SPOC: Deep Learning-based Terrain Classication for Mars Rover Missions

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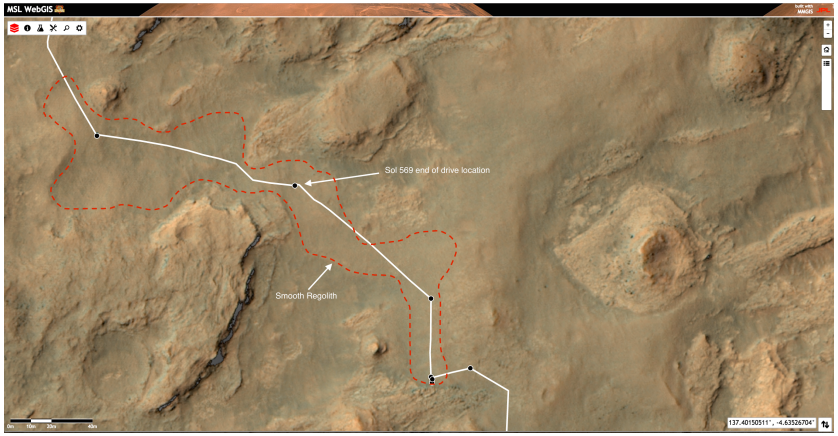
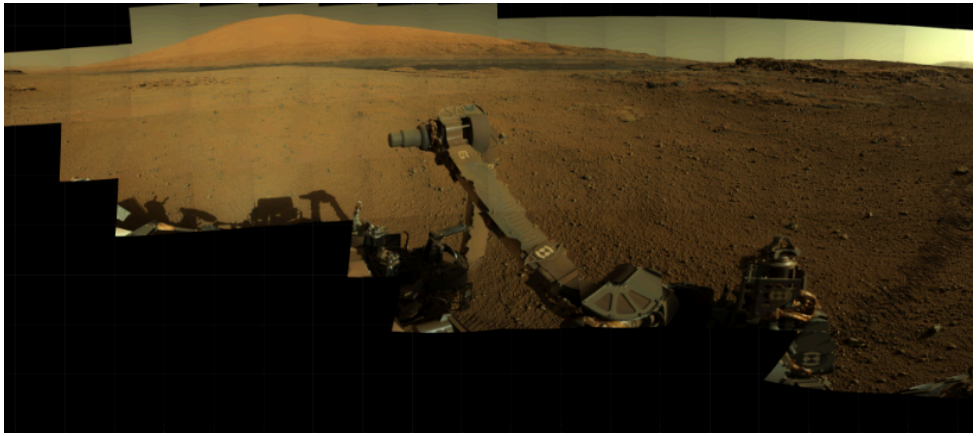
Motivations

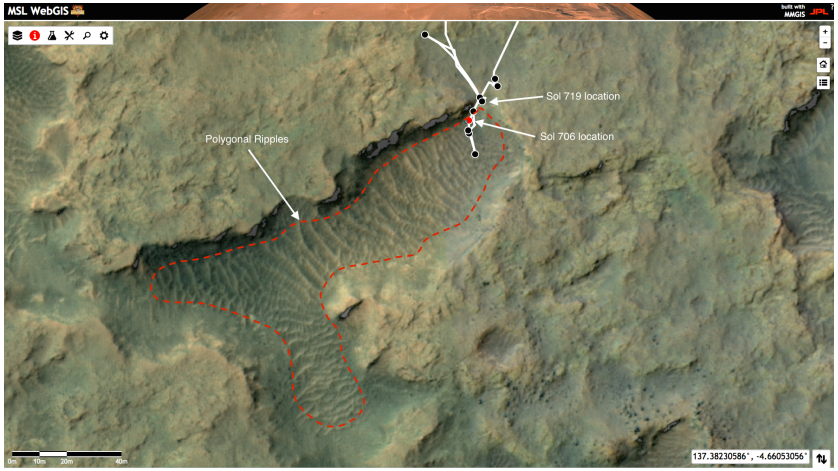
- Rover mobility is highly sensitive to terrain type

Smooth Regolith



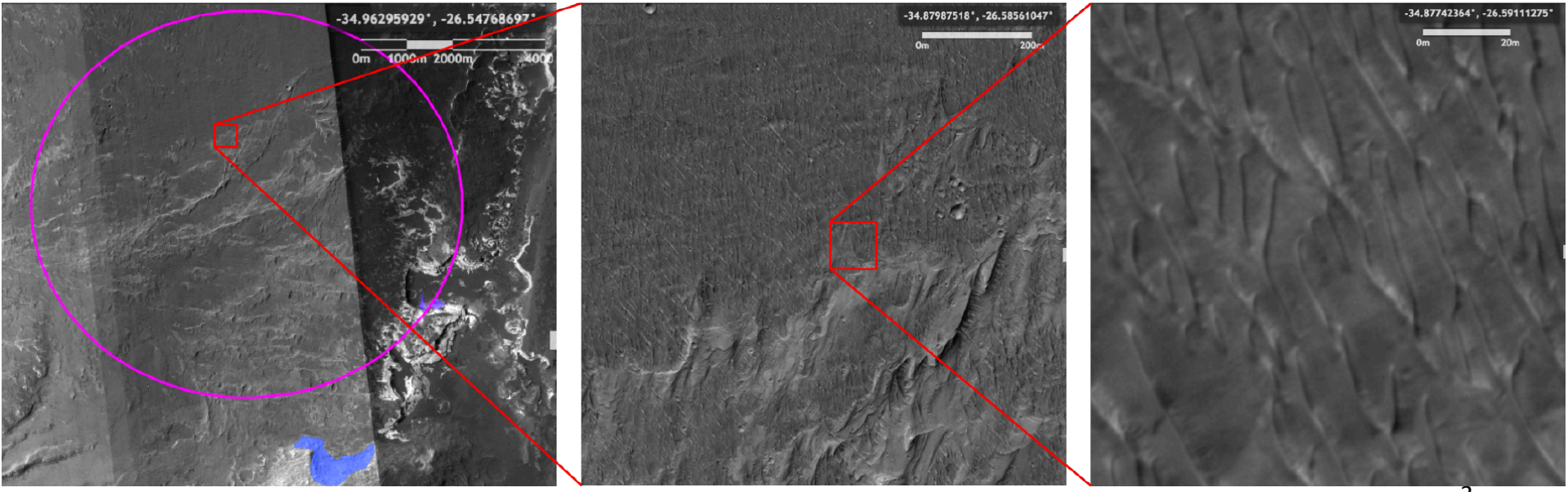


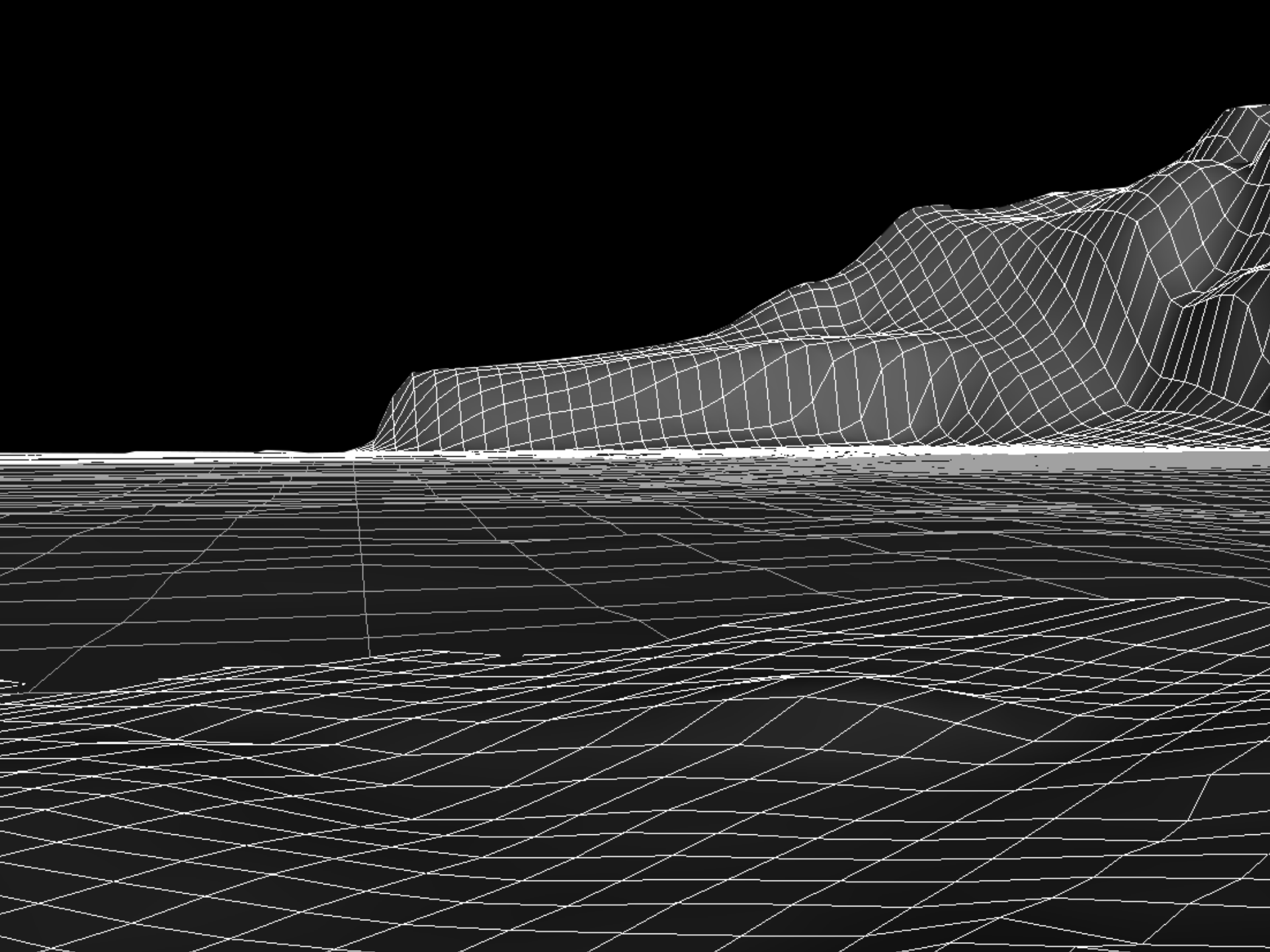
Polygonal Regolith



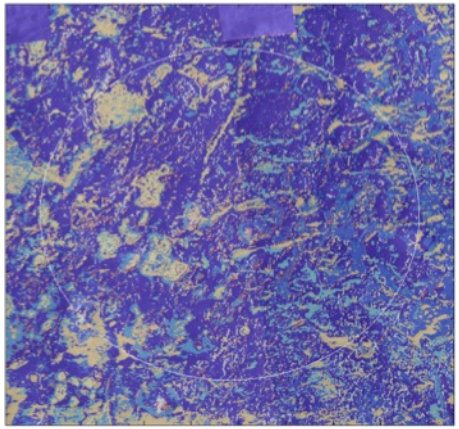
Motivations

- Manual terrain classification is very laborious
- Landing site traversability analysis
  - 8 candidate sites
  - Each site has ~20km x 20km map
  - 40K x 40K pixels on HiRISE!
- Slip analysis
  - 1K x 1K pixels for each NAVCAM image
  - ~8K slip data for MSL



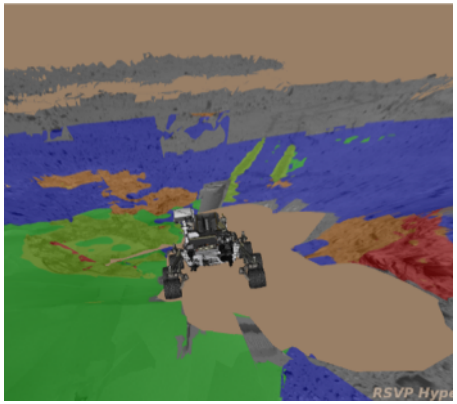


Ongoing Projects



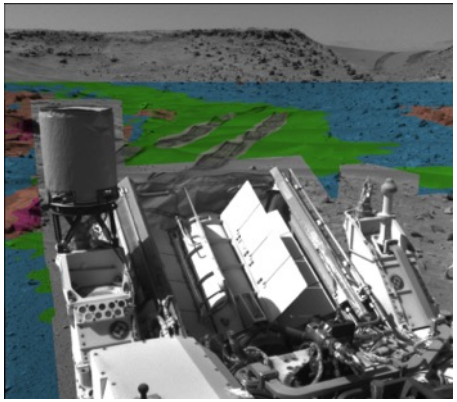
SPOC-H (HiRISE) for M2020 landing site analysis

- Provides dense predictions of 11 terrain classes on 25cm HiRISE imagery
- Based on state-of-art fully-convolutional neural networks
- Developed by Brandon Rothrock



SPOC-G (Ground) for MSL Operation

- Works on NAVCAM images
- Visually identifies six terrain types: sand, cohesive soil, bedrock, large rocks, rocks on outcrop, and wheel track
- Developed by Ryan Kennedy and Jeremie Papon

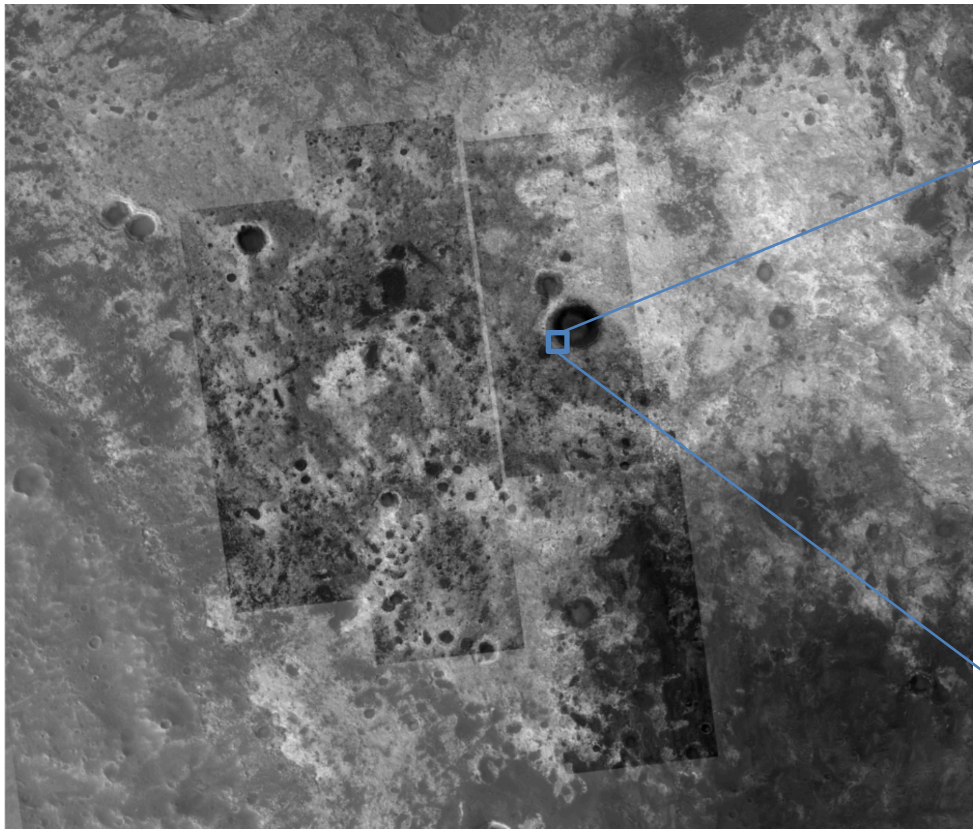


SPOC-R (Rover) for Topic R&TD on Next-Gen AutoNav

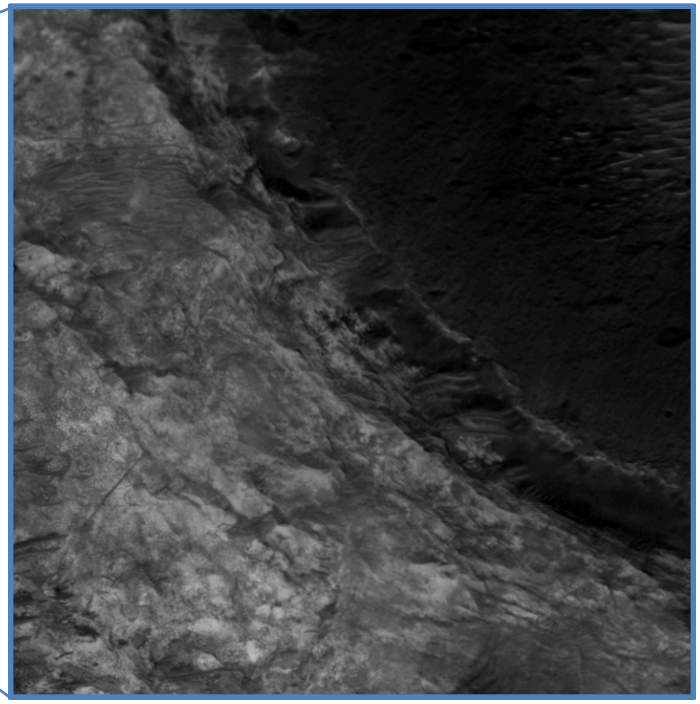
- Developing on-board variant of terrain classifier
- Currently identifying two classes: sand and anything else
- Being developed by Yumi Iwashita

Terrain Classification for HiRISE

40km x 40km site (Mawrth)

