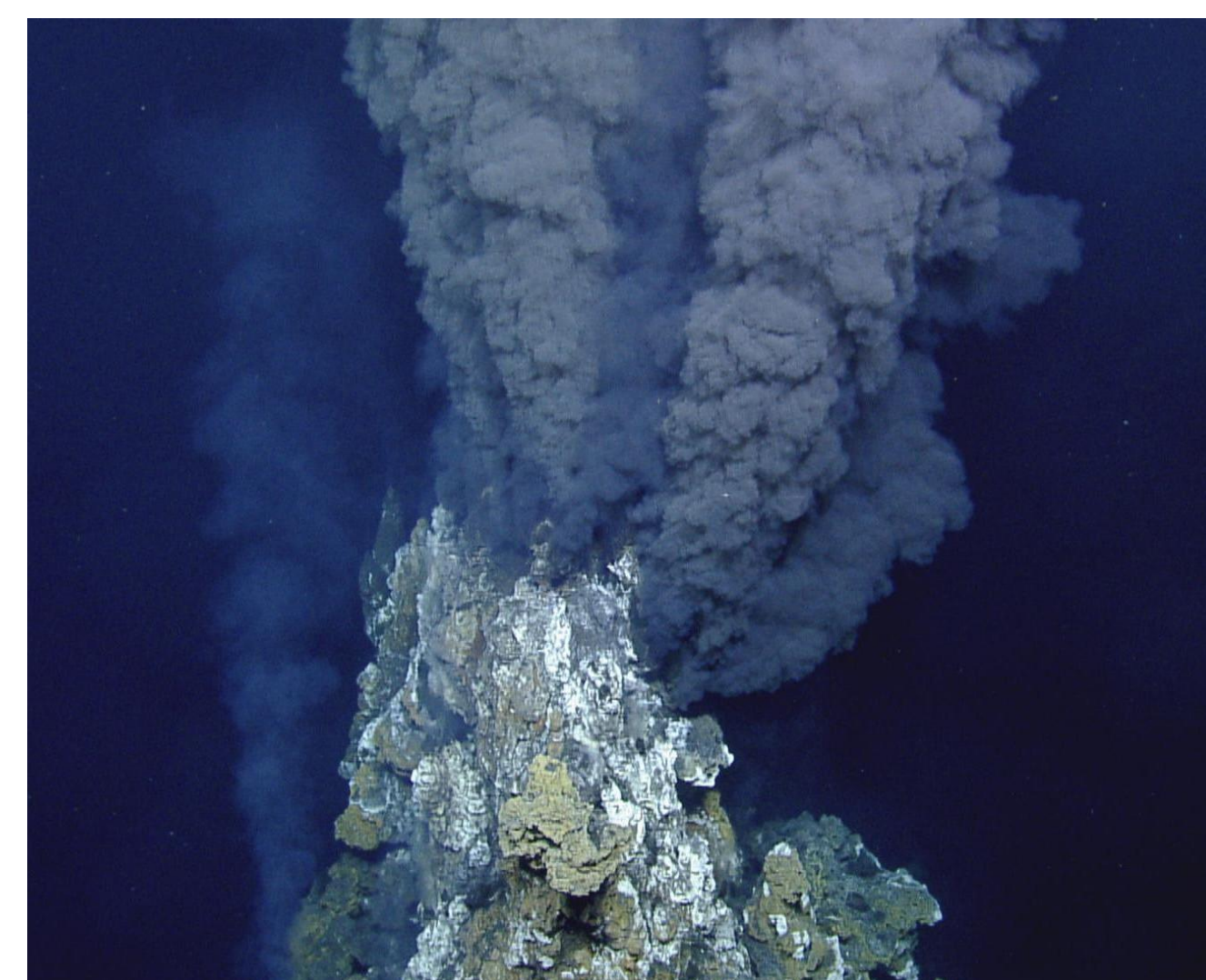


Motivation

Deep-sea hydrothermal vents discharge metal-rich plumes that can spread thousands of kilometers across an ocean basin. These vents:

- Support unique ecosystems
- Form mineral deposits
- Influence global ocean biogeochemistry



Traditional vent detection strategies rely on pre-programmed submersible paths and post-dive analysis, limiting efficiency. This project aims to develop a more efficient way to locate vents by utilizing Gaussian regression and machine learning (ML). By training an algorithm to adapt to the changing conditions of the plume, an autonomous underwater vehicle (AUV) can actively re-align its search pattern to better locate a vent.

