GPU-Accelerated Scalable Geocomputation for Large-Scale Lidar-derived Road Elevation Models

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Objectives

1. Create a road lidar dataset as a baseline dataset for developing the road elevation model
   - Only lidar points on road surface are included
   - Organized by counties or by TxDOT maintenance sections
2. For each road shape (polygon or centerline), add the elevation value *z* to each (*x*,*y*) coordinate on the road shape: 2D → 2.5D
   - Road shape sources: Ecopia, TxDOT road inventory, …
   - GIS format: Polygon → Polygon Z; LineString → LineString Z

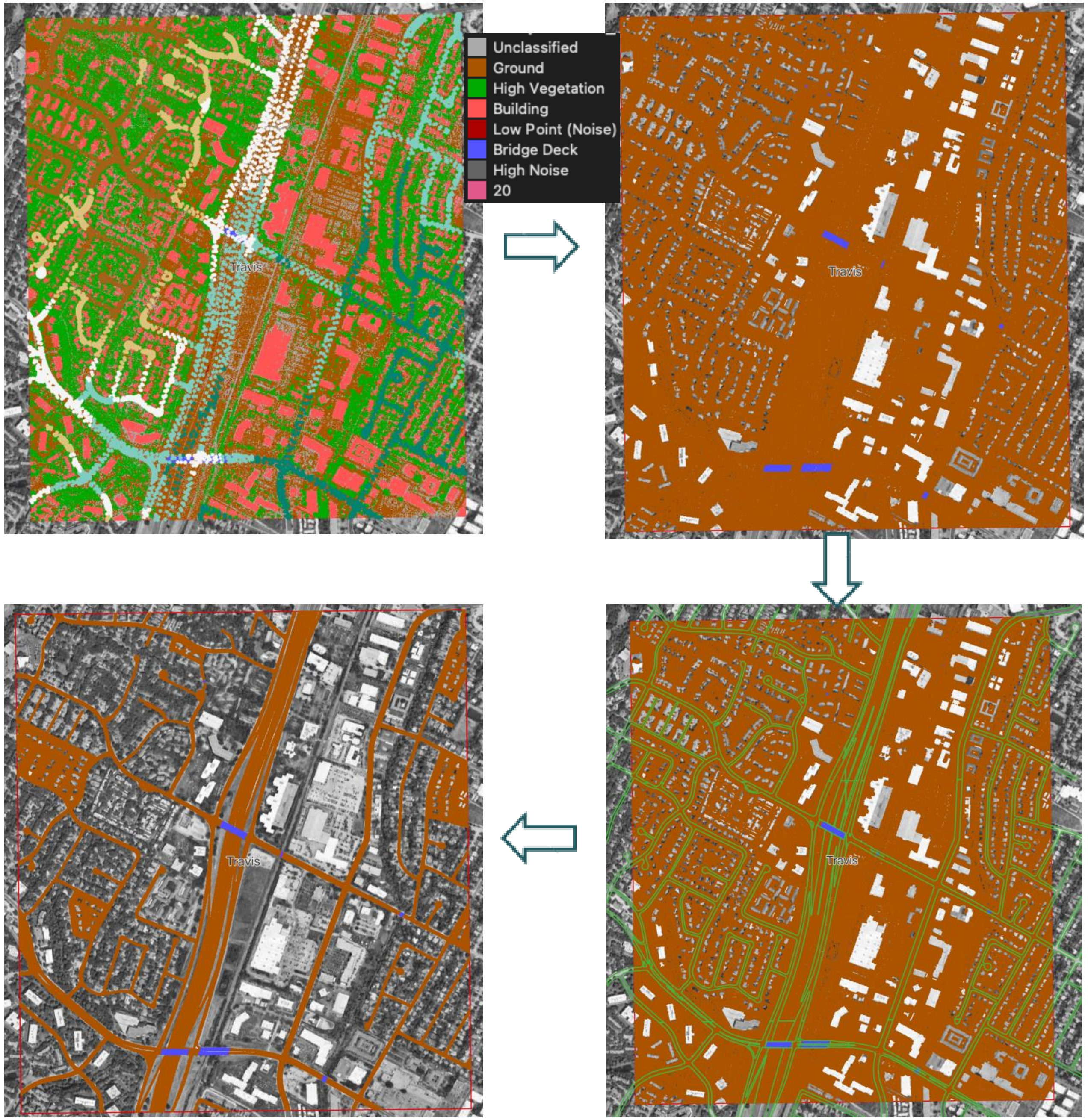
- Status
  - Project started in May 2023; the Austin District is processed in October 2023
    - 3D road shapes are sent to Dr. Maidment (proprietary data, not published)
    - Road lidar data:
      - By counties: https://web.corral.tacc.utexas.edu/nfiedata/road3d/austin_district/AustinCounties_H_epsg6343_V_epsg5703/
      - By maintenance sections: https://web.corral.tacc.utexas.edu/nfiedata/road3d/austin_district/AustinMaintenanceSections_H_epsg6343_V_epsg5703/
  - Software
    - Took longer than expected to develop due to the complexity of lidar data and high-performance computing requirements
    - The workflow software is being polished for open source release

GIS Processing
- road lidar construction

1. Load lidar tile
2. Extract ground and bridge points
3. Load road polygons
4. Point-in-polygon (PIP) test for road lidar points

- Computational intensity
  - Step 4:

num_pip_tests = num_gb_pnts * num_polygons



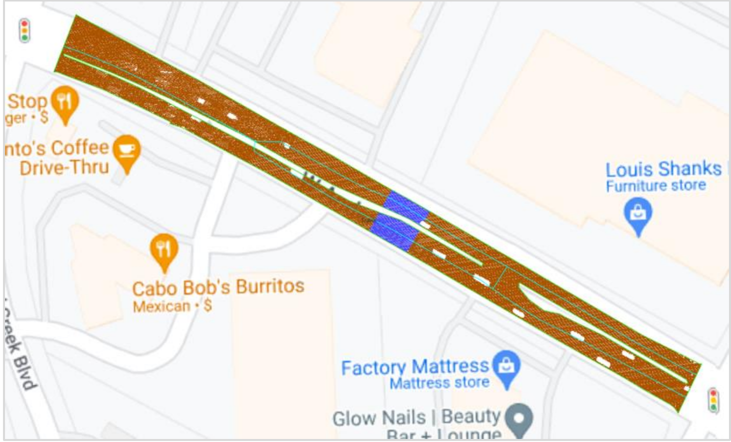
GIS Processing
– z interpolation on road shapes

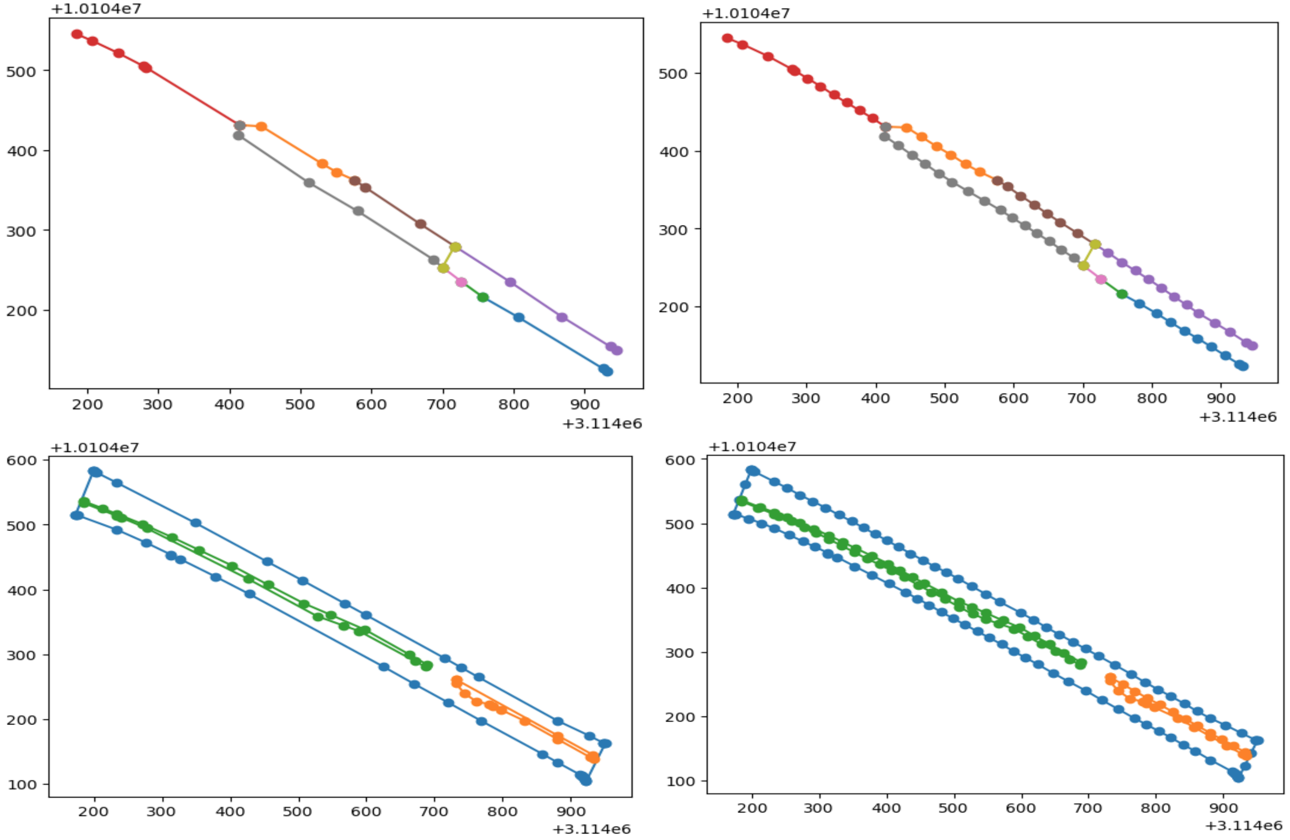
1. Load road lidar tile
2. Load road polygons and centerlines
3. Evenly space each line segment → {*query_points*}
4. For each query point, search neighboring lidar points → z sample
   – Point-in-polygon tests
5. Interpolate z of the query point from the sample