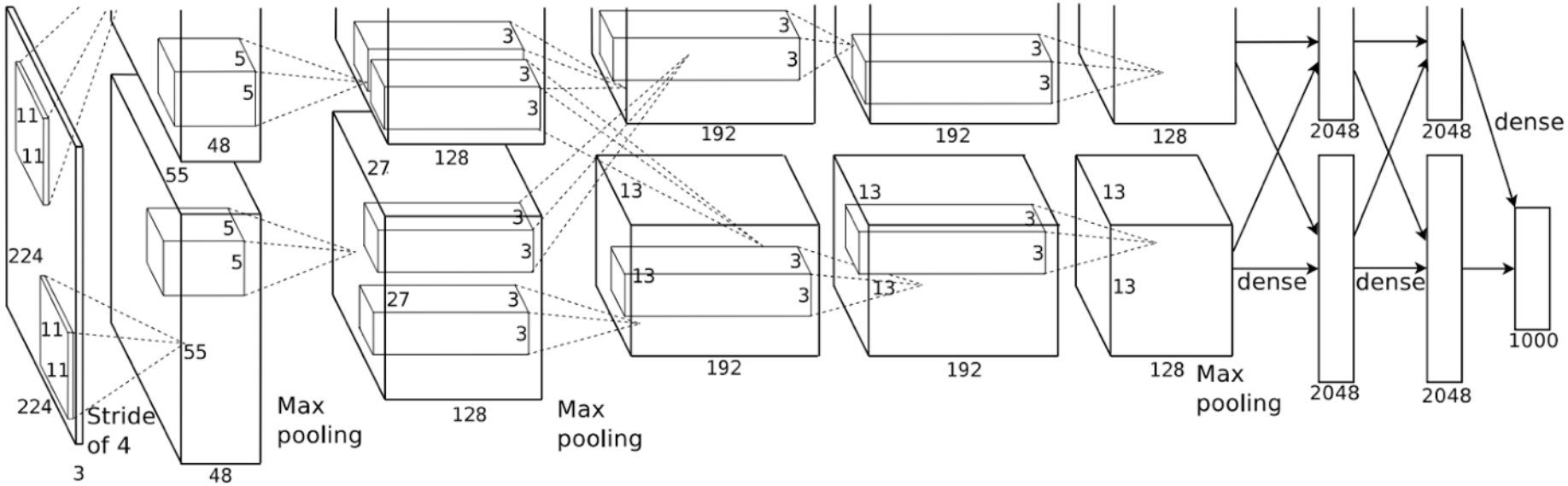


~25cm / pixel from HiRISE



Fully-convolutional neural networks

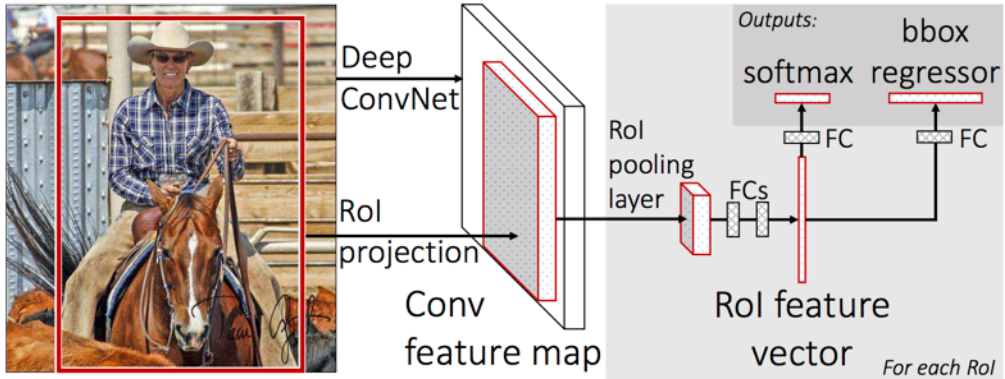
"AlexNet" architecture for image classification on Image Net
(Krizhevski et al., 2012)



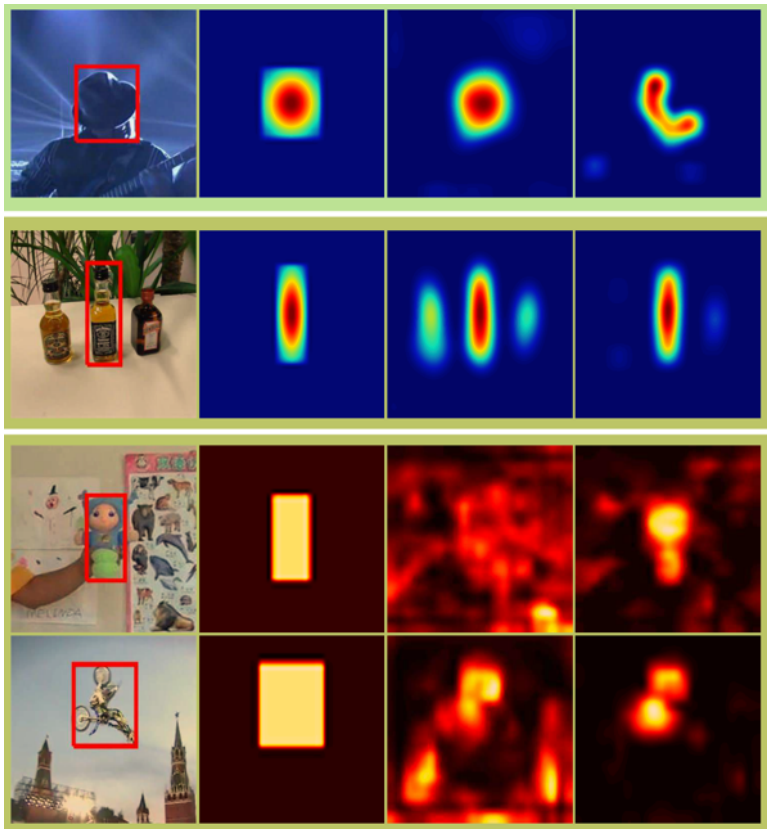
Classification network as a detector

Detection is commonly performed by running a classifier in a sliding-window fashion.

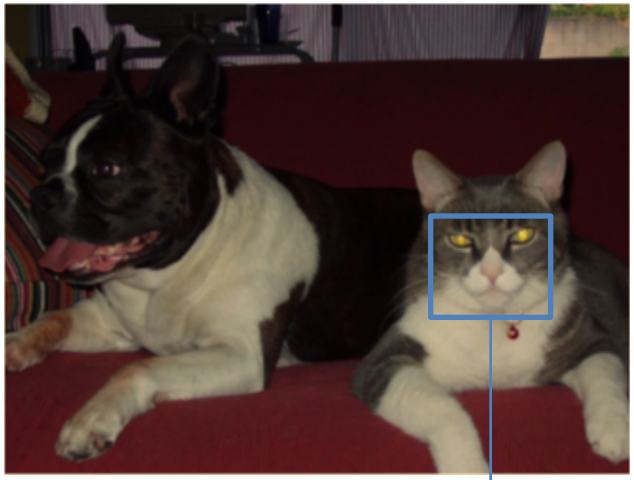
Girshick, 2015



Wang et al., 2015



Sliding window for semantic segmentation



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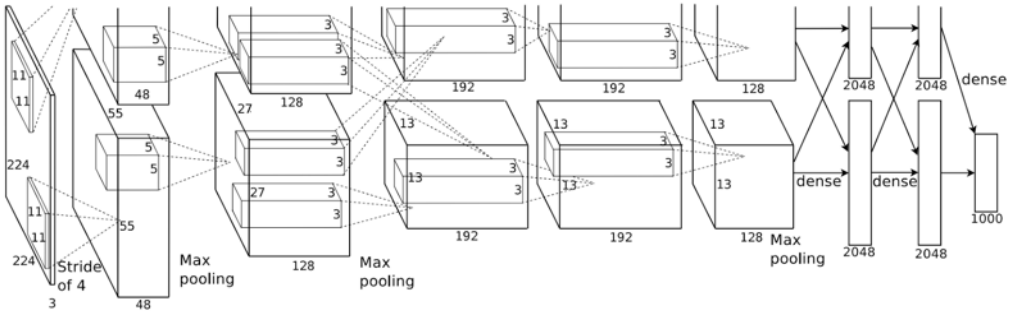
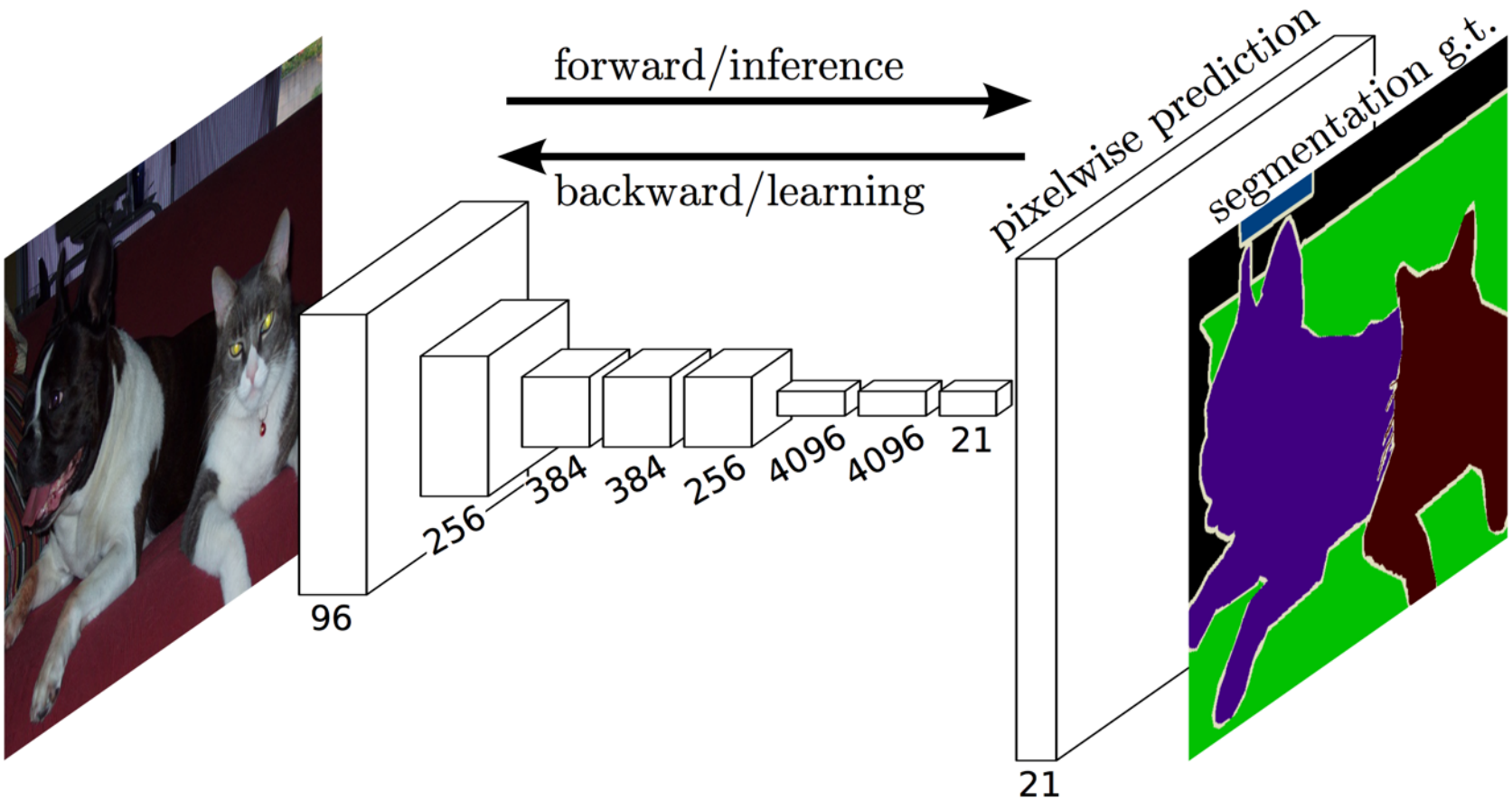


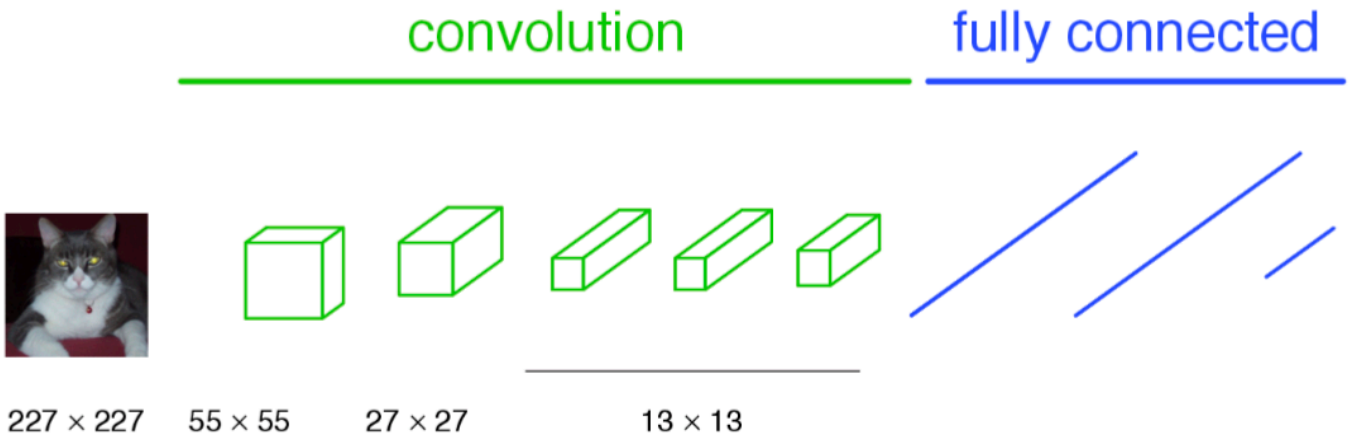
Fully-convolutional neural networks

End-to-end learning of network weights for semantic segmentation
(Long et al., 2015)

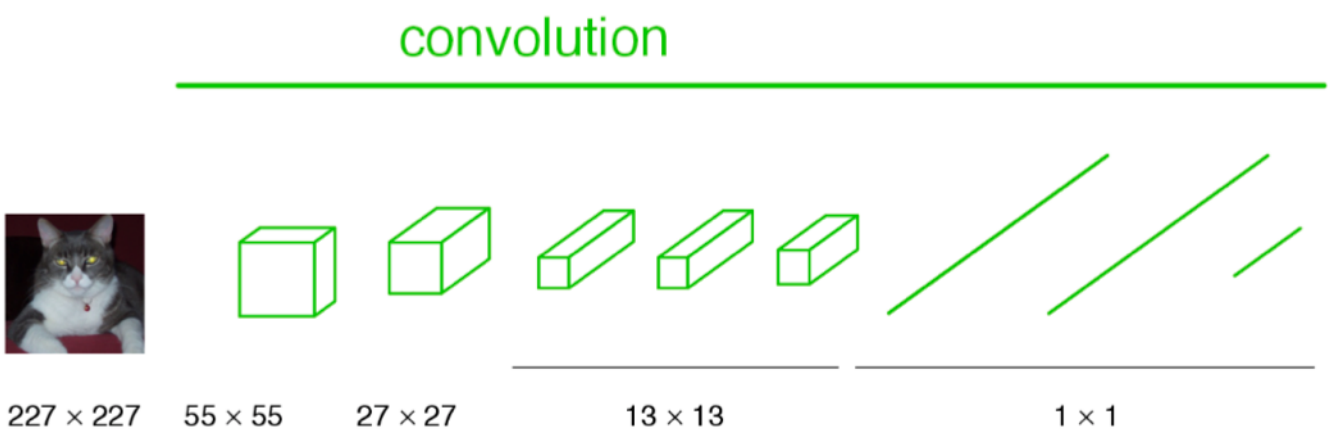


Fully-convolutional neural networks

Classification network:

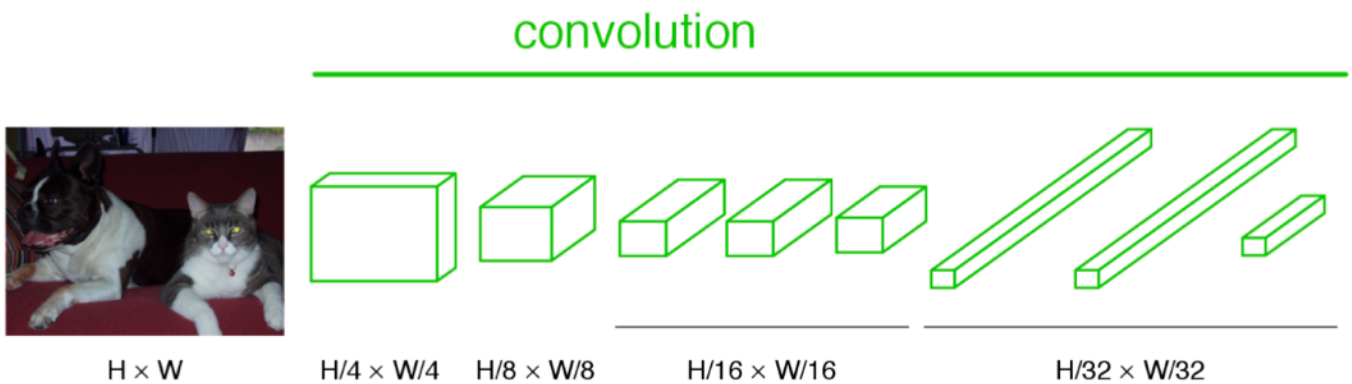


Fully convolutional classification network:

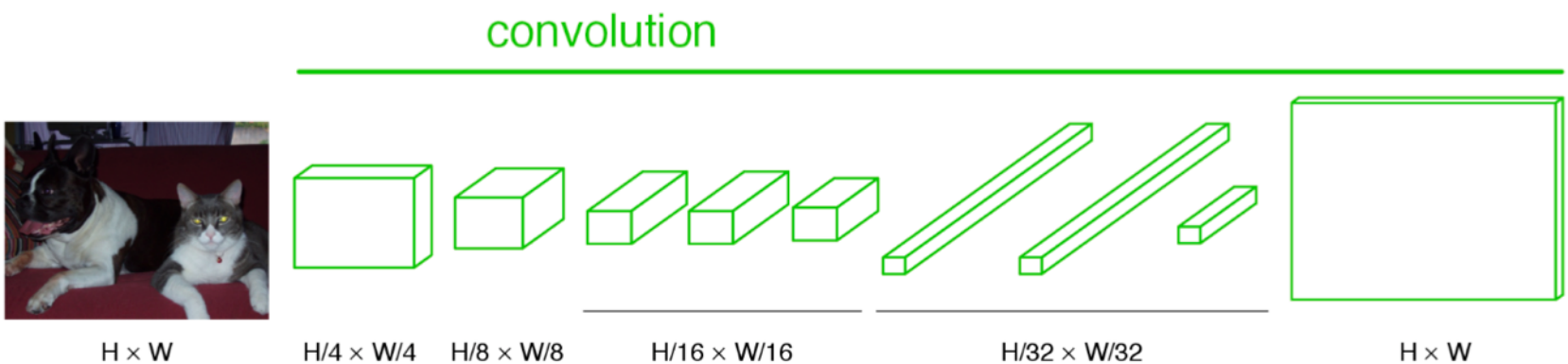


Fully-convolutional neural networks

Fully-convolutional network can now take arbitrary input sizes

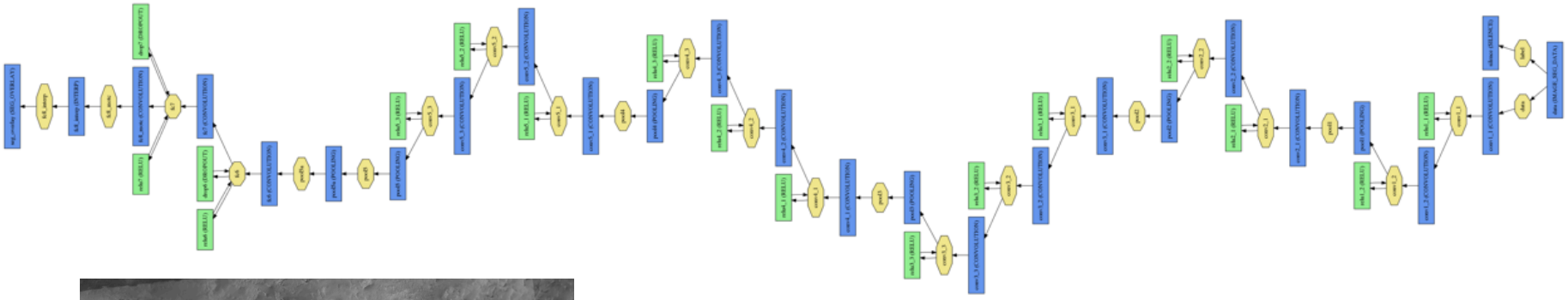


Upsampling on last layer to get output dimension to match input

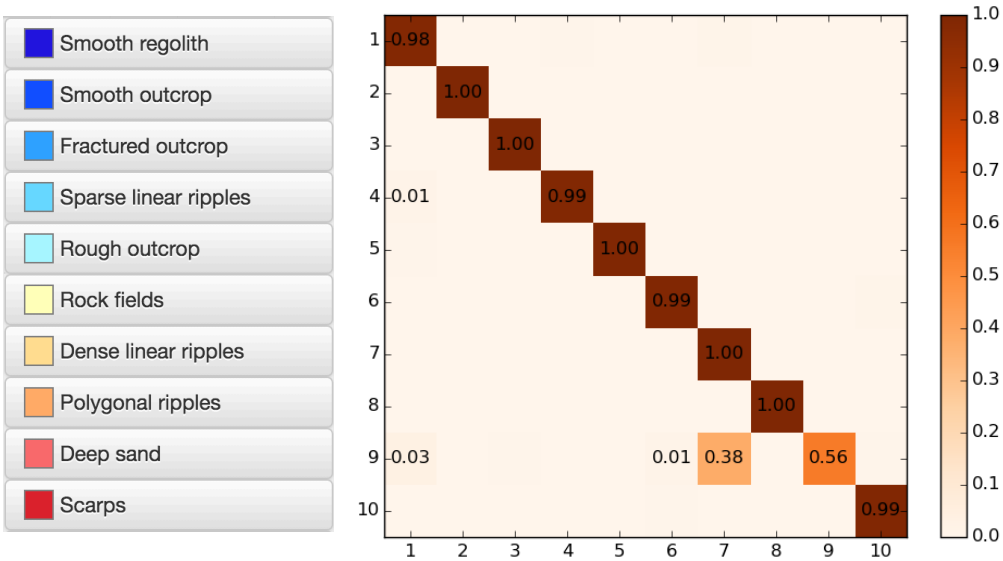


Terrain classification for HiRISE

- Initial network consists of 22 convolutional layers.
- Front 16 layer weights initialized from VGG16. (Simonyan and Zisserman, 2015)

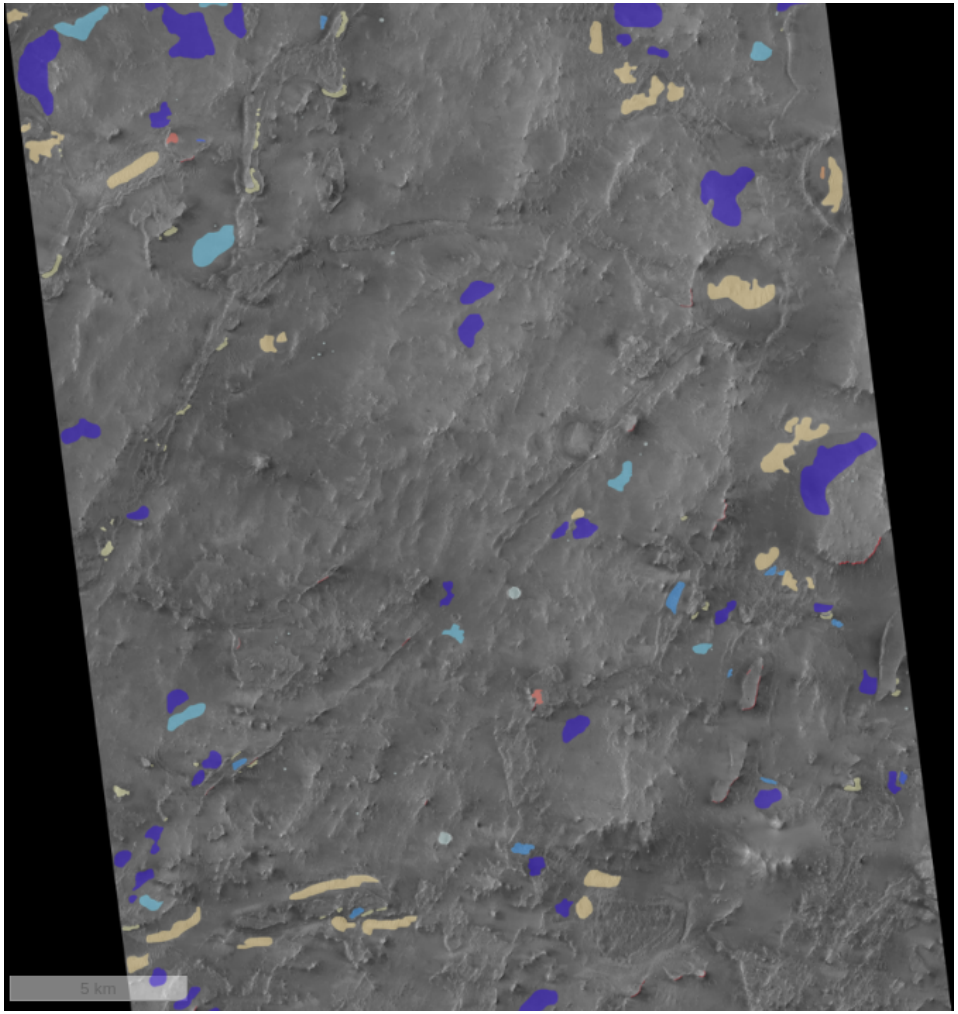


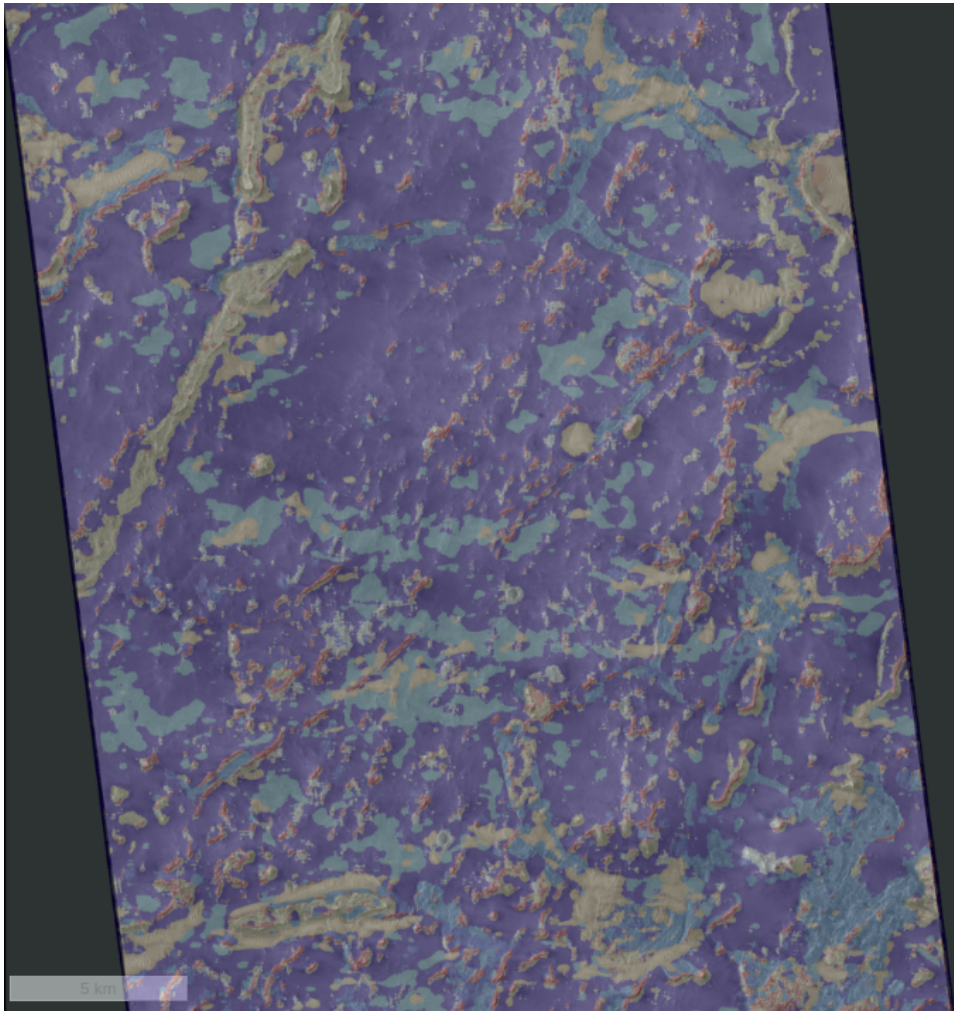
NE Syrtis



Average Precision: 0.949

NE Syrtis





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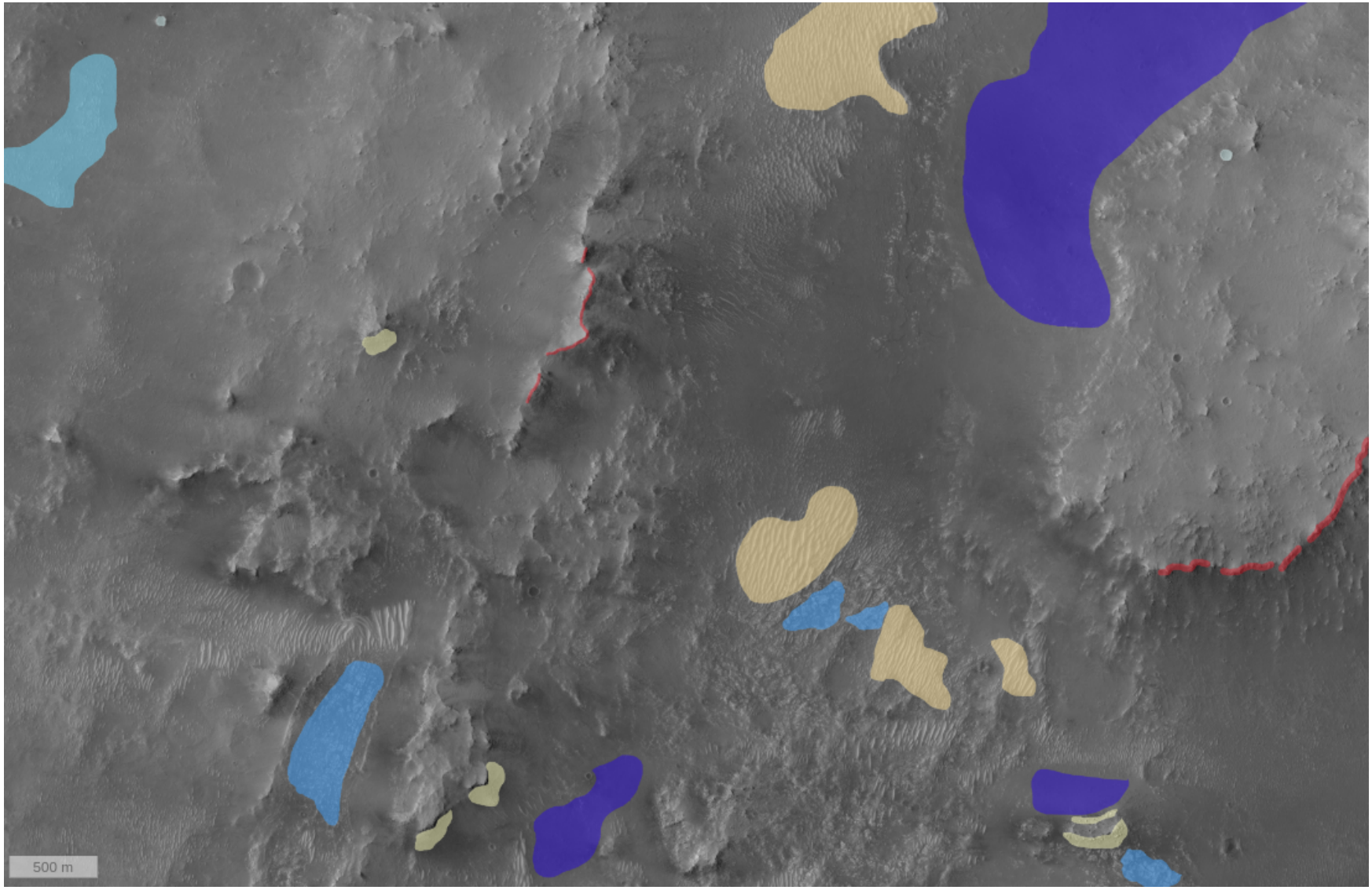

