Distributed Spacecraft with Heuristic Intelligence to Enable Logistical Decisions for Global Navigation Satellite System Reflectometry (GNSS-R) of Wildfires

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AIR NOS with DSHIELD

Adaptive, Intelligent and Responsive New Observing Strategy (AIR NOS) for Wildfires

Adaptive

Science drivers dictating observations, based on previous observations

- Geophysical retrievals
- Data assimilation into NWP
- Value framework, forecast reporter

Intelligent

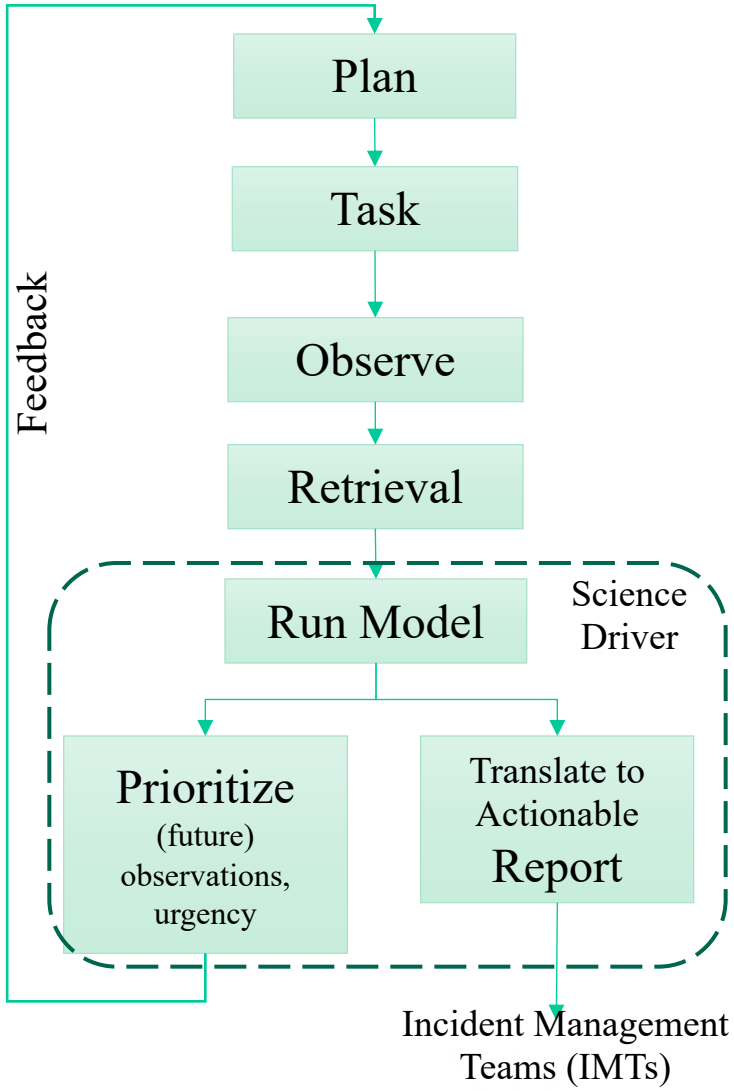
Efficient resource utilization using AI

- Planning, orbit/coverage calculations, satellite sub-system modeling, downlink data prioritization

Responsive

Time of event to delivery of report

- Use of only NRT data, cognizance of processing times, sync of operations



GNSS-R Sci-tech

Global Navigation Satellite Systems Reflectometry (GNSS-R)

- L-band (microwave) observations, can penetrate clouds, smoke
- Observations of specular reflections => complimentary, **unique data** compared to backscatter (SAR), radiances (radiometer)
- Passive bistatic radar => small form factor of satellites => numerous distributed satellites => **high temporal sampling**
  - NASA Cyclone Global Navigation Satellite System (CYGNSS) mission
- Has demonstrated scientific retrieval of surface, including wind speed over ocean, and soil moisture and flooding over land.

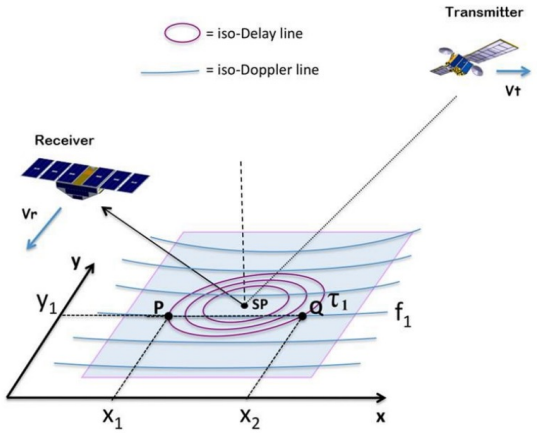


Fig: GNSS-R imaging geometry

Rose, Randy, Scott Gleason, and Chris Ruf. "The NASA CYGNSS mission: a pathfinder for GNSS scatterometry remote sensing applications." *Remote Sensing of the Ocean, Sea Ice, Coastal Waters, and Large Water Regions 2014*. Vol. 9240. SPIE, 2014.

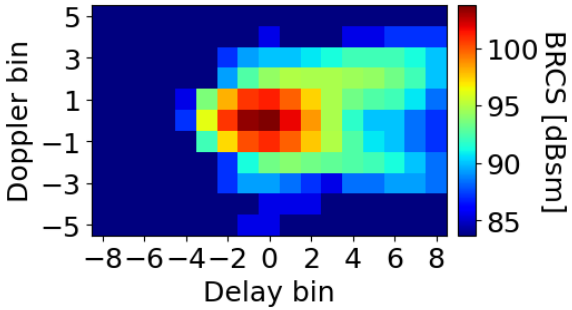


Fig: Delay Doppler Map (DDM)

Target Fire Areas

Adaptation of scientific and technological benefits offered by GNSS-R to the wildfire application.

Pre-fire mission

Prioritize observations over areas where there is greater chances of fire.

