

# Multi-Sensor SLAM in Antarctic Ice Fields: A Field Report

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Figure 1. Shipborne multi-sensor SLAM configuration with onboard computing in the control cabin.

## Introduction

Polar maritime environments present a difficult and underexplored operating regime for robot state estimation. These conditions motivate near field sensing and resilient onboard localization, particularly when visibility is limited, scene structure is ambiguous, or GNSS availability is degraded. Although marine vessels may also carry radar, reliable local state estimation remains critical for close range navigation and perception in ice covered environments. Such resilience is especially valuable for GPS denied operation and is increasingly relevant to defense focused maritime platforms. In this work, we evaluate two representative SLAM systems on a real shipborne Antarctic dataset: a LiDAR-IMU system and a LiDAR-only system. We compare their performance using trajectory accuracy and drift metrics, and use the results to extract practical lessons for future autonomous polar vessels.

## Shipborne Antarctic Field Dataset

We collected a real-world Antarctic shipborne multi sensor dataset aboard the RRS Sir David Attenborough. The sensing platform was deployed on the bow mast, with data logging, system monitoring, and remote debugging managed directly through the onboard system via a WiFi Bullet link and a field laptop, enabling robust data capture under realistic maritime motion and polar operating conditions.

### Dataset scale:

- 819 sequences
- ~10 min each
- ~3 GB per sequence
- Synchronized multi-sensor recordings: LiDAR point clouds (Livox Avia), IMU data (MTI-30), GNSS measurements (D-RTK ANT CA7607A), camera images (FLIR Blackfly S), and radar (Rutter sigma 6) returns

The dataset spans diverse Antarctic operating regimes and provides a rare benchmark for SLAM evaluation in polar maritime environments.

## Methods

We evaluate two representative SLAM paradigms that reflect distinct sensing modalities and estimation assumptions under Antarctic maritime conditions.

| Method        | Primary Sensor Modality |
|---------------|-------------------------|
| FAST-LIO [3]  | LiDAR + IMU             |
| Lio Livox [1] | LiDAR                   |

Table 1. Representative SLAM methods evaluated in this study and their primary sensor modalities.

The estimated trajectories produced by these methods are aligned to reference GPS in a common frame, and evaluation is performed using trajectory accuracy and drift metrics. These methods were selected to compare the performance of LiDAR-IMU and LiDAR-only SLAM under the same Antarctic operating conditions.

## Experimental Setup

We evaluate the methods on six representative Antarctic sequences selected to cover diverse combinations of polar maritime conditions, including close-pack ice, lead flat ice, level ice, variable illumination, and maneuver-intensive segments. This subset was chosen to expose the estimators to distinct operating conditions rather than a single average scenario. The figure 2 below presents a timeline of the six sequences and highlights the temporal distribution of scene characteristics within each run.

