



Autonomous Scheduling of Agile Spacecraft Constellations for Rapid Response Imaging

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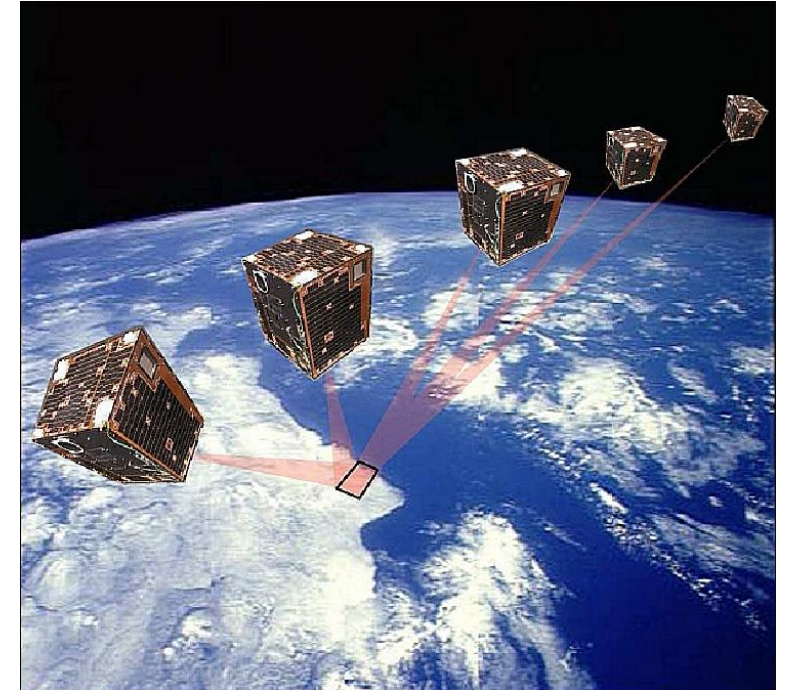
NASA Ames Research Center / Bay Area
Environmental Research Institute

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Multiple Spacecraft Agility



- Earth-science processes are intrinsically dynamic, complex, and interactive. Lots of data, using complementary measurements from multiple vantage points – space, air, ground
- Literature addresses satellite scheduling/coordination for large, steerable satellites OR small, fixed view satellites. Very little reported on *algorithms for controlled pointing and distributed target observation for constellations – w/ current Cubesat maneuverability.*
- Cubesat literature has focussed on downlink routing, more than on command and control for rapid or targeted image capture. Operating s/c individually was cheaper ...but swarms, quick response needs, planetary missions will need autonomy.

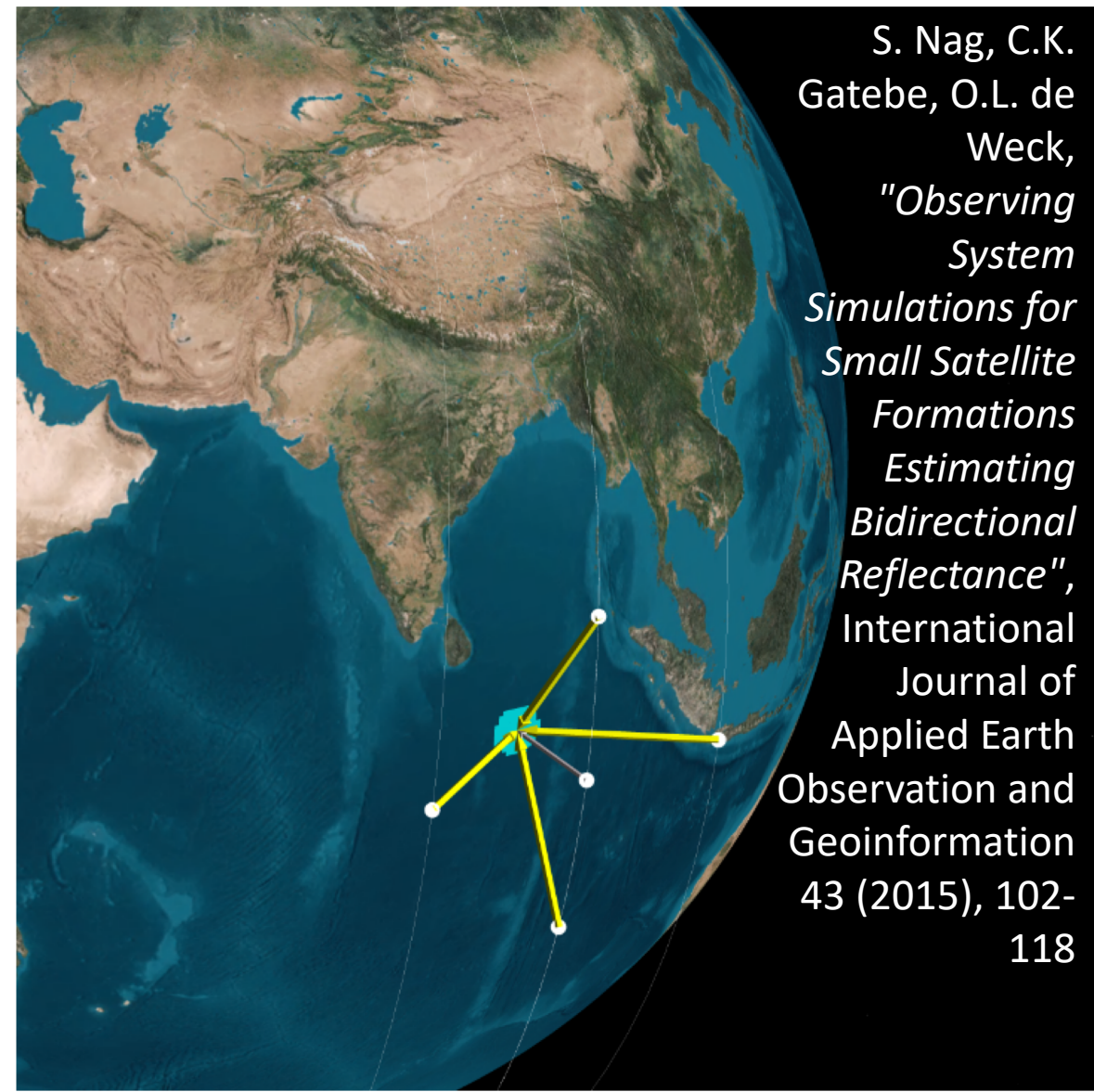
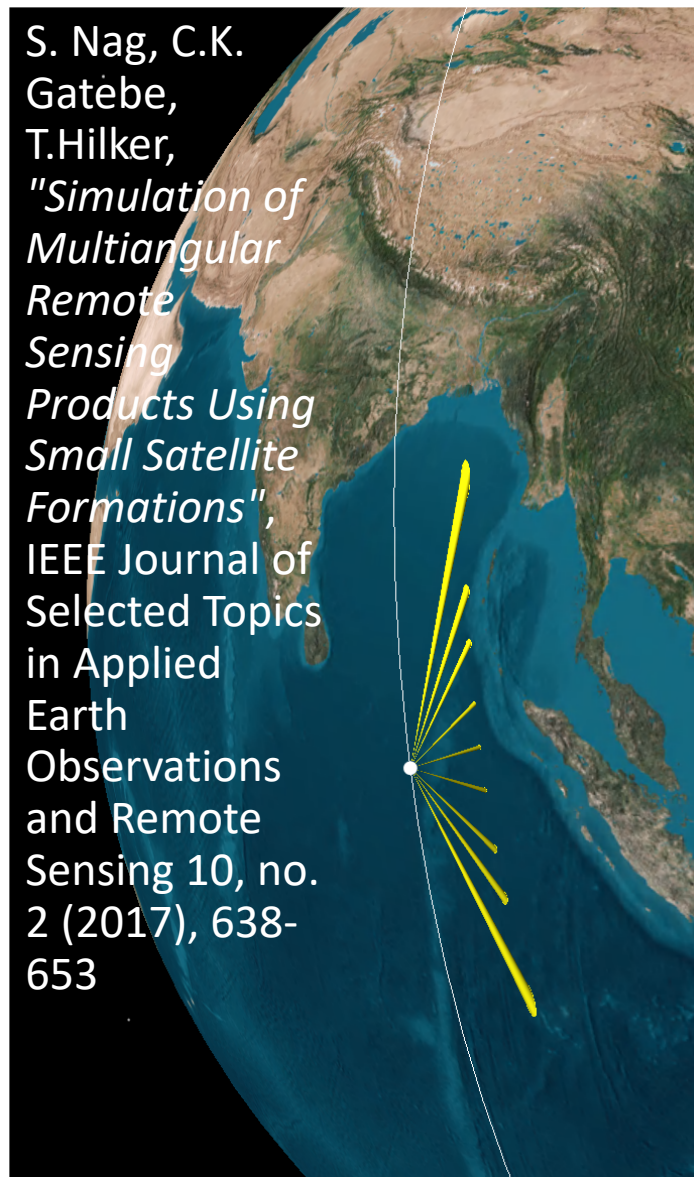