- Use of USGS Fire Danger maps as science driver
- Retrieve from soil moisture derived from (uncompressed) GNSS-R
- Feedback to refine fire-danger predictions

Active fire mission

- Prioritize fast delivery of observations at active fire area
- Retrieve burnt area locations from GNSS-R
- Assimilate into WRF-SFIRE

Default Mission

- Model of 'nominal' mission operations

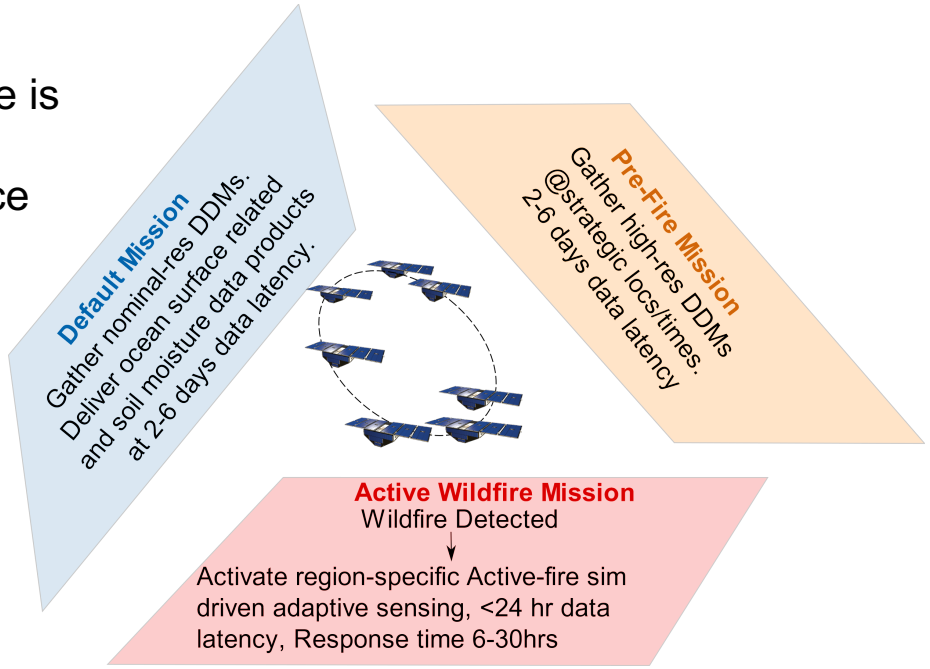


Fig: Simultaneous execution of multiple missions

Key proposed innovations

›Ingestion of GNSS-R products into WRFx
›New Emission module

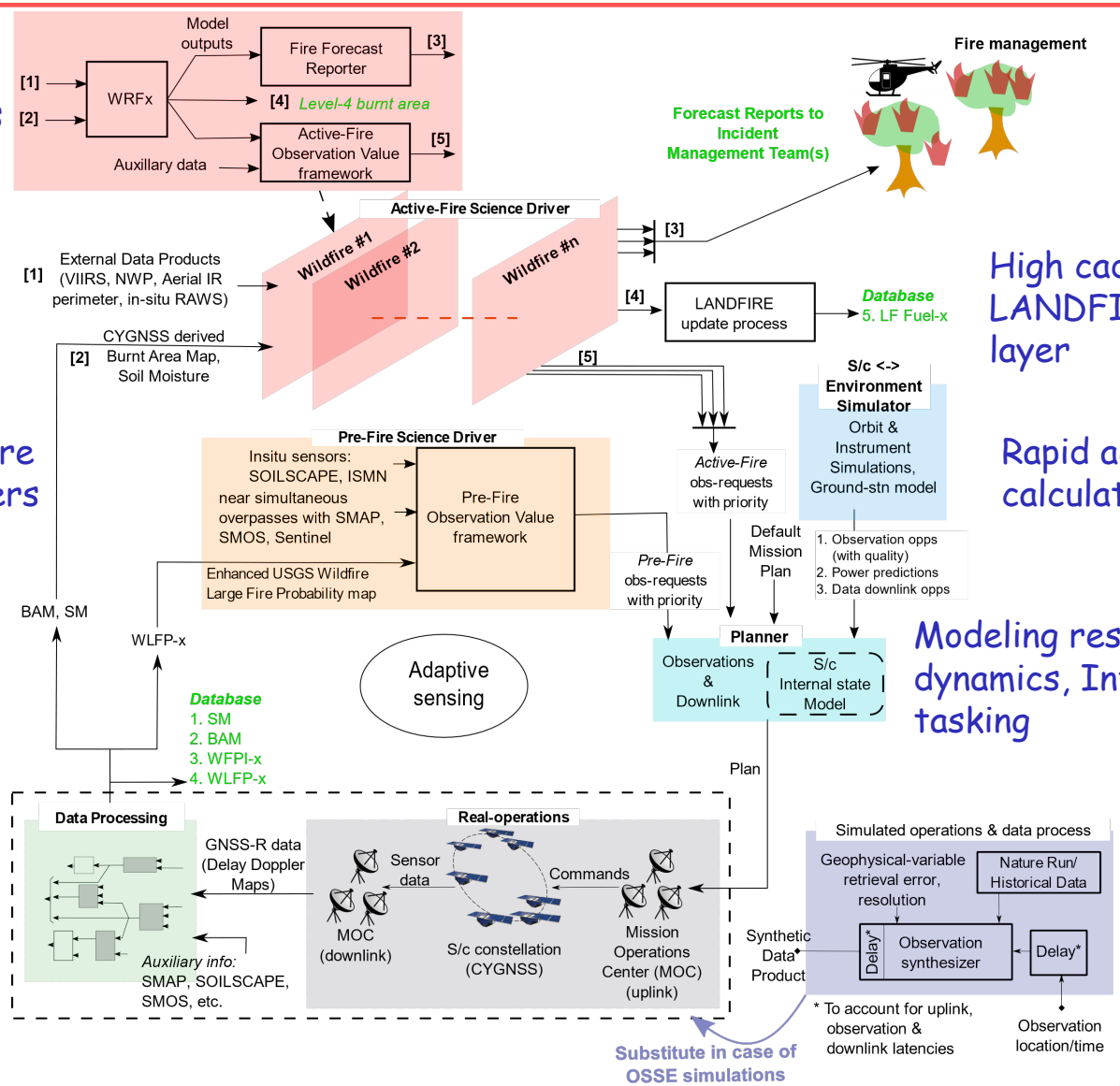
High cadence LANDFIRE fuel-layer

Pre, Active fire Science Drivers

Rapid access calculations

Modeling resource dynamics, Intelligent tasking

› Burnt Area Map
› Enhancement of Fire Danger (WLFP) with SM.
› Enhancement of SM through continuous Cal/Val



Preliminary work

Independent development of components of the proposed adaptive sensing framework

- Enhancing USGS Fire Danger product with GNSS-R (CYGNSS) derived soil moisture
  - Goal: Improved Fire Danger by adjusting Fuel Moisture with observed data

- Exploration of physics-based and ML-based detection of 'burnt-area' with GNSS-R (CYGNSS) Delay Doppler Maps
  - Goal: High cadence 'burnt-area' detections during active fire

- Modeling & Intelligent tasking algorithm development & simulated tests with CYGNSS as example
  - Goal: Efficient use of satellite resources for maximizing science value gathering with low latency

Enhanced Fire Danger product

- USGS Fire Danger Forecasting produces 7-day forecast products for fire potential index, large fire probability, and fire spread probability.
- Utilizes a combination of satellite-derived vegetation indices, various biogeophysical variables, and weather information.
- Modify the nominal workflow of calculating FPI to consider observed **soil moisture anomalies**
- 10hr FM term is adjusted by the anomaly term

