ARC-LIGHT

Algorithm for Robust Characterization of Lunar surface Imaging for Ground Hazards and Trajectory

UNIVERSITY OF MICHIGAN

HUMAN LANDER CHALLENGE

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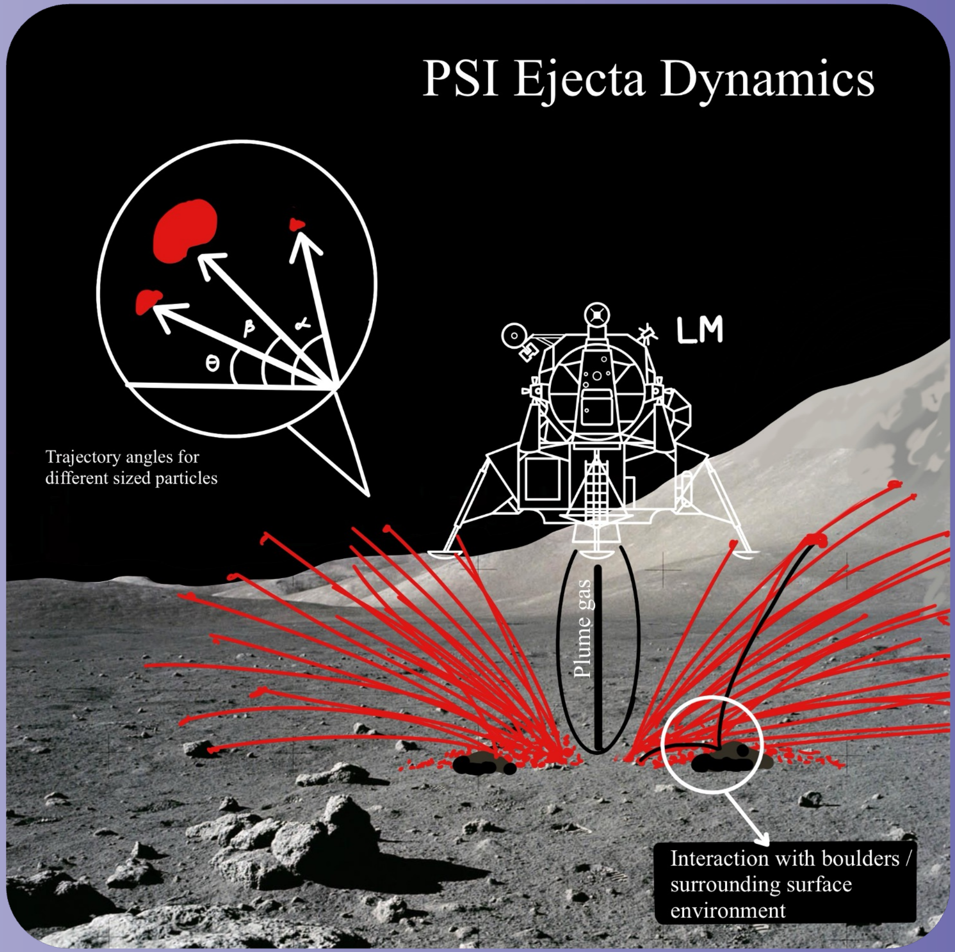
Presentation Contents

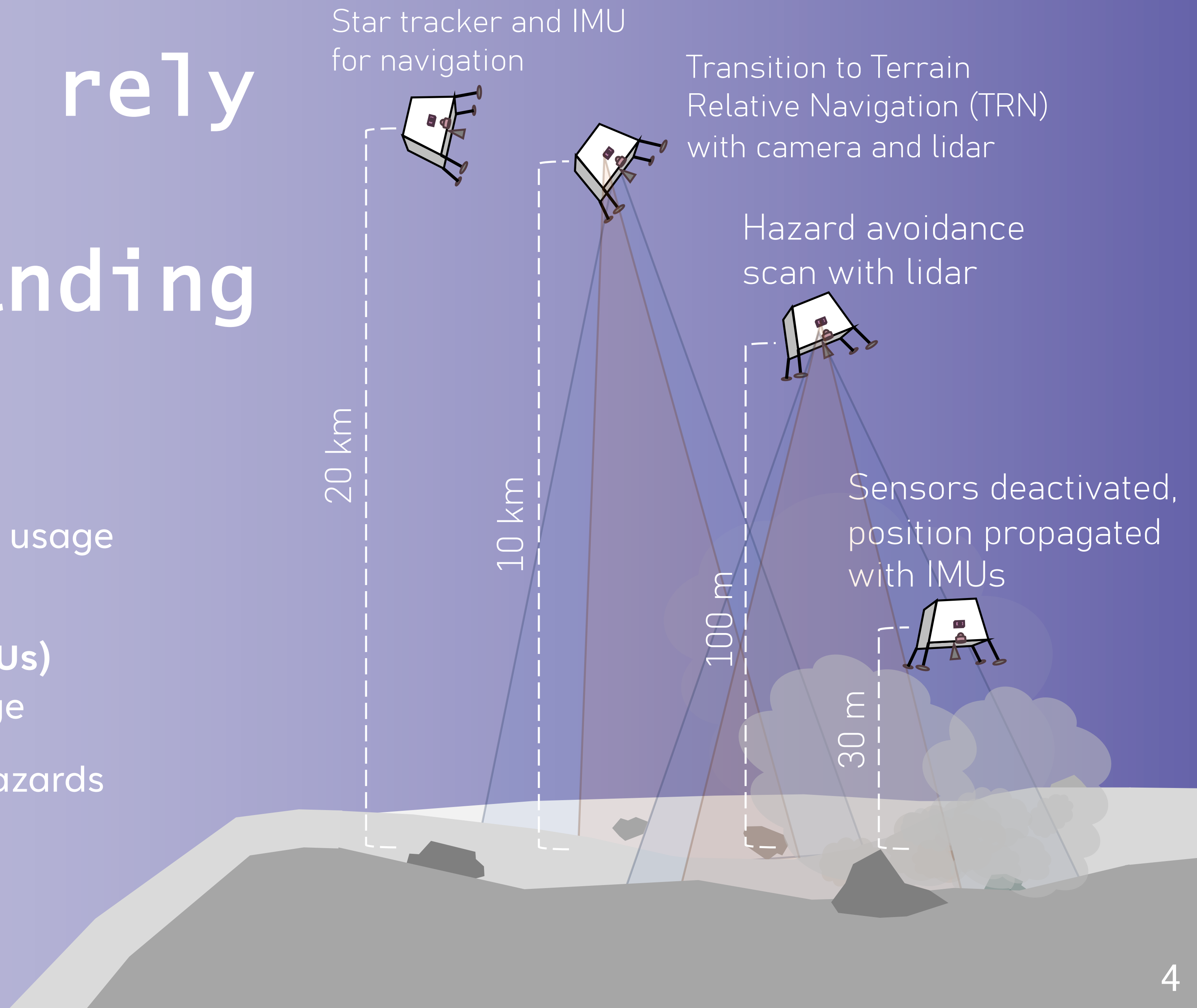
PSI: A threat to lunar landings

- **Plume Surface Interaction** ejects large amounts of dust particles that present key hazards for lunar landings
- **Focus on sensor performance** of navigation systems during PSI
- **Why is this a growing concern?** Upcoming lunar missions like Artemis require frequent and precise landings for crew and cargo.



Lunar landers rely on sensors throughout landing

- **Cameras and lidars** guide the spacecraft to landing site
- **PSI interference** prevents sensor usage for final descent
- **Inertial Measurement Units (IMUs)** provide all guidance at this stage
- **Spacecraft is blind** to surface hazards and unable to correct trajectory



Presentation Contents

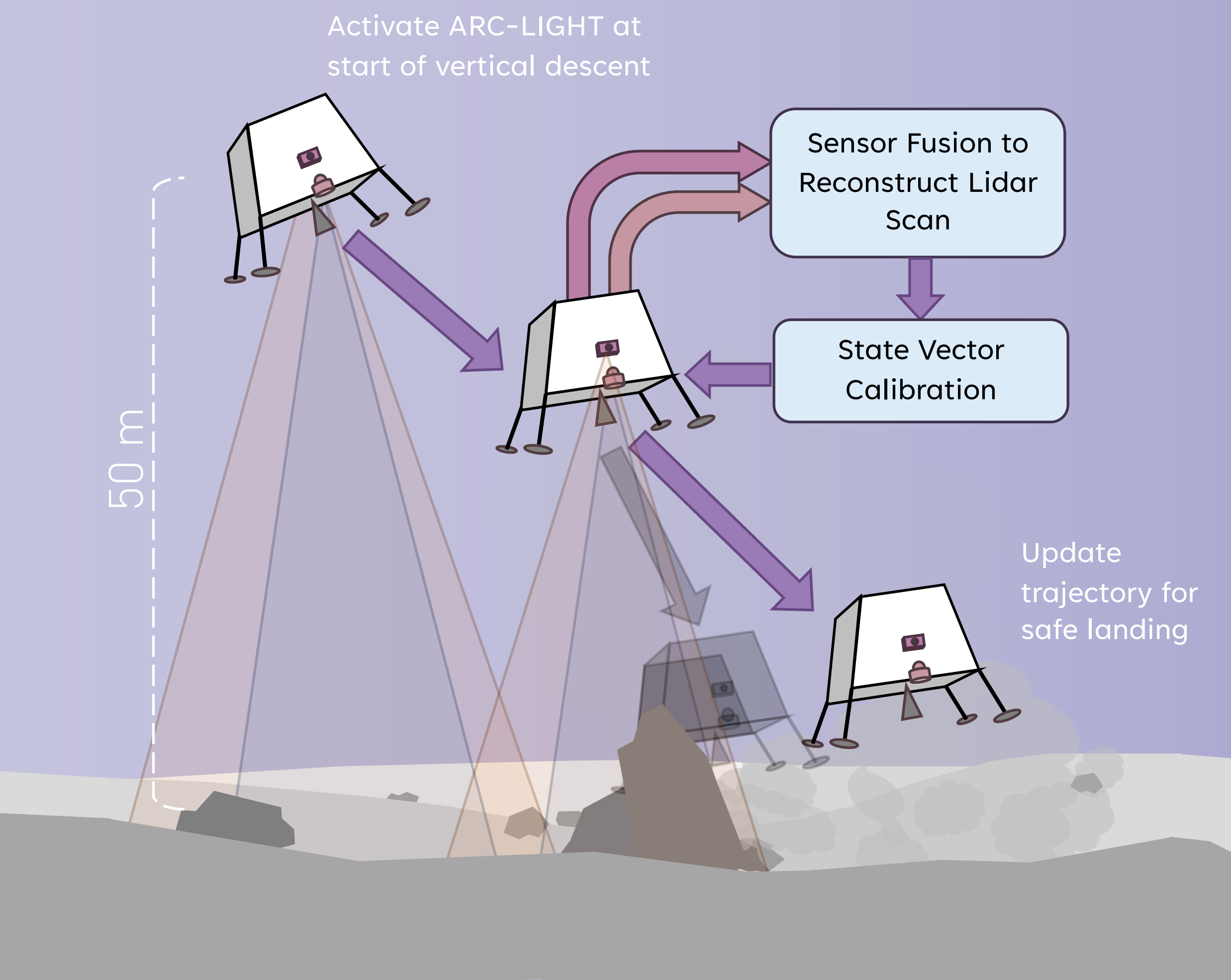
Goals Enabled by ARC-LIGHT

Trajectory Correction: Improve landing accuracy by frequent recalibration of spacecraft position throughout final descent

Hazard Detection: Enhance hazard detection by enabling hazard scans at lower altitudes to spot hidden dangers

Sensor Redundancy: Reduce dependency on Inertial Measurement Units in the event of failure

ARC-LIGHT: enabling lidar and camera use throughout all stages of landing



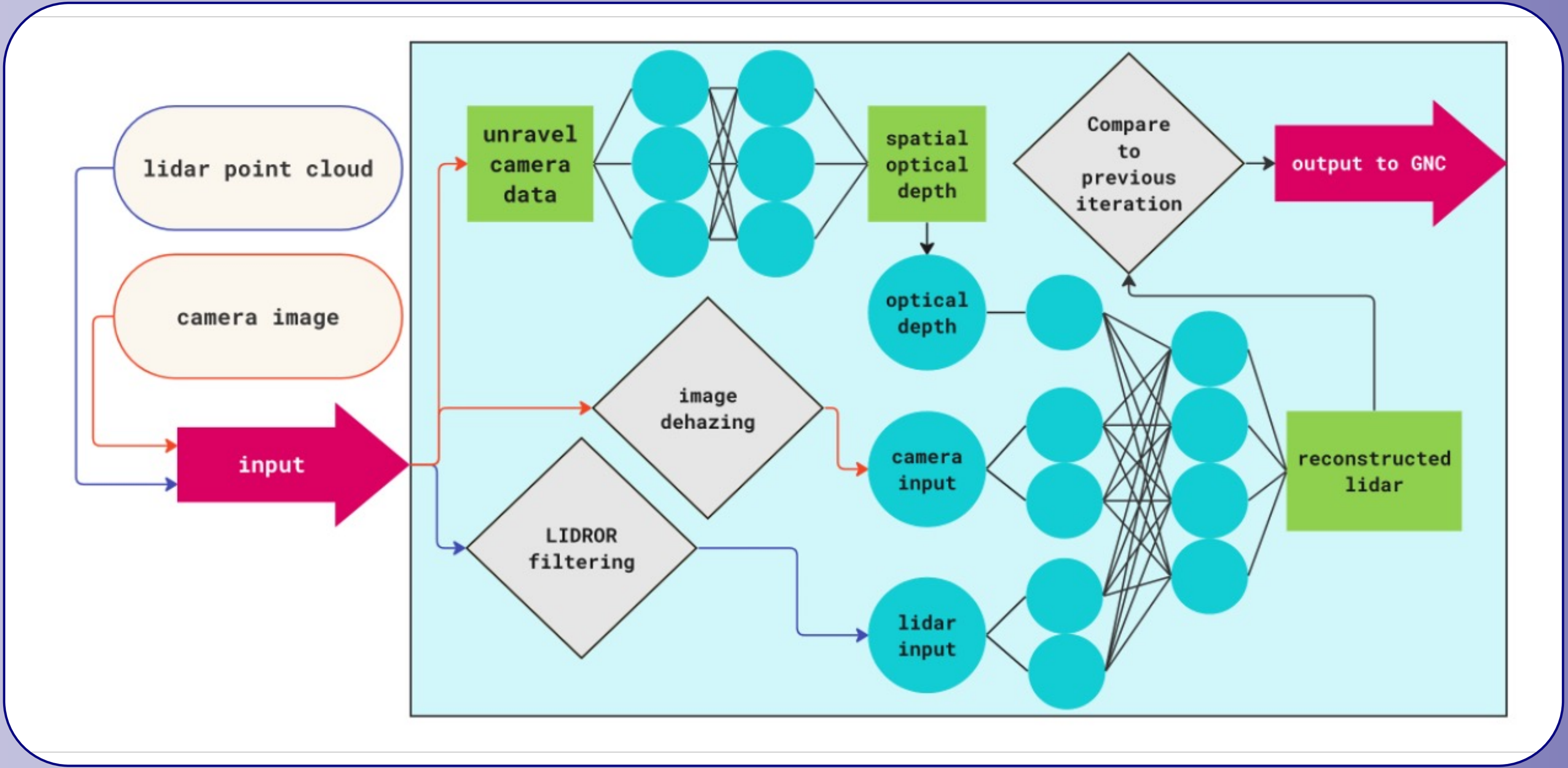
ARC-LIGHT is a **machine learning-based sensor fusion system**