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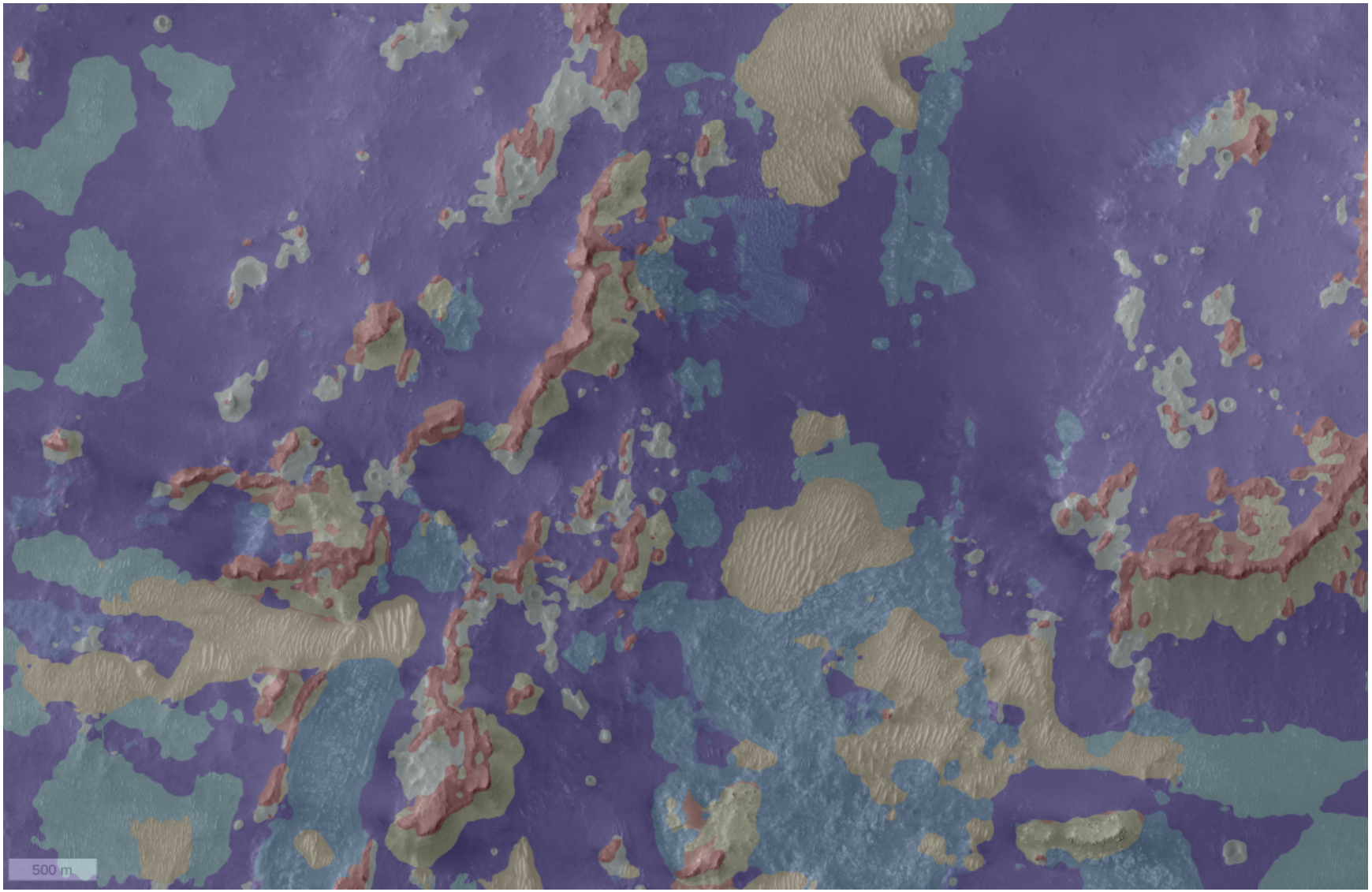
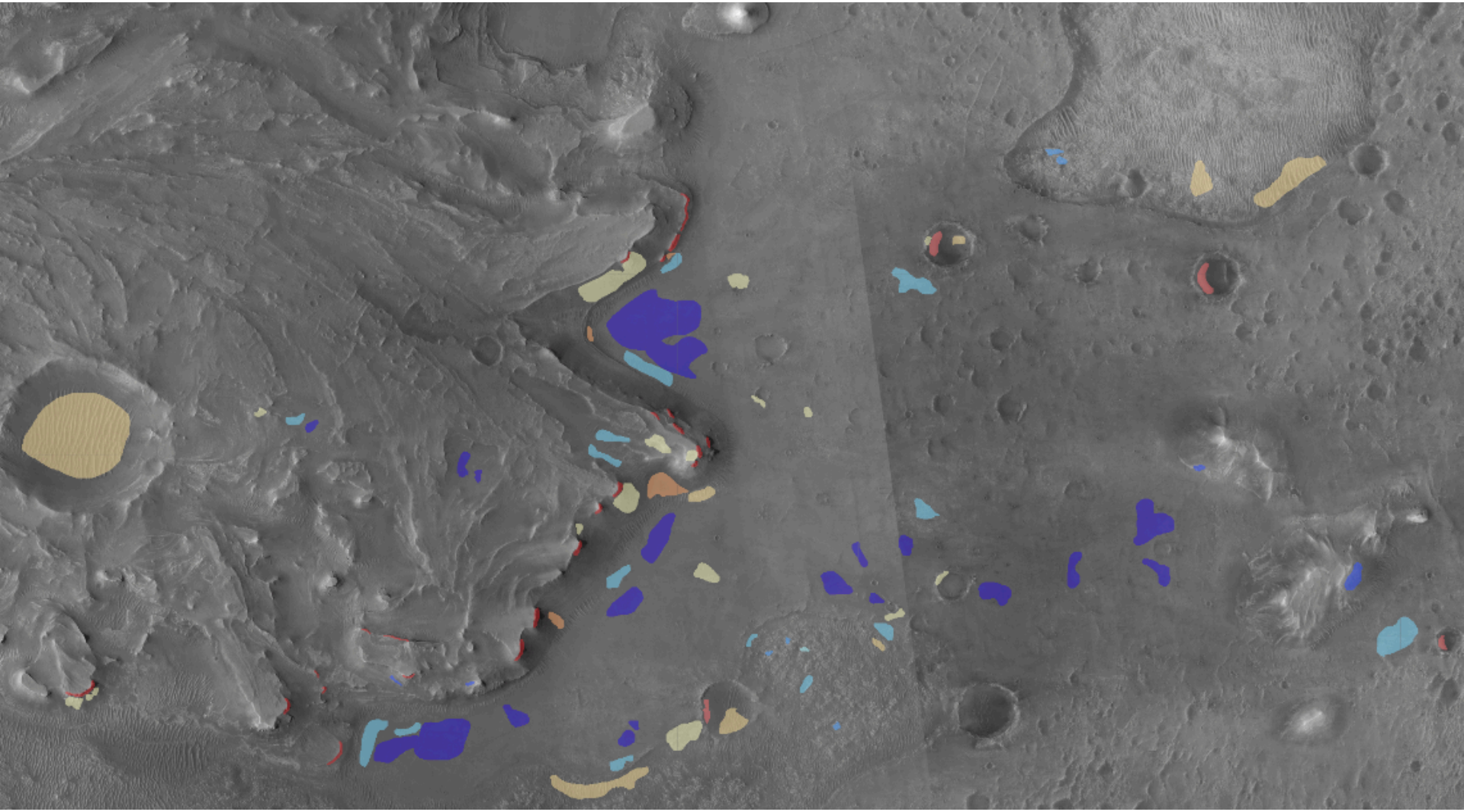


Jezero



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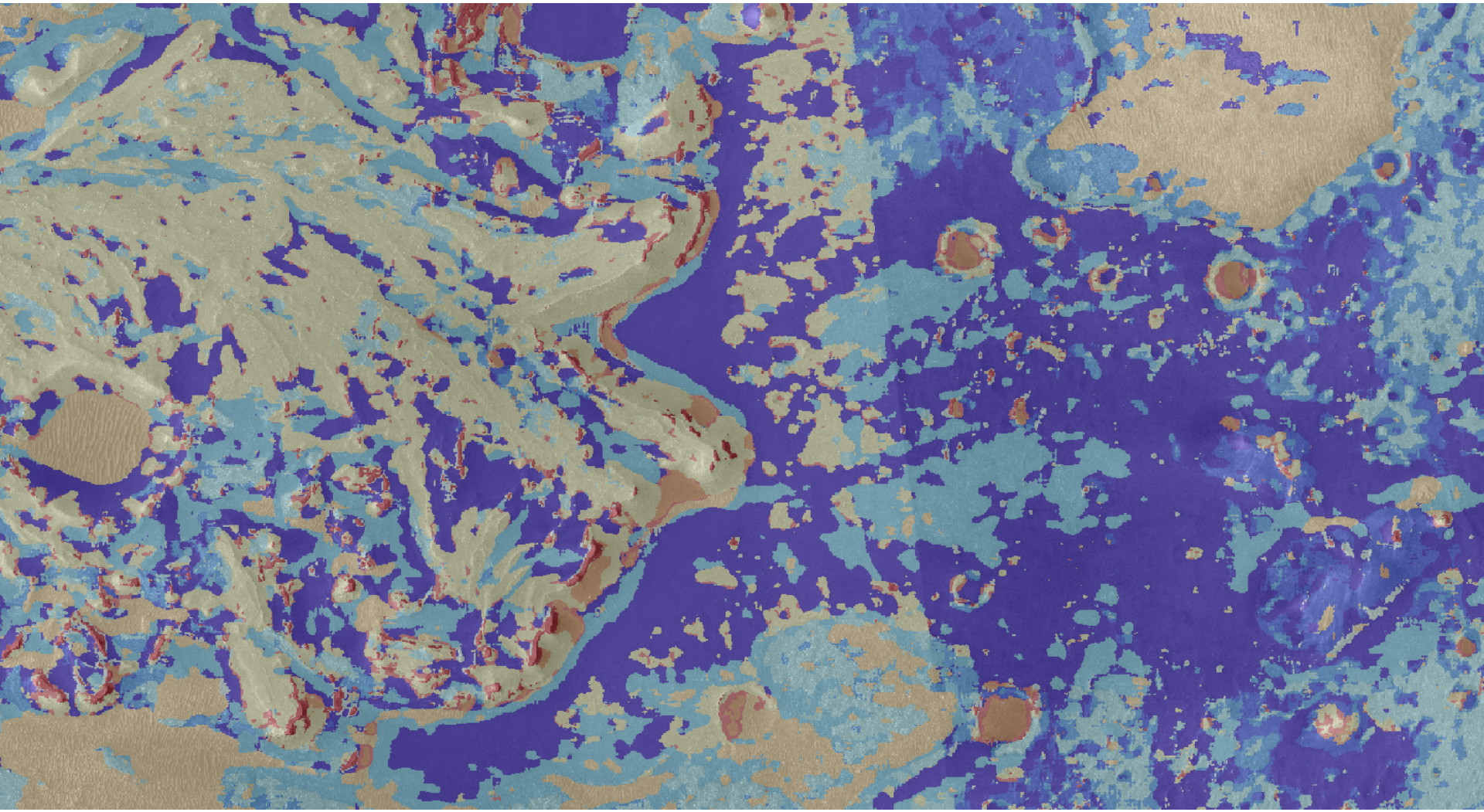
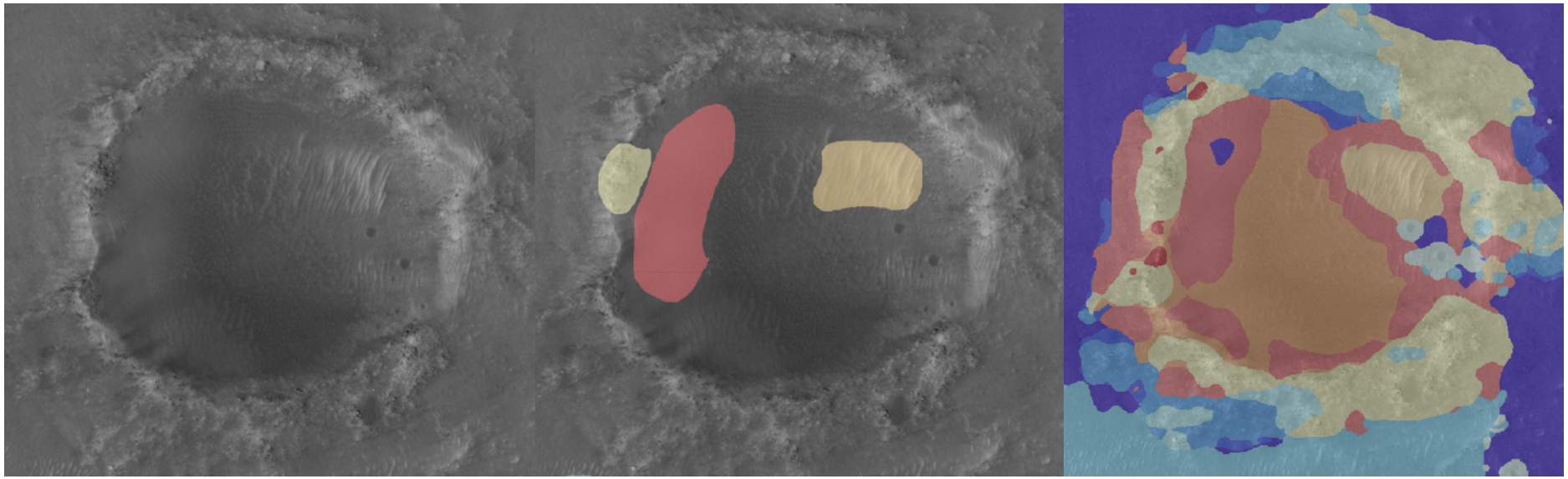
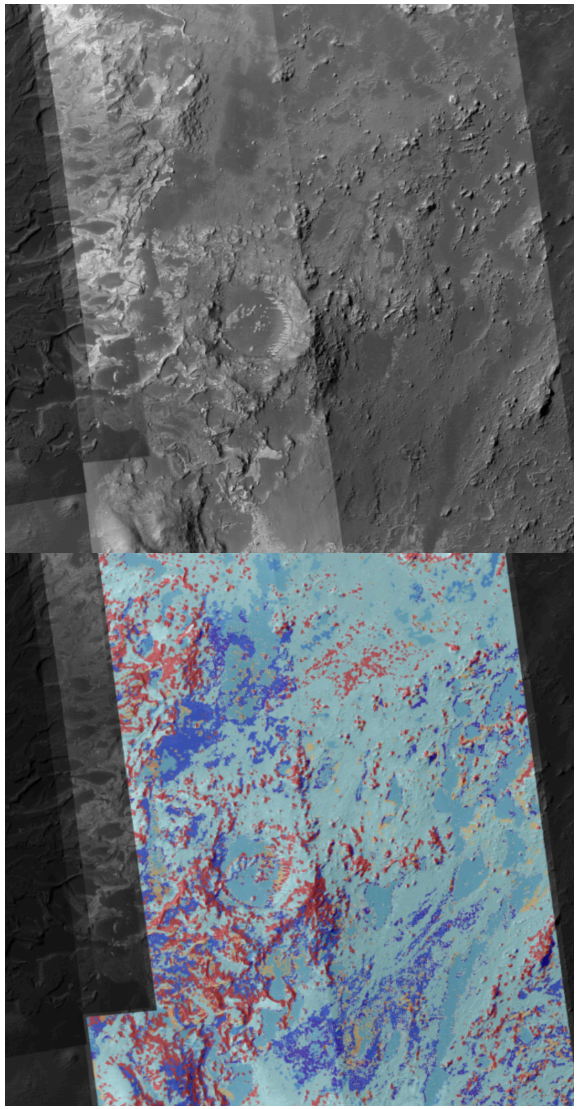


Jezero

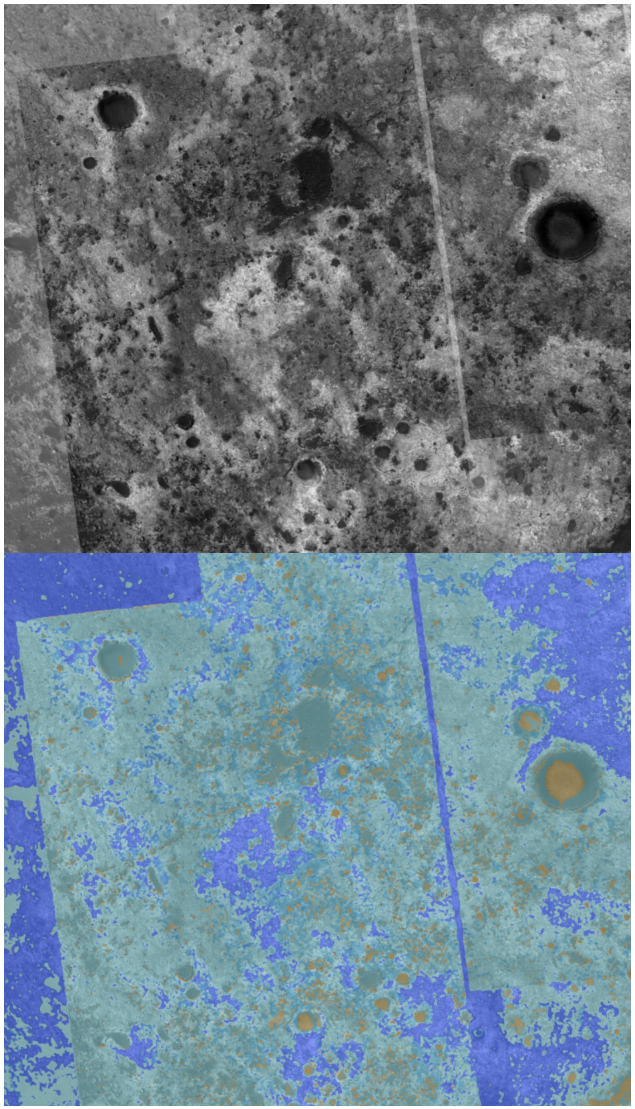
Learning neighboring context is important for many terrain morphologies



More Sites



Eberswalde



Mawrth

Results

Table 2. Confusion matrix of classified terrain on Columbia Hills

Ground Truth	Prediction: SR	SO	SRF	RR	RO	SRS	DLR	PR	% of data
Smooth regolith	81.2%	1.0%	0.0%	13.3%	0.0%	0.2%	0.0%	0.0%	19.8%
Smooth outcrop	0.0%	93.5%	0.0%	0.0%	0.4%	0.0%	0.0%	0.0%	5.4%
Sparse ripples firm	0.6%	0.0%	99.6%	0.0%	0.0%	0.6%	0.0%	0.0%	2.5%
Rough regolith	12.1%	4.7%	0.0%	83.6%	6.2%	1.1%	0.0%	0.2%	11.8%
Rough outcrop	0.0%	0.0%	0.0%	0.6%	71.6%	0.3%	0.0%	0.0%	9.6%
Sparse ripples sandy	5.7%	0.9%	0.2%	1.5%	21.8%	97.6%	0.0%	0.0%	20.8%
Dense linear ripples	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	97.2%	1.9%	6.0%
Polygonal ripples	0.4%	0.0%	0.1%	1.0%	0.0%	0.3%	2.8%	97.8%	24.1%

Talk Overview

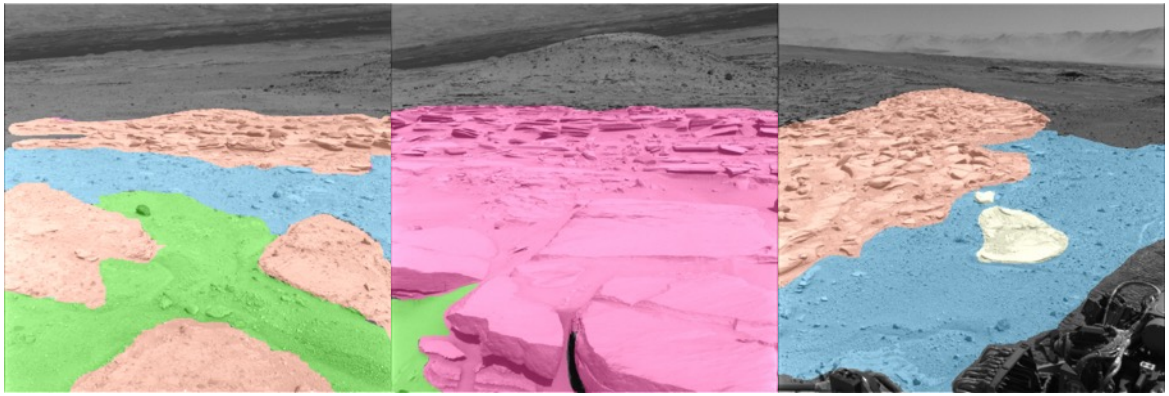
- SPOC-H: HiRISE-based Terrain Classification (Rothrock)
- **SPOC-G: NAVCAM-based Terrain Classification (Papon)**
- SPOC-R: On-board Terrain Classification (Iwashita)
- Use cases: path planning with terrain classes (Ono)

Rover-based Terrain Classification

- **Motivation:** The rover often slips while driving, especially on sand on steep slopes.
- Slip is (primarily) a function of (1) terrain type, and (2) slope
- Risk-aware path planning should estimate the chance of dangerous slipping, which requires knowledge of terrain type
- Two applications:
  - *Off-board slip analysis for MSL*
    - Each day, Rover Planners (RP's) plan a route for MSL to drive and simulate it to ensure it is safe
    - Currently, slip estimation uses models that were created using Earth data and the terrain type must be manually chosen
  - *On-board classification for autonomous navigation*
    - Requires much more computationally-efficient classifiers