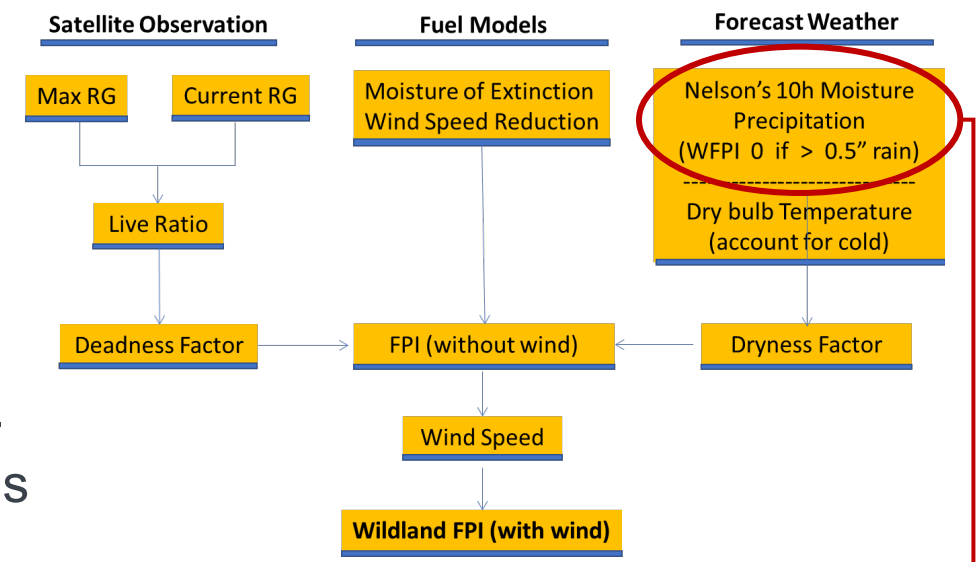


Fig: Fire Potential Index Data Flow

$$\%SM_{rel} = \frac{SM - SM_{avg}}{SM_{avg}}$$

Enhanced Fire Danger product

CYGNSS 9km Soil Moisture products used for adjustment

Validation

- Three test cases from MTBS record:
  - Vivian Fire – 11825 acres, ignition 8/20/2019
  - Game Ranch Fire – 3022 acres, ignition 7/13/2020
  - Gate 5 Fire – 11457 acres, ignition 7/14/2020
- Adjusted WFPI is **higher at locations which later caught fire**
  - Mean difference is +13

Operational WFPI → Adjusted WFPI

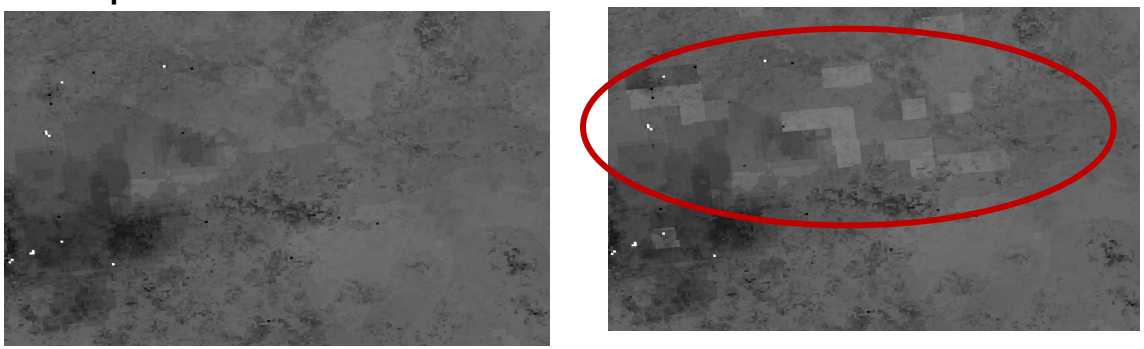


Fig: Grayscale image of operational and adjusted WFPI (unit-less number that ranges from 0 to 150)

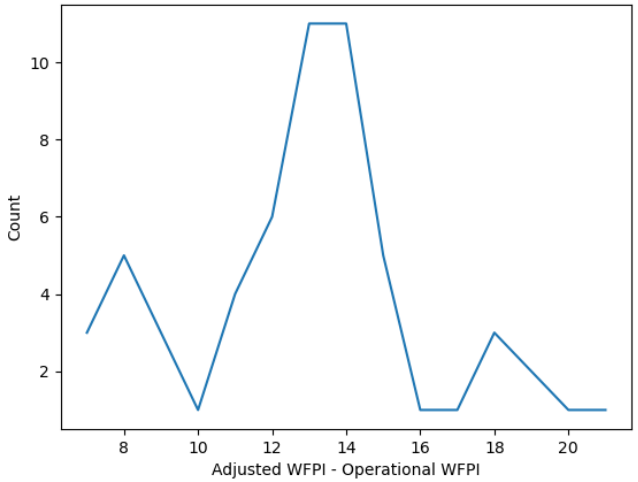


Fig: Histogram of the adjustment at the test events

Next Steps:
Incorporation of quality checks and testing of with more past fires.

GNSS-R Burnt Area detection

Physics based detection

•Improved geometric optics with topography (IGOT) model compute GNSS-R DDM

•Retrieve vegetation parameters, by matching forward-model (IGOT) output with actual observation.

•<u>Change</u> of vegetation characteristics between DDMs before the fire and after is used to for detection.

•SMAP is used for surface soil moisture.

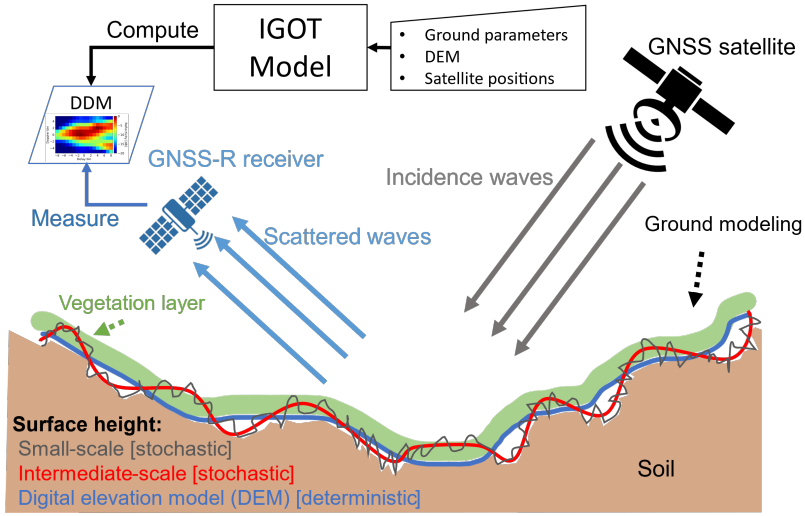


Fig: Physics based retrieval

Optimize to find vegetation params of the IGOT model which produce a matching DDM

