Sense.Lidar

Machine Learning Point Classification

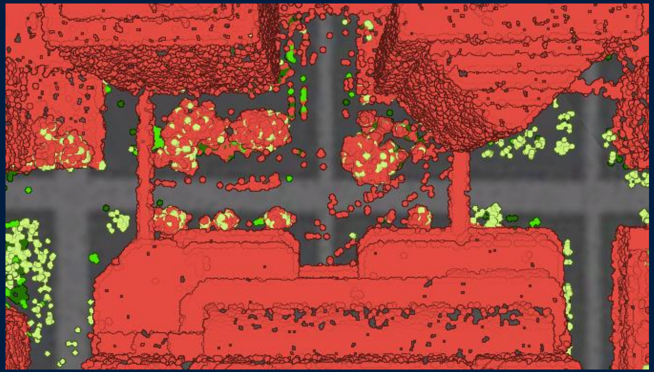
Keith Owens

1
About Sense.Lidar

Sense.Lidar

Why it is necessary

Few classifications



Inaccurate classifications

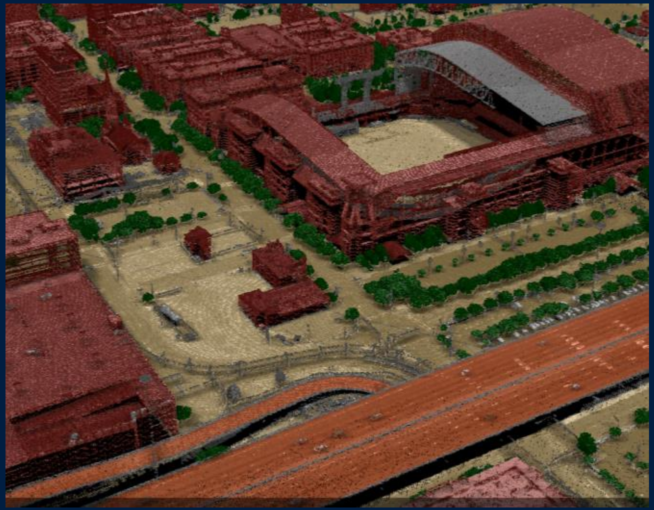
Time consuming

Expensive

Minimal use-cases

Automation for up-scaling

Key features



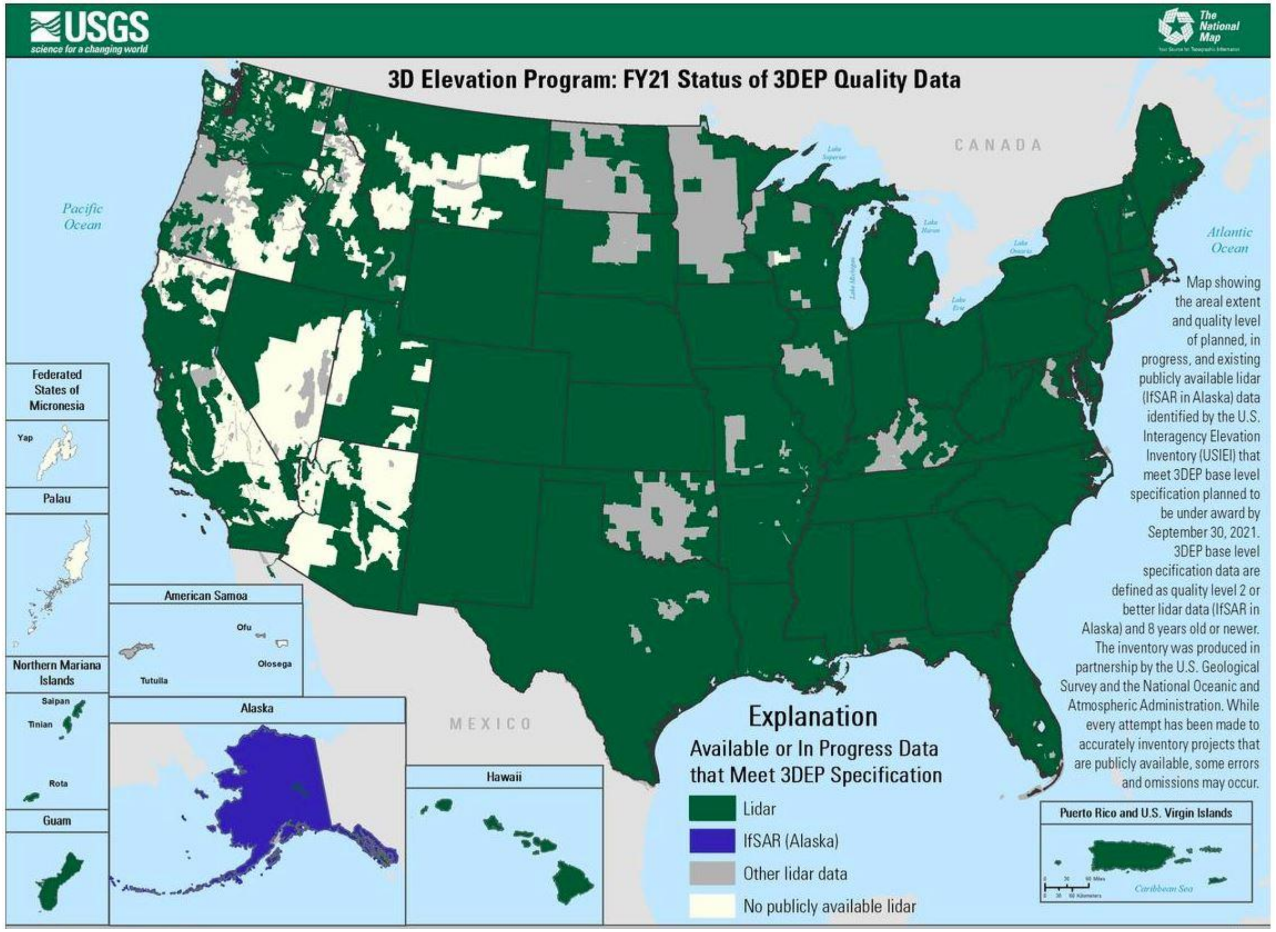
Accurately classifies lidar point clouds to best represent the feature to 95%-99% accuracy.

Efficiently and accurately assists with creating lidar-derived 3D digital twins of natural and built assets.

Can be localised or scaled to city, state or country-wide analyses through cloud-based processing.

Available Lidar

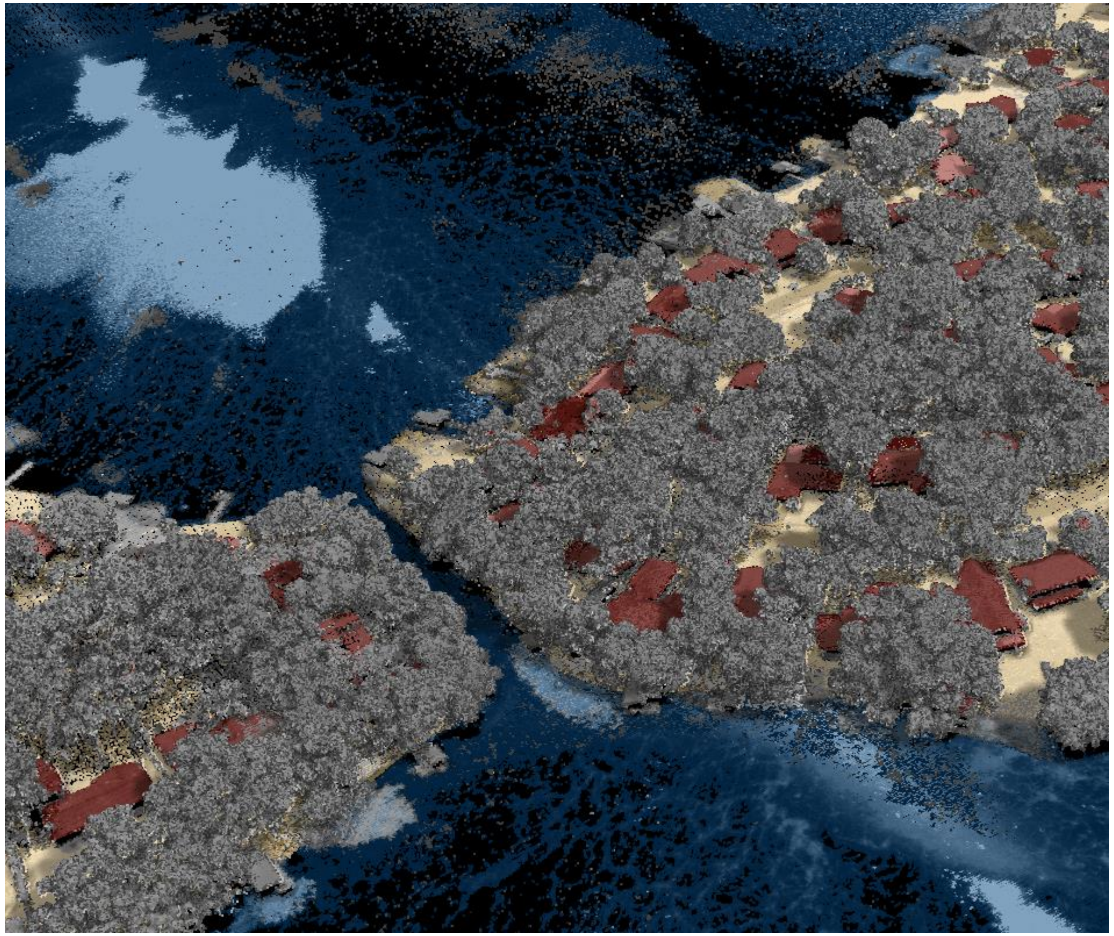
State and federal programs – not all data is created equal