- Computational intensity
  – Step 4:

num_pip_tests = num_qp * num_road_lidar_pnts

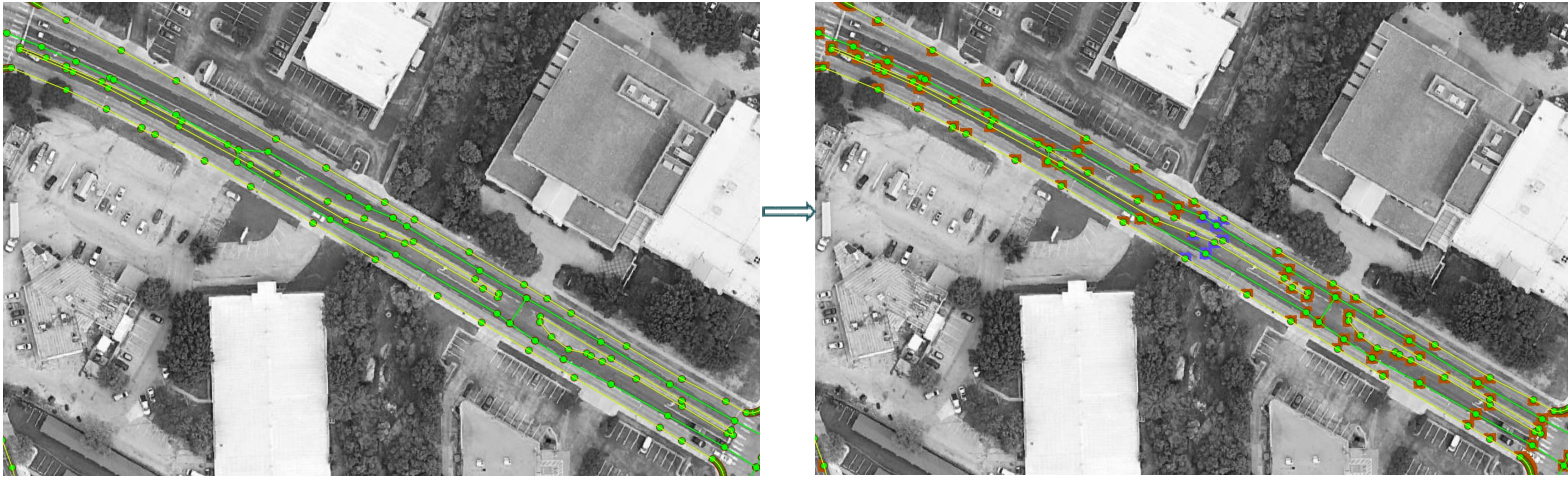
Shoal Creek and Anderson Ln





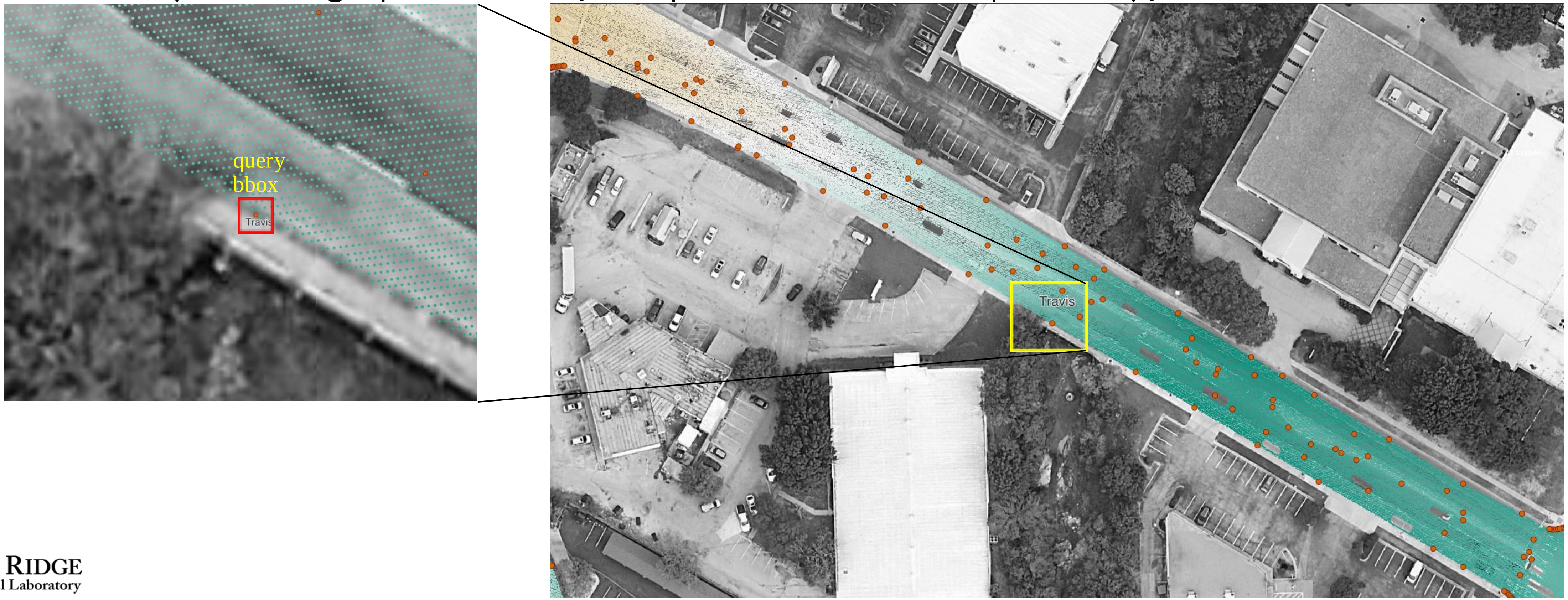
GIS Processing
- radius search for neighboring lidar points

- For each point on a road shape, search for neighboring lidar points within a radius
- Point in polygon/circle search is computationally intensive



GIS Processing
- z Interpolation Algorithm

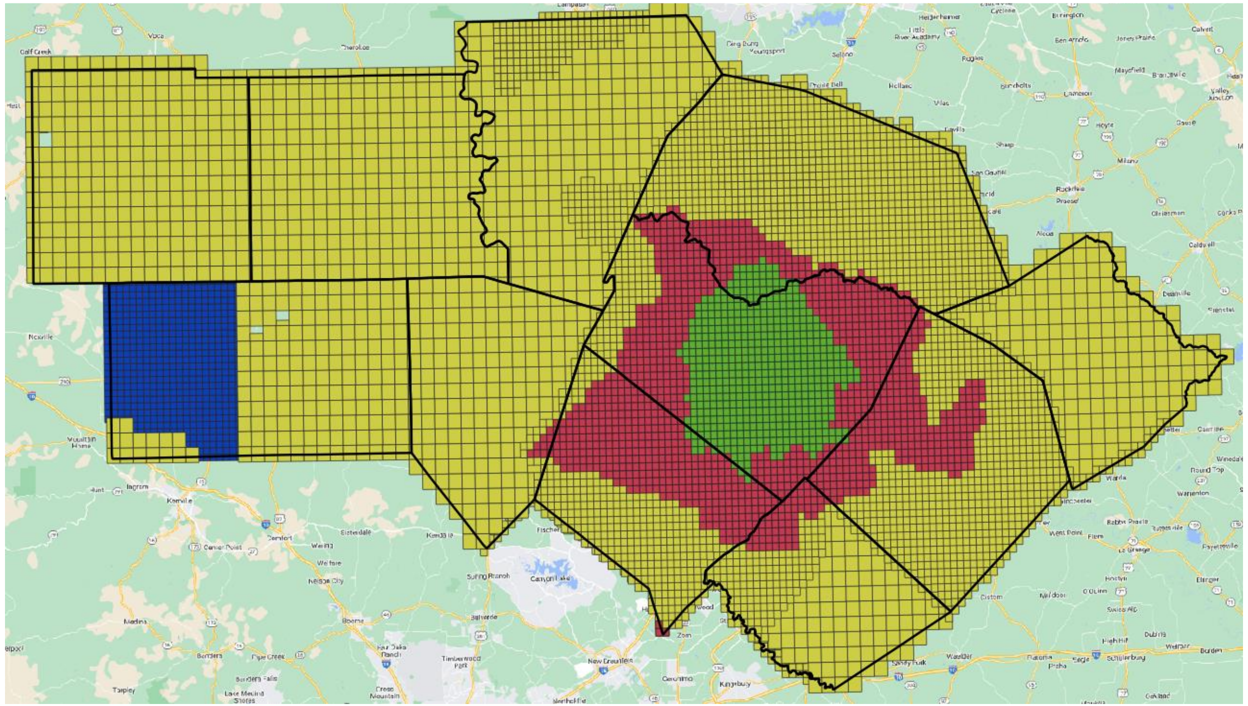
- If num of bridge points > num of neighboring points * 15%, use bridge points only
- Iteratively, smooth the sorted (by *Z*) points if | *Zmean* – *Zmedian* | > 1ft:
  - If *Zmean* – *Zmin* > *2ft,* get rid of the first point (w/ min *Z*)
  - If *Zmean* – *Zmin* > *2ft,* get rid of the last point (w/ max *Z*)
- Otherwise (not enough points left, or | *Zmean* – *Zmedian* | <= 1ft), return *Zmean*



