A Deep Learning Approach Using Social Media Data to Estimate Ground Risk of UAS in Urban Areas

Team: Jeffrey Pattison-PhD Candidate in Aerospace Engineering

Advisors: Dr. Michael Balchanos and Dr. Dimitri Mavris

Category: Assist with the Rapidly Evolving New and Novel Uses of the NAS

Georgia Tech

PATTENT

ASDL
Aerospace Systems Design Laboratory

Outline

- Problem Statement and Background
- Solution Definition
- Methodology
- Results
- Conclusion

Unmanned Aerial Systems (UAS) are the Future

Problem Statement and Background
Solution Definition
Methodology
Results
Conclusion

Delivery UAS[1]

- Lower cost of shipping
- Faster deliveries
- Fewer emissions
- Shorter routes

UAS as a First Responder[2]

- Quicker response time
- Cheaper than sending an officer
- Provides crucial information to responders

Construction and Inspections

- Easily inspect hard to reach infrastructure
- Quickly assess damages for insurance claims

These industries, and many more, are beginning to realize the potential UAS have

1. R. Ifteiha. "The Delivery Drone-Friend or Foe to Transportation and Logistics Workers?" Omnitracs 2020.
2. Photo by Adriana Heldiz.

Significant Limitations on UAS Use

- There are several safety concerns around UAS entering the National Airspace
- Commercial UAS pilots must follow FAA Part 107 rules, including:
  - Avoid manned aircraft
  - Keep the UAS in sight
  - No sustained flights over people
- Regulations on flights over people complicate UAS operations
  - People are dynamic, constantly on the move
  - Hard to predict
- Some areas have been slow to adopt UAS in part due to risk to people on the ground

Safety concerns for people on the ground drive the need for risk assessment and mitigation techniques to fully enable UAS operations

No Flights Over People and Stadiums

No Flights Near Airports and No-Fly Zones

Avoid Tall Buildings and Obstacles

UAS Use for Georgia Tech Police Department

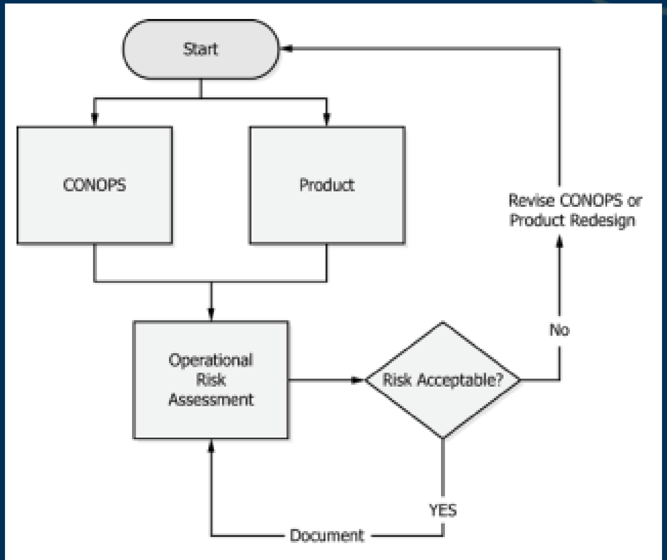
- Georgia Tech Police Department (GTPD) has shown interest in starting a UAS program
- ASDL has collaborated with them in the past with their Concept of Operations (CONOPS)[1]
  - Risk assessment and mitigation need to be incorporated into the CONOPS to ensure safety and regulatory compliance
- Georgia Tech campus very dynamic due to classes and events
  - Need to account for dynamic student population for UAS risk assessment

[2]

[1] S. Ravoory, C. Eggert. "Unmanned Aerial System-based Tactical Operations for Supporting Emergency Response in Campus Communities." 2021 AIAA SciTech Forum
[2] Dylan Callaghan-Croley. "Georgia Tech Football: Jackets Update Schedule for 2021 and 2023"

Manned vs Unmanned Aircraft Risk Assessment

- Risk always present, despite mitigation attempts
- Manned aircraft are required to operate within target level of safety
  - Historical data drives risk assessment for manned aircraft[1][2]
- UAS need target levels of safety for operation and certification as well[3]
  - UAS have little comparable historical data to perform similar risk assessment[4]
  - Difficulty with risk assessment without historical data



Operational Risk Assessment[5]

Likelihood		Severity: No Safety Effect 5	Minor 4	Major 3	Hazardous 2	Catastrophic 1
No Probability Requirement	A	Low	Medium	High	High	High
Probable	B	Low	Medium	High	High	High
Remote	C	Low	Medium	Medium	High	High
Extremely Remote	D	Low	Low	Medium	Medium	High
Extremely Improbable	E	Low	Low	Low	Medium	High* / Medium

*Risk is high when there is a single-point or common cause failure

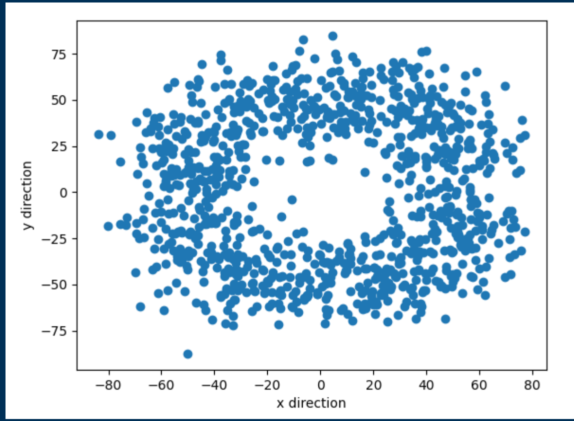
Risk Matrix[6]

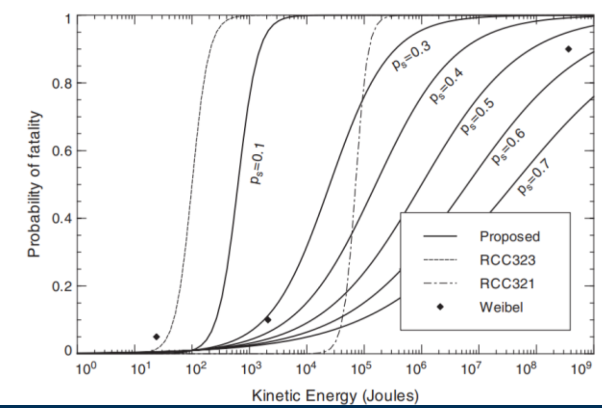
[1] T. Perez et al., "Risk-Management of UAS Robust Autonomy for Integration into Civil Aviation Safety Frameworks"
[2] E. Ancel. "Real-Time Risk Assessment Framework for Unmanned Aircraft System (UAS) Traffic Management" 2017
[3] K. Dalamagkidis, On Integrating Unmanned Aircraft Systems into the National Airspace System. SpringerLink, 2009, ISBN: 978-90-481-2096-3.
[4] J. Luiz de Castro Fortes et al. "Safety Analysis for UAS Operation Using Stochastic Fast-Time Simulation"
[5] J.Larrow. "Building your Operation Risk Assessment". FAA UAS Symposium
[6] L. Barr et al. "Preliminary Risk Assessment for Small Unmanned Aircraft Systems" 2017

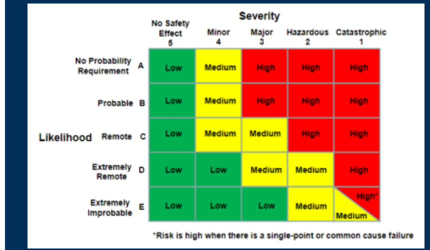
Physics-Based Model for UAS Risk Assessment

- In the absence of historical data, modeling and simulation methods have become the next best option for ground risk assessment[1]
- State of the art modeling and simulation methods for ground risk assessment are physics-based
  - Ground risk measured as expected number of fatalities for a flight (fatalities/flight hour)
  - Acceptable ground risk usually 10^{-7} to 10^{-6} fatalities/flight hour[2][3] for UAS

- Mass
- Speed
- Frontal Area
- Altitude







Likelihood		Severity: No Safety Effect 5	Minor 4	Major 3	Hazardous 2	Catastrophic 1
No Probability Requirement	A	Low	Medium	High	High	High
Probable	B	Low	Medium	High	High	High
Remote	C	Low	Medium	Medium	High	High
Extremely Remote	D	Low	Low	Medium	Medium	High
Extremely Improbable	E	Low	Low	Low	Medium	Medium / High*

*Risk is high when there is a single-point or common cause failure

Initial Conditions → Probable Impact Area → Expected Fatality Rate[2] → Assess the Results

Common Ground Risk Assessment Method Found in Literature

[1] J. Luiz de Castro Fortes et al. "Safety Analysis for UAS Operation Using Stochastic Fast-Time Simulation"
[2] K. Dalamagkidis. On Integrating Unmanned Aircraft Systems into the National Airspace System.
[3] S. Primatesta, A. Rizzo, and A. la Cour-Harbo, "Ground risk map for unmanned aircraft in urban environments," Journal of Intelligent and Robotic Systems: Theory and Applications, vol. 97, pp. 489–509, 3-4 Mar. 2020

