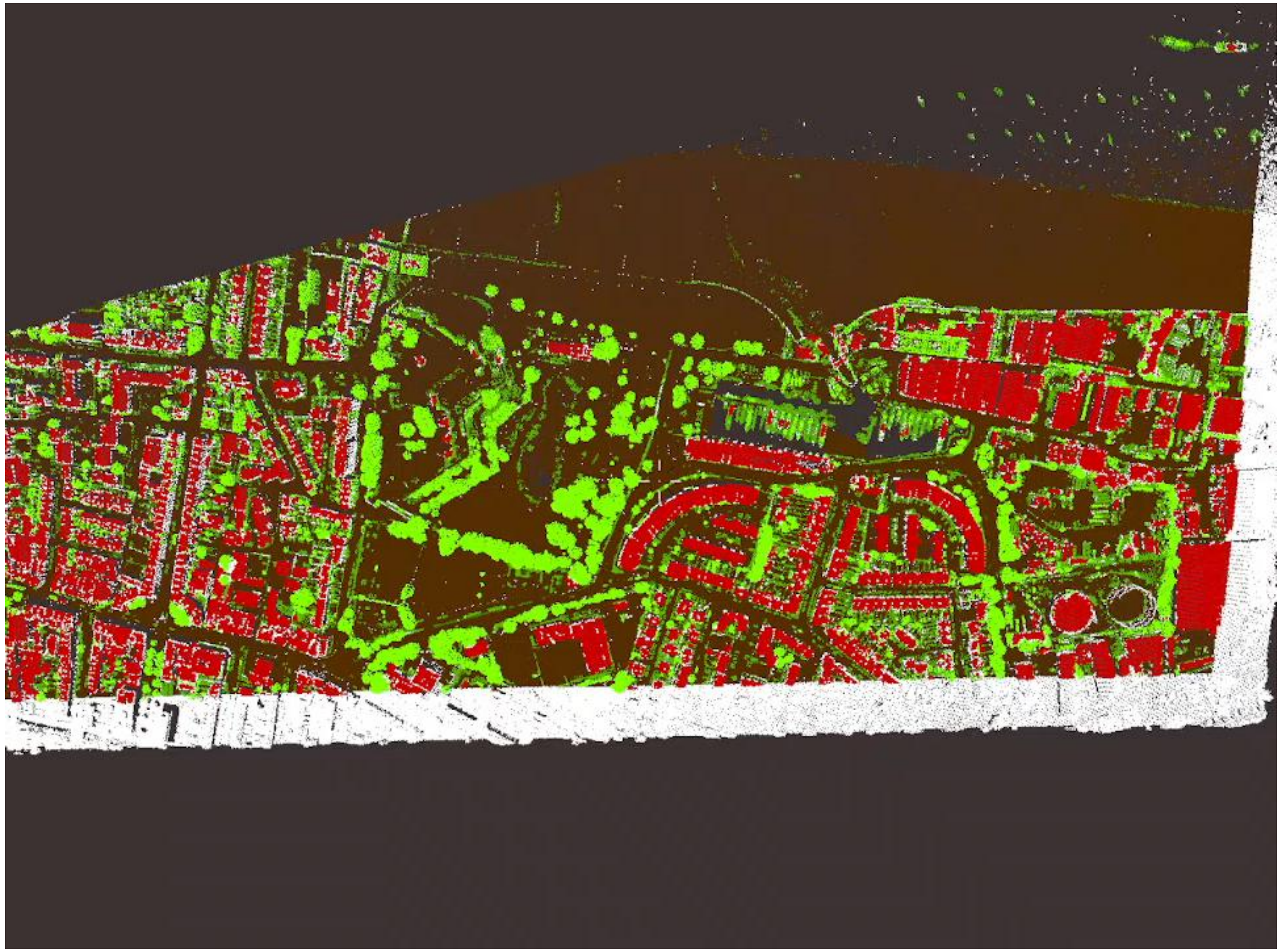
- Individual points in three-dimensional space
- Accuracy and precision depending on some factors (equipment, sensors, processing algorithm used)
- Can be generated from airborne or terrestrial LiDAR, laser scanning, or structured light scanning)