Data Volume and Computing Environment

	#units	Size	Tile extent & size	Projection
Central Texas 2017	5811 tiles	608GB	~1.5km x 1.5km; ~15KB-1.8GB (145M points)	EPSG:26914, NAD83 / UTM zone 14N EPSG:6343, NAD83(2011) / UTM zone 14N EPSG:3721, NAD83(NSRS2007) / UTM zone 14N EPSG:6369, Mexico ITRF2008 / UTM zone 14N
Bexar-Travis 2021	516 + 3157 = 3673 tiles	857GB	28cm: ~15ft x 16ft; ~163MB - 1.3GB 50cm: ~5k ft x 5.7k ft; ~11MB - 350MB	EPSG:6578, NAD83(2011) / Texas Central (ftUS) EPSG:6588, NAD83(2011) / Texas South Central (ftUS)
South Central Texas 2018	528 tiles	30GB	~1.5km x 1.5km; ~40-90MB	EPSG:6343, NAD83(2011) / UTM zone 14N
Total	**10,012**	**1.5TB**		

Ecopia road data: 75,855 polygons, 285,607 centerlines. Projection: EPSG:32614, WGS 84 / UTM zone 14N



High-performance computing environment

- Oak Ridge Research Cloud
- HPC machine specification
  - 96 CPU cores, Intel(R) Xeon(R) Platinum 8268 CPU @ 2.90GHz
  - 800GB memory
  - 100TB storage
  - 4 NVIDIA V100S GPUs
  - Network: Globus transfer on high-speed network between ORNL and TACC
- Future processing may use TACC Lonestart6

Computational Strategies

- Define the basic computing element to enable parallel computing paradigms
  - Each tile is a basic computing element, not a road polygon or centerline
    - To avoid visiting a lidar tiles for multiple times
- Maximize the use of vectorized processing
  - CPU: Numpy vectorized operations
  - GPU: customized batch processing using Rapids tools (*cupy, cudf, cuspatial*)

Assumptions

- Projection
  - Each input/output projection has an EPSG number
  - Only meter ←→ foot conversion is needed
  - Tile processing uses the native projection of the lidar tile → reprojection is needed
- Lidar input
  - Ground | bridge classification among different las point formats is exclusive
    - No conflict: ground = 2 in point format *a* and ground = 4 in point format *b*
- Single output projection
  - Horizontal EPSG:6343 (UTM 14N)
  - Vertical EPSG:5703 (NAVD88 height)

Computing Workflow

1. [S] Create R-tree road polygon index
2. [S] Create lidar tileset table with processing priority
3. [PG] Batch-process all lidar tiles for 3D road shape construction
    1. [S] Filter road polygons and centerlines in the tile
    2. [G] Crop lidar tile to road tile (point-in-road-polygon tests on GPU)
    3. [S] Space road polygons and centerlines; create query points and query bbox
    4. [G] Radius search for each query bbox on GPU
    5. [S] Z-interpolation for each query point (CPU acceleration via vectorization)
    6. [S] Aggregate 3D query points and associate them with road polygon/centerline
4. [PG] check and re-run failed tiles
5. [S] Generate XYZ road polygons and centerlines
6. [P] Reproject road tiles to the output projection using *pyproj*
7. [PG] Crop overlapping tiles ordered by priority
    1. [S] Create tile bbox R-tree
    2. [G] For each tile, skip non-overlapping and completely covered tiles; crop intersected tiles
8. [P] Generate copc tiles using *untwine*
9. [P] Generate road tiles by counties and maintenance sections using *lasmerge*
10. [P] Cleanup

```
After the 1st run: 109 failed tiles,
100 of them are lcra07 old tiles that
have version 1.0, which is no longer
supported. Other 9 were caused by GPU
memory contention, resolved by simply
re-running them with less parallelism
(=2).
```

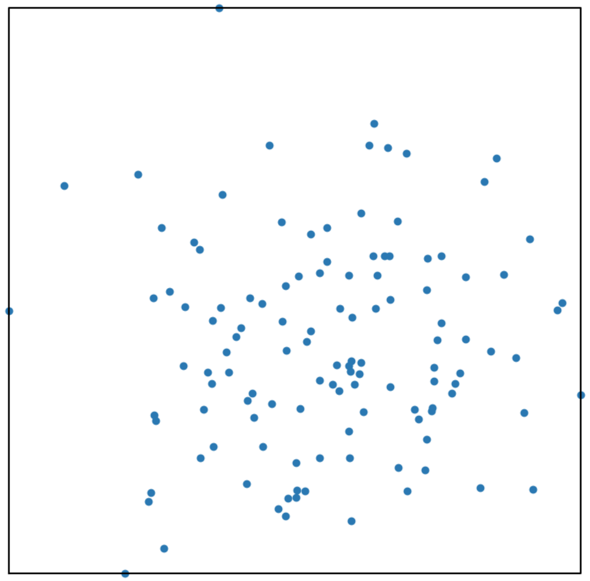
```
Step 7:
  6030 non-overlapping
  1111 completely covered
   811 cropped
```

Step 6-9: road tile processing

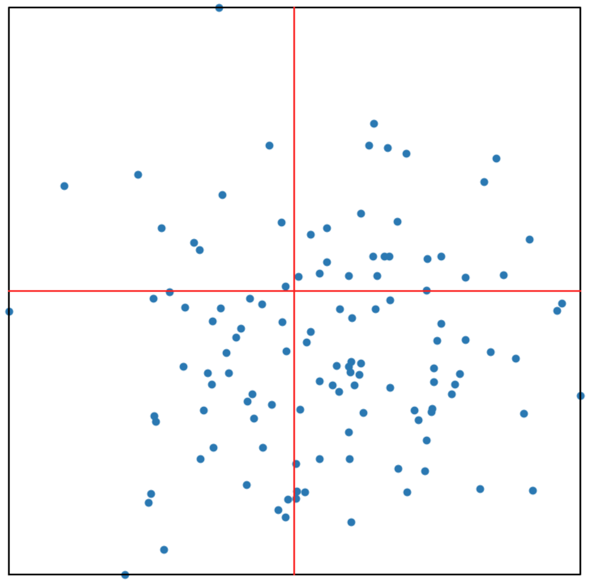
S: sequential computing; **P**: CPU parallel; **G**: GPU parallel

Quadtree Indexing of Road Lidar Points

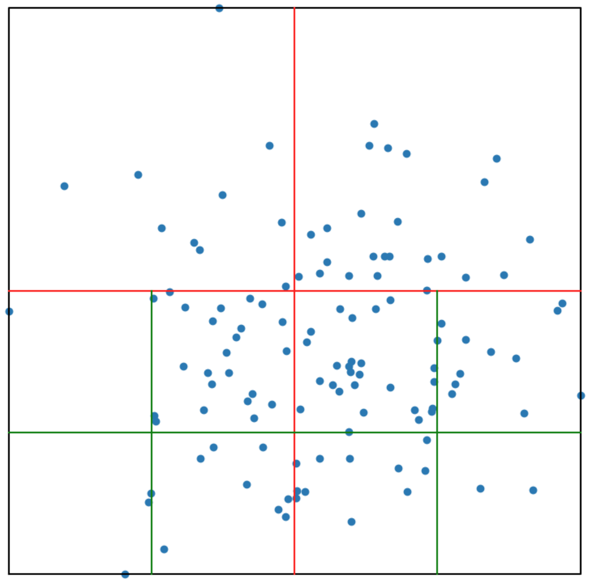
max_size/quad = 30



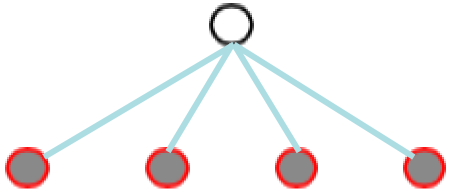
point data

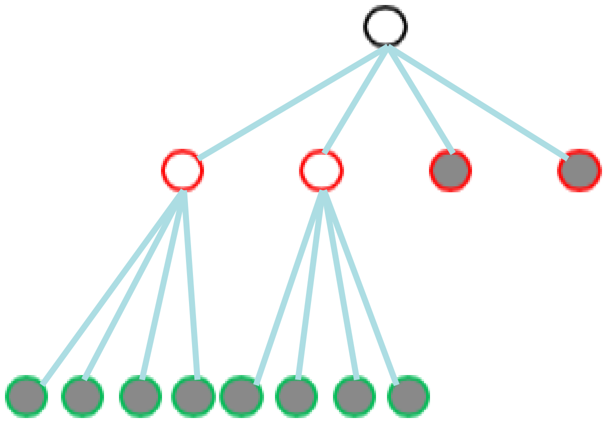


level 0 quadtree



level 1 quadtree





cuSpatial code

```
key_to_point, quadtree = cuspatial.quadtree_on_points(
    points, minx, maxx, miny, maxy, scale, max_depth, max_size
)
```

quadtree data table

num of indexed points: 120

	key	level	is_internal_node	length	offset
0	0	0	True	4	5
1	1	0	True	4	9
2	2	0	False	14	86
3	3	0	False	19	100
4	8	0	False	1	119
5	0	1	False	4	0
6	1	1	False	12	4
7	2	1	False	5	16
8	3	1	False	24	21
9	4	1	False	7	45
10	5	1	False	1	52
11	6	1	False	28	53
12	7	1	False	5	81

Radius Search Using Quadtree

- Intersection of query bounding box and quads
  - Which quads are to be searched next?

