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WELCOME TO

# Real-World AI: How We Apply Machine Learning to Basin-Scale Flood Modeling

www.jonesedmunds.com

Presented by:

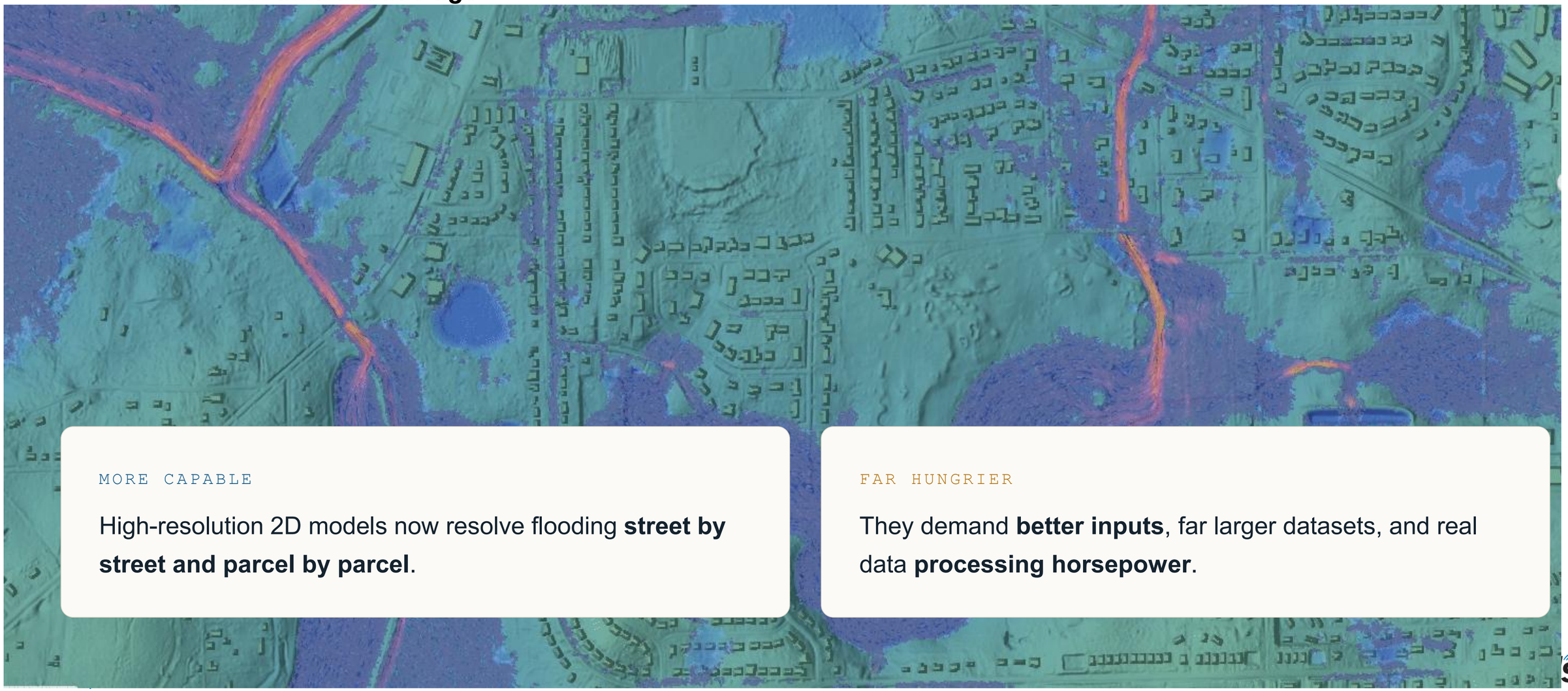
Jones Edmunds

FloridaWCA webinar

June 26, 2026

# The Challenge

**Modern flood models are far more capable — and far more data-intensive — than what we ran a decade ago**



MORE CAPABLE

High-resolution 2D models now resolve flooding **street by street and parcel by parcel**.

FAR HUNGRIER

They demand **better inputs**, far larger datasets, and real data **processing horsepower**.