Uses already **existing navigation sensors** like cameras and lidars = no added mass

Removes erroneous signals caused by PSI **allowing lidar to "see-through"** particle obstruction

Output is sent to lander Guidance, Navigation, and Control (GNC) for use

Machine learning powers ARC-LIGHT



01. Lidar noise cleaning
02. Determine dust distribution
03. Dehaze image
04. Fuse data with neural network
05. Reconstruct surface scan
06. Error Check
07. Send to Guidance

Synthetic data supports ARC-LIGHT training

- Real Moon Data is Scarce
- Synthetic Data to the Rescue!
- Building a Realistic Simulation:
  - High-fidelity PSI simulations
  - Lidar data optical simulation
- Fine-Tuning for Real-World
- Safety First: Error Quantification and Shut-Off Protocol

Presentation Contents

Learning to apply sensor fusion in the lunar environment

Aim

Develop prototype algorithm to test ARC-LIGHT feasibility and inform future work

Question

How do sensors perform in the lunar environment?

Solution

Construct physical testbed to gather data

Question

How can sensor fusion be applied to extract useful measurements?

Solution

Use testbed data to test different signal processing techniques

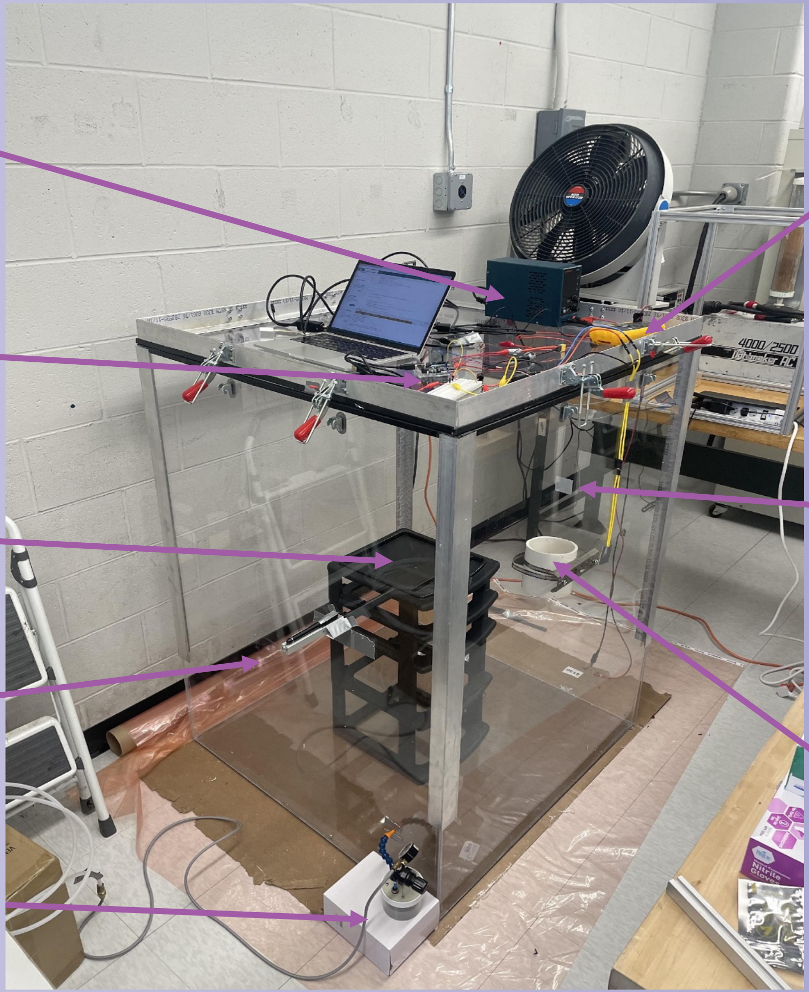
Power Supply:
Provides power to the lidar and ducted fan

Lidar/Camera Mount:
Scans the target

Target
Known obstacle for lidar to detect

Laser:
Aimed at photodiode

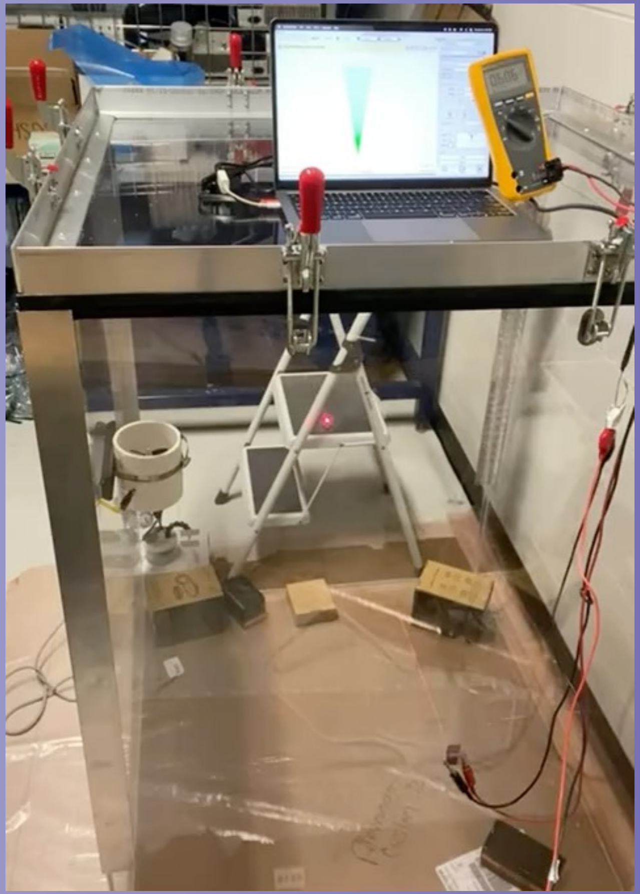
Di-Ethyl-Hexyl-Sebacate (DEHS) Atomizer:
Inject DEHS mist into the chamber



Voltmeter:
Displays voltage measured by photodiode

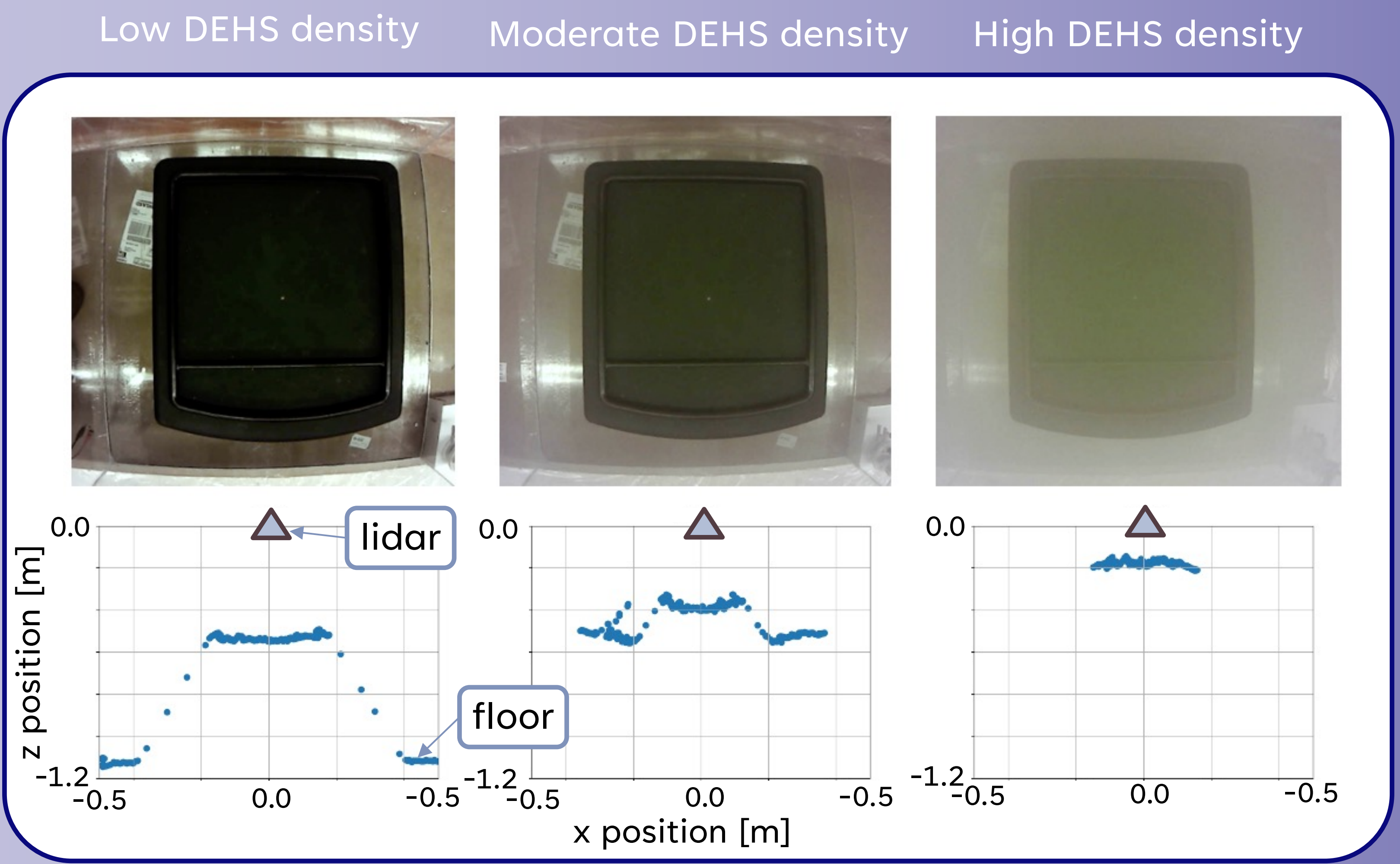
Photodiode:
Measures intensity of received laser light

