Dynamic Targeting to Improve Earth Science Missions

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Introduction

Fundamental physics of remote sensing dictates that high spatial resolution at reduced size (and therefore power, cost) forces reduced swath. This places a premium on measurement on acquiring the highest science value data enabled by pointable instruments in Earth science missions. Dynamic targeting (DT) can improve the efficiency of conventional expensive narrow swath instruments. DT is a decision-making approach that leverages information from a lookahead sensor to identify targets for the primary instrument, which can then be pointed to improve science yield (Fig. 1).

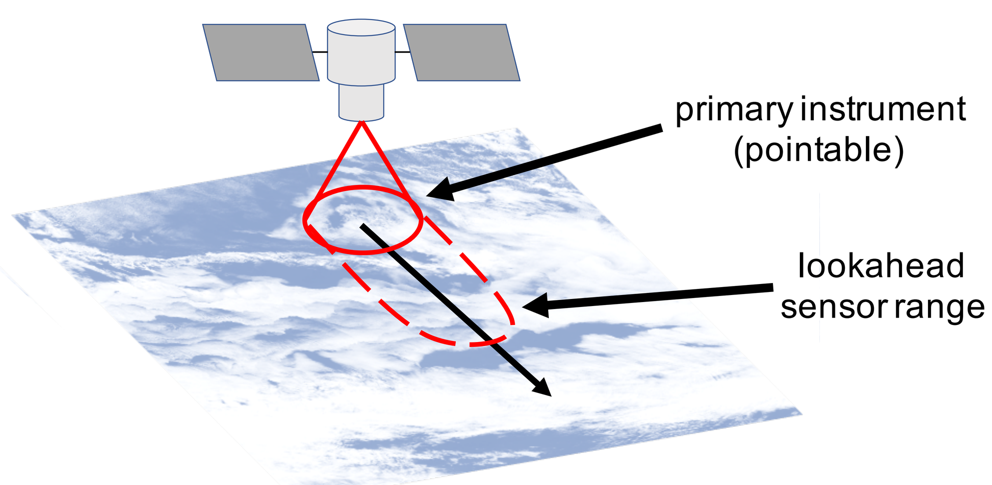

Fig 1. Dynamic targeting leverages information from a lookahead sensor to identify targets for the primary instrument to improve science yield given energy constraints.

Related Work

Most work has focused on screening cloud cover and other poor observing conditions from airborne and spaceborne missions. This work is an extension of a NASA study for the Smart Ice Cloud Sensing (SMICES) satellite concept, whose objective is to employ Artificial Intelligence (AI) to make better decisions while collecting dynamic measurements of ice clouds. We show that DT is applicable across a wide range of missions and can enable better coverage of transient phenomena.

Simulation Study

The approach is evaluated in a simulation study that consists of an Earth-observing satellite with two onboard instruments: a primary radar with a narrow swath (217 km), and a secondary radiometer with a wider field of view (110-1000 km range) that can only be used for lookahead. General Mission Analysis Tool (GMAT) was used to simulate and generate realistic satellite trajectories. The simulation study consists of the following mission scenarios and datasets: 1) the objective is to observe ice storm clouds and data comes from the Global Weather and Research Forecasting (GWRF) model covering two different regions, the Caribbean (tropical) and the Eastern coast of the United States (non tropical); 2) the goal is to observe storm clouds and global data comes from the Global Precipitation Measurement (GPM) mission (Fig. 2); and 3) the purpose is to acquire clear-sky measurements and data comes from global cloud fraction products from the Moderate Resolution Imaging Spectroradiometer (MODIS) (Fig. 3).