Source Data	:	DEFRA
Location	:	East Halton Skitter - Immingham
Tool	:	Displaz

LiDAR 3D Visualization

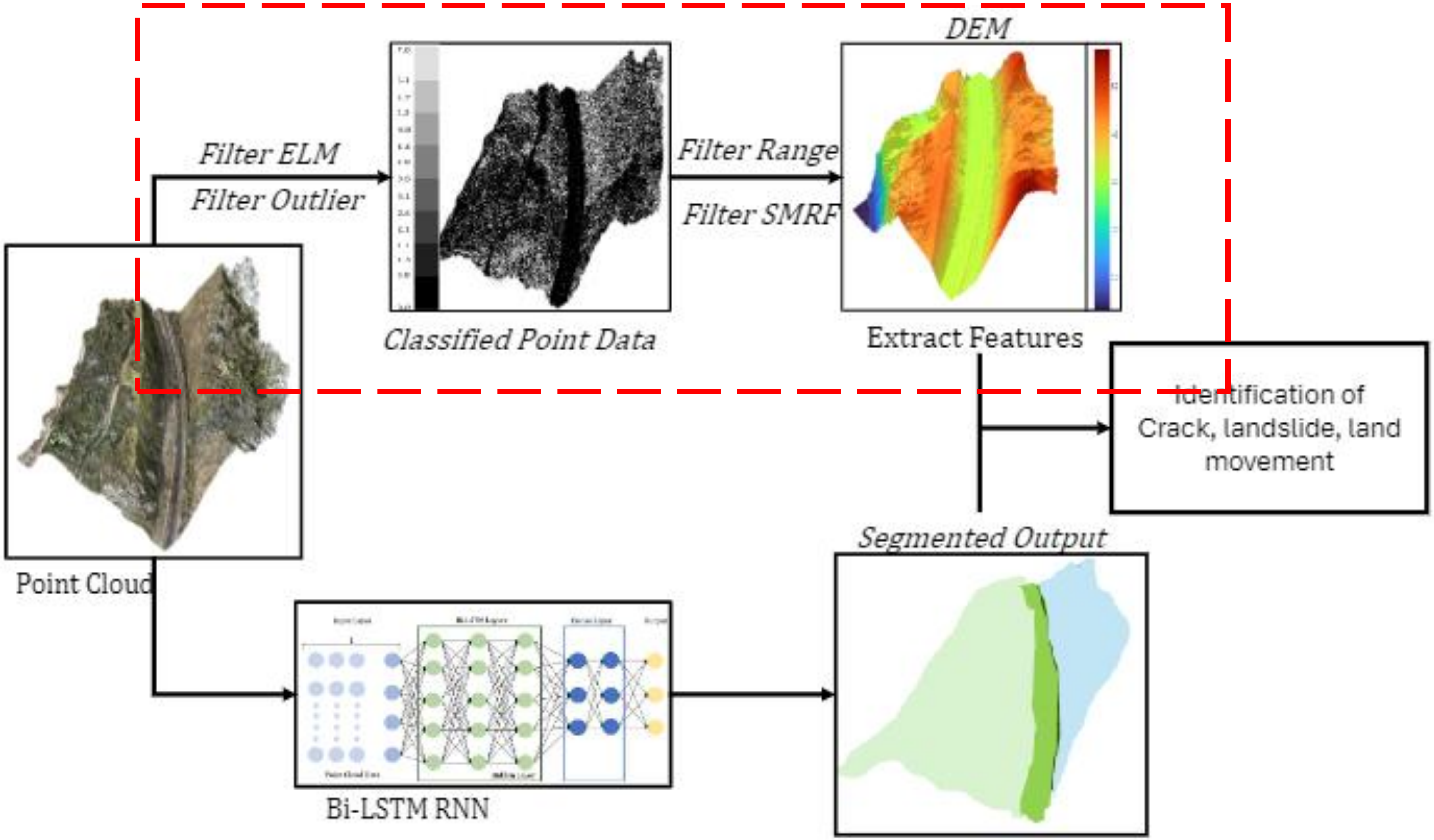
LiDAR Intensity Data

LiDAR Classification

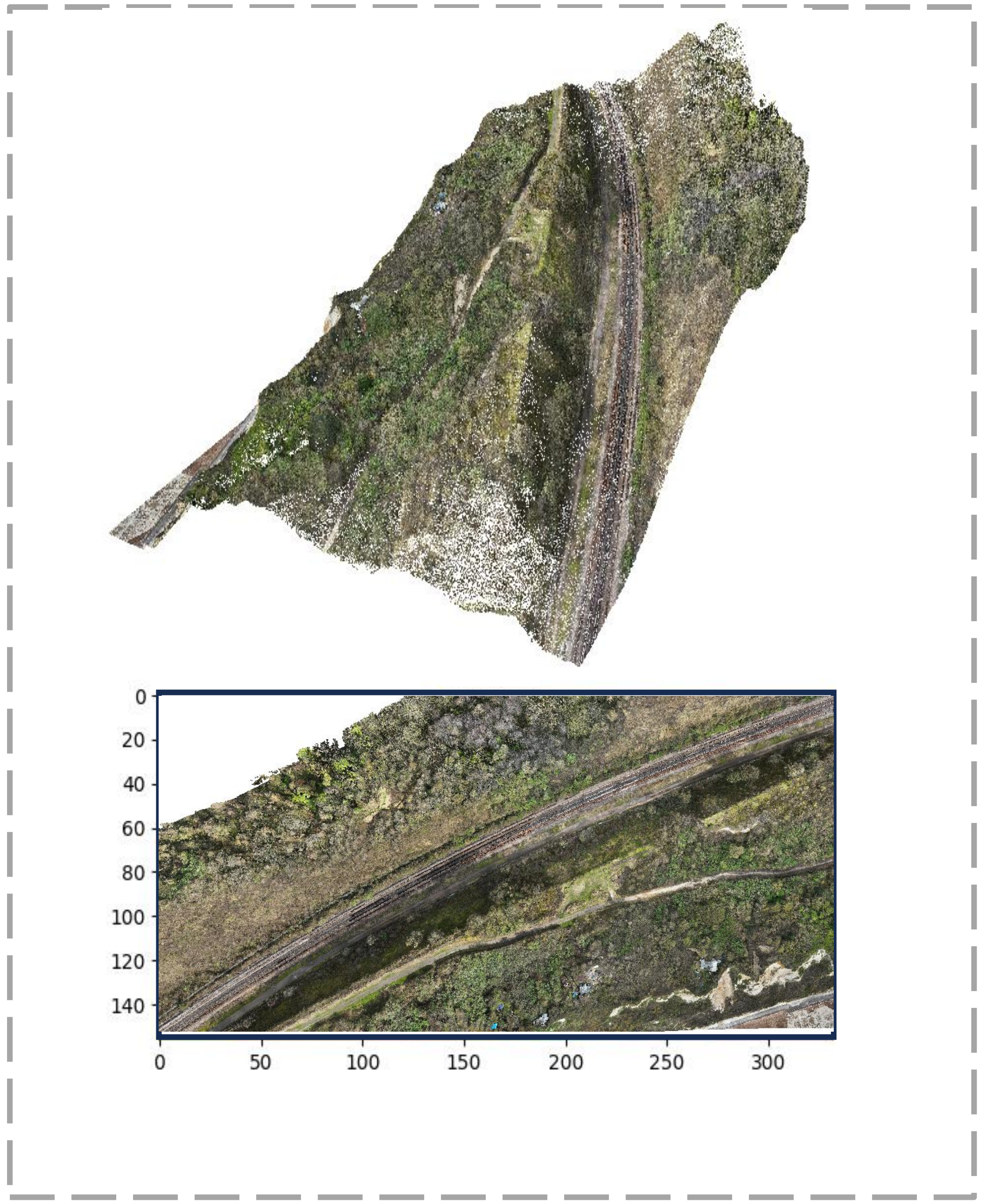


Source Data	:	DEFRA
Location	:	Residential Area in East Tilburn
Tool	:	Displaz, CloudCompare