Physics-Based Model for UAS Risk Assessment: Probable Impact Locations

Problem Statement and Background

Solution Definition

Methodology

Results

Conclusion

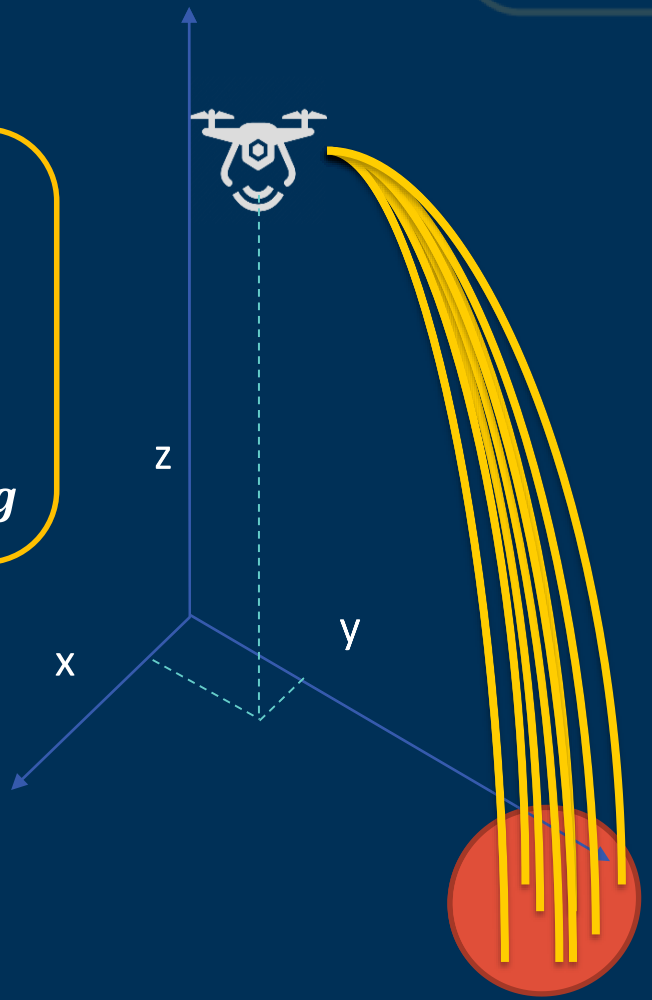
- Mathematical models are used to simulate trajectories for various descent types for a rotorcraft UAS[1]
  - Ballistic descent
  - Uncontrolled glide
  - Parachute descent
- Ground risk is dominated by ballistic descent[1]
- Using initial conditions, find impact area given governing equations[1]
  - To account for UAS uncertainties, need to simulate descent several times

Ballistic Descent

$$m\ddot{x} = -\frac{1}{2}\rho|\dot{x}|\dot{x}C_dA$$

$$m\ddot{y} = -\frac{1}{2}\rho|\dot{y}|\dot{y}C_dA$$

$$m\ddot{z} = -\frac{1}{2}\rho|\dot{z}|\dot{z}C_dA - mg$$



Initial Conditions → Probable Impact Area → Expected Fatality Rate → Assess the Results

1. [1] S. Primatesta, A. Rizzo, and A. la Cour-Harbo, "Ground risk map for unmanned aircraft in urban environments," Journal of Intelligent and Robotic Systems: Theory and Applications, vol. 97, pp. 489–509, 3-4 Mar. 2020

Physics-Based Model for UAS Risk Assessment: Estimating Fatality Rate

Fatality Rate f_F [1][2]

$$f_F = A_{exp} D_p P(fatality|exposure) f_{gia}$$

$$A_{exp} = \pi(r_p + r_{uas})^2 \sin(\gamma) + 2(r_p + r_{uas})(h_p + r_{uas})\cos(\gamma)$$

D_p

$$P(fatality|exposure) = \frac{1}{1 + \left(\sqrt{\frac{\alpha}{\beta}}\left[\frac{\beta}{E_{imp}}\right]^{\frac{1}{p_s}}\right)}$$

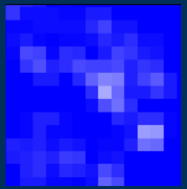
f_{gia}

Area Exposed During Crash (A_{exp})

- Radius of Person r_p
- Radius of UAS r_{uas}
- Height of a person h_p
- Impact angle γ

Population Density (D_p)

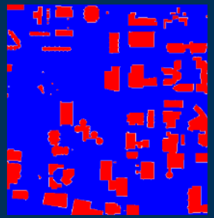
- Number of people per area



Population Density

Probability of Fatality Given Exposure [1][2]

- Impact Energy Required for fatality of 50% if $p_s = 0.5$ (α)
- Energy at Impact E_{imp}
- Sheltering Factor p_s
- Impact Energy Required for fatality of 50% if $p_s \to 0$ (β)



Building Shelter

Shelter	Sheltering Factor p_s
No Obstacle	0.0001
Trees and Low Buildings	5

Ground Impact Failure Rate [1][2]

- Assumed a constant $10^{-6} h^{-1}$

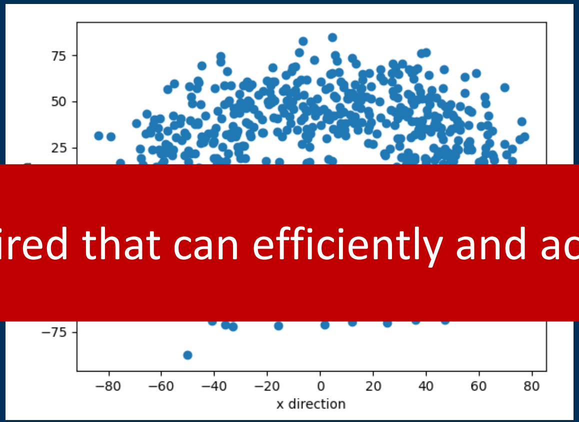
Initial Conditions → Probable Impact Area → Expected Fatality Rate → Assess the Results

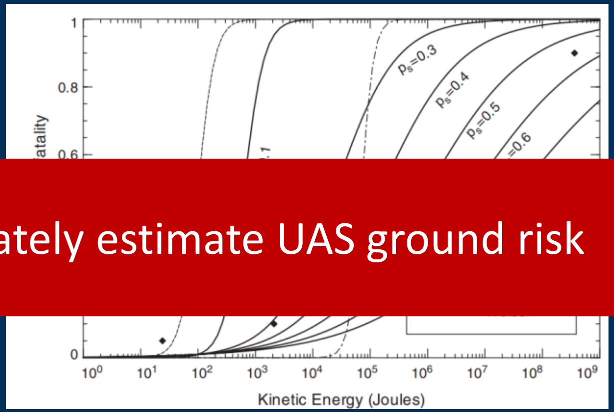
1. [1] Primatesta, Stefano. Et al. "An Innovative Algorithm to Estimate Risk Optimum Path for Unmanned Aerial Vehicles in Urban Environments." International Conference on Air Transport. 2018.
2. [2] Dalamagkidis, K., Valavanis, K.P., Piegl, L.A., 2011. On integrating unmanned aircraft systems into the national airspace system: issues, challenges, operational restrictions, certification, and recommendations. volume 54. springer science & Business Media.

The Limitations of the Physics-Based Model

- High-fidelity, probabilistic solutions mentioned can become computationally expensive and time consuming
  - Provide best estimation for ground risk
  - Not suitable for rapidly changing environments like cities

Altitude





Initial Conditions → Probable Impact Area → Expected Fatality Rate[1]

New methods are required that can efficiently and accurately estimate UAS ground risk

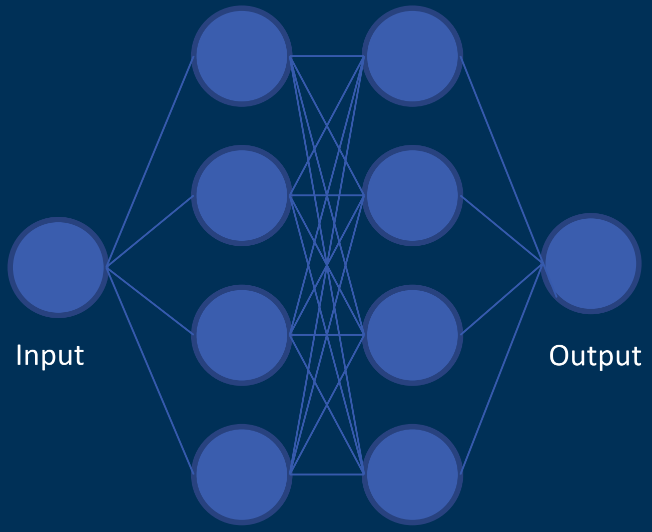
The Physics-Based Model for Ground Risk Quantification

[1] Dalamagkidis, K., Valavanis, K.P., Piegl, L.A., 2011. On integrating unmanned aircraft systems into the national airspace system: issues, challenges, operational restrictions, certification, and recommendations. volume 54. springer science & Business Media
[2] Ancel, E, et atl. "Real-time Risk Assessment Framework for Unmanned Aircraft System (UAS) Traffic Management (UTM)" 17th AIAA Aviation Technology, Integration, and Operations Conference. 2017.

