

ASCENT Project 094



Probabilistic Unmanned Aircraft Systems (UAS) Trajectory and Noise Estimation Tool

Georgia Institute of Technology

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Cost Share Partner: Georgia Institute of Technology

Objective:

Develop a novel noise estimation method/tool that supports computation of noise resulting from the stochastic operation of Unmanned Aircraft Systems (UAS) and other upcoming vehicle concepts with irregular locations and operations in large numbers.

Project Benefits:

- A noise estimation method that can quickly evaluate the noise from large numbers of UAS vehicles that have changing locations and trajectories.
- This tool will help provide decision-makers UAS noise exposure likelihood distributions of where the noise would be located and identify mitigation solutions.

Research Approach:

- Literature Review
 - Sampling techniques for noise footprints
 - Surrogate modeling methods that are specific to noise
- Develop Integrated Probabilistic Noise Computation Methodology
 - Validate approach for speed and accuracy
 - Visualization of probabilistic noise distributions
 - Geospatial display of results
- Extend Existing Prototype Noise Engine Capabilities
 - Build on Ascent Project 9 developments
- Collaboration with Volpe/FAA Team
 - Potential Industry Collaborations

Major Accomplishments (to date):

- Project has not started

Future Work / Schedule:

- Explore reduced order methods for noise footprints as well as efficient probabilistic sampling techniques
- Develop validation and visualization methods
- Extend Prototype Noise Engine
- Explore Industry Collaborations

ASCENT Project 009



Geospatially Driven Noise Estimation Module

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Cost Share Partner: Georgia Institute of Technology

Objective:

Develop a novel geospatially driven noise estimation module to support computation of noise resulting from the operation of Unmanned Aircraft Systems (UAS) and other upcoming vehicle concepts.

Project Benefits:

- A GIS driven noise estimation module to evaluate the noise from large numbers of UAS vehicles.
- This tool will help provide decision-makers UAS noise exposure distributions as well as provide insight on where the noise would be located and identify mitigation solutions.

Research Approach:

- Literature Review and GIS Software Evaluation
- Investigate Emerging Computational Technologies
- Collaboration with ASSURE CoE Team at Mississippi State
 - UAS Source Noise Data Development
 - UAS Noise Computation Module
 - UAS Demand Studies
- Noise Computation Engine Integration

Major Accomplishments (to date):

- Delivered Review of GIS Software
- Noise Computation Engine Prototype
- Implementation of SAE-5534
- Cluster and GPU implementations

Future Work / Schedule:

- Continue benchmarking tests
 - Optimization of parallelization parameters
 - Alleviate bottlenecks
- Improved user interface
- Add more metrics as required
- Improve atmospheric attenuation
- Improve source noise modeling and data

Motivation & Background Information

Context

- Rapidly growing UAS market: projections at \$80 Billion by 2050
- Several emerging operators

Introducing UAS to the airspace brings unique requirements

- Increase in operations, potentially by orders of magnitude
- Smaller and therefore quieter vehicles
 - Relatively localized noise
 - Not necessarily loud but potentially annoying
 - No noise certification required
- UAS mostly do not operate at airports
 - Potentially operate in many non-traditional places
 - Day-to-day changes of locations and trajectories

Accordingly, innovative analysis approaches are needed

- AEDT currently focused on aircraft noise at vicinity of airports
 - UAS operations require large study areas at fine resolutions
- Novel concept of operations brings multiple sources of uncertainty
 - Uncertain staging locations
 - No fixed operational schedule, daily changes to operating locations



Urban Air Mobility (UAM) covers a wide range of potential applications, including eTaxi and drone delivery

UAS Noise Assessments require a proper treatment of uncertainties

Previous Accomplishments UAS Computation Module Development

Noise Engine

- Compute point source moving along trajectory segments
- Compute peak, time, and exposure-based metrics
- Noise metrics: exposure and peak metrics
 - Noise metrics suitable for UAM are still being researched and therefore subject to change → flexibility is required

Implementation Adaptable to Multiple Architectures

- Machine-agnostic implementation using the Dask framework
- Adaptable to various parallelization schemes
 - single node/multi-core
 - many nodes (networked/cloud)
 - MPI – Infiniband
 - GPU/ CUDA