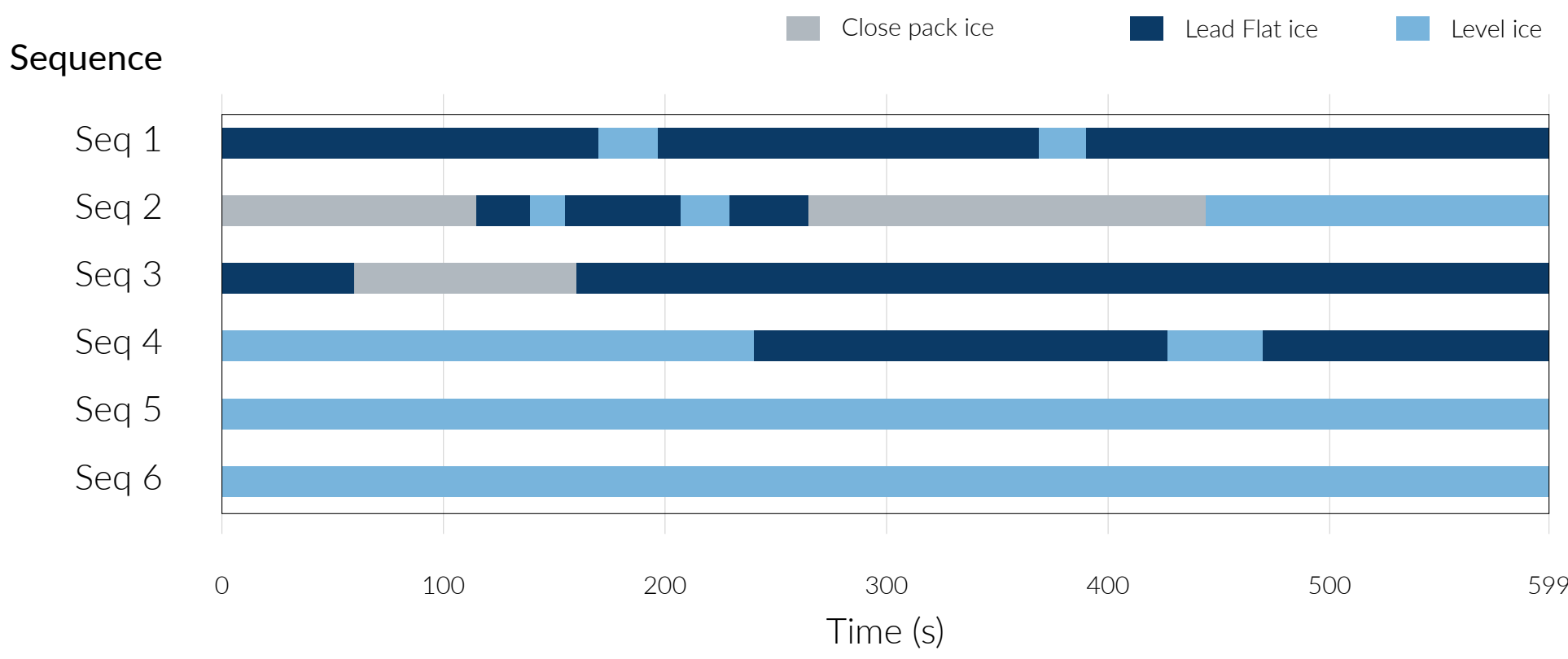


Figure 2. Mission composition of the six sequences over 599 s.

The map below summarizes the ship routes for the six selected evaluation sequences.

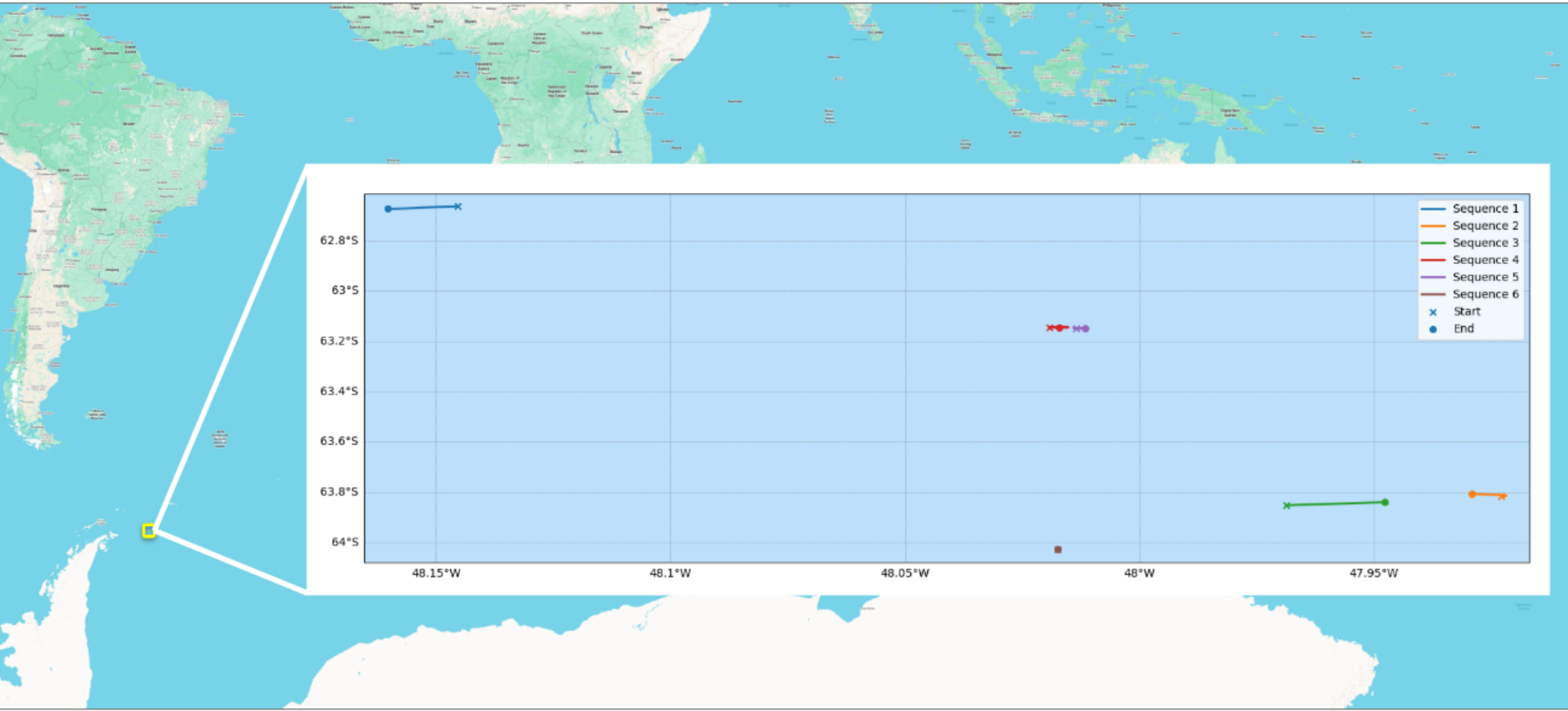


Figure 3. Ship routes for the dataset sequences used in this evaluation. The enlarged image highlights the six sequences shown in Figure 2.

## Evaluation Metrics

| Metric                          | Why it matters                    |
|---------------------------------|-----------------------------------|
| Absolute Trajectory Error (ATE) | Global trajectory accuracy.       |
| Relative Drift Error            | Drift accumulation over motion.   |
| Relative Position Error         | Short-range position consistency. |
| Standard Deviation of Error     | Trajectory error variability.     |

Table 2. Trajectory-based metrics used to evaluate SLAM performance on the selected Antarctic sequences.

