Planetary Lake Lander:
Adaptive Science Initial Results

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Introduction

The Planetary Lake Lander (PLL) robotic probe, an analog to future probes on the lakes and seas of Titan, autonomously learns about its environment, and uses that information to focus its limited resources on the most relevant phenomena, improving science impact. Our general approach is to enable the robot to learn probabilistic models of the environment that improve over time, and use those models to sample at the most interesting times and places, downlink the most interesting samples, and further reduce data volume through smart compression.

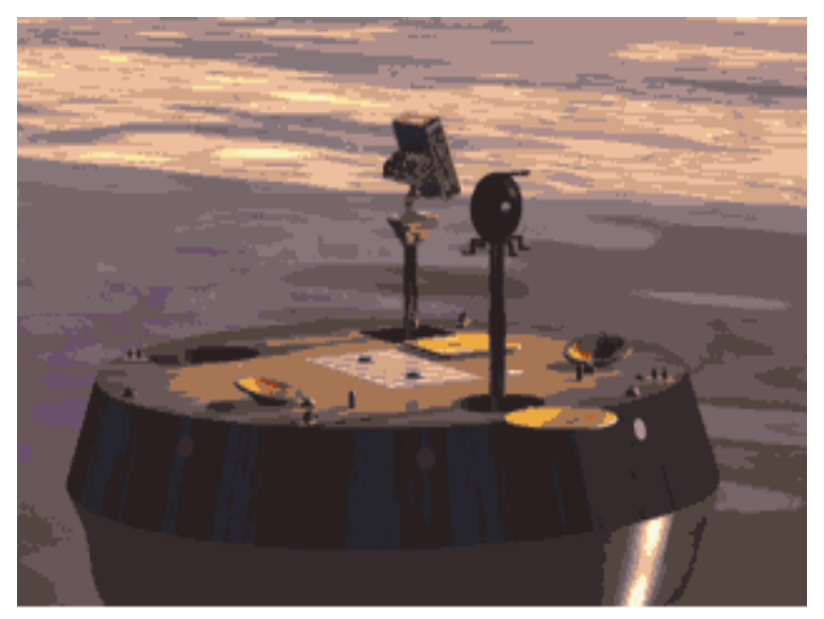


Fig. 1: PLL is an analog to the proposed "Titan Mare Explorer" lake lander

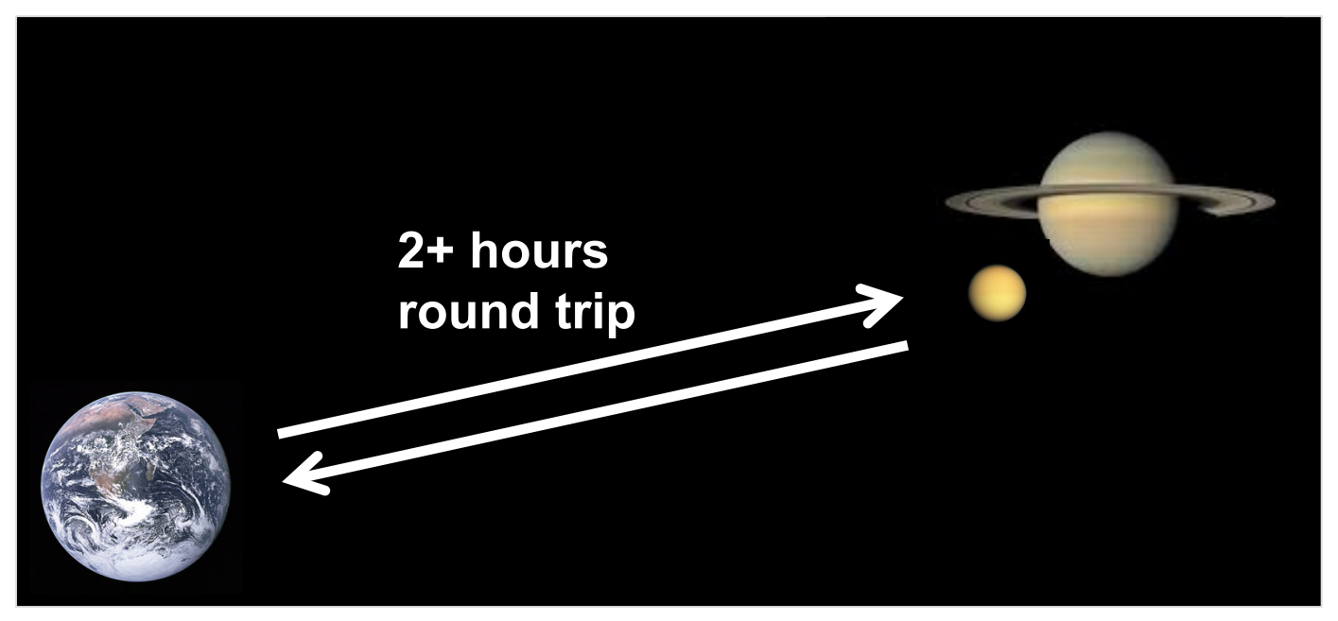


Fig. 2: Autonomy is particularly compelling for outer solar system missions, with long time delays and limited downlink data volume

PLL's primary science objective is to characterize lake physical, chemical and biological processes, and how they are disrupted by rapid deglaciation that affects inflow to the lake. Its primary technology objective is to develop and field test operational scenarios and systems relevant to future Titan missions, in particular to the Titan Mare Explorer (TiME) mission [1].

Lake Lander Platform

The PLL lake lander is deployed at Laguna Negra in the Central Andes of Chile, at 2700 m elevation in the region of the Echaurren glacier.