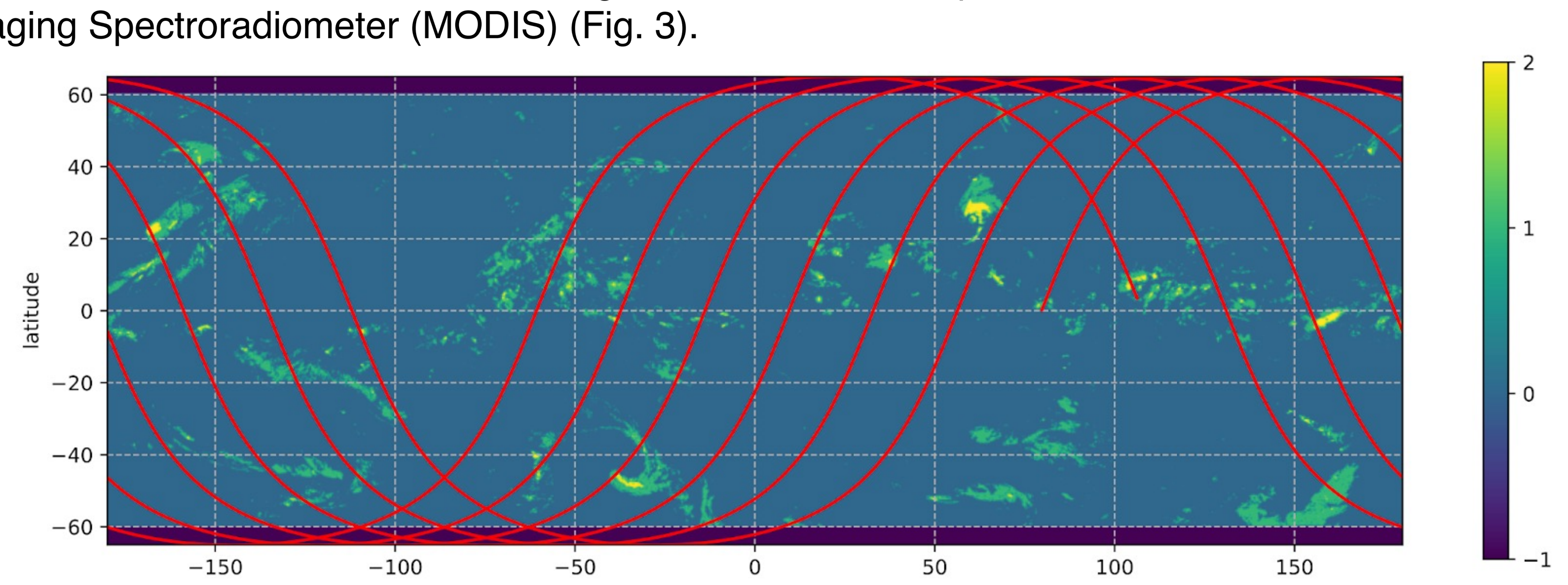

Fig 2. Example of the GPM global storm data set and simulated satellite orbit with a 65 degree inclination. This simulation consists of 36,000 time steps spanning 10 hours.