- Abundance of existing lidar data
- Lidar data vintage (3+ years) considered for new collection
- Older datasets can be improved for better change analysis

Available Lidar

State and federal programs – not all data is created equal



2

TNRIS Classification Project

Texas Enhanced Lidar Data

TWDB / TNRIS

North, Central, and East Texas

- Enhance existing USGS Lidar
- 83,000 square miles
- Accuracy to 99%
- 3rd party inspected and verified

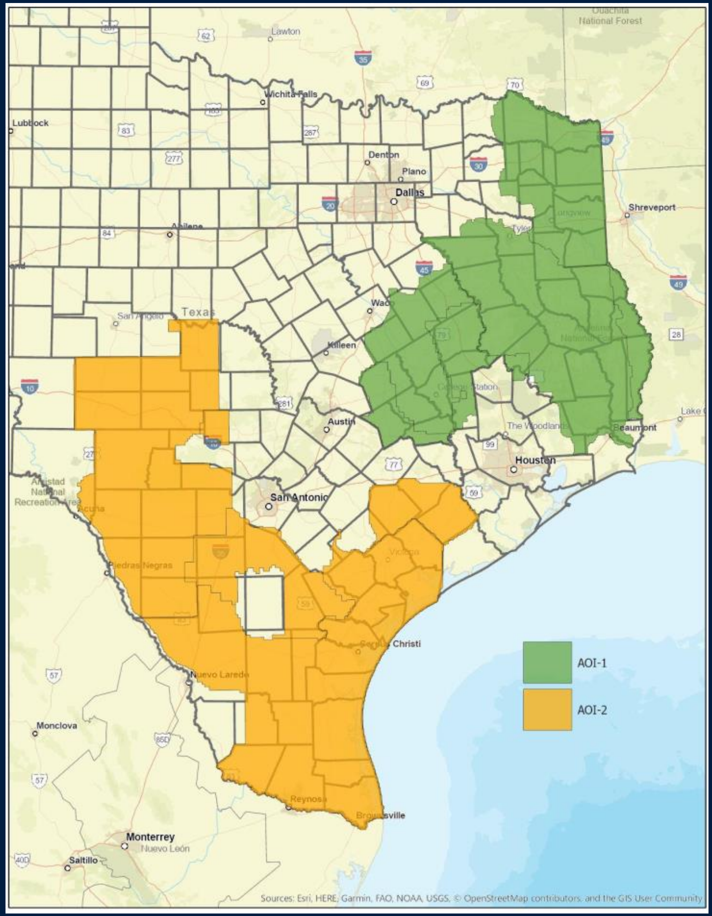
Sense.Lidar is Fugro's machine learning process for accurately classifying USGS lidar data.

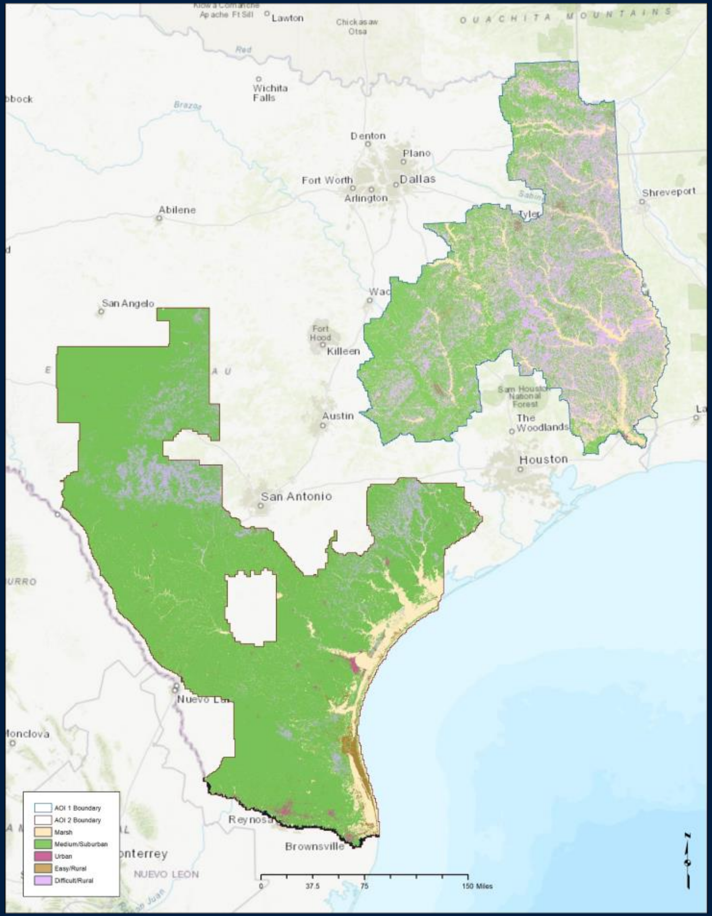
The data is enhanced from the standard USGS classifications to include Buildings, Vegetation, and Culverts to a 99% accuracy.

Accessible at https://data.tnris.org/

Texas Enhanced Lidar Data

Texas Natural Resources Information System





Existing USGS QL2 lidar

- Class 1. processed, but unclassified
- Class 2. bare earth
- Class 7. low noise
- Class 9. water
- Class 10. ignored ground (near breakline)
- Class 17. bridge decks
- Class 18. high noise

97,836 national grid tiles

83,184.5 square miles

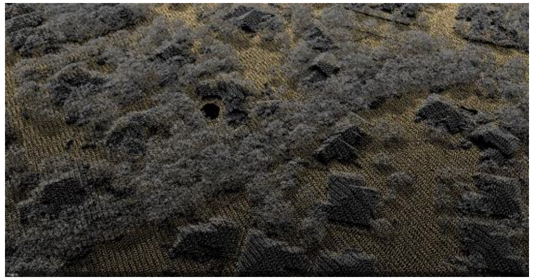
Lidar point cloud classified to TNRIS specifications from class 1

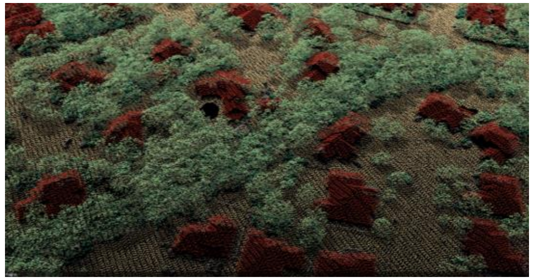
- Class 3. low vegetation
- Class 4. medium vegetation
- Class 5. high vegetation
- Class 6. building
- Class 14. culverts (from class 2. bare earth)

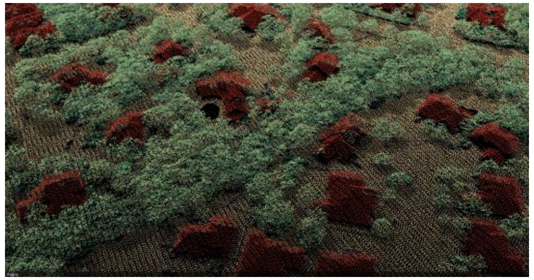
3
Production Workflow

Sense.Lidar Workflow

Fully automated with human assisted feature extraction



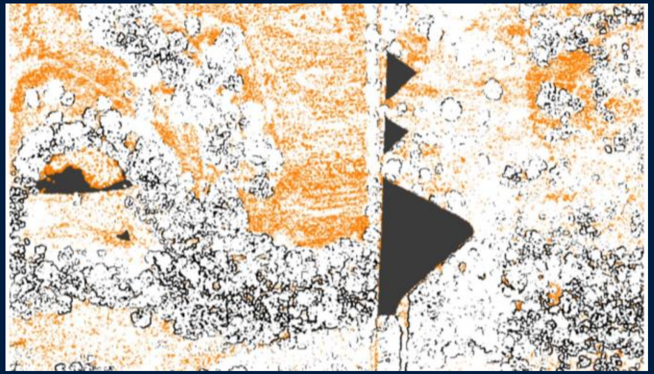




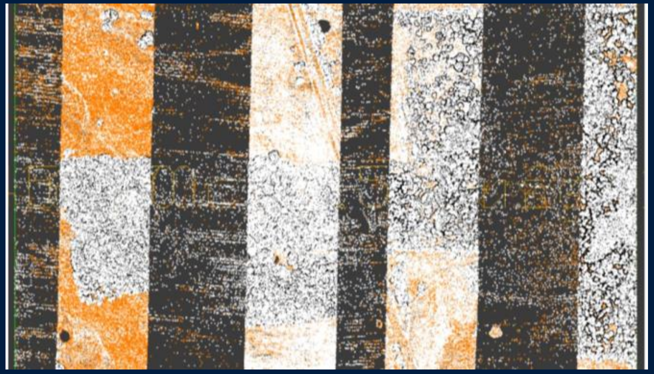
- Data access, formatting, QC, and staging
- Segment data by land cover category
- Create training data sets based on land cover
- Run cloud based auto classification
- Human assisted QC, edit, and cleaning
- QC data product and packaging for cloud delivery