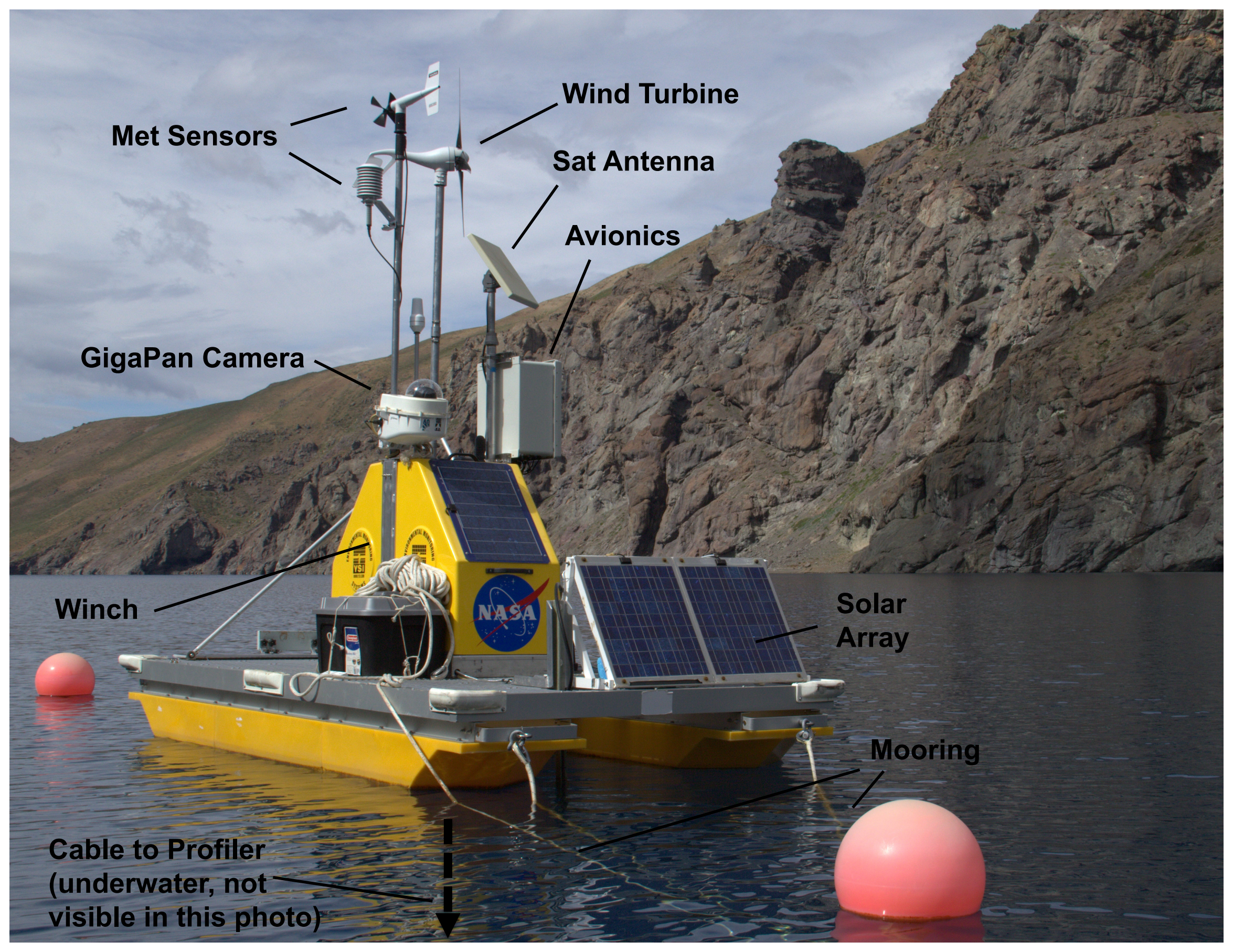


Fig. 3: The Lake Lander in Laguna Negra

The lake lander (Fig. 3) is a pontoon buoy carrying a sensor suite and avionics to support adaptive science. It is powered by solar panels and a wind turbine, with batteries for energy storage. Sensors include: (1) *Water quality:* A sonde, suspended from a winch that can lower it to 50 m maximum depth, measuring oxidation/reduction potential, dissolved oxygen, turbidity, chlorophyll, blue/green algae, conductivity, and temperature. (2) *GigaPan:* A pan/tilt/zoom camera to capture and stitch 360-degree panoramic imagery. (3) *Weather:* Wind speed and direction, air pressure and temperature, and relative humidity. (4) *Depth sounder:* Measures depth with sonar.

The lake lander has operated in two main configurations: (1) When moored, the lake lander has operated unattended for months at a time. (2) During our Dec. 2013 field campaign, the lake lander performed transects across parts of the lake (drifting, or piloted with a trolling motor when necessary).

Adaptive Depth Sampling

The lake lander sonde samples one depth at a time. Raising and lowering the sonde takes a significant part of the lake lander's total energy usage. If the goal of sampling is to reconstruct conditions throughout the water column, what is the optimal sampling strategy?