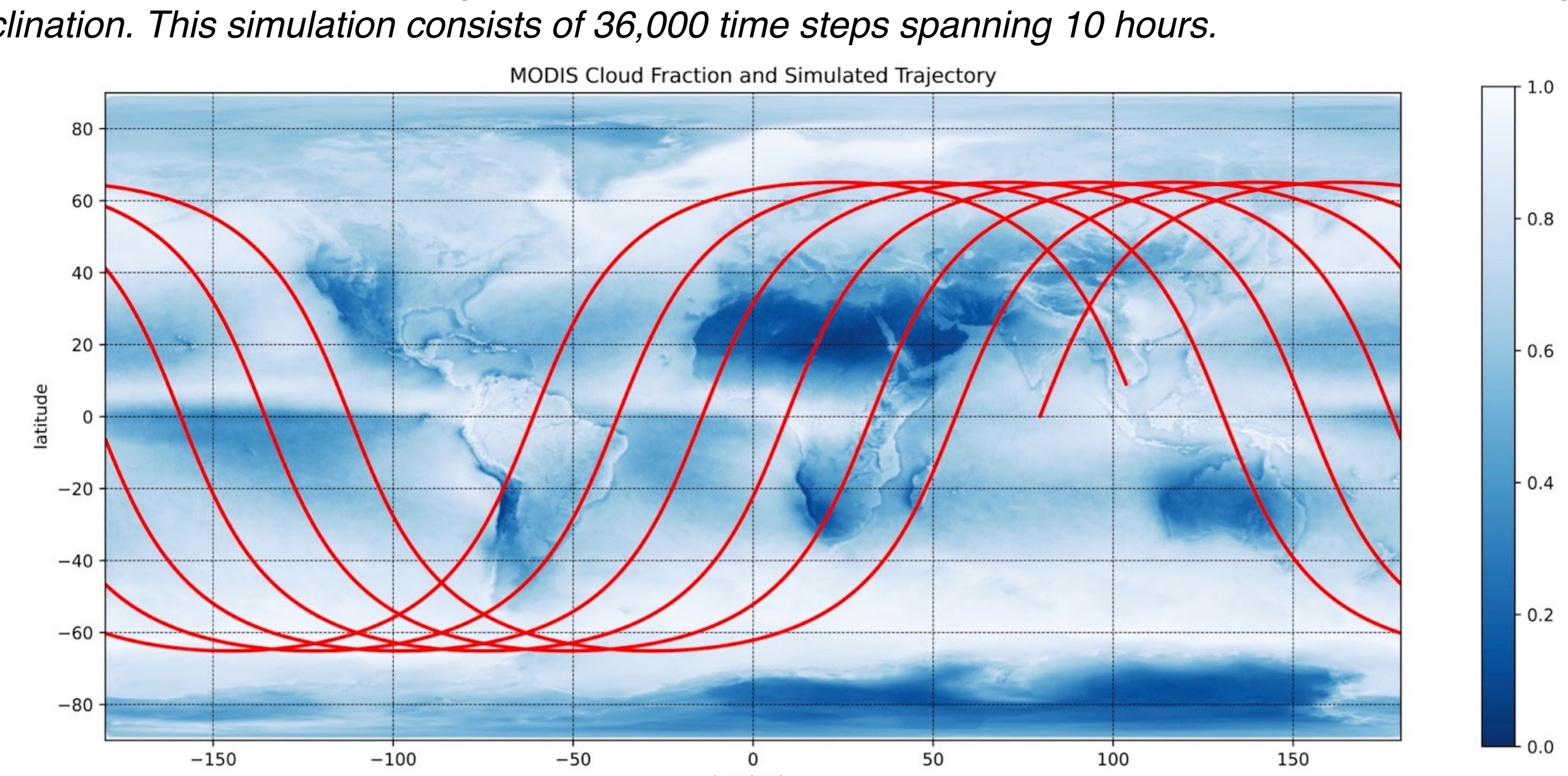

Fig 3. Example of the MODIS global cloud fraction dataset and simulated satellite orbit with a 65 degree inclination. This simulation consists of 36,000 time steps spanning 10 hours.

Algorithms

We formulate DT as a pointing planning problem. The goal is to observe scientific phenomena of interest more often while screening poor observing conditions and respecting the mission's energy constraints. We have developed several DT algorithms that draw from a rich heritage of decision-making methods involving AI, operations research, and heuristic search (Fig. 4).