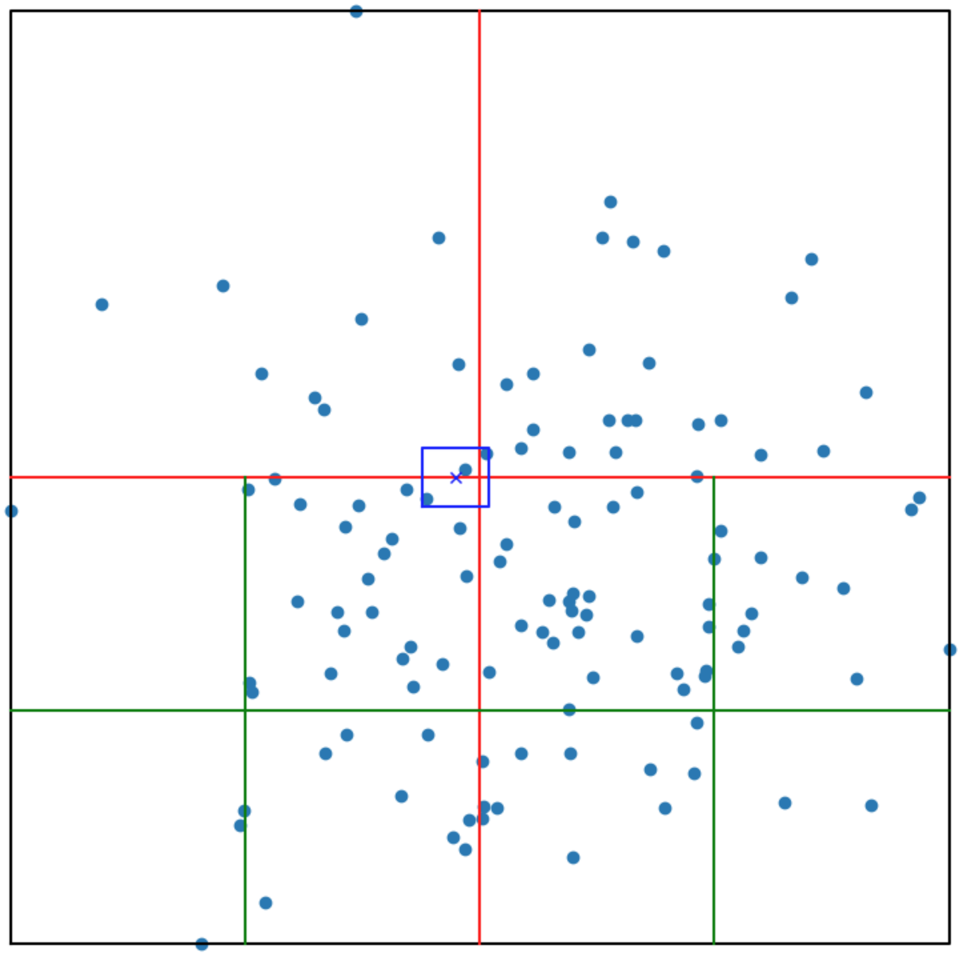
```
intersections = cuspatial.join_quadtree_and_bounding_boxes(
    quadtree=quadtree,
    bounding_boxes=gpu_bboxes,
    x_min=minx, x_max=maxx, y_min=miny, y_max=maxy,
    scale=scale,
    max_depth=max_depth
)
```

	bbox_offset	quad_offset
0	0	8
1	0	11
2	0	2
3	0	3

- Point-in-polygon using quadtree
  - Test if a lidar point in an intersected quad is within the query bounding box

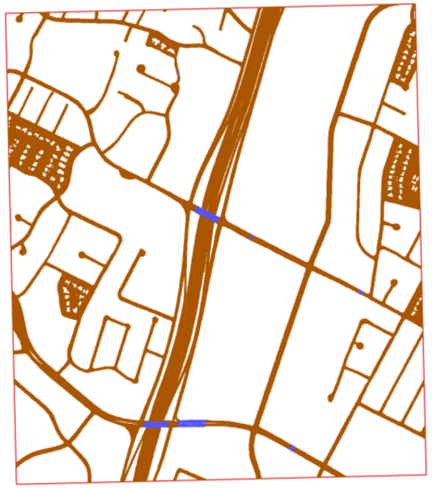
```
polygons_and_points = cuspatial.quadtree_point_in_polygon(
    poly_quad_pairs=intersections,
    quadtree=quadtree,
    point_indices=key_to_point,
    points=points,
    polygons=cuspatial.GeoSeries(pnt_bbox_geoms)
)
```

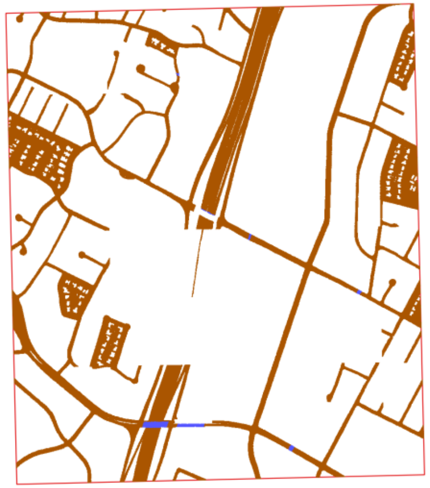
	polygon_index	point_index
0	0	43
1	0	91
2	0	93

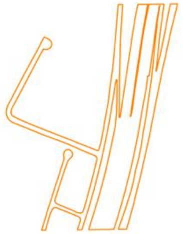


Technical Exploration for Lidar Point Cropping and Radius Search

- PDAL cropping + PCL octree neighborhood search
  - Issue: PCL octree search slows down dramatically on large lidar data. Search on the 1.8GB lidar data could not finish within 30min
- PDAL cropping
  - If the input MultiPolygon is complex, PDAL does not produce correct results
  - Cropping polygon by polygon + lasmerge works, but too slow. 1hr for the 90m-point lidar tile covering Shoal Creek and Anderson Ln







- Laspy + SciPy cKDTree
  - Load lidar points using *laspy;* build a KD-tree; do radius search
  - It works and it is fast (1m for loading data; subseconds for search)
  - Issue: it uses a lot of memory (2GB lidar uses 46GB memory). Not practical for parallel computing of 13k lidar tiles
- GPU: cuSpatial point in polygon for cropping
  - It's super fast (a few seconds to load data, subseconds for search)
  - cuSpatial is part of NVIDIA RAPIDS
    - CUDA memory error when lidar data or polygons are too large

GPU-Acceleration for 3D Road Shape Processing

- Programmability on GPU in Python
  - `cupy – numpy`
  - `cudf – pandas`
  - `cuSpatial – shapely`
    - Not really, but cuSpatial has point-in-polygon test and quadtree search
    - Vector standard - GeoArrow
  - Difficulties
    - No memory management support
    - New → poor documentation
      – Source code reading is necessary
    - Code can crash without useful error messages
- Data parallel computing
  - Desirable for massive data stream processing
  - One GPU card can be shared by multiple processes
  - Multi-GPU computing model is straightforward in our use case
    - Embarrassingly parallel

Accelerated	Solution	CPU/GPU alternatives
Find road shapes in lidar tile	• R-tree search (CPU, <1s) Efficiency: 99.99%	Too slow without indexing
Road lidar cropping	• *laspy* filter (CPU, 1.3s) • point-in-polygon (GPU, 2.4s)	*pdal* pipeline (CPU, 3m) - cannot handle complex polygons
Radius search	• quadtree search (GPU, 5.4s, 0.4GB GPU mem) • search result aggregation (CPU, 0.5s)	• KDtree search (CPU, 4.8s, 46GB mem) • PCL Octree C++: not scalable • aggregation via pandas (5m34s) • aggregation on GPU (>10m)
Z interpolation	numpy vectorization (CPU, 0.6s)	numpy iteration (CPU, 4.2s)