*Agile pointing on PROBA-1
(Project for On-Board
Autonomy - 1)*

<https://directory.eoportal.org/web/eoportal/satellite-missions/p/proba-1>

BRDF Estimation

- Because reflectance values depend on the direction of solar illumination and direction of measured reflection
- Angular sampling is sparse using monolithic spacecrafts presenting an angular challenge
- Dependent products e.g. albedo, GPP



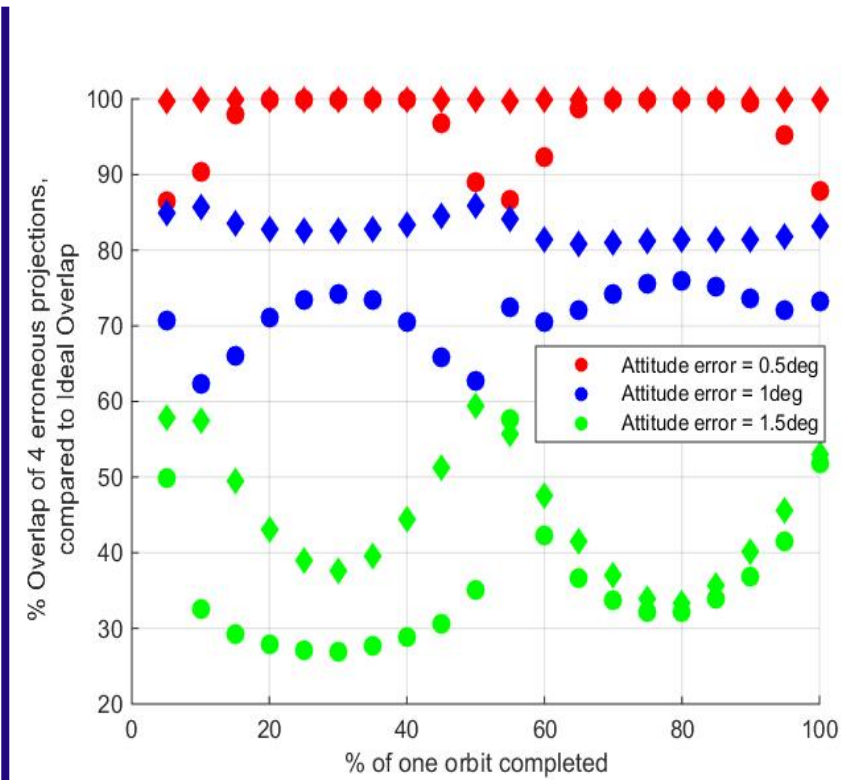
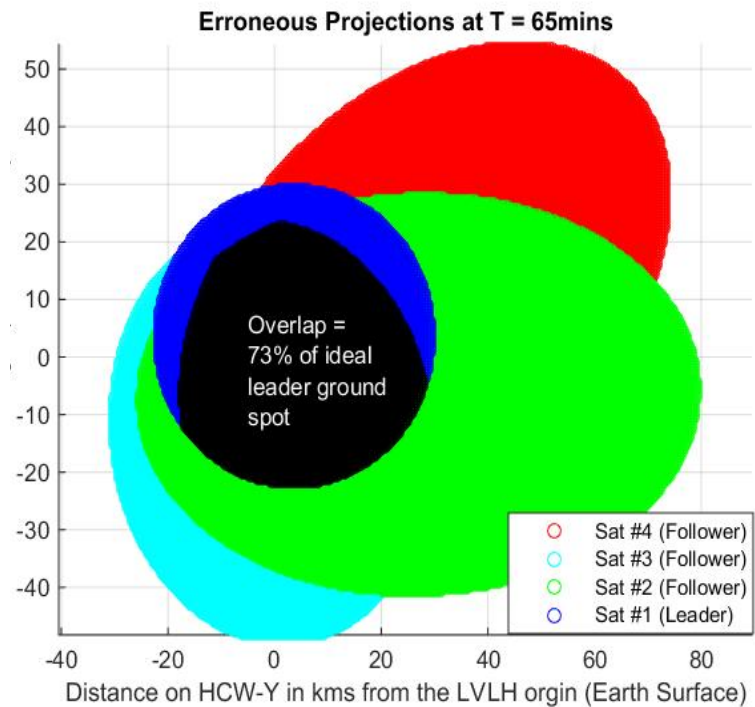
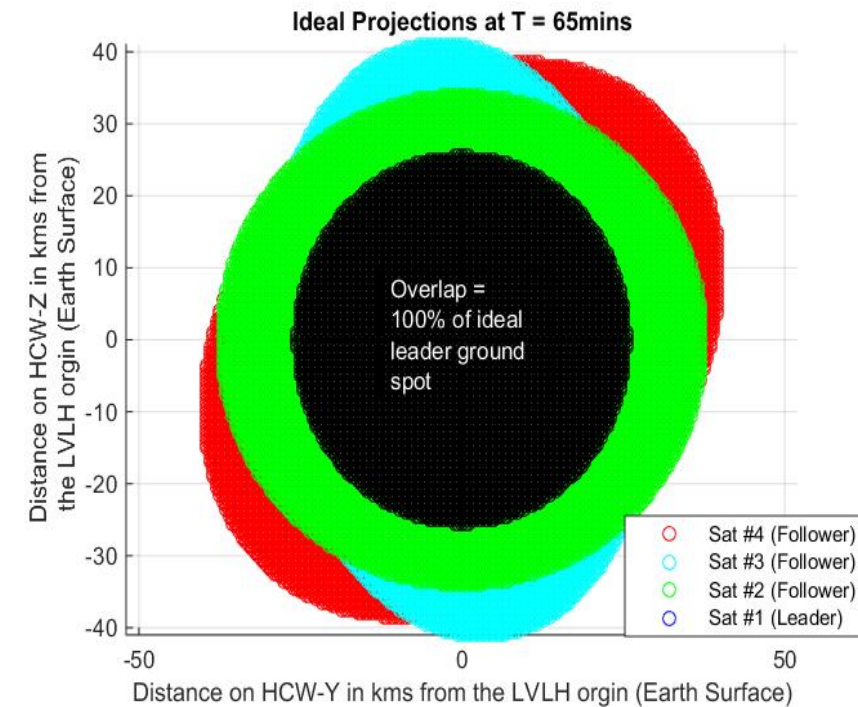
Supporting Agility using Attitude Control



Baseline cluster with 4 satellites and differential RAAN and TA only, propagated on the 650 km/51.6 deg circular, chief orbit.
ONE SNAPSHOT IN TIME: (Figures in LVLH)

Random attitude and position errors are supported by BRITE Constellation's 0.5 deg flight demo. Blue Canyon's XACT control of 0.01 deg, tested on MinXSS.