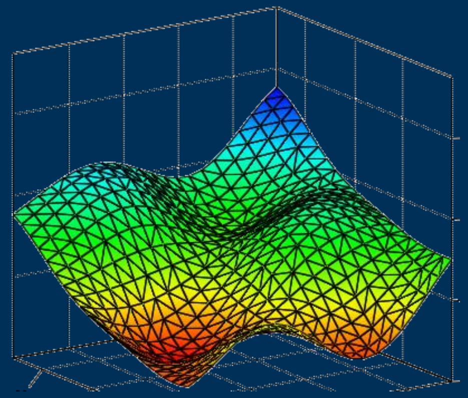
Machine Learning and Surrogate Modeling

- Some engineering systems are computationally expensive to evaluate
- Surrogate modeling and machine learning methods are designed to approximate expensive functions[1]
  - Tradeoff accuracy for efficiency
- Examples of surrogate models include
  - Response surfaces
  - K-nearest neighbor
  - Random forest
  - Neural networks
- Some machine Learning models require data for training
  - Can rely on the physics-based models to generate data

Objective: Use Machine Learning techniques to estimate UAS ground risk more efficiently using a high fidelity physics-based model to generate training data



An Artificial Neural Net

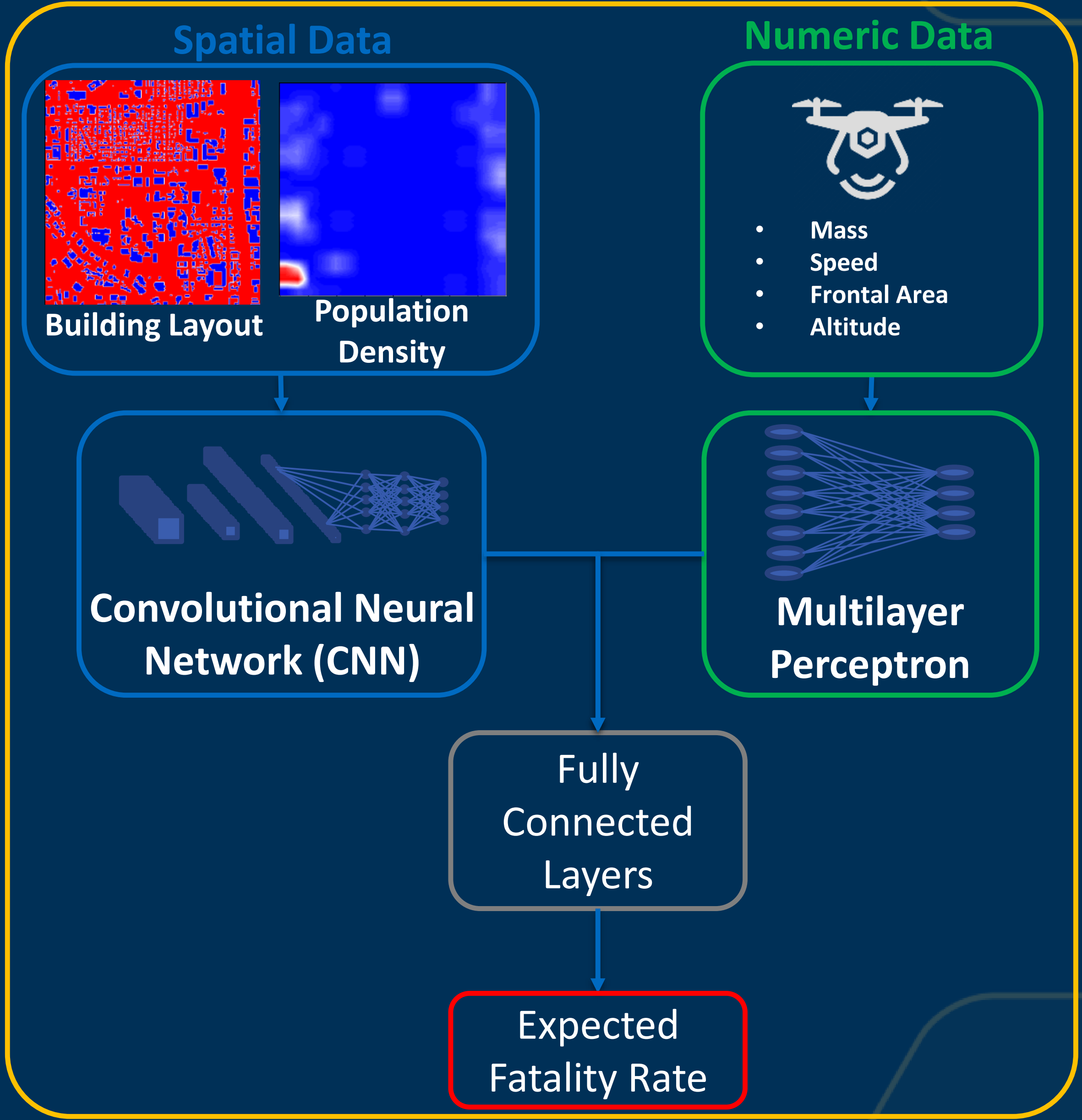


A Response Surface

[1] Graeme J. Kennedy, Brian German. "AE6310: Optimization for the Design of Engineered Systems Surrogate Modeling" 2020.

Machine Learning Architecture for UAS Risk Assessment

- Ground risk dependent on UAS characteristics affecting descent trajectory and impact energy
  - Mass
  - Frontal area
  - Speed
  - Altitude
- Spatial data also a major component for estimating ground risk
  - Population density
  - Shelter factor
- Proposed solution for UAS ground risk assessment needs to account for:
  - Numerical data
  - Spatial data



Proposed Machine Learning Solution[1]

[1] A. Rosenbrock, "Keras: Multiple Inputs and Mixed Data" pyimagesearch. 2019. https://pyimagesearch.com/2019/02/04/keras-multiple-inputs-and-mixed-data/

Data Collection: UAS Parameters

- For robustness, need to estimate risk for a variety of combinations of UAS parameters
  - Ranges for UAS parameters found based on common UAS used commercially
- Can use a Latin Hypercube Design of Experiments (DoE) to explore the design space
  - Creates points evenly spread throughout the design space[1]
- 248,000 UAS combinations created using the Latin Hypercube DoE

Property	Min Value	Max Value
Mass (kg)	2	9
Frontal Area (m^2)	0.347	0.81
Horizontal Speed (m/s)	5	35
Initial Altitude (m)	15	140

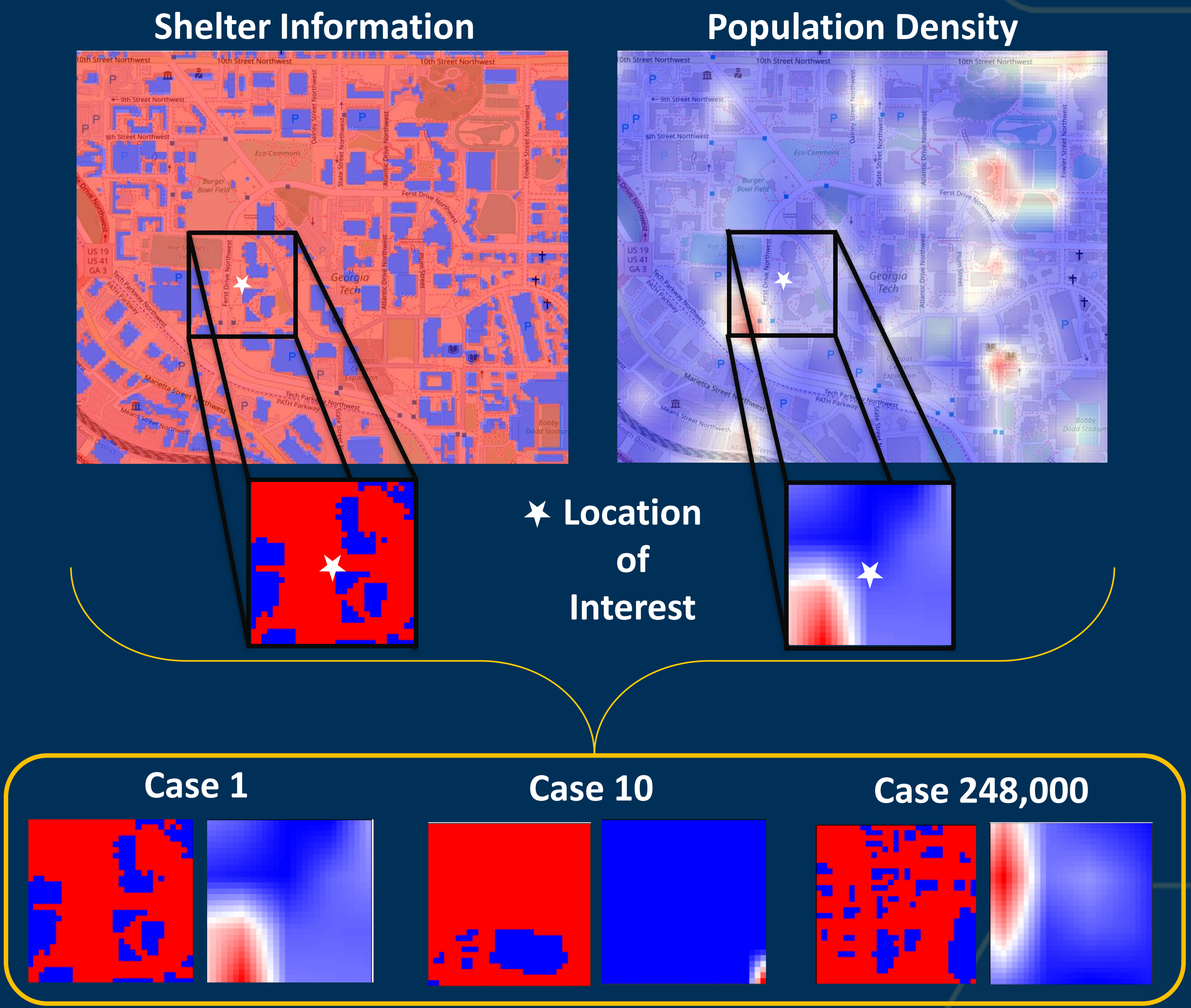
Latin Hypercube Design of Experiments

Property	Case 1	Case 2	Case 3	…	Case 248,000
Mass (kg)	8.25	2.05	8.83	…	4.56
Frontal Area (m^2)	0.41	0.66	0.70	…	0.77
Horizontal Speed (m/s)	18.38	14.95	7.29	…	5.73
Initial Altitude (m)	24.36	60.30	70.75	…	83.95