Ducted Fan:
Lofts stimulants to produce a cloud of suspended particles

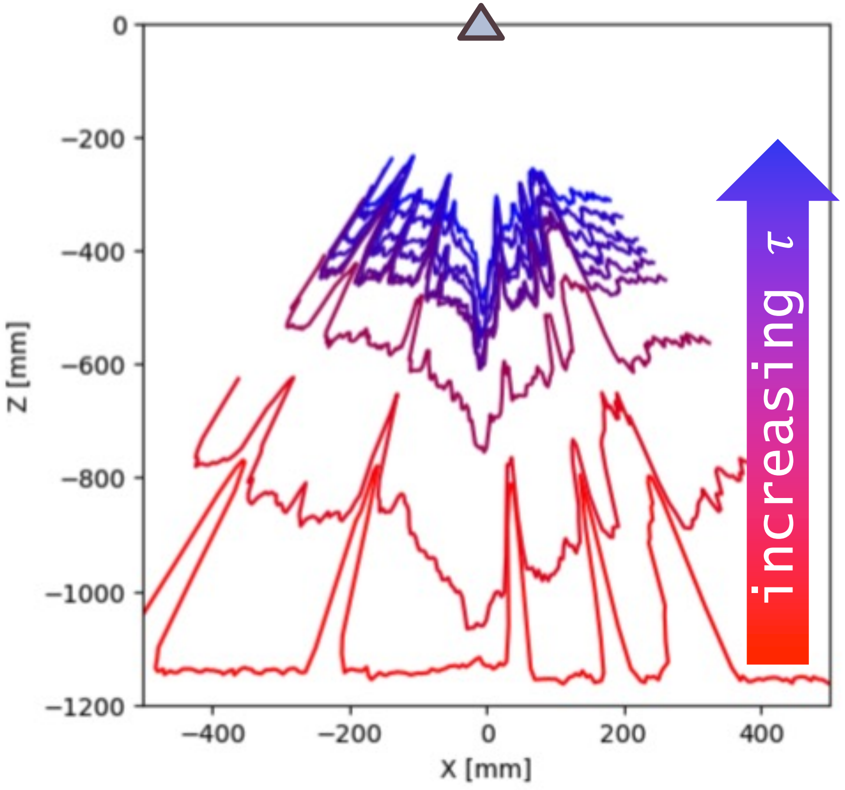


SELENE: Sensor Efficacy in the Lunar ENvironment Experiment

Result: camera provides context, lidar provides spatial data



Result: lidar attenuation is controlled by DEHS optical depth



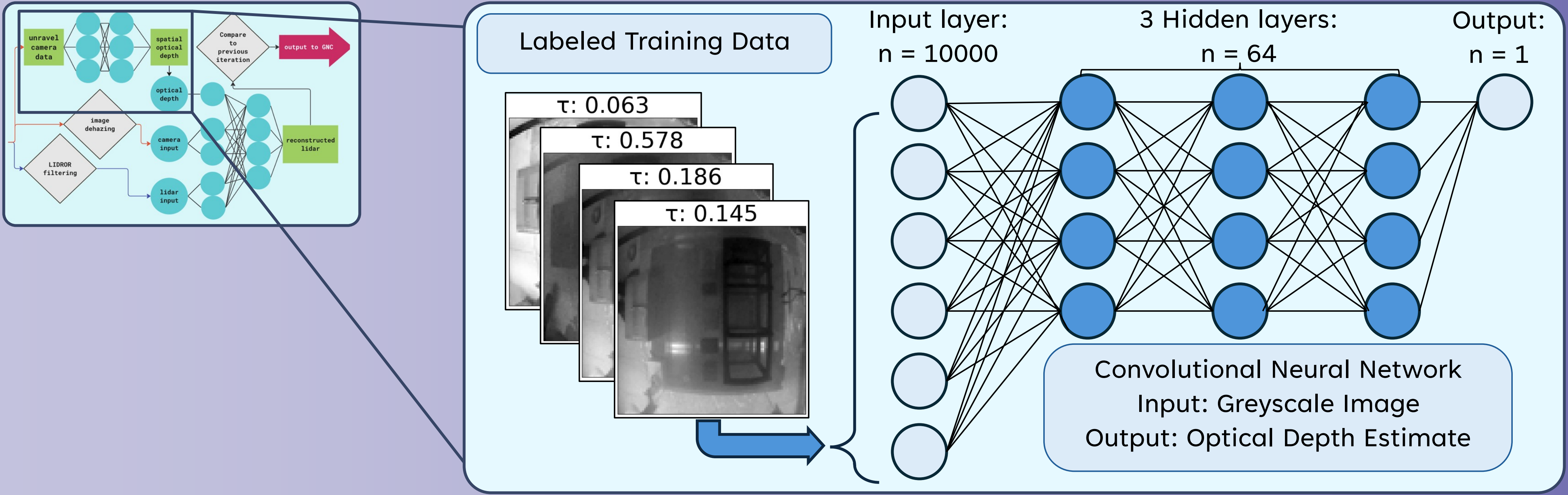
Compute optical depth from photodiode voltage

$$\ln\left(\frac{V_0}{V}\right) = \tau$$

Compute lidar attenuation at different optical depths

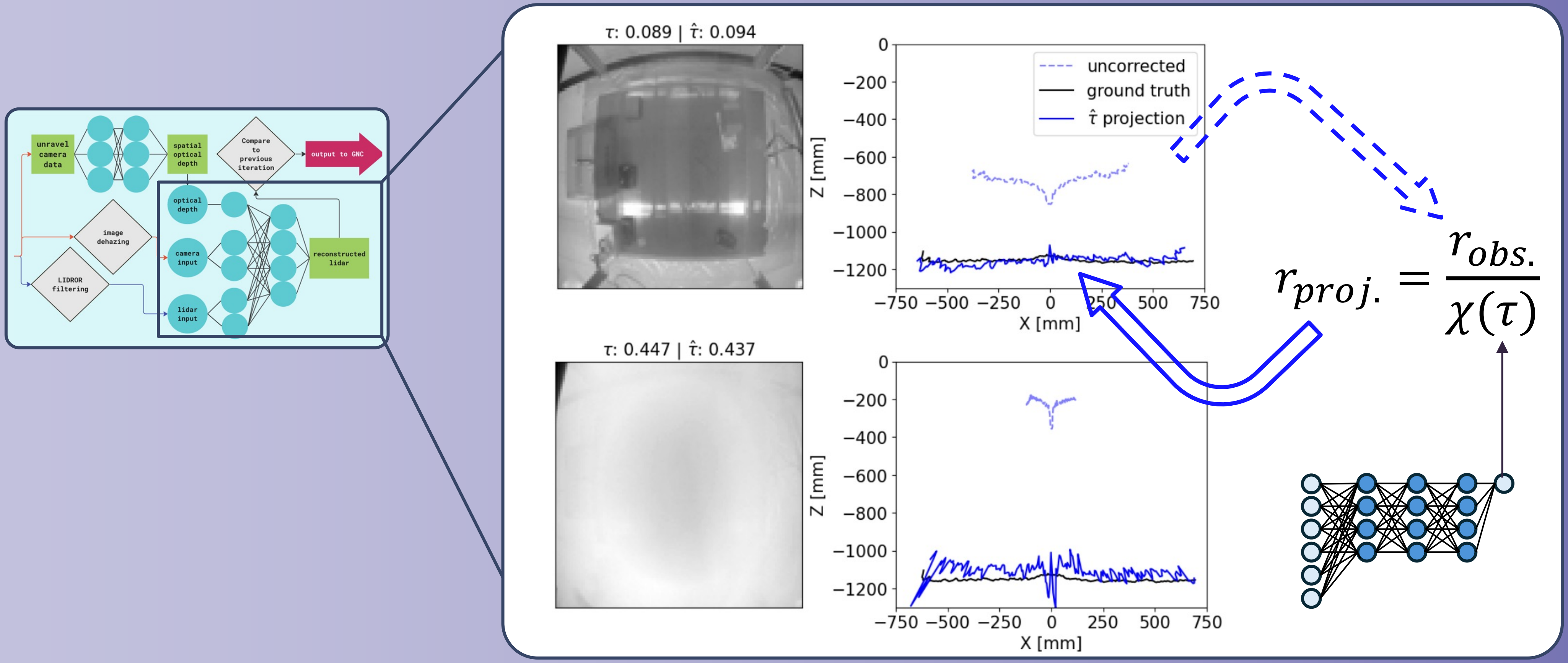
$$\frac{r_{obs.}}{r_{truth}} = \chi(\tau)$$

SELENE data is used to develop prototype algorithm



Camera-based neural network **predicts optical depth of DEHS**

Lidar and camera work together to remove interference from scan



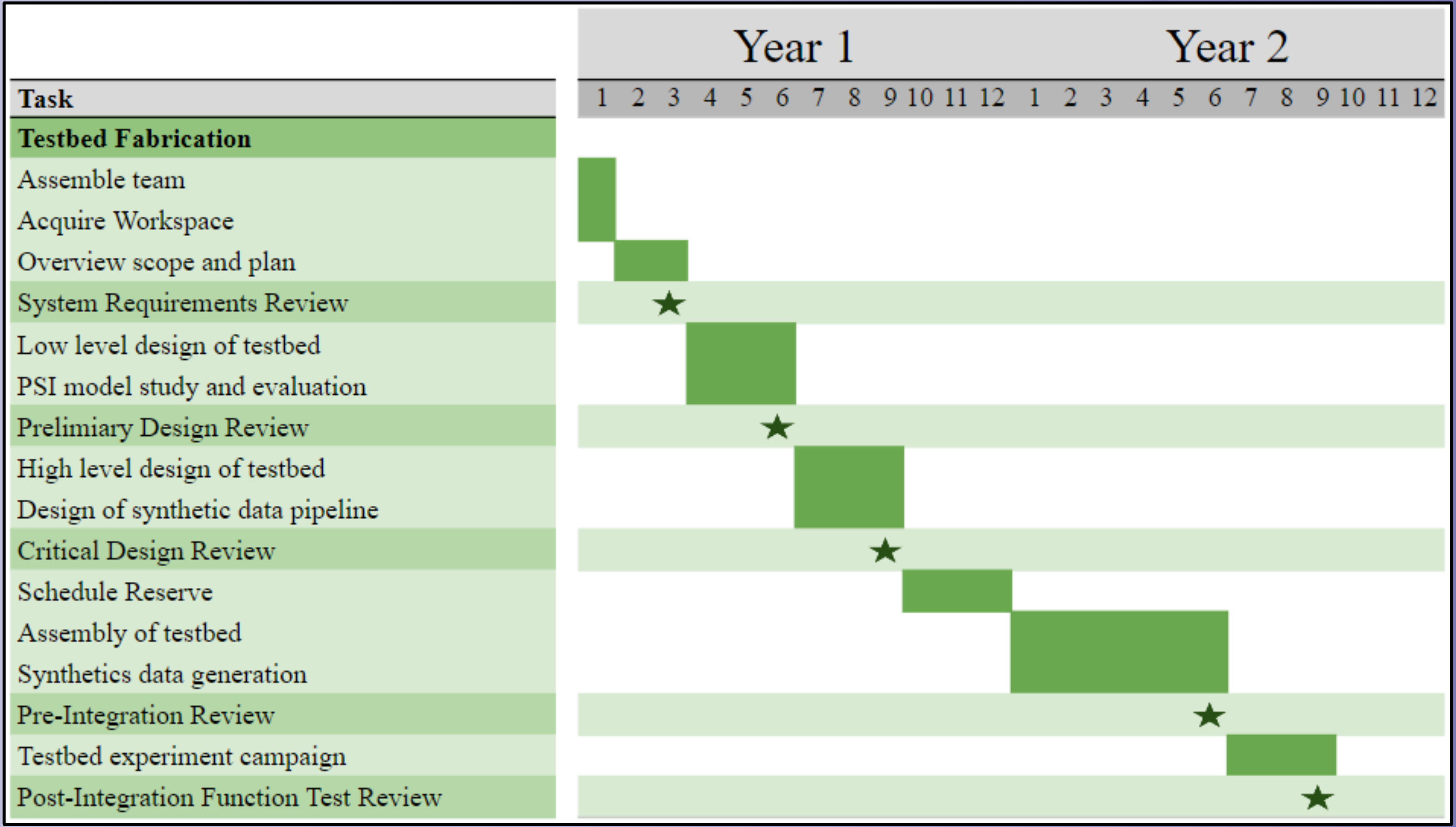
Optical depth is used to project lidar scan back out, **revealing the floor of SELENE**