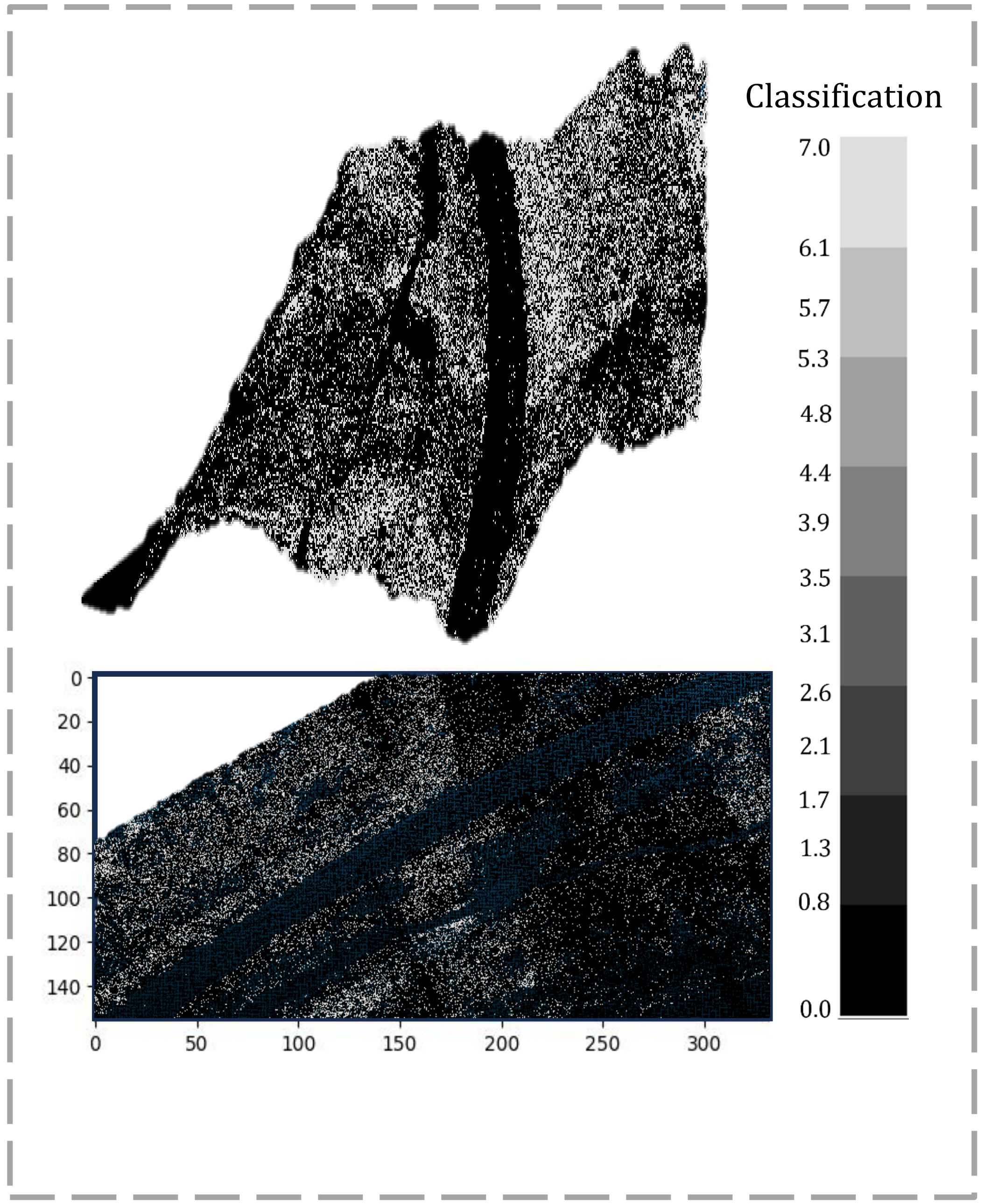
Segmentation



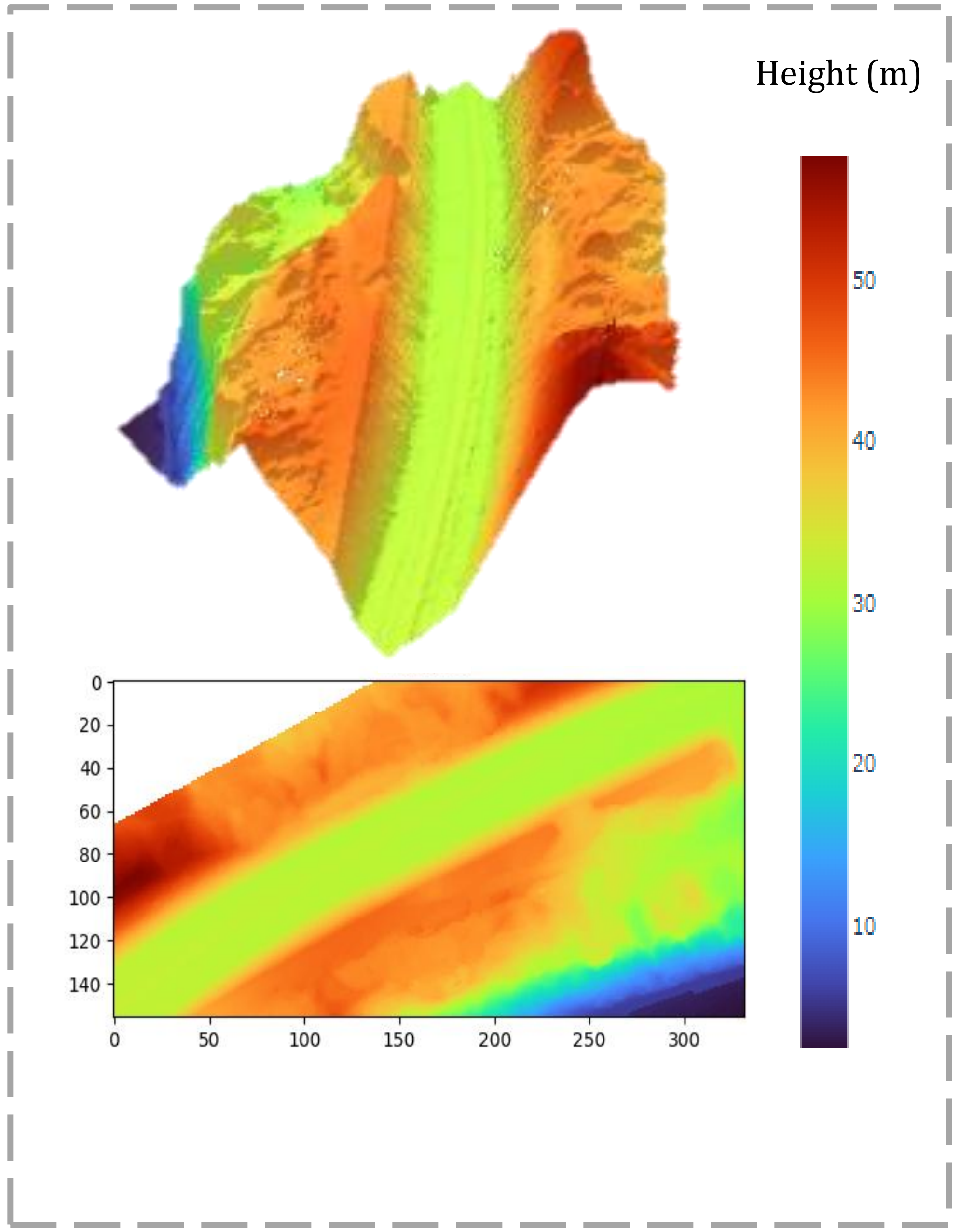
DEMs



Point Cloud Data



Filter Assign
+ Filter ELM
+ Filter Outlier



+ Filter SMRF

+ Filter Range

Output DEM

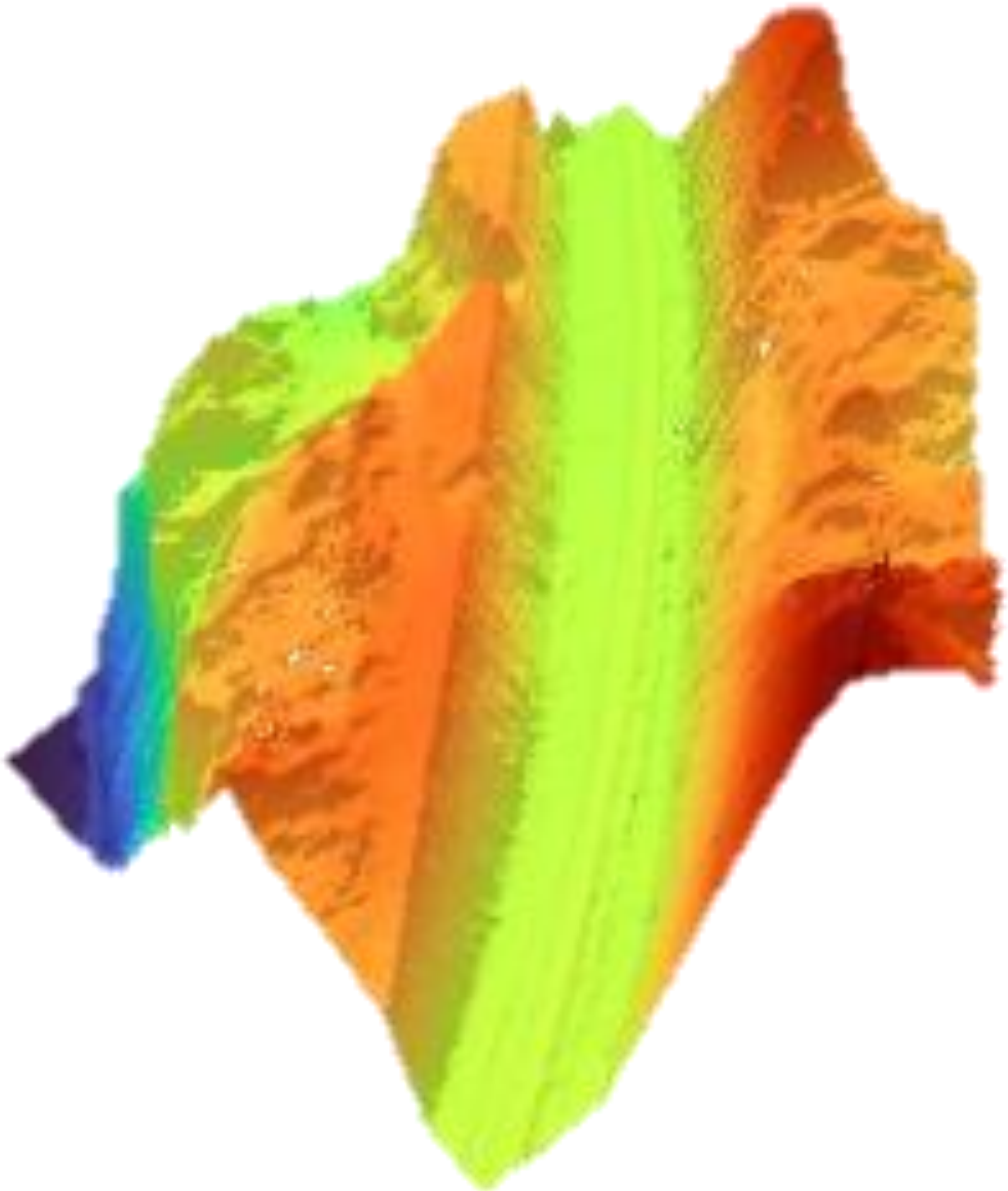
Filtering Pipeline

Filter ELM

Filter Outlier

Filter SMRF

Filter Range



Future Potential

Key Point

3D point cloud data provided by a terrestrial laser scanner could play an interesting role for flood mapping.

Challenge

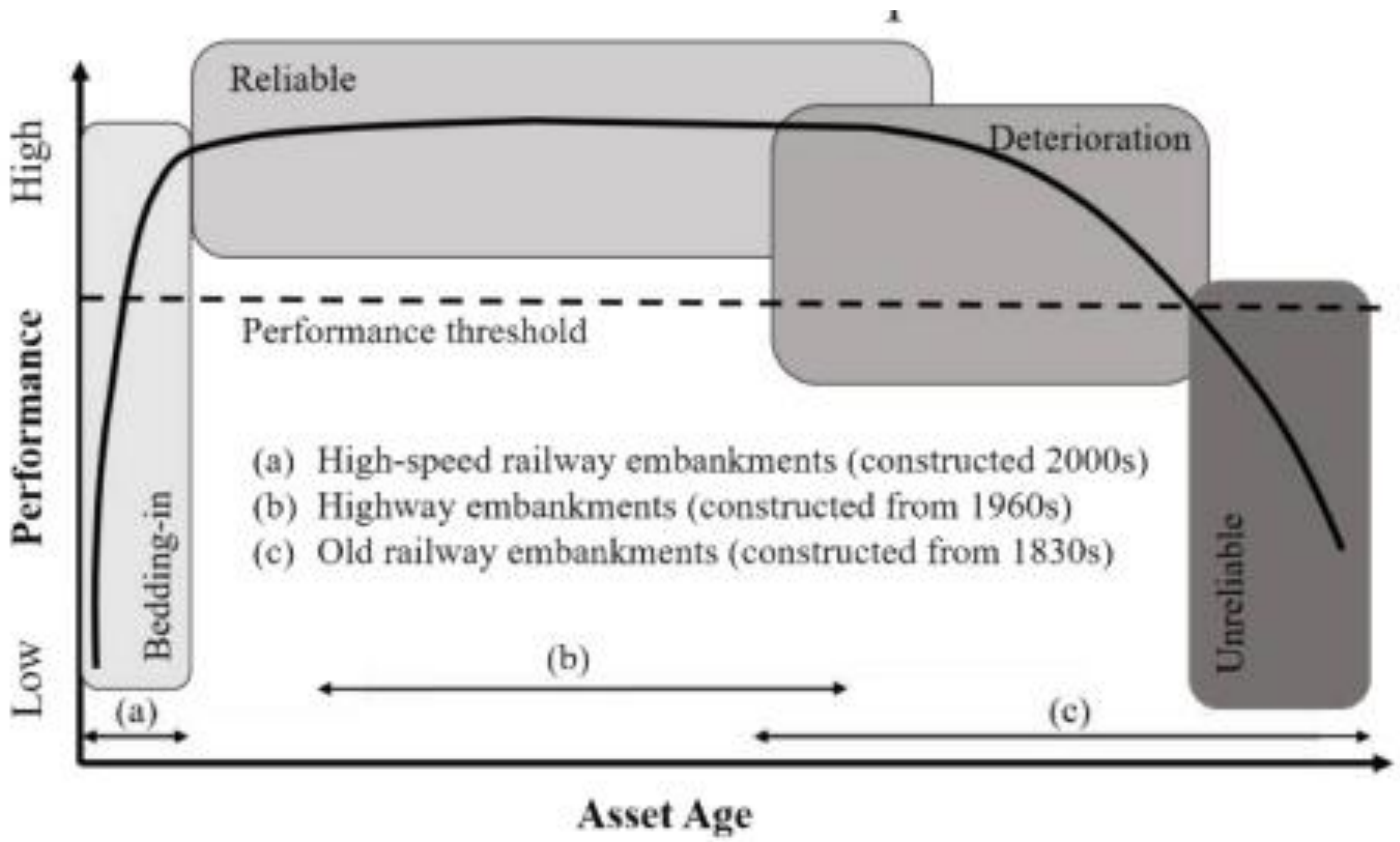
No one single dataset in the public domain is properly detailed to describe for primary research. Water loss from subgrade soil subjected to dry weather is possible to cause soil cracking. On the contrary, intruded water will cause failures because of the wetting swelling or collapsing of the subgrade soils.