# Where AI shows up

**Examples 1 & 2**

## Inputs

- Drainage infrastructure
- Land cover mapping

**Example 3 & 4**

## Processing

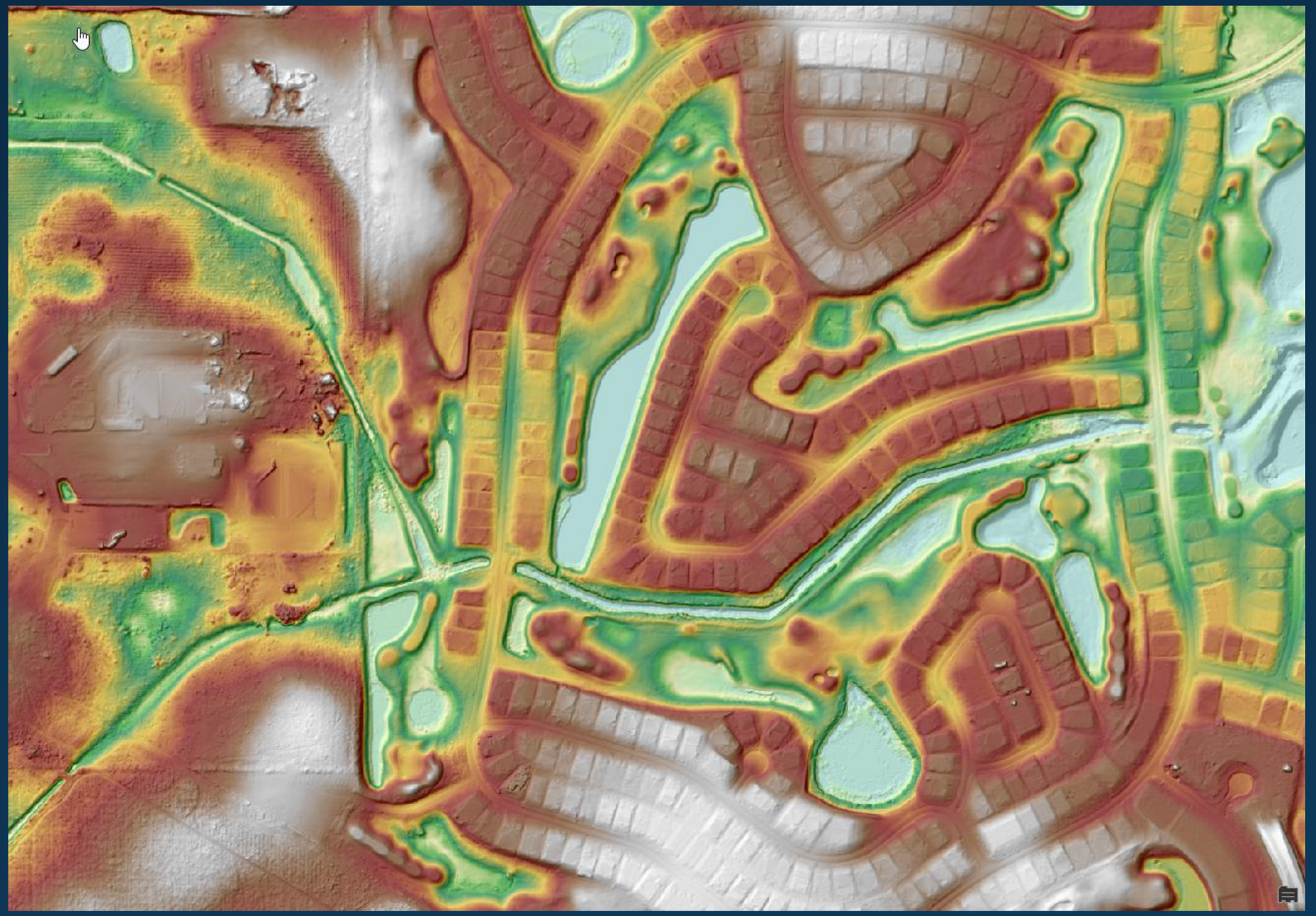
- Model development
- QC

**Examples 5 & 6**

## Outputs

- Communication Support

# Example 1 – Subsurface Drainage

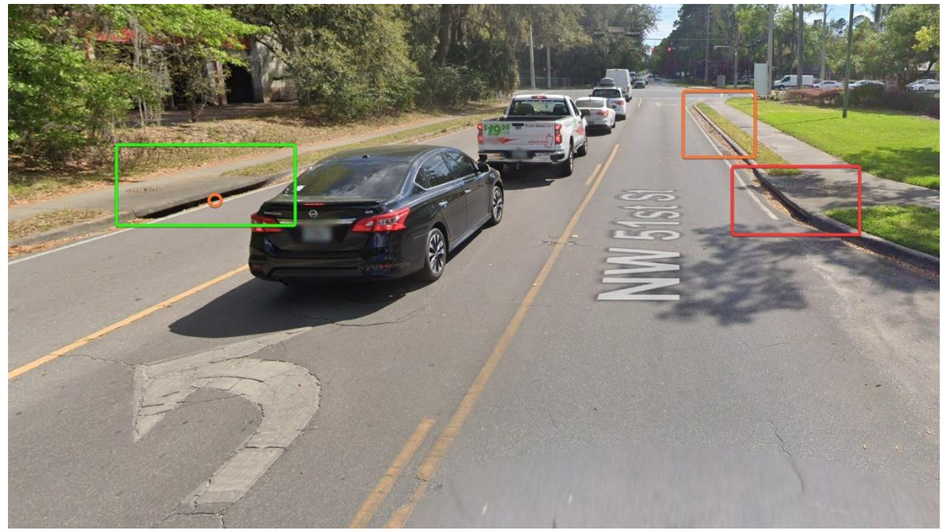


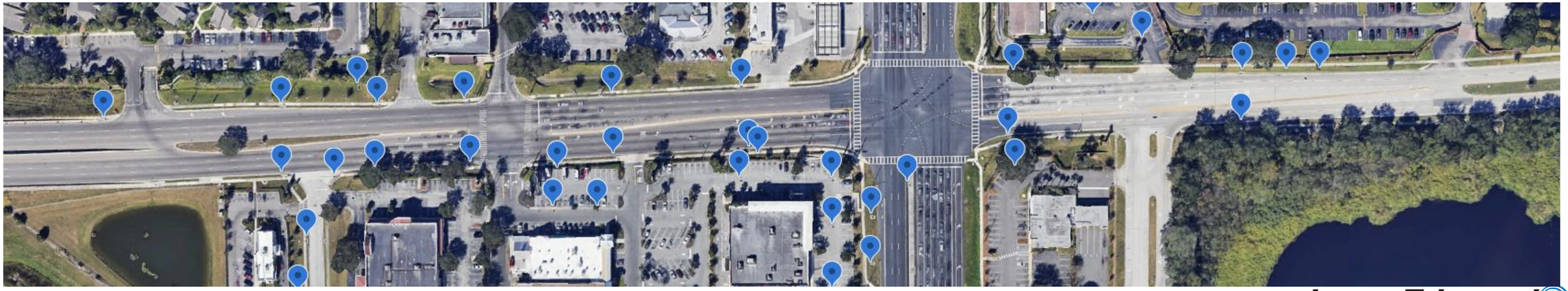
## Why it matters:

- LiDAR DEMs characterize the surface with increasing detail — but are **blind to how water moves below grade**
- Mapping hidden conveyance lets us **condition the DEM** so predicted flow paths match reality
- Unlocks high-res 2D modeling and more efficient subbasin delineation for 1D.

# Example 1 – Task A. Street-level Imagery

- Detect the surface signatures of buried stormwater networks — **grates, inlets, manholes**.
- **Google Earth / Street View**
  Meta's **Mapillary**.
- Identify **piped storm sewer** areas from **open-swale** areas.



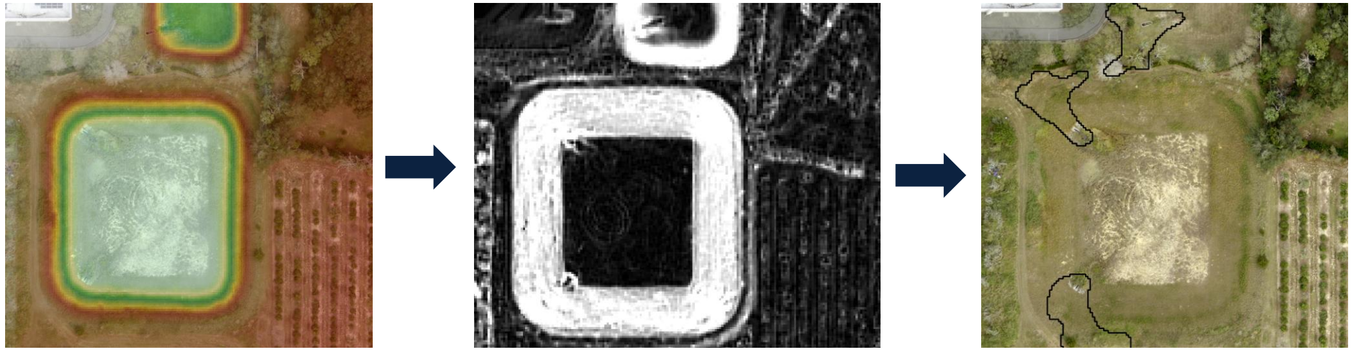



# Example 1 – Task B. Deep-Learning Culvert Detection

| STEP 1 | STEP 2 | STEP 3 | STEP 4 | STEP 5 |
|---|---|---|---|---|
| **Known culverts** | **Training chips** | **Train U-Net** | **Predict locations** | **GIS layers** |

## KEY INSIGHT

The model learns the **terrain signature** of a culvert



- U-Net trained on **tens of thousands** of known culvert locations in Florida
- Input: a **max-downslope-change** raster from 2.5 ft LiDAR DEM, in 256×256 chips.

Builds upon: Lidberg, W. *Deep learning-enhanced detection of road culverts in high-resolution digital elevation models.*