[1] R. Myers. "Response Surface Methodology Third Edition" John Wiley and Sons, Inc. 2009

Data Collection: Spatial Information

- Use campus of Georgia Tech as example area
    - Discretize campus into 10m x 10m cells
    - Each cell is a unique location for risk assessment
- Buildings provide information on appropriate shelter factor to use
    - Building locations obtained from open source OpenStreetMap[1]
- High-resolution population density obtained from LandScan[2][3]
    - 90m x 90m resolution
- Extract 29 cell x 29 cell areas for each of the 248,000 cases at various locations



[1] OpenStreetMap contributors, "Planet dump retrieved from https://planet.osm.org" 2017. URL: https://www.openstreetmap.org
[2] Oak Ridge National Laboratory LandScan Database URL:https://web.ornl.gov/sci/landscan
[3]J. Breunig et. al. "Modeling Risk-Based Approach for Small Unmanned Aircraft Systems" The MITRE Corporation. 2018

Data Collection: Population Density Estimates with Social Media

Problem Statement and Background

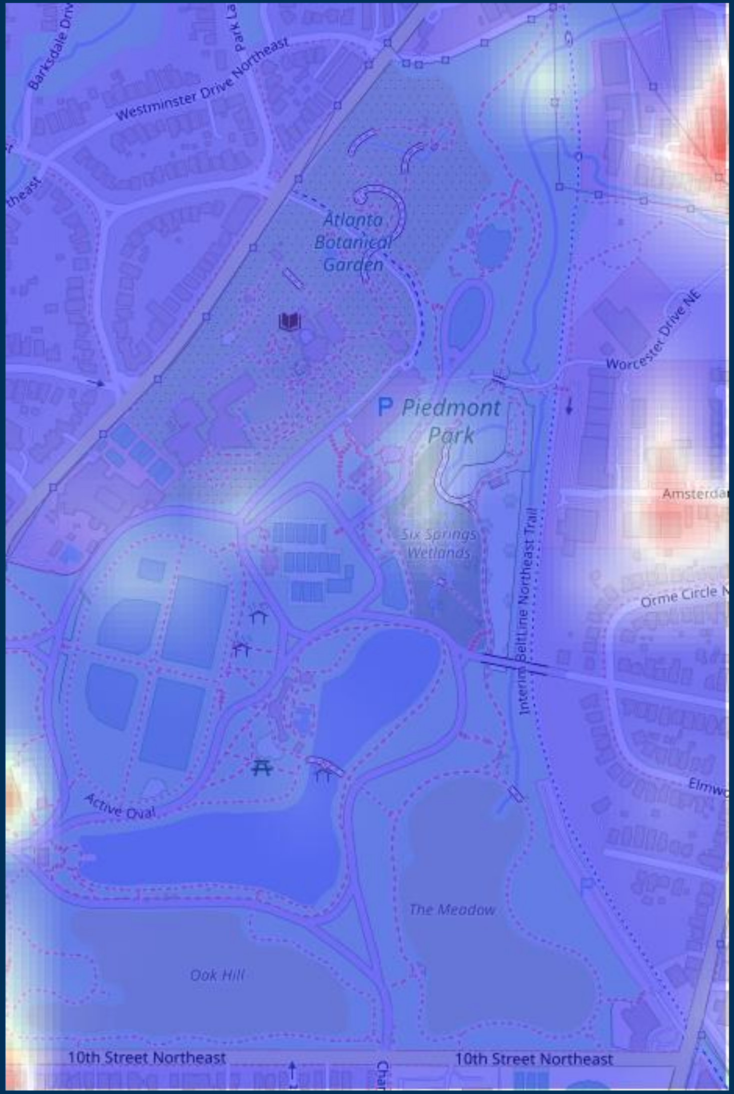
Solution Definition

Methodology

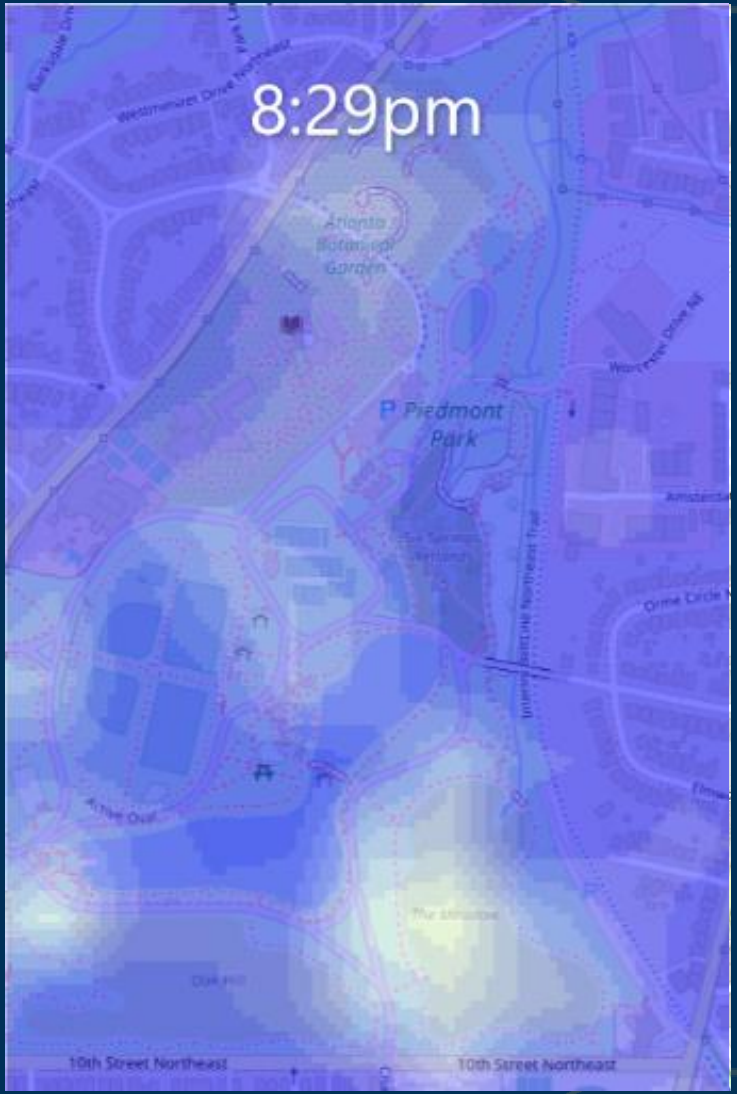
Results

Conclusion

- Various papers rely on the LandScan database for risk estimations[1][2][3]
- LandScan can provide averages for daytime and nighttime
  - Fails to account for anomalous events like concerts, festivals, etc.
- Can rely on social media activity to supplement historical data
  - Useful for capturing anomalous events not accounted for



LandScan Population Density Estimate



Social Media Activity During the Atlanta Dogwood Festival

Georgia Tech
Aerospace Systems Design Laboratory

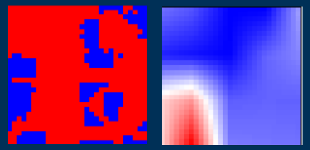
[1] Gobin, B. "Quantitative Approach and Departure Risk Assessment for Unmanned Aerial Systems" Thesis submitted to Virginia Polytechnic Institute and State University. 2020.
[2] Adie, D. "Quantitative Approach and Departure Risk Assessment for Unmanned Aerial Systems (QUADRA)" " Thesis submitted to Virginia Polytechnic Institute and State University. 2022.
[3]J. Breunig et. al. "Modeling Risk-Based Approach for Small Unmanned Aircraft Systems" The MITRE Corporation. 2018

Training the Machine Learning Model

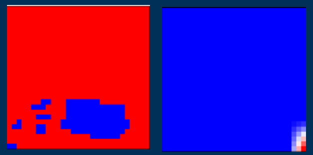
Property	Case 1	Case 2	Case 3	...	Case 248,000
Mass (kg)	8.25	2.05	8.83	...	4.56
Frontal Area (m^2)	0.41	0.66	0.70	...	0.77
Horizontal Speed (m/s)	18.38	14.95	7.29	...	5.73
Initial Z Position (m)	24.36	60.30	70.75	...	83.95