VARIATION OVER TIME:



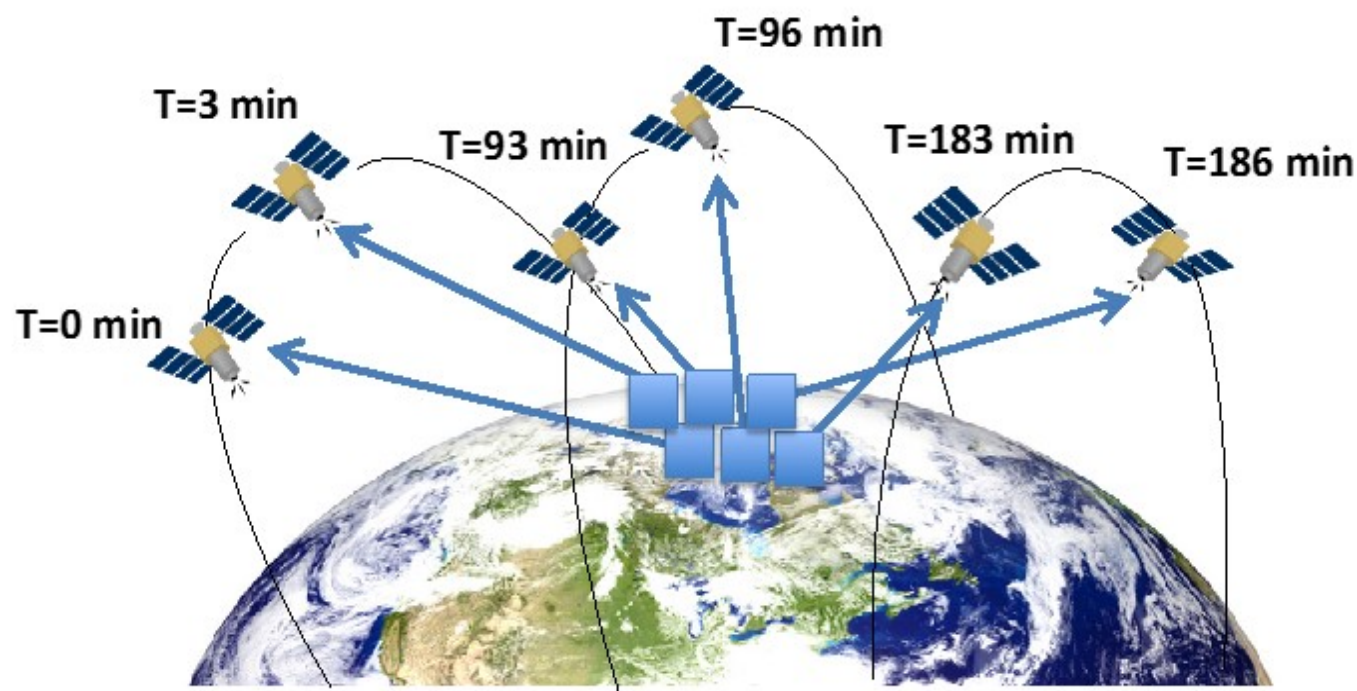
S. Nag, C.K. Gatebe, D.W. Miller, O.L. de Weck, "Effect of Satellite Formation Architectures and Imaging Modes on Global Albedo Estimation", Acta Astronautica 126 (2016), 77-97

Scheduling for Rapid Response Imaging

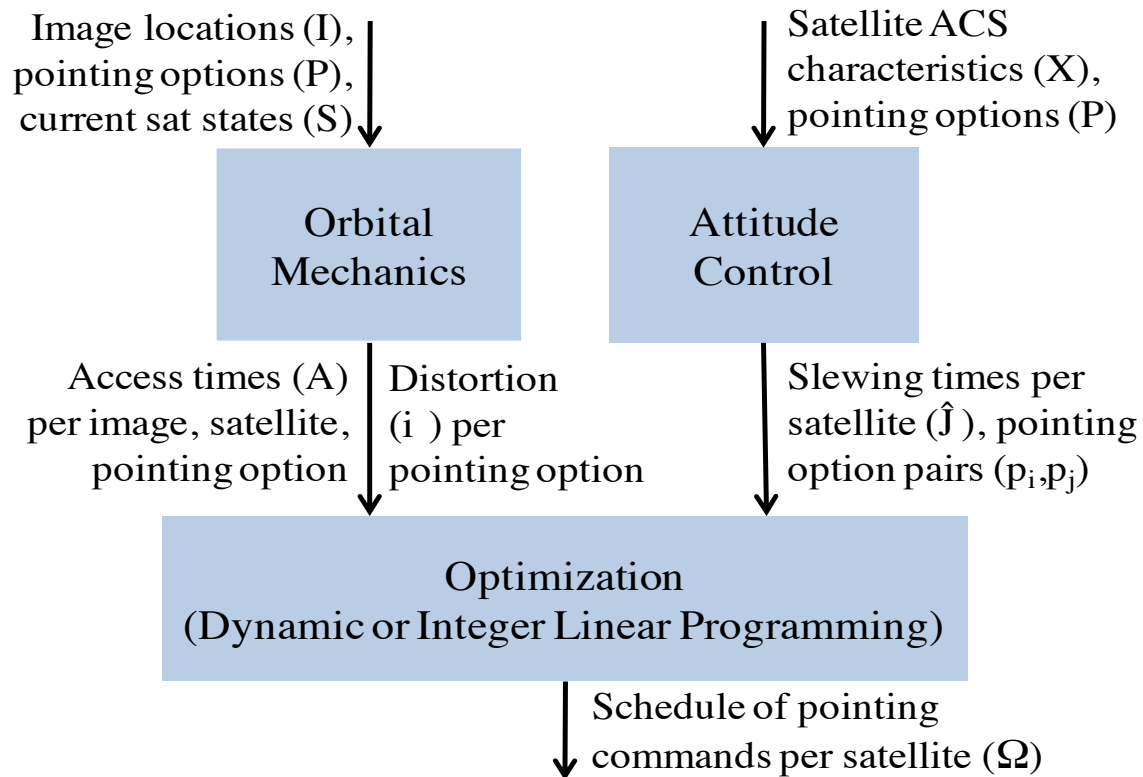


Given a global set of images, a fixed constellation of satellites with agile ADCS, MOI/ADCS specs and coverage constraints, what is the fastest route to cover those images?