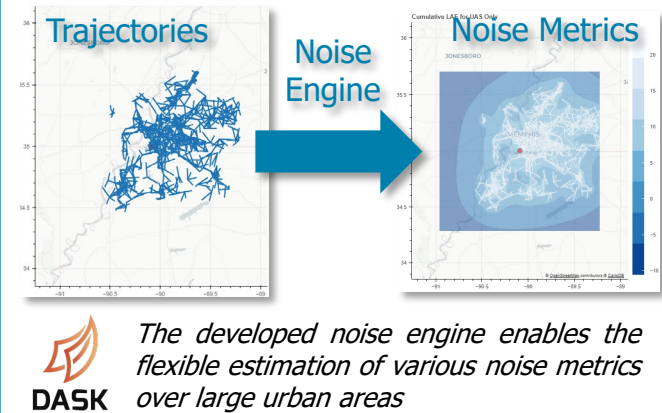
Graphical User Interface

- Map-based visualization of large-scale noise metric datasets
- Enabled by the bokeh/datashader/rioxarray libraries

Preliminary Monte-Carlo Study

- Ran 10,000 simulated days
- Relatively coarse grid (250k points), 100 deliveries/day
- Multiple weeks of CPU time on Georgia Tech's PACE cluster

Dask-Based Computation Module



Interactive Visualization



Recent Accomplishments

Atmospheric Absorption (SAE-5534) Model Implementation

- Computed noise metrics now account for more complex standardized atmospheric absorption

Support for GPU-Backed Computations and Scaling Study

- Noise engine was ported to allow execution on GPU, bringing significant runtime savings

Workflow Definition and Upgraded User Interface

- GUI was upgraded to match the step-by-step process for setting up and running analyses

Study of Interactions Between Trajectories

- Assumption that flights can be processed independently by the noise engine was verified

Uncertainty Propagation Leveraging GPU

- Monte-Carlo study was repeated on GPU, allowing to increase resolution and number of flights while reducing runtime to a fraction of the original study

UAS Computation Module capabilities were enhanced and expanded

Recent Accomplishments

GPU-Backed Computations

GPU Implementation

- Leverages Google's JAX computational framework for running transparently on GPU(s)

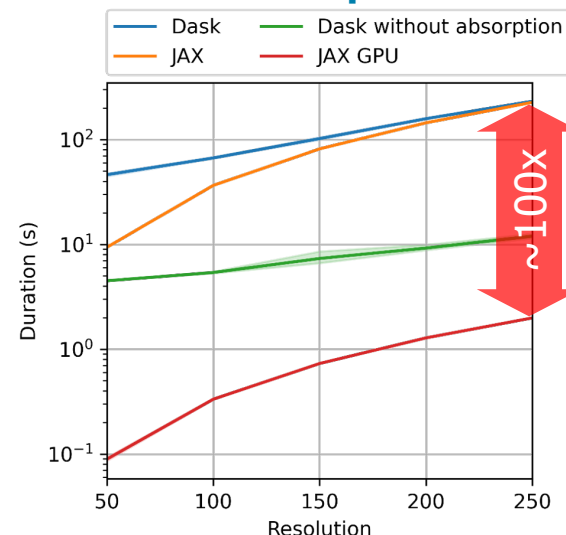
Step 1: CPU vs. GPU Comparison

- Using Tesla V100 (32GB)
- Observed ~100x speedup on large problems
- Depending on cloud service ~30x cost