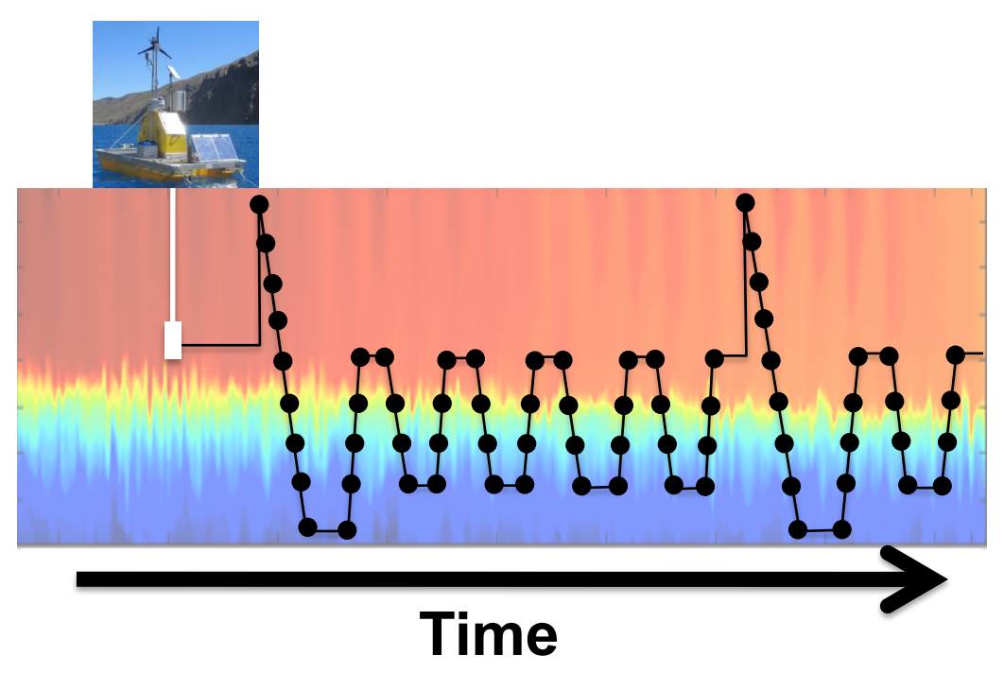


Fig. 4: Adaptive depth sampling concept. More frequent sampling in less predictable areas near the thermocline can yield better reconstruction