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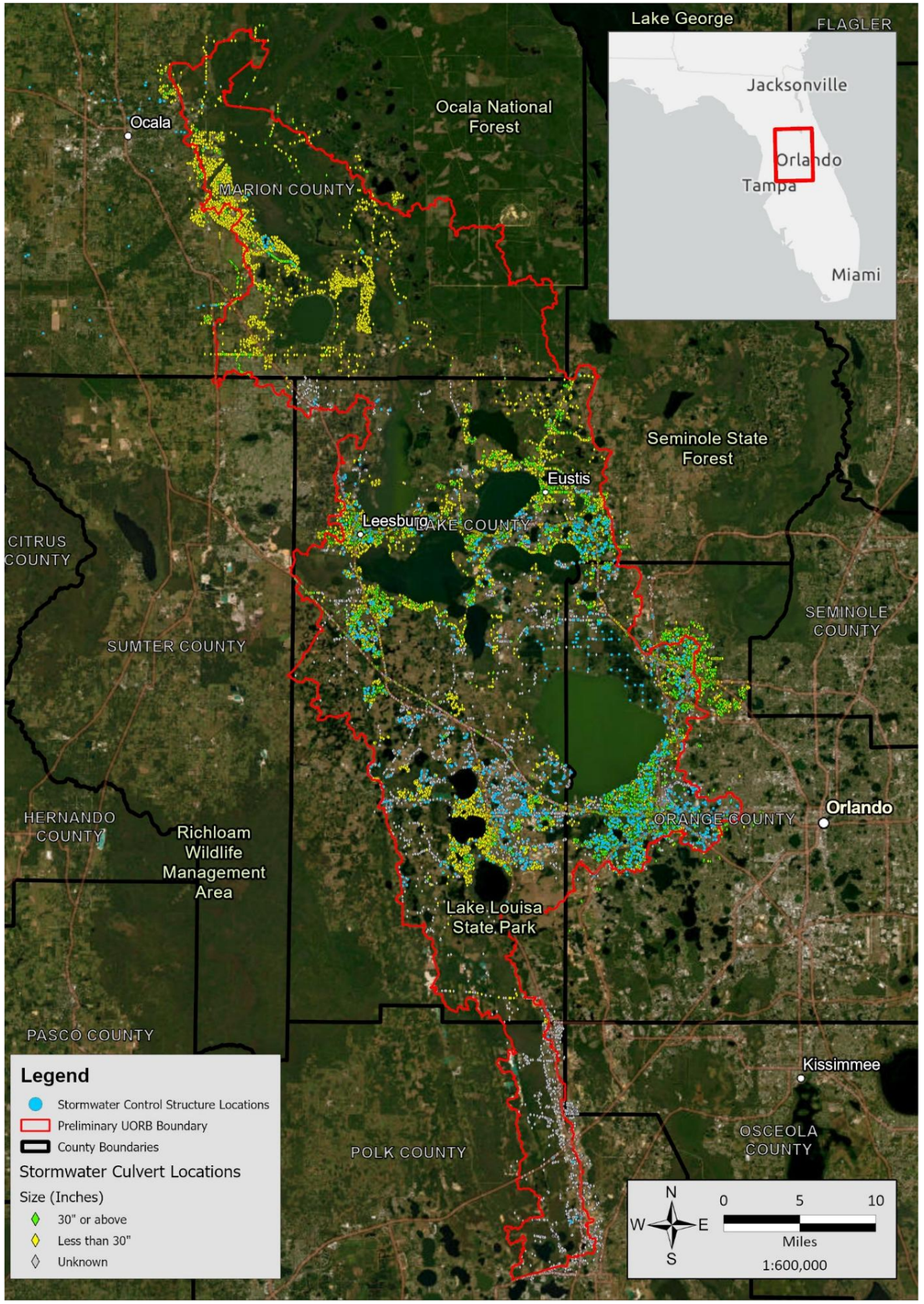
# Example 1 – Results

# ~17,000 structures

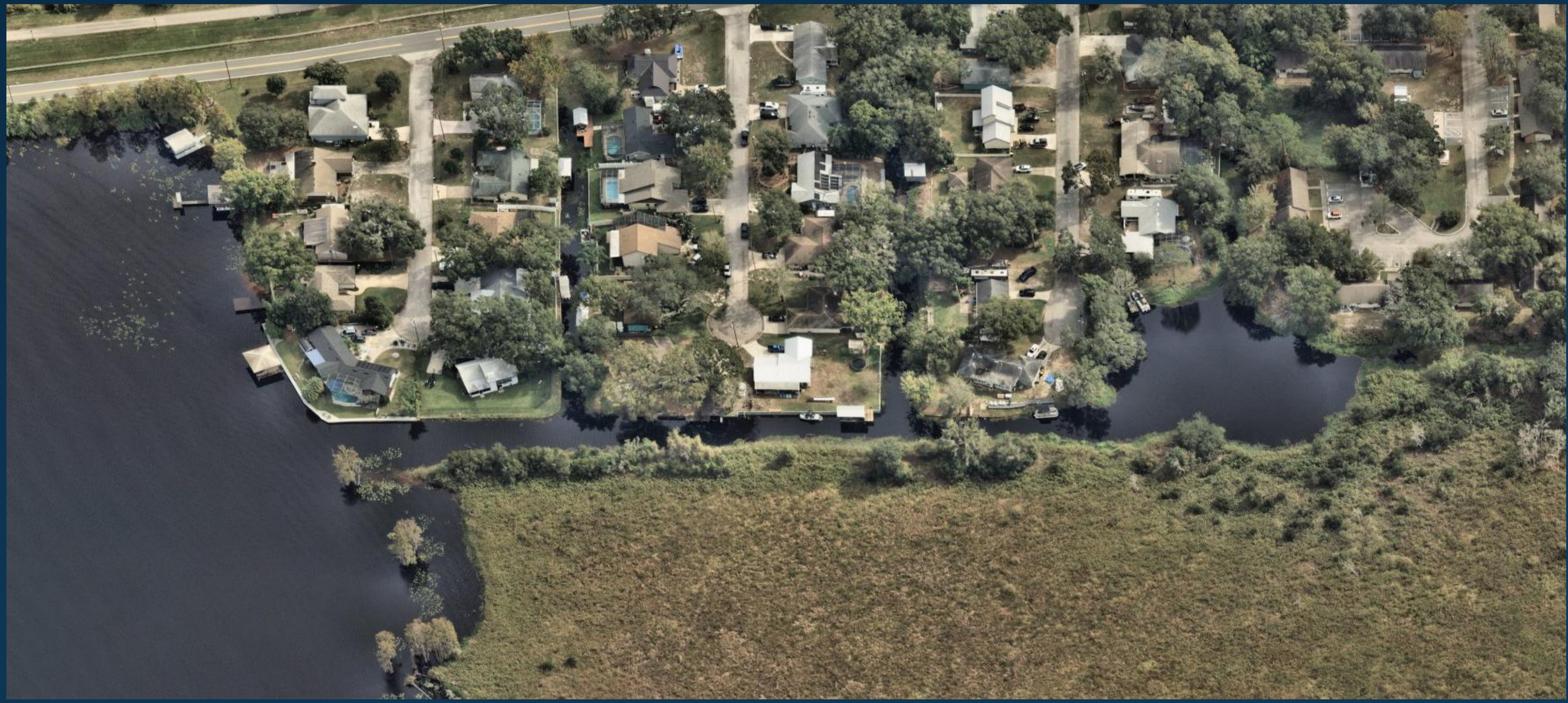
Deep learning results supported structures mapped across the ~1,000 sq mi **Upper Ocklawaha** watershed