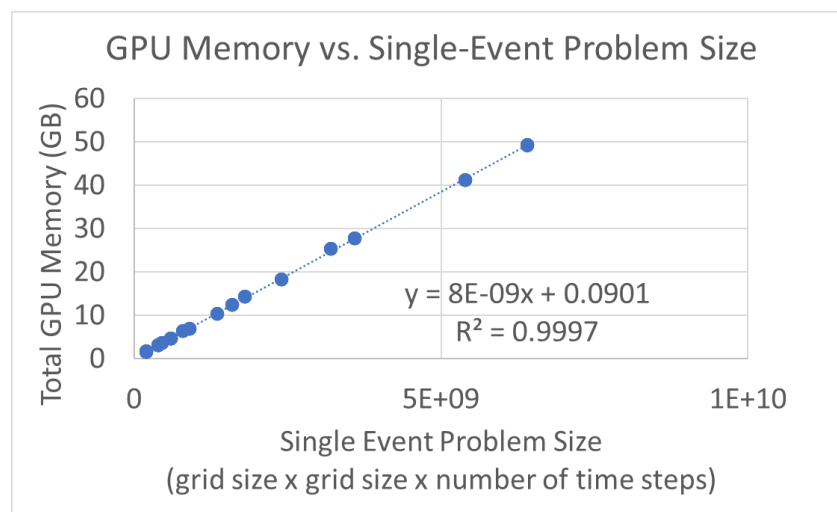
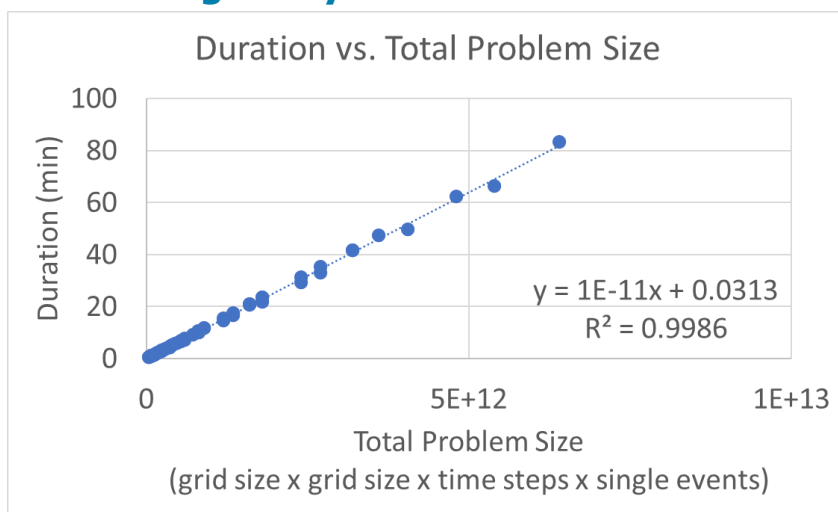
Step 2: Dual-GPU Scaling Study

- Analysis duration scales linearly with total problem size
- GPU memory is a fixed constraint: however, problems can be split into sequential or multi-GPU runs

CPU vs. GPU Comparison



GPU Scaling Study



Recent Accomplishments Upgraded User Interface

Newly Developed Features

- Simplified dashboard with straightforward design
- Map integration
- Integrated different metrics/data into drop down menu on map
- Trajectory input and generation with overlay toggle
- Users input for the location of hubs and delivery locations
- Vehicle noise characteristics library
 - Mode-based data (e.g., take-off/landing, delivery hover, cruise with/without payload)
- Input dialogs to input noise data for new UAS/UAM vehicles

Structured Workflow

Step 1: Specify Inputs

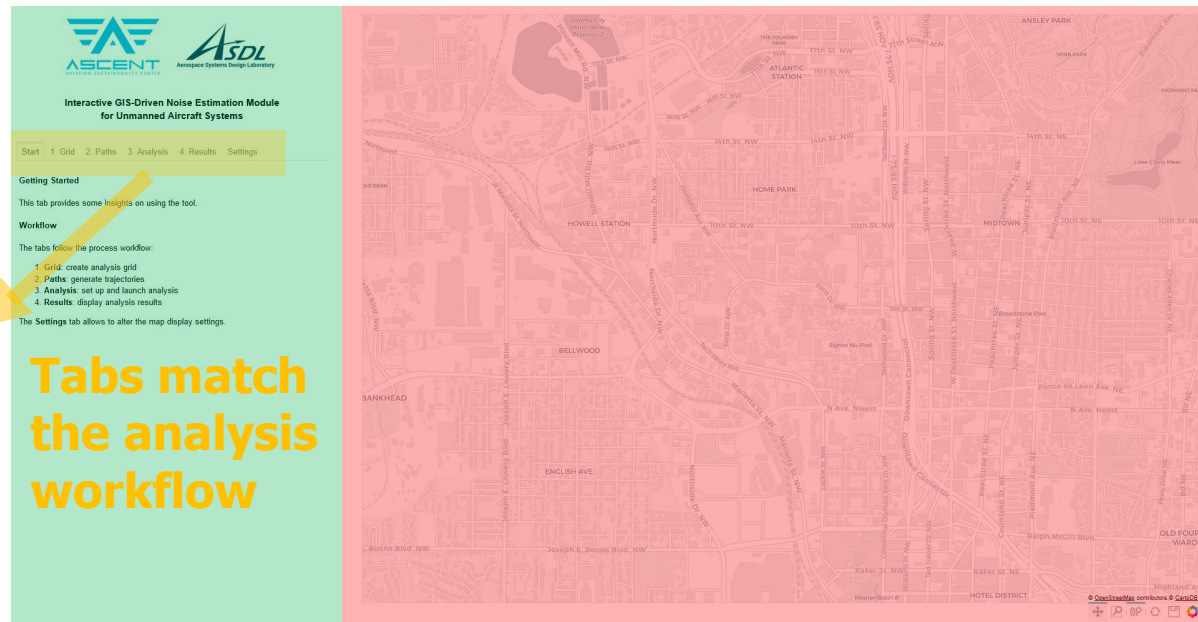
- Define Analysis Area
- Generate/retrieve trajectories
- Retrieve background noise