Sense.Lidar Data Management

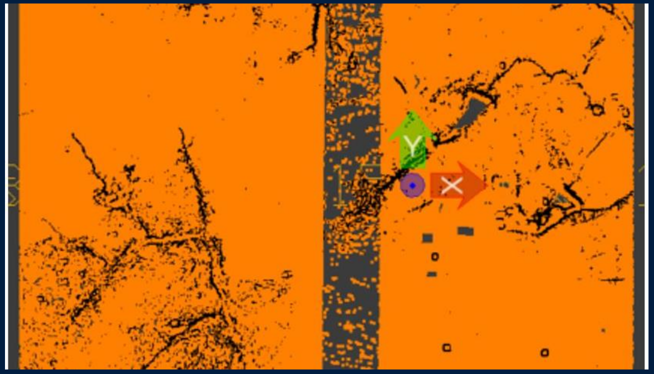
Managing data imperfections at ingest



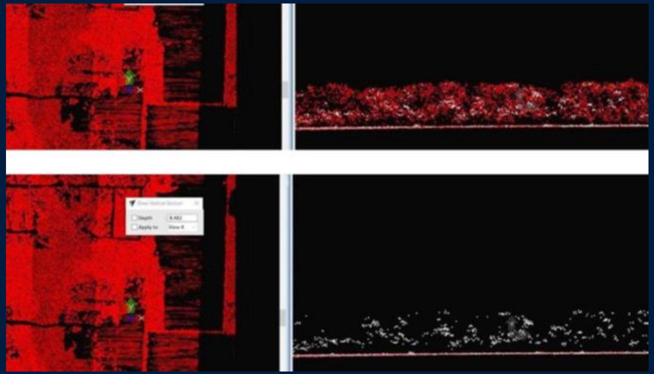
Data gaps in Class 1 & 2



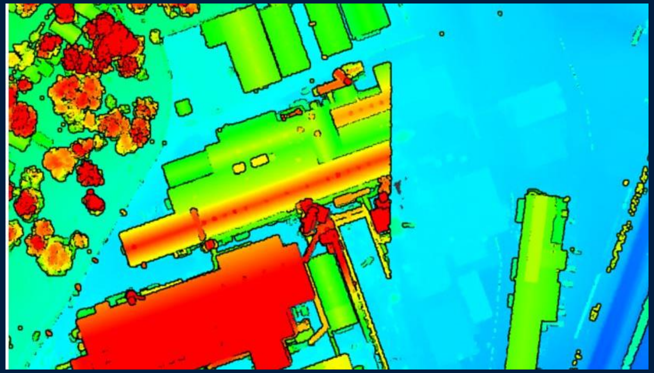
Low point density in Class 1 & 2



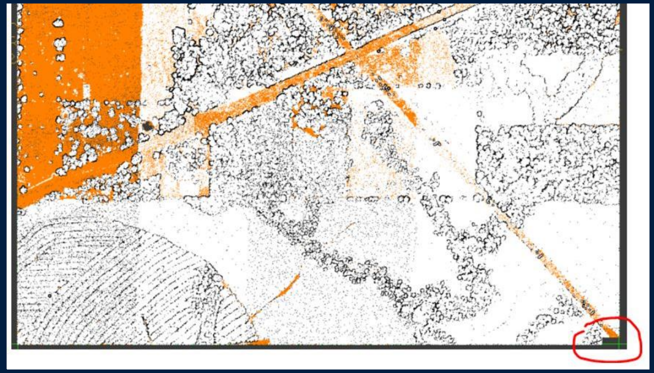
Data gaps and low point density in class 2



Improper class 7



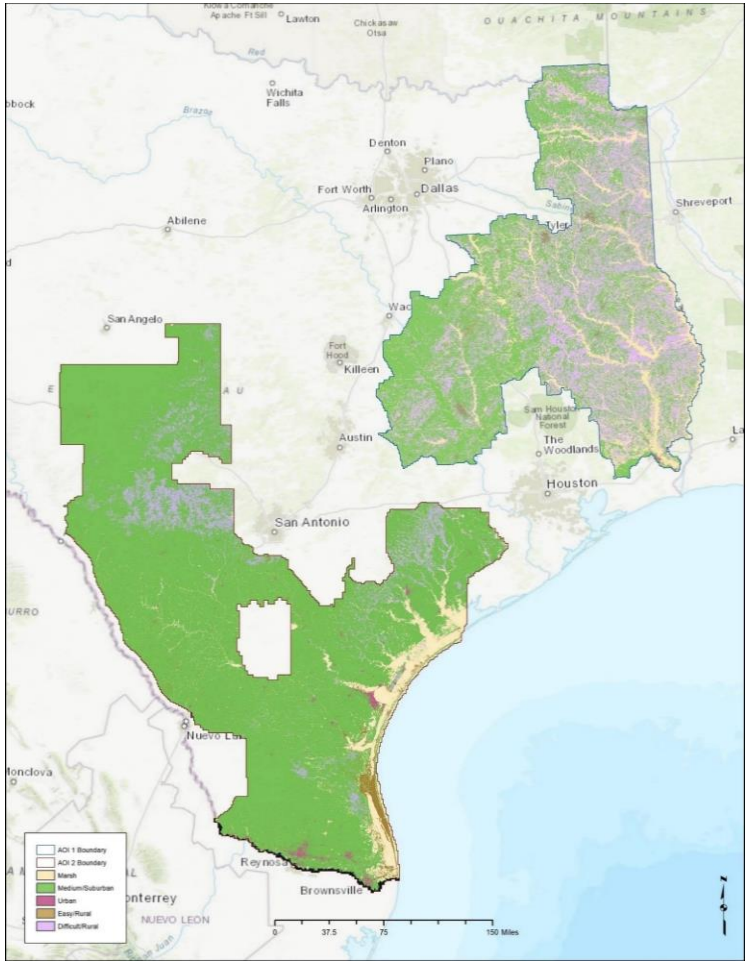
Missing partial buildings



Data gap

Sense.Lidar Land Cover

Segment lidar AOI by land cover for training



Area and Land Cover Type

1. 97,836 national grid tiles
2. 15 NLCDs
    1. Open water
    2. Developed Open space
    3. Developed Low intensity
    4. Developed Medium intensity
    5. Developed High intensity
    6. Barren land
    7. Deciduous forest
    8. Evergreen forest
    9. Mixed forest
    10. Shrub/scrub
    11. Herbaceous
    12. Hay/pasture
    13. Cultivated crops
    14. Woody wetlands
    15. Emergent herbaceous wetlands

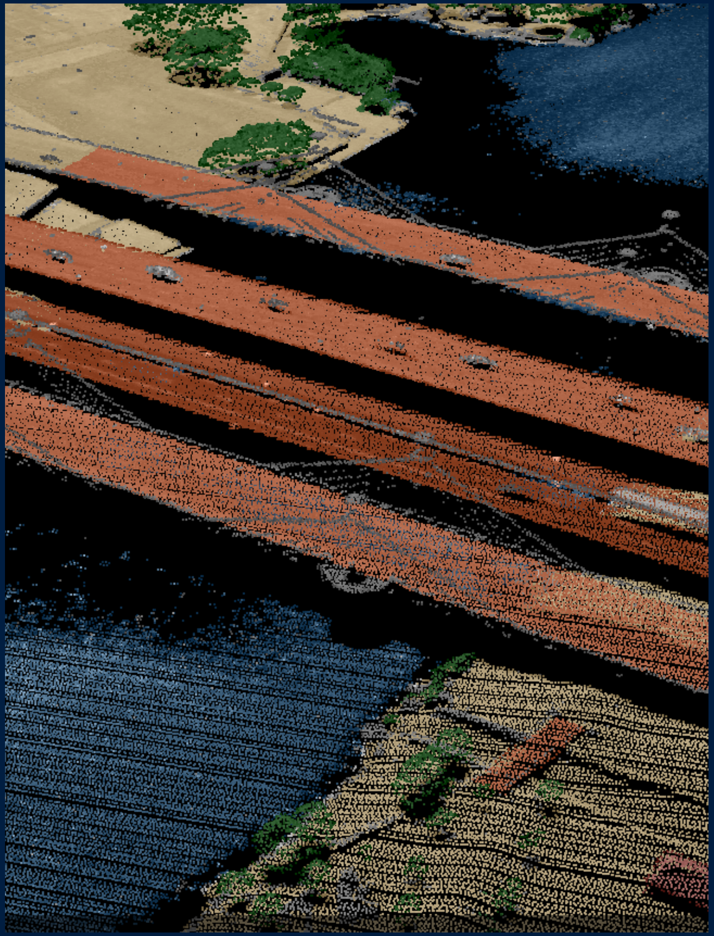
Project Specifications

1. USGS QL2
    1. Processed (1)
    2. Bare earth (2)
    3. Low noise (7)
    4. Water (9)
    5. Bridge deck (17)
    6. High noise (18)
    7. Ignored ground (20)

2. Sense.Lidar classifications
    1. Low vegetation (3)
    2. Medium vegetation (4)
    3. High vegetation (5)
    4. Building (6)
    5. Culverts (14)