- Need a linear-time algorithm, generalizable for any constellation and targets
- Using Landsat as first case study (710 km, SSO, 15 deg FOV) w/ a 14 day revisit. Daily revisit needs ~15 satellites or 4 satellites with triple the FOV.
- Instead assuming a 20 kg satellite platform to try the option of agile pointing
- The images, constellation/satellite number, specs and constraints (e.g. clouds, ground station outage) are assumed modular for generality

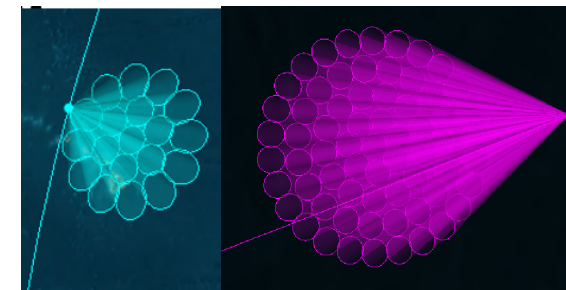


Breaking Down the Problem



- Use MATLAB, STK, MS Connect to simulate **orbital mechanics** and compute access reports: For every satellite, every pointing option and every image, when to when is it visible
- Use MATLAB Simulink to compute pointing switch time
- Use an optimization method (DP, MILP) to find the best schedule of pointing per satellite, that stably views (for upto one second) the maximum number of given images in given time

S. Nag, A.S. Li, J.H. Merrick, "Scheduling Algorithms for Rapid Imaging using Agile Cubesat Constellations", COSPAR Advances in Space Research - Astrodynamics 61, Issue 3 (2018), 891-913



Breaking Down the Problem



- Access Matrix (includes constraints, based on the **orbital mechanics** solution)
- Cost Matrix (Pointing change based on the **ADCS solution**)

Pointing Options (1-19) per satellite ->

	1	2	3	4	5	6	7	8	9	10	11	12
378	10180	10188	10189	NaN	NaN	10173	10179	11310	10203	10191	NaN	NaN
379	10180	10188	10189	NaN	NaN	10173	10179	11310	10203	10191	NaN	NaN
380	10180	10188	10189	NaN	NaN	10173	10179	11310	10203	10191	NaN	NaN
381	10180	10188	10189	NaN	NaN	10173	10179	11310	10203	10191	NaN	NaN
382	10180	10188	10189	NaN	NaN	10173	10179	11310	10203	10191	NaN	NaN
383	10180	10188	10189	NaN	NaN	10173	10187	11310	10203	10191	NaN	NaN
384	10180	10188	10189	NaN	NaN	10173	10187	11310	10203	10191	NaN	NaN
385	10180	10188	10189	NaN	NaN	10173	10187	11310	10203	10191	NaN	NaN
386	10180	10188	10189	NaN	NaN	10173	10187	11310	10203	10191	NaN	NaN
387	10180	10188	10189	NaN	NaN	10172	10187	11310	10202	10191	NaN	NaN
388	10180	10188	10189	NaN	NaN	NaN	10187	11310	10202	10191	NaN	NaN
389	10180	10188	10189	NaN	NaN	10179	10187	11310	10202	10191	NaN	NaN
390	10180	10188	10189	NaN	NaN	10179	10187	11310	11311	10191	NaN	NaN
391	10180	10188	10189	NaN	NaN	10179	10187	11310	11311	10190	NaN	NaN
392	10180	10201	10189	NaN	NaN	10179	10187	11310	11311	10203	NaN	NaN
393	10188	10201	10189	NaN	NaN	10179	10187	11310	11311	10203	NaN	NaN
394	10188	10201	10189	NaN	NaN	10179	10187	11310	11311	10203	NaN	NaN
395	10188	10201	10189	NaN	NaN	10179	10187	11310	11311	10203	NaN	NaN
396	10188	10201	10189	NaN	NaN	10179	10187	11310	11311	10203	NaN	NaN
397	10188	10201	10189	NaN	NaN	10179	10187	11310	11311	10203	NaN	NaN
398	10188	10201	10189	NaN	NaN	10179	10187	11310	11311	10203	NaN	NaN
399	10188	10201	10189	NaN	10180	10179	10187	11310	11311	10203	NaN	NaN
400	10188	10201	10202	NaN	10180	10179	10187	11310	11311	10203	10190	NaN
401	10188	10201	10202	NaN	10180	10179	10187	11310	11311	10203	10190	NaN
402	10188	10201	10202	NaN	10180	10179	10187	11310	11311	10203	10190	NaN
403	10188	10201	10202	NaN	10180	10179	10187	11310	11311	10203	10190	NaN
404	10188	10201	10202	10189	10180	10179	10187	11310	11311	10203	10190	NaN
405	10188	10201	10202	10189	10180	10179	10187	11324	11311	10203	10191	NaN
406	10188	10201	10202	10189	10180	10179	10187	11324	11311	10203	10191	NaN
407	10188	10200	10202	10189	10180	10179	10187	11324	11311	10203	10191	NaN
408	10188	10200	10202	10189	10180	10179	10187	11324	11311	10203	10191	NaN
409	10188	10200	10202	10189	10180	10179	10199	11324	11311	10203	10191	NaN
410	10188	10200	10202	10189	10180	10179	10199	11325	11311	10203	10191	NaN
411	10188	11309	10202	10189	10180	10179	10199	11325	11311	10203	10191	NaN
412	10188	11309	10202	10189	10180	10187	10199	11325	11311	10203	10191	NaN
413	10188	11309	10202	10189	10180	10187	10199	11325	11311	10203	10191	NaN

<= Time Steps over simulation time (1-86400)

From Pointing Option #1-19

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1	1	5	5	5	5	5	5	11	11	11	11	11	11	11	11	11	11	11	11
2	6	1	5	5	10	9	5	5	8	10	11	11	11	11	12	11	11	9	5
3	5	5	1	5	8	10	11	9	5	5	8	11	11	10	11	11	12	11	10
4	5	9	5	1	5	5	10	11	10	9	5	5	8	11	11	11	11	10	12
5	5	10	9	5	1	5	5	11	12	11	10	9	5	5	8	10	11	10	11
6	6	8	10	11	5	1	5	10	11	11	12	12	11	10	5	5	8	10	11
7	9	5	5	10	9	5	1	10	11	10	11	11	12	11	11	10	5	5	8
8	10	6	10	11	12	11	11	1	6	9	11	11	12	12	11	12	12	10	5
9	10	9	7	11	10	11	11	5	1	6	9	11	11	12	12	12	12	12	10
10	11	11	6	5	11	12	11	10	5	1	6	9	11	11	12	12	11	12	11
11	11	11	9	8	10	10	12	11	10	5	1	6	10	10	11	12	12	11	12
12	10	11	11	6	5	11	12	12	11	10	5	1	6	9	11	11	12	12	11
13	11	11	11	10	7	11	9	11	12	11	10	5	1	6	9	10	11	12	12
14	11	12	11	11	6	5	10	12	11	12	12	10	5	1	6	9	10	11	12
15	10	10	11	11	10	7	10	12	12	11	12	12	10	5	1	6	9	10	11
16	10	11	12	11	11	6	5	11	12	12	11	12	12	10	5	1	6	9	10
17	10	11	10	12	11	10	9	10	11	12	12	11	12	12	10	5	1	6	9
18	9	5	11	12	11	11	6	9	10	11	12	12	11	12	12	10	5	1	6
19	10	7	11	10	11	11	10	6	9	11	11	12	12	11	12	12	11	5	1