Step 2: Launch Analysis

- Choose backend
- Other analysis settings

Step 3: Visualize Results

- Select metric



Controls on the left-hand side, tab-based navigation

Map on the right-hand side

Recent Accomplishments

Interactions Between Simultaneous Flights (1/2)

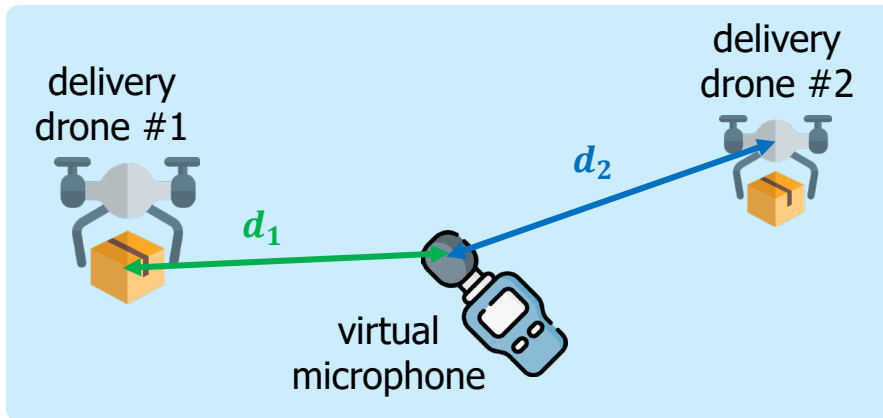
Motivation

- Noise engine does not account for possible concurrency of flights
- No impact on integrated noise metrics, but possible impact on $L_{A,max}$
- If multiple UAS fly nearby at the same time, the maximum noise level may be higher than either individual maximum

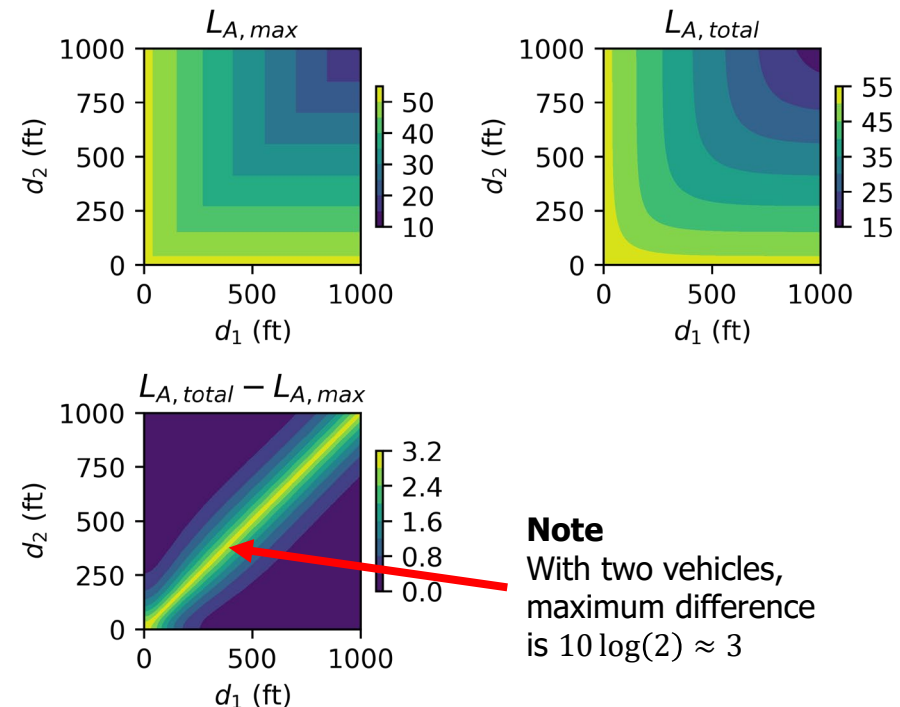
Study aimed at:

1. Characterizing the approximation made when concurrency is neglected
2. Estimating the frequency of situations where vehicles are close to each other

Step 1: considering two vehicles, start assessing approximated $L_{A,max}$ computation



Observation #1: multiple vehicles need to be at a similar distance from virtual microphone to see an impact on computed $L_{A,max}$ metric

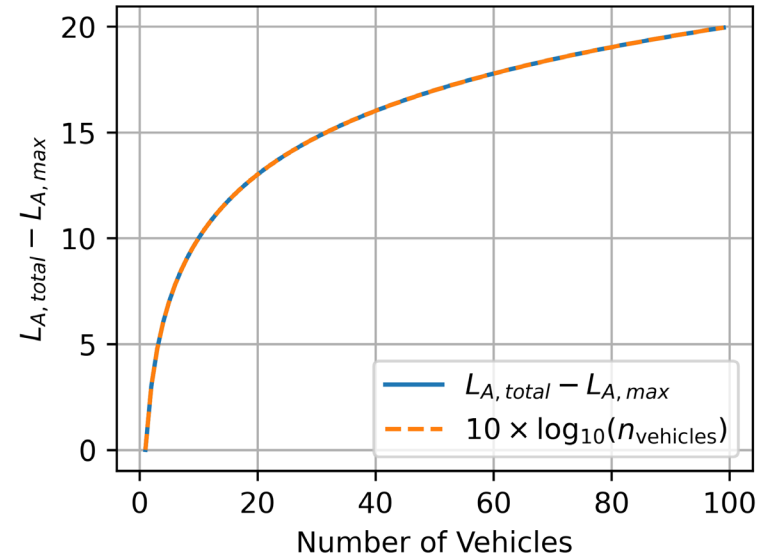
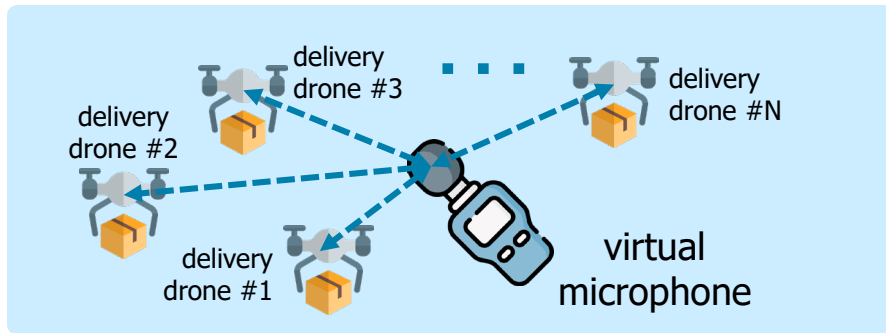


Recent Accomplishments

Interactions Between Simultaneous Flights (2/2)

Step 2: increased the number of nearby vehicles

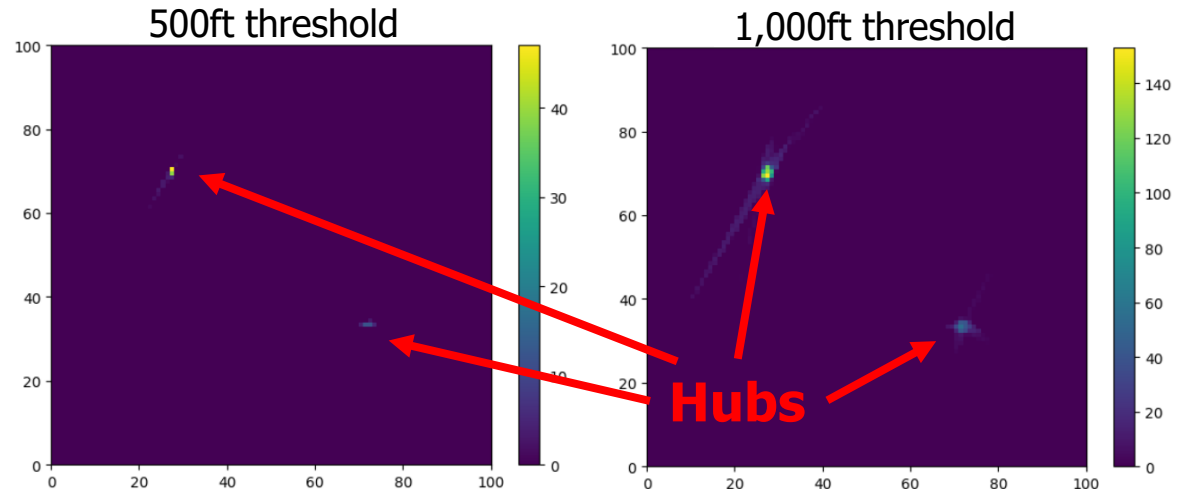
Observation #2: discrepancy between approximated $L_{A,max}$ and actual $L_{A,total}$ increases with the number of vehicles simultaneously close to virtual microphone