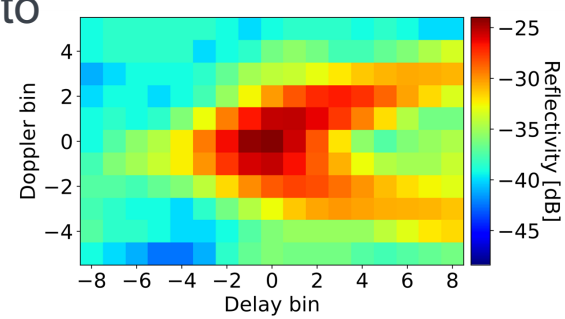


Fig: Observed CYGNSS DDM

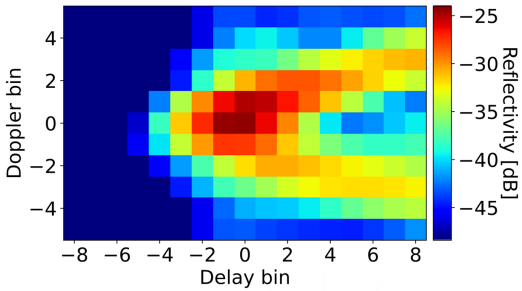


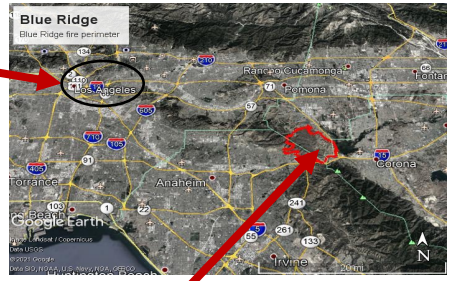
Fig: Simulated IGOT DDM

GNSS-R derived Burnt Area Maps

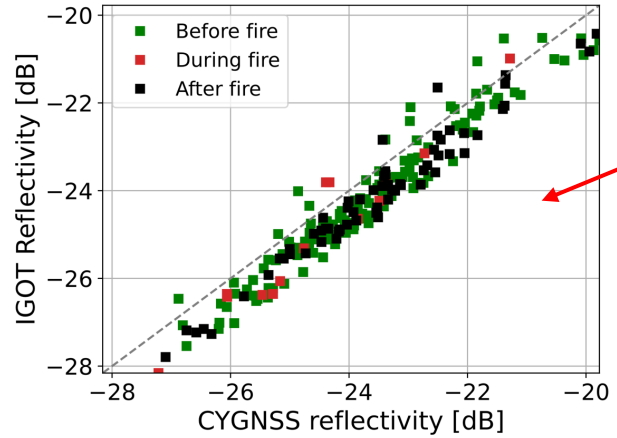
Test case: *Blue Ridge fire*

- Duration: Oct 26, 2020 – Nov 7, 2020 (11 days)
- Burned area: 13,964 Acres

Los Angeles

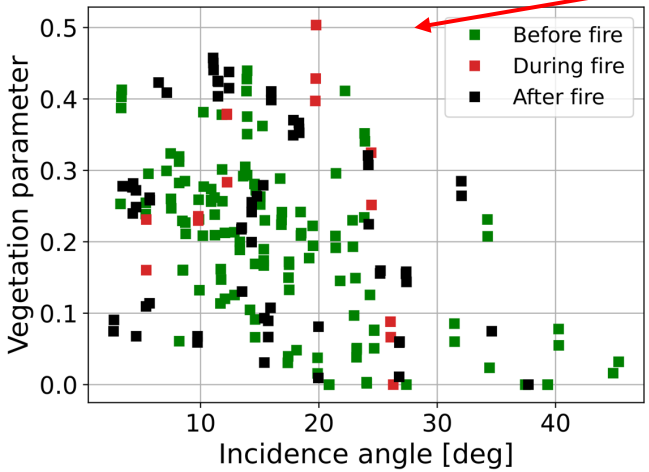


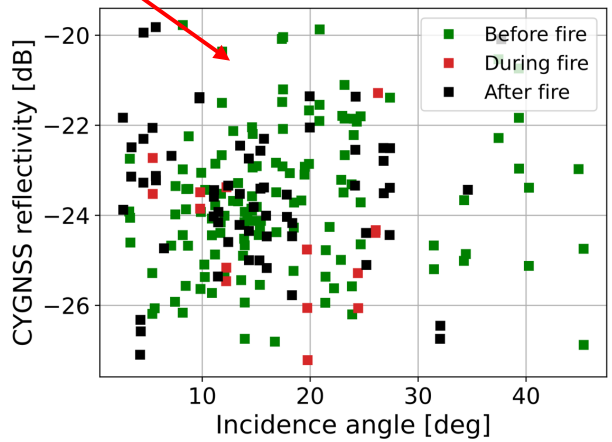
Fire perimeter



Good matching between CYGNSS and forward model specular point reflectivity [RMSE: 0.5 dB]

Cannot classify based on vegetation parameter retrievals or specular point reflectivity





Next Step:
Retrieval of *both* Soil Moisture &Veg params with *multiple* DDMs.

GNSS-R Burnt Area detection

ML based detection

•Random Forest Model

Inputs

- CYGNSS DDM: Specular point incidence angle, SNR, Reflectivity of specular point

Ancillary data

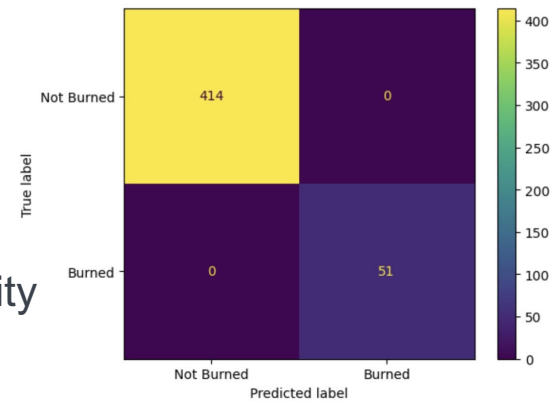
- SRTM: Elevation, Slope, Aspect
- SMAP: Soil Moisture, Vegetation Water Content, Surface Temperature, Precipitation

Truth data

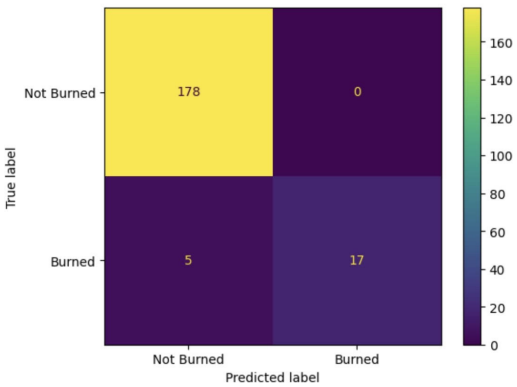
Overlapping dataset created with:

- Landsat Collection 2 Level-3 Burned Area Science Product,
- MODIS Burned Area,
- ESA CCI Burned Area.

