

Human Geoscientist Objective Functions for Robot-Aided Field Data Collection Decisions

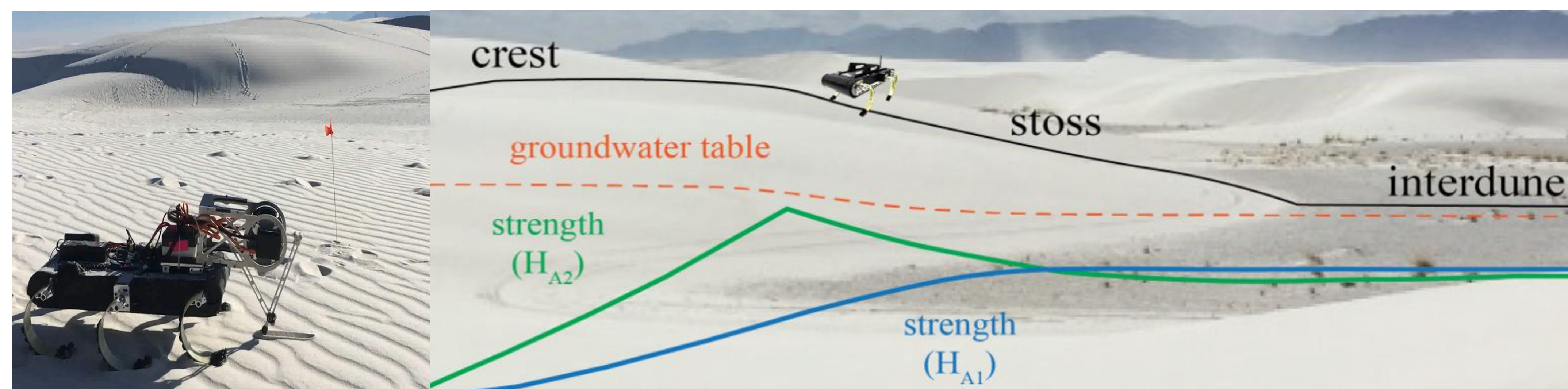
Shipeng Liu¹, Cristina G. Wilson², Bhaskar Krishnamachari¹ and Feifei Qian¹

¹Department of Electrical and Computer Engineering, University of Southern California, Los Angeles, CA, USA.

²Department of Electrical and Systems Engineering, University of Pennsylvania, Philadelphia, PA, USA