These metrics capture complementary aspects of performance. ATE reflects overall agreement with the reference trajectory, while relative drift error and relative position error reveal how well each method maintains local consistency during motion. Reporting all three provides a more informative assessment than any single error measure alone.

## Results

Figure 5 illustrates representative mapping outputs from FAST-LIO for six selected Antarctic sequences, including close-pack ice, lead flat ice, level ice, maneuver-intensive segments, and apparent ice drift. These examples provide qualitative insight into map structure and trajectory behavior under realistic polar maritime operating conditions.

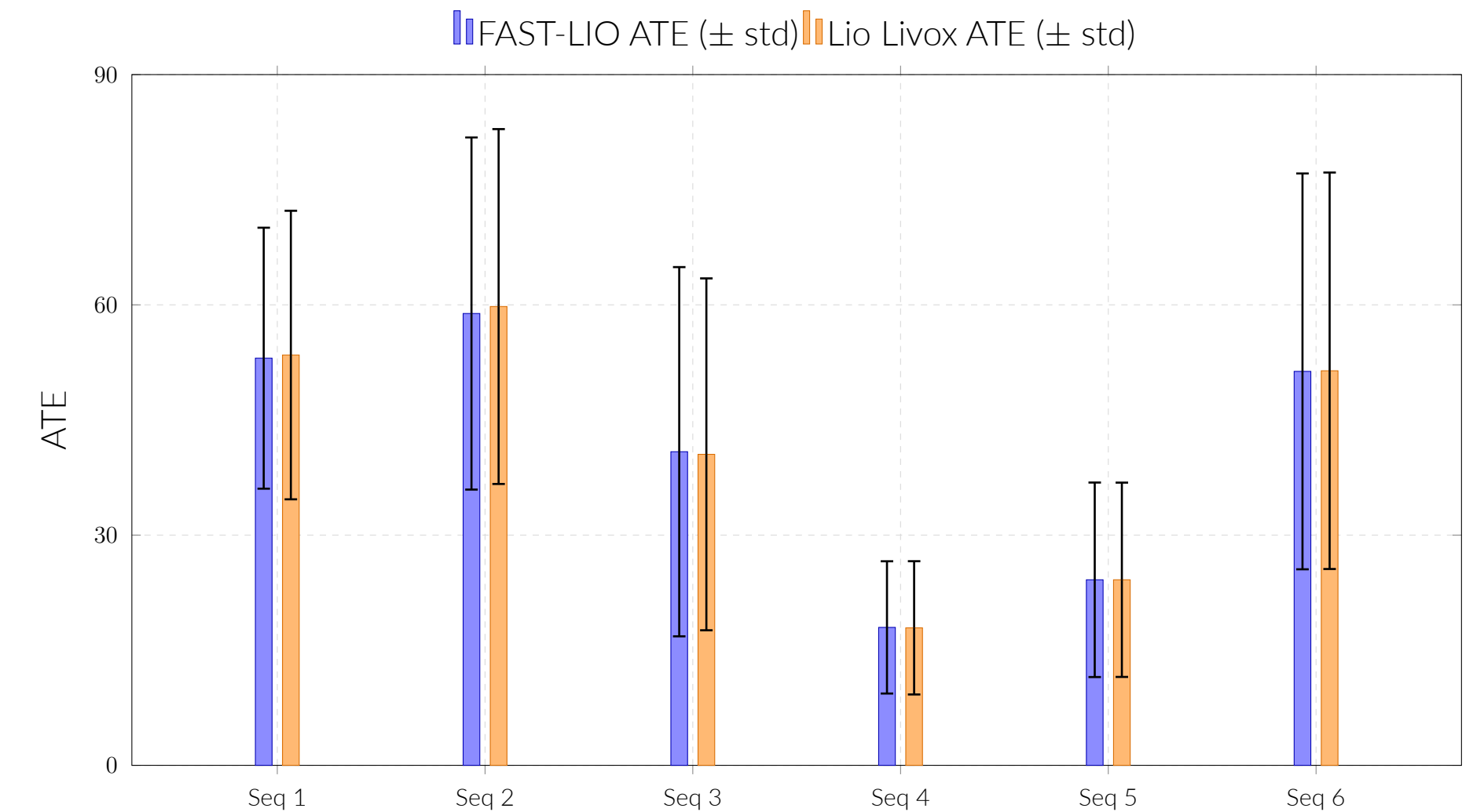


Figure 4. Sequence-wise comparison of absolute trajectory error for FAST-LIO and Lio Livox across the six selected Antarctic sequences. Error bars indicate the standard deviation for each sequence.

Figure 4 provides a quantitative comparison across methods using ATE, and standard deviation of error for each scenario. The results show that performance varies strongly with operating condition rather than following a single consistent ranking across all scenes.