Test case: Blue Ridge Fire



Train Confusion Matrix



Test Confusion Matrix

	Train (70%)	Test (30%)
Accuracy	100 %	97.5 %
F1 score	1.0	0.8717

- The burned area data is highly imbalanced.
- Good accuracy and F1 score improvement with important features (Reflectivity, SNR, incidence angle, Soil moisture, VWC, surface temperature)

Next Work: Explore more locations with less complex topography.

Intelligent Tasking & Modeling

While LEO small satellites enable distributed, high-temporal sampling, they are highly constrained

- Onboard data, downlink rate, power, re-orientation speed, etc.

Numerous options

- Observation modes, Selection of target, Downlink priority

Multiple objectives

- How to balance priorities of Pre-fire, Active-fire, Default missions?
- Different missions shall have different
  - Pre-fire: Data latencies can be relaxed
  - Active-fire: Data latency is critical

Some of the agility features

Mode	Integration time (s)	Bit depth	# specular locations	Data Volume increment factor
Nominal	0.5 (2 Hz)	9	**4 (max SNR)**	**1**
Modified	0.25 (4 Hz)	9	4 (max SNR)	2
Full DDM	0.5 (2 Hz)	32	4 (max SNR)	~48.7
RawIF	N/A	32	**Unrestricted (L1 band)**	**6724.30**

Table: Operational modes of observation available on CYGNSS

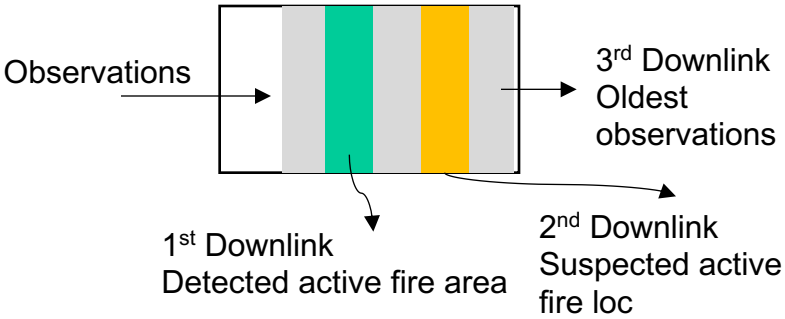


Fig: Prioritized downlink from onboard data buffer

Each choice comes with an associated reward/ cost which can be modeled with satellite orbit, subsystem (data, power) dynamics. Coupled with intelligent tasking, we can operate efficiently.

Intelligent Tasking & Modeling

Monte Carlo Tree Search (MCTS), Coulom 2006

Rémi Coulom (2006). "Efficient Selectivity and Backup Operators in Monte-Carlo Tree Search". Computers and Games, 5th International Conference, CG 2006, Turin, Italy, May 29–31, 2006.

- First algorithm to beat a human champion in the game 'Go'.
- Used by Tesla cars to avoid collisions
- Good for extremely large search spaces (decision spaces)
- Integrates Planning with Reinforcement Learning (RL)
- Explores search spaces using Monte Carlo simulations ("rollouts")
- Collects outcomes from each rollout to update reinforcement learning statistics
- Each rollout is a training case for reinforcement learning
  - Keeps statistics on *expected reward* for different choices
- Search involves balancing choices between *Exploration* vs. *Exploitation*
  - Exploration: Prefer new choices *which have not yet been simulated*
  - Exploitation: Prefer choices which worked best in prior simulations (highest expected reward based on RL)
- "Anytime Algorithm"
  - Planning can be interrupted at "any time" and a valid solution will be returned
  - More planning time is guaranteed to monotonically improve solution

Feature important for responsive missions.

- Specialized D-SHIELD adaptations to optimize satellite observation planning

Intelligent Tasking & Modeling

Simulation Scenario:

Pre-Fire Mission (1st Aug 2020, 1 day)

- 1 CYGNSS satellite
- 3 ground-stations @ HI, Chile & W. Aus.
- RawIF mode (high data volume) observation over locations of high fire danger
- FIFO data buffer

Objective formulation

Maximize the cumulative sum of WLFPs of the imaged & downlinked locations.

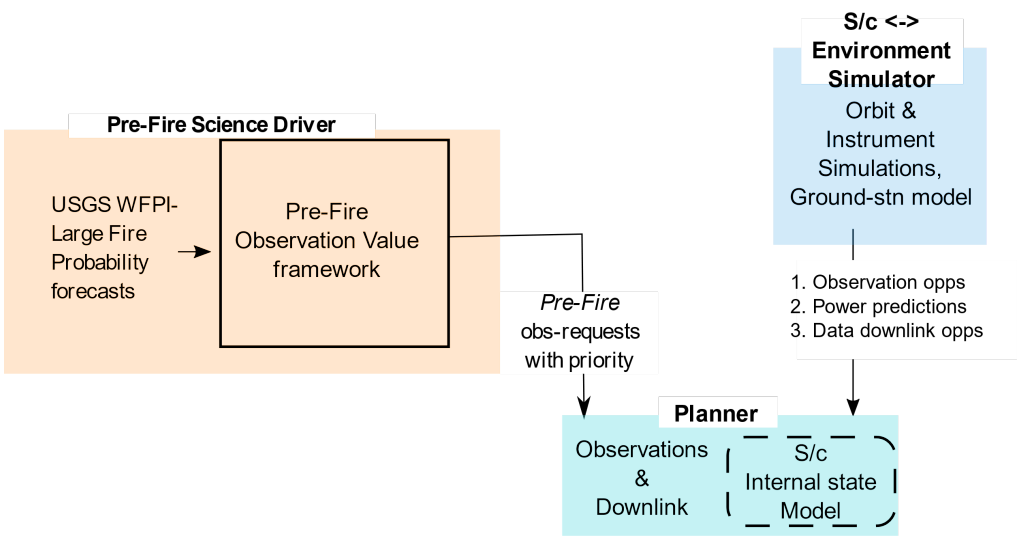


Fig: Pre-fire mission execution flow

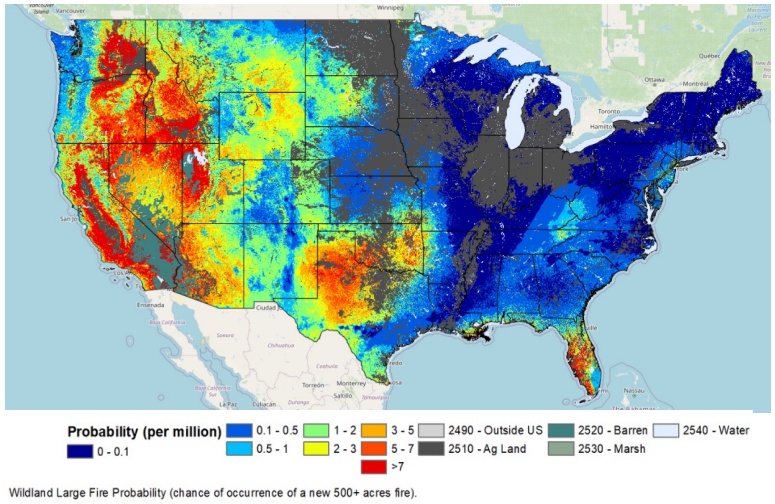


Fig: USGS WFPI-based Large Fire Probability (WLFP) as science driver

Intelligent Tasking & Modeling

Orbits Access

- GNSS-R specular coverage calculation with multiple GNSS satellites

Data

- Max capacity **~ 5.7 Gb,** RawIF mode data rate = **96.22 Mb/s,** Downlink rate = **4 Mb/s**