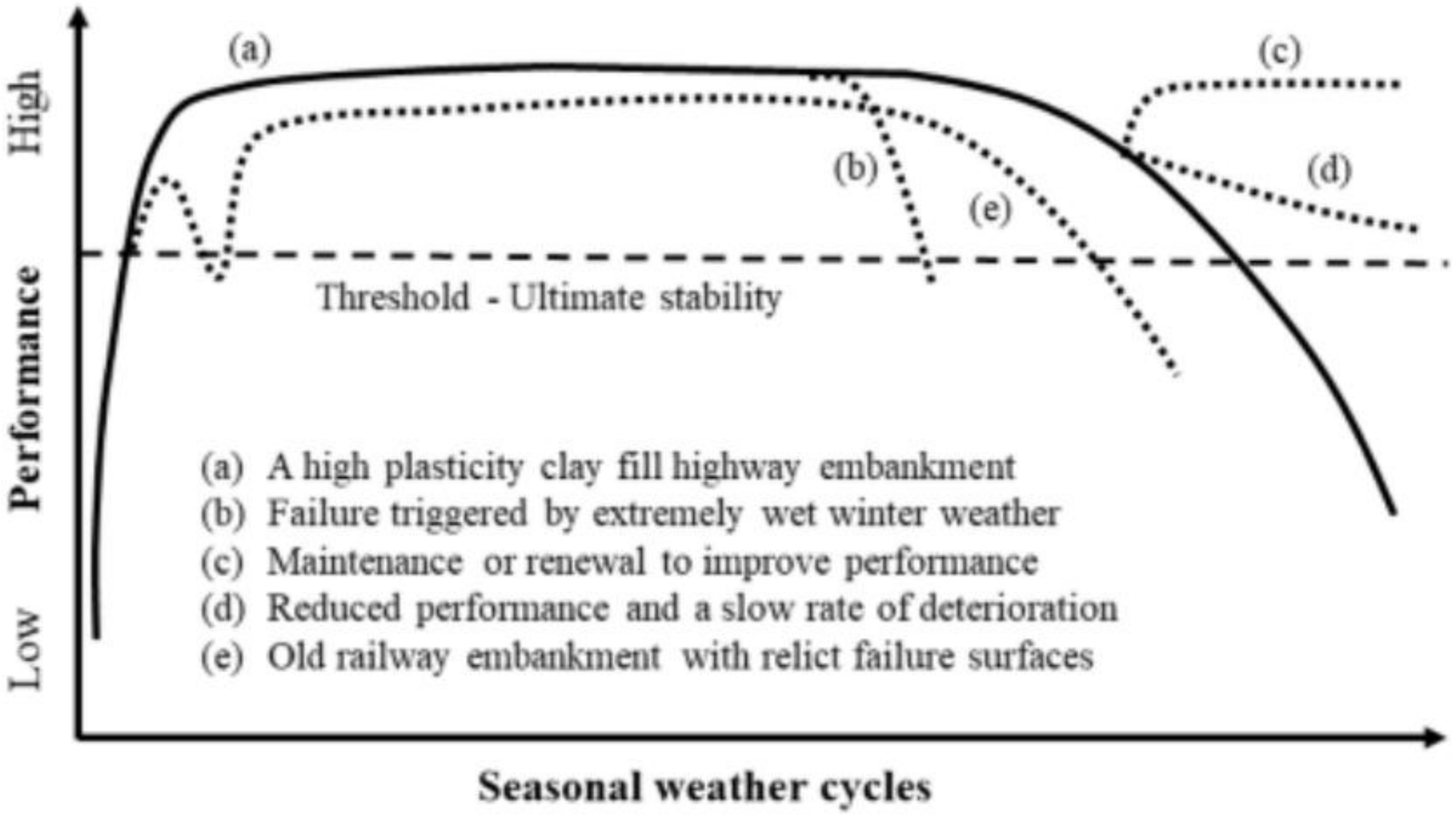
Solution

Currently, the risk of floods is mapped on a global scale using technology like satellite imagery and remote sensing. LiDAR derived flood inundation model can be used to simulate flood hazard estimation using probability analysis and flood scenario.

Source: Johnston et al., 2021

Consideration: Asset Performance





(a) deterioration and then failure due to strain softening of the clay fill, progressive slope failure and ultimate failure of the embankment

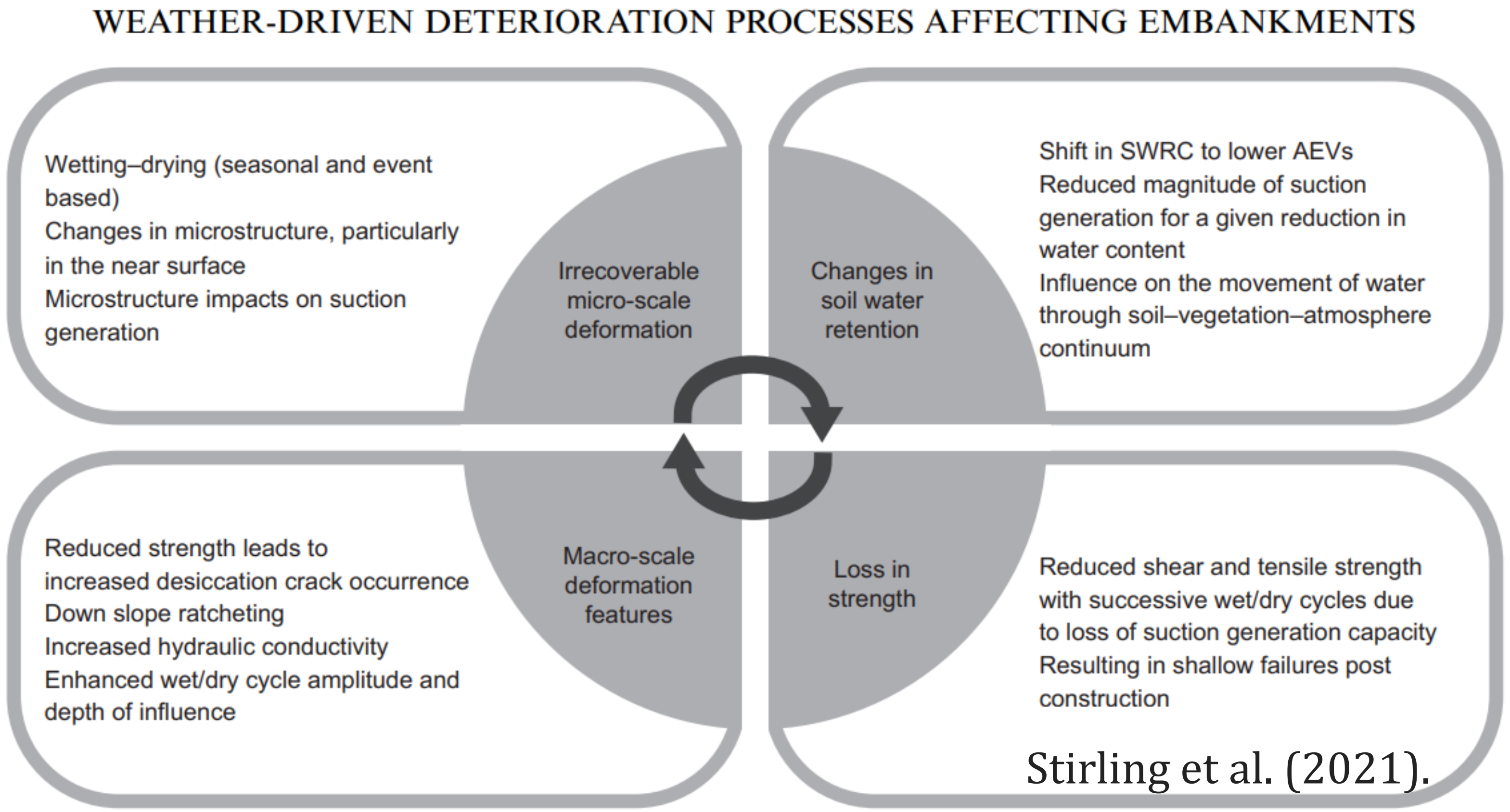
(b) extreme loading due to extremely wet winter weather might trigger a slope failure

(c) Once deterioration has been detected, the performance of the embankment can be improved by maintenance or renewal activities within an appropriate timeframe