Development Objectives

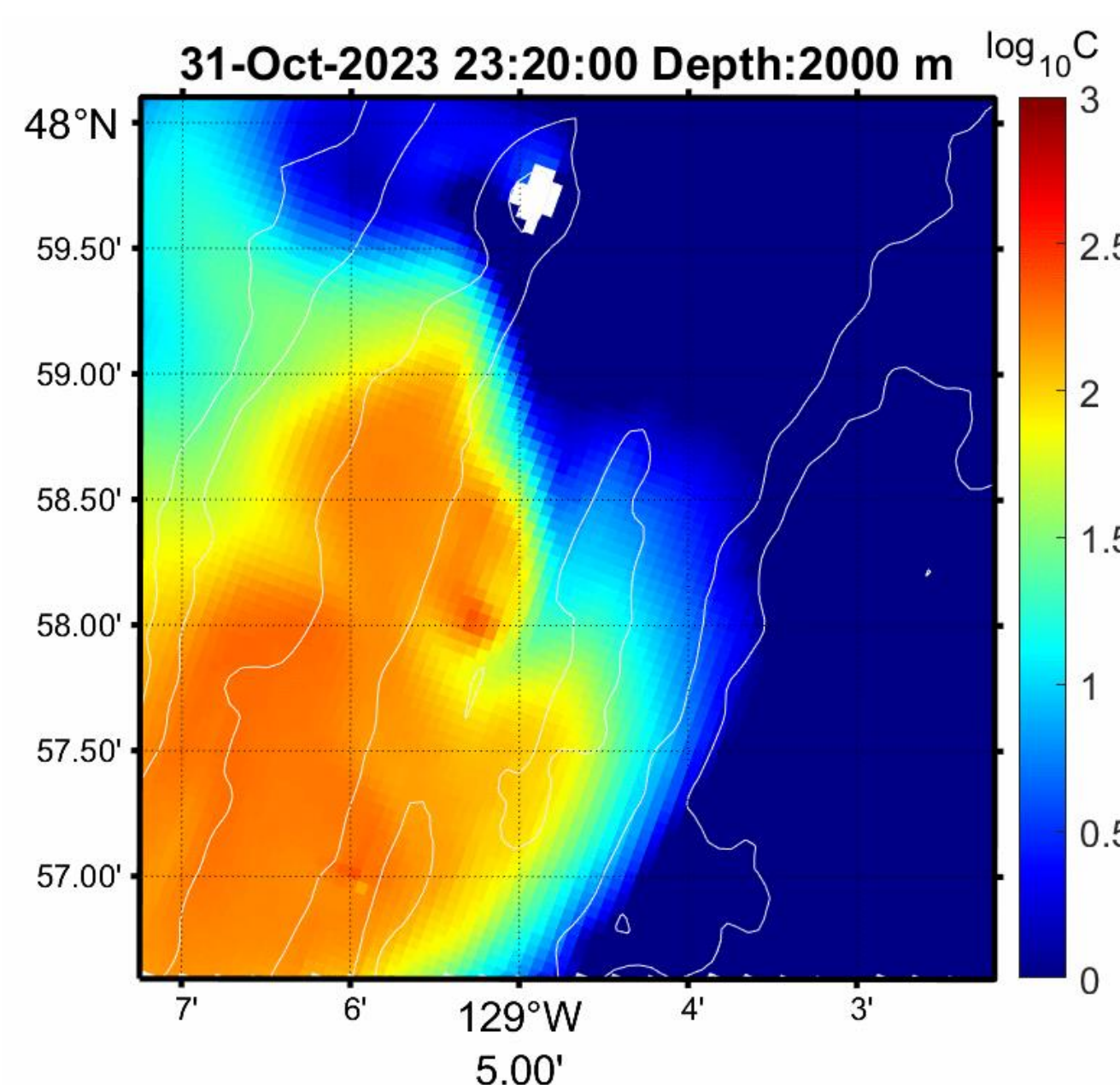
Task 1
Tracking Algorithm
Laura & Jiwei

Task 2
AUV Simulator
Garrett & Arpan

Task 3
ML Algorithm
Yang

- **Tracking algorithm:** conducts onboard analysis of sensor measurements to guide AUV towards plume source
- **AUV Simulator:** tests the deployment, integration, and capabilities of the tracking algorithm
- **ML Algorithm:** identifies plume presence in sonar backscatter images when within 100-200m of plume source

Plume Model Data



Development relied on time-varying plume data generated from a high-resolution hydrodynamic model.