Power

- Max charge: 86.4 Watt-hours, Avg Solar power in: **70 W,** Bus + sensor power consumption: **38.3 W,** Downlink power consumption: **22.6 W,** Minimum charge: 55% of max charge

Constrained Onboard data storage, downlink rate, and available power

Intelligent Tasking & Modeling

D-SHIELD Fire search space is immense

For each satellite in a 24-hour period:

~ 10,000 decision variables

Each decision variable represents 1 second when the planner must make a **binary choice**:

- Make an observation or not
- Downlink data or not

The # of states to explore is:

2E10000 = Infinity (Google Exponent Calculator)

*Snapshots of the **Best Plan** after 200k rollouts (15hr process time)*

Idling

```
time: 1, ***, bat. 89.99 % (eclipse)
time: 2, ***, bat. 89.98 % (eclipse)
time: 3, ***, bat. 89.96 % (eclipse)
time: 4, ***, bat. 89.95 % (eclipse)
```

Downlink

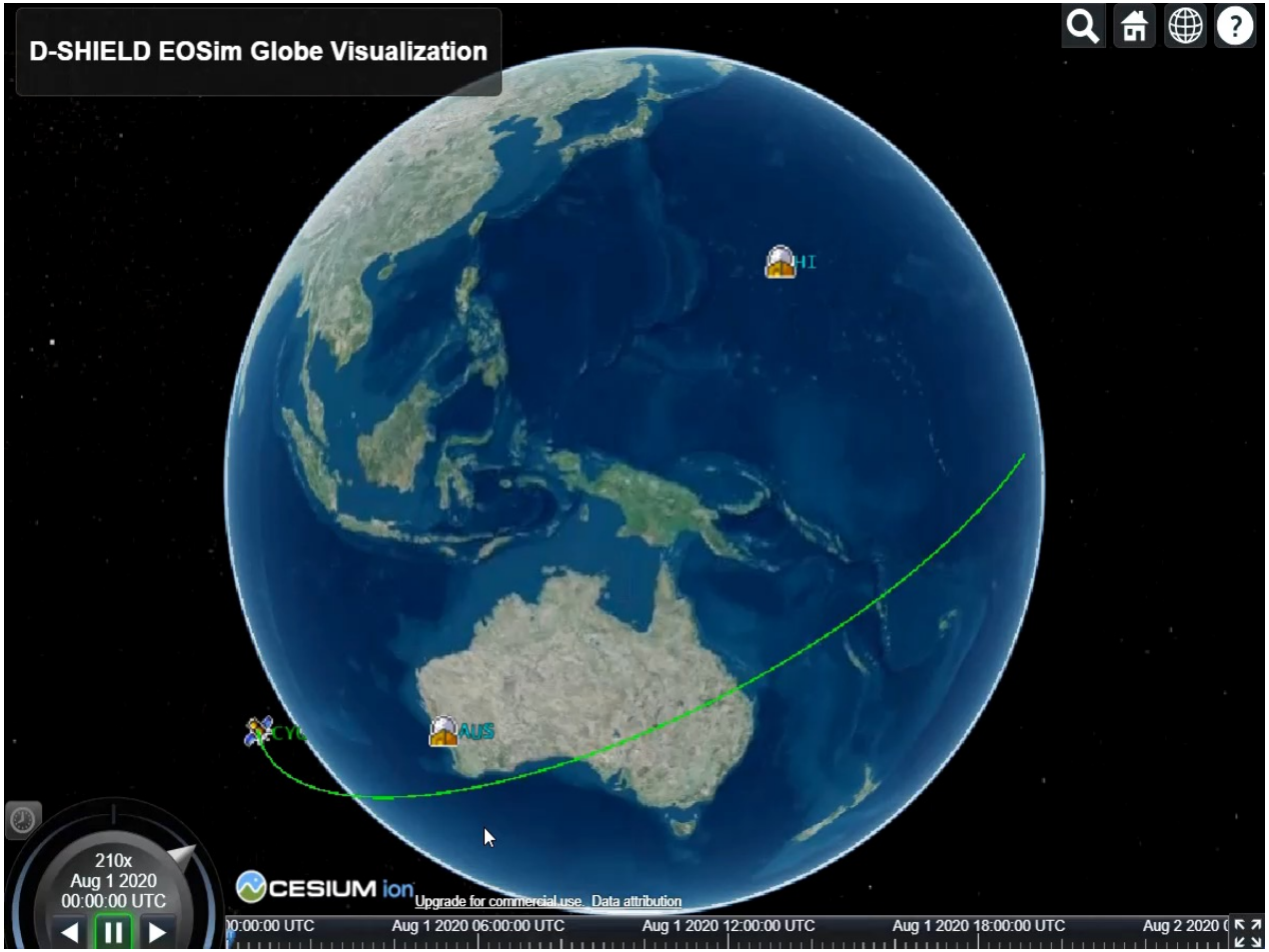
```
time: 22209, ***, bat. 83.3 % (eclipse)
time: 22210, ***, bat. 83.29 % (eclipse)
time: 22211, DNL, bat. 83.27 %, storage: 4586.568, gpCount: 0, score: 1398.514, targets: CHI (eclipse)
time: 22212, DNL, bat. 83.26 %, storage: 4582.568, gpCount: 0, score: 1398.903, targets: CHI (eclipse)
time: 22213, DNL, bat. 83.24 %, storage: 4578.568, gpCount: 0, score: 1399.292, targets: CHI (eclipse)
time: 22214, DNL, bat. 83.22 %, storage: 4574.568, gpCount: 0, score: 1399.686, targets: CHI (eclipse)
time: 22215, DNL, bat. 83.2 %, storage: 4570.568, gpCount: 0, score: 1400.08, targets: CHI (eclipse)
```

Imaging

```
time: 3074, RAW, bat. 99.99 %, storage: 2694.076, gpCount: 0, score: 289.817, targets: [24688, 25019, 27928, 31294, 33800, 34085, 35231, 42057, 42287]
time: 3075, IDL, bat. 99.99 %
time: 3076, RAW, bat. 99.99 %, storage: 2790.293, gpCount: 0, score: 305.391, targets: [24689, 25020, 27929, 31001, 31295, 31593, 31870, 33525, 34080, 35232, 35502, 35507, 35770]
time: 3077, RAW, bat. 99.99 %, storage: 2886.51, gpCount: 0, score: 318.177, targets: [25021, 27606, 31296, 34086, 34354, 35503, 42059, 42289]
time: 3078, IDL, bat. 99.99 %
```