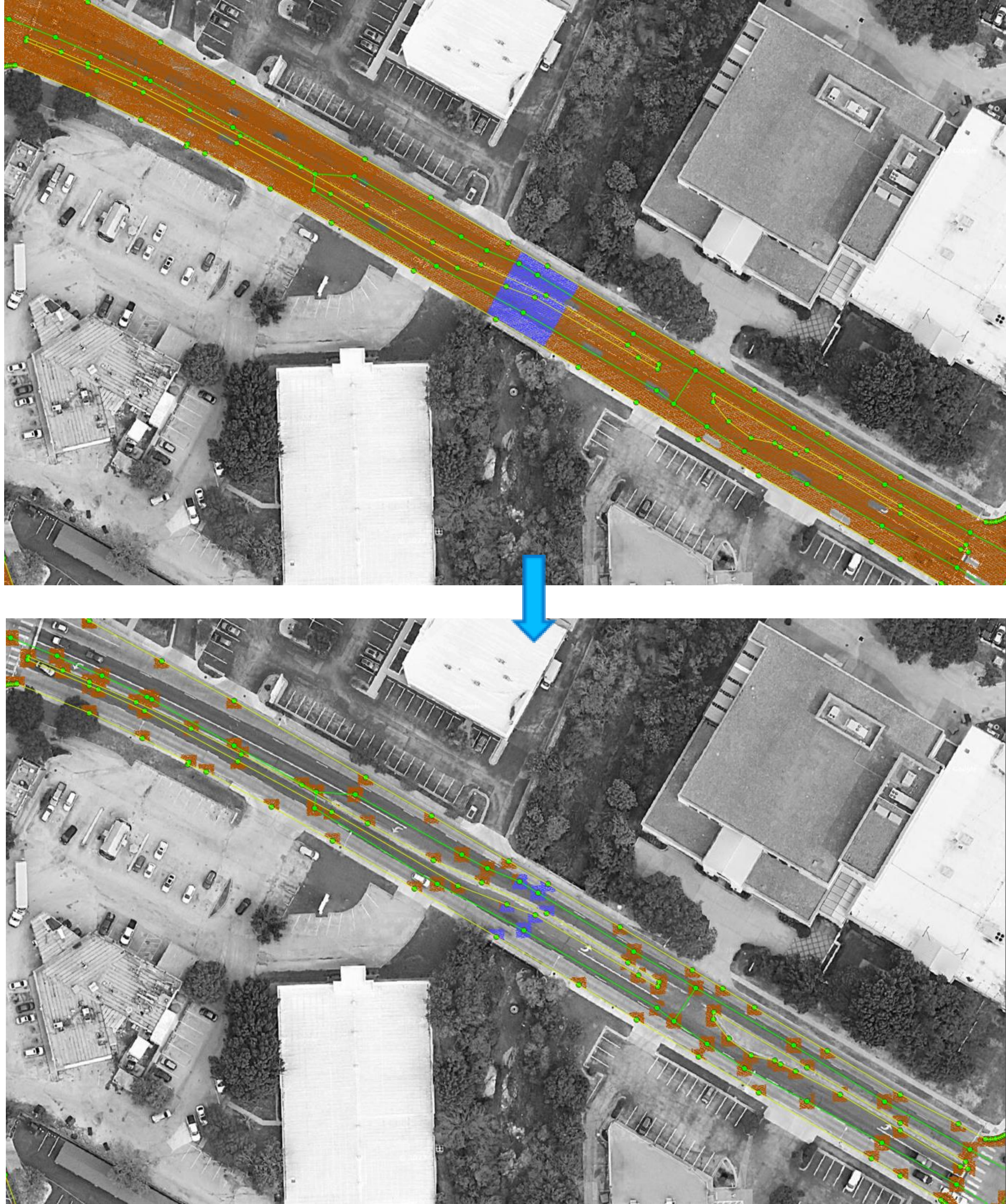
image source: https://www.servethehome.com/inspur-nf5488m5-review-a-unique-8x-nvidia-tesla-v100-server/

Benchmark data: 90m lidar points

GPU Batch Processing

- *cuSpatial* limitations
  - GPU memory limitation on how many lidar points can be quadtree-indexed at a time
  - Point-in-polygon search for multiple query bounding boxes is supported, but GPU memory limits how many query points can be served at a time
- Batch processing of radius search
  - Batch construction for both lidar points and query bounding boxes
    - Quadtree search on a batch of lidar points generates generates a subset of lidar points within the radius. Aggregation needed to get the final result
  - Pseudo code

```
• for each batch of lidar points
  – construct quadtree
  – for each batch of query bboxes
    • intersect bboxes and quads
    • point-in-polygon test for each lidar
      point in intersected quads
• For each query point
  – aggregate lidar points within the radius
```



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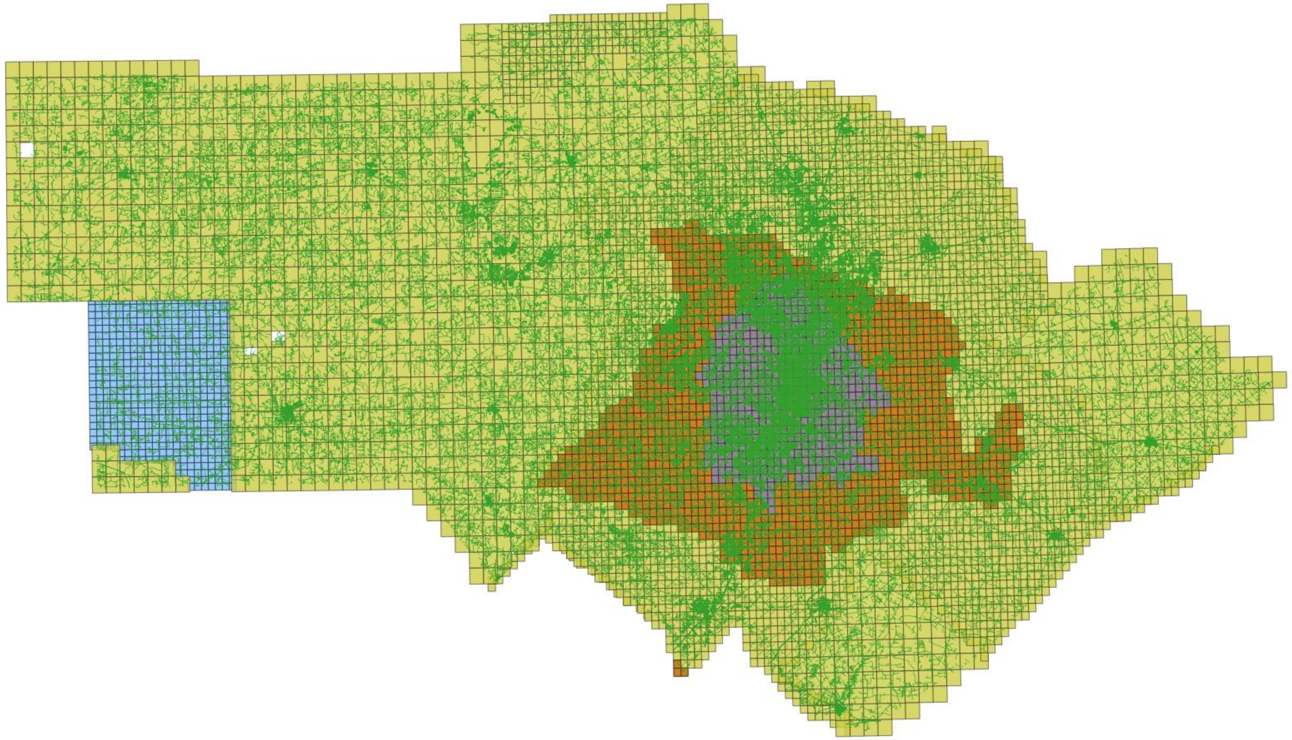
Results: 3D Road Shapes

Austin District Output

- Road lidar dataset
  - 3.85 billion points
- Road shape datasets
  - 3D LineString Z: 285,558 / 285,607
  - 3D Polygon Z: 75,833 / 75,855



Computational Performance

computing	4 GPUs, parallelism/gpu=6
road shape R-tree indexing	6 minutes
10,012 lidar tiles	skipped: 2060 (Bexar tiles) processed: 7952 success: 7843 failed: 109 • 3: GPU quadtree search error • 6: GPU memory access error • 100: old lcra0 las V1.0 not supported
tile computing time	3 hours 20 minutes GPU parallelism: 6
rerun of failed tiles	success: 109, time: 12 minutes GPU parallelism: 1
road shapes aggregation	8 minutes 32 seconds
road lidar aggregation	3 hours (to double check)