Presentation Contents

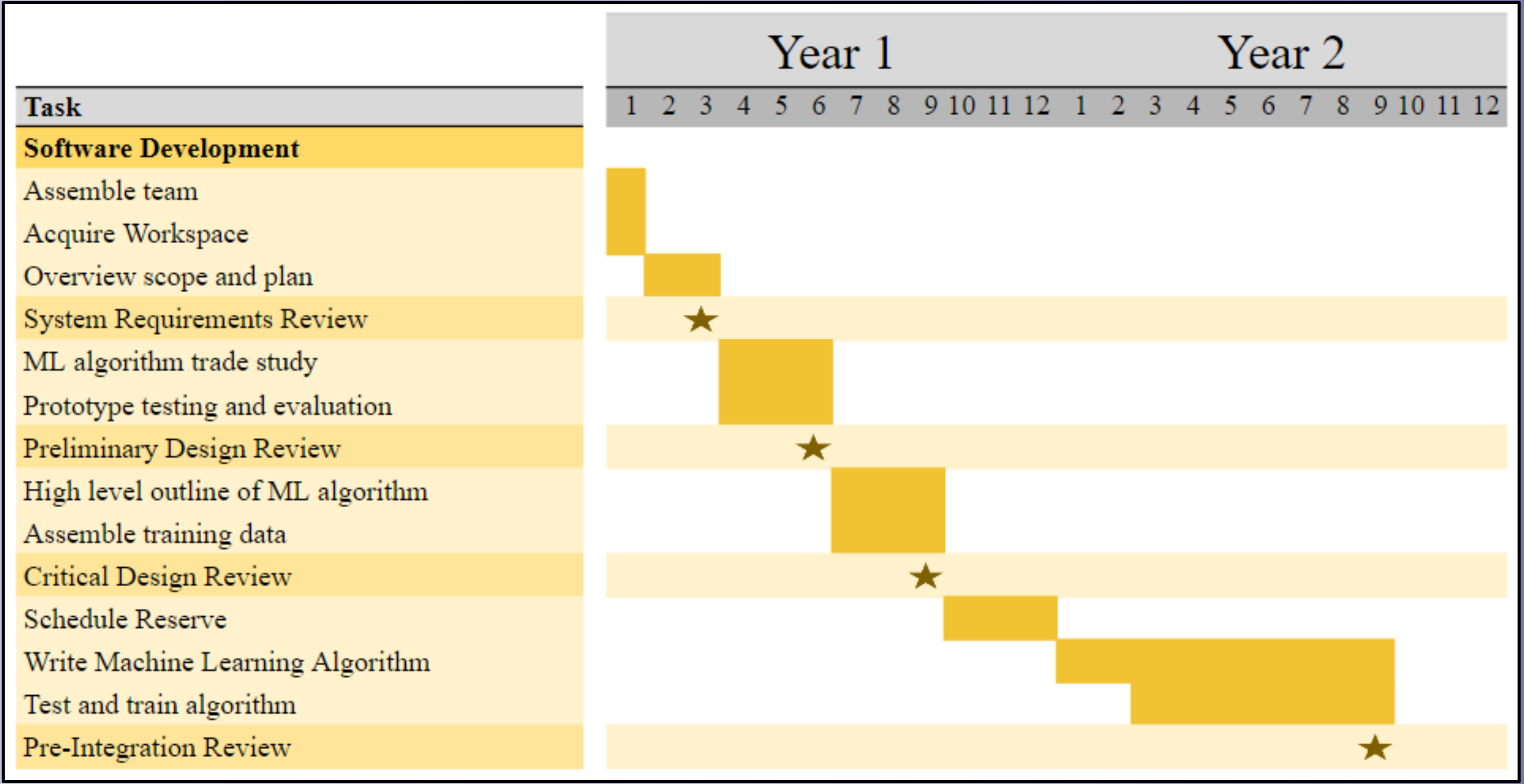
3 main tasks to develop ARC-LIGHT

- Synthetic data generation
- Software development
- Integration and Validation

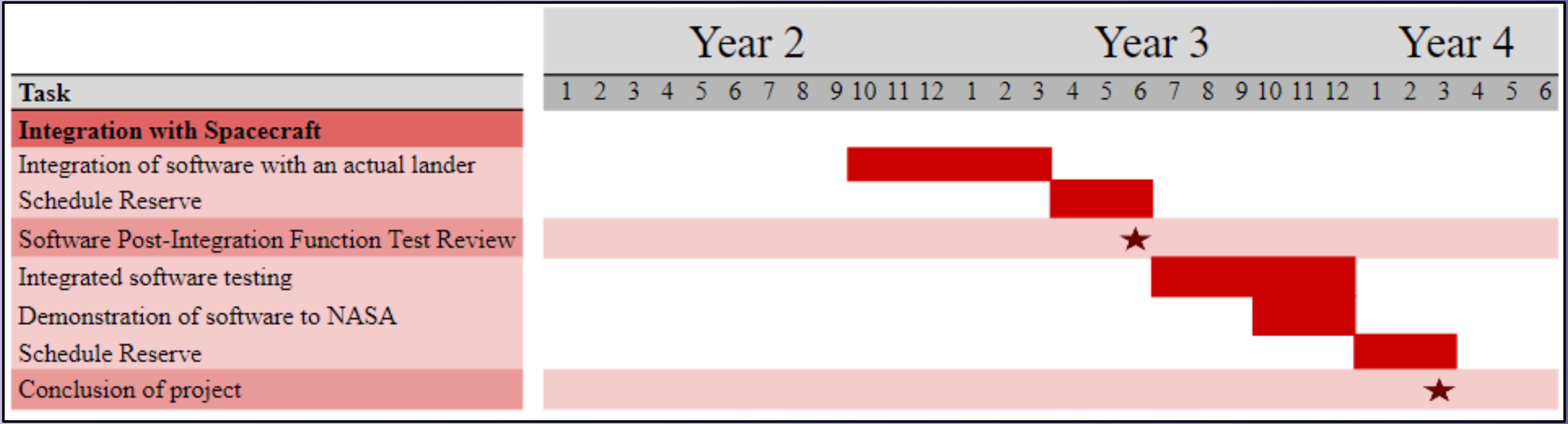
Synthetic data generation



Software development

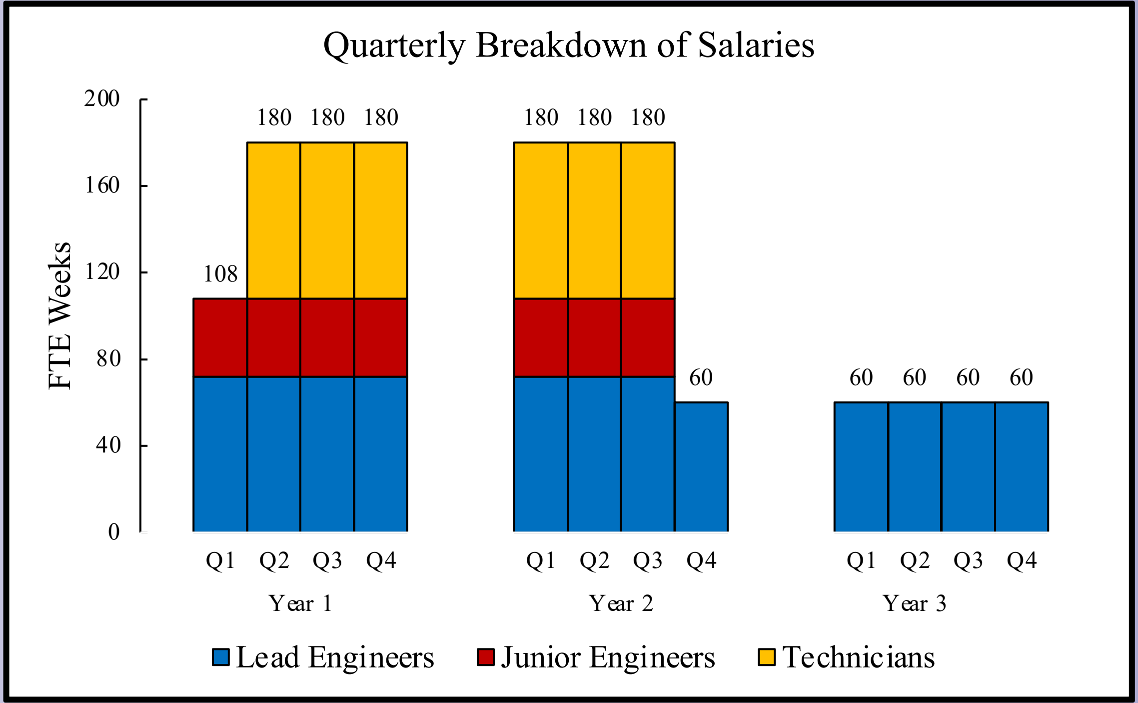


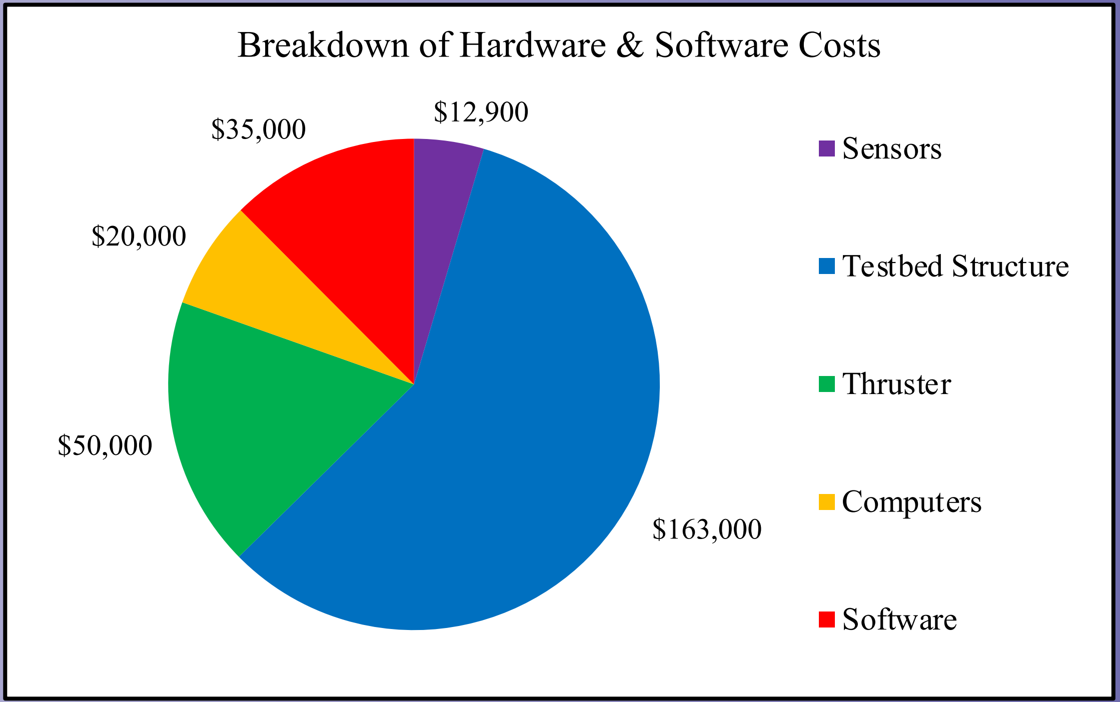
Integration & validation



The development of ARC-LIGHT requires:

1. 1,548 FTE Weeks - Salaries
2. $281,000 – Hardware & Software





Project development risks

Risk	Likelihood	Consequences	Mitigation
Lack of Personnel Expertise	Unlikely	Minor	- NASA has a high amount of personnel - Large team allows for an array of skillsets
Computational Cost & Reliability	Unlikely	Minor	- Formatted to match the sensors on a given spacecraft - No added components to the spacecraft
Error during spacecraft integration	Likely	Significant	Schedule reserve has been allocated to minimize the risk of delay
Error during training	Unlikely	Severe	- Failsafes within algorithm to combat outlying error - Testbed experiment will validate the code and catch error
Lack of training data	Likely	Major	- Synthetic data will serve to model PSI -The testbed experiment will model PSI

Presentation Contents

Let’s put our sensors back to work

Using machine learning-enabled sensor fusion, ARC-LIGHT reconstructs a clear view of lunar surface during final descent

Output is sent to lander guidance to calibrate position, avoid hazards, and provide sensor redundancy

Requires lander computational resources without adding mass or sensors

Prototype algorithm demonstrates sensor fusion efficacy

\$3300k, $3\frac{1}{4}$ year development plan

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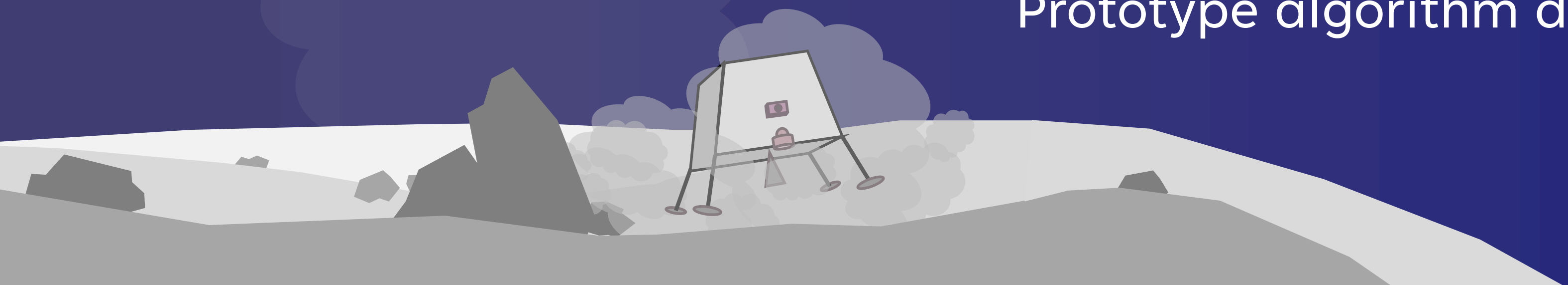