Step 3

- Simulated moderately dense traffic within a short timeframe
- 100 flights/1 hour/12mi×12mi area
- Figures show locations on map where two or more UAS are frequently close

Observation #3: For moderately dense traffic, impact of simultaneous flights is only visible at hubs



Recent Accomplishments

Probabilistic Assessment Using GPU (1/2)

UAS operations are subject to multiple sources of variability

- Daily individual flight trajectories are dependent on orders/demand
- Staging locations may change day-to-day (e.g., when using trucks for staging drones)
- Operator strategy on trajectory planning may include noise dispersion and altitude constraints to minimize noise

UAS operations should therefore be modeled as a stochastic process

- Annual average day metrics do not capture daily changes

Question: What is the likelihood of exceeding some threshold on any given day and at how many locations?

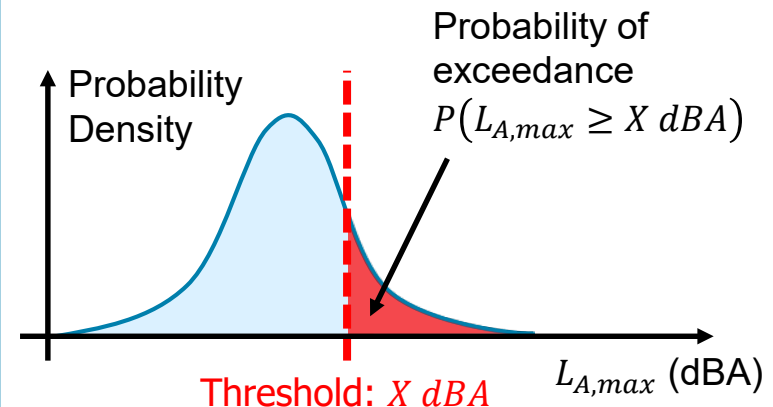
- Second attempt at a Monte-Carlo simulation, now taking advantage of GPU speedup
- Results are $P(L_{A,max} \geq X \text{ dBA})$, the probability for $L_{A,max}$ to exceed $X \text{ dBA}$
- Results are depicted as contours on a map of the study area
- The level X is varied, leading to different contour plots