This model contains data such as:

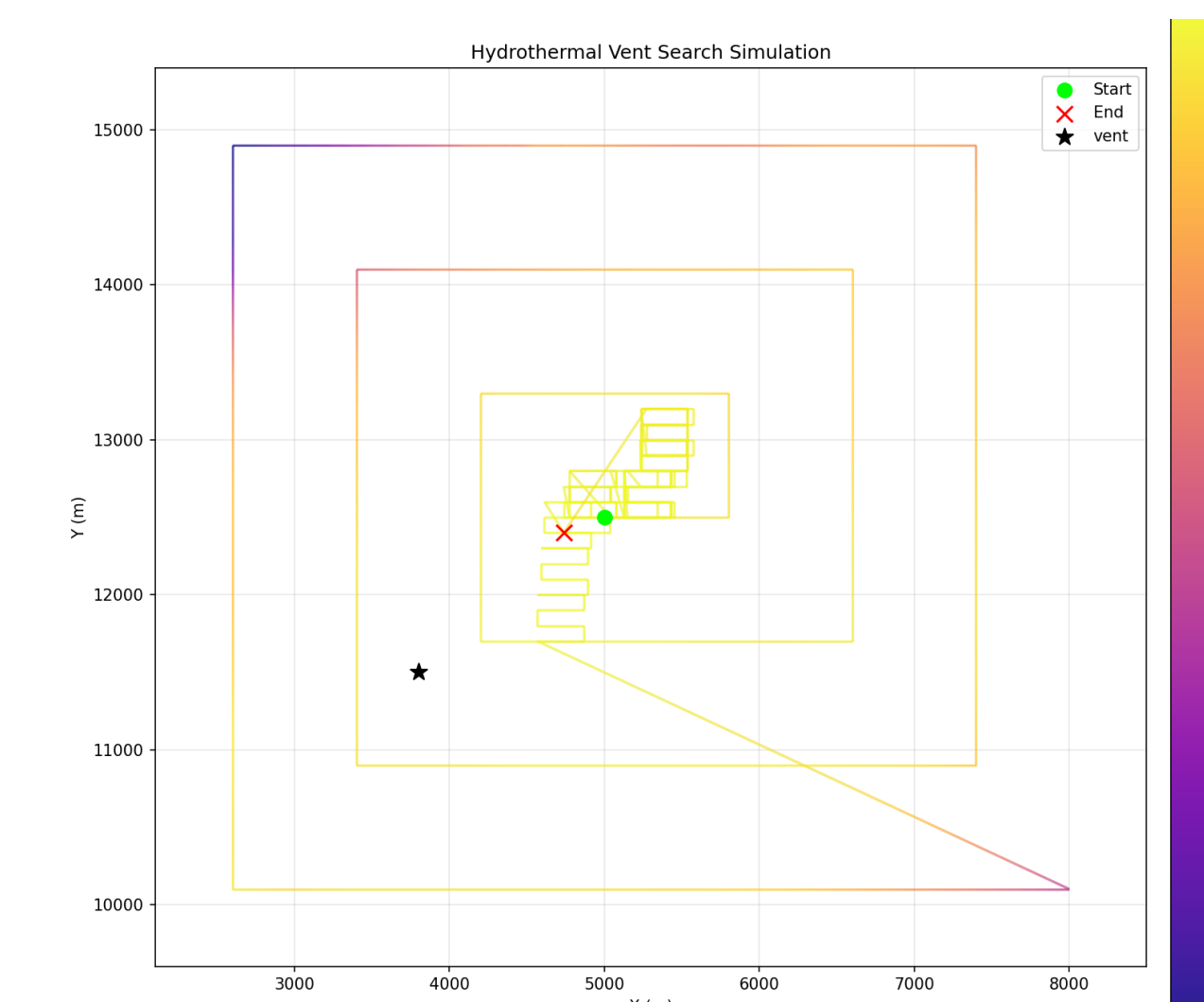
- Spiciness (temperature and salinity)
- Plume tracer concentration
- Ocean geometries

This model allows us to simulate an evolving plume and feed data to our algorithms.