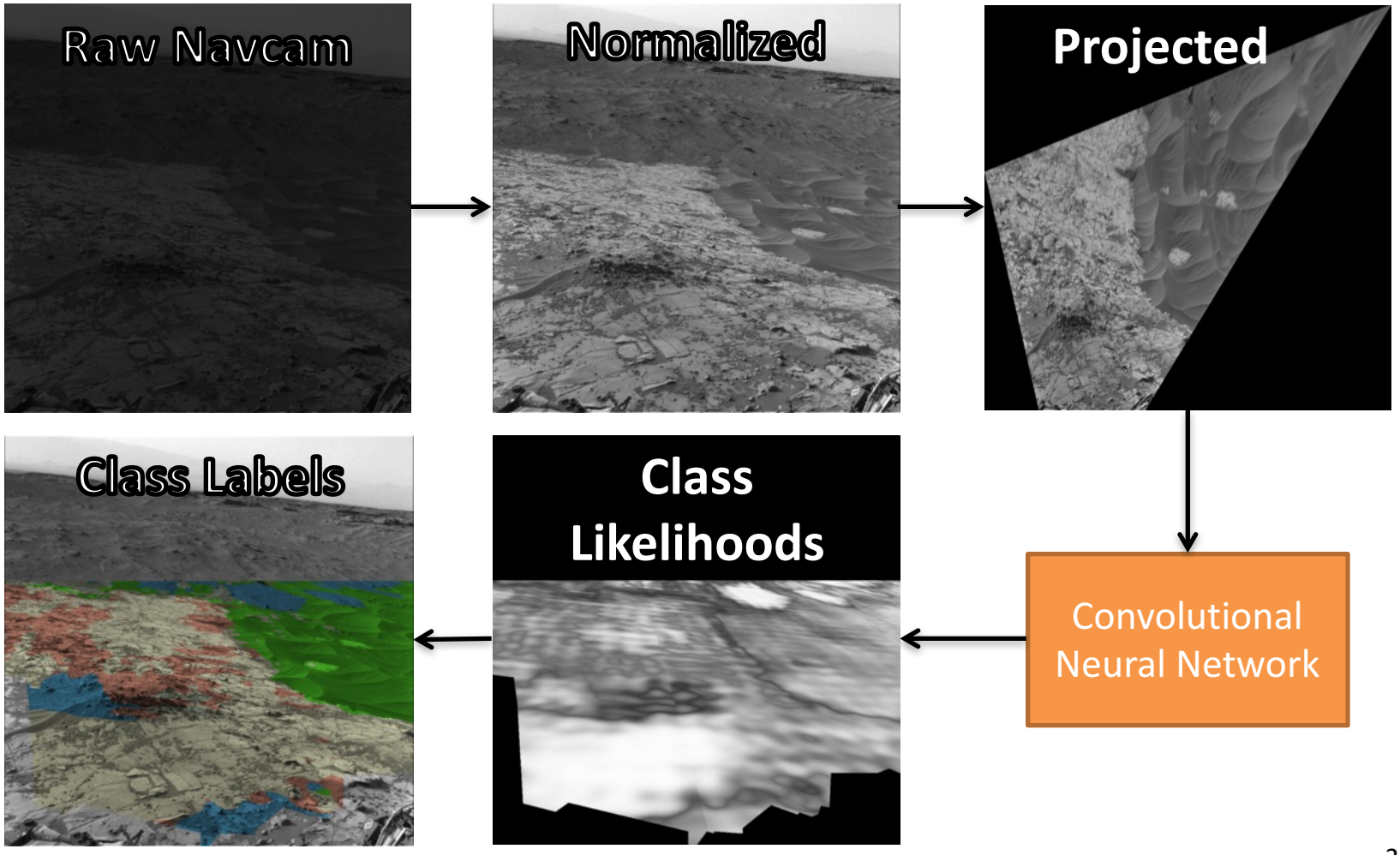
Dataset/Problem

- Trained on 650+ labeled images produced by an intern under the supervision of Prof. Ray Arvidson and Amanda Steffy
- 10-point color scale. For now, we use 6 classes (5-point scale + wheel tracks)
- Terrain classes:
  - **Green**: sand
  - **Blue**: small rocks
  - **Orange**: large rocks
  - **Yellow**: bedrock
  - **Red**: outcrop
  - **Cyan**: wheel tracks
    - Wheel tracks have “texture” and are mistakenly classifier as rocks



Off-board approach

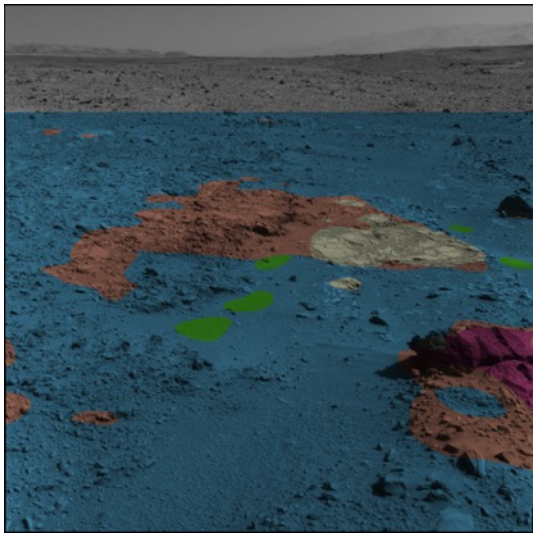
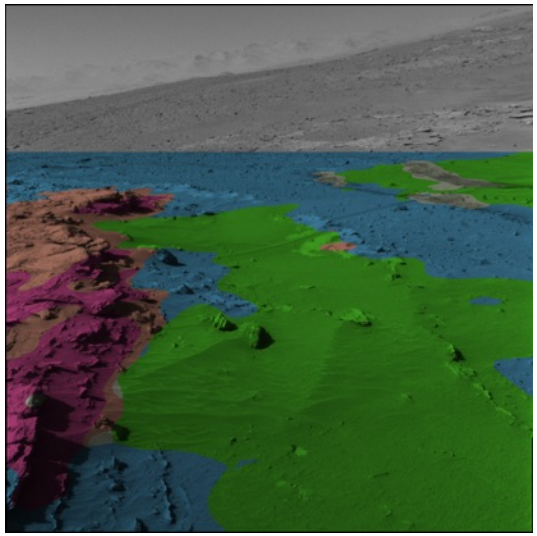
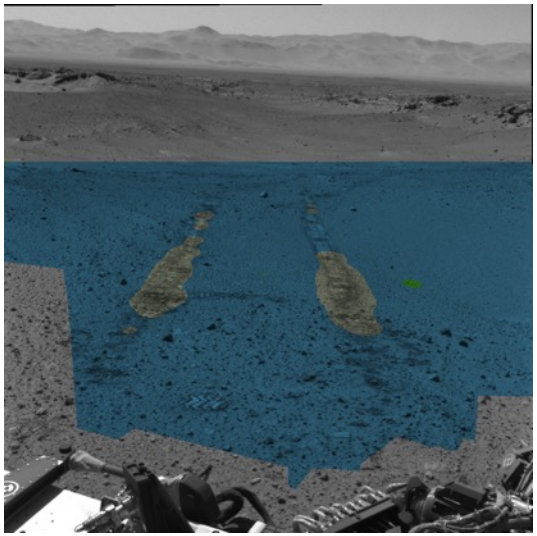
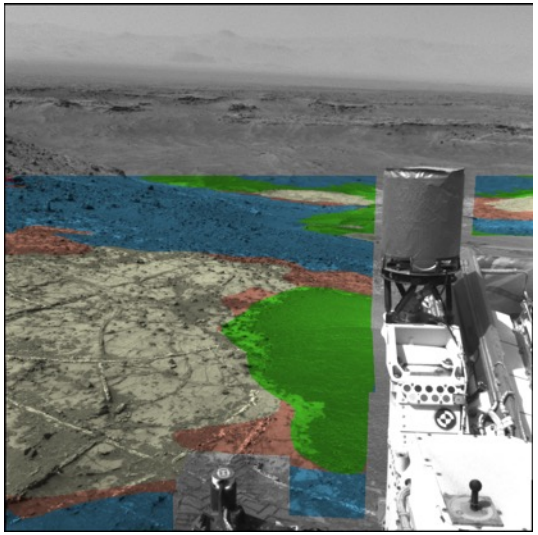
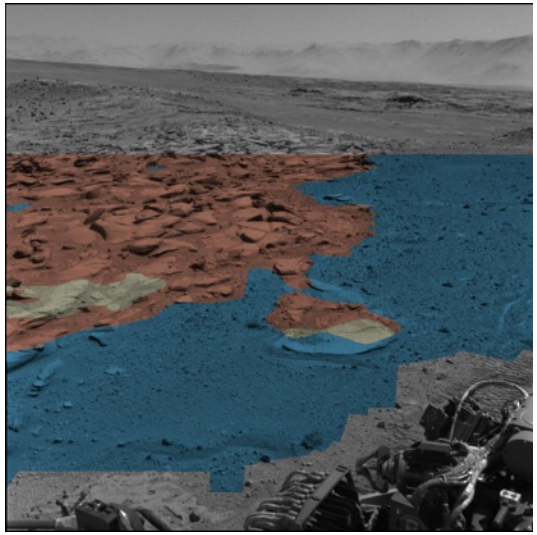
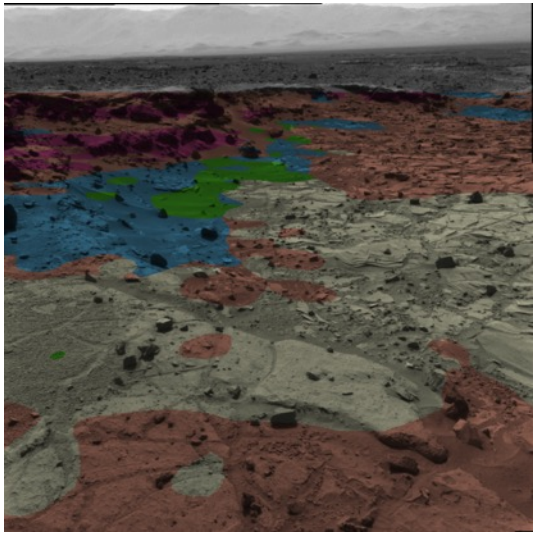
- Deep convolutional neural nets!
  - Based on VGG networks from Oxford [Simonyan, 2015][Chen, 2015]



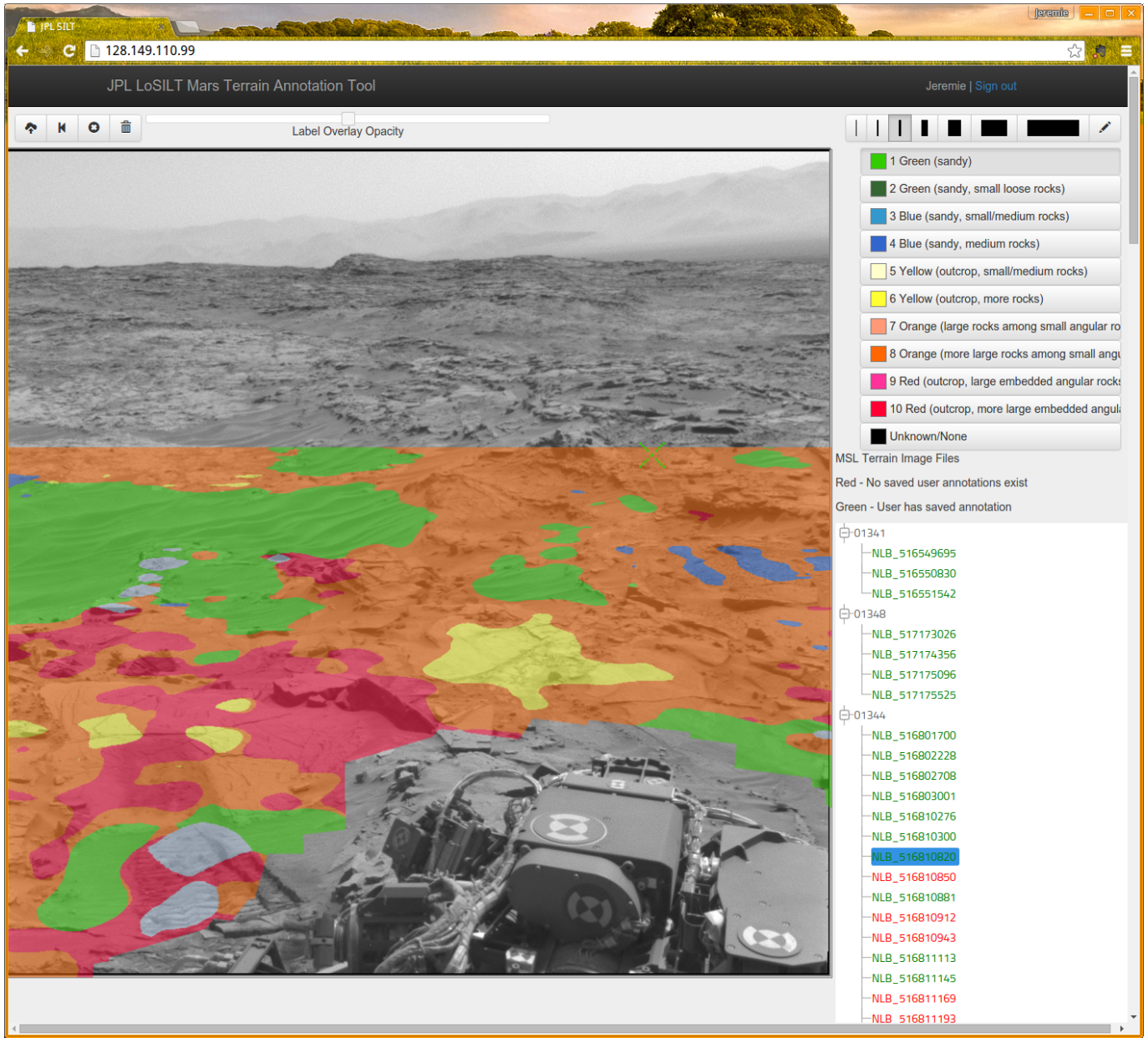
Details…

- Normalization is done by adjusting the image such that its median intensity is 0.5
  - Still problems with low-contrast image and shadows
- Projection
  1. Using sparse 3D (X,Y,Z) data from stereo correspondence, fit ground plane
  2. Find transformation so that image plane is parallel to ground plane
  3. Transform image, scale so that there are X pixels per meter, cut off anything >30m
     - Right now, there are 9 meters per 1024 pixels, and the neural net has a receptive field size of 224 (?) pixels, or 2 meters
- Classification is done by cutting the image into tiles so that it fits in the GPU's memory, classifying each, re-tiling them back together, then "un-projecting" the image
- **Total time**: ~10sec for classification (on a Titan X), ~1min for everything (image conversions, writing to file, etc.)

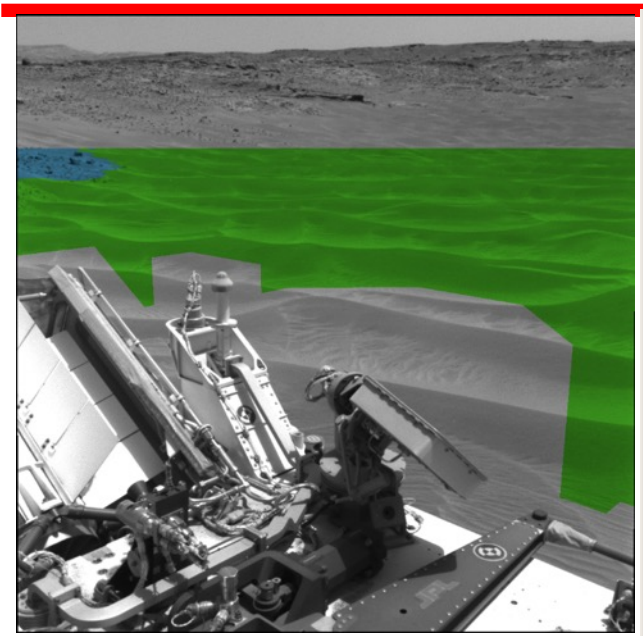
Results

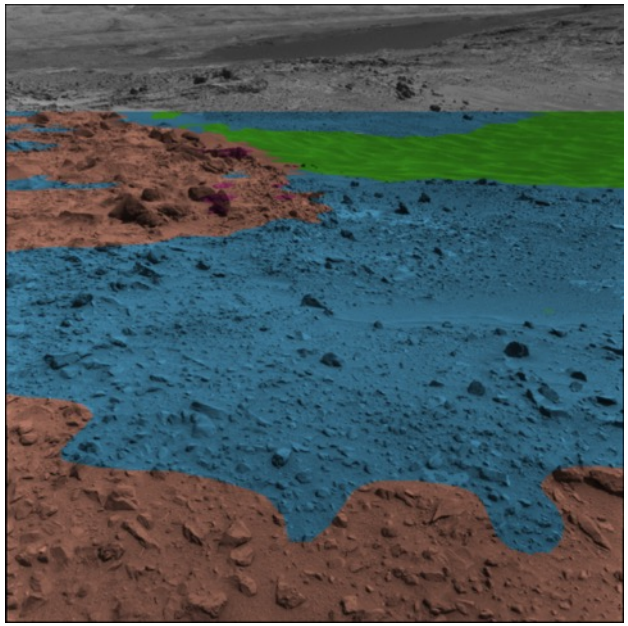







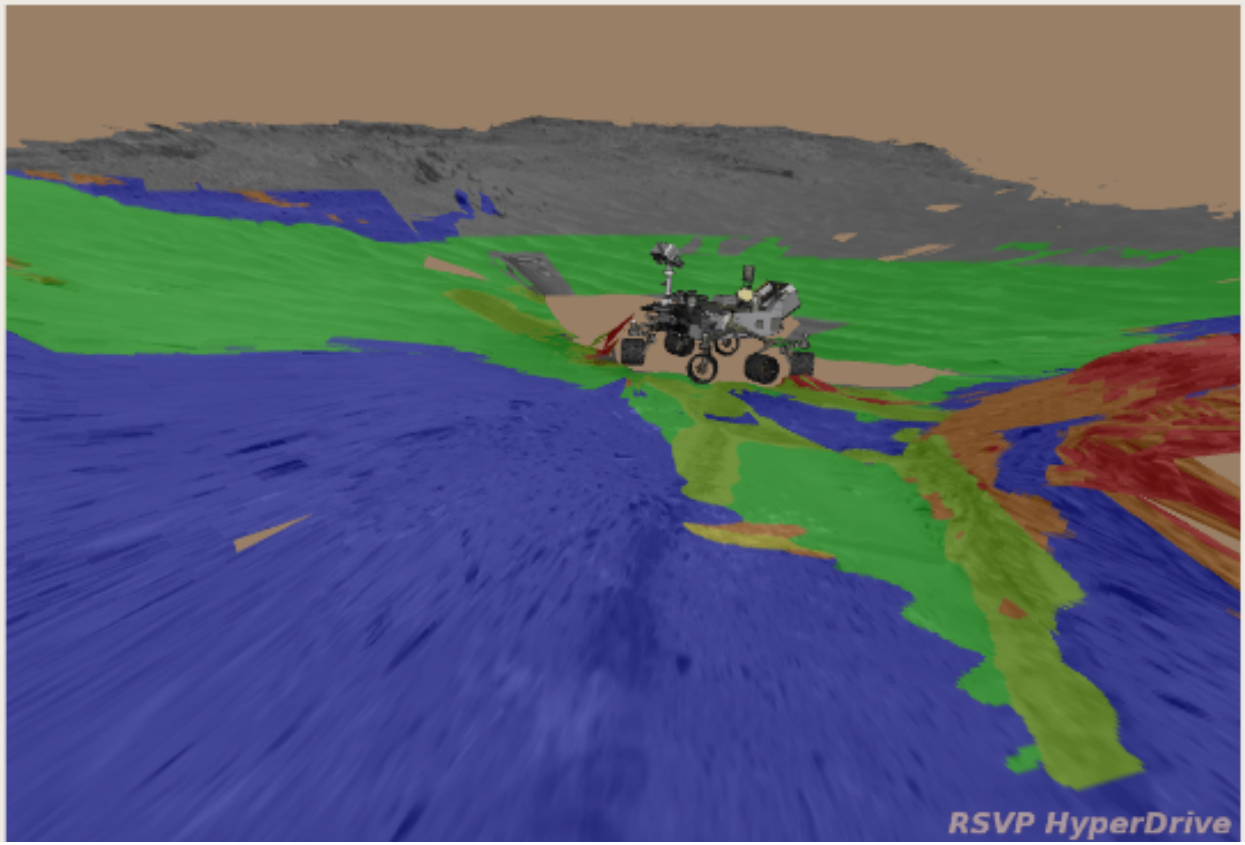
Annotation Tool



Hidden Valley (Sol 710)