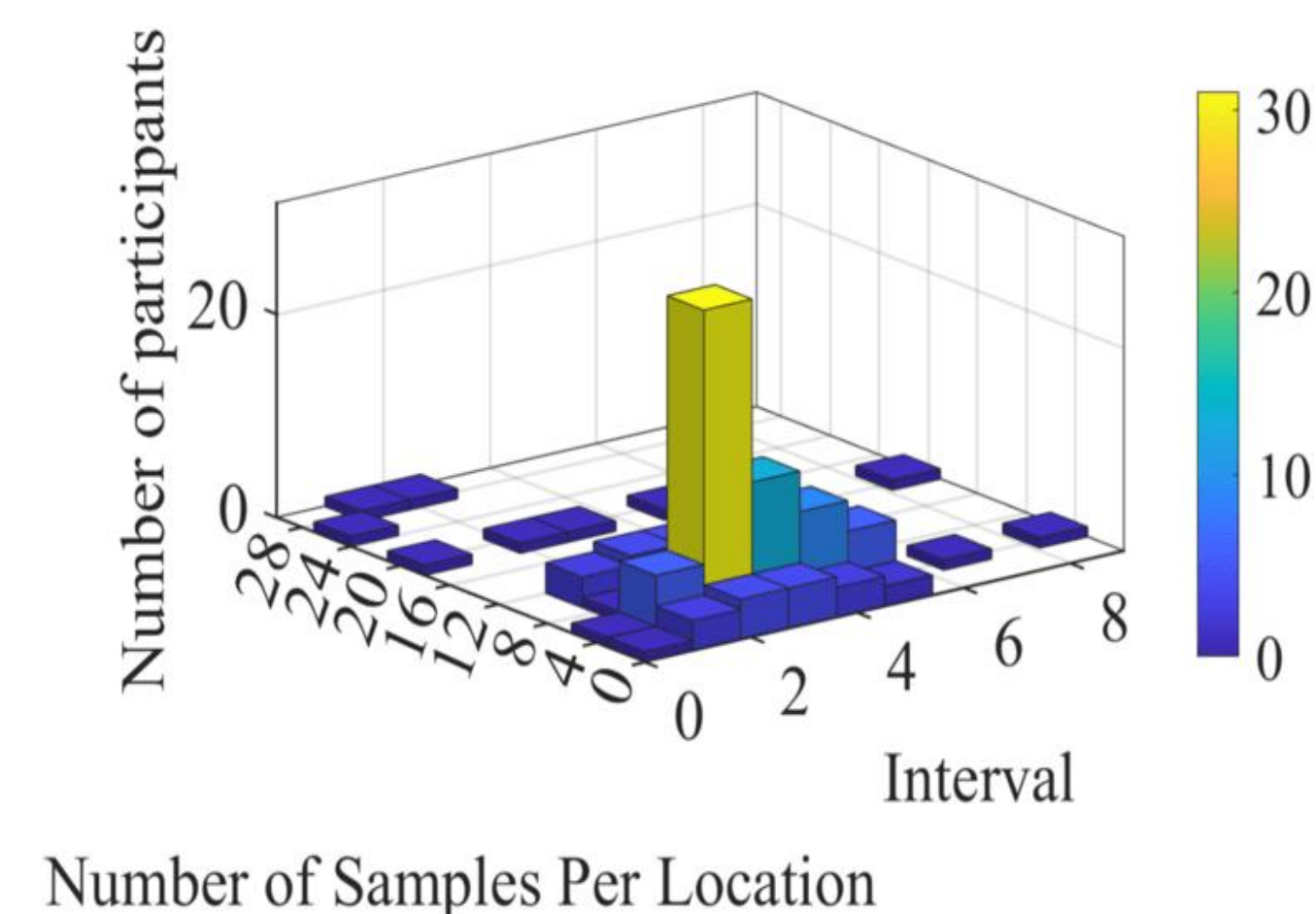
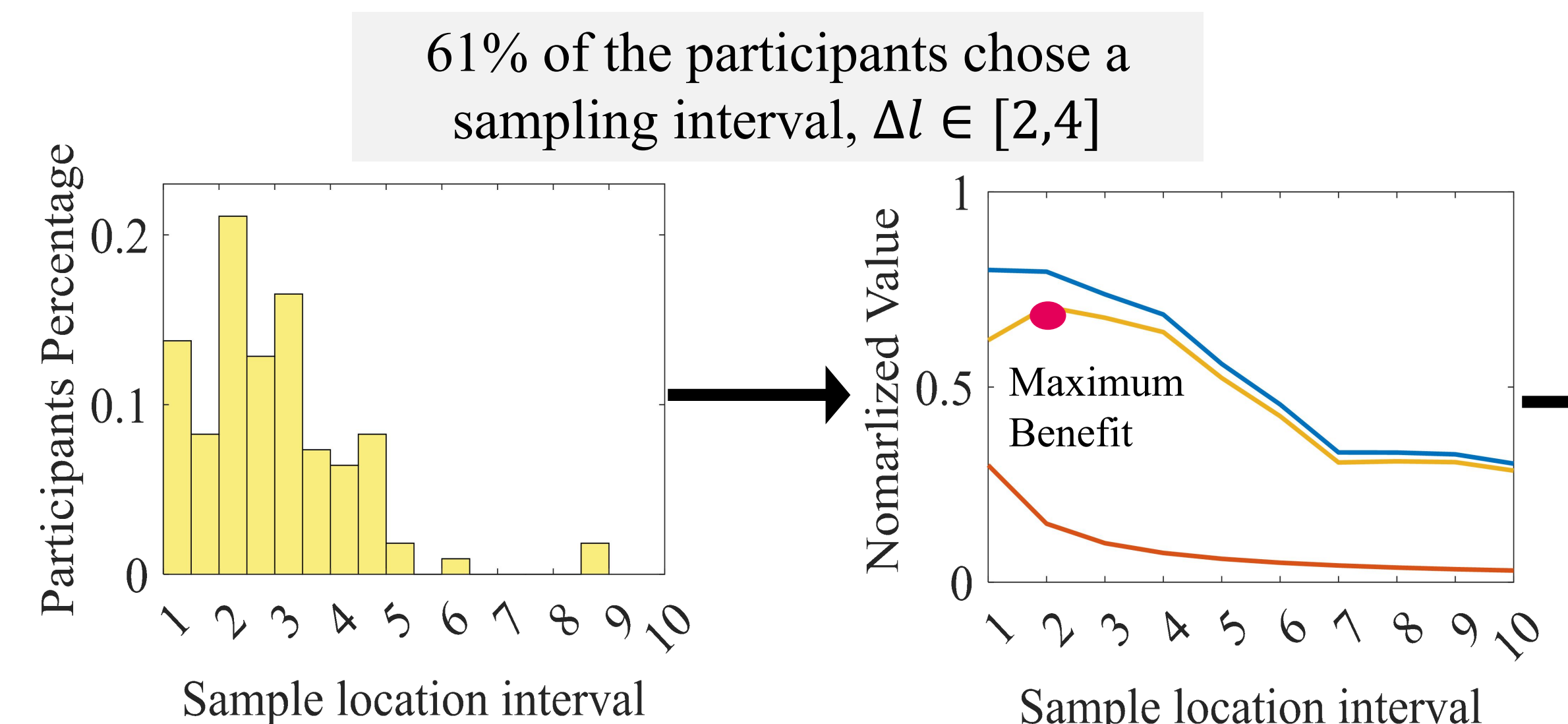