Table 3 summarizes the per-sequence evaluation metrics for all methods and provides the detailed numerical evidence behind the trends observed in Figure 4. This table is intended to support direct comparison across sequences and methods, while preserving the variability that is often hidden by aggregate summaries.

| Sequence | Metric                         | FAST-LIO | Lio Livox |
|----------|--------------------------------|----------|-----------|
| Seq 1    | Absolute Trajectory Error (m)  | 53.049   | 53.459    |
|          | Relative drift error (RMSE)    | 106.104  | 98.661    |
|          | Relative position error (RMSE) | 0.553    | 0.539     |
|          | Standard deviation of error    | 17.002   | 18.798    |
| Seq 2    | Absolute Trajectory Error (m)  | 58.870   | 59.779    |
|          | Relative drift error (RMSE)    | 121.113  | 118.397   |
|          | Relative position error (RMSE) | 0.523    | 0.523     |
|          | Standard deviation of error    | 22.940   | 23.119    |
| Seq 3    | Absolute Trajectory Error (m)  | 40.863   | 40.523    |
|          | Relative drift error (RMSE)    | 105.063  | 102.499   |
|          | Relative position error (RMSE) | 0.479    | 0.451     |
|          | Standard deviation of error    | 24.054   | 22.924    |
| Seq 4    | Absolute Trajectory Error (m)  | 17.973   | 17.916    |
|          | Relative drift error (RMSE)    | 38.285   | 38.334    |
|          | Relative position error (RMSE) | 0.514    | 0.514     |
|          | Standard deviation of error    | 8.616    | 8.682     |
| Seq 5    | Absolute Trajectory Error (m)  | 24.175   | 24.177    |
|          | Relative drift error (RMSE)    | 49.996   | 49.816    |
|          | Relative position error (RMSE) | 0.377    | 0.379     |
|          | Standard deviation of error    | 12.672   | 12.659    |
| Seq 6    | Absolute Trajectory Error (m)  | 51.330   | 51.410    |
|          | Relative drift error (RMSE)    | 101.814  | 101.938   |
|          | Relative position error (RMSE) | 0.631    | 0.631     |
|          | Standard deviation of error    | 25.788   | 25.828    |

Table 3. Sequence-wise comparison of trajectory error metrics for FAST-LIO and Lio Livox.

## Conclusions and Future Work

We presented a field evaluation of two shipborne SLAM systems, FAST-LIO and Lio Livox, on a real Antarctic multi-sensor dataset collected aboard the RRS Sir David Attenborough. Sequence-wise trajectory metrics show that LiDAR-based SLAM remains feasible in challenging polar maritime conditions, while performance is strongly affected by scene structure, vessel motion, and apparent environmental motion. These results highlight the need for localization pipelines that remain stable under both structured ice environments and low-structure maritime regimes.

Future work will focus on:

- Joint LiDAR, IMU, and GPS fusion for improved global consistency and robustness.
- Visual feedback for regimes where open water is detected and LiDAR structure becomes weak.
- Adaptive estimator switching based on scene conditions and platform motion.
- Improved handling of apparent environmental motion and non-stationary ice.

Antarctic autonomy will require SLAM systems designed for environmental ambiguity, sensing degradation, and changing scene structure, not only for sensor noise.