## Leverage for Many Uses

The same key infrastructure inventory can serve multiple agency needs — asset management, planning, permitting, etc



# Example 2 – Land Surface Characterization



# Example 2 – Land Surface Characterization

FREE BASELINE

## NOAA C-CAP

Free for Florida · 1 m · NAIP-derived · impervious area + water bodies. 97% **percent** accurate at subbasin scale.

WHEN NEWER OR FINER DETAIL IS NEEDED

## Ecopia · ecopia.ai

Deep-learning land cover from very-high-res imagery (e.g., **Nearmap**) on smaller-scale projects.



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# Example 2 – Land Surface Characterization

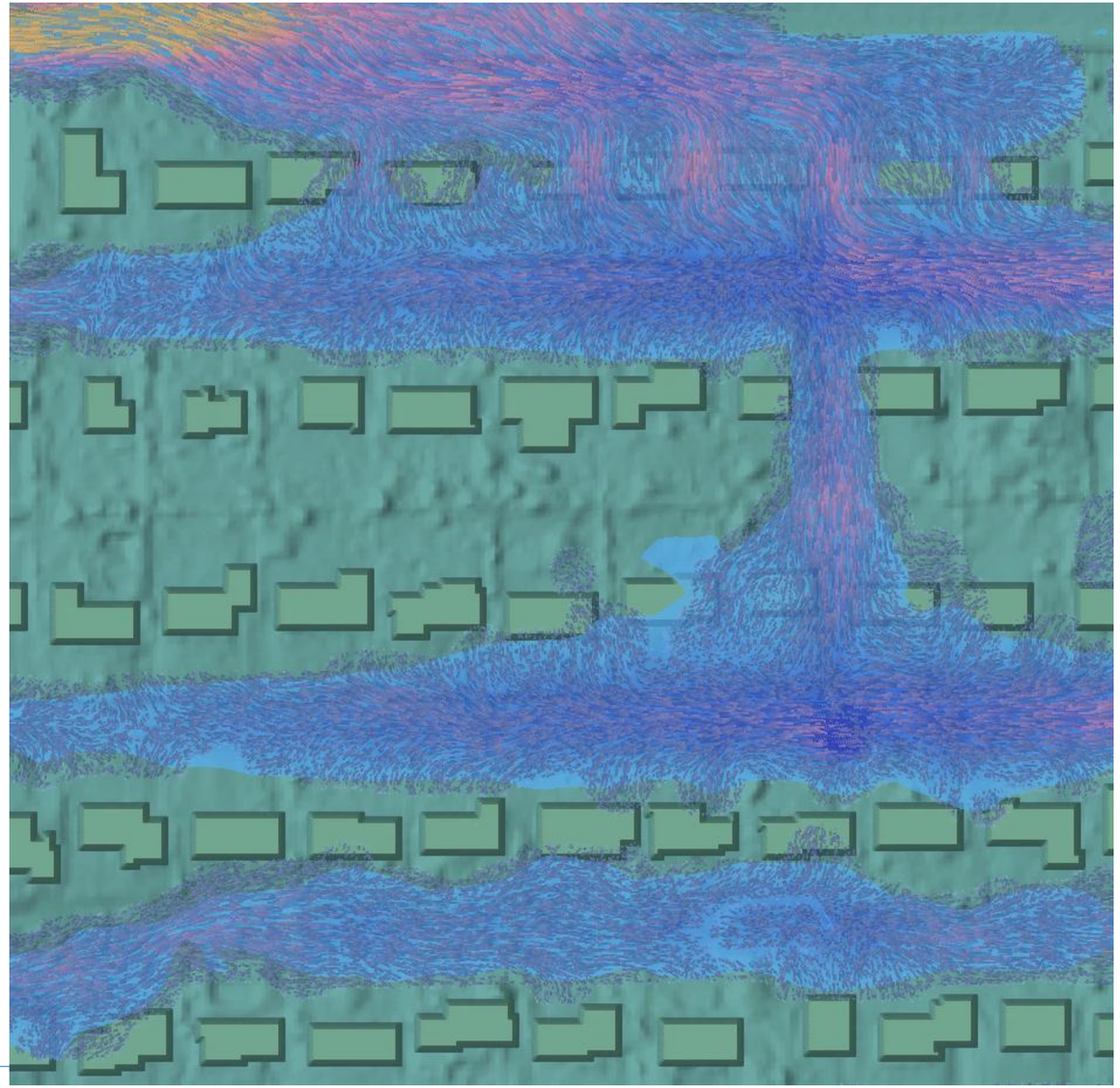
**-Buildings impact flows and are what's at risk**
**-Mapping them is increasingly essential as we move to high-resolution 2D modeling**

Microsoft

Google

→

**Overture Maps**
deduplicated · consistent · clean access



Both footprint sets are deep-learning-derived from imagery; Overture consolidates and deduplicates them.