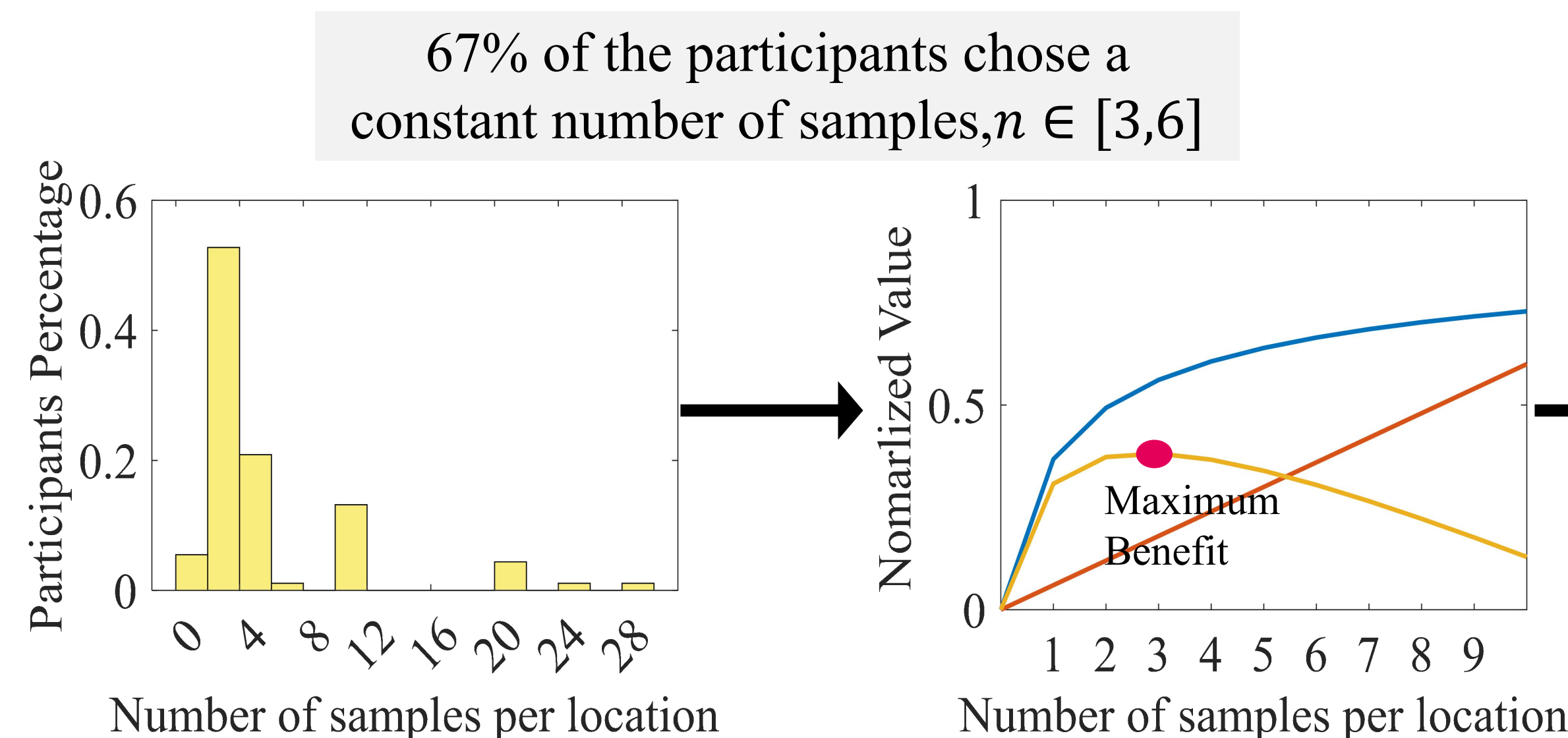
Study human experts' spatiotemporal data collection behavior