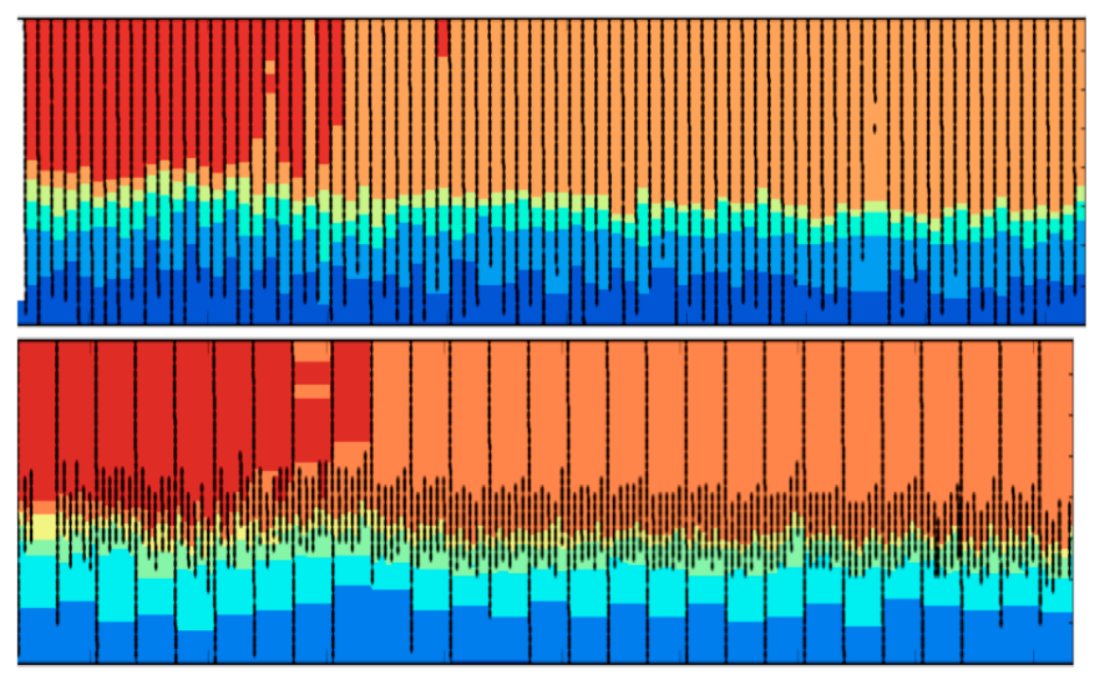
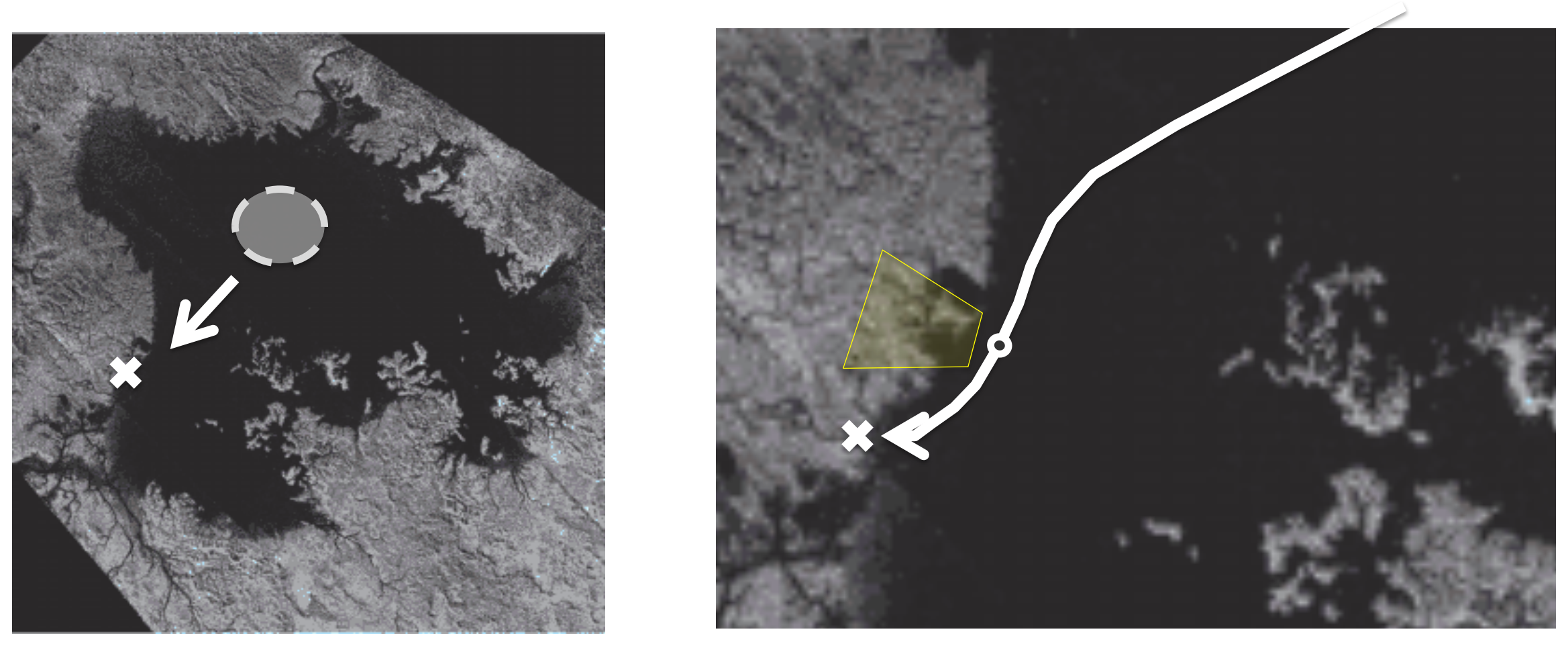


Fig. 5: Simulation. Color indicates reconstructed temperature (redder is warmer). Black points mark sample locations. (Top) Baseline strategy. (Bottom) Adaptive sampling thermocline tracking.

A relevant insight is that some parts of the water column are more predictable than others. The largest temporal variations are often observed near the thermocline, a sharp temperature gradient marking the boundary between near-surface and deeper waters. This observation suggests a strategy of sampling more frequently at the less predictable depths near the thermocline, and carrying forward the predictable values at other depths using an environment model.