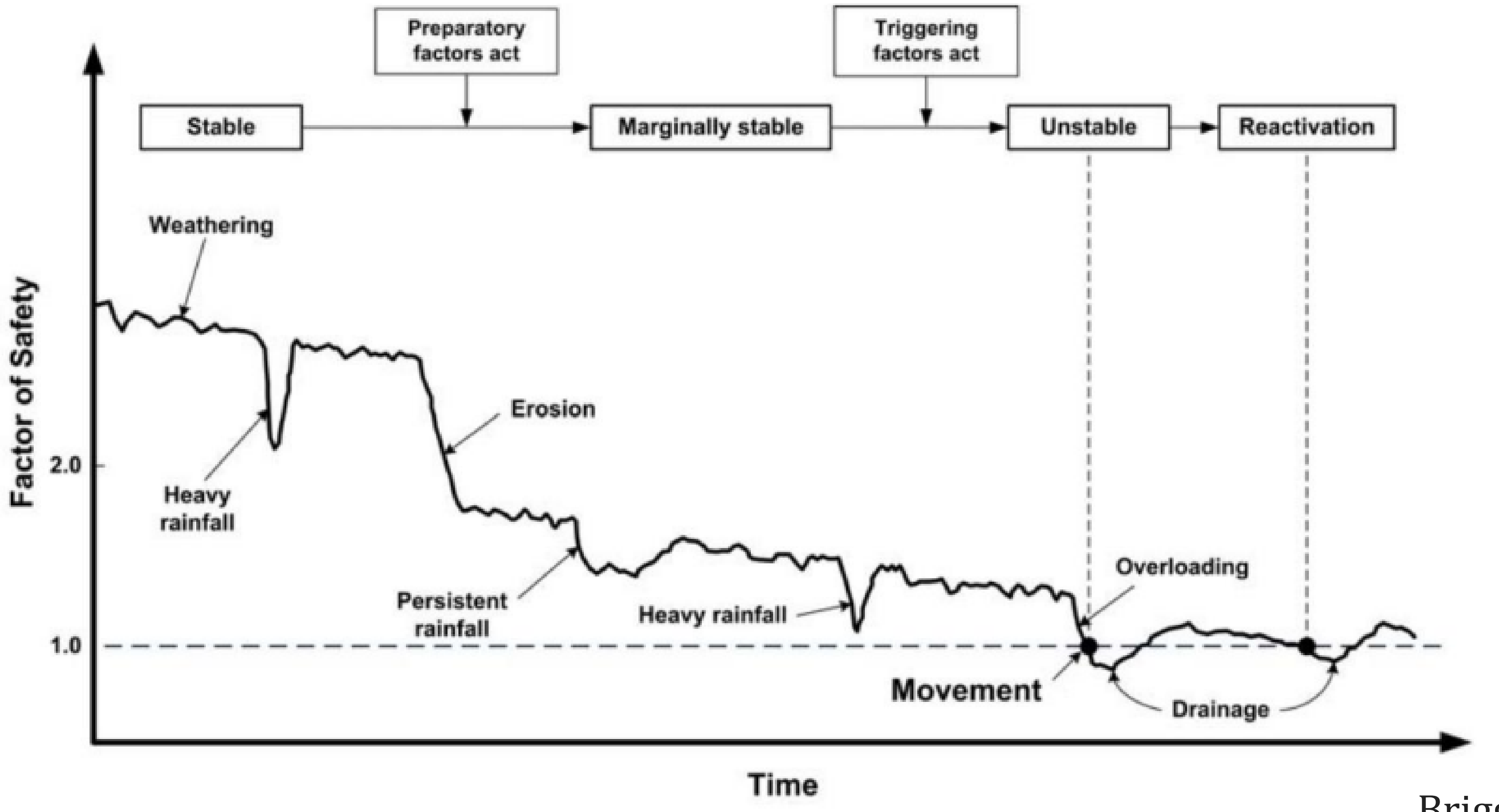
(d) Alternatively, monitoring and inspection might show that an embankment is deteriorating at a slower rate than projected, so that interventions can be delayed or reduced

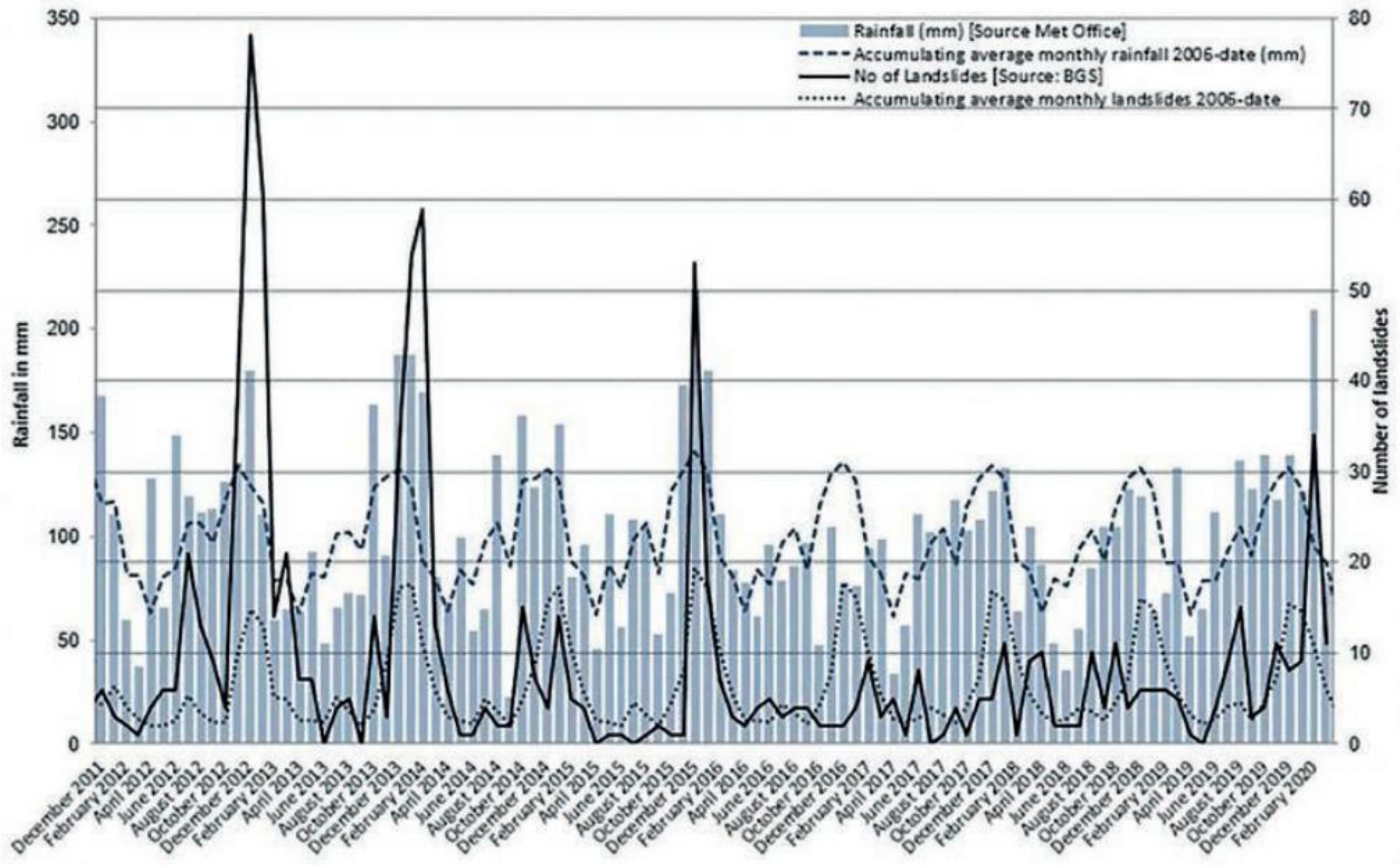
Briggs et al. (2019)

Consideration: Rainfall Impacting to Slope Condition



Stirling et al. (2021).





Briggs et al. (2019)

Possible Dataset : Regional Climate Model (RCM)

Background Data	Model Data Source	Resolution
Global Climate Model (GCM) Reanalysis Data Surface Data (topography, Land use & Land Cover, Soil Data) Climate data (rainfall, temperature, etc) Oceanographic Data (Sea surface temperature, sea current, etc) Aerosol and GHGs Emission Scenario	CORDEX (Coordinated Regional Climate Downscaling Experiment)	0.11° x 0.11° (approximately 12.5 km x 12.5 km)
	RCMES (Regional Climate Model Evaluation System)	0.1° to 0.5° (approximately 10 km to 50 km)
	Meteoblue	3 km for high-resolution local models. For broader regional models, the resolution might range from 10 km to 25 km
	ECMWF (European Centre for Medium-Range Weather Forecasts)	0.11° (approximately 12.5 km) for Europe

Type of Data	Potential Data Availability
Temperature	Surface temperature
	Extreme heat
Precipitation	Total precipitation
	Extreme precipitation
Wind	Wind speed
	Wind direction
Humidity and Evapotranspiration	Relative humidity
	Evapotranspiration
Radiation	Solar radiation
	Longwave radiation
Soil and Surface Data	Soil moisture (water content)
	Surface fluxes (heat, moisture)
Sea Surface	Sea surface temperature
	Sea Ice Extent
Aerosol and air Quality	Trace gases (ozone, co2), Aerosol Concentration

Challenge

Challenge		
Dataset	Noise	Sequences of (multisensor) satellite observations have diverse noise sources, uncertainty levels, missing data, and (often systematic) gaps (e.g., acquisition, storage, and transmission distortions). Aerial and satellite images have a varied
	Heterogeneity	Climate and ecosystem processes reveal a high level of heterogeneity due to differences in geography, topography, and climatic conditions in diverse areas of the earth.
	Deluge of dataset	airborne LiDAR surveys, SAR satellites, stereophotogrammetry, and mobile mapping systems are increasingly used and produce data volumes that raise computational challenges for spectral, spatial, and temporal dimensionalities
Class Imbalance	Data-level technique	Random oversampling can improve the classification of imbalanced image data. Random undersampling can decrease the amount of class imbalance for pretraining a deep CNN.
	Algorithms-level techniques	Cost-sensitive deep learning methods are emerging, which learn network weight parameters and class misclassification costs during training and thus give higher importance to samples with a higher cost.
Data Interpretation		Well-trained neural networks still have the typical issue of the lack of interpretability. Given their complexity, landslides prevention models in the earth system are often not easily traceable back to their assumptions, limiting their interpretability.
Machine Learning		Regardless of the model, it is necessary to select the proper parameters and thresholds of each feature.

Ma, Z., Mei, G., & Piccialli, F. (2021). Machine learning for landslides prevention: a survey. *Neural Computing and Applications*, *33*(17), 10881-10907.