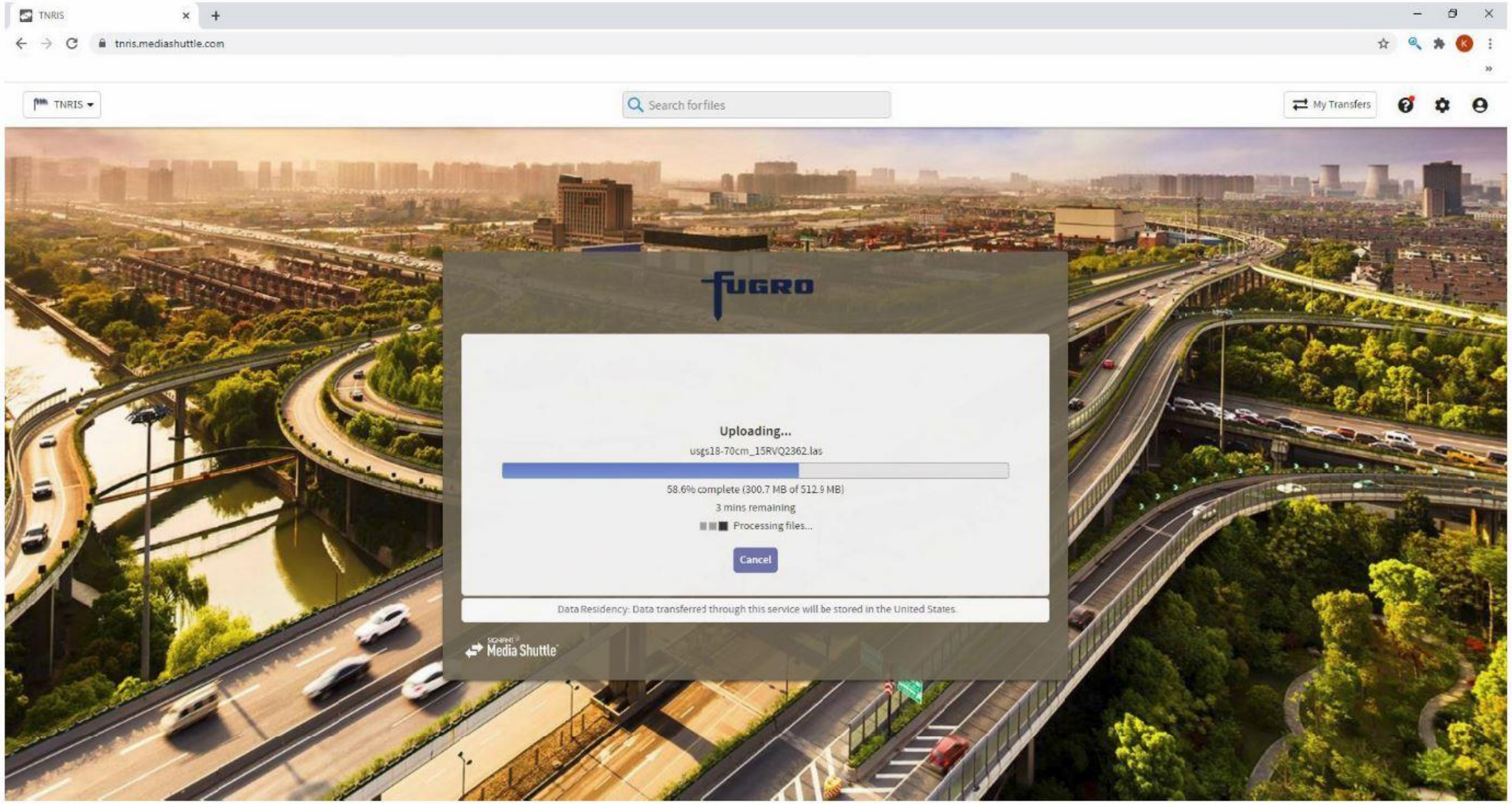
Sense.Lidar Training

Create lidar training datasets based on land cover type



Sense.Lidar Edit and Delivery

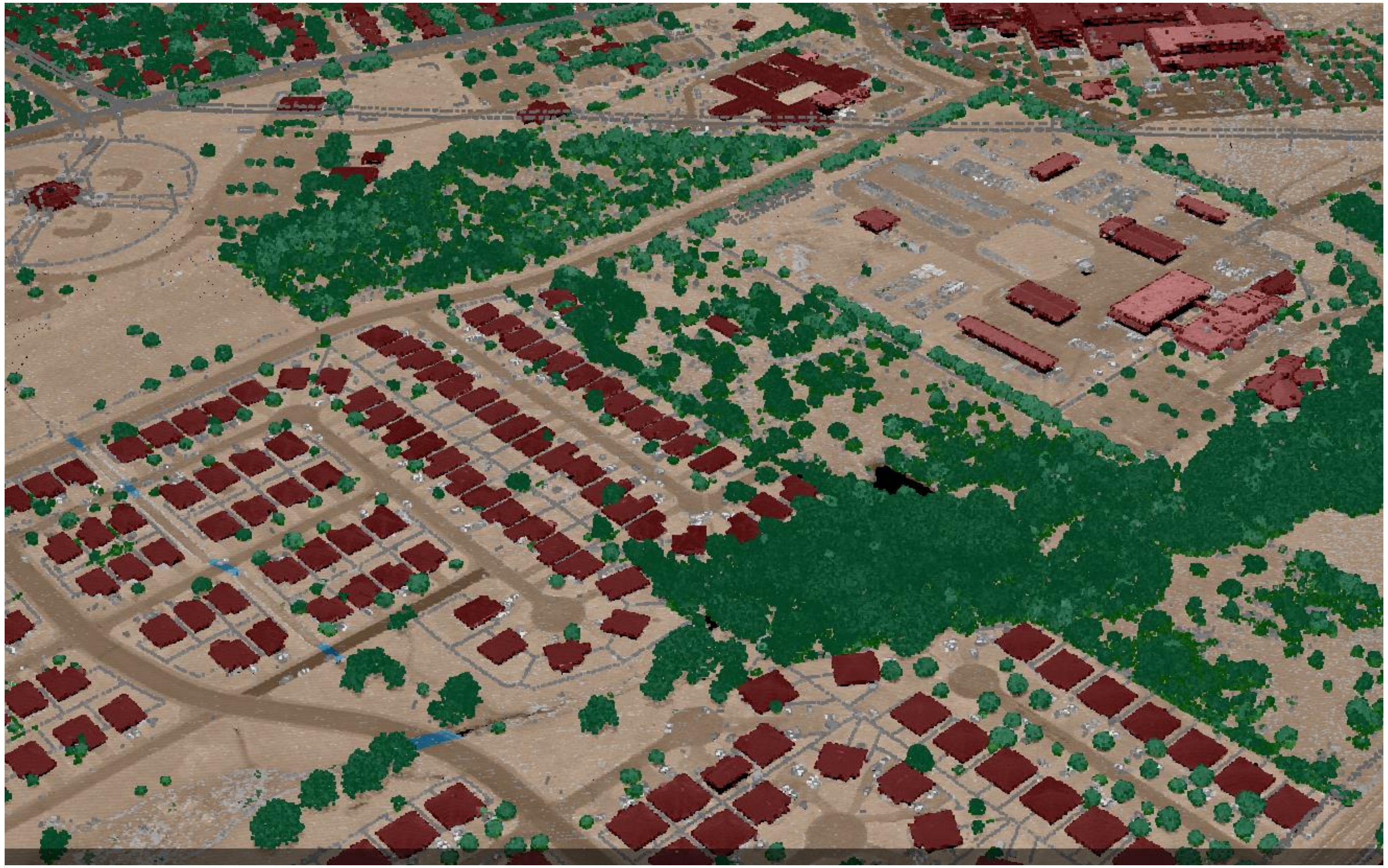
Human-assisted edit and cloud delivery



4
Accuracy

Sense.Lidar Accuracy

Accuracy is key for performing analysis



1. Create near-perfect accuracy check lidar tiles
2. Run comparison between near perfect tiles and auto classification tiles