Tracking Algorithm

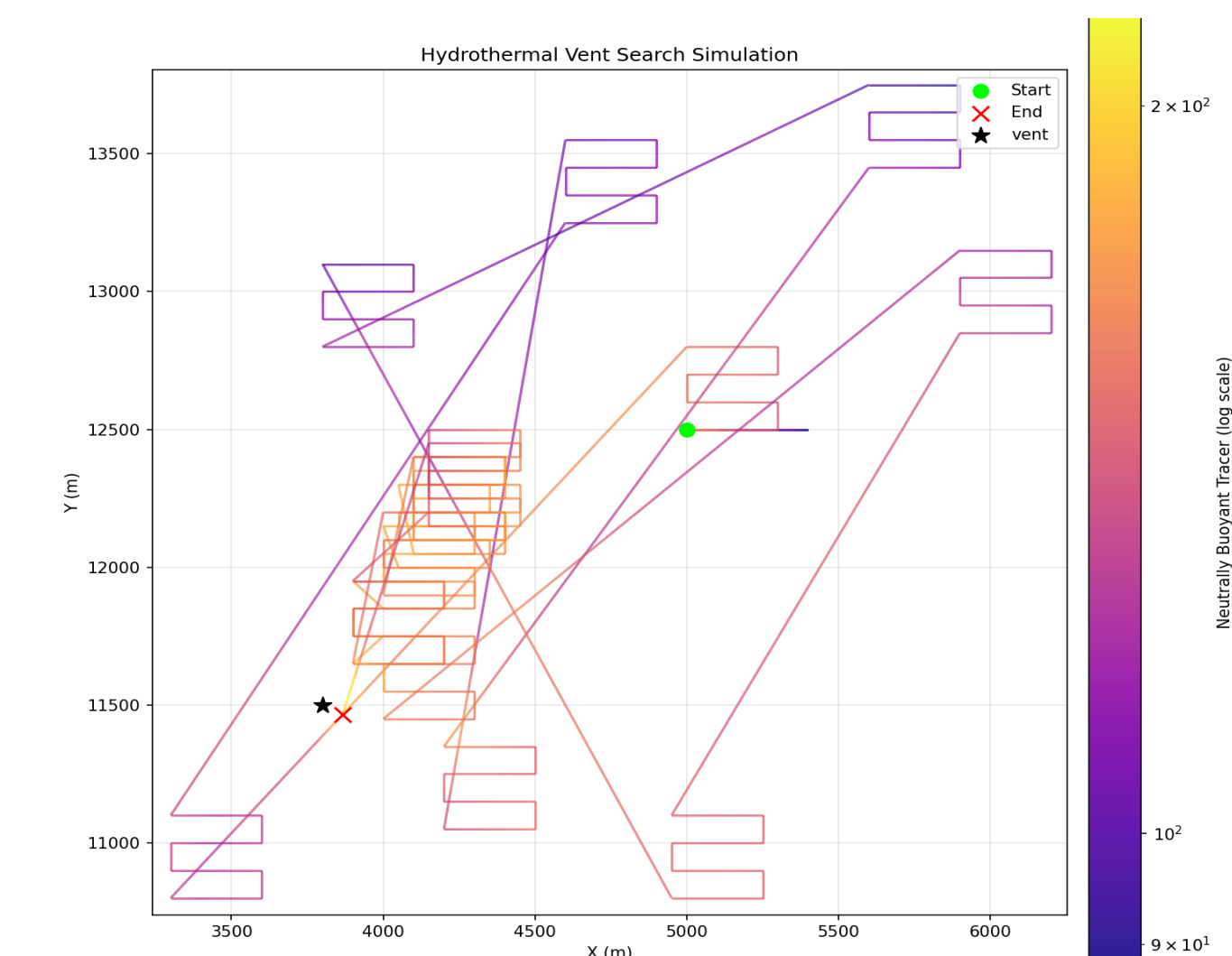
Baseline, Local Maxima:

- Record highest plume value in path
- Start next search at peak location
- Repeat, converging towards vent
- Downside: true peak may be missed



Improvement, GPR & UCB:

- Fit Gaussian Process Regression to all data
- Predict concentration & uncertainty of region
- Use Upper Confidence Bound to explore unknown areas; converges on high concentration

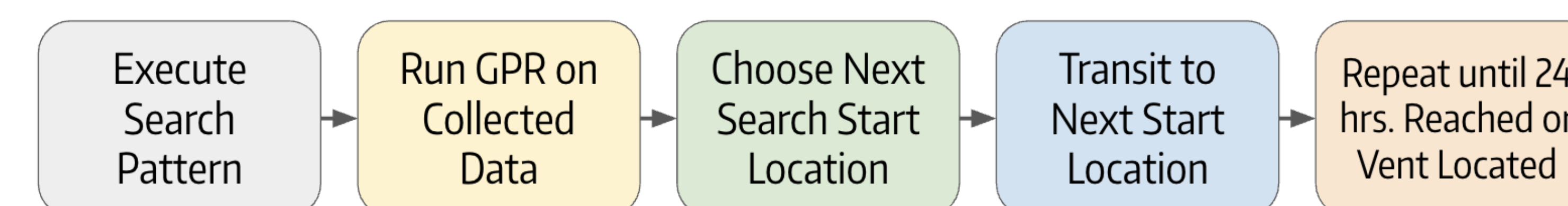


AUV Simulator

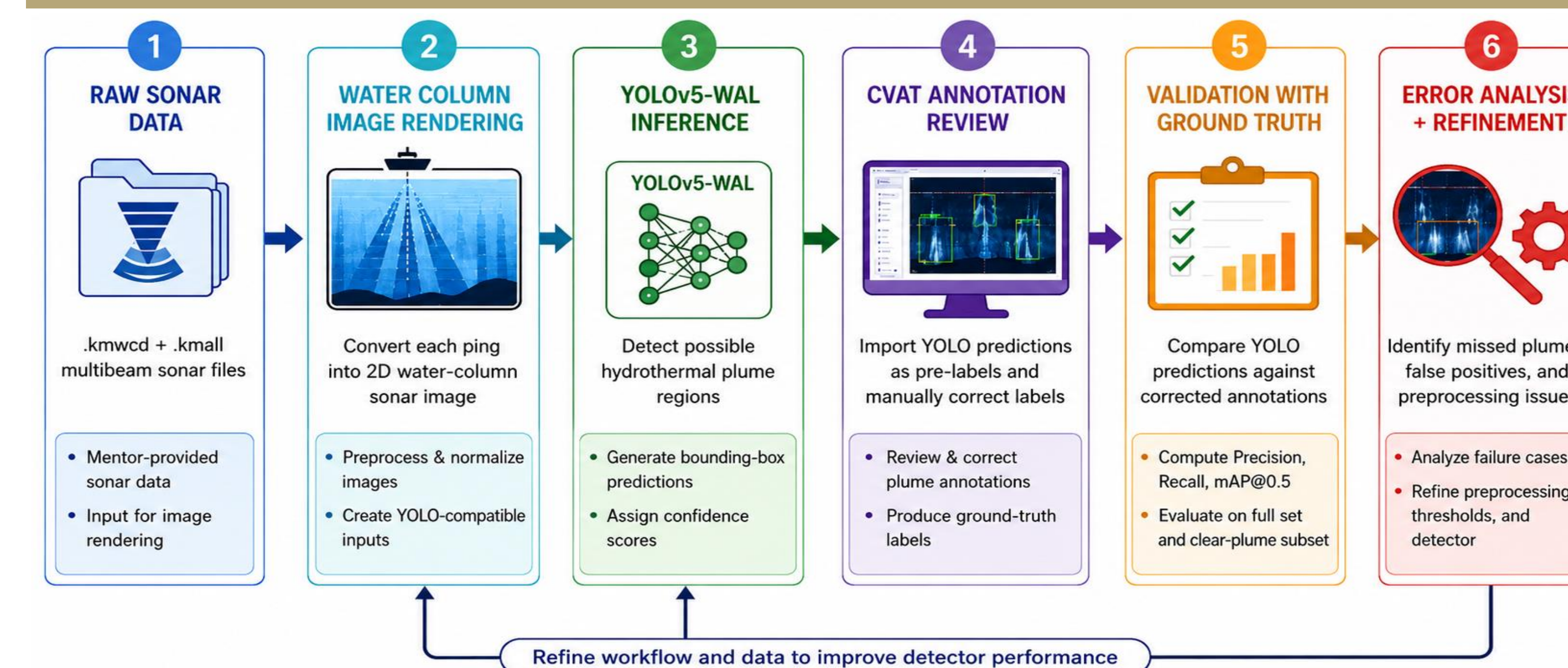