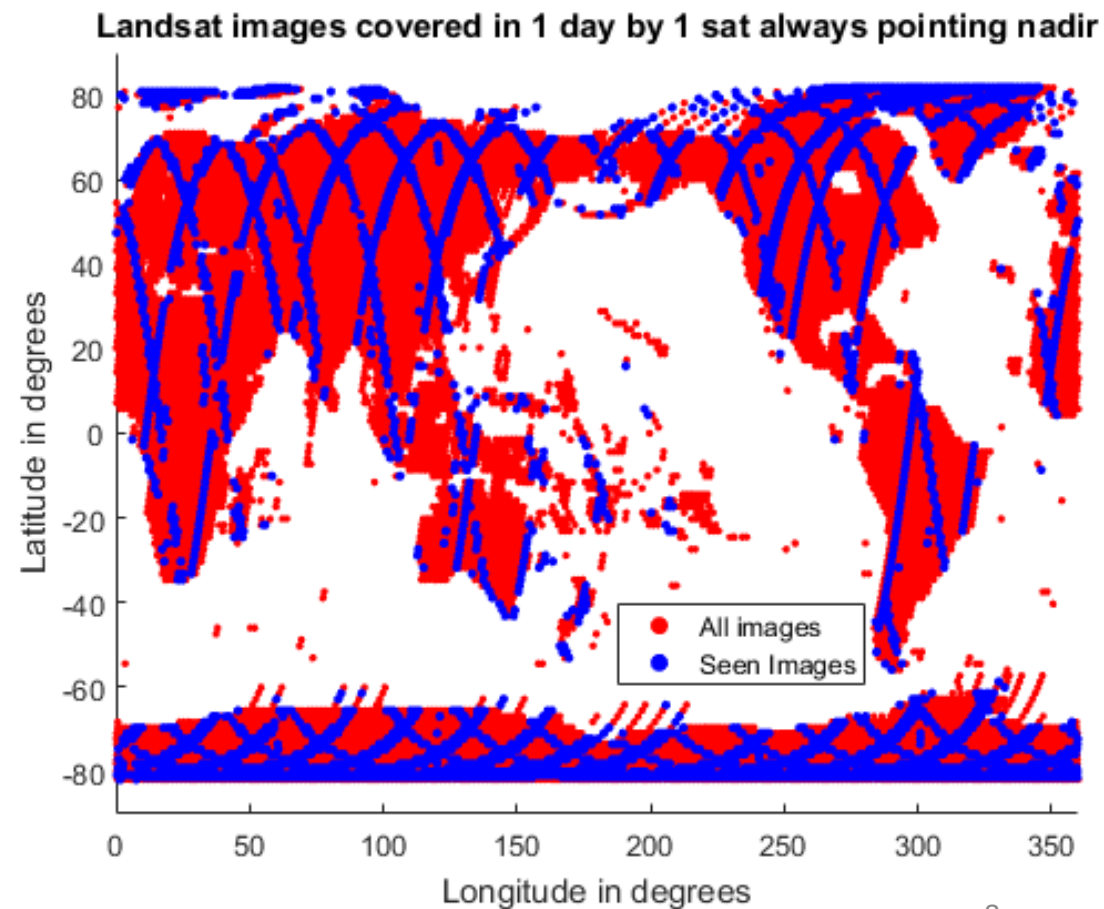
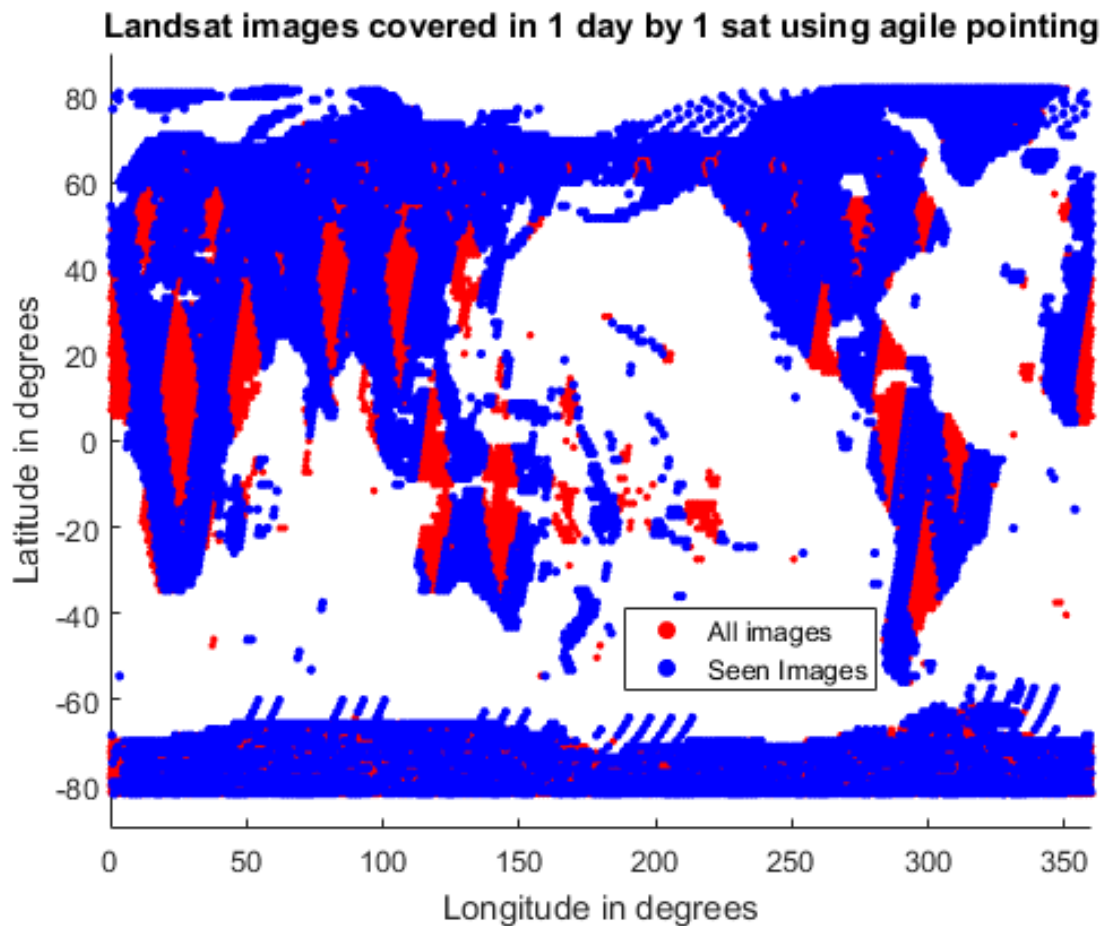
To Pointing Option #1-19

Dynamic Programming, followed by MILP for verification and potential improvement

Results using a Single Satellite

Over a full day's worth of simulation/86400 seconds on Landsat images

- Using our proposed DP algorithm
- Using a fixed Landsat sensor, as is



Results using a Single Satellite



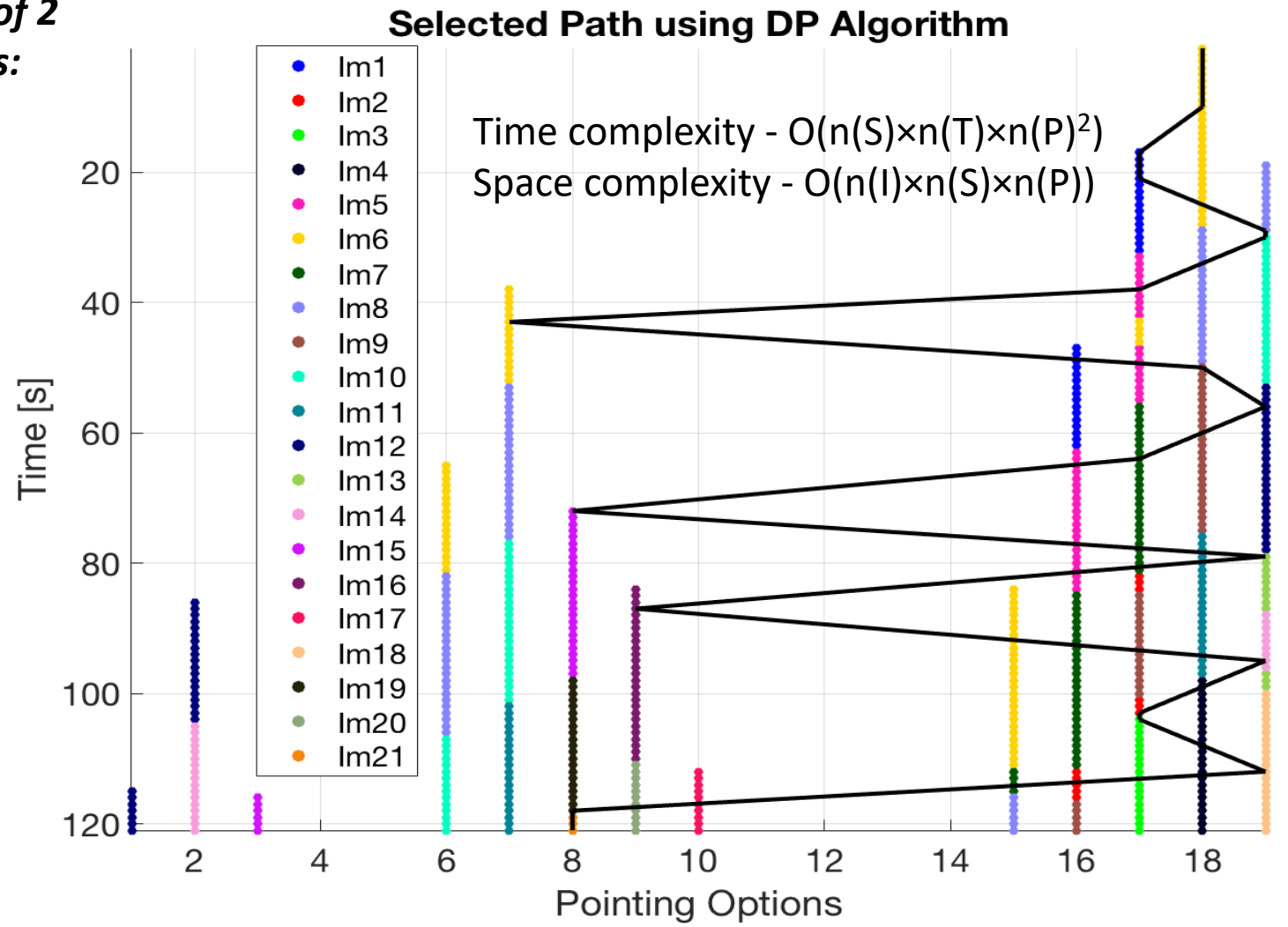
All algorithms are linear in time. Verified in simulation.