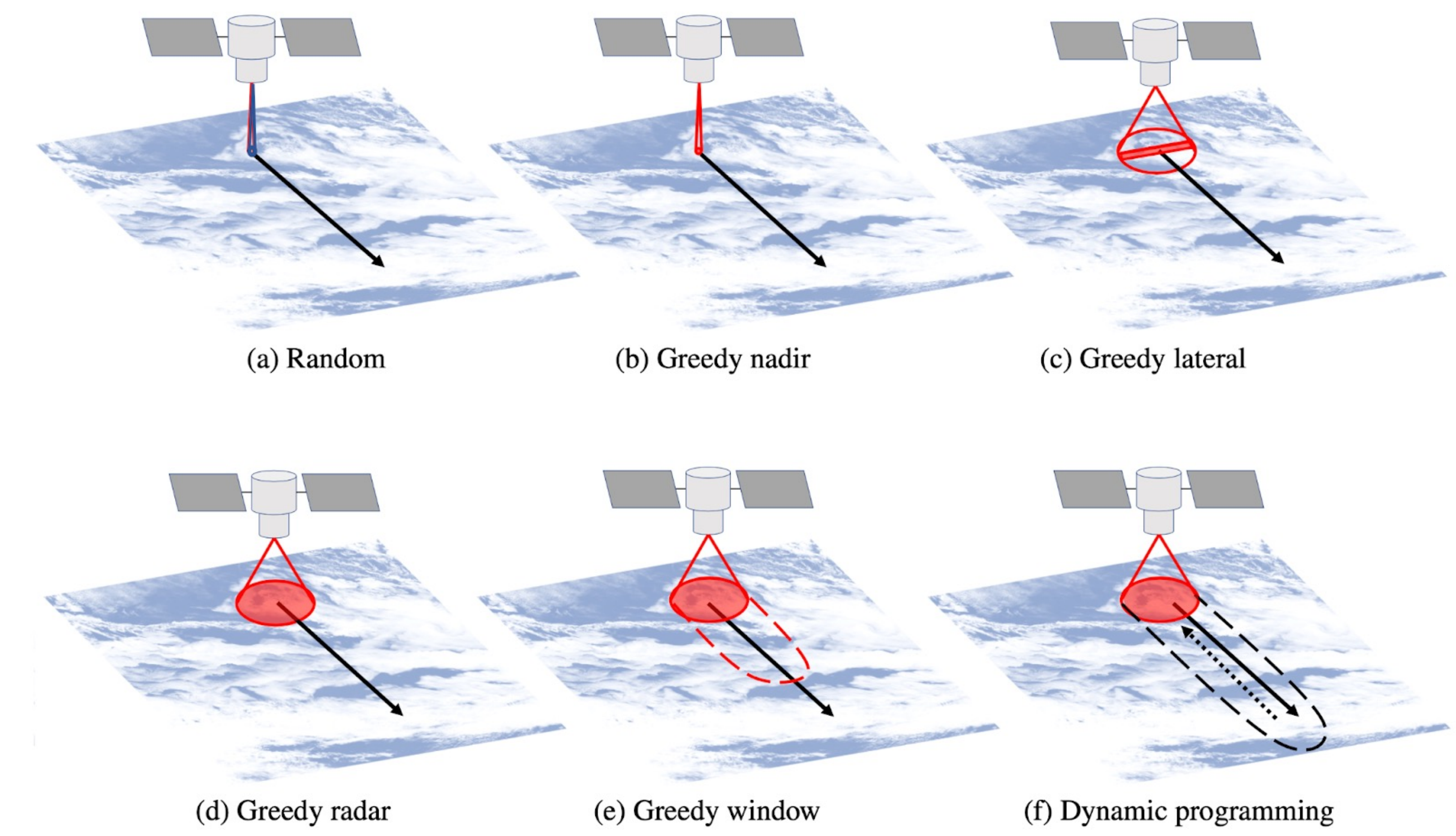

Fig 4. Dynamic targeting algorithms. The random and greedy nadir algorithms are exclusively aimed at nadir (a and b). The greedy lateral algorithm can collect samples along the cross-path direction (c). The greedy radar algorithm has an even wider field of view, but is restricted by the primary instrument's swath (d). The greedy window algorithm leverages a lookahead sensor with a farther reach to better allocate resources for future measurements (e). The dynamic programming approach has a full lookahead (assuming the path is finite) and achieves optimality via backward induction, however it cannot be deployed using realistic instrument and computational resources (f).