Numeric Data

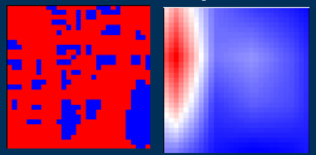
Case 1

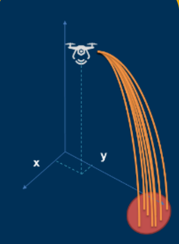


Case 10

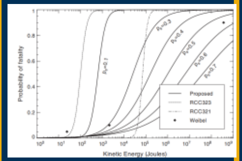


Case 248,000





Determine Probable Impact Locations

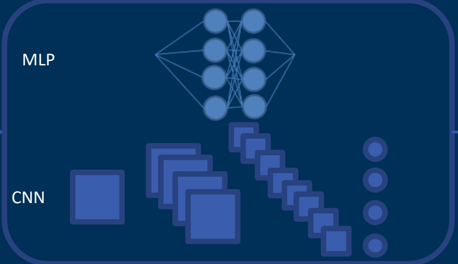


Find Fatality Rate for Data Point

Input Data

Output Data

Training Data



Machine Learning Model

Machine Learning Model Performance

Random Search

	Number of Layers	Min Number of Neurons per Layer	Max Number of Neurons Per Layer
Multi-Layer Perceptron	2	4	100

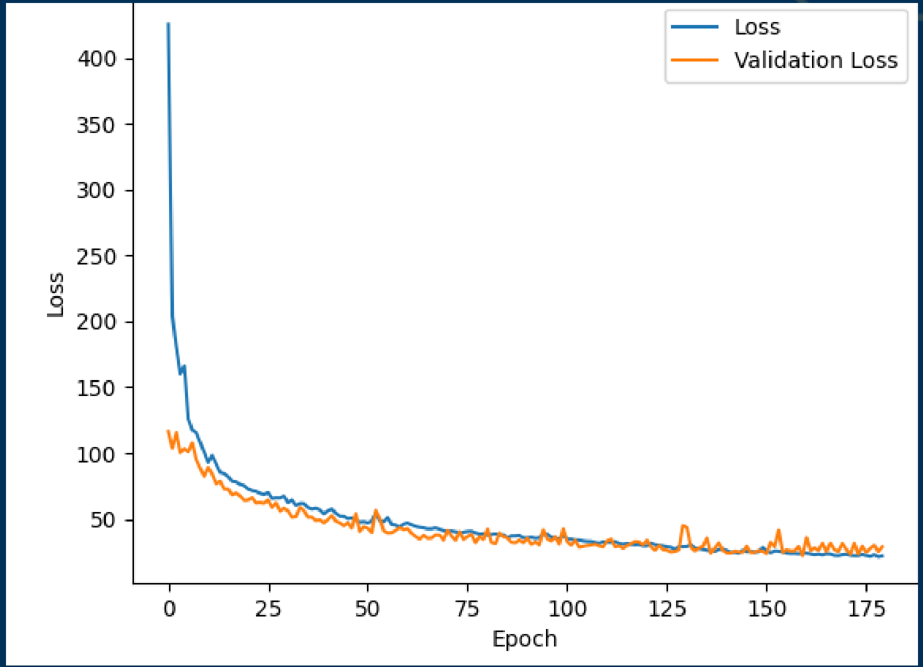
	Number of Convolutional Layers	Min Number of Filters per Convolutional Layer	Max Number of Filters per Convolutional Layer
Convolutional Neural Net	2	4	128

Machine Learning Model Architecture Parameters

Machine Learning Training Results

- Problem Statement and Background
- Solution Definition
- Methodology
- Results
- Conclusion

- Mean Absolute Percent Error (MAPE) used as the cost function for training
- Common risk values $O(10^{-7})$ or $O(10^{-6})$ fatalities per flight hour
  - 1 fatality every 10,000,000 hours (1,140 years)
  - 1 fatality every 1,000,000 hours (114 years)

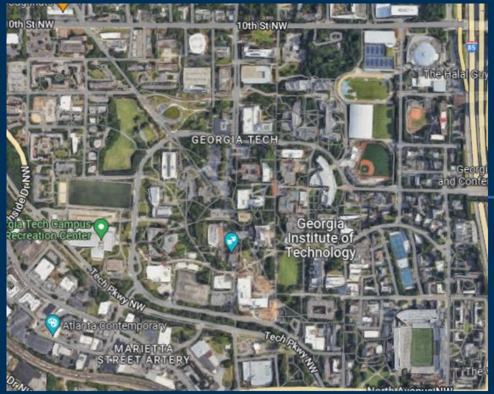


Best Model Training Summary

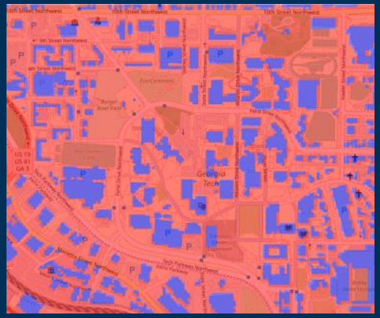
	Training Loss	Validation Loss
Mean Absolute Percent Error (MAPE)	16%	22%

22% error is the difference between 0.78 fatalities ~100 years vs 1 fatality ~100 years

Machine Learning Model vs Physics-Based Model Risk Maps



Georgia Tech Campus

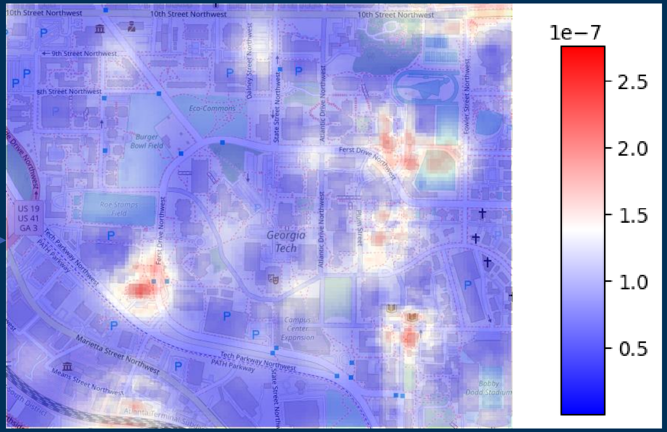


Building Layouts

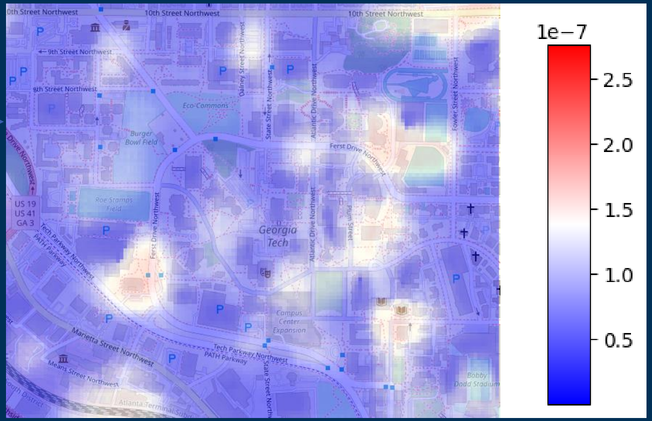
Population Density

- Mass: 6 kg
- Cross Section Area: 0.6 m^2
- Speed: 25 m/s
- Altitude: 35 m

Model Inputs



Physics-Based Model Results



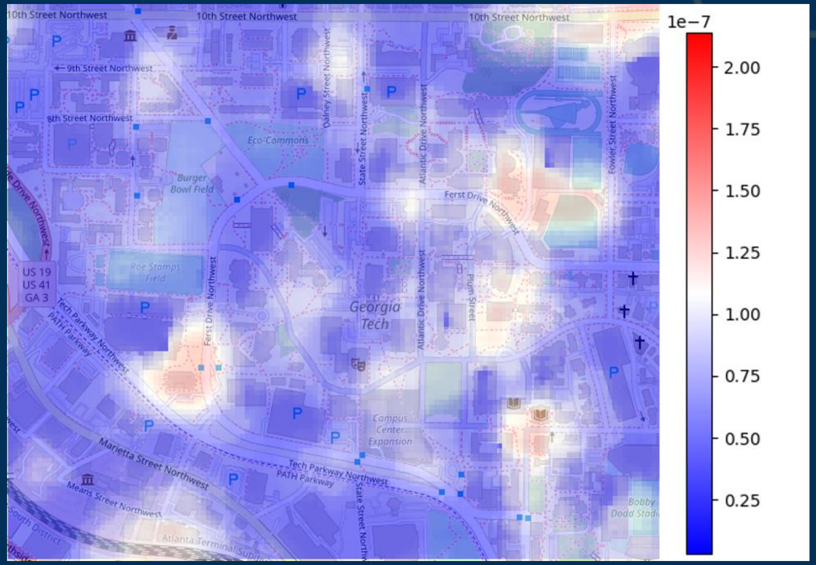
Machine Learning Model Results

The Machine Learning model was able to produce the risk map with a MAPE of 19% compared to the physics-based results