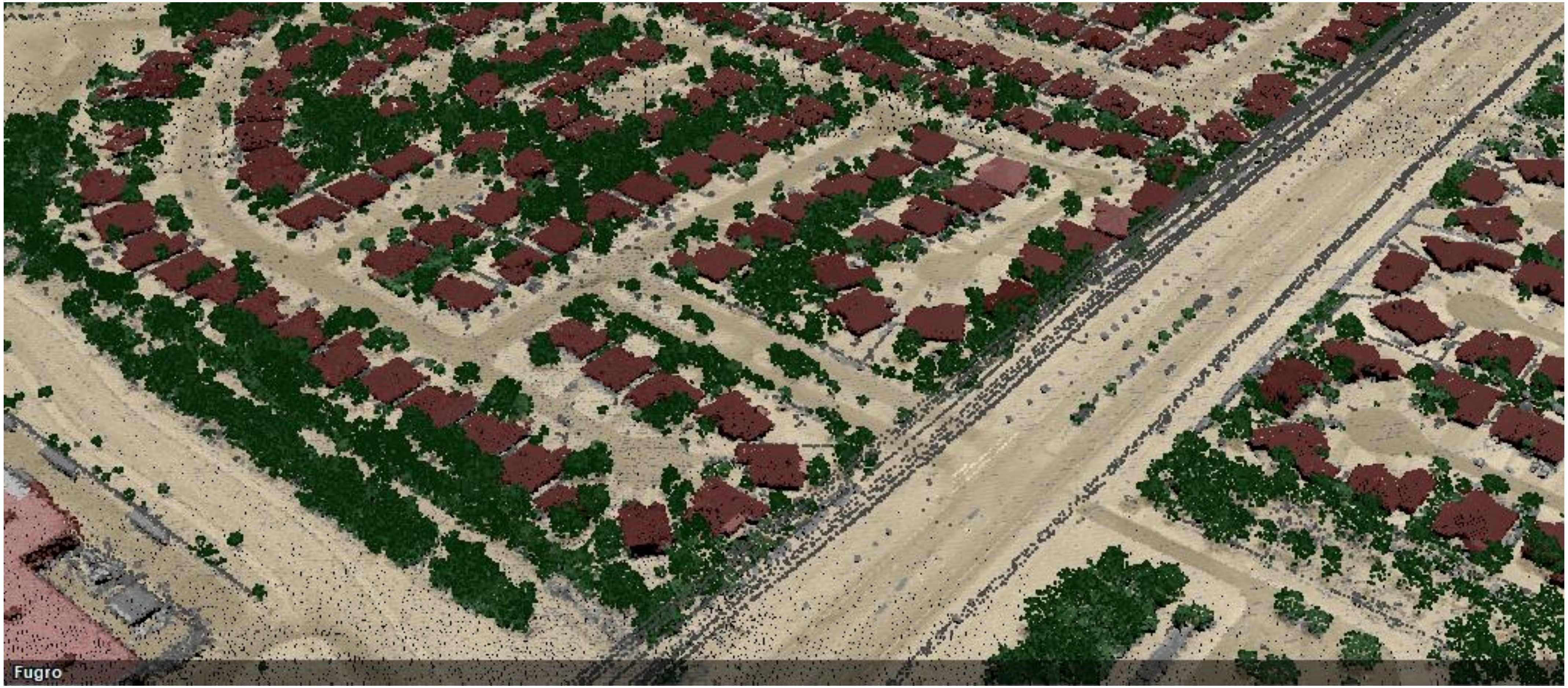
Adding classifications

1. Low vegetation (3)
2. Medium vegetation (4)
3. High vegetation (5)
4. Building (6)
5. Culverts (14)

5
USGS to State Specifications Results

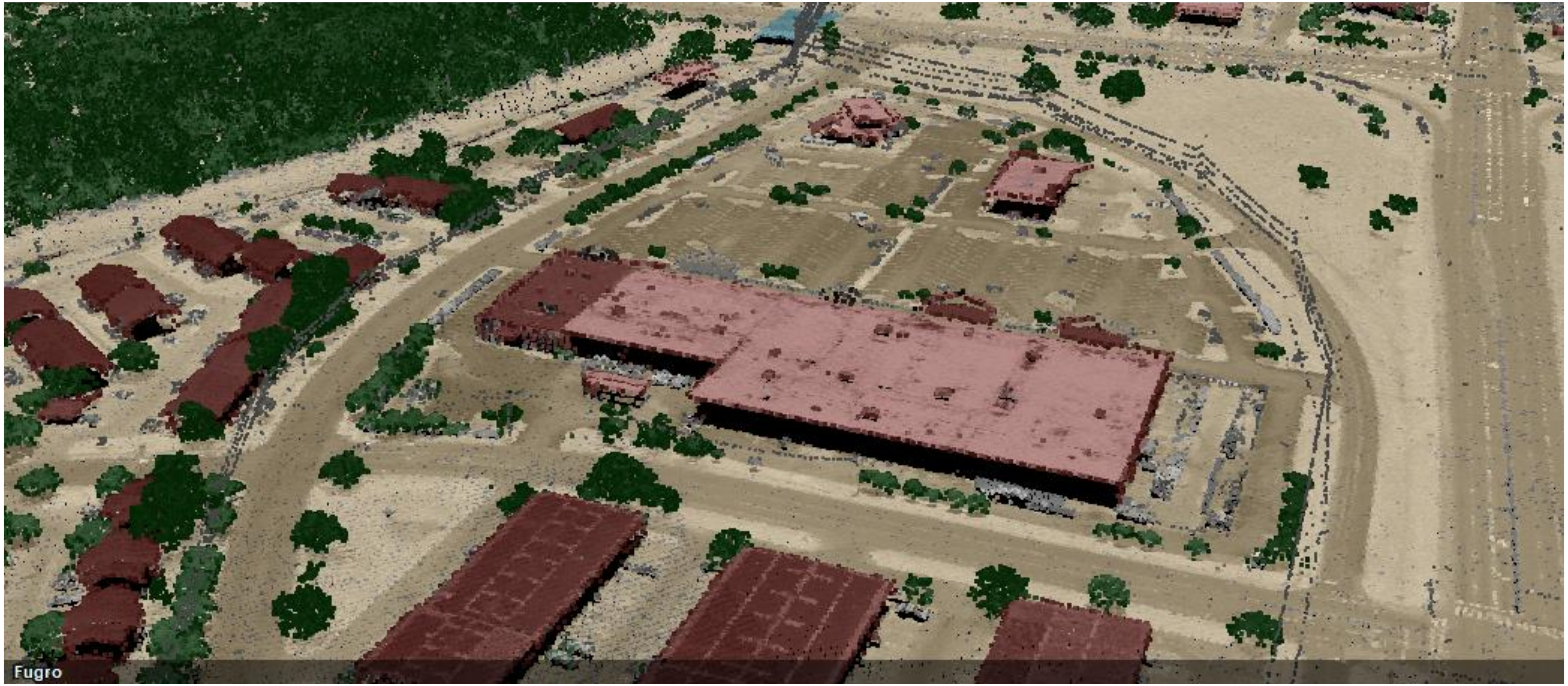
Sense.Lidar Results

Enhanced USGS Lidar to include Buildings, Vegetation, and Culverts



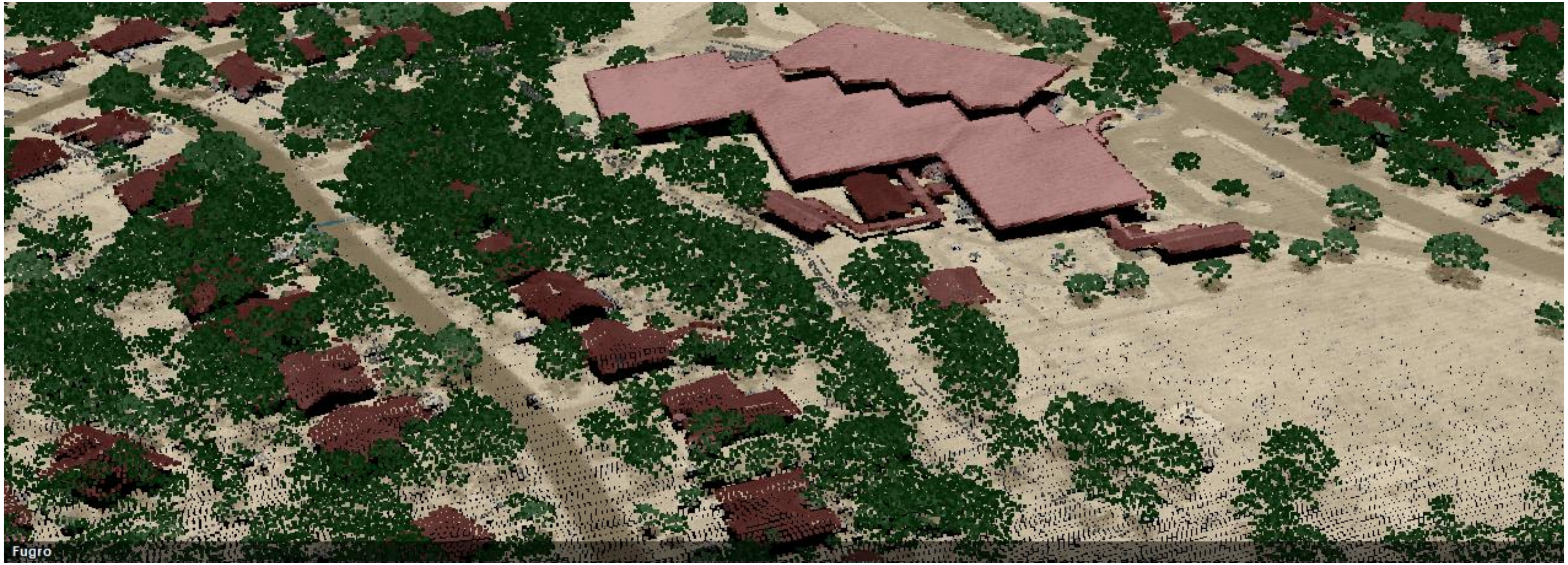
Sense.Lidar Results

Enhanced USGS Lidar to include Buildings, Vegetation, and Culverts



Sense.Lidar Results

Enhanced USGS Lidar to include Buildings, Vegetation, and Culverts



6
Enhancing Existing Texas Data

Sense.Lidar

Urban area test area in Houston Texas

- Using Fugro-developed 2018 topographic lidar to TNRIS specifications
- Sense.Lidar used to determine the accuracy of enhancing legacy data
- Fugro removed the lidar classification and ran the tiles through Sense.Lidar to reclassify the vegetation and buildings from the 4ppsm data

Sense.Lidar

Existing 2018 Houston data review

- Existing/vintage data used macros combined with manual techniques for classifying lidar data
- This required a production workflow that was labor intensive and expensive
- Projects often sacrificed quality to fit budgets and schedules.
- Many points in unclassified or misclassified from COTS Macro development and human assisted editing

Sense.Lidar

Existing 2018 Houston data review

- Unclassified removed to visualize existing/vintage data classification imperfections
- Powerlines, poles, buildings and other utility features show up in veg class