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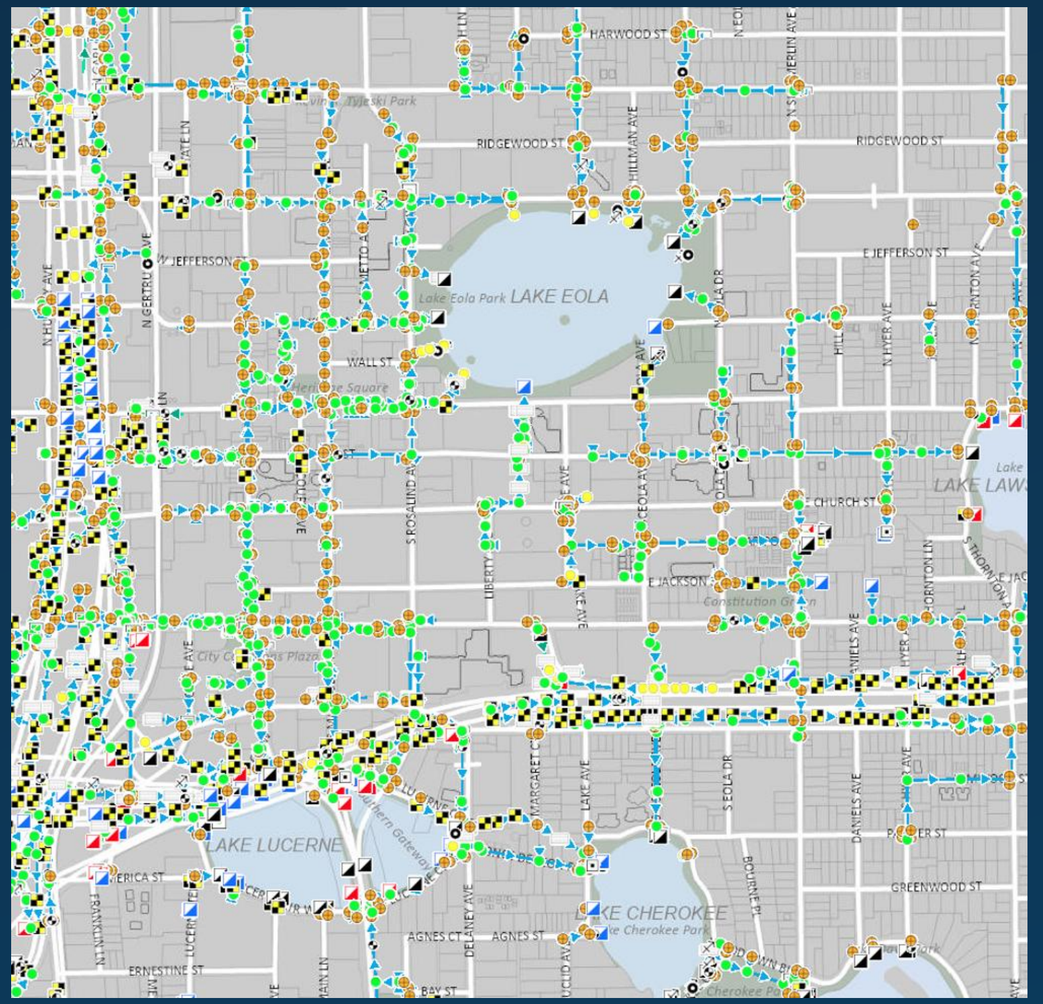
# Example 3 – Data Processing

## The scale problem.

**Orders of Magnitude Increase in Size of Model Dataset**

**~20×** more pipe features in the same ~1,000 sq mi model

Data Processing & QC tooling refined over **20 years** couldn't keep up.