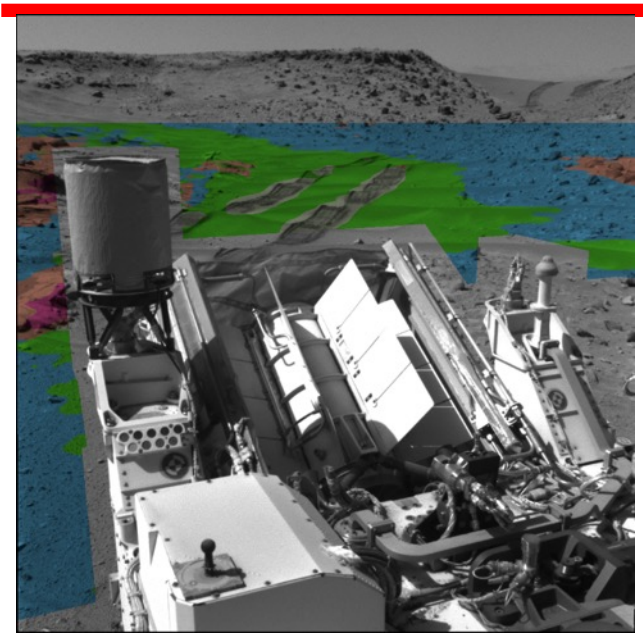


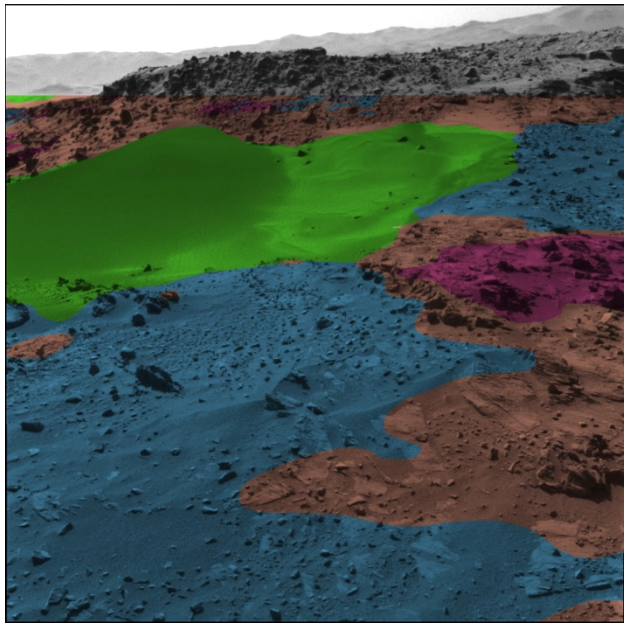


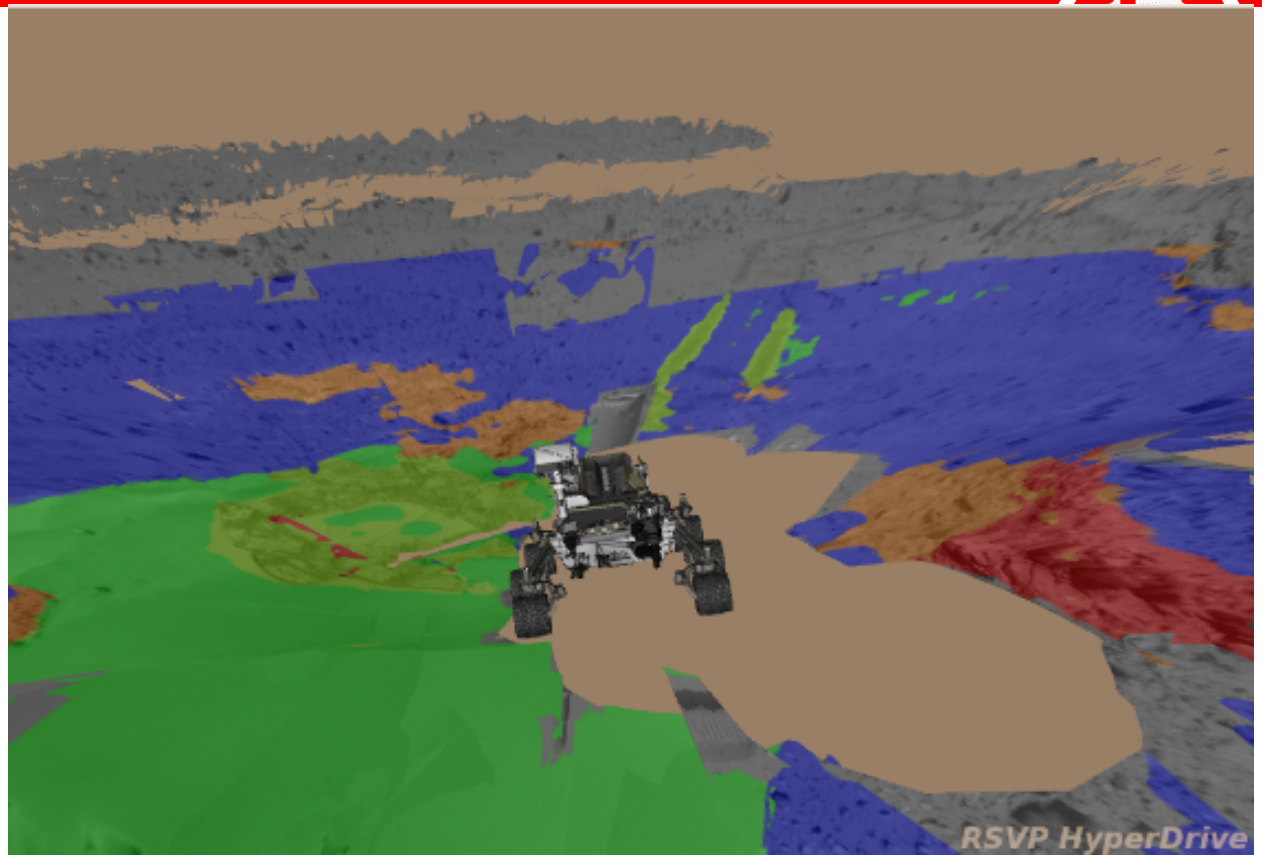


Sand
Smooth
Outcrop
Rocks
Rocks on outcrop

Dingo Gap (Sol 533)

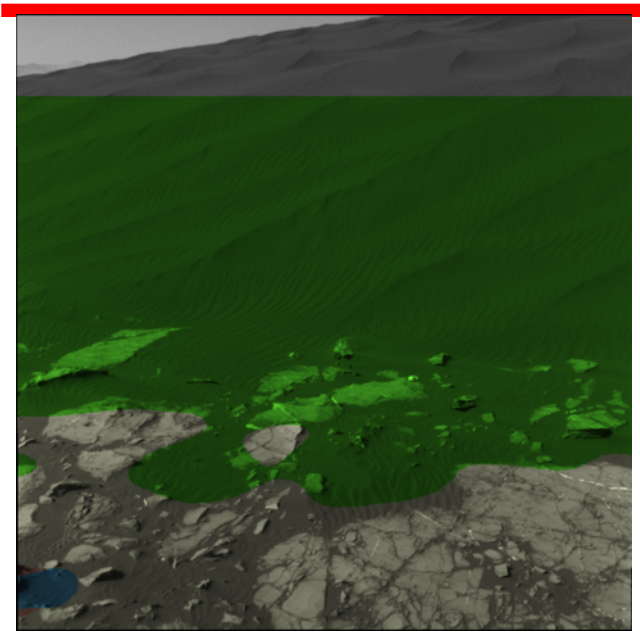


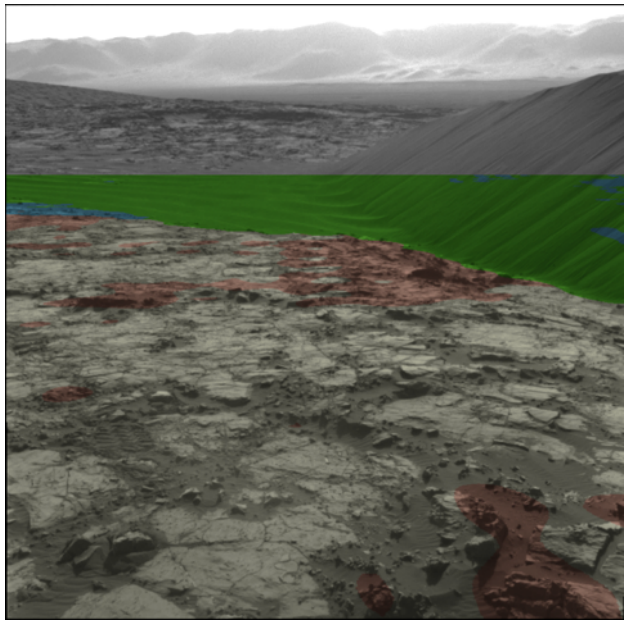


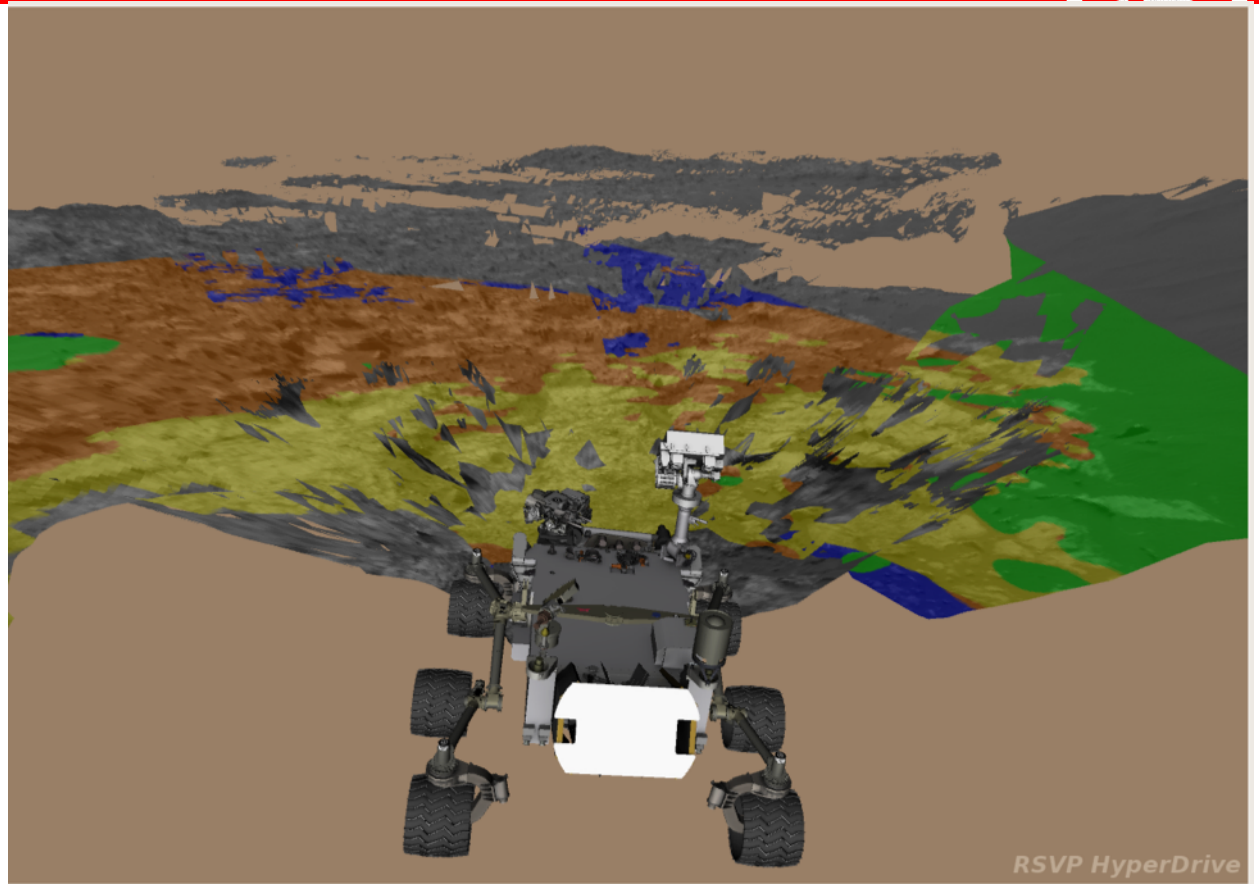


Sand
Smooth
Outcrop
Rocks
Rocks on outcrop

Namib Dune (Sol 1215)







Sand
Smooth
Outcrop
Rocks
Rocks on outcrop

Results

Table 3. Confusion matrix of terrain classification on MSL Navcam imagery.

Ground Truth	Prediction: Sand	S. Rocks	Bedrock	L. Rocks	Outcrop	Tracks	% of data
Sand	50.5%	44.4%	0.8%	1.7%	0.2%	2.4%	10.9%
S. Rocks	2.0%	90.2%	0.6%	7.0%	0.2%	0.02%	54.6%
Bedrock	9.9%	16.8%	44.5%	28.6%	0.3%	0.0%	7.7%
L. Rocks	1.1%	57.5%	1.81%	38.3%	1.3%	0.02%	23.5%
Outcrop	1.6%	34.6%	0.0%	34.0%	28.6%	1.1%	2.2%
Tracks	0.7%	39.0%	0.0%	0.9%	0.8%	58.6%	1.1%

Talk Overview

- SPOC-H: HiRISE-based Terrain Classification (Rothrock)
- SPOC-G: NAVCAM-based Terrain Classification (Papon)
- SPOC-R: On-board Terrain Classification (Iwashita)
- **Use cases: path planning with terrain classes (Ono)**

M2020 Landing Site Analysis

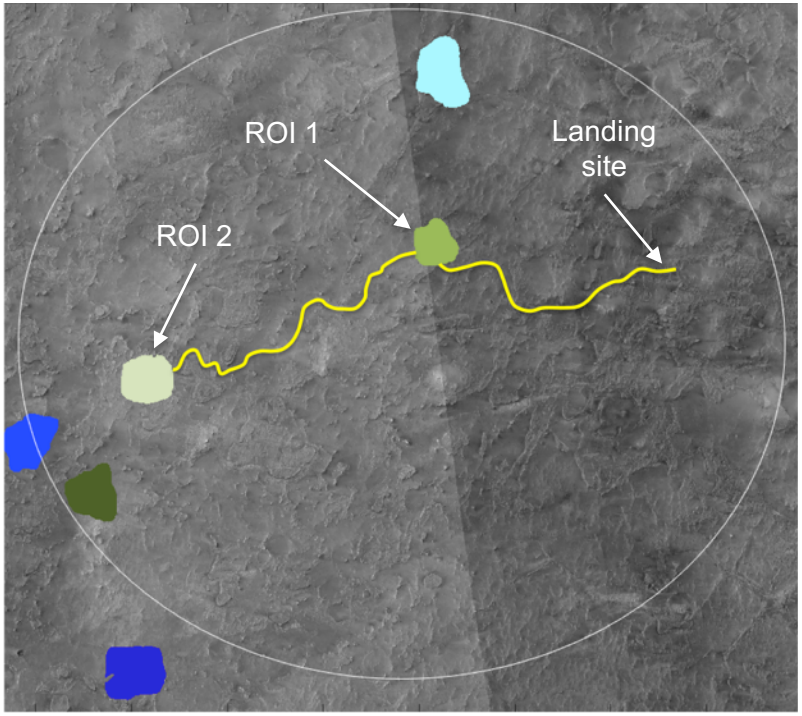
Baseline Reference Scenario

The Baseline Reference Scenario (BRS) is a representative mission scenario that gives a target for the design of the system and the mission.