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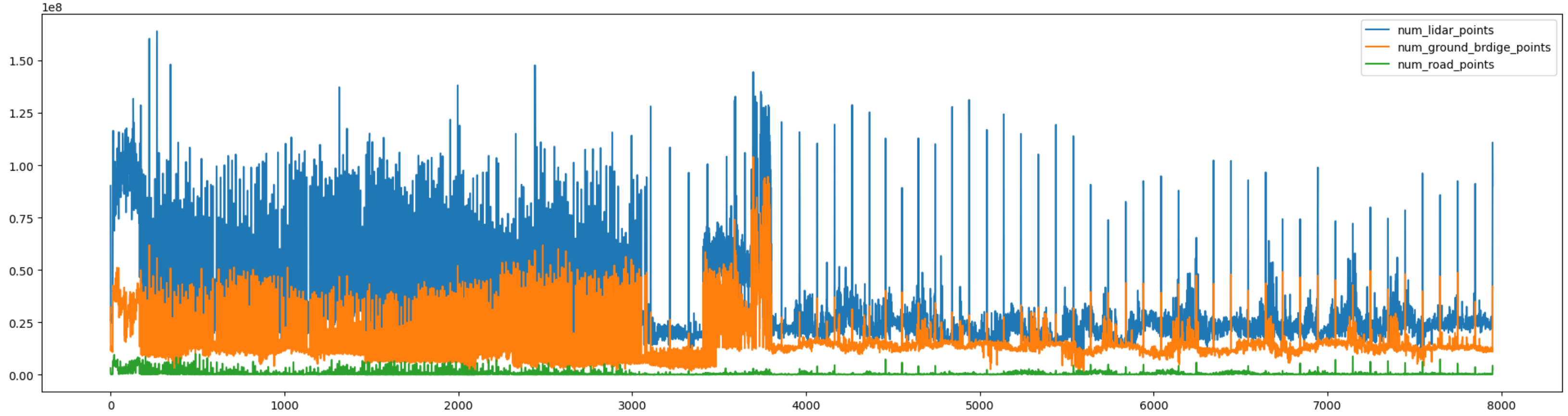
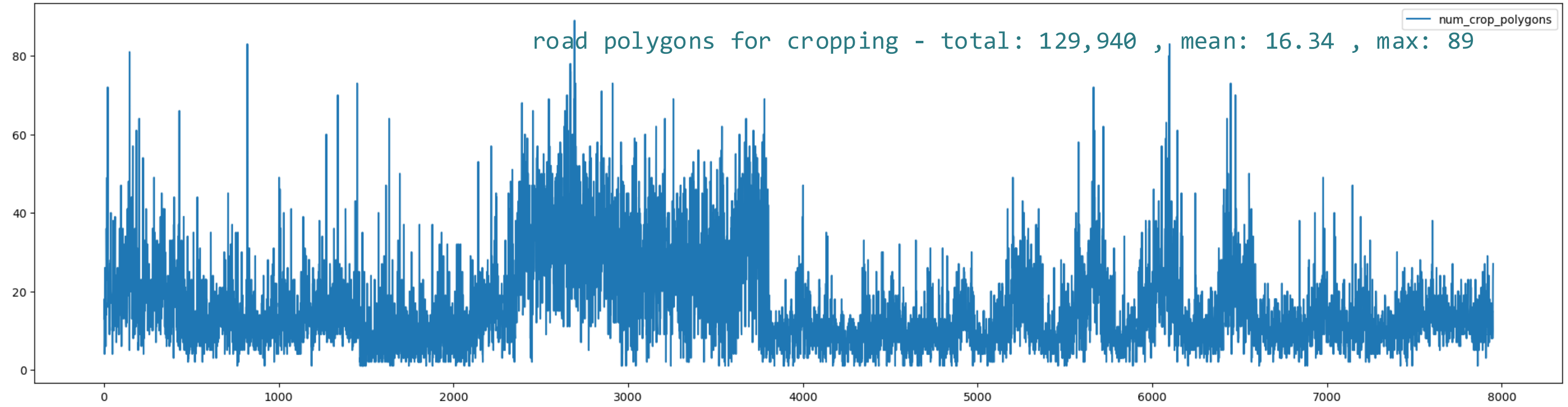
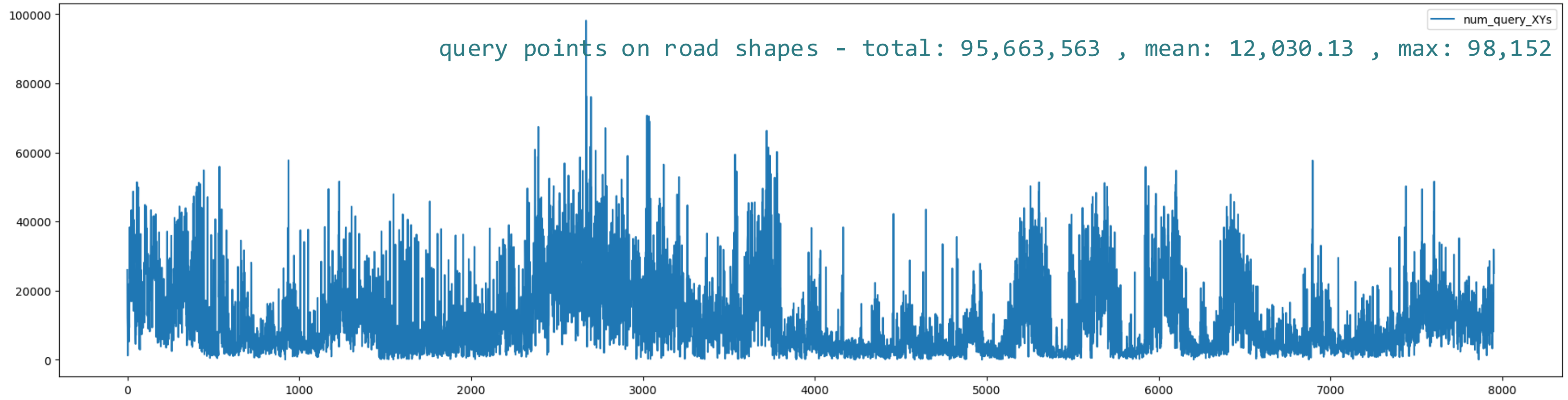
Statistics

- 230 billion lidar points in 7,952 lidar tiles are scanned
- 3.86 billion road lidar points are extracted
- 1.96 trillion point-in-polygon tests
  - point-in-polygon tests after R-tree search for tile-road polygon intersection
  - road lidar has 1.67% of original lidar points, on average
- number of radius search operations w/o quadtree
  - 369,015 trillion
  - quadtree search significantly reduced this number
- 95.6 million Z values are added to road centerlines and polygons
  - evenly spaced. more points than in the original Ecopia data

lidar points - total: 230,420,449,907 , mean: 28,976,414.73 , max: 163,961,040
ground/bridge points - total: 112,709,640,901 , mean: 14,173,747.6 , max: 103,955,779
road points - total: 3,857,431,762 , mean: 485,089.51, max: 9,888,605