Over a full day's worth of simulation/86400 seconds:

- Of 14724 possible images, 11900 were seen.
- In comparison, max 4894 images were seen using the static single-look conops and 3079 images using the whiskbroom/scanning approach
- Algorithm covered 77.5% from possible images and 70% from total ... 2.5 times the static case and 3.86 times the scanning approach
- However, <6% of the seen images are nadir-viewing and >65% have maximum distortion
- Image distortion can be added to the path-selection algorithm by weighting the seen images with $*(1-\text{distortion}\%)$ where $\% = f(\text{pointing})$ and leftover images with $*(1+\text{distortion}\%)$

Results using a Single Satellite

An example subset of 2 minutes:



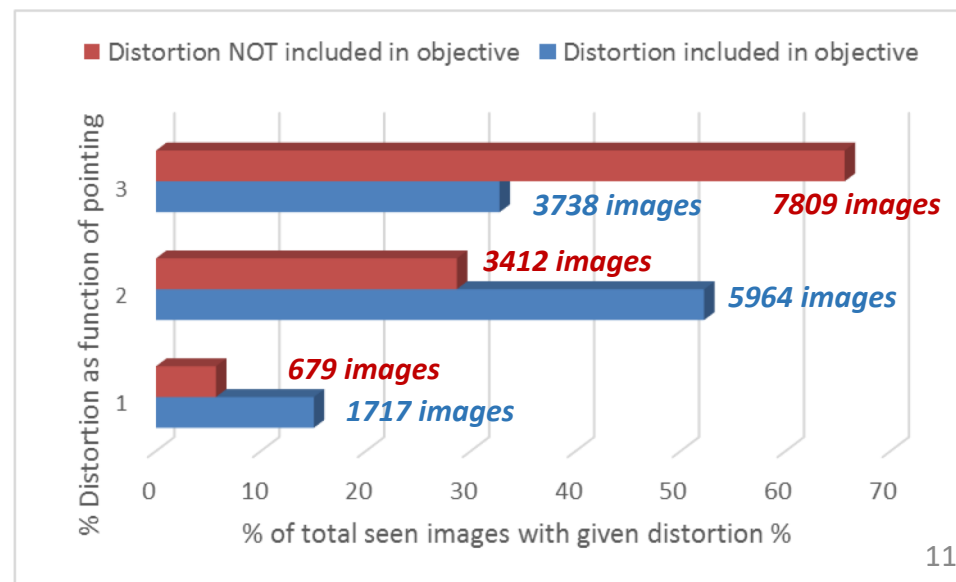
- Image #1 is not an image
- Of 21 possible images in these 2 minutes, 18 were seen.
- In comparison, 2-7 images were seen for fixed pointing and only 1 when scanning
- Note the preference for off-nadir pointing

Modified Results using a Single Satellite



Over a full day's worth of simulation/86400 seconds:

- Of 14724 possible images, 11418 were seen instead of 11900.
- The algorithm covered 77.5% of the possible and 67% from the total Landsat selection.
- As before, fixed pointing covers only 32% of the possible images so the algorithm does ~2.4 times better than the static conops
- Adding distortion minimization to the objective function moves more images to the 0% and 8% GSD distortion.
- 9548.5 effective images (weighted by 1-percDist) were seen instead of 8785.4 effective images (w/o weights)