This concept was tested in simulation using historical data. Sampling strategies in simulation were restricted to use less energy than was available on the real lake lander, thus could only collect a subset of the samples from the historical data set, and were evaluated on their ability to reconstruct the entire data set. Two strategies were compared (Fig. 5): The baseline strategy periodically took full profiles (samples at all depths). The adaptive strategy took less frequent full profiles and more frequent partial profiles centered on the thermocline. Using the adaptive strategy reduced the error of the temperature reconstruction from 1.22 C to 0.63 C (RMS). The adaptive strategy is now being evaluated onboard the lake lander.

Adaptive Shore Approach



The TiME mission would splash down in a Titan lake and drift passively until running aground on the shore

As the lake lander approaches shore, there may be a unique opportunity to observe shoreline features such as inflow channels. The imager should be pointed toward shore and run at a higher rate.

In Earth lakes, shallows near shore often have higher concentrations of unusual water constituents, and are areas of special interest

Similarly, the shallows of Titan lakes may be especially interesting. Scientists may want to sequence different sampling activities during different phases of the shore approach

Fig 6: Adaptive shore approach motivation

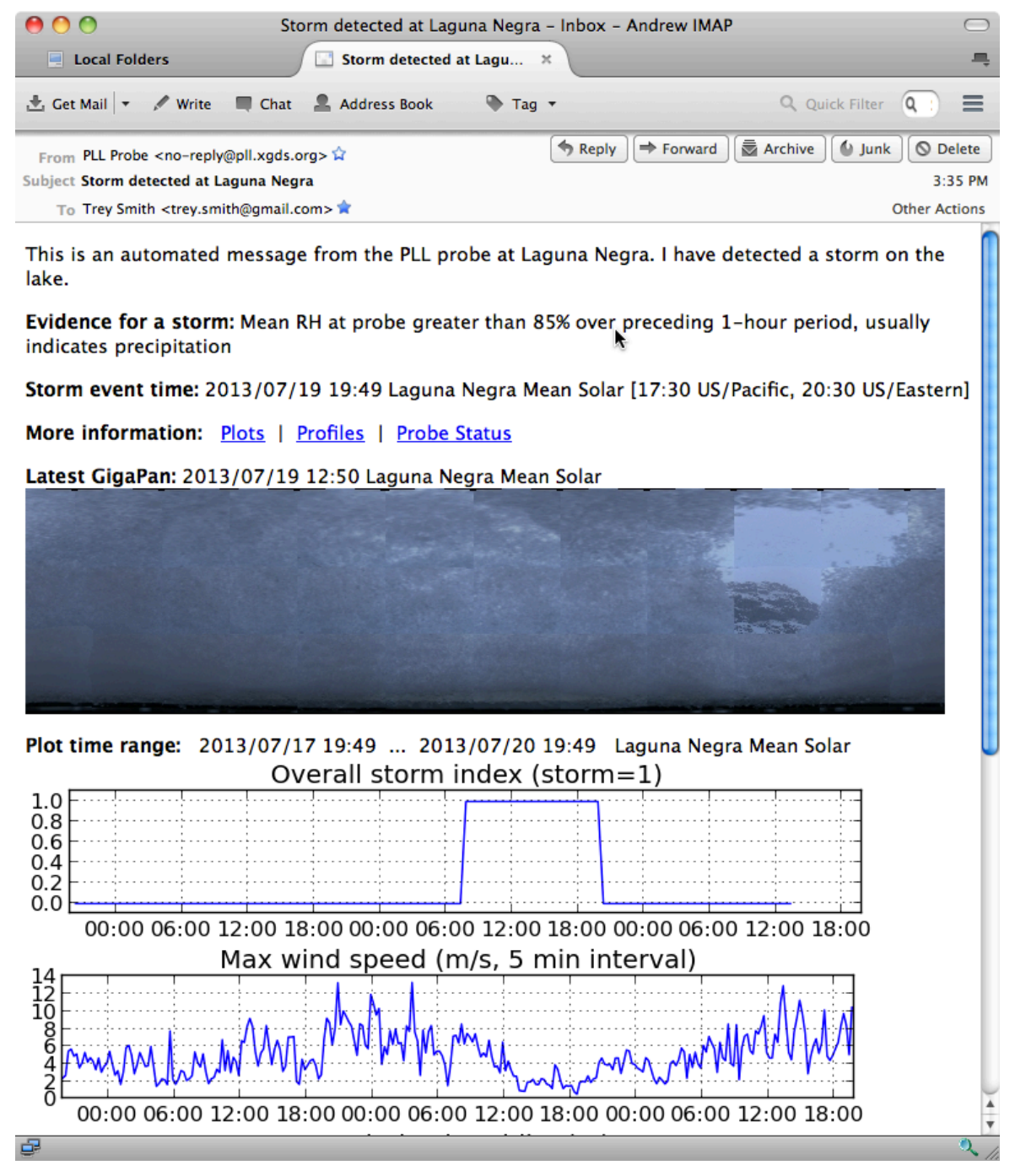
During the Dec. 2013 field test, the lake lander performed several near-shore transects, and demonstrated increasing its sampling rate when it approached the shore, as detected using a simple depth threshold. In future work, these transect data sets will be used to develop more sophisticated adaptive behaviors, such as controlling the GigaPan camera pointing to optimize coverage of shoreline features.

