In domains requiring effective situational awareness with limited resources, prioritizing focus is critical. Search and rescue tasks require fast identification of safe avenues for rescuers to traverse the area. Inspection tasks must realize trends over long durations to identify issues caused by the confluence of high-stress modes that compound into catastrophic failure. Deploying robots to persistently perform these tasks is an attractive option as it can be accomplished using commercially available aerial robots outfitted with ranging sensors. However, deploying teams of robots over extended durations in dynamic environments requires effective resource management as robots can only deploy for limited durations and typical recharging times far exceed flight times.

Traditional approaches map an environment using a spatial probability distribution, which is updated when a robot observes the environment. Unless the environment dynamics are specifically tracked, a model will maintain high confidence regardless of changes that occur. To counter this, the model can be designed to constantly degrade back to unknown as time progresses, necessitating periodic revisitation. Due to the limitations of team size and energy capacity, however, robots cannot be deployed to constantly observe the entire environment. Additionally, motion through the environment must be confined to areas that are known to be unoccupied with high confidence while respecting energy constraints.

While there are many approaches to modeling an environment as a probability distribution and some of these track dynamic objects to mitigate their influence, none track a spatially distributed measure of the frequency of change to inform deployments when regions require additional observation. Active perception tasks identify potential observations of high utility in order to direct motion, but state of the art approaches tend to use a greedy planning strategy and none consider the implications of energy constraints. Combinatorial optimization techniques are typically used to resolve task assignment problems with resource constraints, but travel costs between tasks are typically known a priori and few works address the challenge of simultaneously allocating tasks and generating motion trajectories.

We propose to address this problem by designing a framework that tightly integrates environment modeling, task allocation, and path planning. Deployments are planned over a sliding horizon window to maintain map accuracy as high as possible, given the resource limitations. The key contributions of this effort will include: 1) an environment modeling approach that combines state of the art probabilistic representations with a decay model learned from observed dynamics, 2) a routing strategy that interleaves task allocation and path planning to generate informative, energy-feasible routes, 3) improvements to the core framework that reduce computational complexity, and 4) modifications to the routing strategy to improve scalability and generalizability with respect to heterogeneous teams of robots. We will evaluate the proposed approach in simulation and show how model confidence and map accuracy is managed under various team sizes, energy constraints, and environment dynamics.