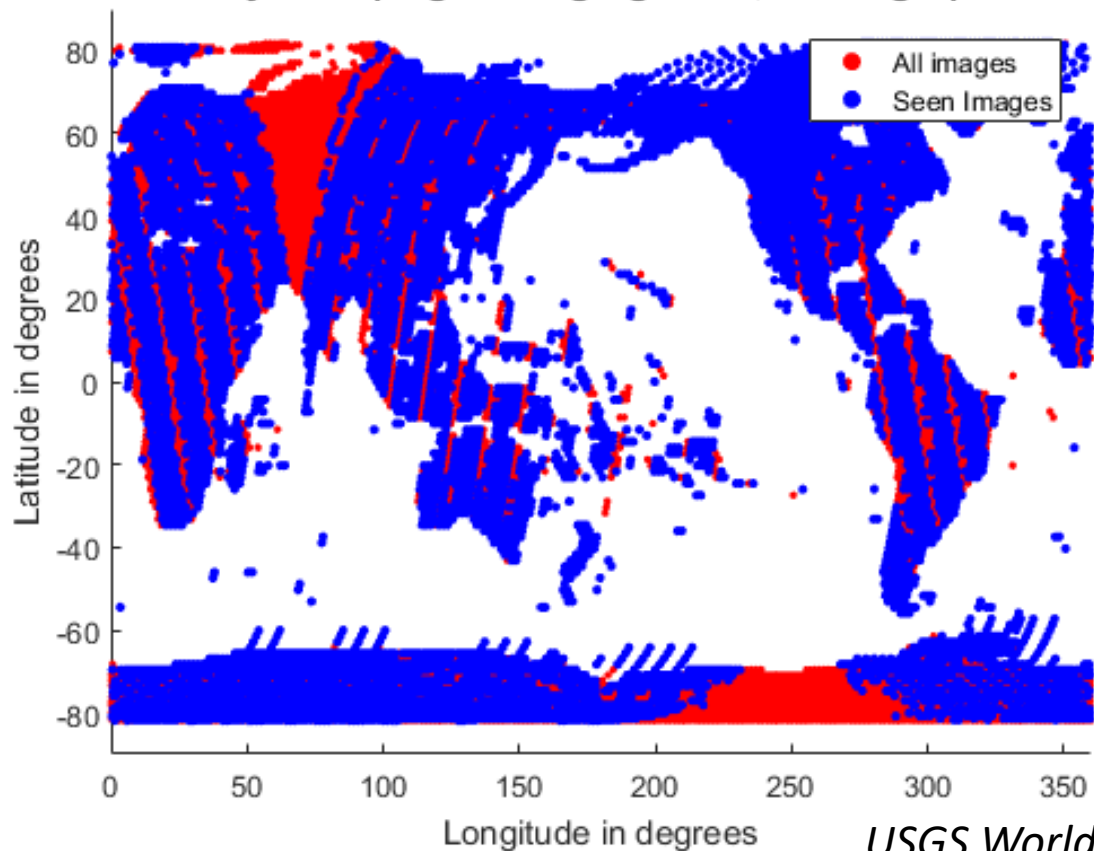


Results using a Constellation

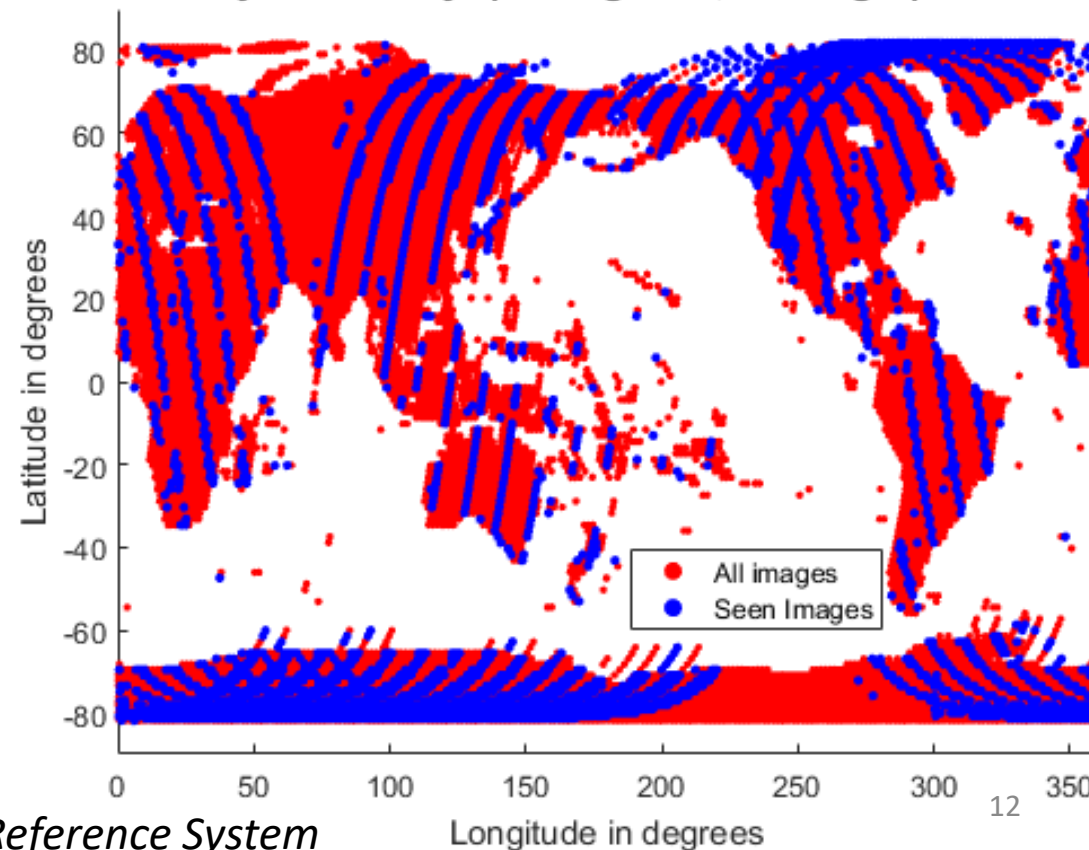
Over 6 hours of simulation/43200 seconds using 2 co-planar satellites, 180 deg apart :

- Using our proposed DP algorithm
- Using a fixed Landsat sensor, as is

Landsat images covered in 12 hours, by 2 sats pointed via the dynamic programming algorithm, in a single plane



Landsat images covered in 12 hours, by 2 sats always pointing nadir, in a single plane

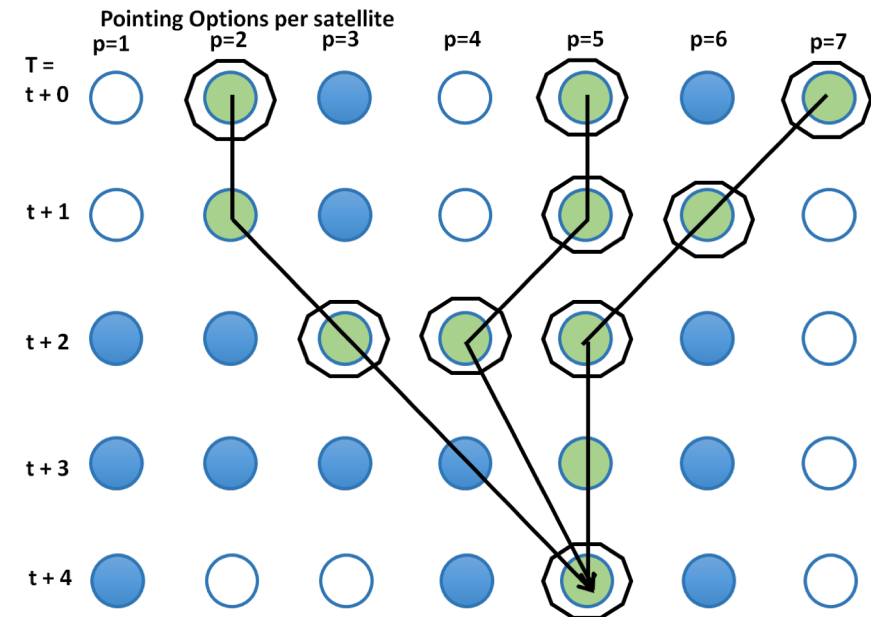


Results using a Constellation



Over 6 hours of simulation/43200 seconds using 2 co-planar satellites, 180 deg apart :

- Of 14163 possible images, 10847 were seen (note half the time as before).
- In comparison, 4366 images were seen using the static fixed pointing conops, where in the satellite always points nadir, i.e. 60% lower images
- Our algorithm covered 76.6% from possible images and 65% from total ... 2.5x the number obtained using the fixed pointing approach
- BUT there were 2230 unique images, common between those imaged by the two satellites because the DP algo evaluates uniqueness per satellite path.
- To optimize for all sats and all pointing options simultaneously will increase the time complexity of the algo to $O(n(t) \times n(P)^{2 \times n(S)})$
- Need a better way to integrate the sat threads...



Results using an **Informed** Constellation



Same algorithm implemented on the constellation simulation however, individual path optimization is for every X hours AND each satellite is made aware of the images seen by the optimum schedule/path of all others every X hours

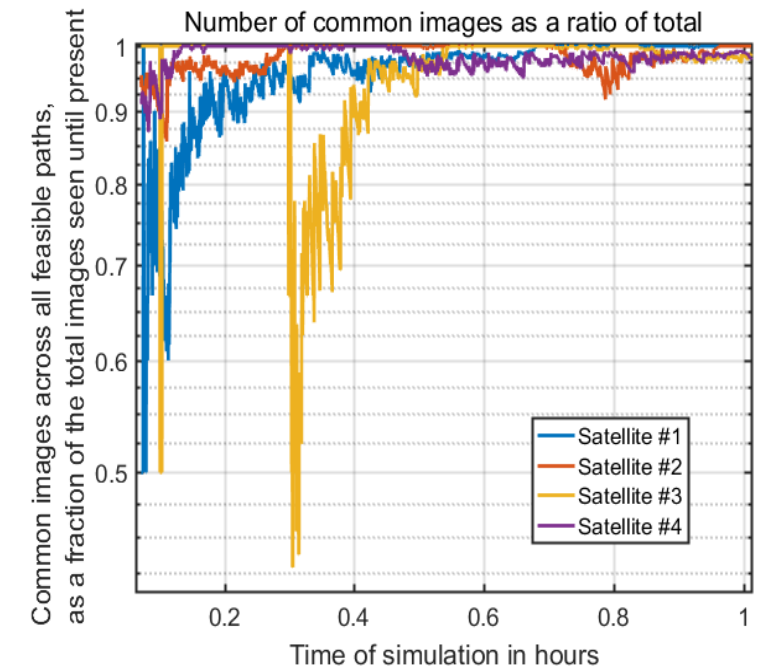
Two co-planar satellites, 180 deg apart

X	Unique Images seen	Repeat images (not counted)	Improvement from no agility	Improvement from X=12 hrs
6 hours	10948	1751	150.7%	0.9%
3 hours	11027	1410	152.5%	1.6%
1.5 hours	11137	1018	155%	2.7%
45 minutes	11430	0	161.8%	5.4%