- In 1.25 Mars Years, we will explore 2 Regions of Interest
  - Each requiring 6 km of long traverse length to achieve
  - Each requiring 1.5km of local traverse length to explore

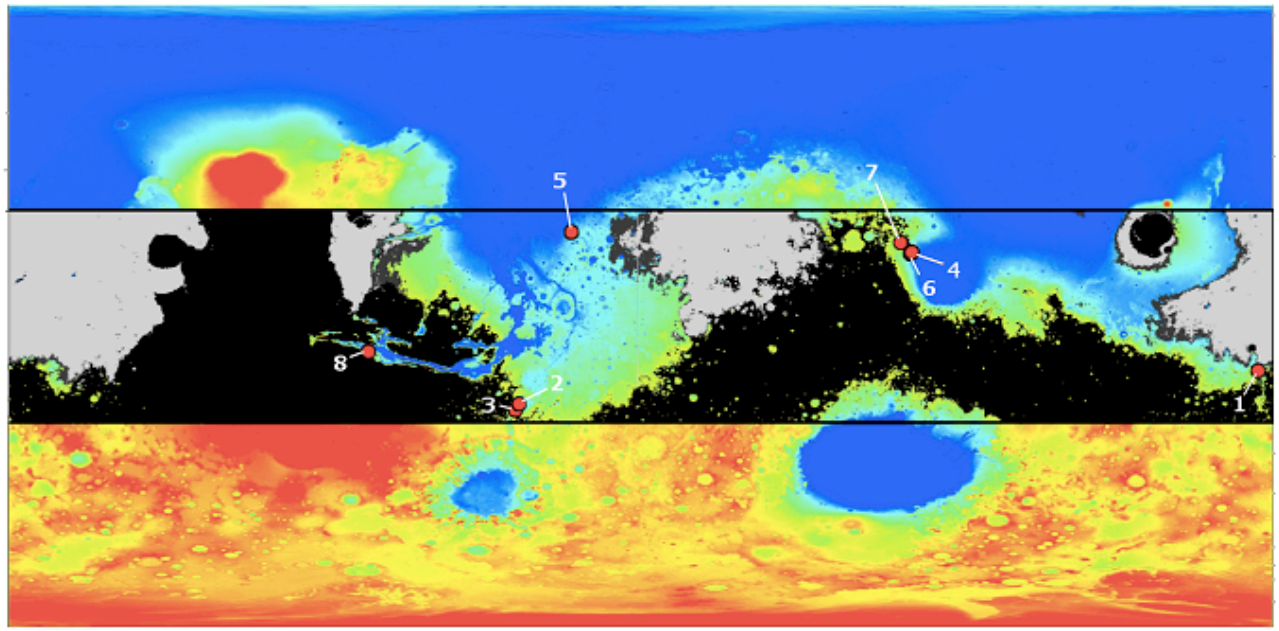
12 km of traverse between ROIs

3 km of traverse inside the ROIs



Pre-Decisional: For Planning and Discussion Purposes Only.

M2020 Candidate Sites



(alphabetical order)

1- Columbia Hills (Gusev)
2- Eberswalde
3- Holden
4- Jezero
5- Mawrth
6- NE Syrtis
7- Nili Fossae
8- SW Melas

Elevation above MOLA Geoid (m)

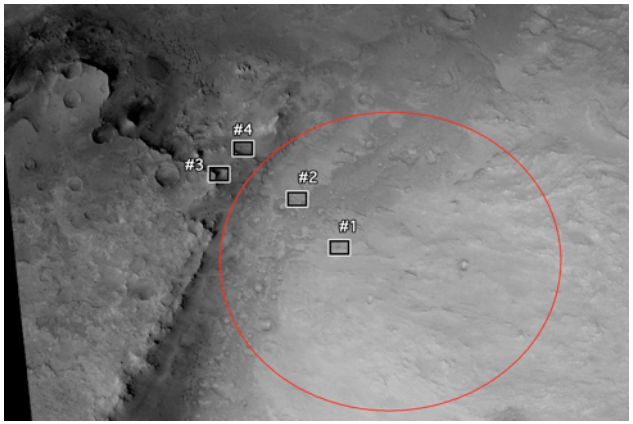
High: 4000 Low: -5000

Black elevation mask > 0.5 km
Thermal Inertia masks:
< 150 = Dark Gray
< 100 = Light Gray

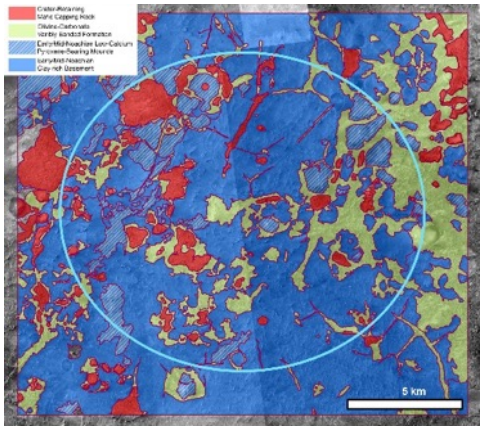
Pre-Decisional: For Planning and Discussion Purposes Only.

Regions Of Interest (ROIs)

- Site proposers submitted ROIs specific to the exploration of that site
- Site proposers defined what ROIs need to be visited for scientific success at the site
- ROI definition and “must visit” set have a big impact on traverse requirements at the site.
  - Project science team to work with site proposers after project PDR to refine ROIs and develop site specific mission scenarios
- Current evaluation is for visiting 2 ROIs per site



Nili Fossae Trough
Olivine rich deposit (ROI #3)
&
Either #1 or #2



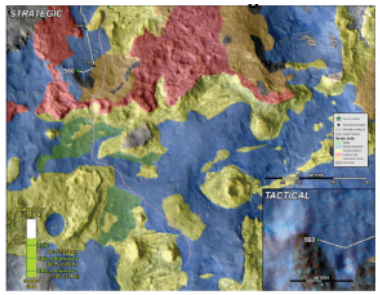
North East Syrtis
Any Olivine-Carbonate formation (green)
&
Any of the Crater-Retaining Capping Mafic Rock (red)

Pre-Decisional: For Planning and Discussion Purposes Only.

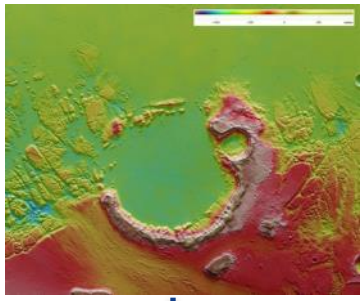
MTTTT Overview (Planned)

Raw HiRISE/CTX images

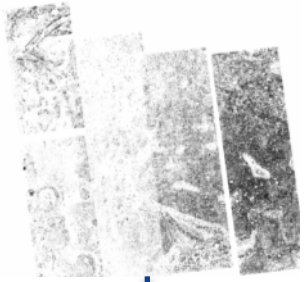
Terrain classes



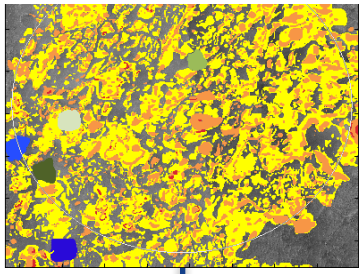
DEM/Slope



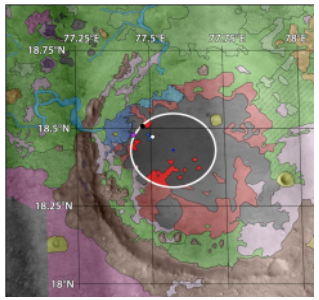
Rock abundance



Manual traverasability assessment

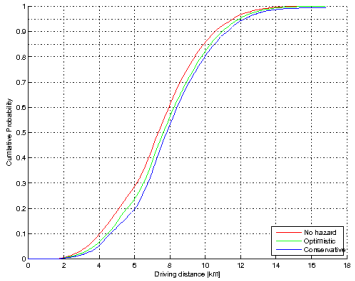


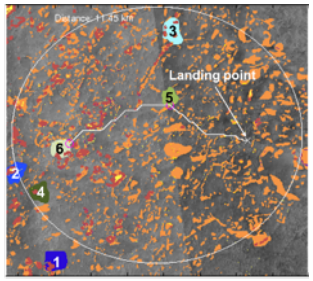
ROIs

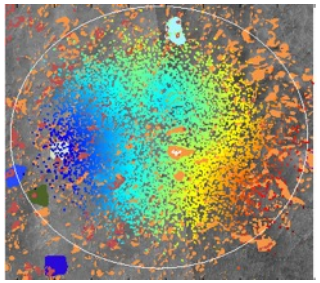


Mobility Model

Traversability Analysis



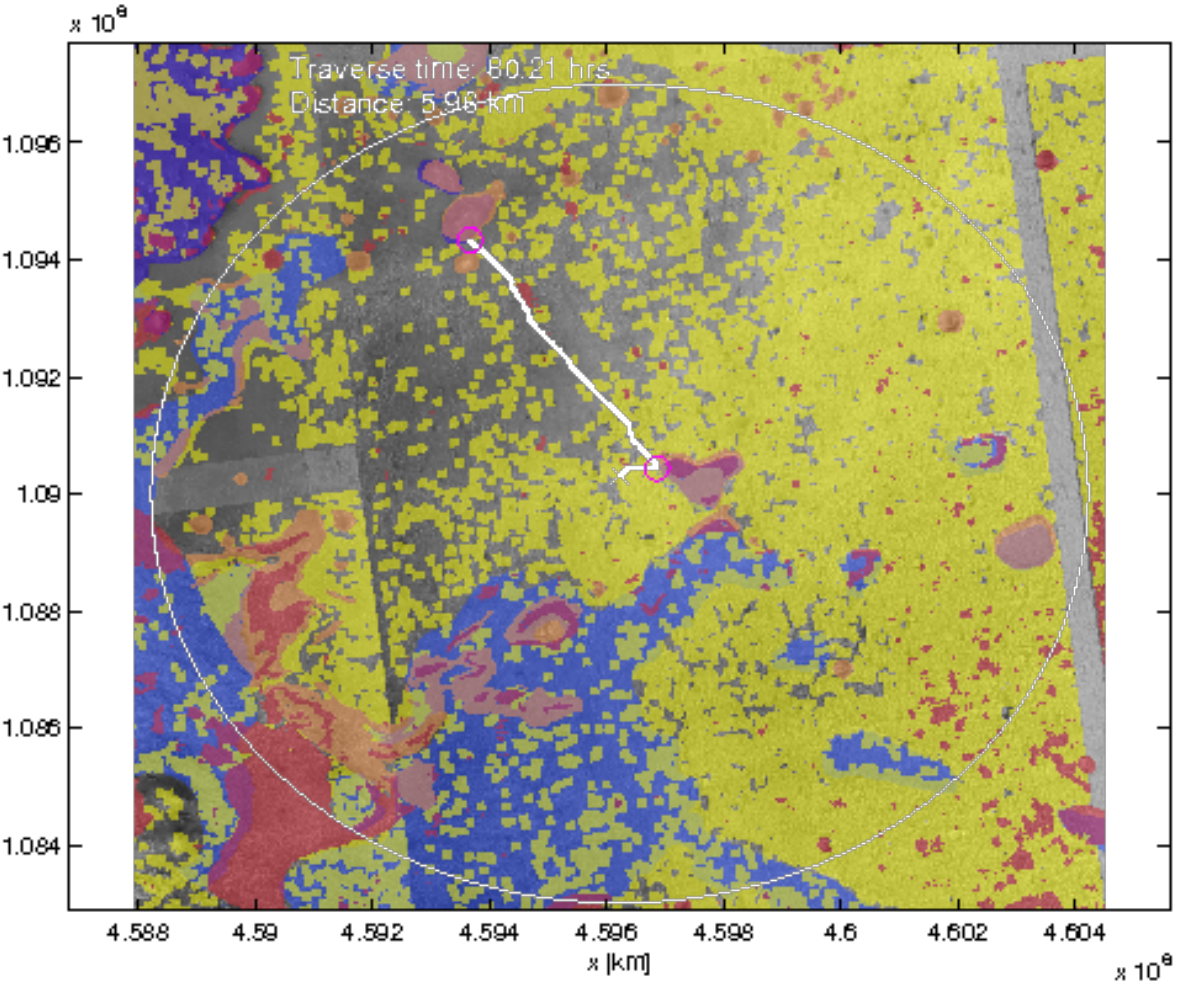




Pre-Decisional: For Planning and Discussion Purposes Only.

Optimal Route Planning

Example: Jezero

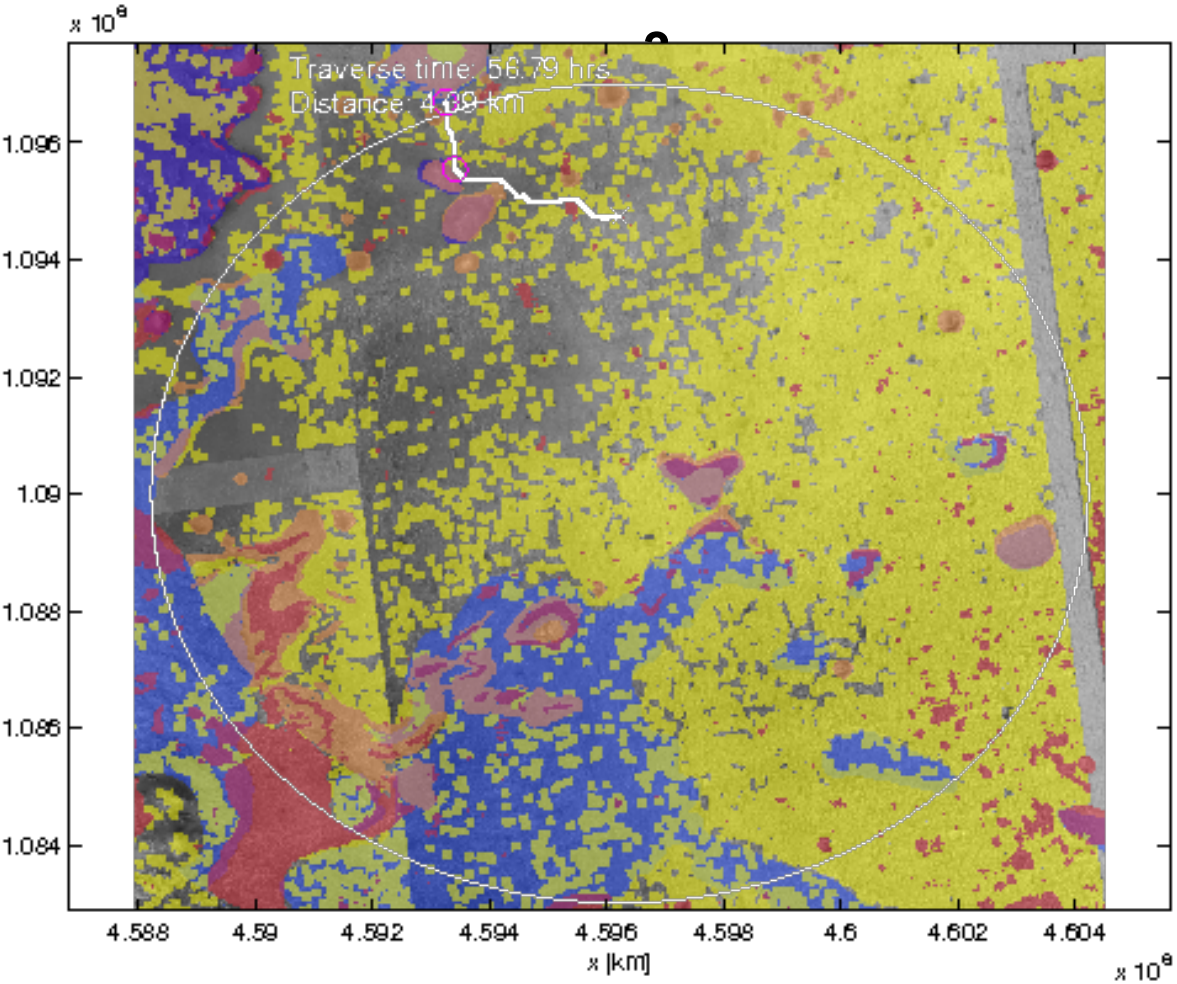


- Minimize time to achieve the minimum ROI requirement from a given landing point
- Driving speed estimated from local terrain type, rock abundance, and slope (details on later slides)
- Optimal route computed by the Sequential Dijkstra algorithm
- Online route planner at: http://lorentz.jpl.nasa.gov:5002/

Pre-Decisional: For Planning and Discussion Purposes Only.