Results

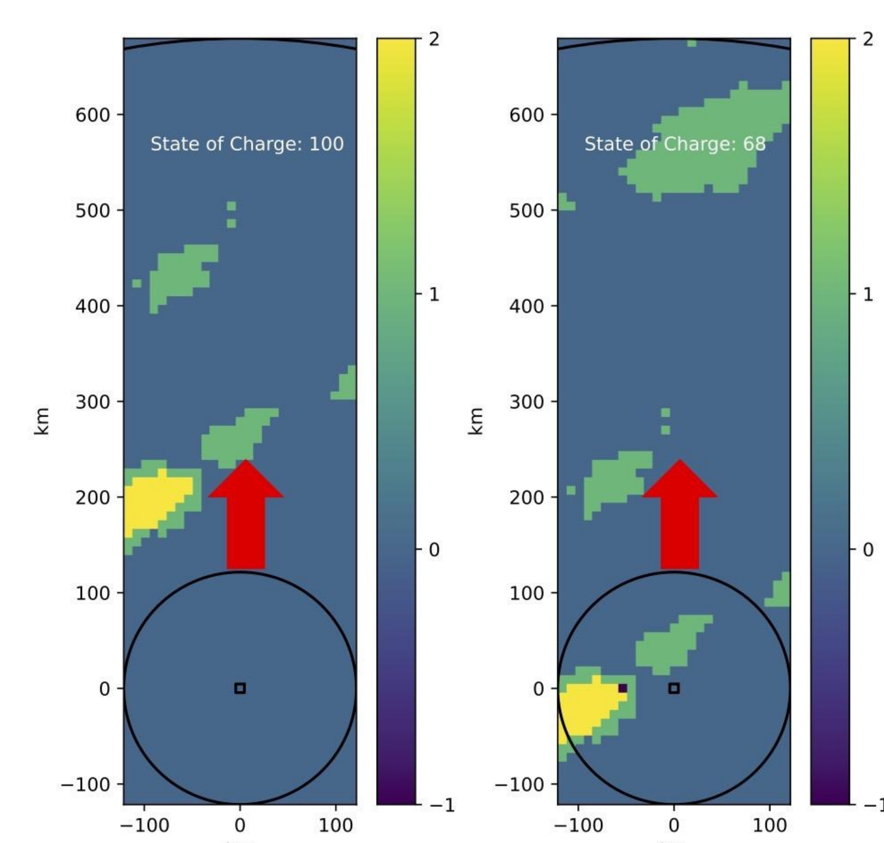

Fig 5. Example of the greedy window algorithm for storm hunting. Left: It saves energy for observations in the near future, in this case within the lookahead sensor range. Right: The algorithm then uses the saved energy to collect measurements now within the primary instrument's reach.

Table 1. Comparison factor between greedy window and the baselines regarding observations of interest .

Mission Scenario	Baseline	Optimal
Tropical Storms	22.65	0.74
Non Tropical Storms	3.19	0.84
Global Storms	88.45	0.69
Global Clear Skies	2.63	0.79

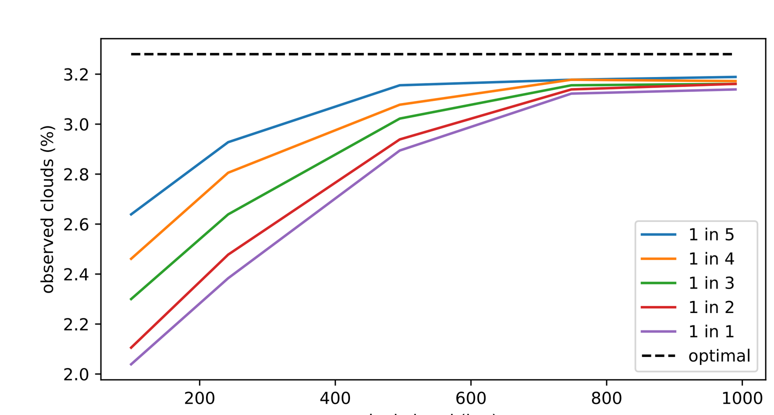

Fig 6. Greedy window converges to optimality as a function of the lookahead range.

Table 2. Average computation times for each algorithm

Average Time (μs)	*Random (20% on)*	Greedy Nadir	Greedy Lateral	Greedy Radar	Greedy Window	*Dynamic Programming*
SMICES T	*2.1*	3.9	6.2	8.4	10.7	*154,349.5*
SMICES NT	*2.2*	3.8	6.3	8.6	10.3	*156,401.2*
GPM	*3.9*	6.7	9.3	12.8	20.8	*9,840,236.4*
MODIS	*2.3*	4.4	6.8	8.9	10.8	*162,658.6*

Conclusions and Future Work

Experimental results indicate that DT is a promising approach. When comparing the best performing algorithm, greedy window, against the baseline random algorithm, significantly more observations of interest are collected. Also, its computation time is quite fast. Furthermore, its performance tends to optimality when the lookahead range is increased.

Future work will keep improving the realism of the simulation study; for instance, we plan to capture more physical phenomena such as off-nadir measurements with deteriorating quality. Further research will continue to investigate the advantages of DT via other data sets and scenarios. Finally, working closely with application scientists and specialists. we will refine use cases and quantify performance improvement for other application domains.

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