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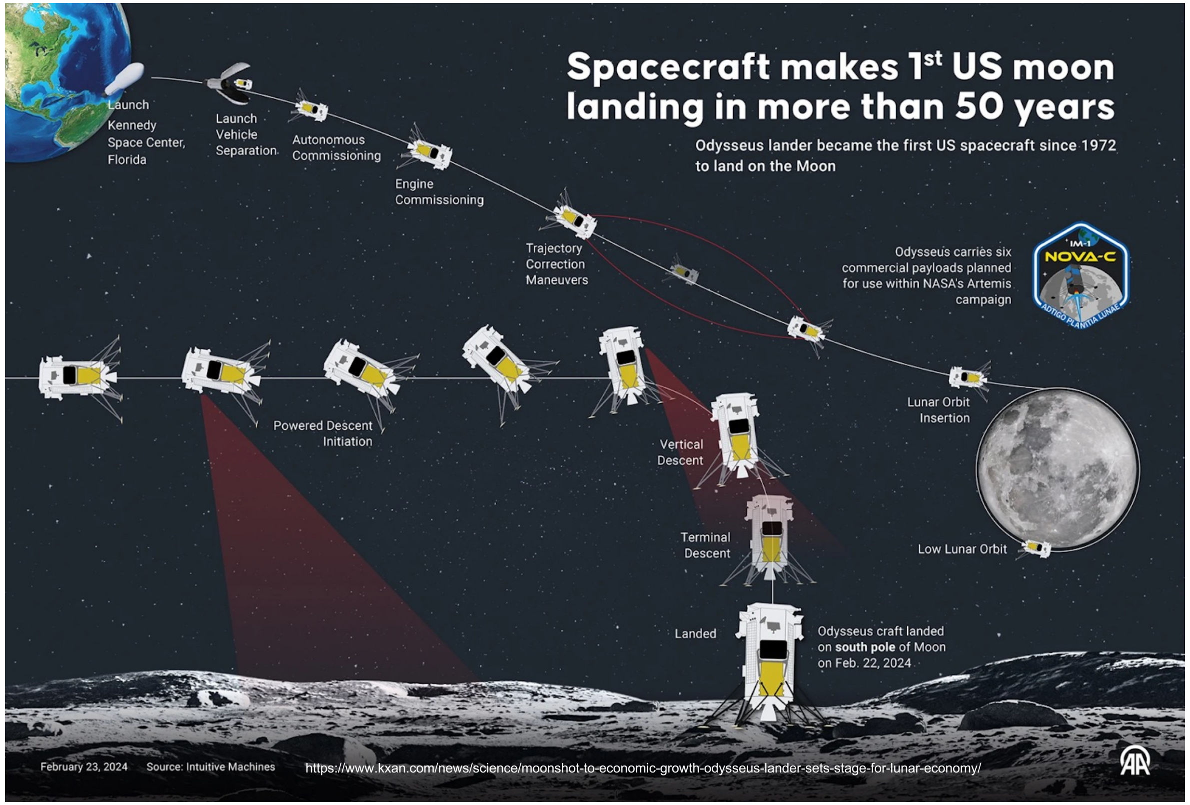
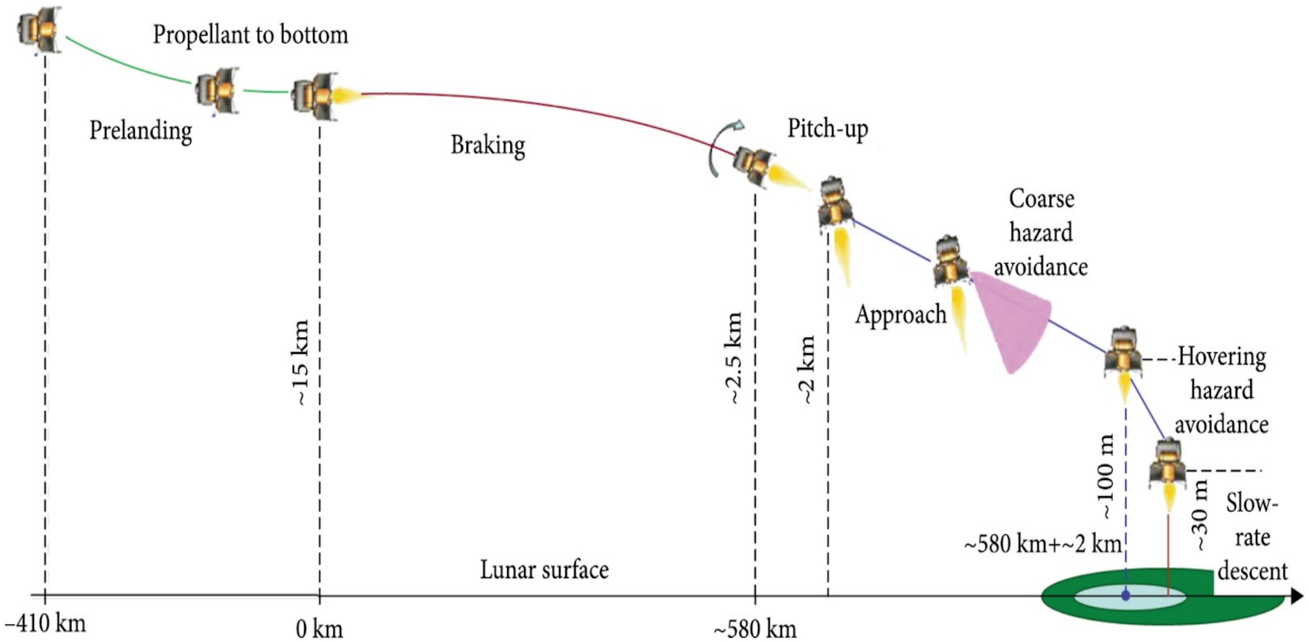
Extra slides

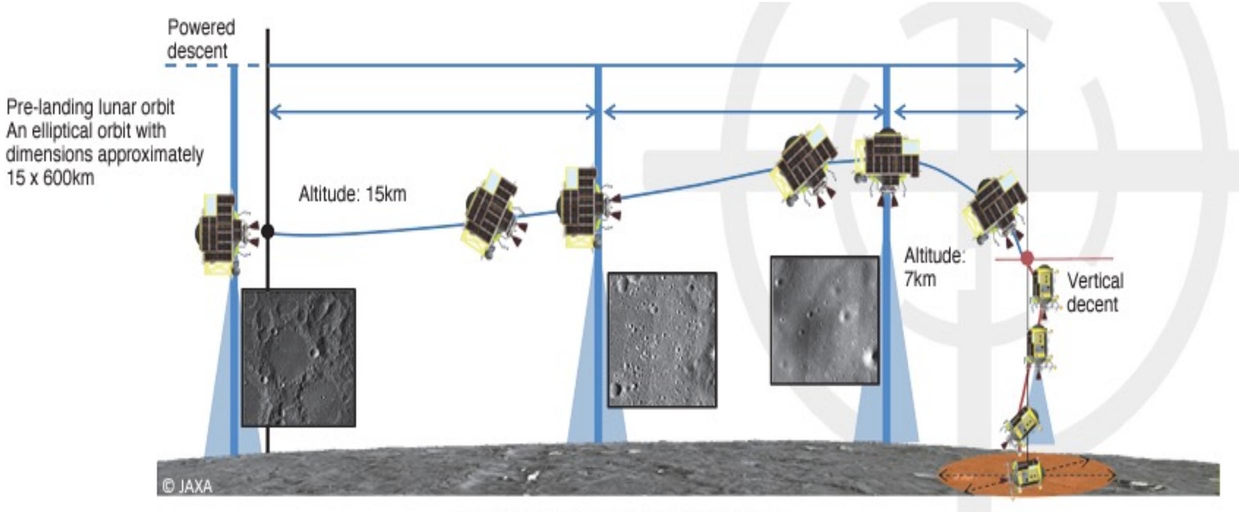
Characteristics of Robotic Landers

Lander	Thrust	Mass	Altitude of HDS	Descend Velocity	Notes
Chandrayaan – 3	Main Engine: 800 N Attitude thruster: 58 N	Lander: 1752 kg Propulsion: 2148 kg Total: 3900 kg	~120 – 130 m above the surface, Vertical descent beginning at 7.4 m	≤ 2 m/s	This landing had the smallest observed dust plume in history. This is most likely due to the low thrust and a diagonal angle for the thruster.
Chang'e – 5	Main Engine: 7500 N Attitude thruster: 150 N	Lander: 2200 kg Launch Mass: 8200 kg	100 m above the surface, Vertical descent beginning at 30 m	1.5 m/s until altitude reaches 20 m, at which constant acceleration until touchdown	
SLIM	Main Engine: 500 N 12 small thruster: 22 N each	Dry mass: 120 kg Launch mass: 590 kg	~50 m above the landing site	1.4 m/s	The Lander had an issue with its thruster during descent and ended up landing 55 meters away from its intending landing spot.



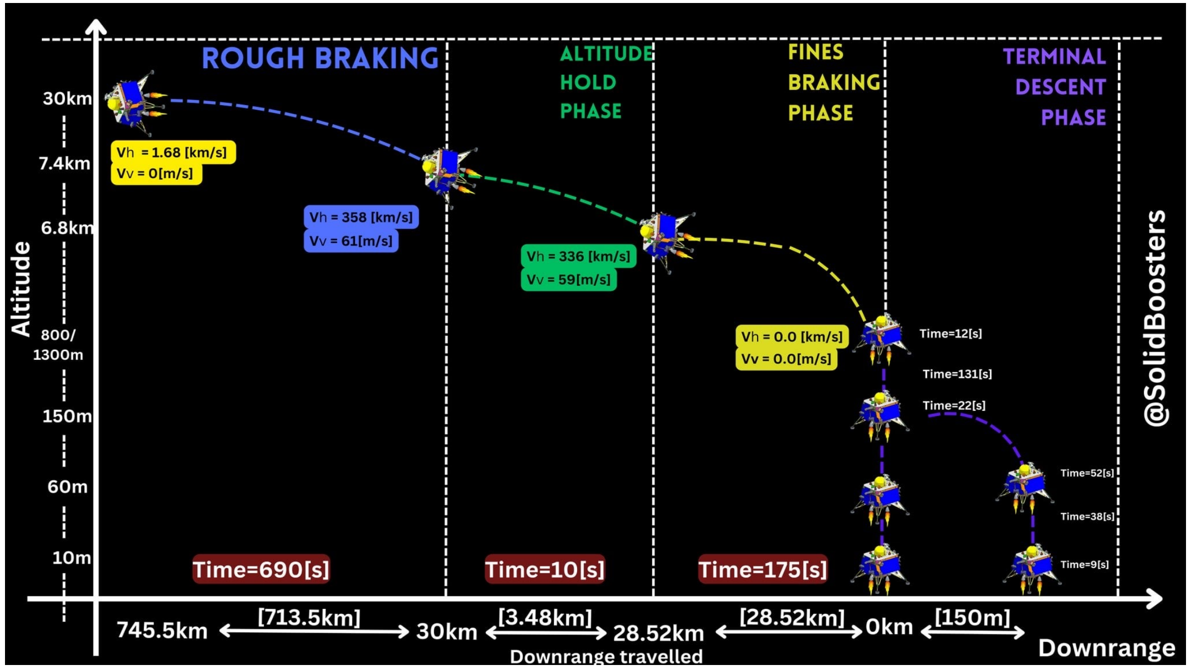


Zhang, Honghua & Li, Ji & Wang, Zeguo & Guan, Yifeng. (2021). Guidance Navigation and Control for Chang'E-5 Powered Descent. Space: Science & Technology. 2021. 1-15. 10.34133/2021/9823609.

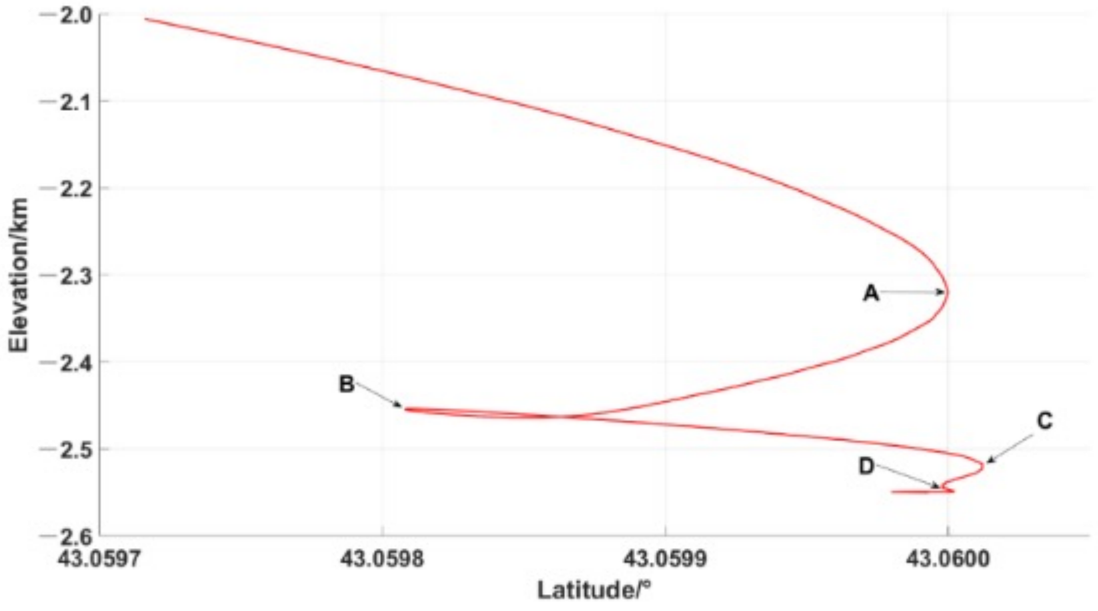


Landing sequence during powered descent

https://spaceflightnow.com/2023/12/06/three-robotic-missions-target-moon-landings-over-one-week-in-january/



The displacement of the lander during vertical descent increases exponentially



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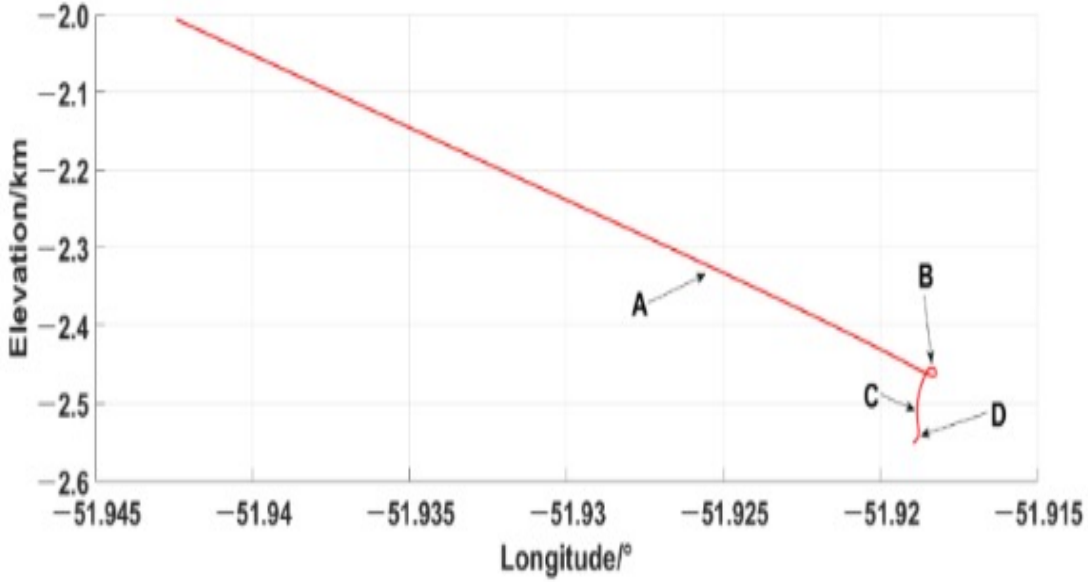
https://www.mdpi.com/2072-4292/13/23/4837