Our simulation environment, using the hydrodynamic model data, achieves the following:

- Creates an evolving plume render using model data variables and ocean floor geometries
- Simulates an AUV's path through the environment and feeds positional data to it
- Receives survey commands from the tracking algorithm and executes them on the SENTRY AUV network API



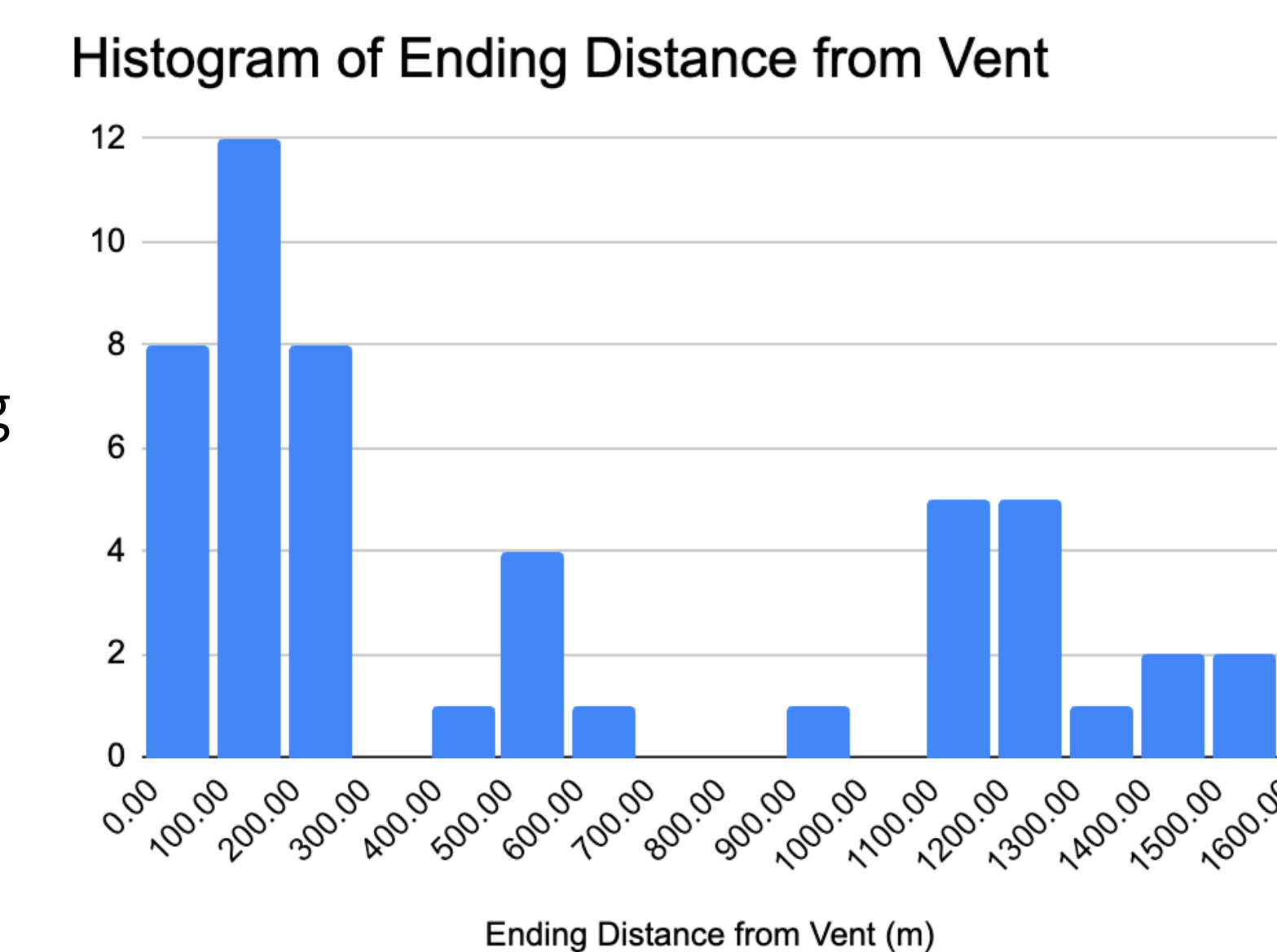
ML Plume Detector Evaluation/Refine Pipeline