Sense.Lidar

Existing 2018 Houston data review

- Sense.lidar machine learning outperforms COTS software macros and human editing
- The automated process achieves, on average, a 95% accuracy
- This provides opportunity for human-assisted feature extraction (HAFI) to focus on the fine details to achieve 99% accuracy

Sense.Lidar

Existing 2018 Houston data review

- Nadir view of lidar points shows the magnitude of unclassified points in vegetation class
- This reduces the amount of available veg points for further analysis
- Misclassified points skew analysis results or measurements like vegetation density, geolocation and inventory

FUGRO

Sense.Lidar

Existing 2018 Houston data review

- Unclassified points removed reveals vegetation classification in transportation features, utility assets, cars, and buildings
- To perform detailed analysis of urban area assets and urban forestry inventory Sense.Lidar is used to correct the legacy errors

Sense.Lidar

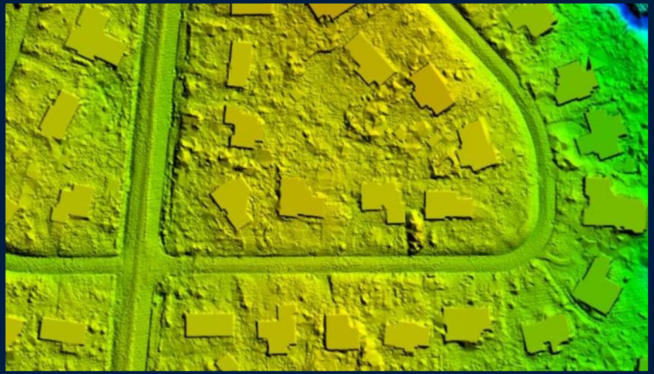
Existing 2018 Houston data review

- Sense.Lidar results show better classification of utility assets, transportation features, buildings, and vegetation
- This improves Geo-data analysis allowing users to make better decisions based on better data

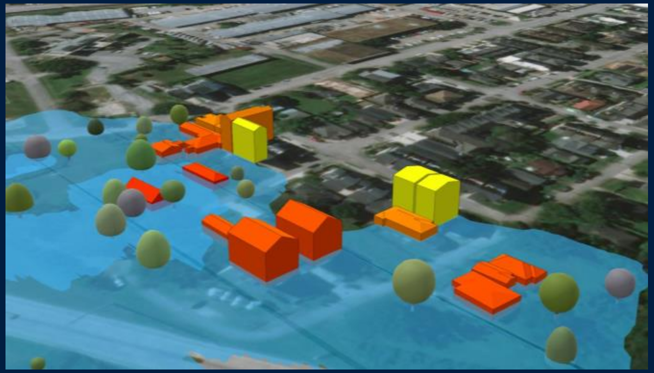
7
Expanded use of Sense.Lidar

Better Data with Sense.Lidar

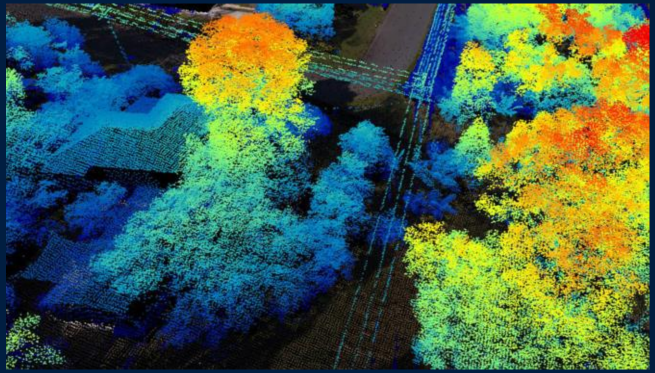
Better point classifications assist in created better data



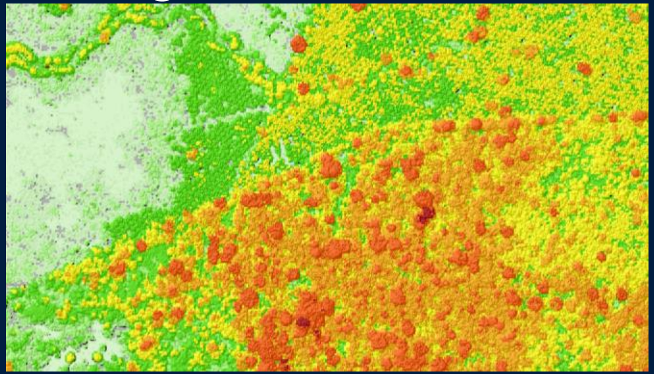
Building footprints and building flattened DEM



Improved LOD1 and LOD2 building models

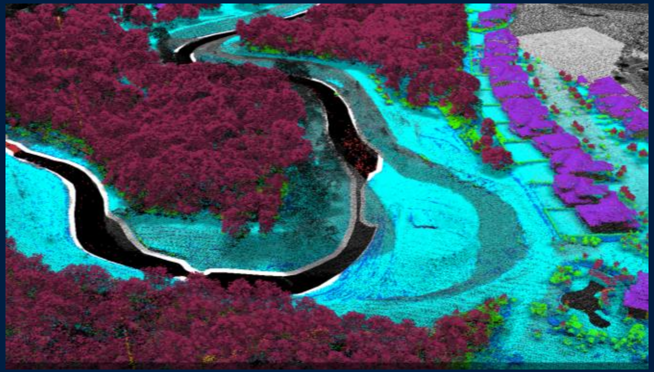


Improved asset identification



Accurate vegetation geolocation and density

Accurate vegetation height



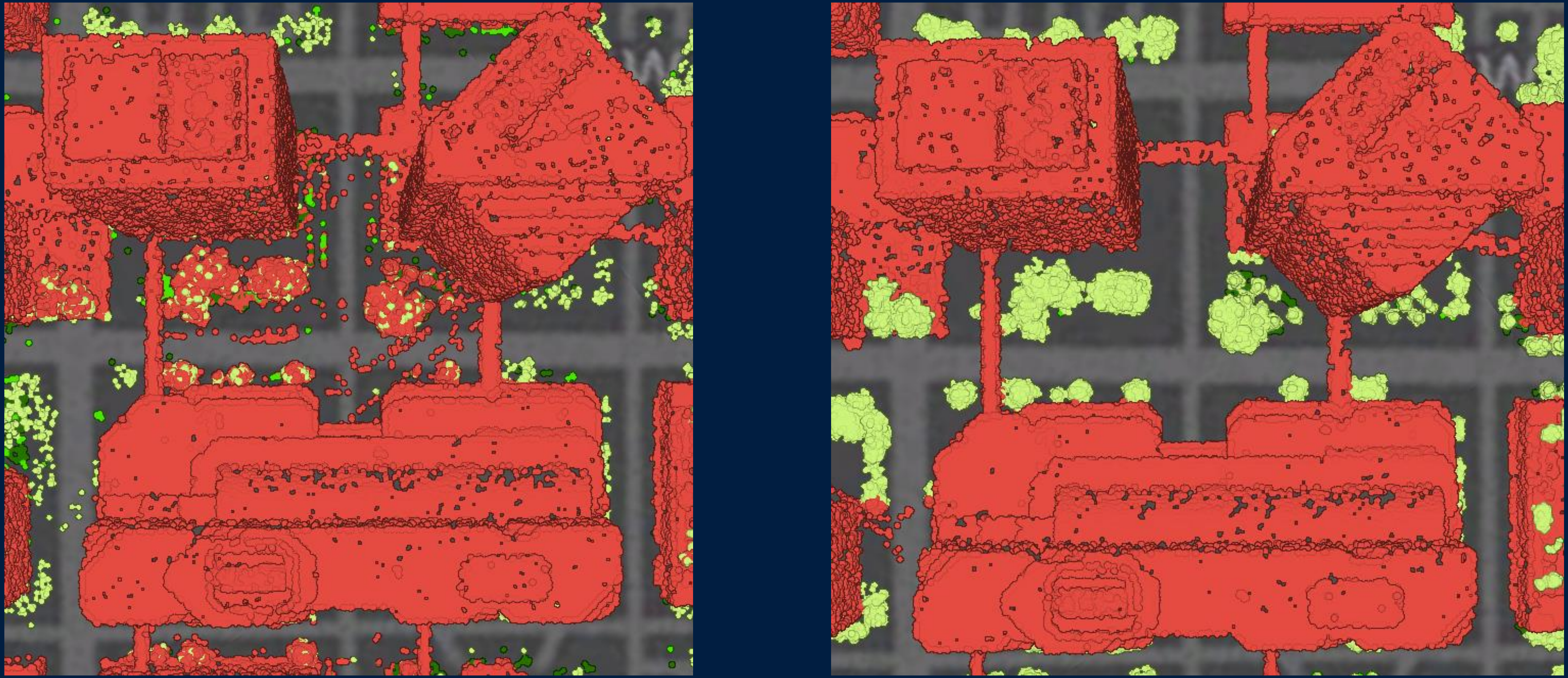
Accurate and efficient change analysis

Expanding the Use of Lidar

With more classifications, more analysis can be done!