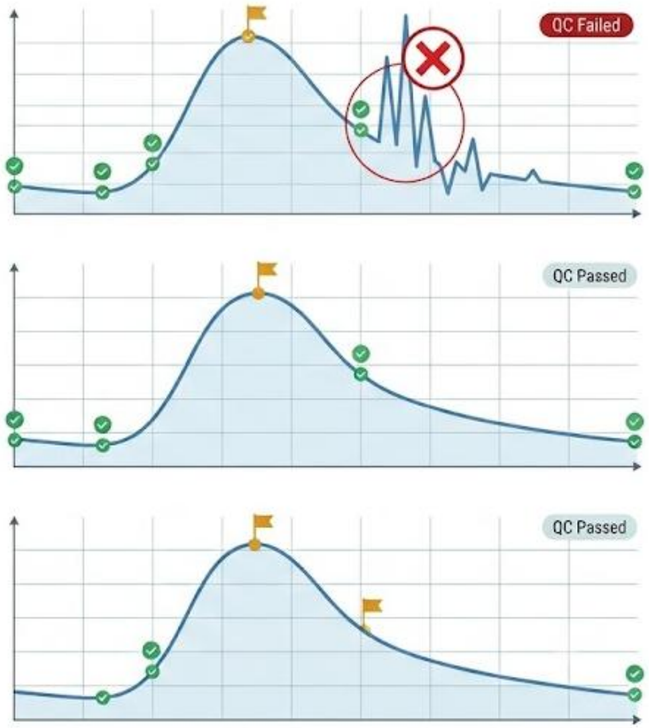


# Example 3 – Data Processing

**Example:** We recoded internal QC tools to be **more thorough and more efficient**

~~Weeks~~ of manual recoding → **Hours** with LLM assistance

| TIMESTAMP | STAGE (feet) | DISCHARGE (cfs) | QC STATUS |
|---|---|---|---|
| 2024-06-28 18:50:00 | 1.45 | 10.50 | QC Failed |
| 2024-06-28 18:50:00 | 1.45 | 13.75 | ✓ |
| 2024-06-28 18:50:00 | 1.35 | 13.70 | ✓ |
| 2024-06-28 16:50:00 | 1.35 | 13.30 | ✓ |
| 2024-06-28 16:50:00 | 1.35 | 13.25 | ✓ |
| 2024-06-28 15:50:00 | 1.65 | 13.30 | ✓ |
| 2024-06-28 15:50:00 | 1.65 | 13.65 | ✓ |
| 2024-06-28 14:30:00 | 1.65 | 13.50 | ✓ |
| 2024-06-28 15:50:00 | 1.65 | 13.90 | ✓ |
| 2024-06-28 17:30:00 | 1.55 | 12.75 | ✓ |
| 2024-07-28 17:30:00 | 1.65 | 13.25 | ✓ |
| 2024-01-28 17:30:00 | 1.65 | 13.40 | ✓ |
| 2024-01-28 18:30:00 | 1.6.5 | 12.75 | ✓ |
| 2024-01-28 15:30:00 | 1.7.0 | 12.65 | ✓ |
| 2024-01-28 18:30:00 | 1.7.5 | 12.90 | ✓ |
| 2024-01-28 15:30:00 | 1.7.5 | 13.10 | ✓ |
| 2024-01-28 15:30:00 | 1.7.2 | 13.00 | ✓ |
| 2024-01-28 15:30:00 | 1.6.5 | 13.25 | ✓ |
| 2024-01-28 15:30:00 | 1.6.3 | 13.80 | ✓ |
| 2024-01-28 15:30:00 | 1.8.5 | 12.35 | ✓ |
| 2024-01-28 15:30:00 | 1.9.5 | 13.56 | ✓ |
| 2024-01-28 18:30:00 | 1.9.5 | 12.60 | ✓ |
| 2024-01-28 15:30:00 | 1.0.3 | 11.80 | ✓ |
| 2024-01-28 15:30:00 | 1.8.4 | 13.30 | ✓ |




**Key Insight:** LLM's supported scripting & coding enhance our ability to process large data sets, improving the quality of inputs and outputs



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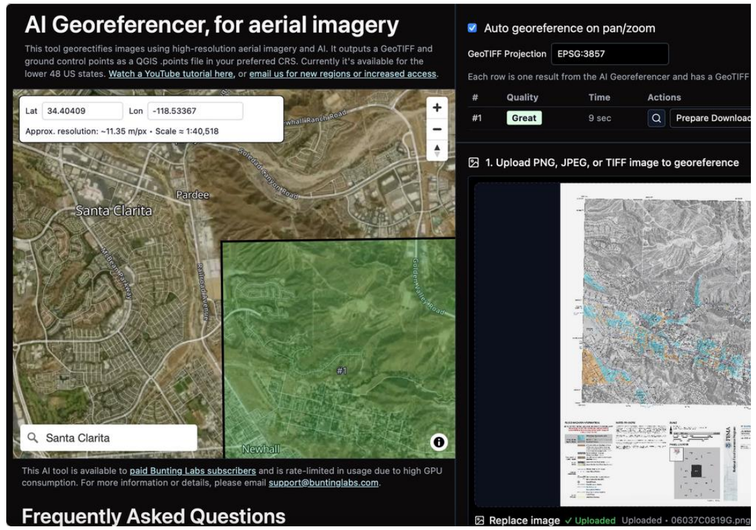
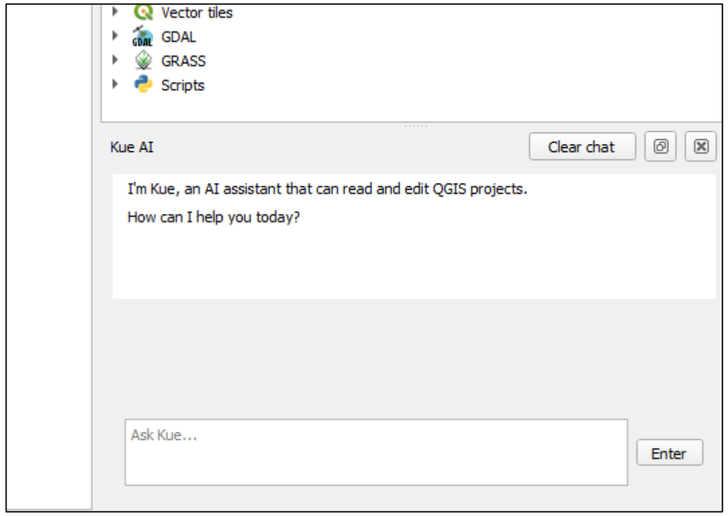
# Example 4 – GIS Data Processing

## BUNTING LABS · EXAMPLE OF WHERE SPATIAL-DATA WORK IS HEADING




### AI Vectorizer

Pulls features off old or scanned plan sets & historic maps.