Four co-planar satellites, 90 deg apart

X	Unique Images seen	Repeat images (not counted)	Improvement from no agility
3 hours	14038	10400	42.13%
45 minutes	14594	3929	47.8%
22 minutes	14779	0	49.63%

This approach is generalizable to any sparse structure



Verification using Integer Programming



- The full problem comprises 9 mill constraints, >800k binary variables, Eq 7 being the major source of rows
- DP soln is 4.79% less in quality to MILP found solution and 9.88% to the best possible bound
- Confirmed that image quality notwithstanding, the DP schedule can observe within 1.5% of the optimum number of images for any sat, at 1e3x speed

	MILP	DP
Objective Value	818.43	779.23
Best possible bound	864.7	
Number images captured	930	917
Images at increasing distortion	207,546,177	135, 528, 254

***performed on the Sherlock cluster at Stanford University in 15.5 hrs*

$$v_t = \sum_{s=1}^{Smax} \sum_{p=1}^{Pmax} o_{t,p,s} * \Delta[p] * a_{t,p,s} \quad (1)$$

$$a_{t,p,s} = \sum_{i=1}^{I_{max}} A[t, i, p, s] \quad \forall s \in S, p \in P, t \in H \quad (2)$$

$$\text{maximize} \sum_{t=1}^{Tmax} v_t \quad (3)$$

$$\sum_{p=1}^{Pmax} o_{t,p,s} \leq 1 \quad \forall s \in S, t \in H \quad (4)$$

$$\sum_{s=1}^{Smax} \sum_{p=1}^{Pmax} \sum_{t=1}^{Tmax} o_{t,p,s} * A[t, i, p, s] \leq 1 \quad \forall i \in I \quad (5)$$

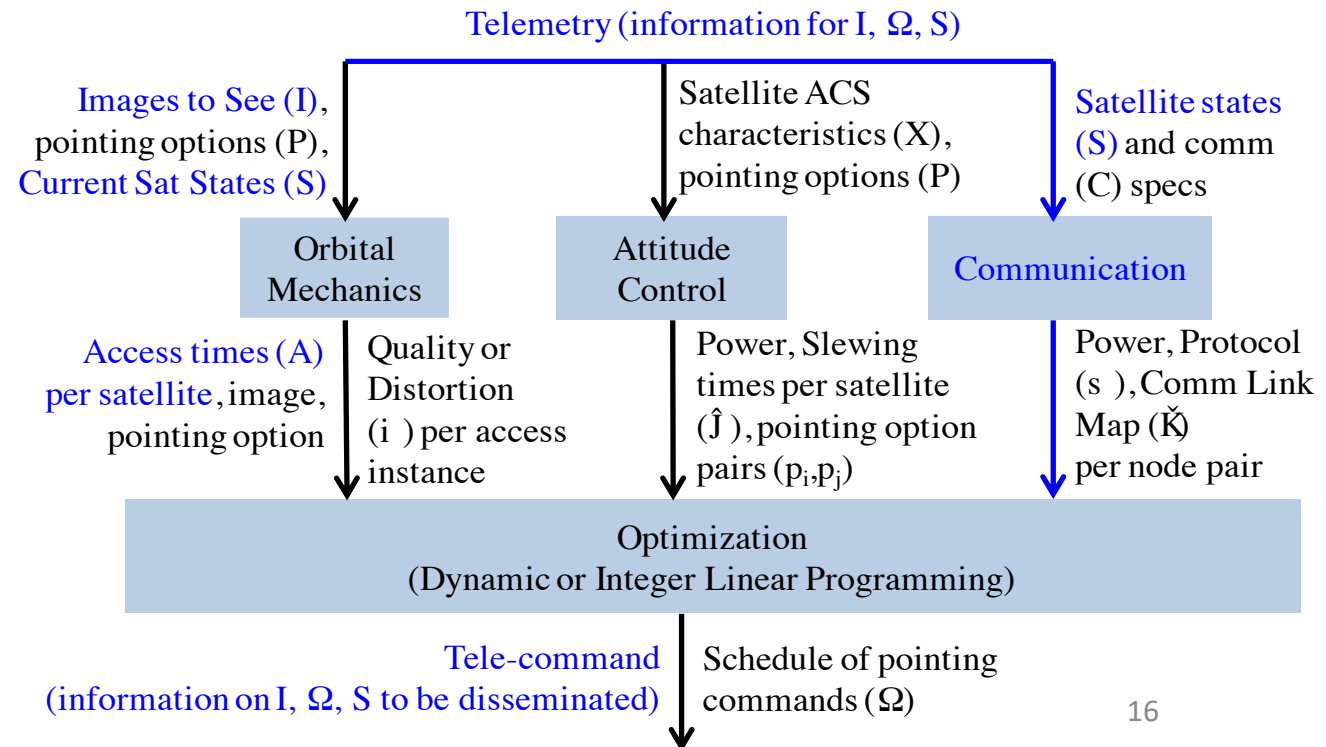
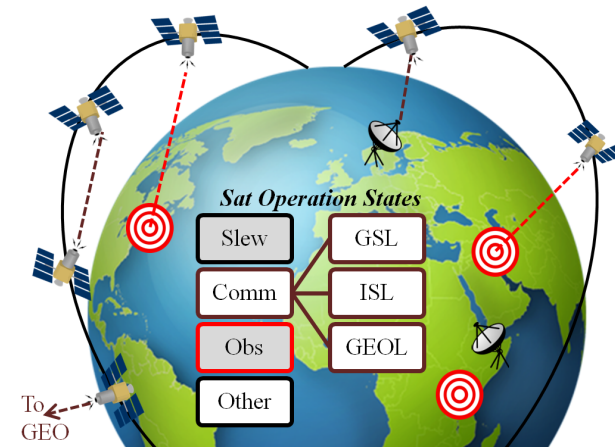
$$o_{t+k,p_i,s} + o_{t,p_j,s} \leq 1 \quad \forall k \in [1, \Gamma(p_i, p_j)], s \in S, p \in P, t \in H \quad (6)$$

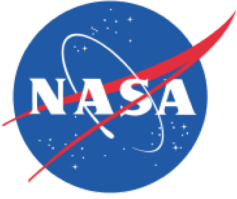
$$\sum_{pi=1}^{Pmax} o_{t+k,p_i,s} + o_{t,p_j,s} \leq 1 \quad \forall k \in [1, \Gamma(p_i, p_j)], s \in S, p \in P, t \in H \quad (7)$$

Follow-on Project 2018-21



- Onboard Autonomy modification of presented algorithm for rapidly changing observation requirements, e.g. floods (UGA, GSFC), wildfires (ARC), cloudbows (GSFC).
- Will need inter-sat comm, onboard orbit det., onboard processing software that approximates an OSSE and makes decisions for next obs (NEX).
- Will leverage DTN protocol for routing command and control across constellation (JPL)
- Testing expected in conjunction with NASA's Core Flight Software and COSMOS ground control software (Univ. of Hawaii)





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Questions?

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