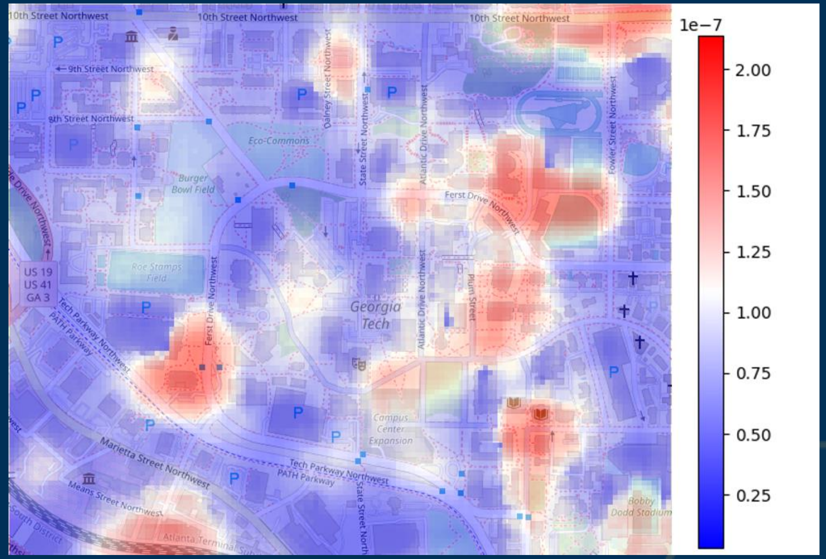
Rapidly Generating Risk Maps

- Time to calculate a risk map decreases from hours to seconds using the Machine Learning model
- Allows for generating risk maps for a variety of UAS characteristics and operating conditions quickly
  - Account for rapidly changing population densities

Rapid generation of risk maps can assist in generating safe routes

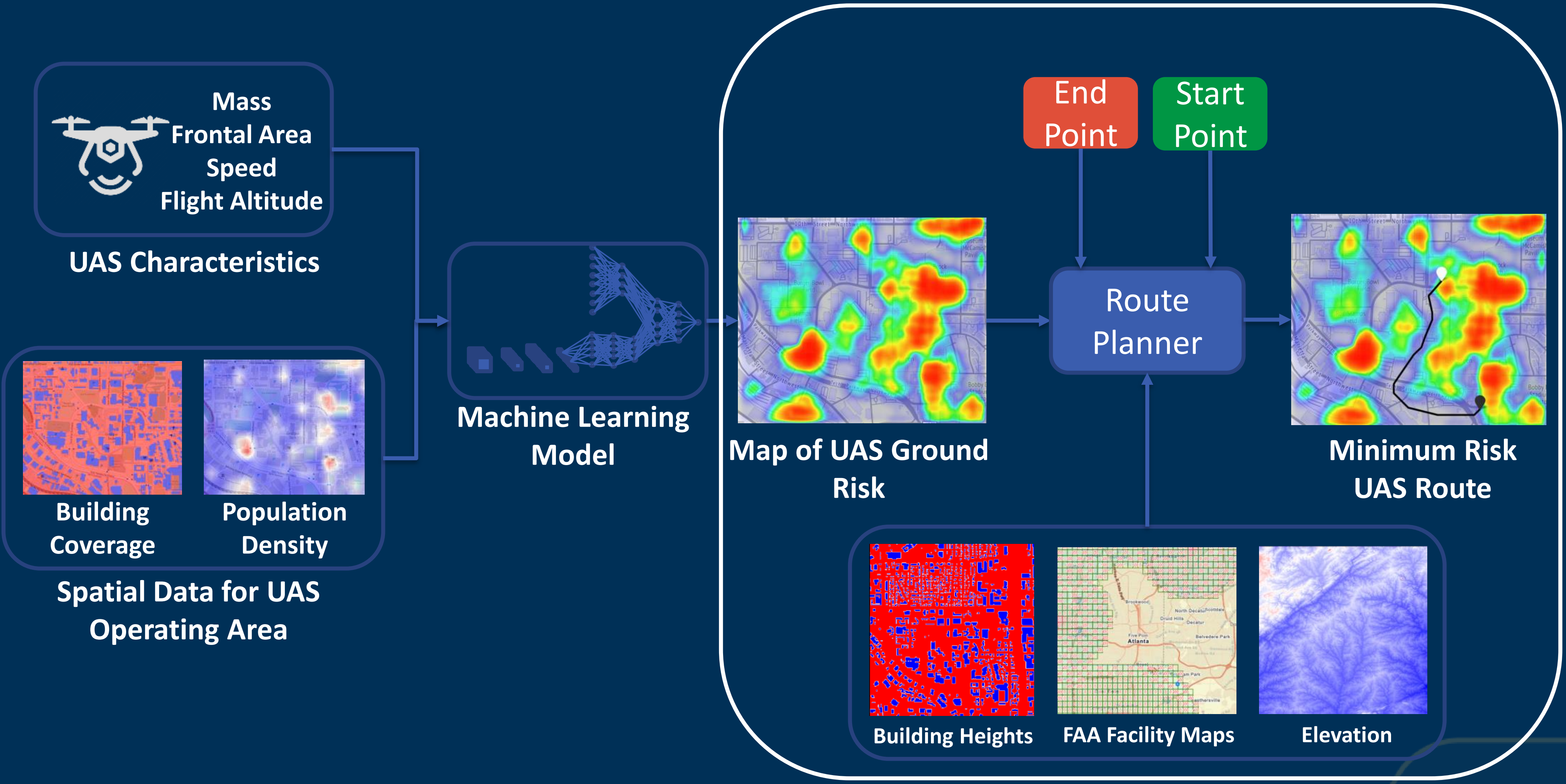


Mass: 2kg,Cross-Sectional Area: 0.4m^2, Speed:25m/s, Altitude:35m



Mass: 8kg, Cross-Sectional Area: 0.75m^2, Speed: 30m/s, Altitude:35m

Route Scout: A Tool for Generating Safe Routes



Route Scout Demonstration

Comparing Machine Learning with Physics-Based Route Planning

Problem Statement and Background

Solution Definition

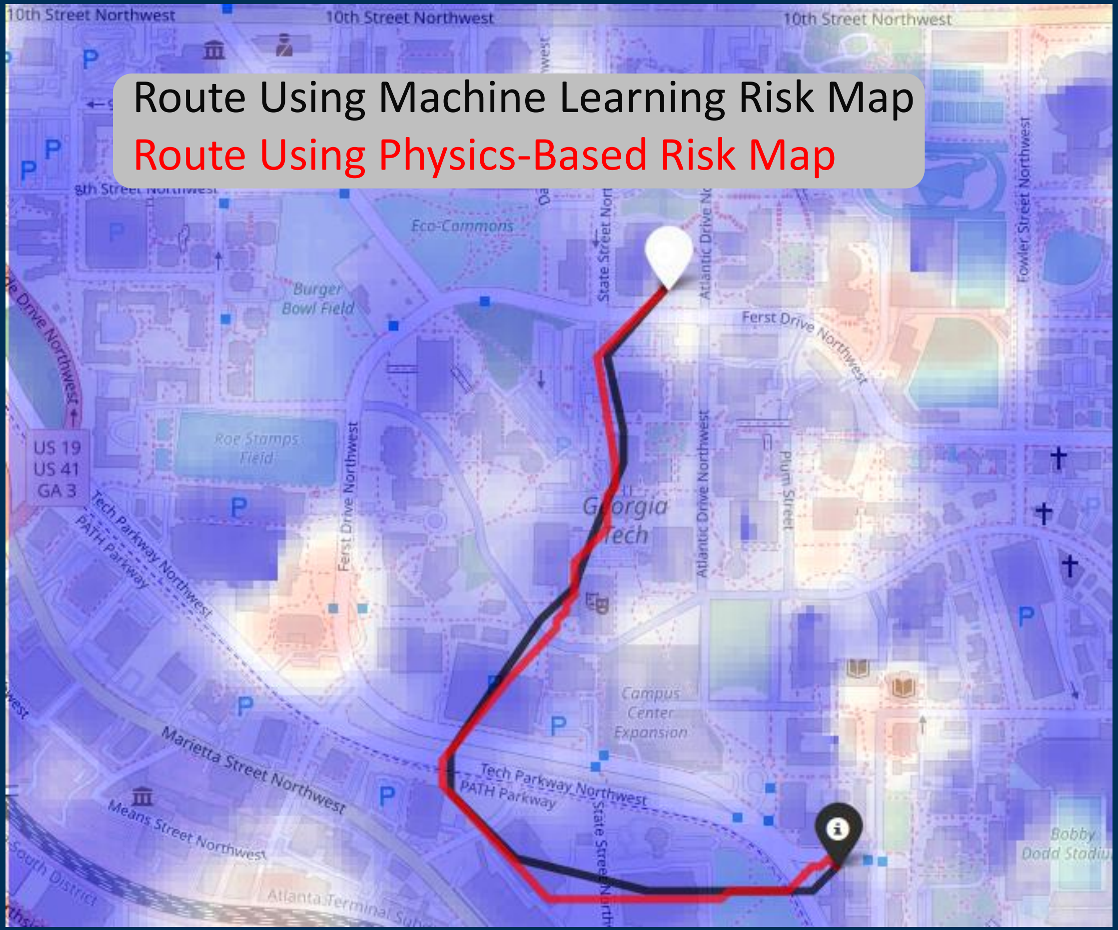
Methodology

Results

Conclusion

- Created routes using two different risk maps for comparison
  - Risk map from physics-based model
  - Risk map from machine learning model

The physics-based risk map and the Machine Learning risk map result in similar route solutions



Routes Created Using the Physics-Based Risk Map and the Machine Learning Risk Map