Reference

[1] Iqbal, Z., Shahid, S., Ismail, T., Sa'adi, Z., Farooque, A., & Yaseen, Z. M. (2022). Distributed hydrological model based on machine learning algorithm: Assessment of climate change impact on floods. *Sustainability*, *14*(11), 6620.

[2] United Nations Office for Disaster Risk Reduction. (2020). The Human Cost of Disasters: An Overview of the Last 20 Years (2000-2019). Retrieved from https://www.undrr.org/publication/human-cost-disasters-overview-last-20-years-2000-2019

[3] Allsop, W., & Harrop, J. (2009). Flood risk management: research and practice. In *Proceedings of the European Conference on Flood Risk Management Research into Practice (Floodrisk 2008). Oxford, UK, CRC*.

[4] Aanstoos, J. V., Hasan, K., O'Hara, C. G., Dabbiru, L., Mahrooghy, M., Nobrega, R., & Lee, M. A. (2012, October). Detection of slump slides on earthen levees using polarimetric SAR imagery. In *2012 IEEE Applied Imagery Pattern Recognition Workshop (AIPR)* (pp. 1-7). IEEE.

[5] Morris, J. H. T. M., Hess, T. M., Gowing, D. J. G., Leeds-Harrison, P. B., Bannister, N., Vivash, R. M. N., & Wade, M. (2005). A framework for integrating flood defence and biodiversity in washlands in England. *International Journal of River Basin Management*, *3*(2), 105-115.

[6] Mahrooghy, M., Aanstoos, J. V., Nobrega, R. A., Hasan, K., Prasad, S., & Younan, N. H. (2015). A machine learning framework for detecting landslides on earthen levees using spaceborne SAR imagery. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, *8*(8), 3791-3801.

[7] Kim, S. Y., Kwon, D. Y., Jang, A., Ju, Y. K., Lee, J. S., & Hong, S. (2023). A review of UAV integration in forensic civil engineering: From sensor technologies to geotechnical, structural and water infrastructure applications. *Measurement*, 113886.

[8] Kahraman, S., & Bacher, R. (2021). A comprehensive review of hyperspectral data fusion with lidar and sar data. *Annual Reviews in Control*, *51*, 236-253.

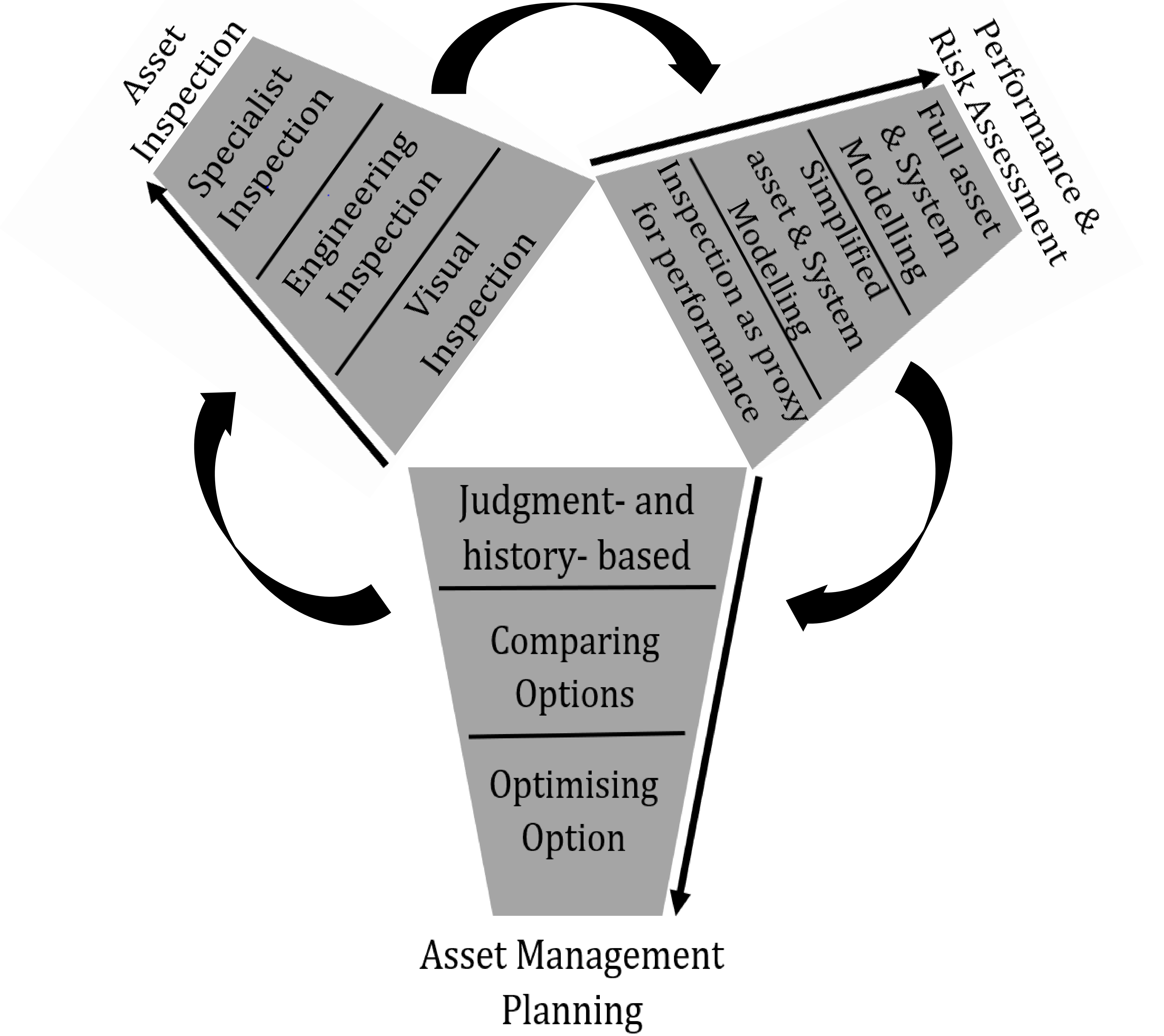
[9] Mezaal, M. R., & Pradhan, B. (2018). An improved algorithm for identifying shallow and deep-seated landslides in dense tropical forest from airborne laser scanning data. *Catena*, *167*, 147-159.
[10] Jaboyedoff, M., Oppikofer, T., Abellán, A., Derron, M. H., Loye, A., Metzger, R., & Pedrazzini, A. (2012). Use of LIDAR in landslide investigations: a review. *Natural hazards*, *61*, 5-28.
[11] Guo, C., Xu, Q., Dong, X., Li, W., Zhao, K., Lu, H., & Ju, Y. (2021). Geohazard recognition and inventory mapping using airborne LiDAR data in complex mountainous areas. *Journal of Earth Science*, *32*, 1079-1091.
[12] Xu, Q., Zhao, B., Dai, K., Dong, X., Li, W., Zhu, X., ... & Ge, D. (2023). Remote sensing for landslide investigations: A progress report from China. *Engineering Geology*, 107156.
[13] Cheng, H., Li, Y., Li, H., & Hu, Q. (2023, April). Embankment crack detection in UAV images based on efficient channel attention U2Net. In *Structures* (Vol. 50, pp. 430-443). Elsevier.
[14] Yuheng, S., & Hao, Y. (2017). Image segmentation algorithms overview. *arXiv preprint arXiv:1707.02051*.
[15] O'Shea, K., & Nash, R. (2015). An introduction to convolutional neural networks. *arXiv preprint arXiv:1511.08458*.
[16] Johnston, I., Murphy, W., & Holden, J. (2021). A review of floodwater impacts on the stability of transportation embankments. *Earth-Science Reviews*, *215*, 103553.
[17] Congalton, R.G. and Green, K., 2009. "Assessing the accuracy of remotely sensed data: principles and practices." CRC Press.
[18] Lillesand, T.M., Kiefer, R.W., and Chipman, J.W., 2015. "Remote sensing and image interpretation." John Wiley & Sons.
[19] Colomina, I., and Molina, P., 2014. "Unmanned aerial systems for photogrammetry and remote sensing: A review." ISPRS Journal of Photogrammetry and Remote Sensing, 92, pp.79-97.
[20] Li, Y., Bu, R., Sun, M., Wu, W., Di, X., & Chen, B. (2018). Pointcnn: Convolution on x-transformed points. *Advances in neural information processing systems*, *31*.
[21] Xiang, T. Z., Xia, G. S., & Zhang, L. (2018). Mini-UAV-based remote sensing: techniques, applications and prospectives. arXiv 2018. *arXiv preprint arXiv:1812.07770*.