Intelligent Tasking & Modeling

*Animation of **Best Plan** after 200k rollouts (15hr process time)*



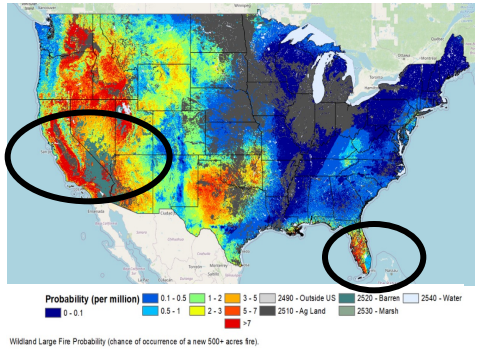
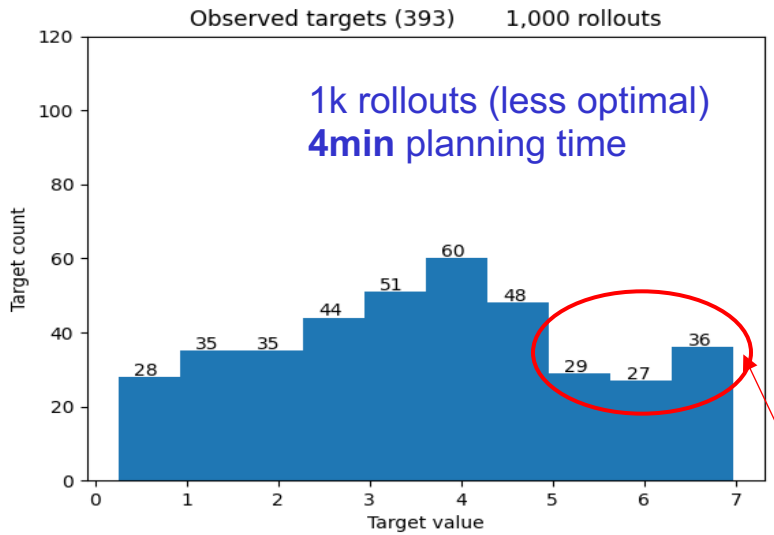


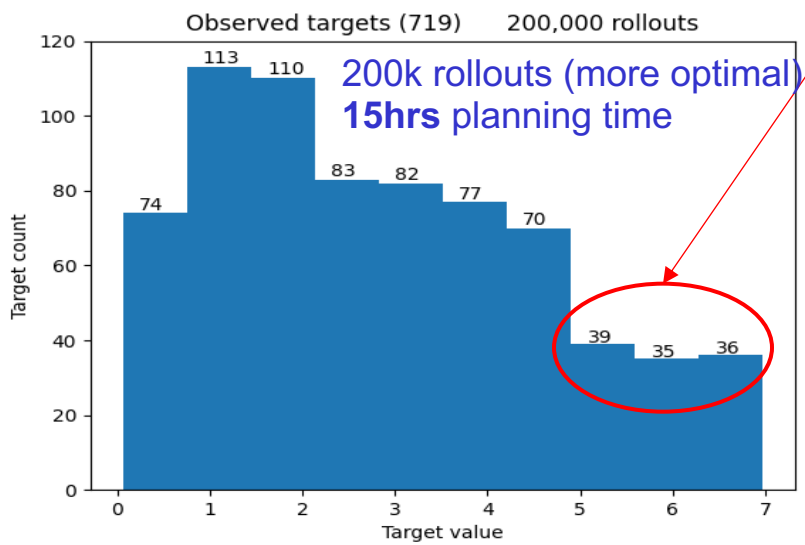
Fig: USGS WFPI-based Large Fire Probability (WLFP) as science driver

Intelligent Tasking & Modeling

Analysis

- Performance seems to saturate at ~ 40K rollouts
- Still exploring only, a tiny fraction of the search space
  - Max learning depth of 472 (after 200k rollouts) is only the first 472 decisions out of ~10,000
- Limited storage capacity and downlink opportunities constrain how many images may be taken





Tradeoff b/w planner process time and optimality

More rollouts => more reinforcement learning (more process time) => better target selection

Next Steps:
More analysis. Multiple satellites, Active fire mission.

Future Work

- Near real time retrievals are challenging with limitations of auxiliary data which can be used.
- We shall explore GNSS-R retrievals from commercial sources such as Spire, available through the NASA Commercial Smallsat Data Acquisition (CSDA) program.
- We shall start work on incorporating the GNSS-R derived data with Active fire simulation models.
- Continue to keep focus on minimizing the responsive time of the system and evaluate the tradeoff with the performance.

Questions?

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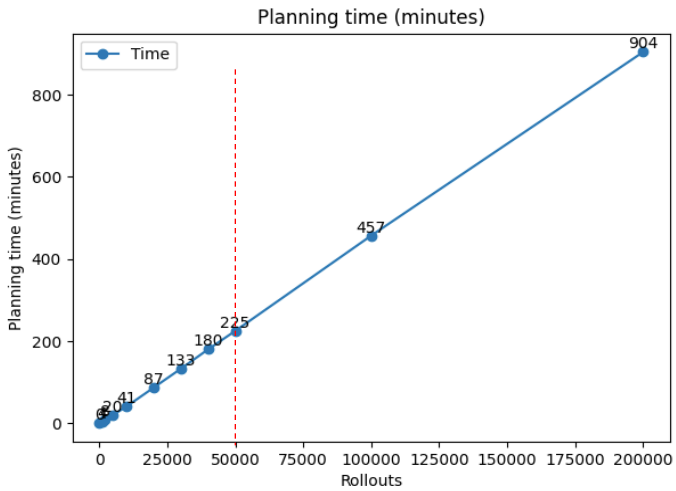
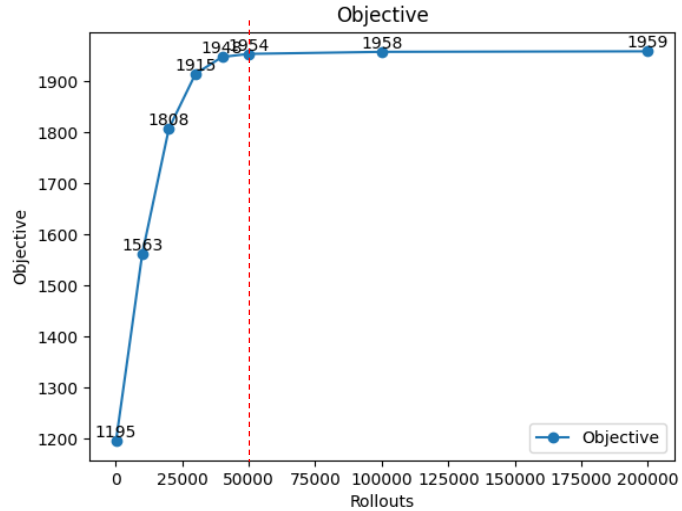
BACKUP SLIDES