## References

- [1] Livox. A robust lidar-inertial odometer with lio-livox open-source algorithm. <https://www.livoxtech.com/showcase/12>, 2021. Accessed: 2026-04-26.
- [2] Tong Qin, Peiliang Li, and Shaojie Shen. Vins-mono: A robust and versatile monocular visual-inertial state estimator. *IEEE transactions on robotics*, 34(4):1004–1020, 2018.
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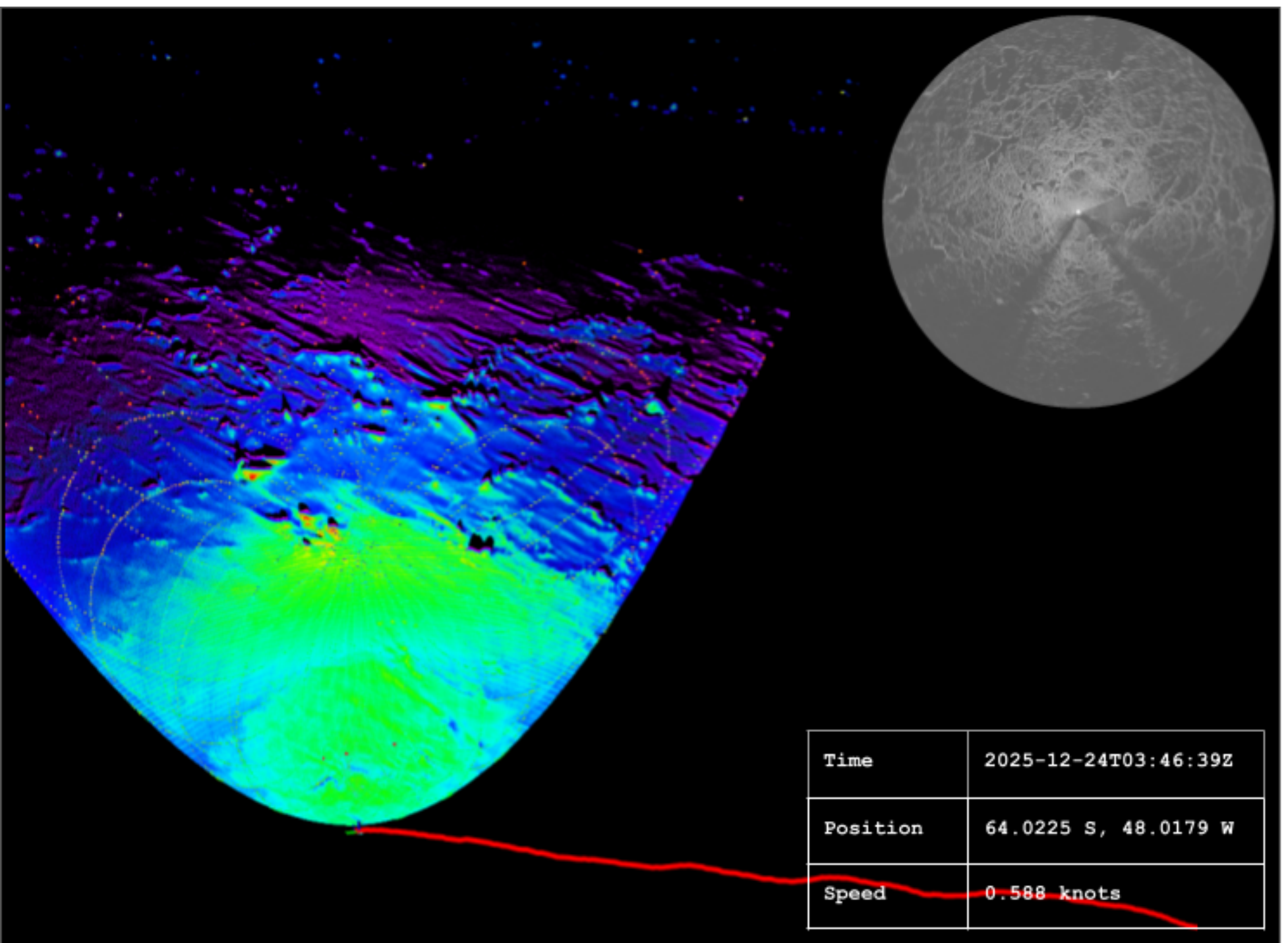
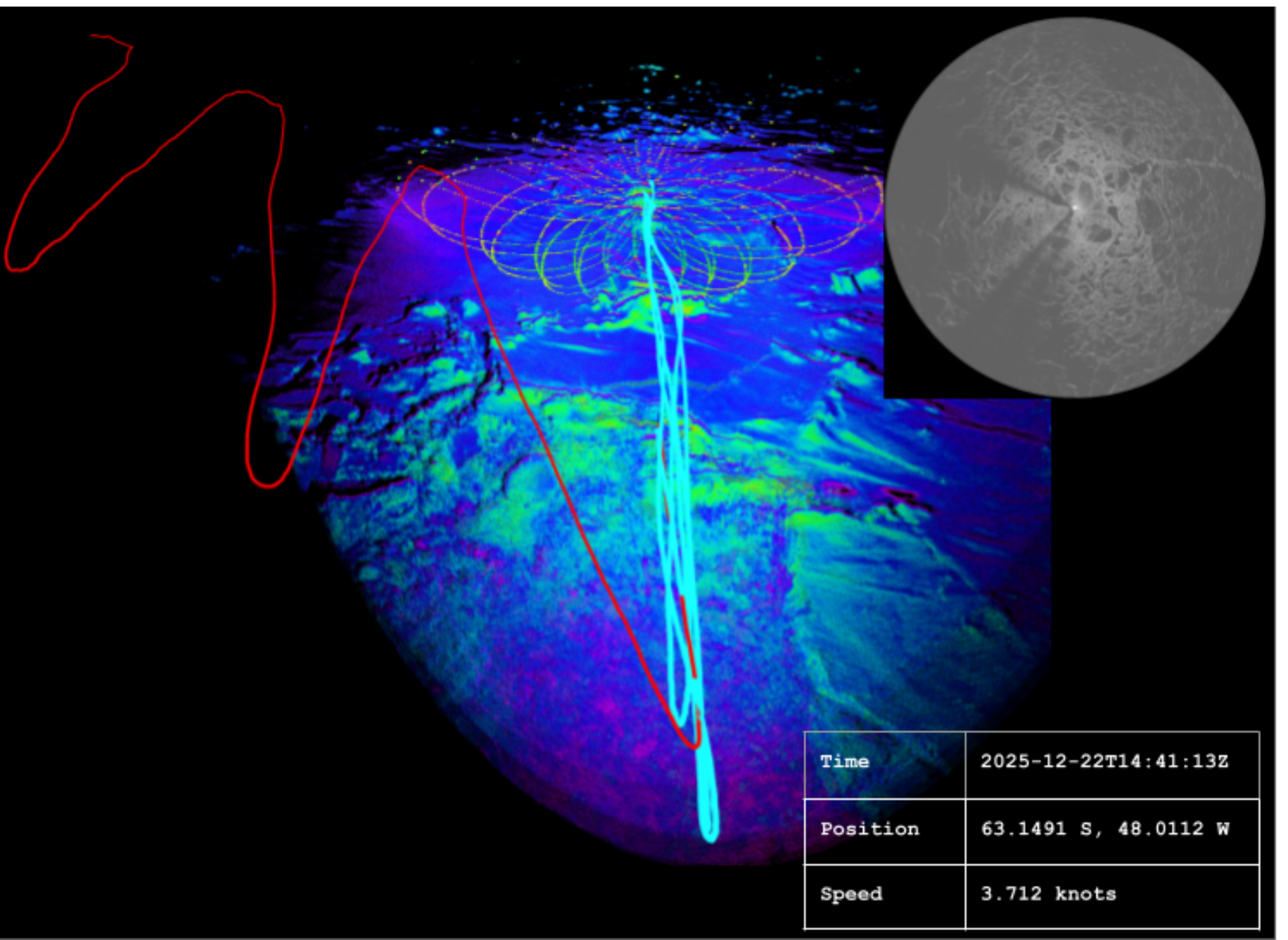
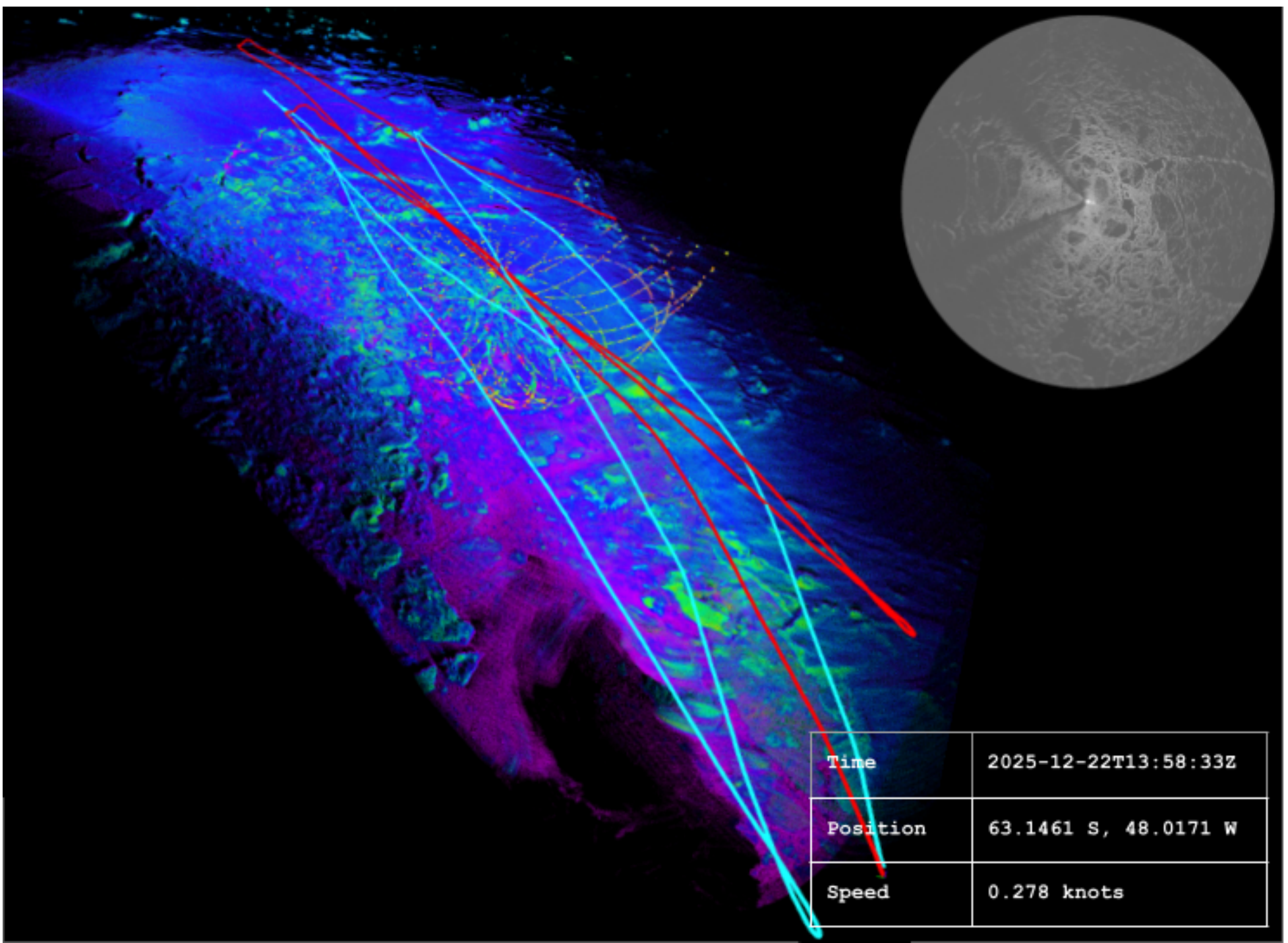
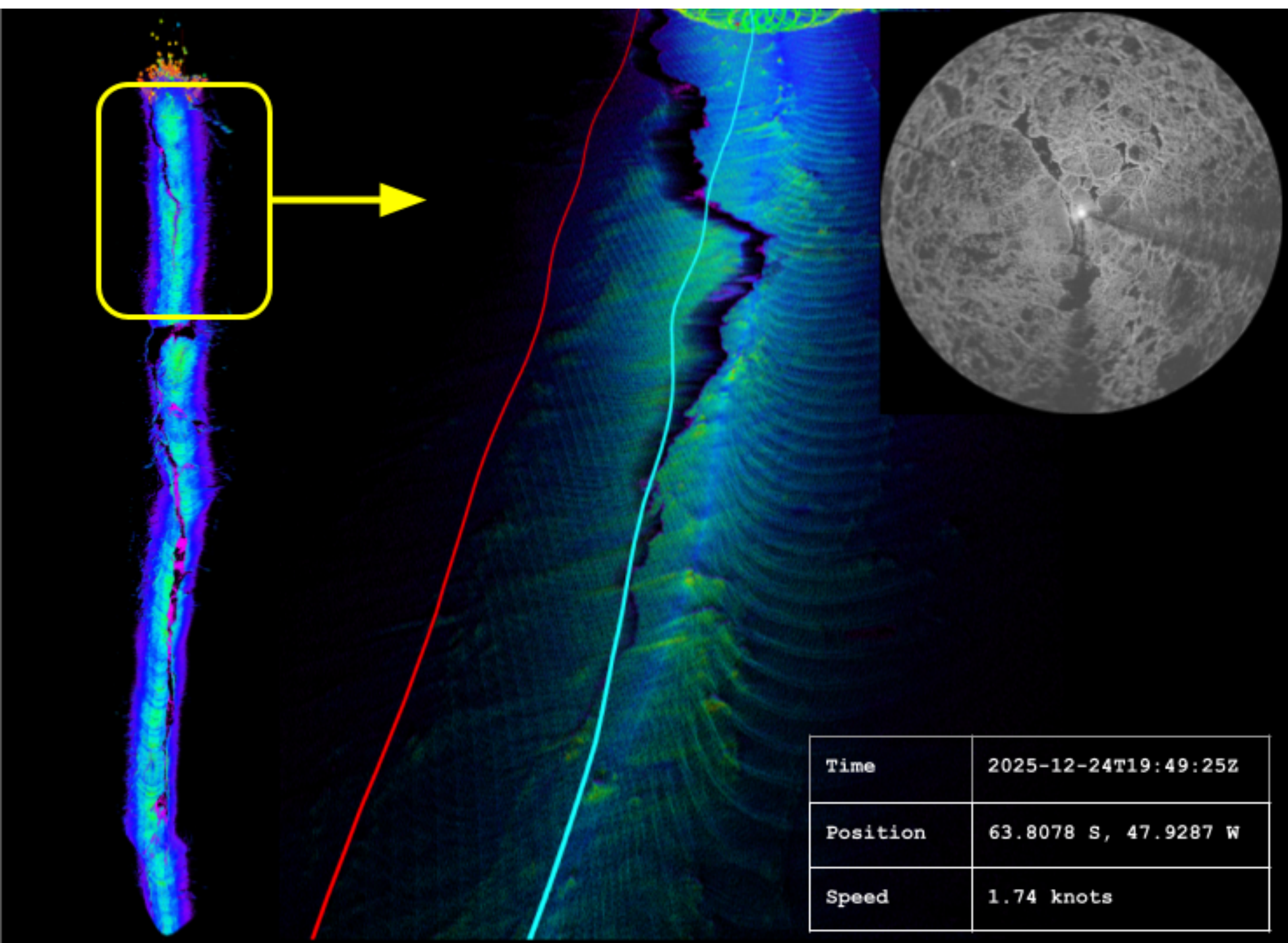