Storm Detection

Storms are interesting due to their effect on lake processes. For example, precipitation runoff can increase nutrient inflow, and windstorms can blow soil into the lake. Storms may also be rare and important events in Titan lakes, enabling study of Titan's methane cycle.

When the lake lander detects a storm, it responds by taking a burst of high-rate samples and sending an alert email to the science team.

The past few months with the simple storm detector emphasize the importance of context sensitivity and relative thresholds in event detection. First, of nine detected storms, three were judged to be false alarms—afternoon wind may indicate a storm in winter but is normal in spring. Second, a strategy that takes into account the system energy constraints (e.g., lowering the response threshold on a sunny day with nearly full batteries) could safely collect more opportunistic samples. Initial work in classifying weather states using an HMM also appears promising.



From PLL Probe <no-reply@pll.xgds.org>
Subject Storm detected at Laguna Negra
To Trey Smith <trey.smith@gmail.com>
3:35 PM

This is an automated message from the PLL probe at Laguna Negra. I have detected a storm on the lake.

Evidence for a storm: Mean RH at probe greater than 85% over preceding 1-hour period, usually indicates precipitation

Storm event time: 2013/07/19 19:49 Laguna Negra Mean Solar [17:30 US/Pacific, 20:30 US/Eastern]

More information: Plots | Profiles | Probe Status

Latest GigaPan: 2013/07/19 12:50 Laguna Negra Mean Solar

Plot time range: 2013/07/17 19:49 ... 2013/07/20 19:49 Laguna Negra Mean Solar

Fig. 7: A sample storm notification email sent by the probe. Note the snow covering the GigaPan dome.

Novelty Detection

Statistical novelty detection is useful for identifying unusual events. Response to such events includes prioritized downlink of data collected around their occurrence and follow up data collection.

We use Hidden Markov Models (HMM's) [2] to model both weather data (over time) and water quality parameters (along a traverse). The HMM is learned from unlabeled data which is then classified by it to a finite set of abstract states. Transitions to rarer states are flagged as novelties.

HMM classification of water quality is shown in Fig. 8. Measurements were taken along the western shore of Laguna Negra. The color scale indicates number of standard deviations of the state mean from base state (blue). Several of the high-novelty areas correspond to stream inflows.