Probabilistic Assessment Process

Step 1: generate daily random delivery trajectories for many days

Step 2: compute $L_{A,max}$ over the study area for each day

Step 3: overlay the results obtained on a map of the study area



Recent Accomplishments

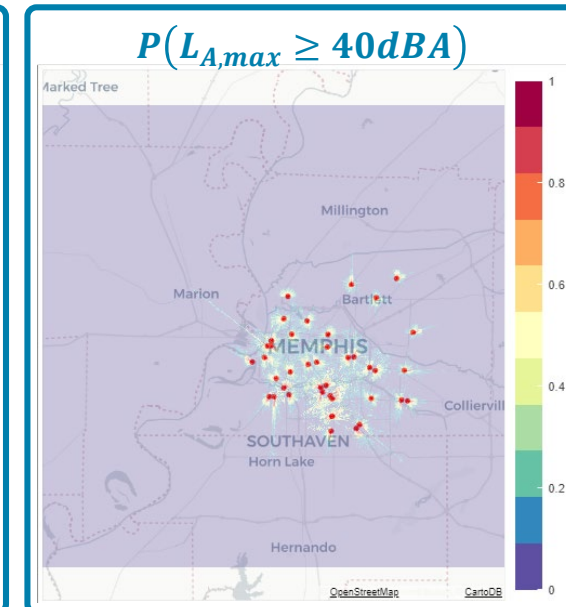
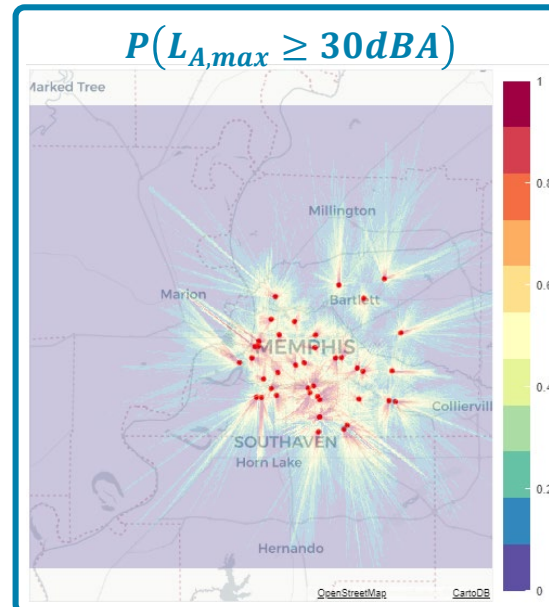
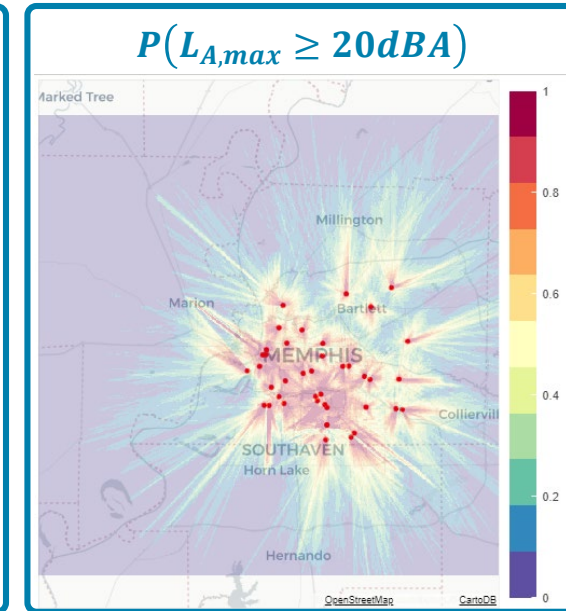
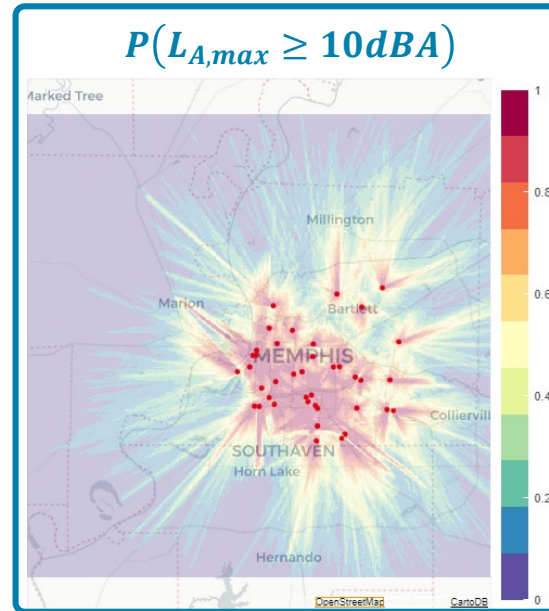
Probabilistic Assessment Using GPU (2/2)

Setup

- Study area covers Memphis, TN
 - 60mi x 60mi surface area
 - 41 warehouses
- Finer discretization
 - 1056x1056 cells
 - Each cell is 300ft x 300ft
- 500 deliveries per day
- 10,000 days
- Resulting problem size is ~20 times larger than first attempt
- Warehouses shown as red dots

Results

- High-probability area shrinks as threshold increases
- Ran in ~7 hours using 50 GPUs
- Each run takes ~2 minutes
- Runtime is orders of magnitude shorter than first attempt on CPU (hours instead of weeks)



Closeout Project 9

- Continue benchmarking tests
 - Increasing levels of UAS operations
 - Scaling of computational time
 - Cloud-based execution
- Improve source noise modeling and data

Start Project 94

- Define and characterize sources of uncertainty
- Explore stochastic noise modeling without huge computational expense
- Potential candidate approaches
 - Surrogate modeling for speeding up portions of the model
 - Dimension reduction to enable large-scale predictions