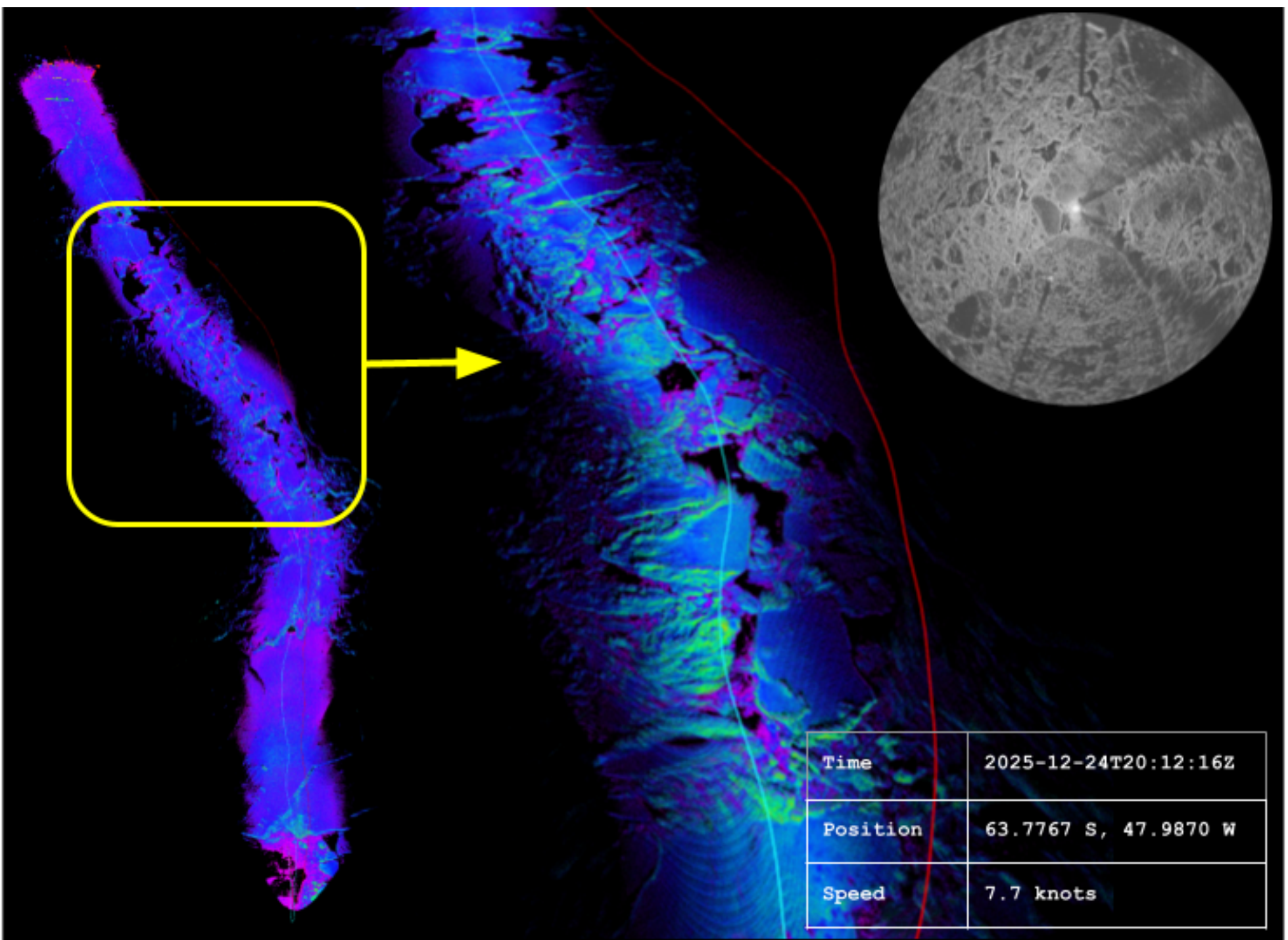
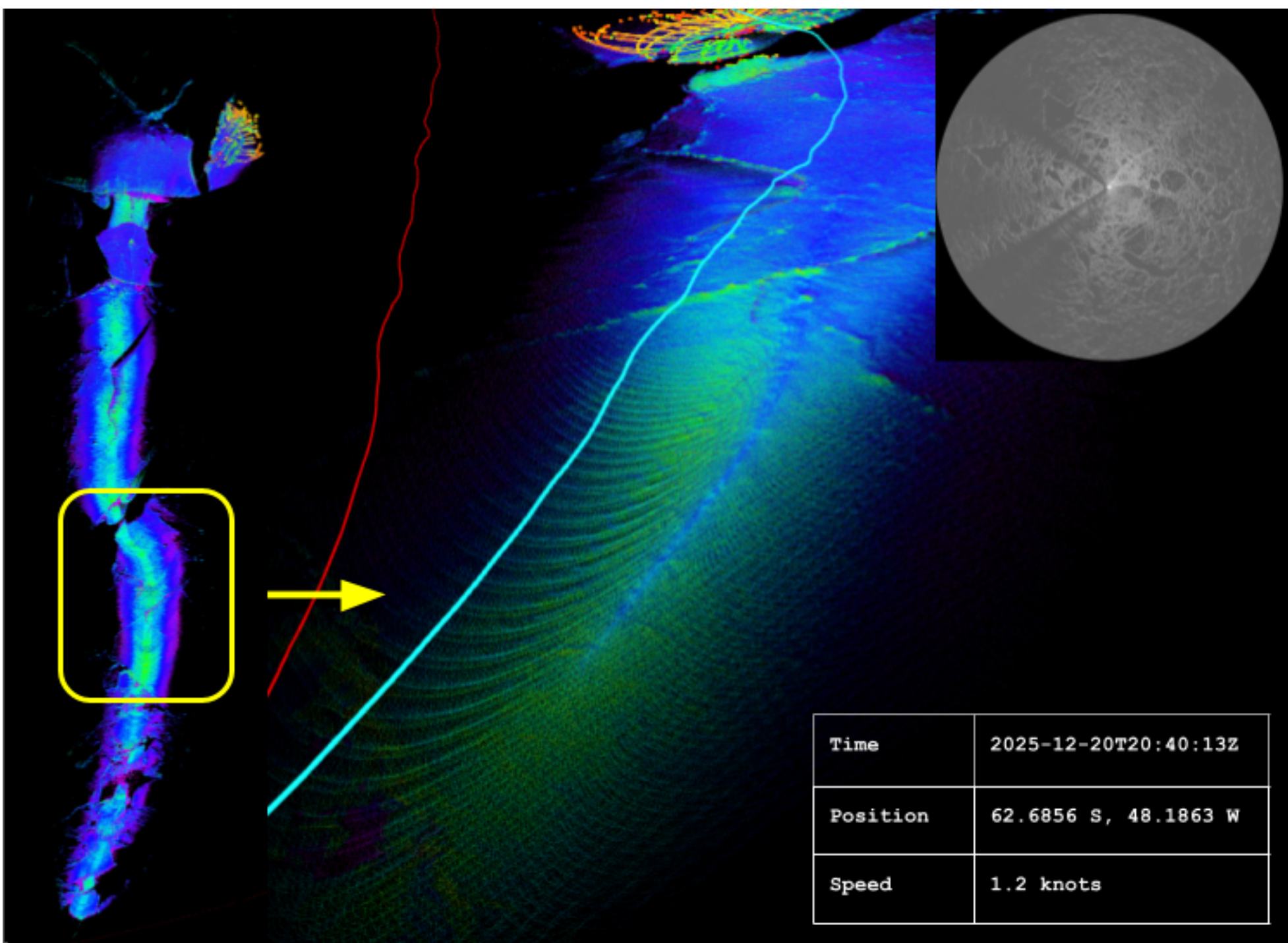


Figure 5. Representative environmental and operational regimes captured in the Antarctic dataset.