This approach successfully flags storm events (in weather data) and stream discharges into the lake as novelties *without any prior knowledge* of the environment

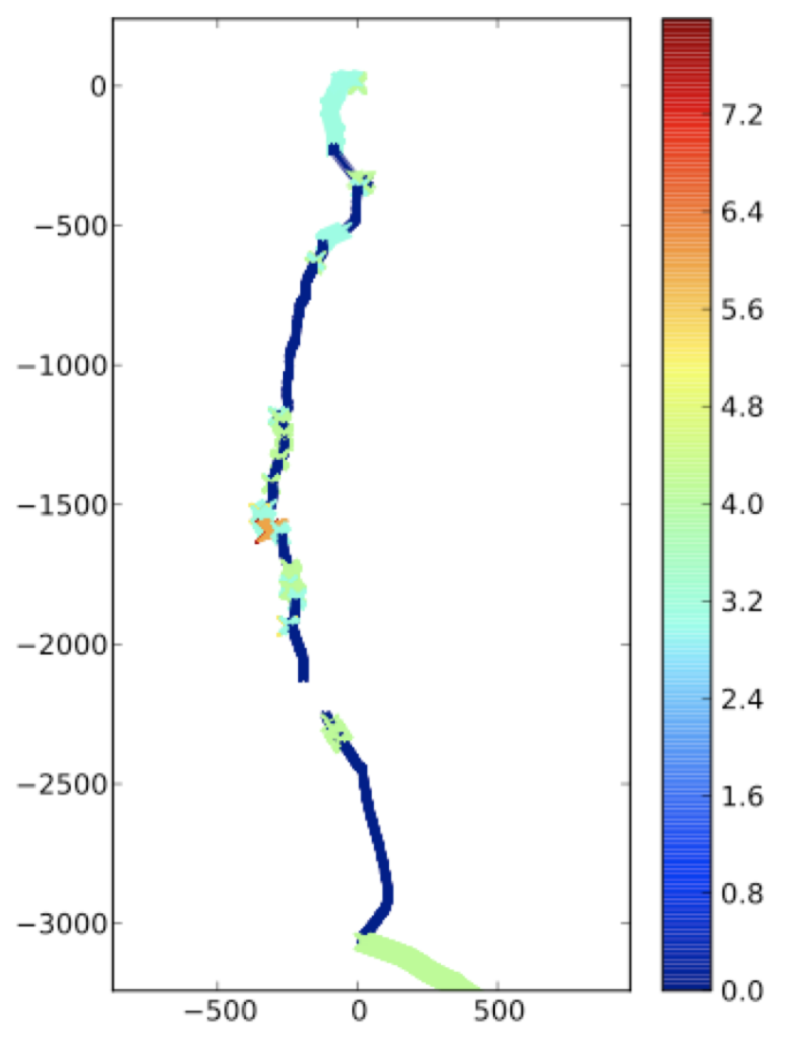


Fig. 8: HMM classification of water quality.

Conclusions

Since 2011, the lake lander has collected a massive amount of data from Laguna Negra, and we are now using that corpus as a training ground for new adaptive science ideas that can enable future exploration of the lakes of Titan. These initial results only scratch the surface of that resource.

We have shown promising results in the area of automated event detection (both anticipated events such as storms, and unanticipated novel events) and adaptive sampling that optimizes information gain, and we have posed the new challenge of optimizing adaptive shore approach, which is unique to drifting probes, but closely related to challenges in fly-by and descent planning.

In future work, we will improve our technical approach and work more closely with groups developing future Titan mission concepts, to make sure this technology is used to its full potential.

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References

1. Stofan, E. (2009), *Titan Mars Explorer (TiME): The first exploration of an extraterrestrial sea.* Presentation to the NASA Decadal Survey.
2. Thompson, D. R., et al. (2008) "Information-Optimal Selective Data Return for Autonomous Rover Traverse Science and Survey." In *Proc. ICRA.*
3. Dunbabin, M. and Marques, L. (2012). "Robotics for environmental monitoring." *IEEE Robotics and Automation Magazine*, 19(1).
4. Hitz, G., Pomerleau, F., Garneau, M.-E., Pradalier, C., Poschy, T., Pernthaler, J., and Siegwert, R. (2012). "Autonomous inland water monitoring - design and application of a surface vessel." *IEEE Journal of Robotics and Automation*, 19(1).