Route Planning Using Machine Learning Risk Assessment

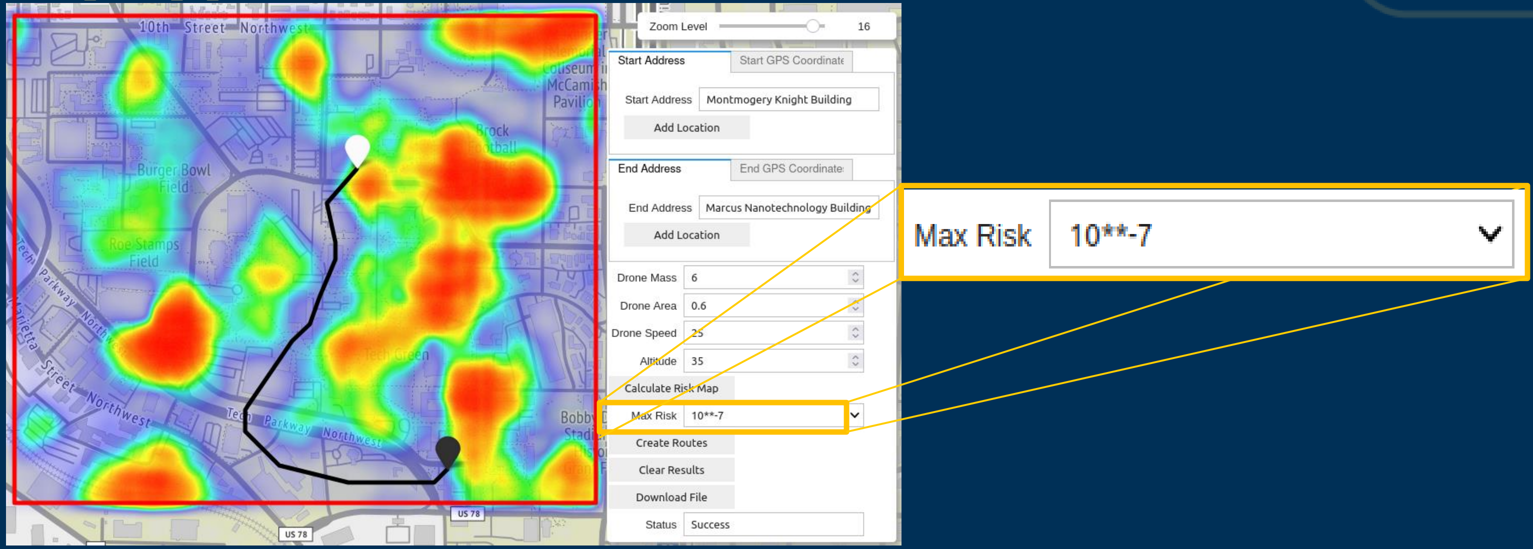
Problem Statement and Background
Solution Definition
Methodology
Results
Conclusion

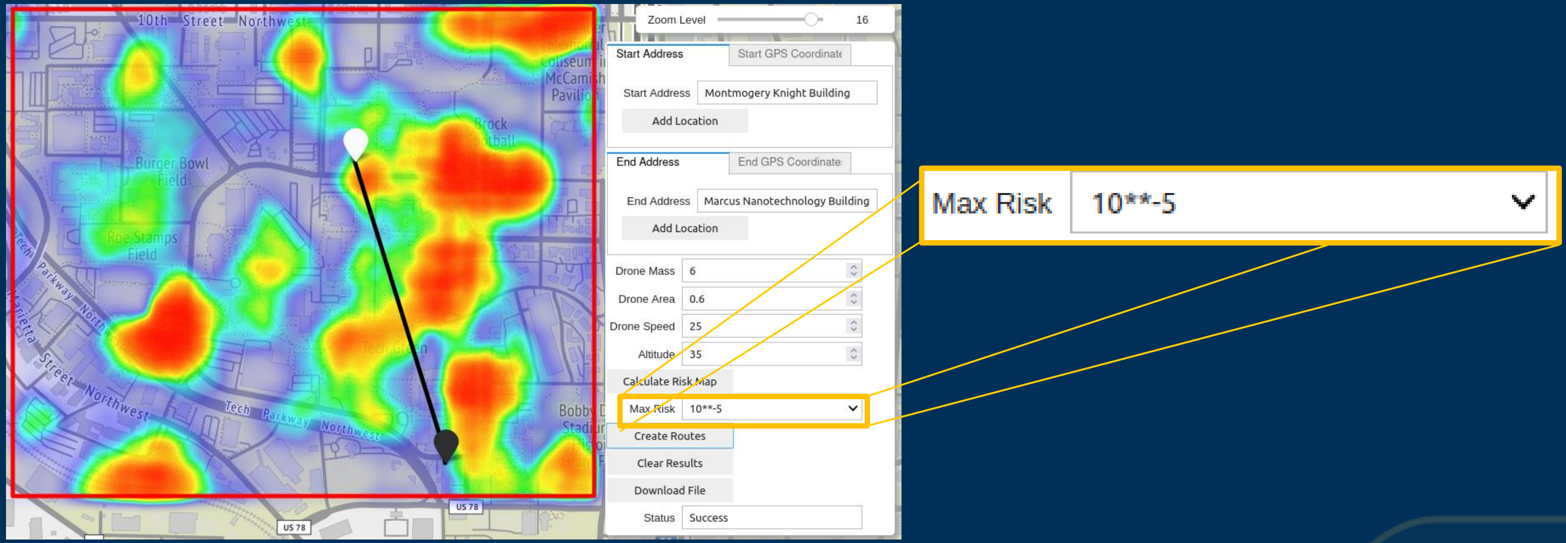
- Desired level of risk ensures solution does not surpass target level of safety
  - Target Level of Safety in this example: 10^{-7} fatalities/hour
- Predicted mean risk from Machine Learning model comparable to actual mean risk calculated using physics

	Predicted (fatalities/flight hour)	Actual (fatalities/flight hour)	MAPE(%)
Max Risk	8.55e-8	7.13e-8	19.8
Mean Risk	1.72e-8	1.8e-8	4.19

Routes Tailored for Every Application

Problem Statement and Background
Solution Definition
Methodology
Results
Conclusion





Flexible Target Level of Safety allows for urgent applications to trade off safety for response time