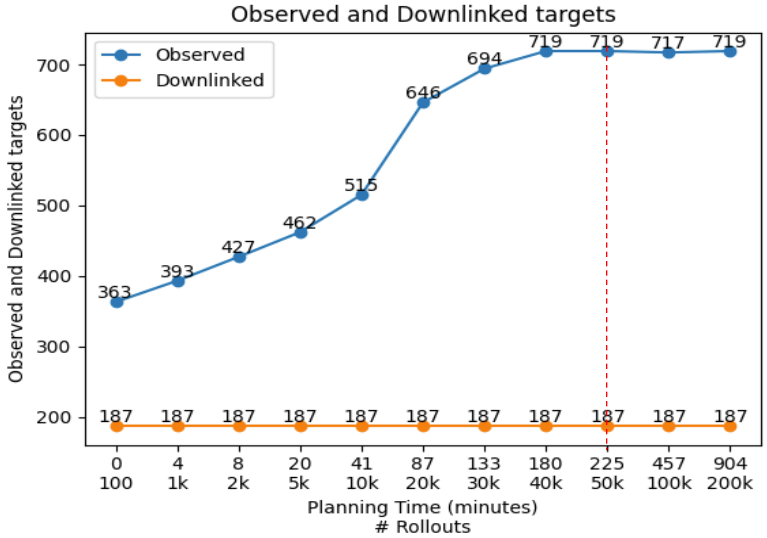
Intelligent Tasking & Modeling

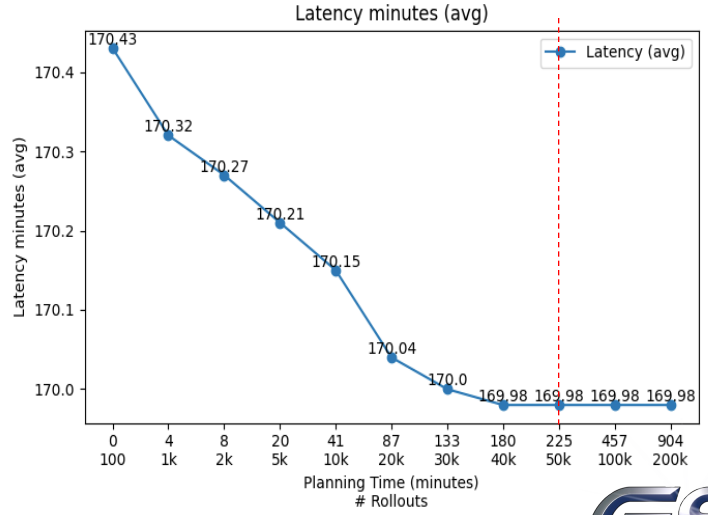




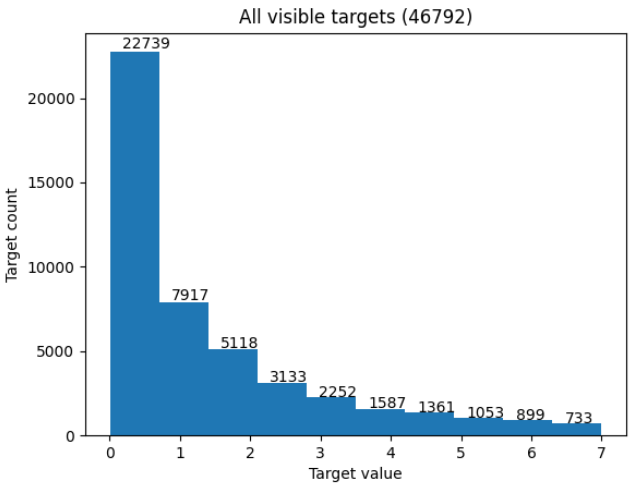
Planning time scales linearly with the # of rollouts

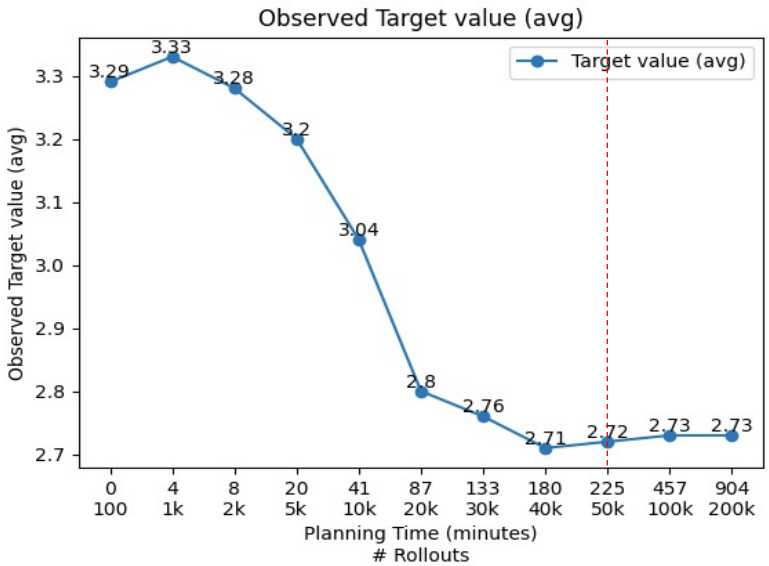
target = 10km dim location

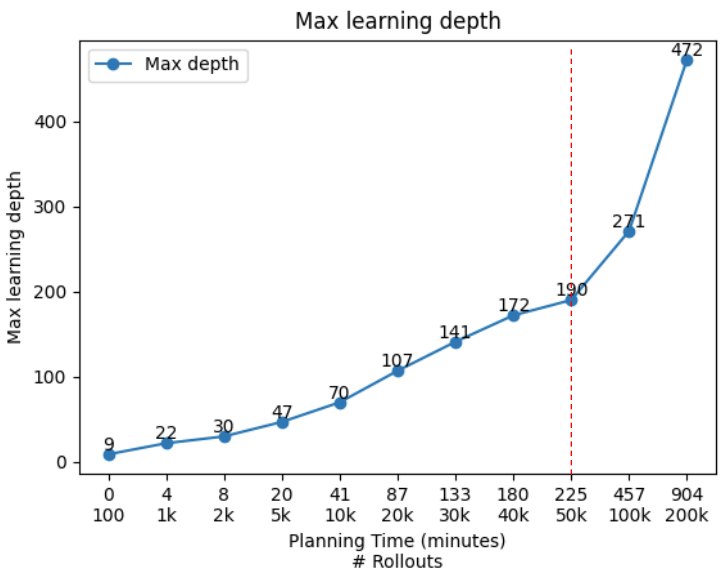




Intelligent Tasking & Modeling







Max learning depth:
Deepest level in the search tree with reinforcement learning stats