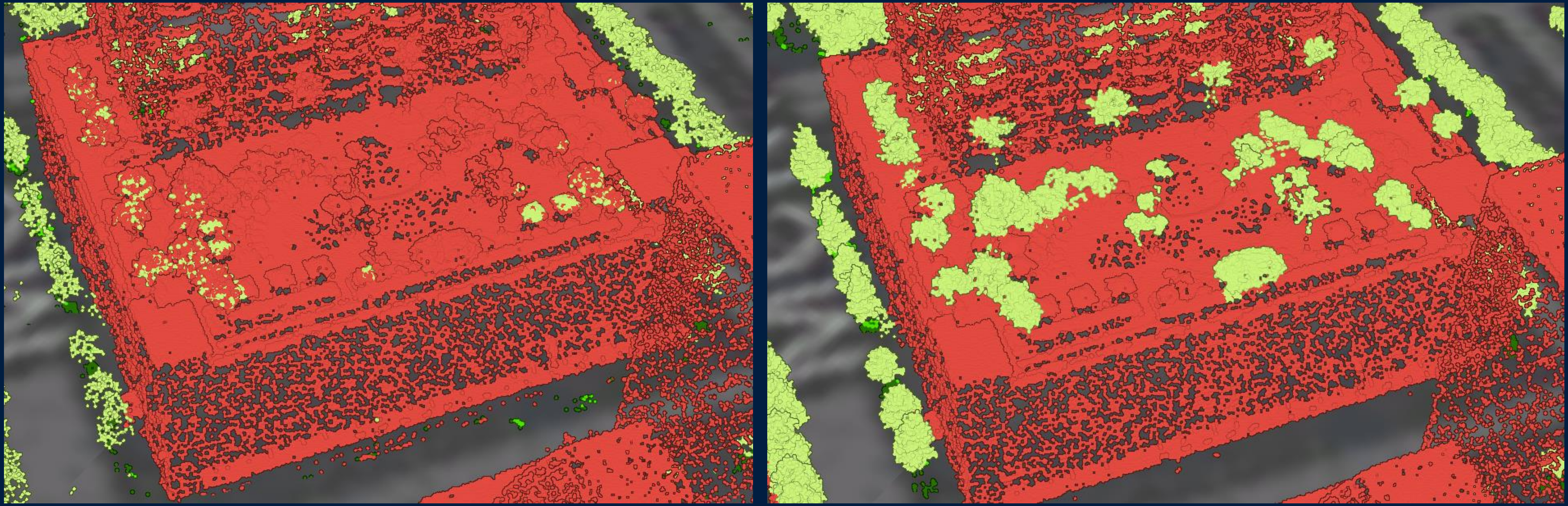
Improving Existing Lidar

Showing promise for building models from updated building classification



Improving Existing Lidar

Showing promise for building models from updated building classification

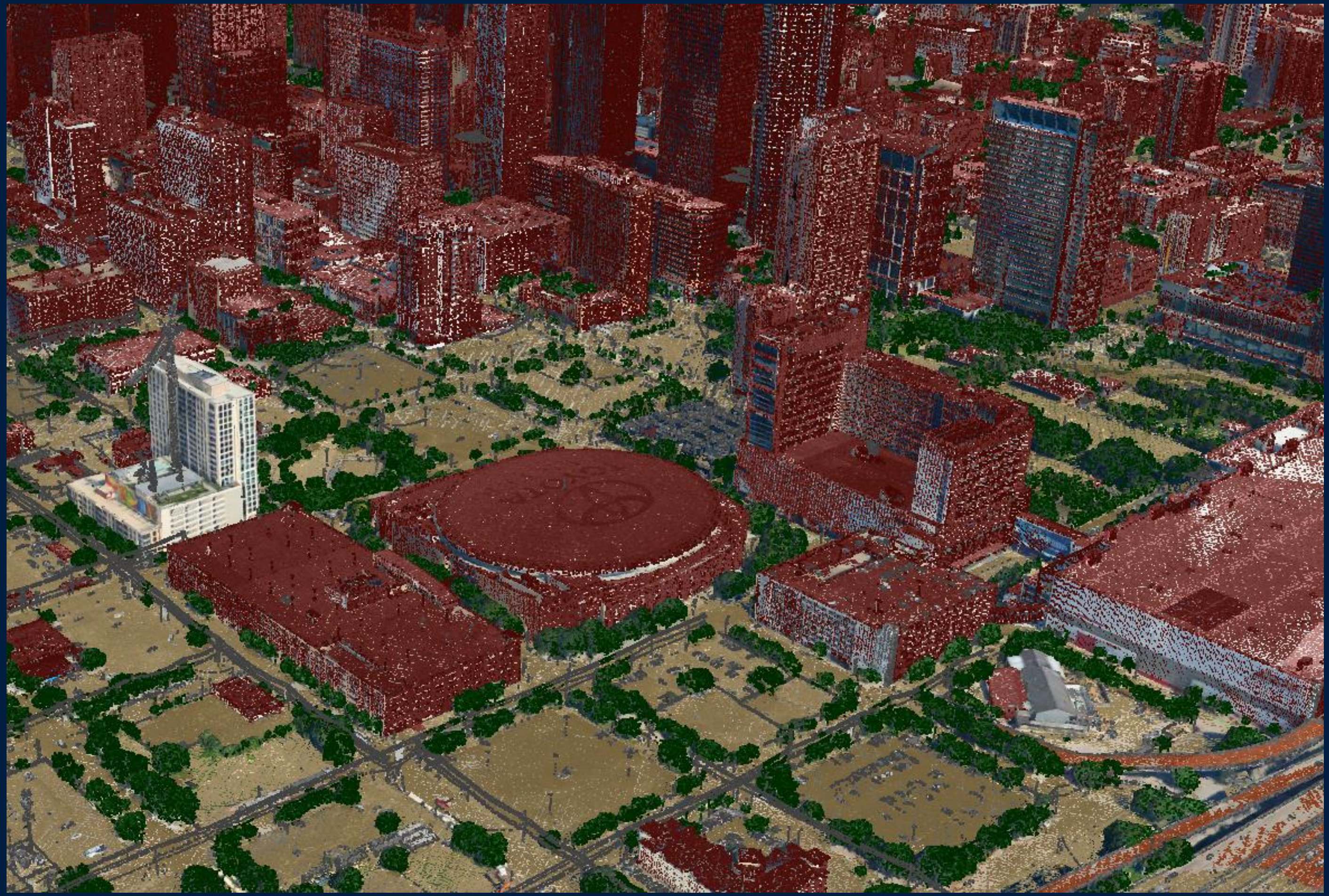


Helping Improve 3D Models

Using better classified lidar data to improve 3D model output

Combining Accuracy and Visualization

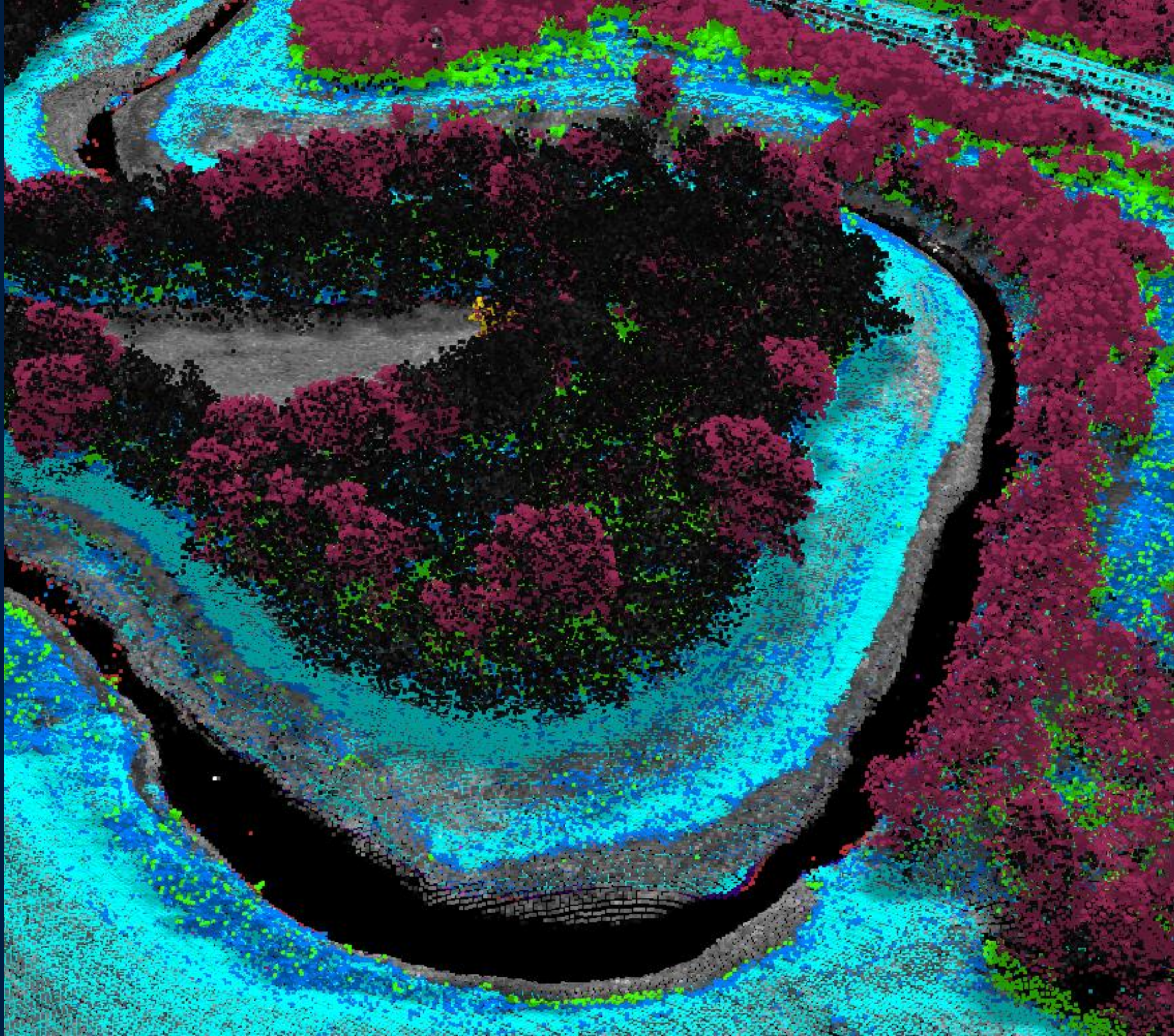
Merging Sense.Lidar results with 3D model processing expands options for product output