Results

Gaussian Tracking Results

- Nearly 60% of randomized runs end within vent's 200m radius of success
- Starts that encounter a misleading plume offshoot or canopy often result in a failed run
- Results fall into distinct distance buckets and are not randomly distributed; failures can be pinpointed and optimized against

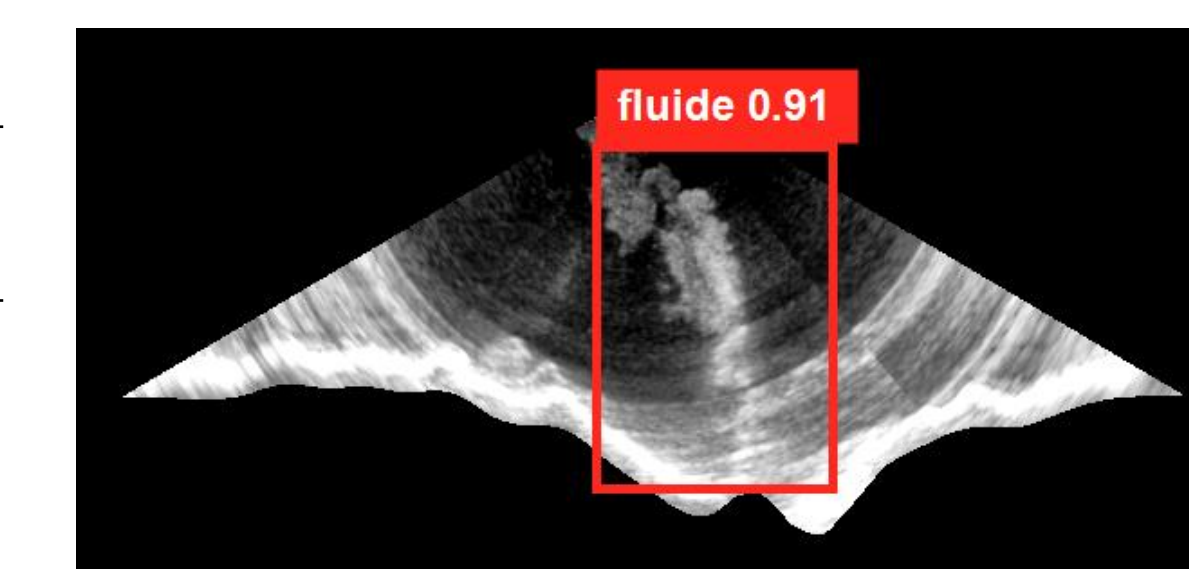


Starting Distance	Avg. Ending Distance	Standard Deviation	Avg. Ending Distance of Top 25 Trials	Standard Deviation of Top 25 Trials
3000 (n=50)	557.75	527.38	129.35	66.28

*All distances in meters.

Plume Detector Performance

Model	Evaluation Set	Images	Plume Labels	Precision	Recall	mAP@0.5
Pretrained	Full Set	363	297	0.779	0.557	0.595
Pretrained	Clear Subset	230	260	0.923	0.623	0.664
Fine-tuned	Held-out 40% Subset	143	115	0.848	0.696	0.845



Future Work

- Optimize the developed algorithms; tune parameters for Gaussian regression and ML hyperparameters, implement distraction detection and avoidance
- Deployment on the SENTRY AUV for real data collection to identify weaknesses in the current implementation

References and Acknowledgements

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