Robots can help geoscientists collect high spatiotemporal resolution in-situ measurements to understand the causes of ongoing global climate changes such as desertification, dust storms, and sediment loss. A key challenge in developing more intelligent robots that could aid human experts with sampling decisions, is the lack of understanding of how scientists make sampling decisions and how they adapt data collection strategies when presented with new information *in situ*. Here we study geoscientists' sampling decisions in field sampling and a simulated decision-making scenario, to reveal human experts' dynamic sampling objectives, and develop robots that can infer experts' desired data collection strategies based on their abstract scientific objectives.



Experts' initial sampling strategy is exploration-oriented and heuristic driven

Observation: Most human scientists chose evenly-spaced sampling location interval and constant number of samples at each location
Implied Human Objectives: to balance efficiency and cost when increasing information coverage



Direct information reward: Diminished reward with increased number of samples

- With the increasing number of samples taken from the same location, the amount of new information decreases

Indirect information reward: Information inferred from nearby sampled locations

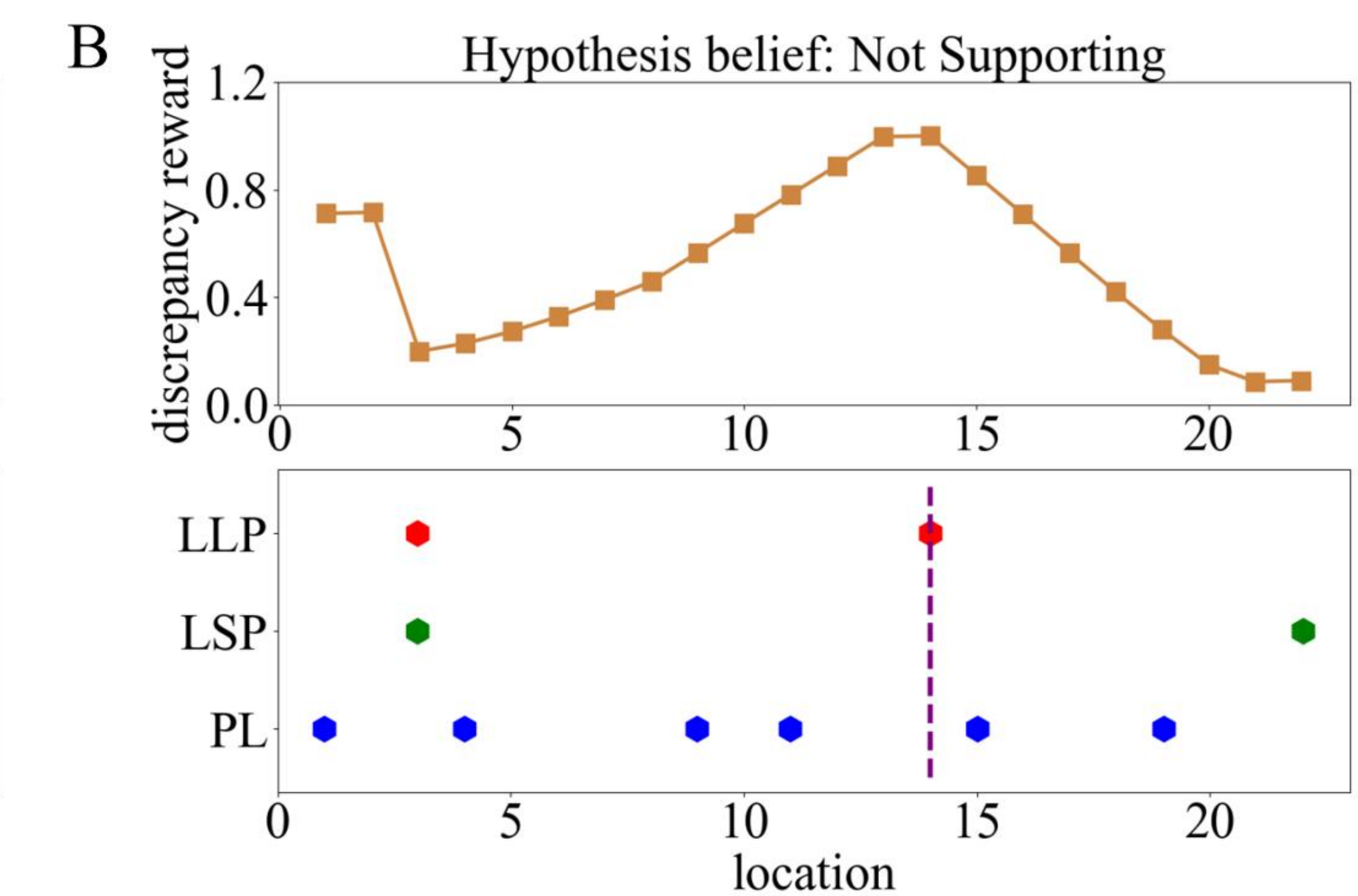
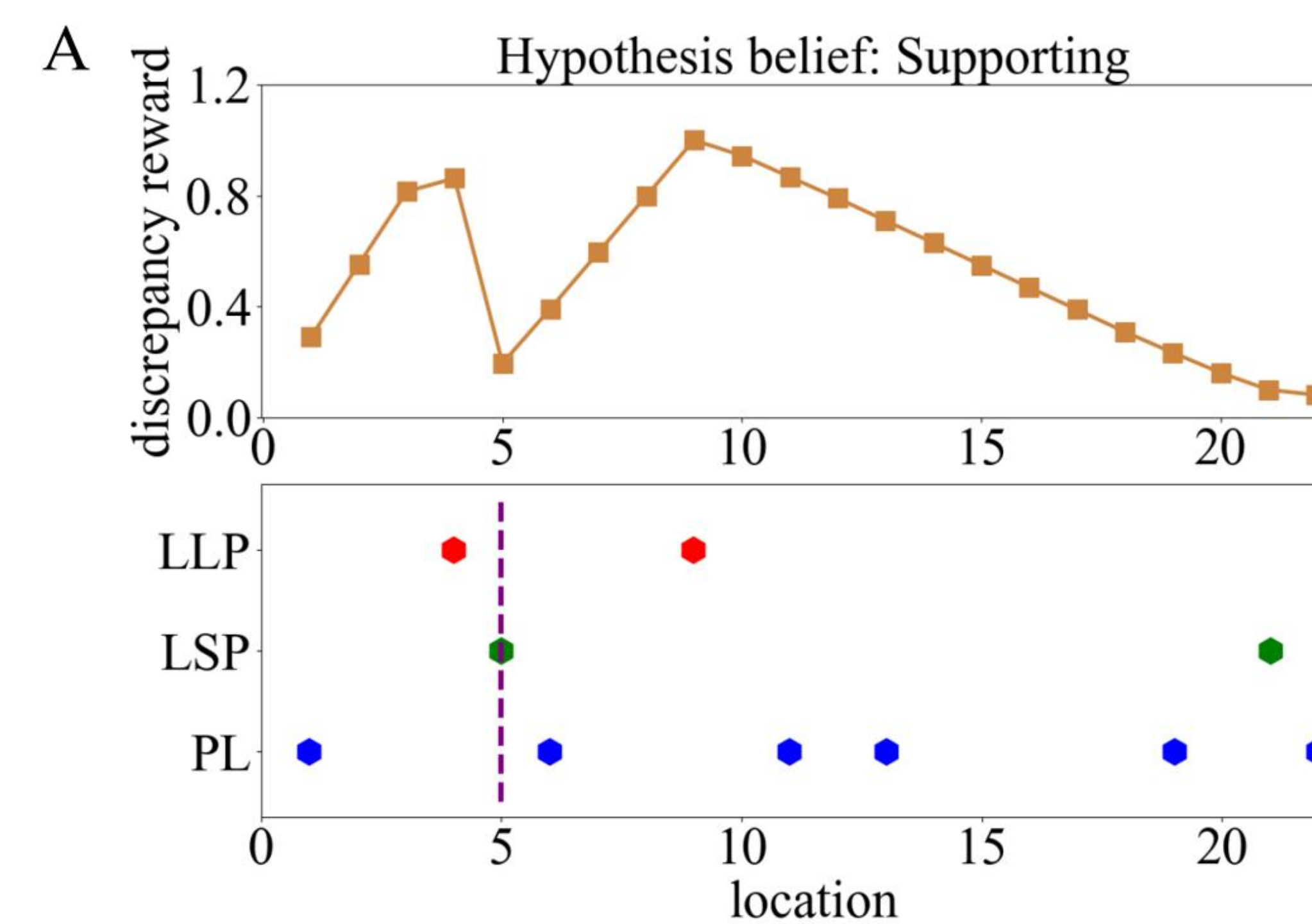
- Experts could obtain indirect information from nearby sampled locations, and the observed sampling location interval allows a balance between information and sampling cost.