Routes Tailored for Every UAS

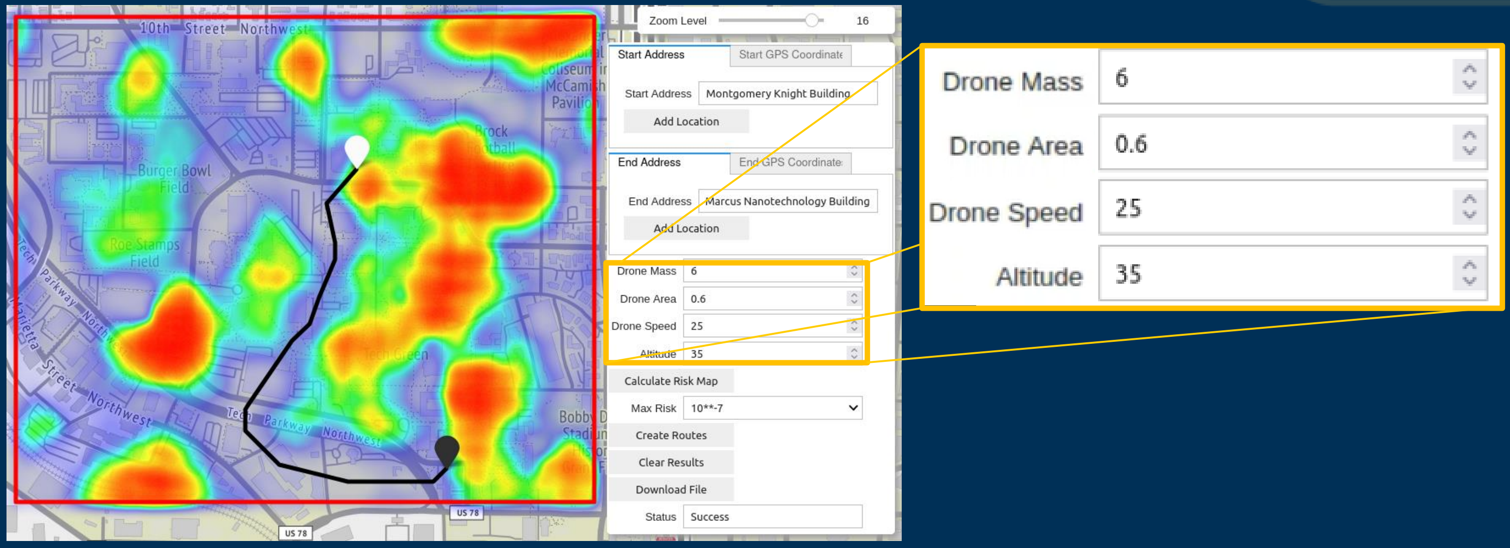
Problem Statement and Background

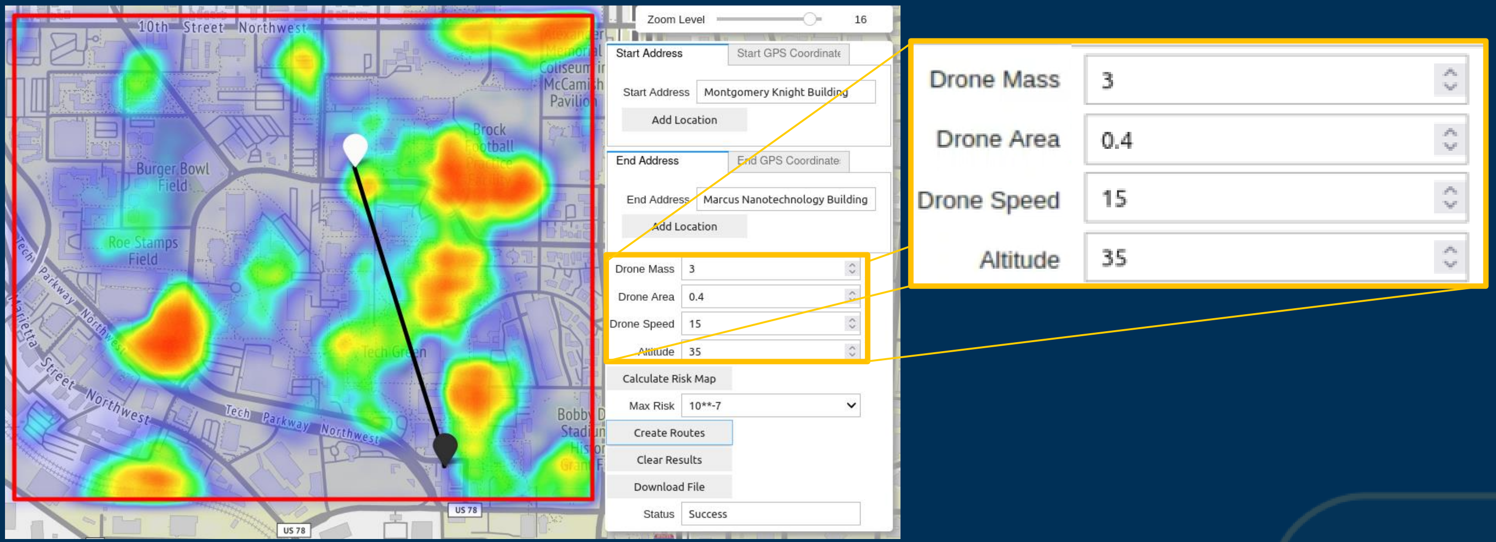
Solution Definition

Methodology

Results

Conclusion





Easily change the UAS parameters and flight conditions to observe how that affects the routing solution

Conclusion and Future Work

Problem Statement and Background
Solution Definition
Methodology
Results
Conclusion

- Traditional methods for UAS ground risk estimation can be time consuming and inefficient
- Developed novel way to estimate ground risk using Machine Learning techniques
  - Reduce computation time without significantly sacrificing accuracy
  - Explore how UAS design and operating conditions affect predicted risk
- Can use this Machine Learning method to create low risk routes
  - Flexible for any UAS
  - Tailored for any application
- Future work
  - Incorporate wind and additional UAS failure types
  - Improve accuracy of Machine Learning model
  - Create different Machine Learning models for different classes of UAS

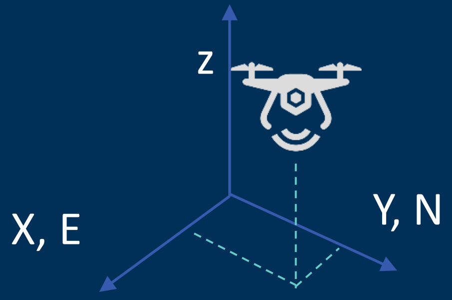
Thank you!

Questions?

Backup Slides

Uncertainties in Descent Trajectory

- The initial conditions of the UAS descent trajectory and impact risk level[1]
  - Mass (m)
  - Frontal Area (A)
  - Drag Coefficient (C_d)
  - UAS Speed $\left(V_x, V_y, V_z\right)$
  - Position (x, y, z)
- Some parameters are probabilistic
  - Requires repeated simulations to account for uncertainty
  - Pull parameters from normal distribution with given standard deviation

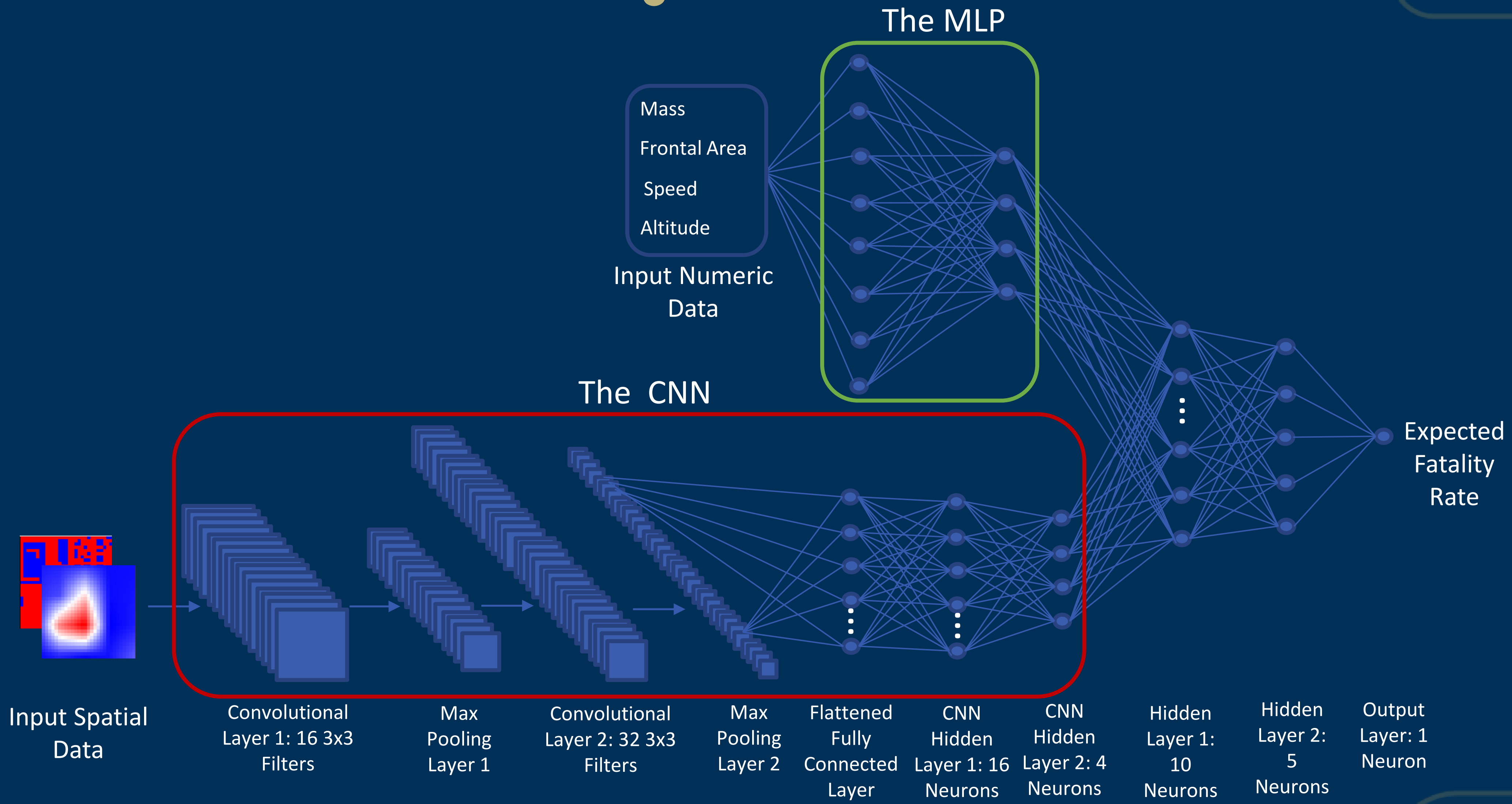


Property	Standard Deviation
Drag Coefficient C_d	0.2
Horizontal Speed (m/s)	0.5
Vertical Speed (m/s)	0.5
Initial X Position (m)	1.5
Initial Y Position (m)	1.5
Initial Z Position (m)	0.5

Probabilistic Characteristics Based on Off-The-Shelf UAS[2][3][4]

1. [1] S. Primatesta, L. S. Cuomo, G. Guglieri, and A. Rizzo, "An innovative algorithm to estimate risk optimum path for unmanned aerial vehicles in urban environments," vol. 35, Elsevier B.V., 2018, pp. 44–53.
2. [2]Cour-Harbo A. "Ground Impact Probability Distribution for Small Unmanned Aircraft in Ballistic Descent." 2020 International Conference on Unmanned Aircraft Systems
3. [3] DJI Matrice 300 RTK Specs
4. [4] DJI Mavic 3 Specs

Architecture for Machine Learning Model



Machine Learning Generalization

- Applied the Machine Learning model to a different part of the city not used in training
- 62% MAPE for new area
  - Likely a result of higher population densities than found at training location
- Machine Learning model still accurate at less populated areas used in route planning
  - Routing solution from Machine Learning model also similar to that from physics-based model

Machine Learning Model Results

Physics-Based Model Results

	Predicted	Actual	MAPE(%)
Max Risk (fatalities/flight hour)	1.8e-7	2.39e-7	24.4
Mean Risk (fatalities/flight hour)	6.14e-8	5.883-8	4.5