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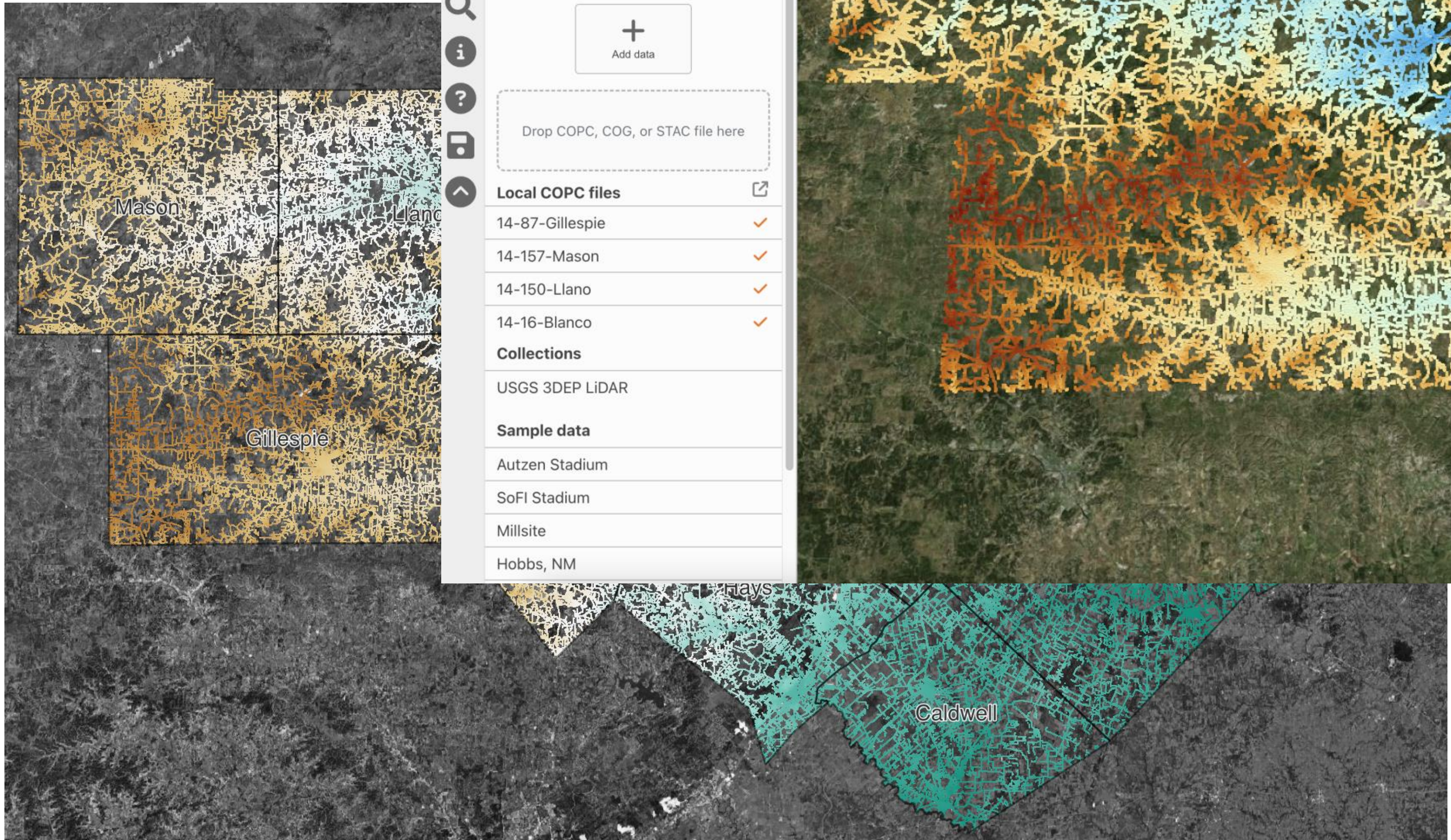
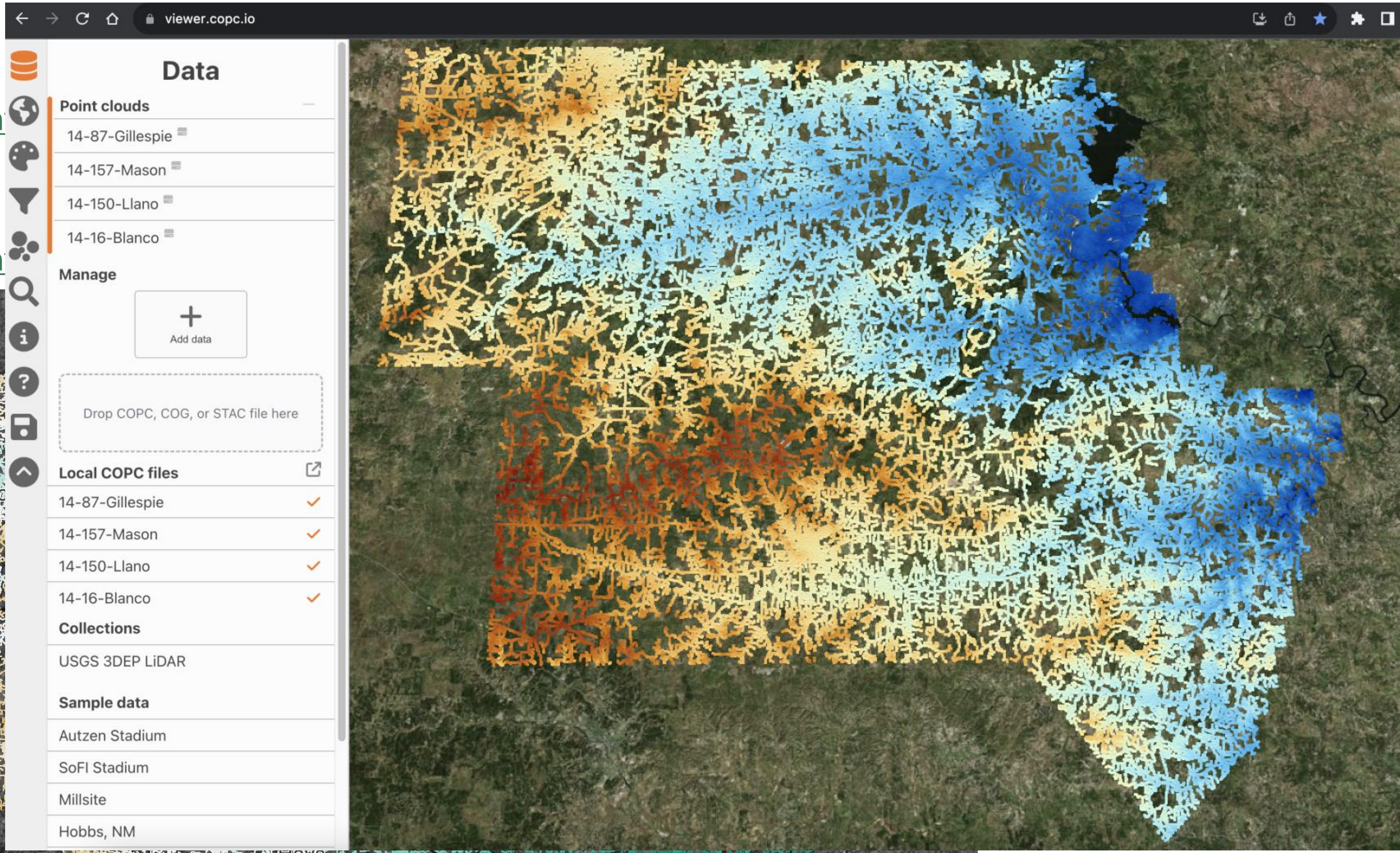
Results: road lidar points for the Austin District

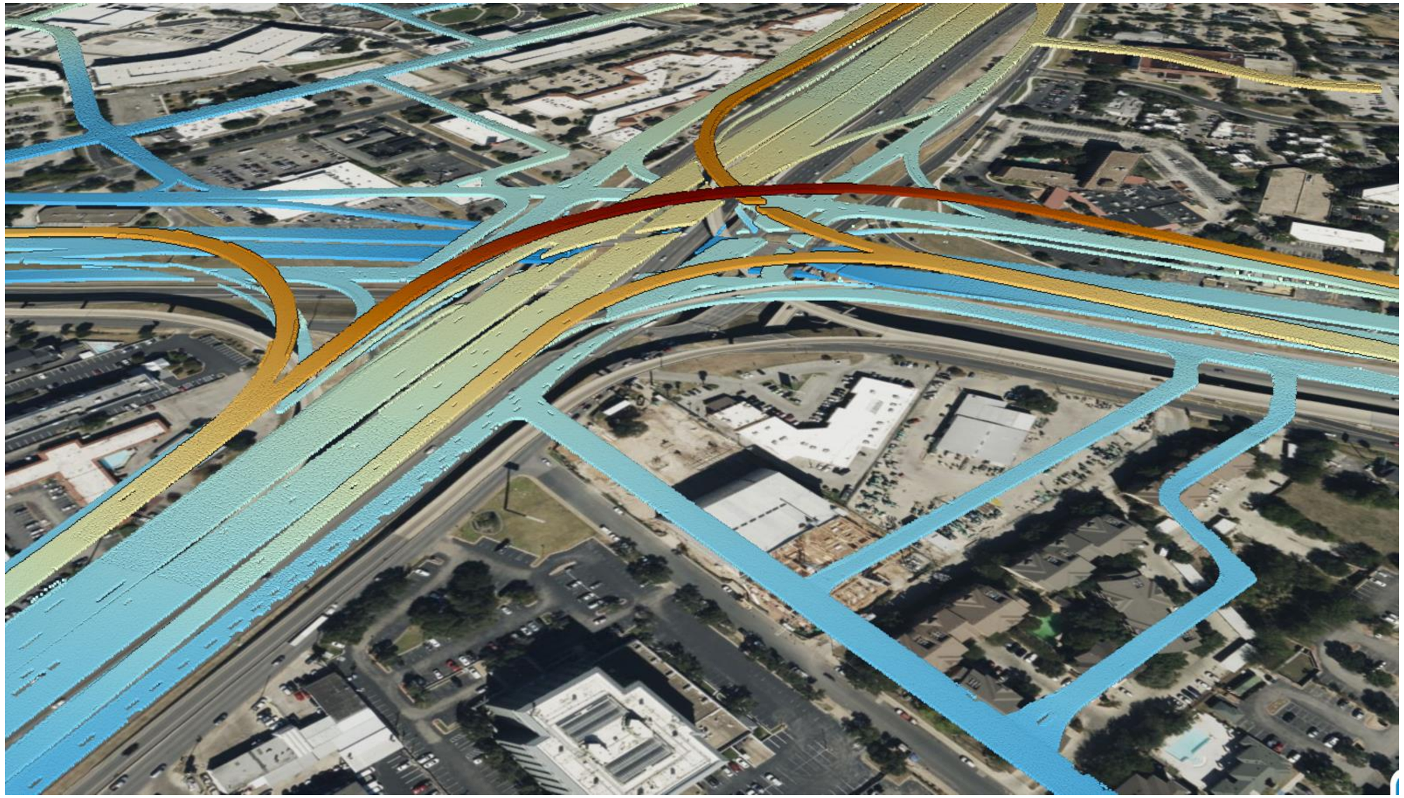
- By counties:
  - https://web.corral.tacc.utexas.edu/n
- By maintenance sections:
  - https://web.corral.tacc.utexas.edu/n





Results: road lidar points for the Austin District - copc

- All the road lidar tiles have the copc version
- Loadable and viewable on https://viewer.copc.io/



Summary: Lidar Data Processing Issues

- Incorrect projection information encoding in las
  - "PDAL: readers.las: Global encoding WKT flag not set for point format 6 - 10."
  - Solution
    - Input handling: find WKT info. in metadata
    - Output handling: header info may be carried over to output las. Explicitly override header info.
- Las version 1.0 in some lidar tiles in the LCRA lidar collections is no longer supported
  - "laspy.errors.FileVersionNotSupported: 1.0"
  - Solution: upgrade to version 1.1 in writing the road lidar tile
- Misclassification of road surface points
  - Current filtering rule: ground (2), bridge (17), and culvert (13 and 14). Some bridge areas may be classified as other classes or “Other”

Conclusion and Discussions

- GPU-acceleration made the computation of the Austin District feasible
- Scaling to all 25 TxDOT districts using the same computing environment is feasible (~200 hours)
- Road tiles can be contributed back to each participating lidar data collection
- Road tiles are published
  - 3D road shapes are proprietary data
- Next steps
  - Processing for all the districts
  - Road surface geometry fitting using road tiles
  - …