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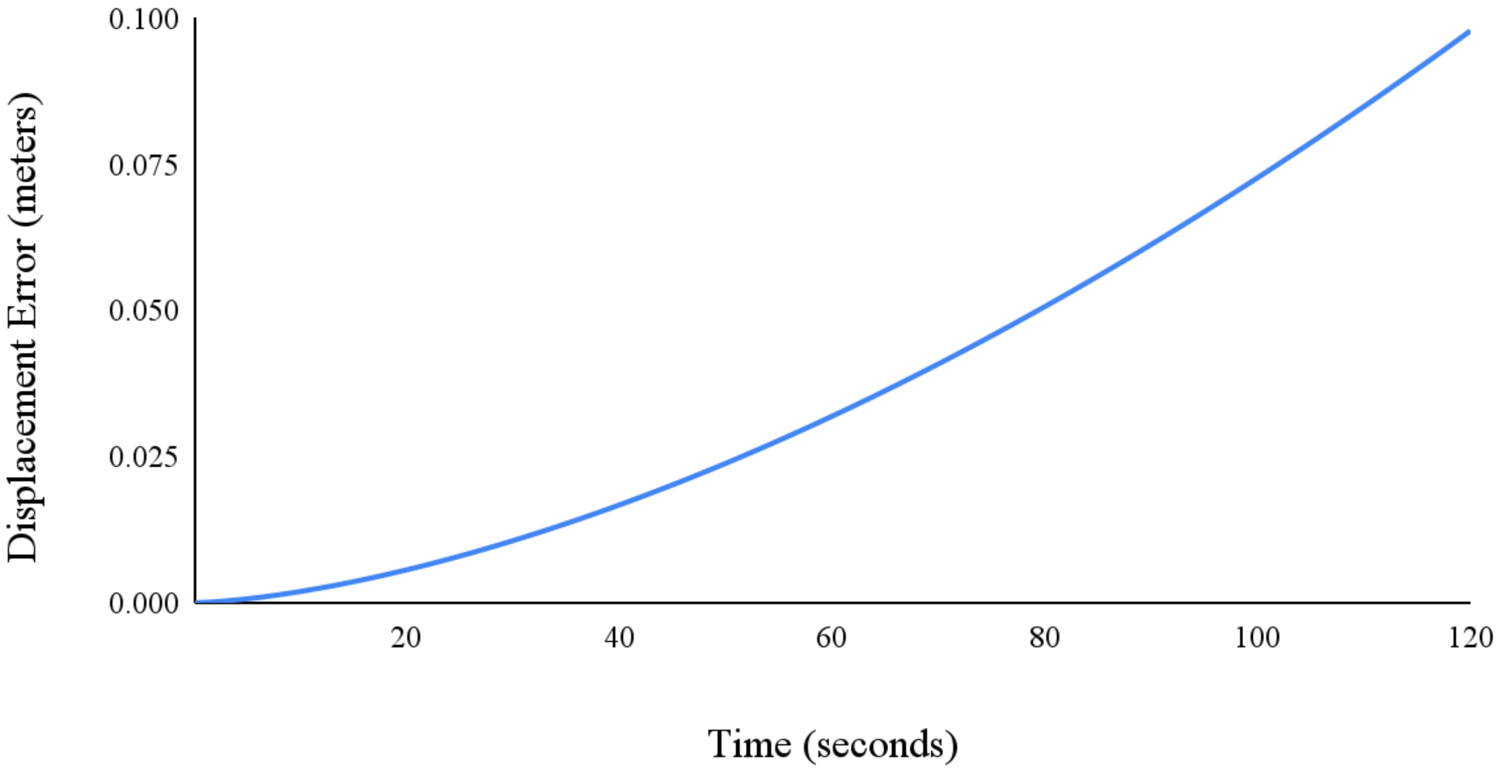
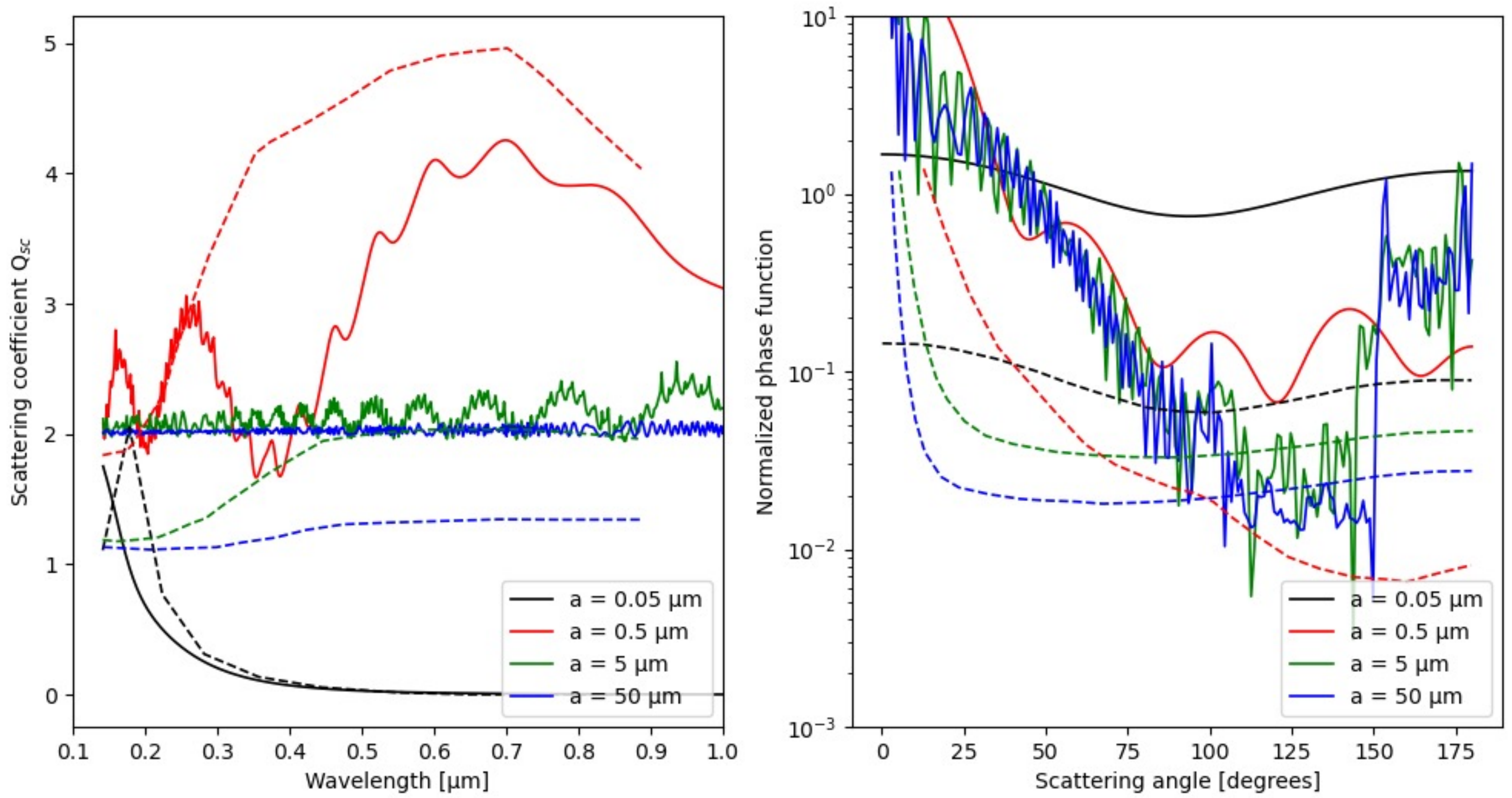
Estimate displacement error of an IMU over time



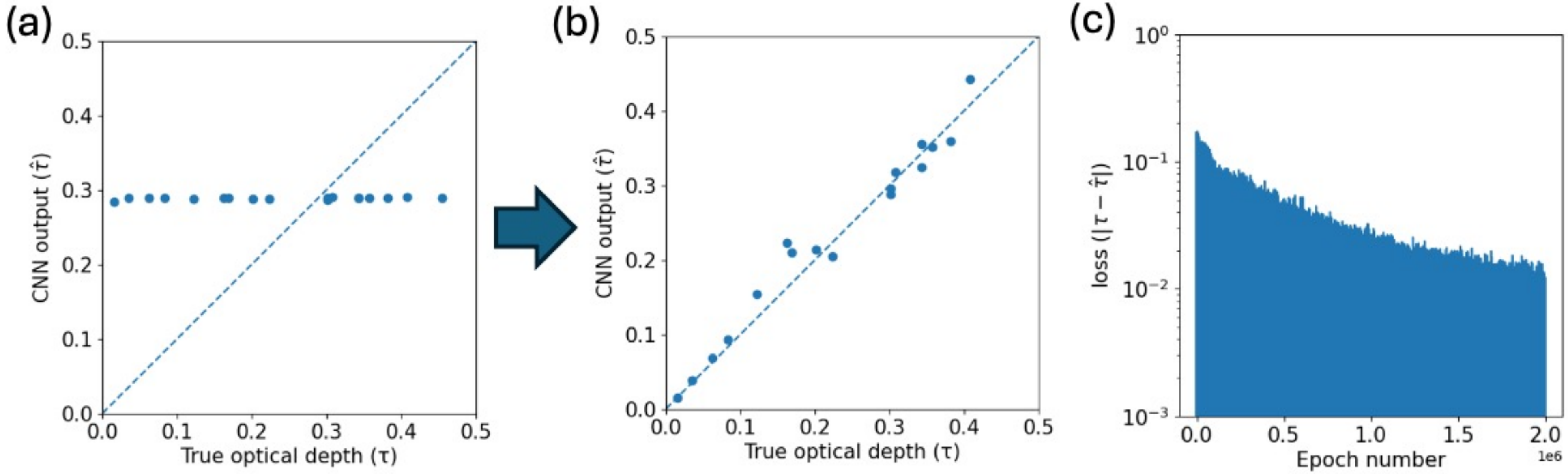
$$Error = v * t * sin(\frac{ARW}{60}\sqrt{t}) + v * t * sin(\frac{BI}{3600}t)$$

Mie scattering analysis

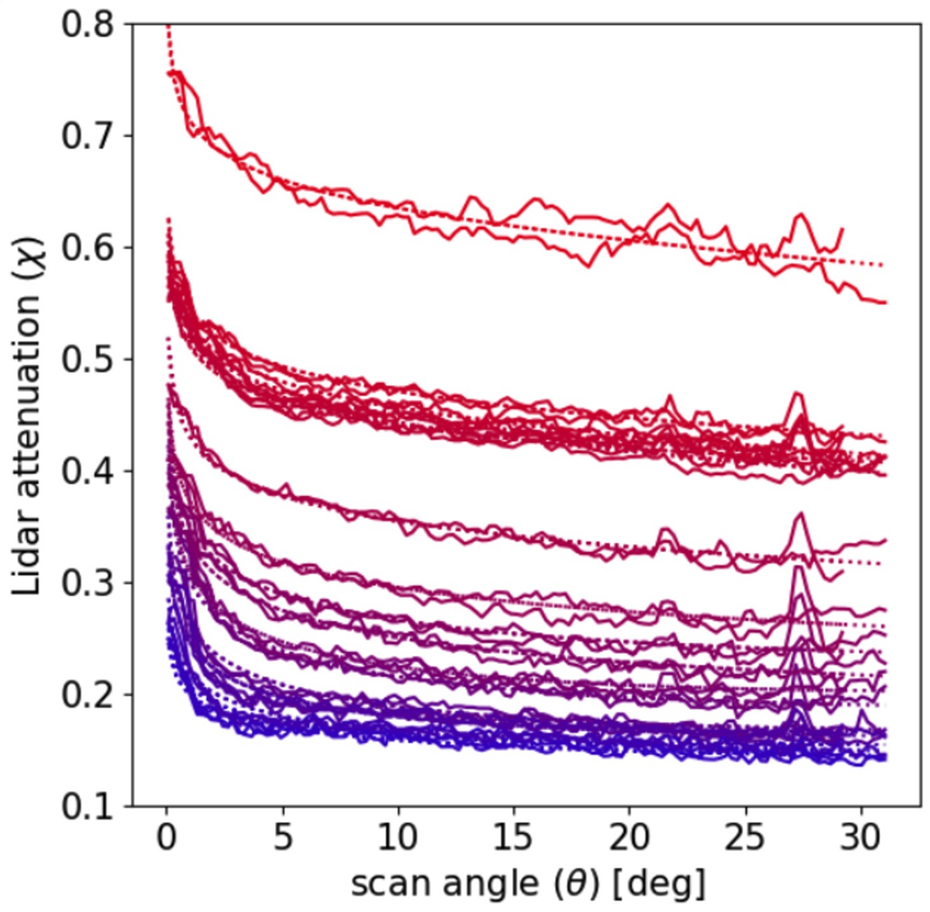


Left: Dimensionless scattering coefficients for irregular regolith grains (dashed) and spherical DEHS droplets (solid) of different radii. Right: Normalized phase function of the same particles for 0.65 µm wavelength light