[22] Casagli, N., Intrieri, E., Tofani, V., Gigli, G., & Raspini, F. (2023). Landslide detection, monitoring and prediction with remote-sensing techniques. *Nature Reviews Earth & Environment*, *4*(1), 51-64.
[23] Zhao, L., Hu, Y., Yang, X., Dou, Z., & Kang, L. (2024). Robust multi-task learning network for complex LiDAR point cloud data preprocessing. *Expert Systems with Applications*, *237*, 121552.
[24] Zhang, H., Wang, C., Tian, S., Lu, B., Zhang, L., Ning, X., & Bai, X. (2023). Deep learning-based 3D point cloud classification: A systematic survey and outlook. *Displays*, 102456.
[25] Bisheng, Y. A. N. G., & Zhen, D. O. N. G. (2019). Progress and perspective of point cloud intelligence. *Acta Geodaetica et Cartographica Sinica*, *48*(12), 1575.
[26] Zeng, J., Wang, D., & Chen, P. (2022). A survey on transformers for point cloud processing: An updated overview. *IEEE Access*, *10*, 86510-86527.
[27] Defra and Environment Agency (2007). Management of flood embankments – a good practice review, Technical Report FD2411/TR1. Environment Agency. Available from: http://sciencesearch.defra.gov.uk/Document.aspx?Document=FD2411_6509_TRP.pdf.
[28] Mora, O. E., Liu, J. K., Gabriela Lenzano, M., Toth, C. K., & Grejner-Brzezinska, D. A. (2015). Small landslide susceptibility and hazard assessment based on airborne lidar data. *Photogrammetric Engineering & Remote Sensing*, *81*(3), 239-247.
[29] Zhong, C., Liu, Y., Gao, P., Chen, W., Li, H., Hou, Y., ... & Ma, H. (2020). Landslide mapping with remote sensing: Challenges and opportunities. *International Journal of Remote Sensing*, *41*(4), 1555-1581.
[30] Fahlstrom, P. G., Gleason, T. J., & Sadraey, M. H. (2022). *Introduction to UAV systems*. John Wiley & Sons.
[31] Qi, Charles Ruizhongtai, et al. "Pointnet++: Deep hierarchical feature learning on point sets in a metric space." *Advances in neural information processing systems* 30 (2017).
[32] Li, X., Hu, X., & Yang, J. (2019). Spatial group-wise enhance: Improving semantic feature learning in convolutional networks. *arXiv preprint arXiv:1905.09646*.
[33] Thomas, H., Qi, C. R., Deschaud, J. E., Marcotegui, B., Goulette, F., & Guibas, L. J. (2019). Kpconv: Flexible and deformable convolution for point clouds. In *Proceedings of the IEEE/CVF international conference on computer vision* (pp. 6411-6420).

[34] Wang, Y., Sun, Y., Liu, Z., Sarma, S. E., Bronstein, M. M., & Solomon, J. M. (2019). Dynamic graph cnn for learning on point clouds. *ACM Transactions on Graphics (tog)*, *38*(5), 1-12.
[35] Zhao, H., Jiang, L., Jia, J., Torr, P. H., & Koltun, V. (2021). Point transformer. In *Proceedings of the IEEE/CVF international conference on computer vision* (pp. 16259-16268).
[36] Yan, X., Zheng, C., Li, Z., Wang, S., & Cui, S. (2020). Pointasnl: Robust point clouds processing using nonlocal neural networks with adaptive sampling. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition* (pp. 5589-5598).
[37] Yu, L., Li, X., Fu, C. W., Cohen-Or, D., & Heng, P. A. (2018). Pu-net: Point cloud upsampling network. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 2790-2799).
[38] Hu, Q., Yang, B., Xie, L., Rosa, S., Guo, Y., Wang, Z., ... & Markham, A. (2021). Learning semantic segmentation of large-scale point clouds with random sampling. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *44*(11), 8338-8354.
[39] Huan Lei, Naveed Akhtar, and Ajmal Mian. Spherical kernel for efficient graph convolution on 3d point clouds. Transaction on Pattern Analysis and Machine Intelligence, X(X):1–17, 2020.
[40] You, Y., Wang, Y., Chao, W. L., Garg, D., Pleiss, G., Hariharan, B., ... & Weinberger, K. Q. (2019). Pseudo-lidar++: Accurate depth for 3d object detection in autonomous driving. *arXiv preprint arXiv:1906.06310*.
[41] Wang, F., Zhuang, Y., Gu, H., & Hu, H. (2019). OctreeNet: A novel sparse 3-D convolutional neural network for real-time 3-D outdoor scene analysis. *IEEE Transactions on Automation Science and Engineering*, *17*(2), 735-747.
[42] Huang, Z., Yu, Y., Xu, J., Ni, F., & Le, X. (2020). Pf-net: Point fractal network for 3d point cloud completion. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition* (pp. 7662-7670).
[43] Briggs, K. M., Dijkstra, T. A., & Glendinning, S. (2019). Evaluating the deterioration of geotechnical infrastructure assets using performance curves. In *International Conference on Smart Infrastructure and Construction 2019 (ICSIC) Driving data-informed decision-making* (pp. 429-435). ICE Publishing.


D-RTK
Antennas
LiDAR Sensor
LiDAR Sensor
Auxiliary
Positioning
Vision Sensor

Example approach of flood defense asset management



Source: The International Levee Handbook

1980s

The concept of 3D Scanning

1990s

- Non-contact 3D scanners become more widespread.
- Software for point cloud begin to emerge.

2000s

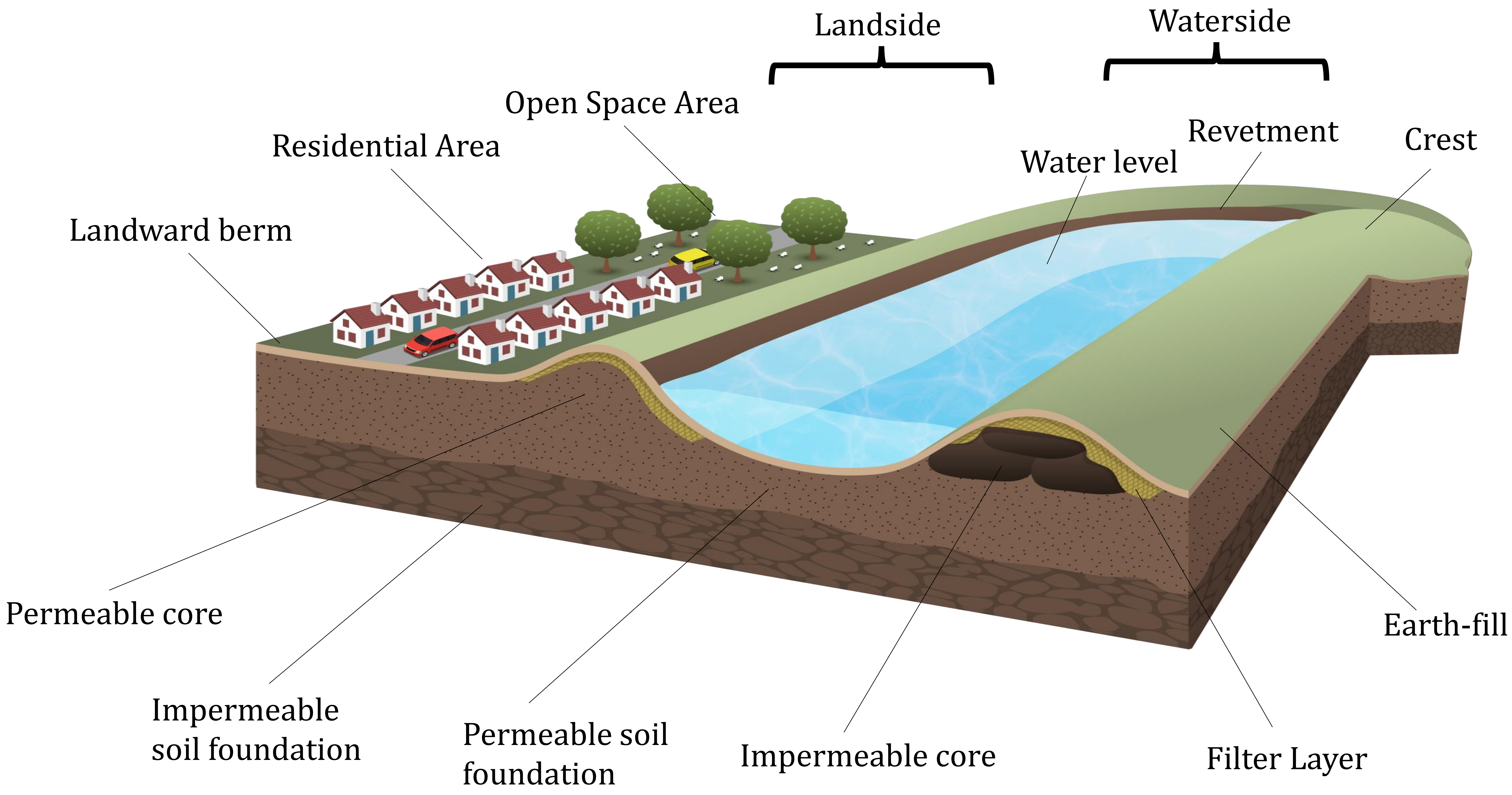
- Point Cloud Data widely used
- **The Introduction of LiDAR**