Acknowledgements

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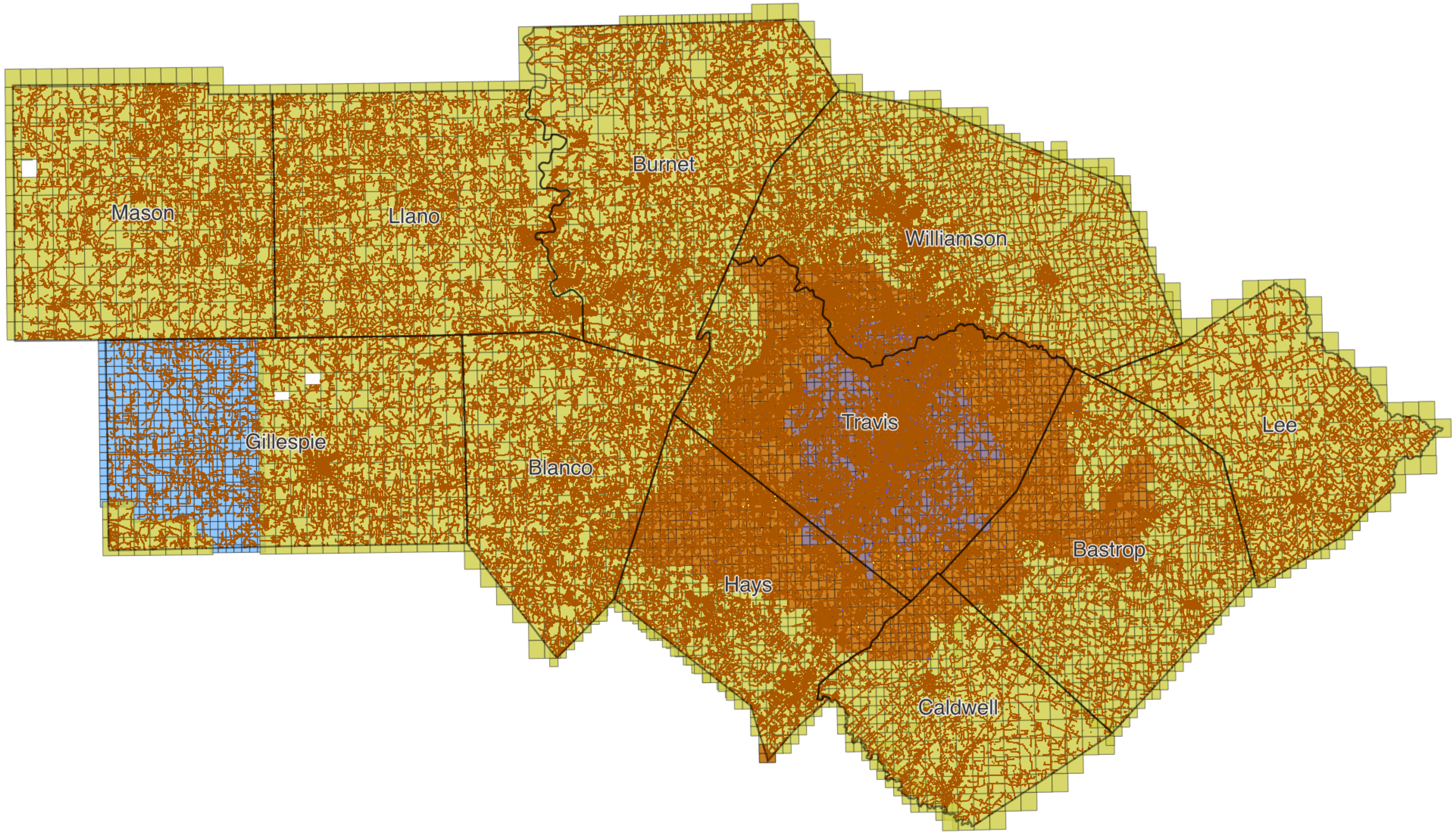
Disclaimer

Backup slides

Road lidar points for Austin District overlaid with lidar tile extents



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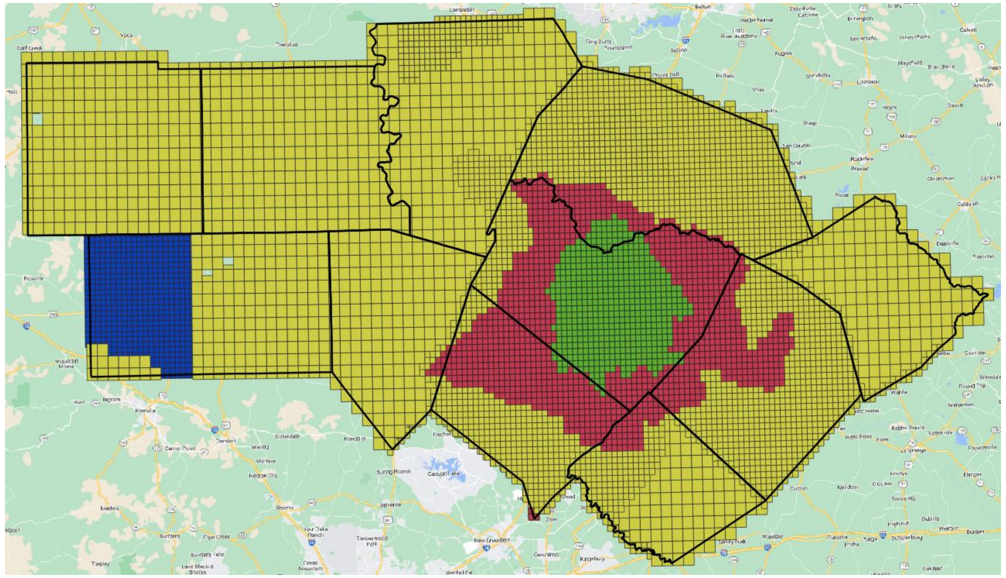
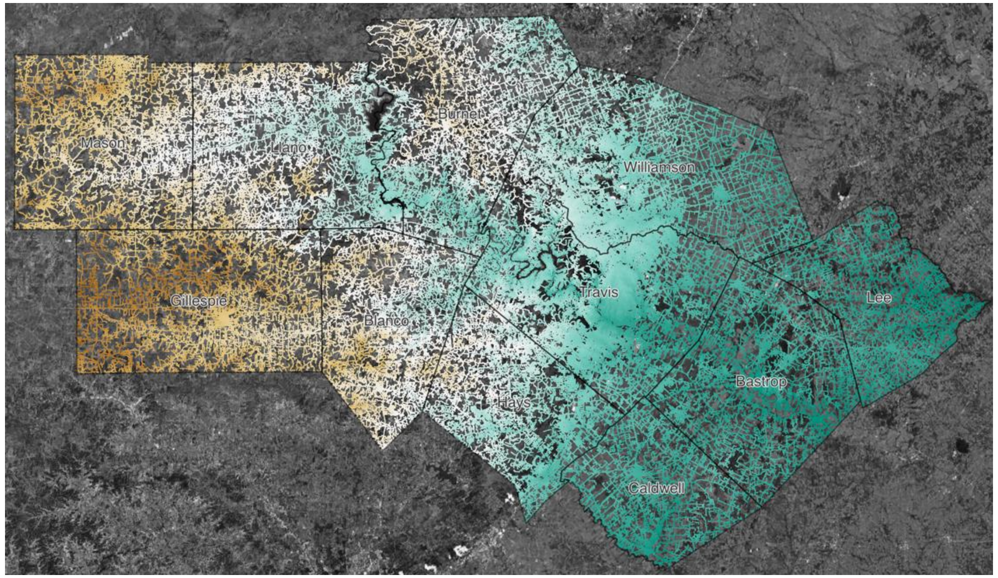
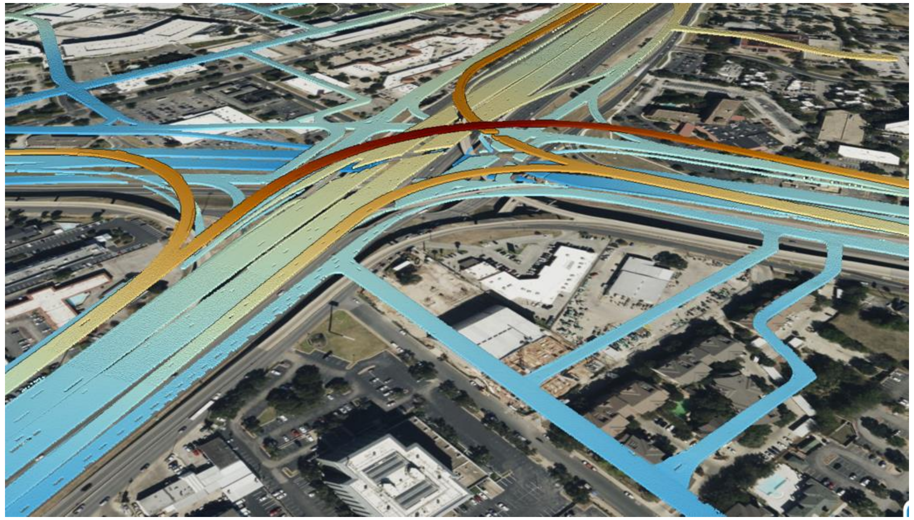


(a) Lidar data coverage



(b) Road lidar data product

(c) Road lidar details



(c) 3-D view of road lidar