Sense.Lidar Roadmap

Roadmap of Sense.Lidar

- Continue creating land category machine learning datasets
- Build programs for 2, 4, 8, 16, 32, 64+ ppsm lidar data input
- Add classifications to support transportation, facilities, water management, forestry and agriculture
- Improve existing data to support more accurate change analysis

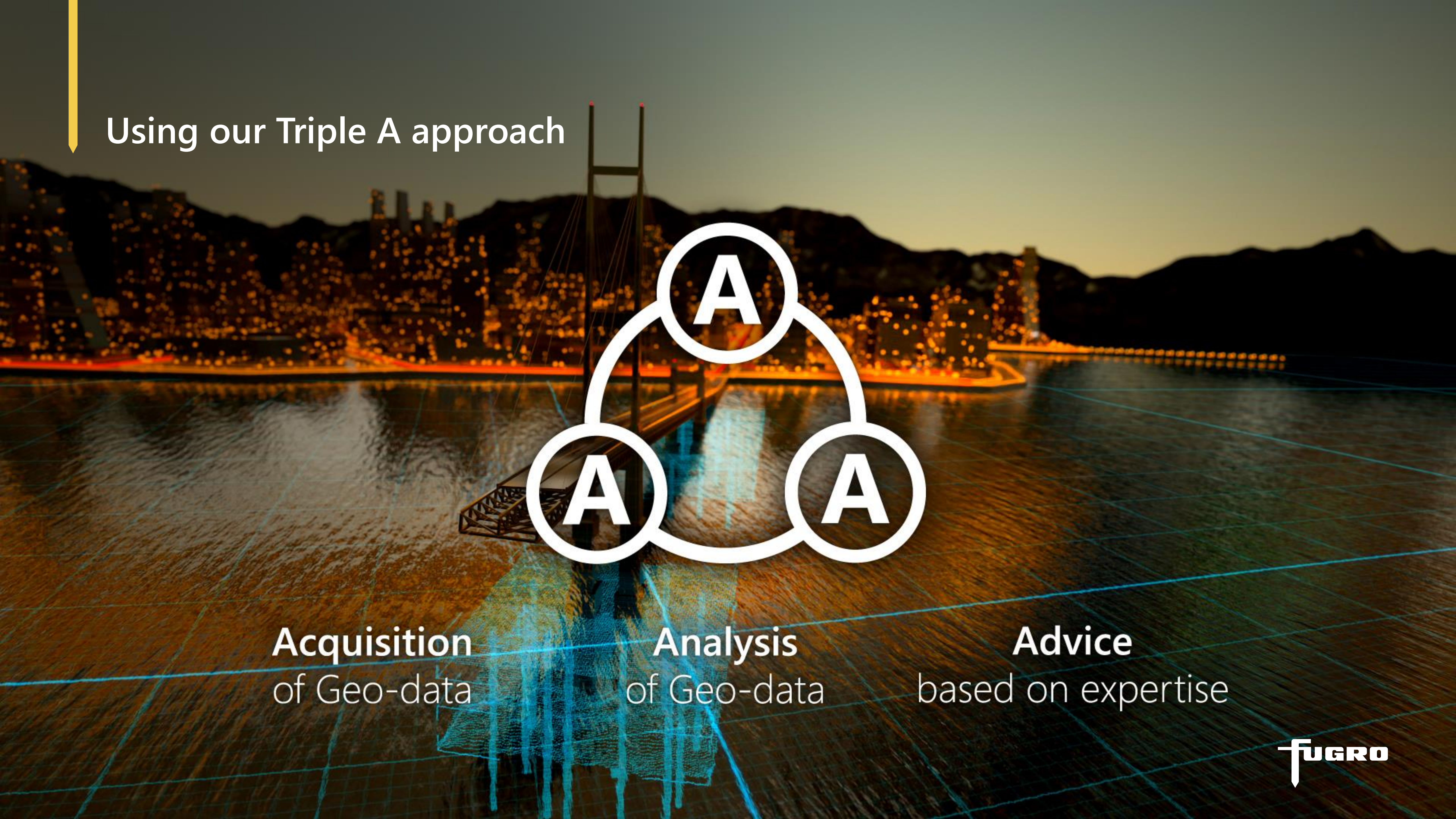


About us

Brief overview of Fugro

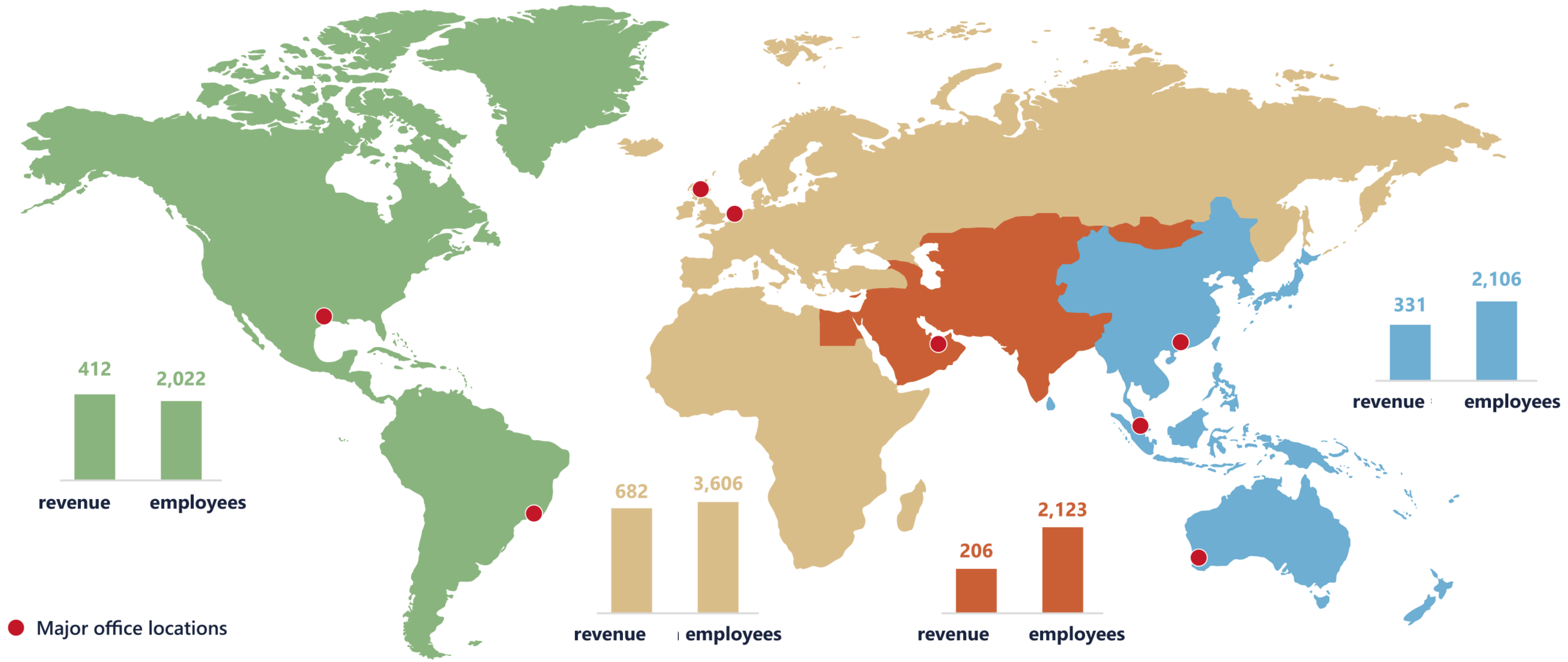
Introduction to Fugro

June 2021


Using our Triple A approach
A
A
A
Acquisition
of Geo-data
Analysis
of Geo-data
Advice
based on expertise
FUGRO

Global player with local presence

We meet our clients' local Geo-data needs by mobilising global resources quickly and effectively



Note: Revenue in EUR million. Charts are based on FY2020 results

Market-agnostic assets

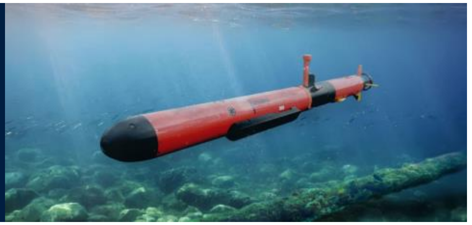
Our Geo-data assets are easily deployable across global markets

7 Aircraft

25 specialised service vessels

5 uncrewed surface vessels

7 autonomous underwater vehicles



69 remotely operated vehicles

113 cone penetration testing systems

8 remote operations centres

36 laboratories

31 jack-up platforms

Contact

Keith Owens

Technical and Business Development Manager

k.owens@fugro.com

(775) 287-2661

www.fugro.com

Unlocking **Insights**
from **Geo-data**