2010s

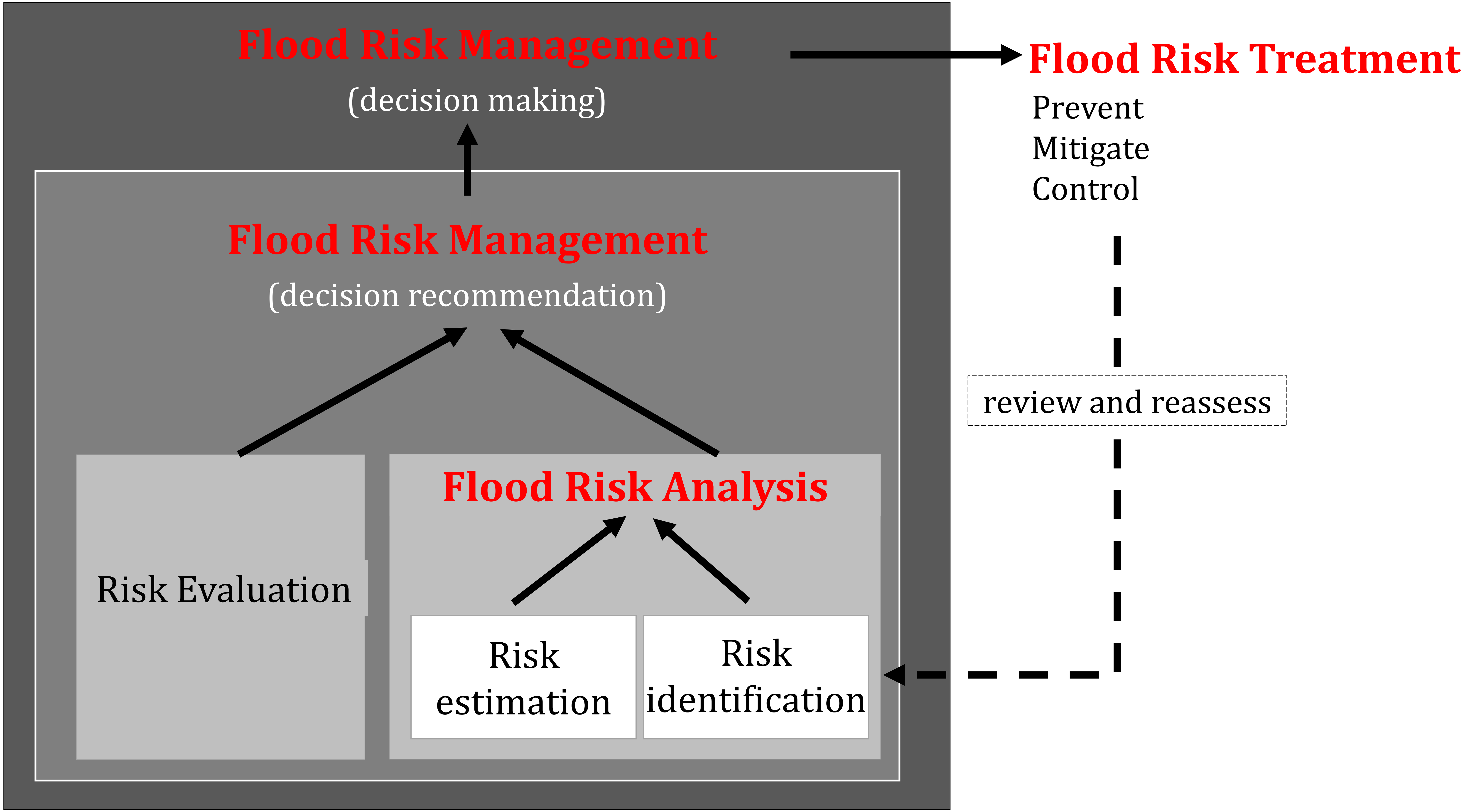
- Big Data and Machine Learning **Integration**
- **Advancement** point cloud algorithm (feature extraction, noise reduction, **segmentation**)

2020s

- The focus is on **enhancing the efficiency** of point cloud data processing
- Advancement point cloud data analysis

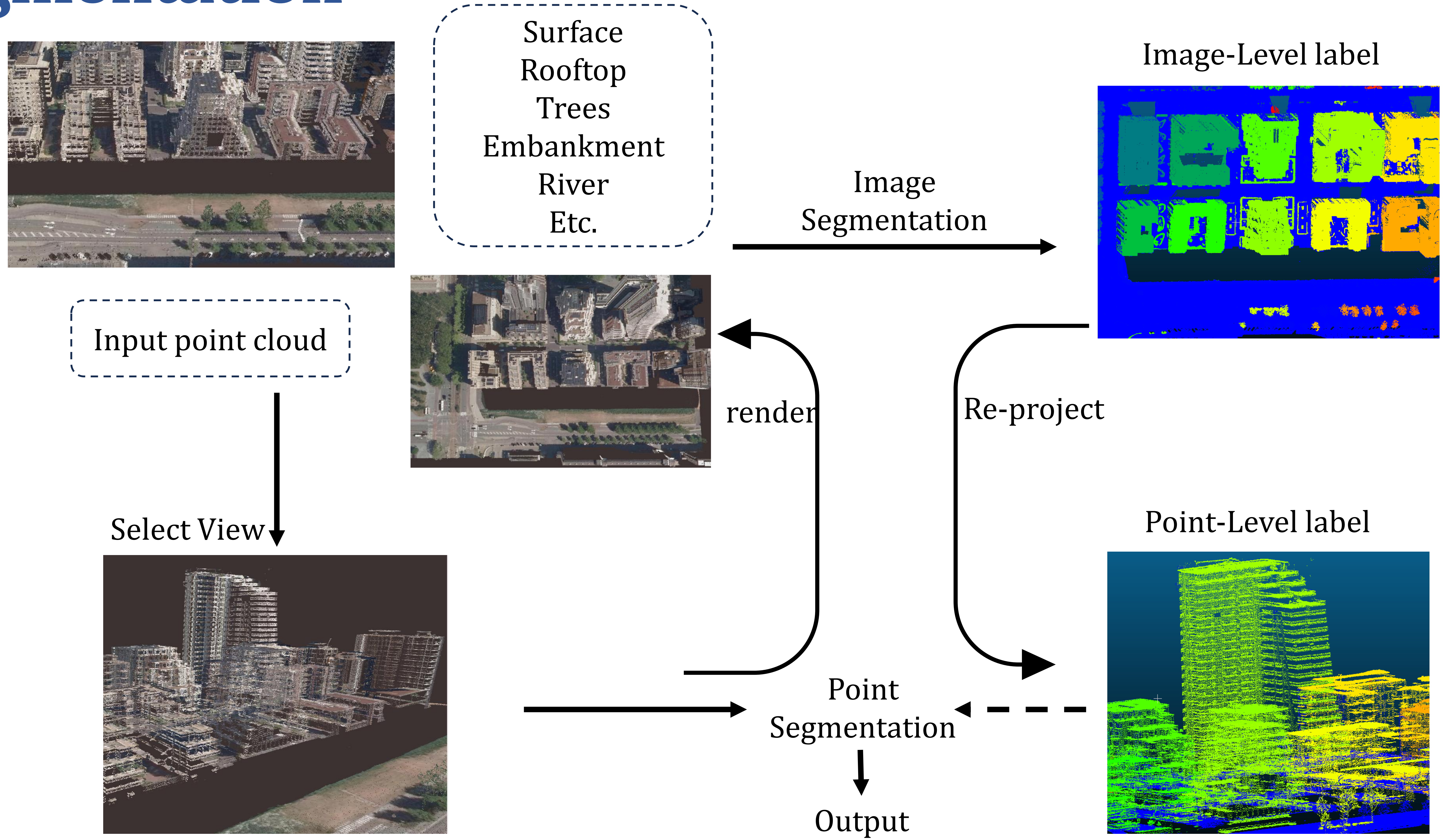

Landside
Waterside
Open Space Area
Residential Area
Revetment
Crest
Water level
Landward berm
Permeable core
Impermeable
soil foundation
Permeable soil
foundation
Impermeable core
Filter Layer
Earth-fill

Outline



Source: The International Levee Handbook

Segmentation



The Evolution of Segmentation Usage

2017

PointNet (1)
Pioneer of deep learning architecture for point cloud

PointNet++ (1)
Extend the capabilities of PointNet by incorporating hierarchical feature learning

2018

PointCNN (2)
Introducing a convolutional neural network architecture

PU-Net (3)
Pointcloud Upsampling Network focusing on generating dense point clouds from sparse ones

2019

KPConv (4)
Utilising kernel convolution operation

RSNet (5)
Utilising relation-shaped convolutions to capture long-range dependencies between points

DGCNN (6)
A dynamic graph CNN architecture is constructed from a k-nearest neighbour graph to capture local geometric structures and perform graph convolutions

OctreeNet (7)
an octree-based neural network architecture for point cloud segmentation, leveraging the spatial hierarchy of octrees to efficiently process large-scale point cloud data

Pseudo-LiDAR++ (8)
focuses on generating high-quality depth maps from LiDAR point clouds, enhancing the accuracy of 3D object detection and segmentation tasks

Source: Qi et al. (1), Li et al. (2), Yu et al. (3), Thomas et al. (4), Li et al. (5), Wang et al. (6), Wang et al. (7), You et al. (8),

The Evolution of Segmentation Usage

2020

2021

PointASNL (1)
Adaptive Sampling and Neighborhood Locality to improve efficiency and accuracy

SPH3D-GCN (2)
Spherical 3D Graph Convolutional Network extends graph convolutional networks to a spherical coordinate system, enabling improved feature learning for spherical point clouds data.

PF-Net (3)
(Point-wise Fusion Network) proposes a novel fusion mechanism for integrating information from multiple scales and modalities in point cloud segmentation tasks, improving segmentation accuracy and robustness

RandLA-Net (4)
Randomize algorithm Network is the method to segment point cloud efficiently and effectively

Point Transformer (5)
Applies the transformer architecture to point clouds, enabling effective long-term dependency modelling and feature extraction

Source: Yan et al. (1), Huan et al. (2), Huang et al. (3), Hu et al. (4), Zhao et al (5)