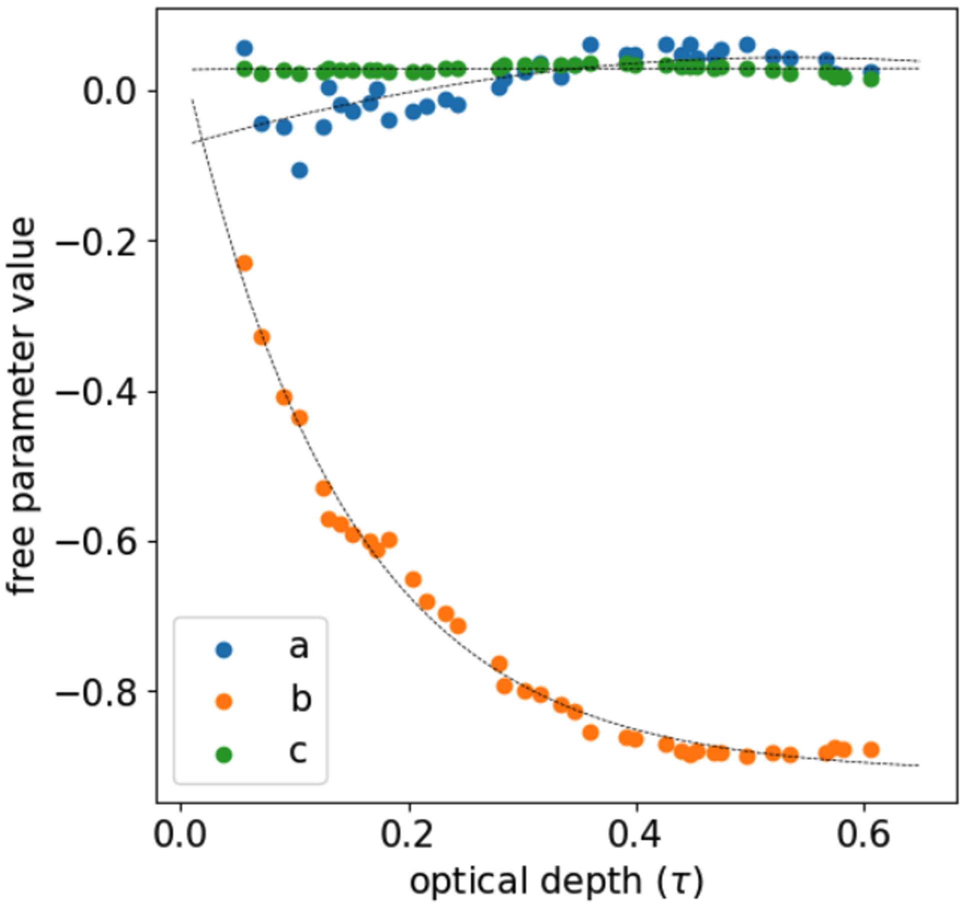
CNN loss / testing



Chi fitting



$$\chi = a\theta + b + \theta^{-c}$$

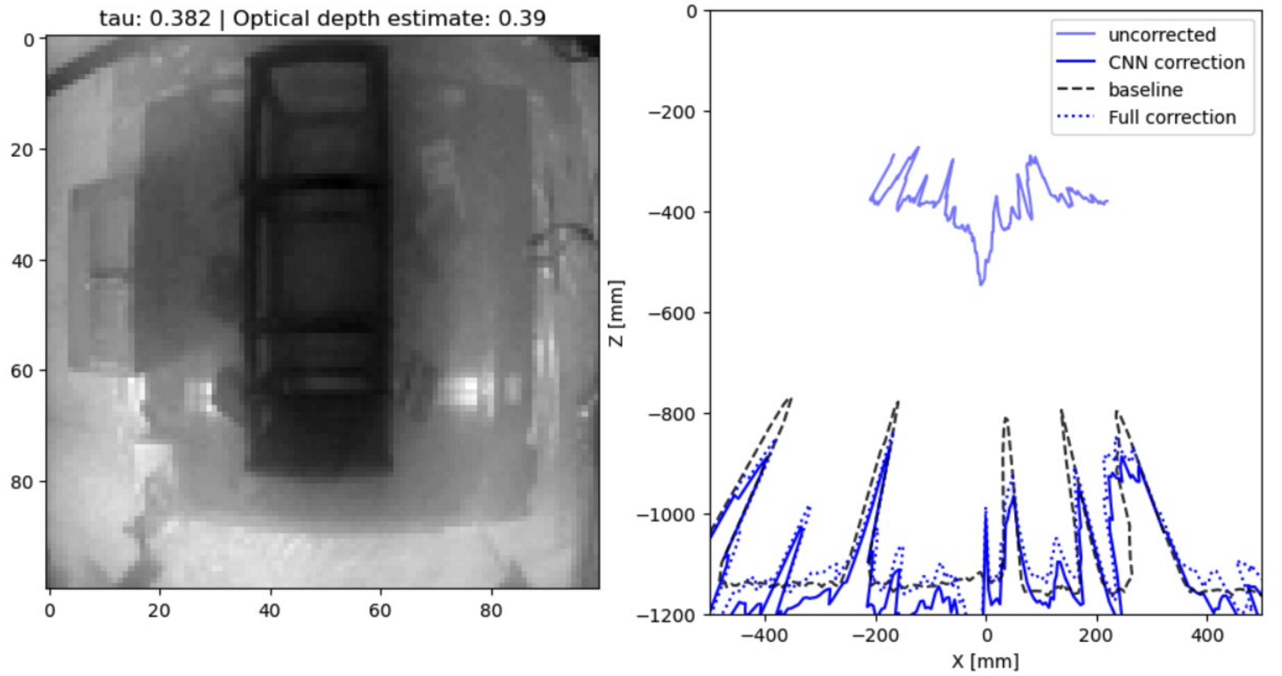


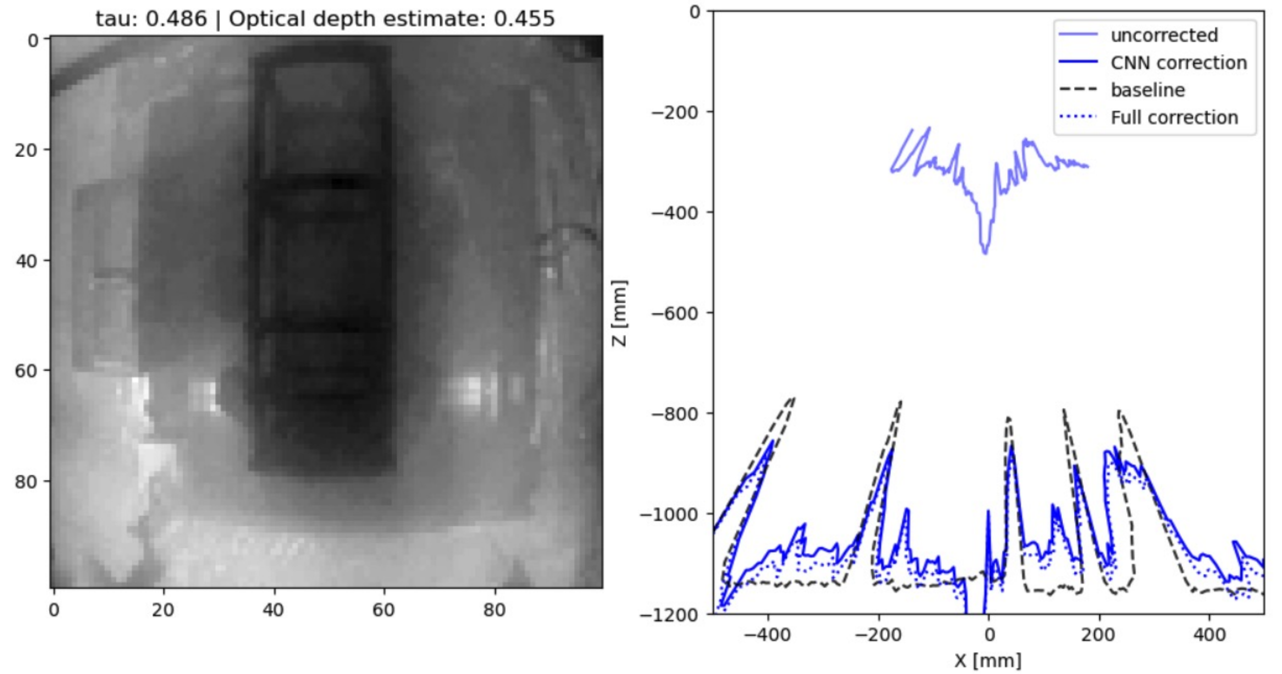
$$a = a_1\tau^2 + a_2\tau + a_3$$

$$b = b_1 e^{-b_2\tau} + b_3$$

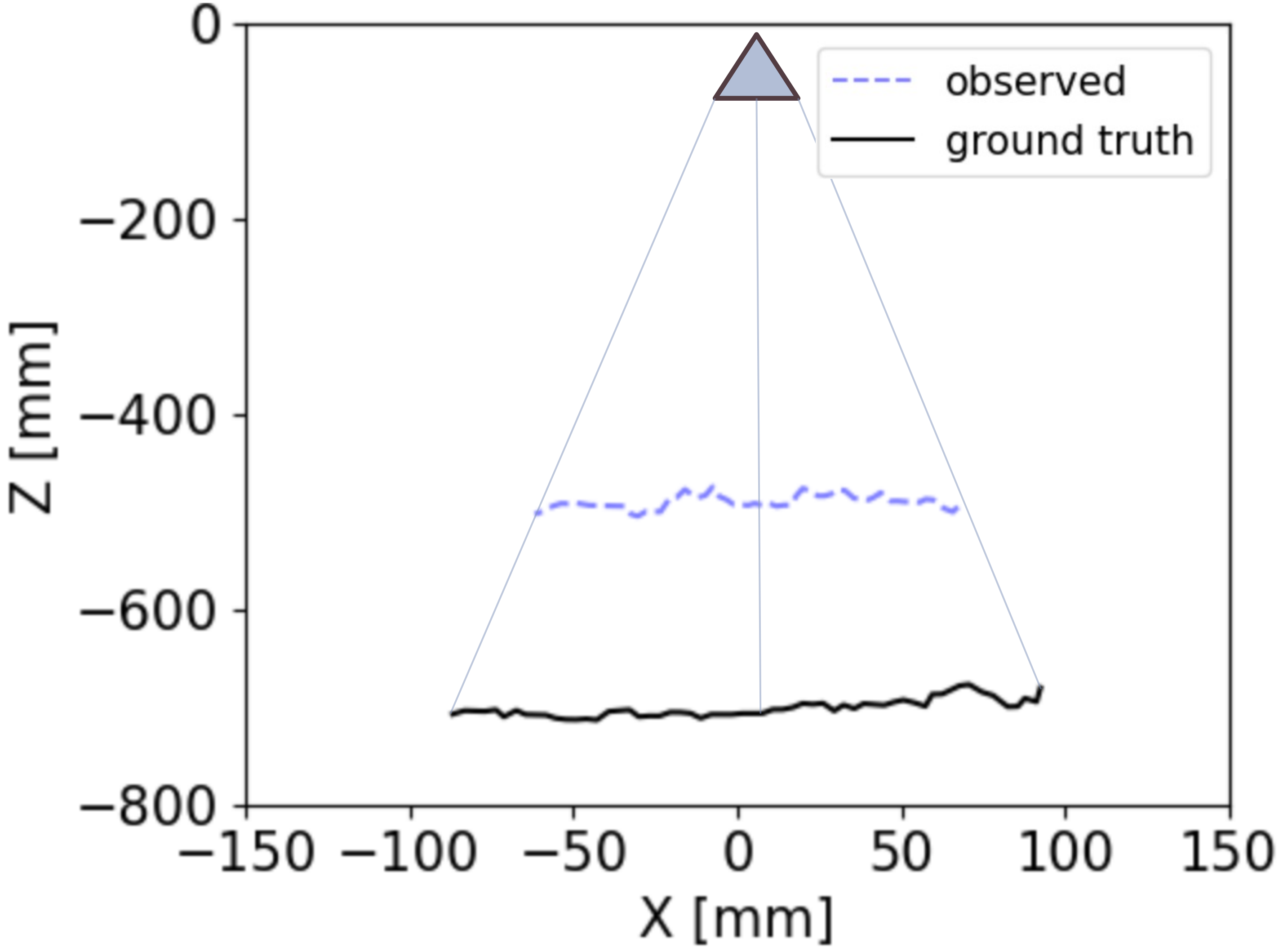
$$c = c_1\tau^{-c_2} + c_3$$

Obstacle example

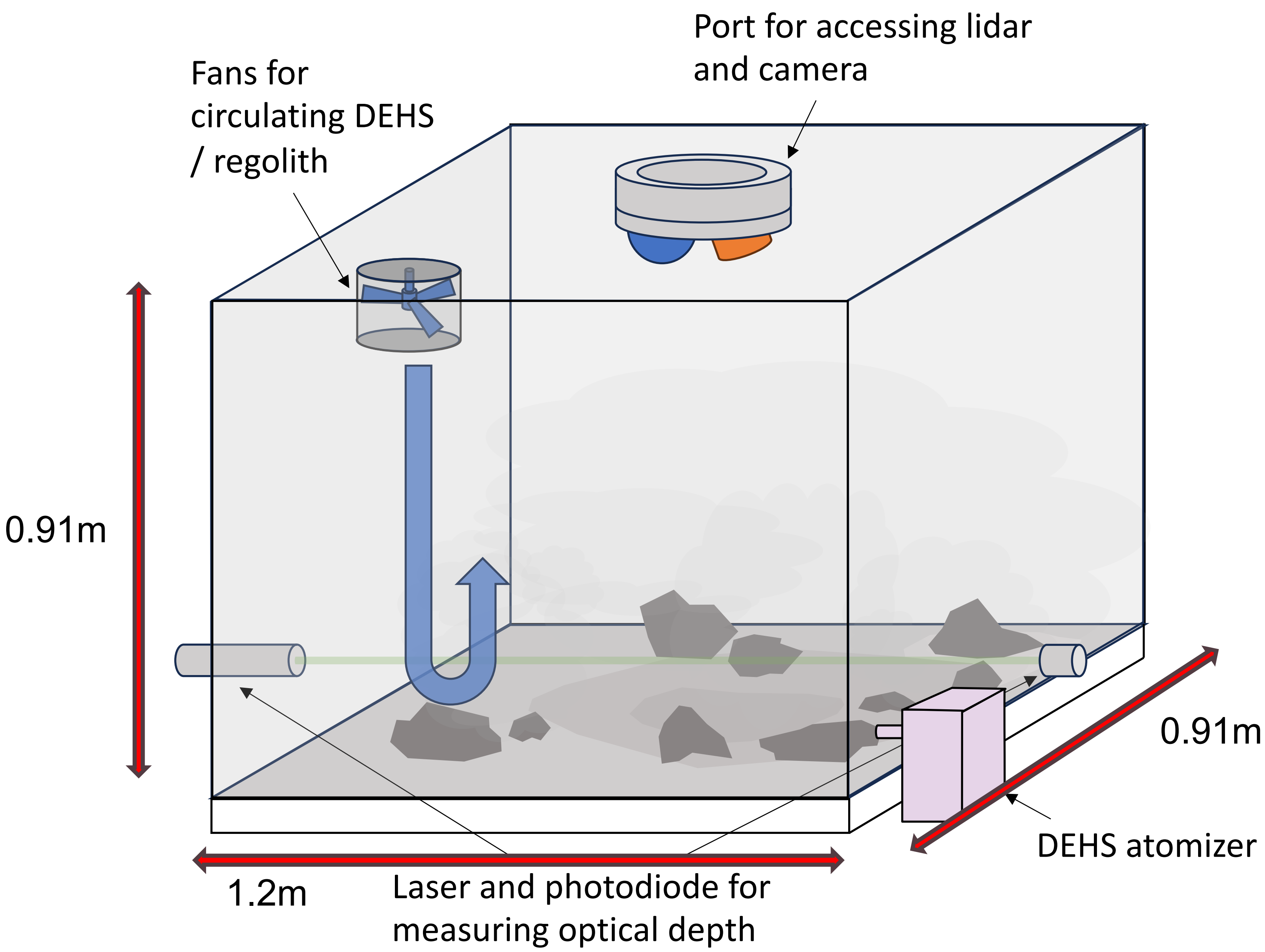


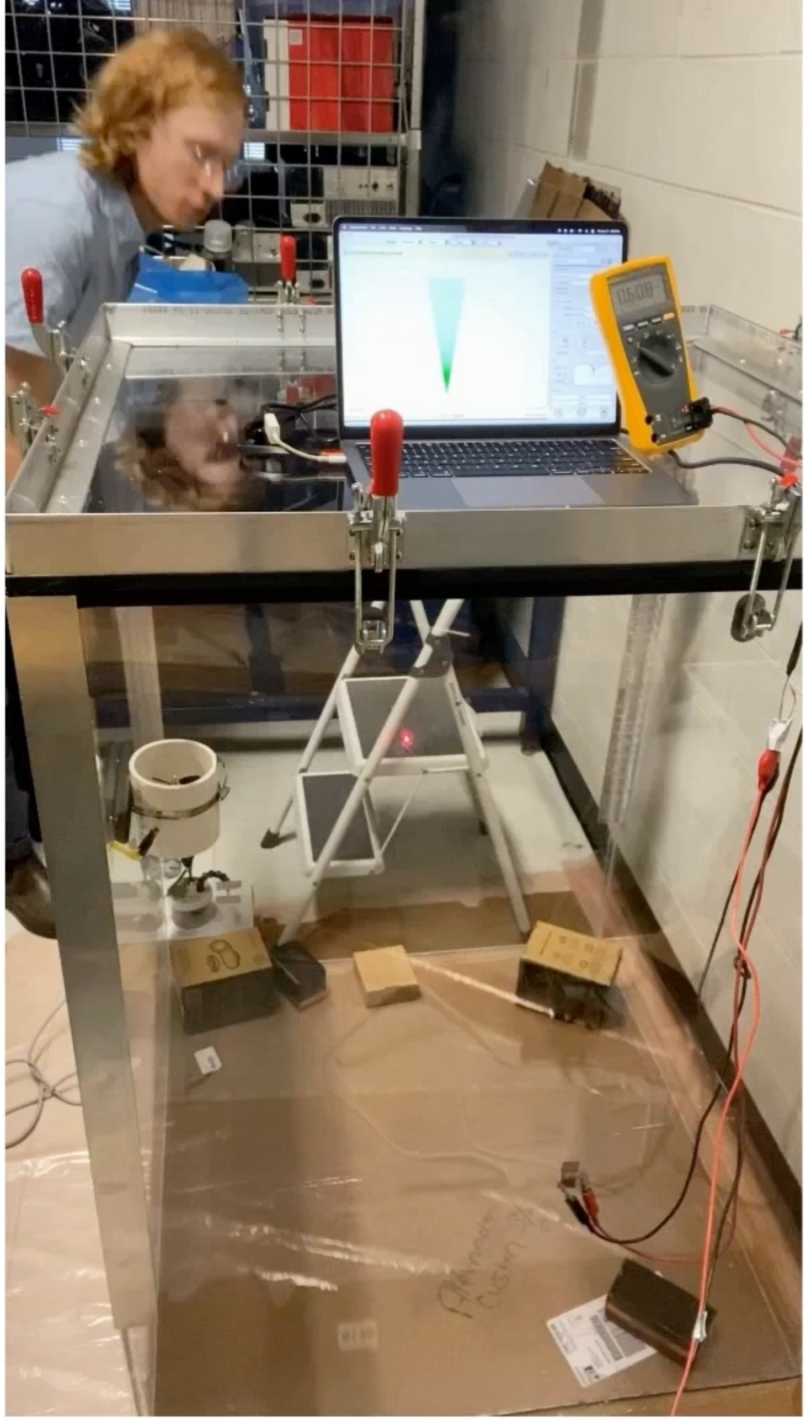


Simple obstruction demo

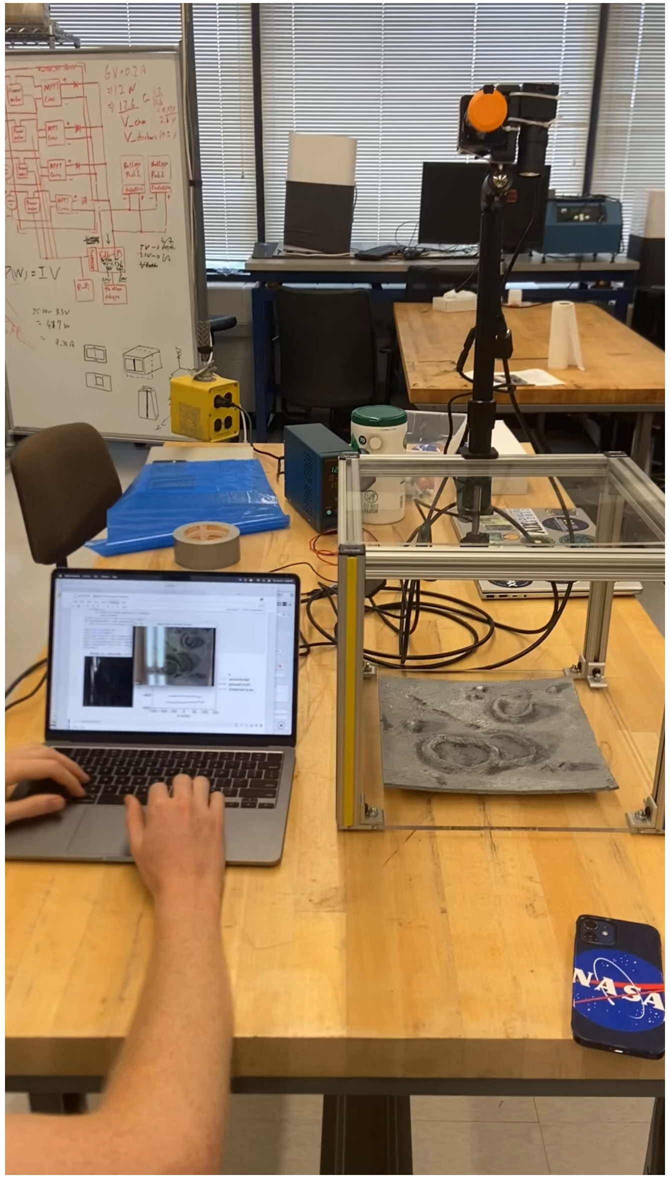


$$\frac{r_{obs.}}{r_{truth}} = \chi(\tau)$$


Port for accessing lidar
and camera
Fans for
circulating DEHS
/ regolith
0.91m
0.91m
DEHS atomizer
1.2m
Laser and photodiode for
measuring optical depth



Algorithm demo

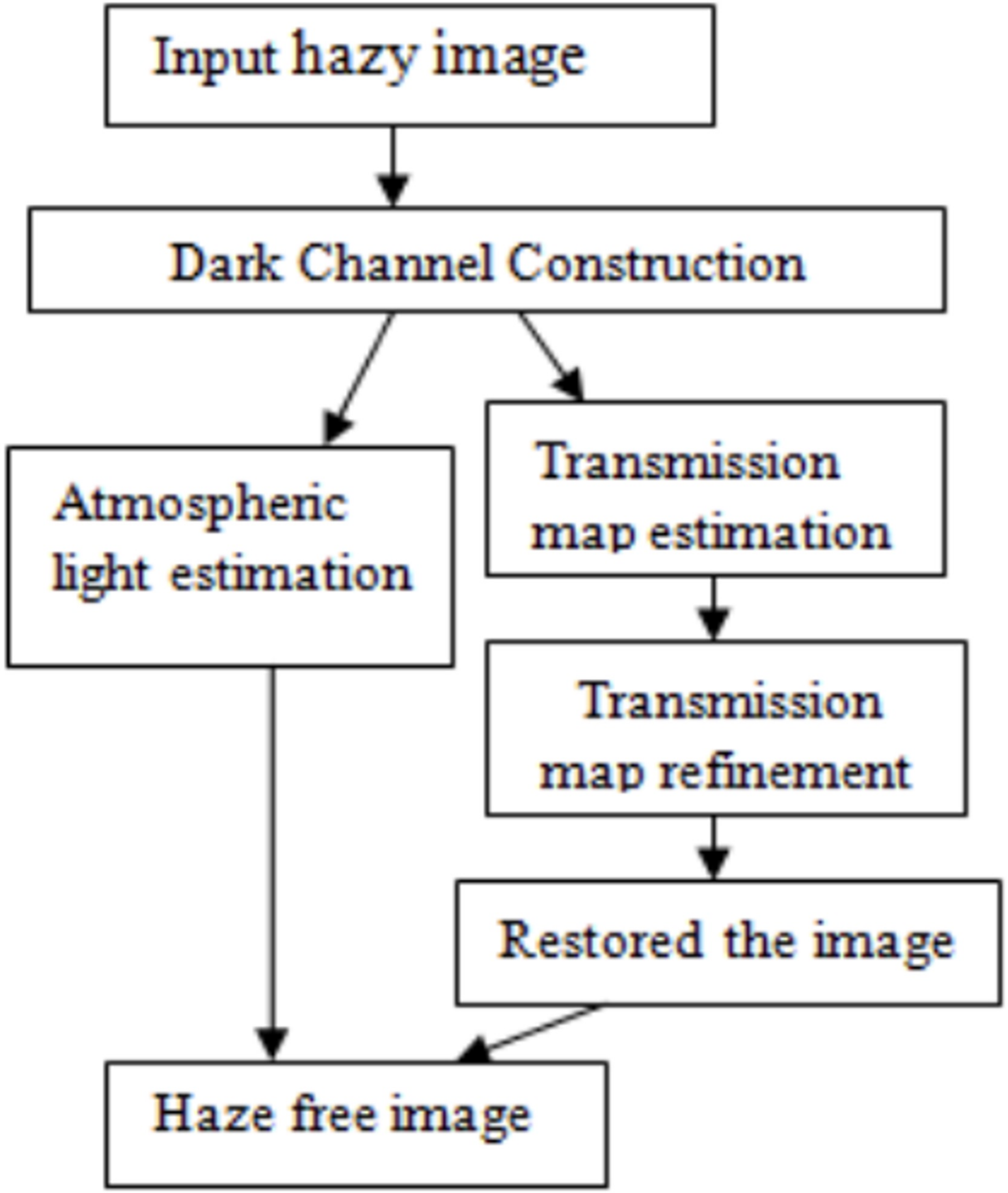


LIDROR Filter Algorithm

FOR (Each point in the point cloud)
  IF (point intensity > threshold intensity)
    Inliers $\leftarrow$ point
  ELSE
    IF (search radius < minimum search radius)
      search radius = minimum search radius
    ELSE
      Search radius $\leftarrow \phi \times \alpha \times \sqrt{x_p^2 + y_p^2}$
    ENDIF
    $n \leftarrow$ Find number of points inside SR
    IF (n < threshold point)
      Outliers $\leftarrow$ point
    ELSE
      Inliers $\leftarrow$ point
    ENDIF
  ENDIF
ENDFOR

Origin

Dehazing (Dark Channel Prior)



Origin

Recalibration/Cadence

- ARC-LIGHT provides the lander data (The optical depth estimate, dehazed image, and filtered lidar data are then fed into a second CNN, which integrates these data streams to recreate the lidar scan of the surface) to make periodic re-calibrations of the state vector throughout vertical descent to account for any drift
- This state vector correction is performed by the GNC with the same software already used during earlier descent stages.
- This is done using an extended Kalman filter that combines observational data with the propagated position estimate, accounting for the computational delay of processing surface observation data
- Assuming the output is within bounds, the lidar reconstruction is returned to the lander GNC in the native lidar format for immediate use at a target 1 Hz cadence.
- This cadence is subject to computational cost and precision requirements of the mission but is feasible to achieve given the low computational cost of using trained CNNs.
- Heuristics strategies may also help to improve computational efficiency. These are techniques to constrain the decision-making processes and choose optimal solutions without expending unnecessary computational resources trying to find a mathematically perfect one.