### AI Georeferencer

Fast geo-rectification of scanned maps.

### Kue

Automates GIS routines and SQL.



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# Example 5 – Enhanced Project Communication


Traditional flood mapping is not always easily understood by the public

# Example 5 – Photorealistic Flood Visualization

Generative AI, combined with model results
— flood risk the public can actually imagine



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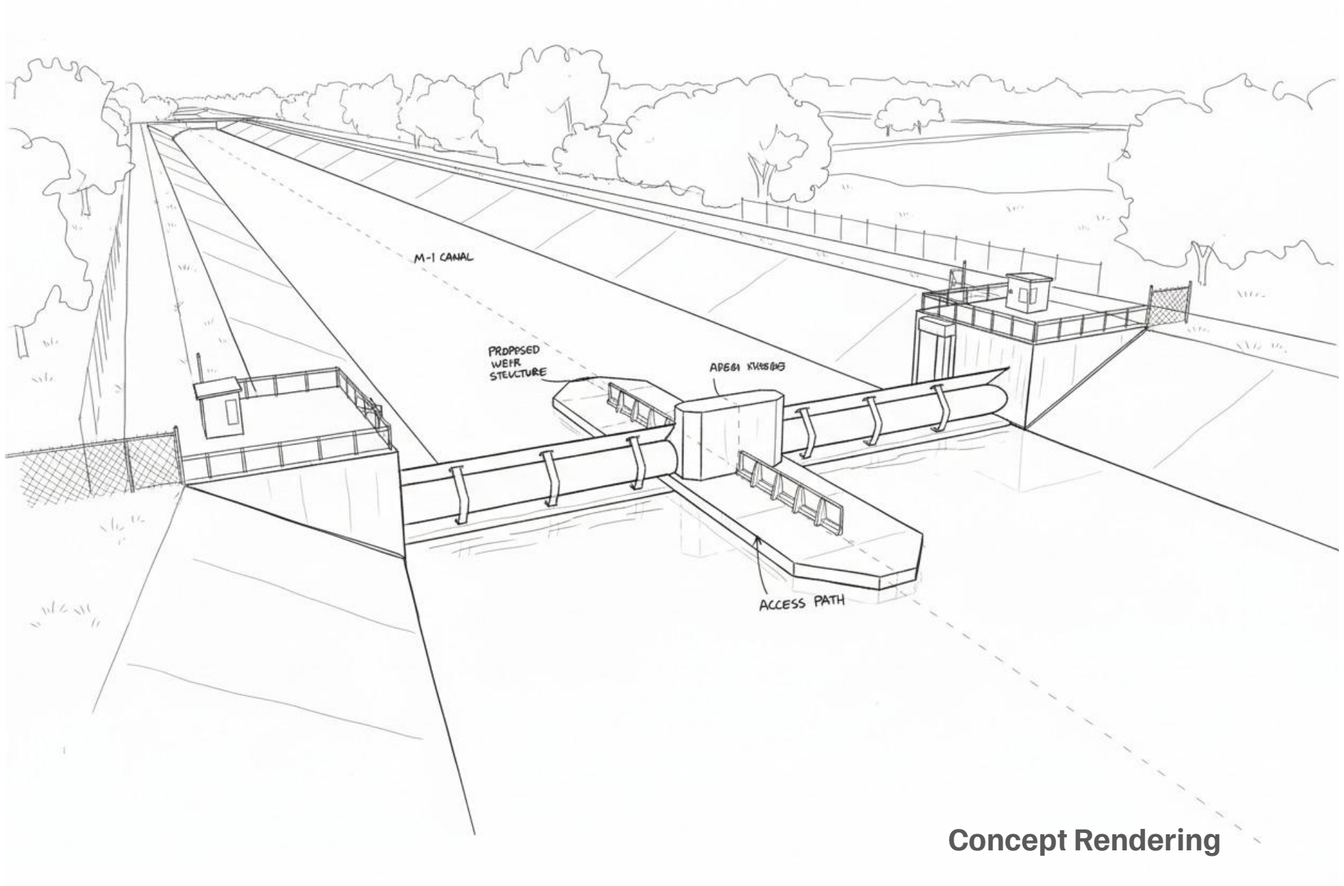
# Example 5 – Photorealistic Flood Visualization

Generative AI, combined with model results — flood risk the public can actually imagine



**Key Insight:** Illustrating the effects of flooding on the ground enhances public understanding.

# Example 6 –Rapid Concept Renderings




Concept Rendering

- Quickly render proposed structures
- Visualize **multiple design options** within tight time and budget.
- Faster, richer **stakeholder conversations** early in a project.



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# Example 6 – Rapid Concept Renderings


- Quickly render proposed structures
- Visualize **multiple design options** within tight time and budget.
- Faster, richer **stakeholder conversations** early in a project.



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# Summary of AI in Basin-Scale Flood Modeling

| INPUTS | PROCESSING | OUTPUTS |
| --- | --- | --- |
| **Data we never had**<br>Subsurface infrastructure — plus land cover & footprints that are cheaper and more accurate | **We could not keep up with the processing demands.**<br>Retooling to match modern model scale. | **Communication that was not always effective**<br>More accessible results for stakeholders |

THE CONSTANT

A human owns the judgment at every step; AI removes the manual bottleneck.



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# Questions?


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