Experts' sampling strategy adaptation is verification-oriented and discrepancy driven

Observation: Once sufficient information coverage is achieved, experts tend to select sampling locations that allow them to verify their current beliefs

Participants with high confidence in the given hypothesis were often observed to select sampling location with the smallest potential discrepancy (A) to further **CONFIRM** their belief .

Participants with low confidence in the given hypothesis were often observed to select sampling locations with the largest potential discrepancy (B) to **INVALIDATE** the hypothesis



A participant who is trying to **confirm** the given hypothesis.

A participant who is trying to **invalidate** the given hypothesis.

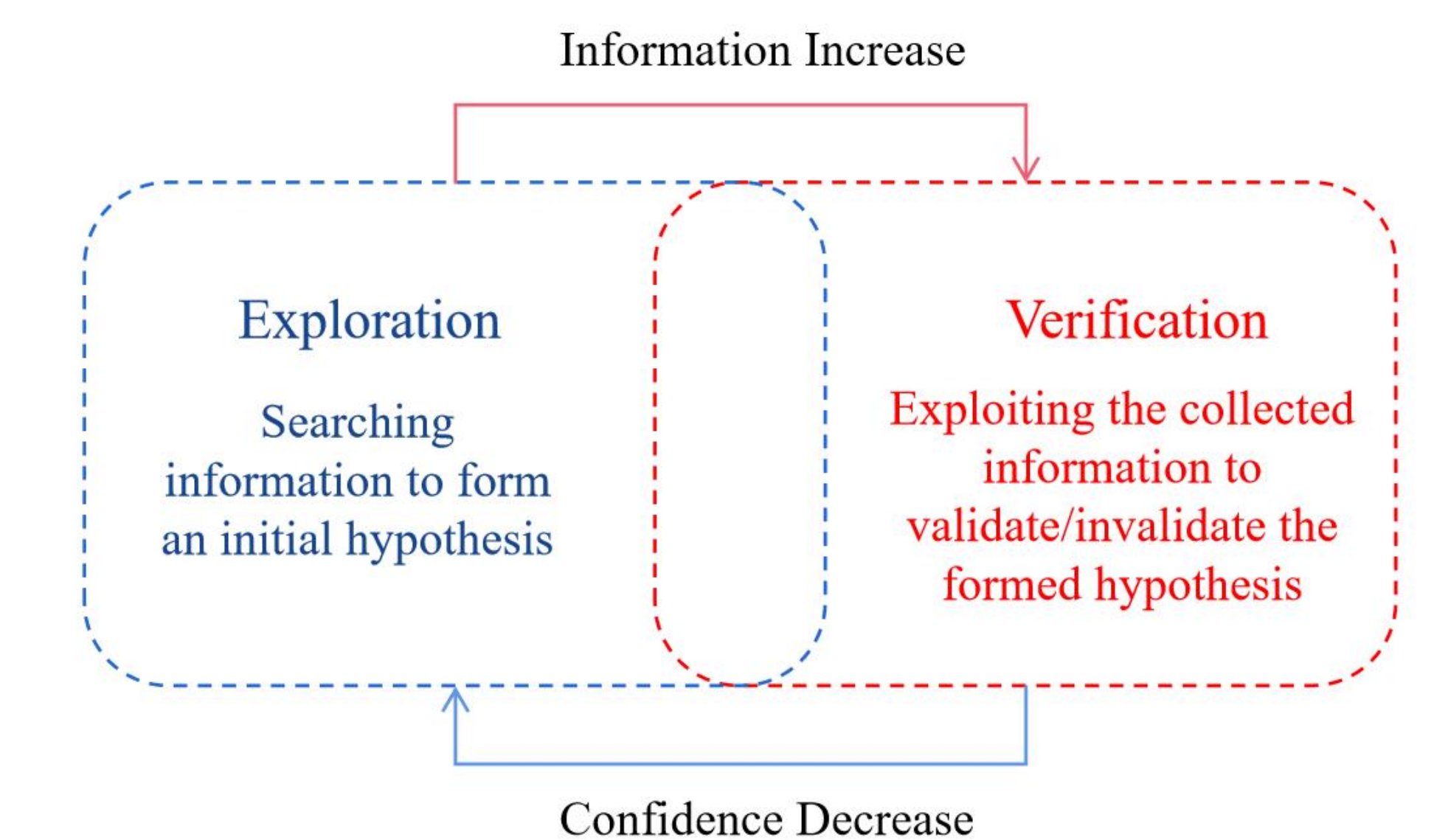
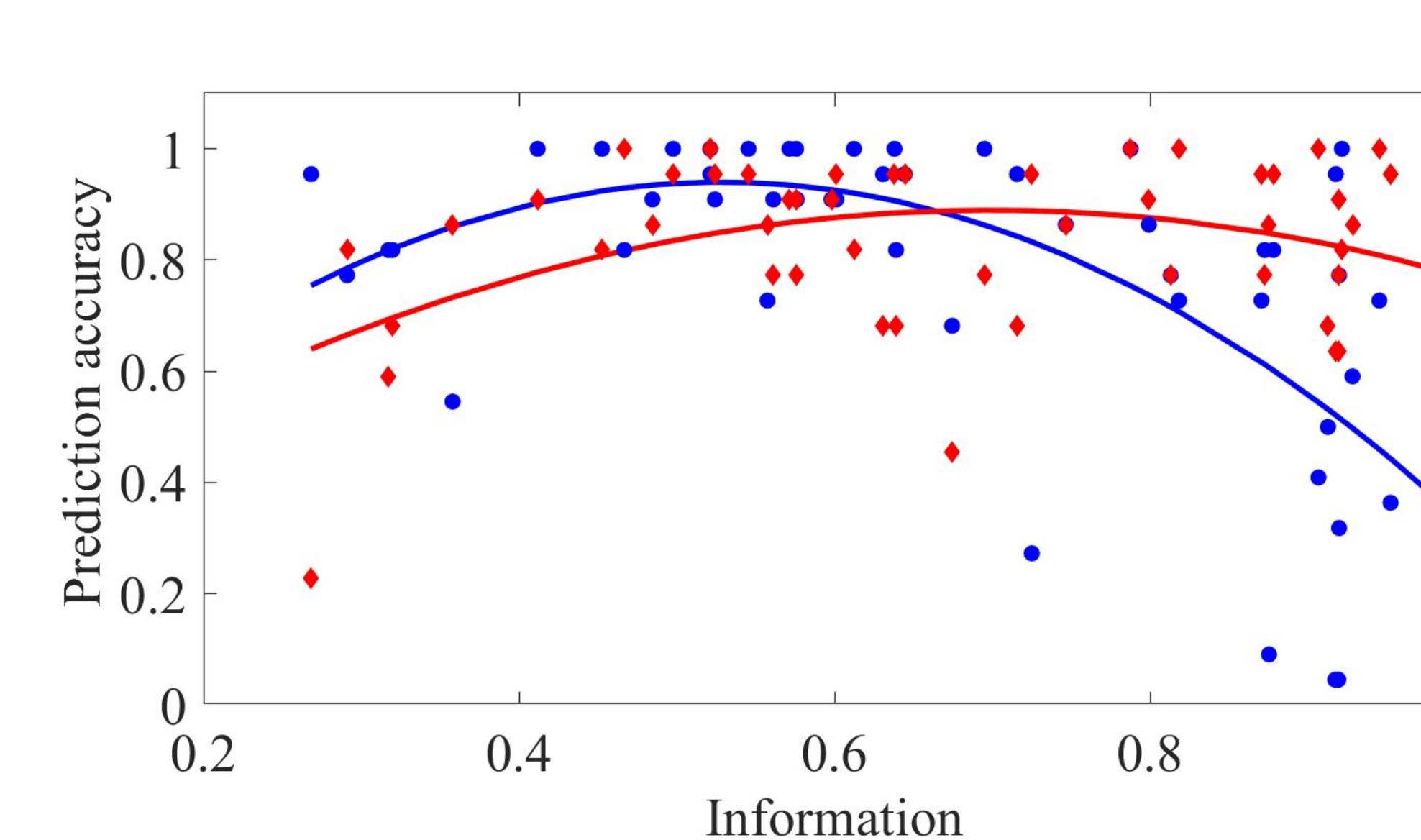
Red markers: locations with large potential discrepancies.
Blue markers: sampled locations.

Green markers: locations with small potential discrepancies.
Purple line: expert's selected location to sample next

Reward Function: $\operatorname{argmin}_l(R_d(l))$

Reward Function: $\operatorname{argmin}_l(R_d(l))$

Dynamic human sampling objectives shifts from exploration to verification



Blue: an information-based objective to maximize information coverage (exploration)

Red: a discrepancy-based objective to maximize hypothesis verification (verification)

- Human experts' sampling priority shifts from **Exploration mode** to **Verification mode** as information coverage increases. Sampling strategies in Verification mode depend on human's dynamic belief towards the hypothesis.
- By understanding how human experts' scientific objectives are connected to their sampling behaviors, robotic teammates can begin to infer scientists' abstract objectives and better support their exploration and understanding of complex earth environments vulnerable to desertification processes compounded by the effects of global climate change.