Optimal Route Planning

Example: Jezero



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Optimal Route Planning

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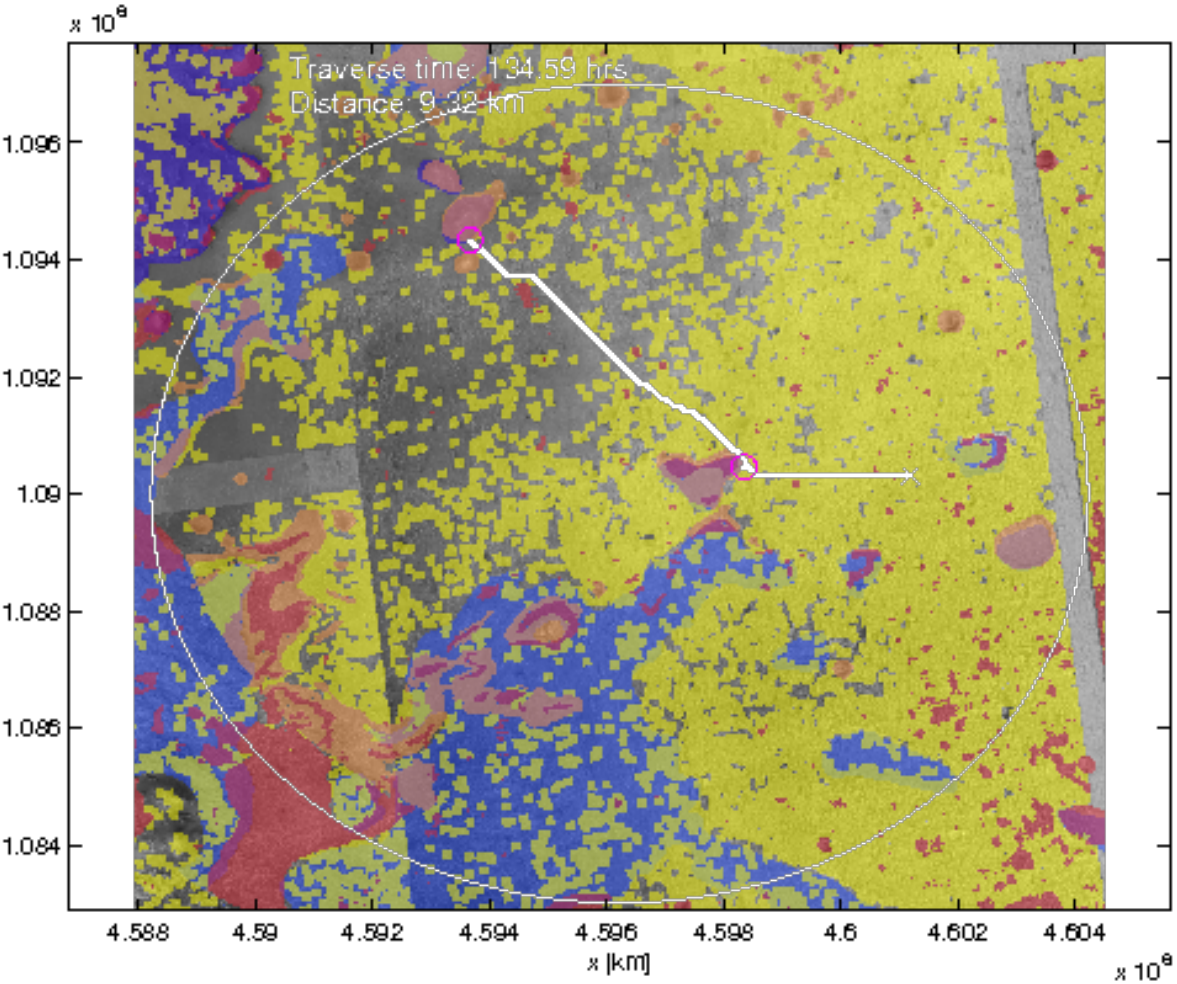

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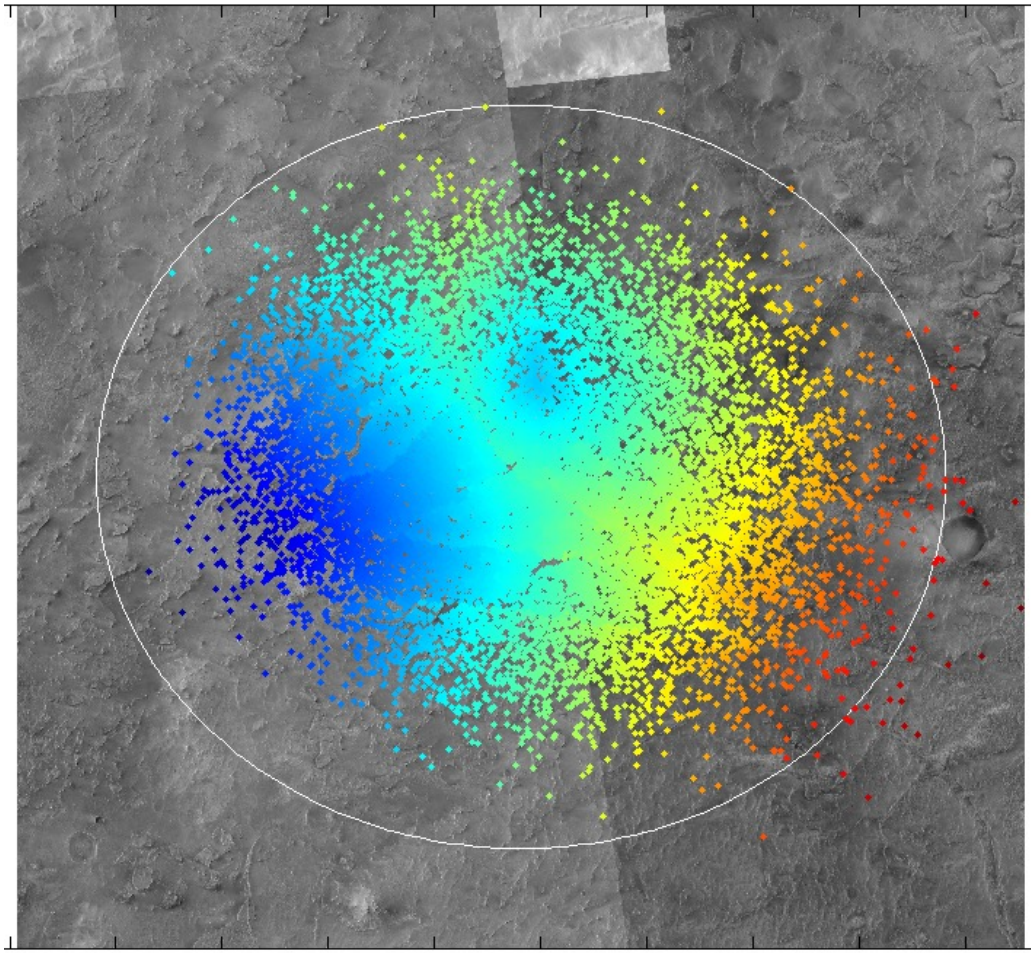
Pre-Decisional: For Planning and Discussion Purposes Only.

Monte-Carlo Simulation



Landing points provided by EDL team

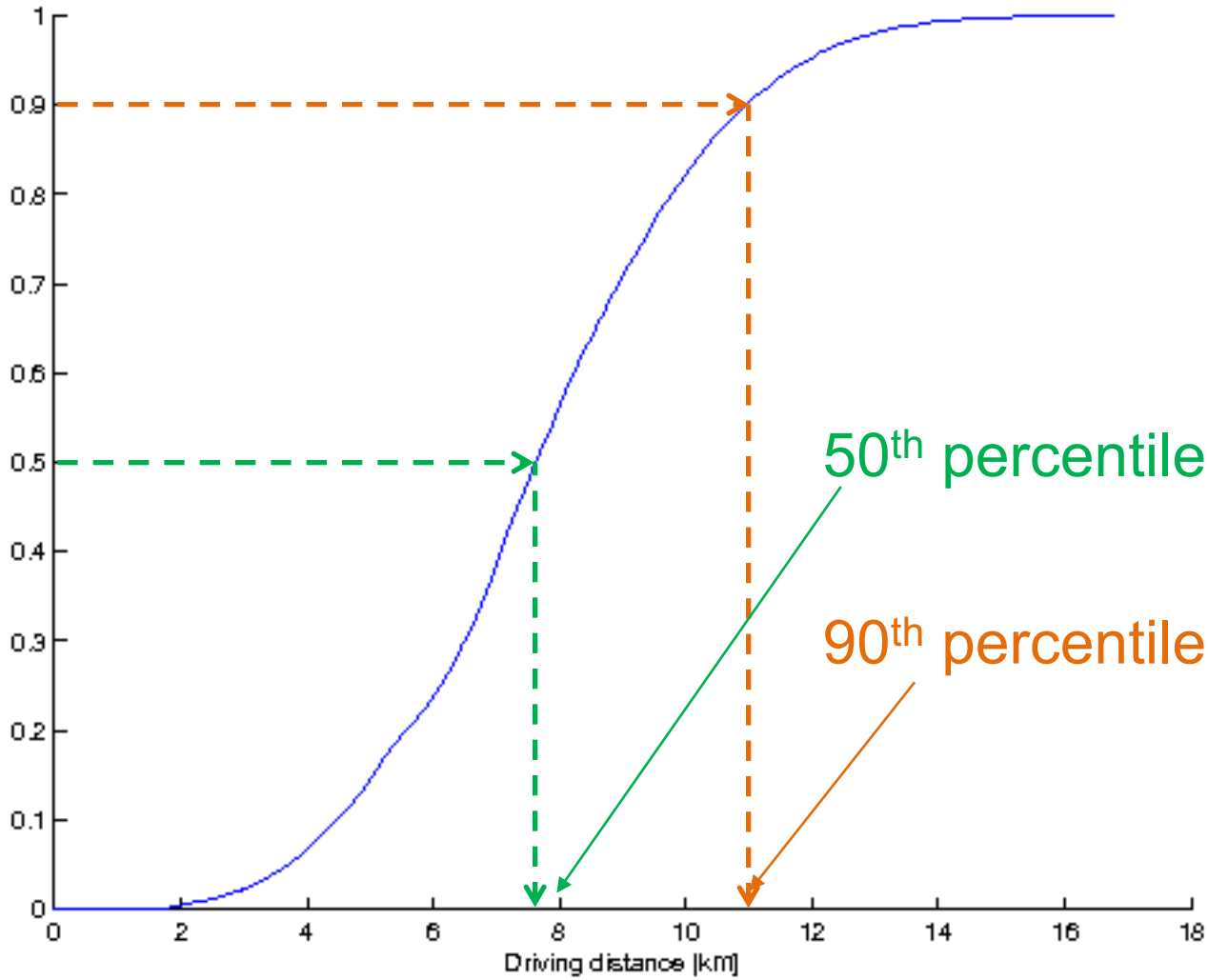
16,000 samples are provided; downsampled to 2,000

Optimal route computed from *all* samples

Pre-Decisional: For Planning and Discussion Purposes Only.

Cumulative Distribution of Distance

- Generate CDFs for distance AND time



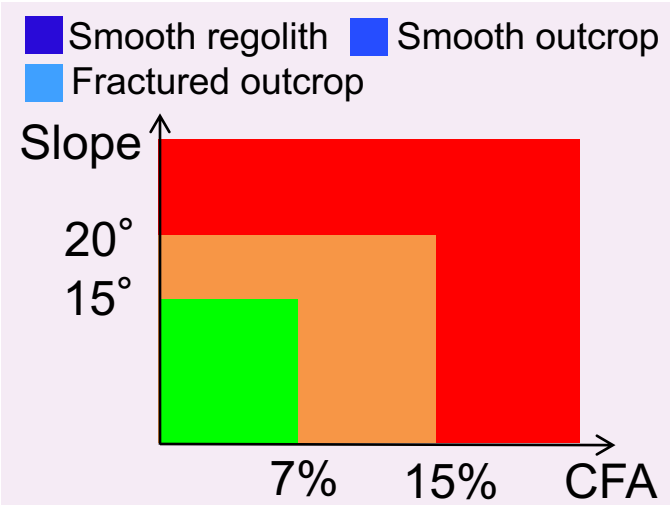
50th percentile distance: 7.8 km

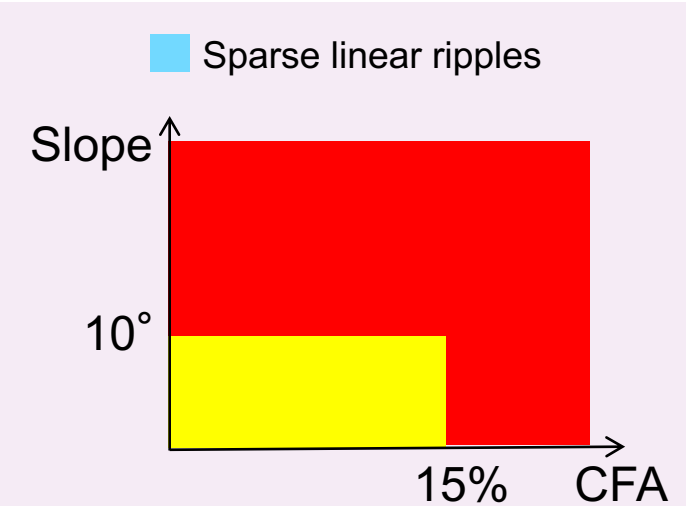
90th percentile distance: 11.2 km

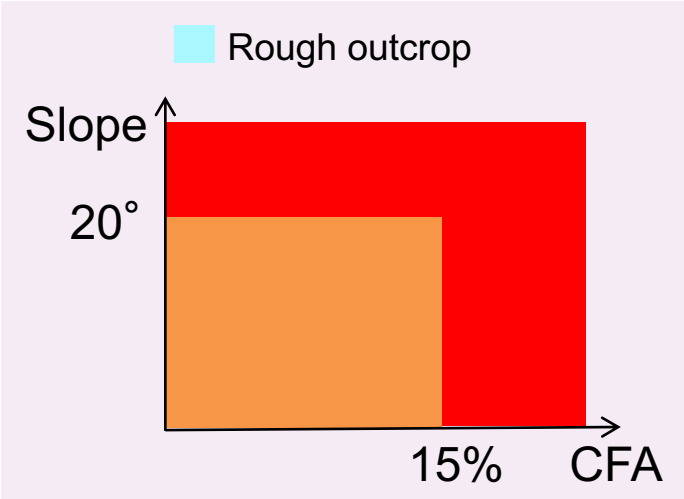
Pre-Decisional: For Planning and Discussion Purposes Only.

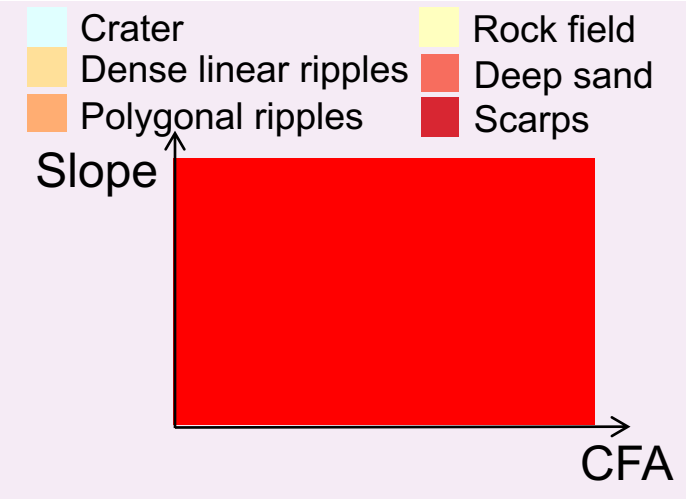
Mobility model

- Maps terrain type, slope, and cfa to driving speed
- Used for the time-minimum route planning





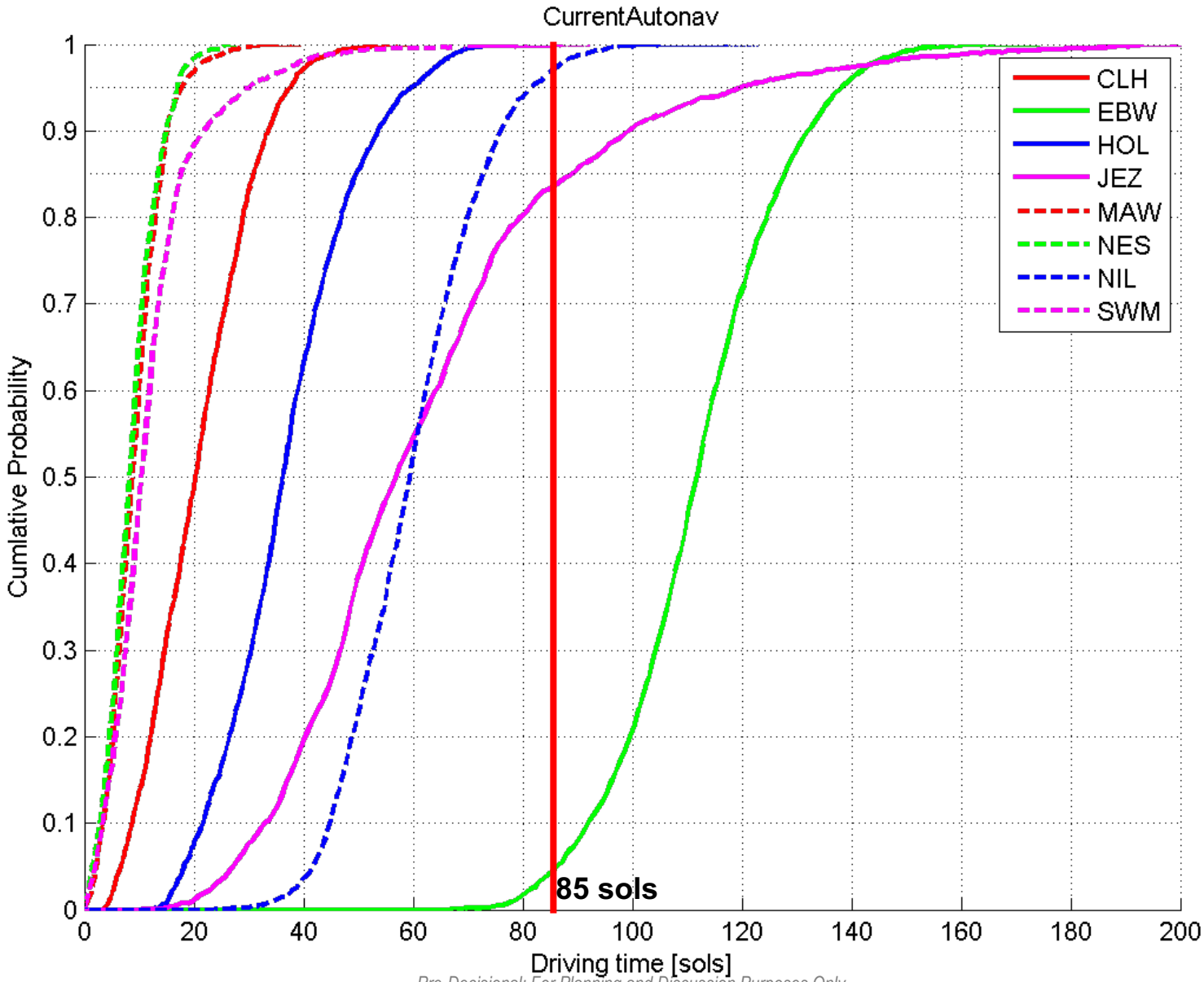




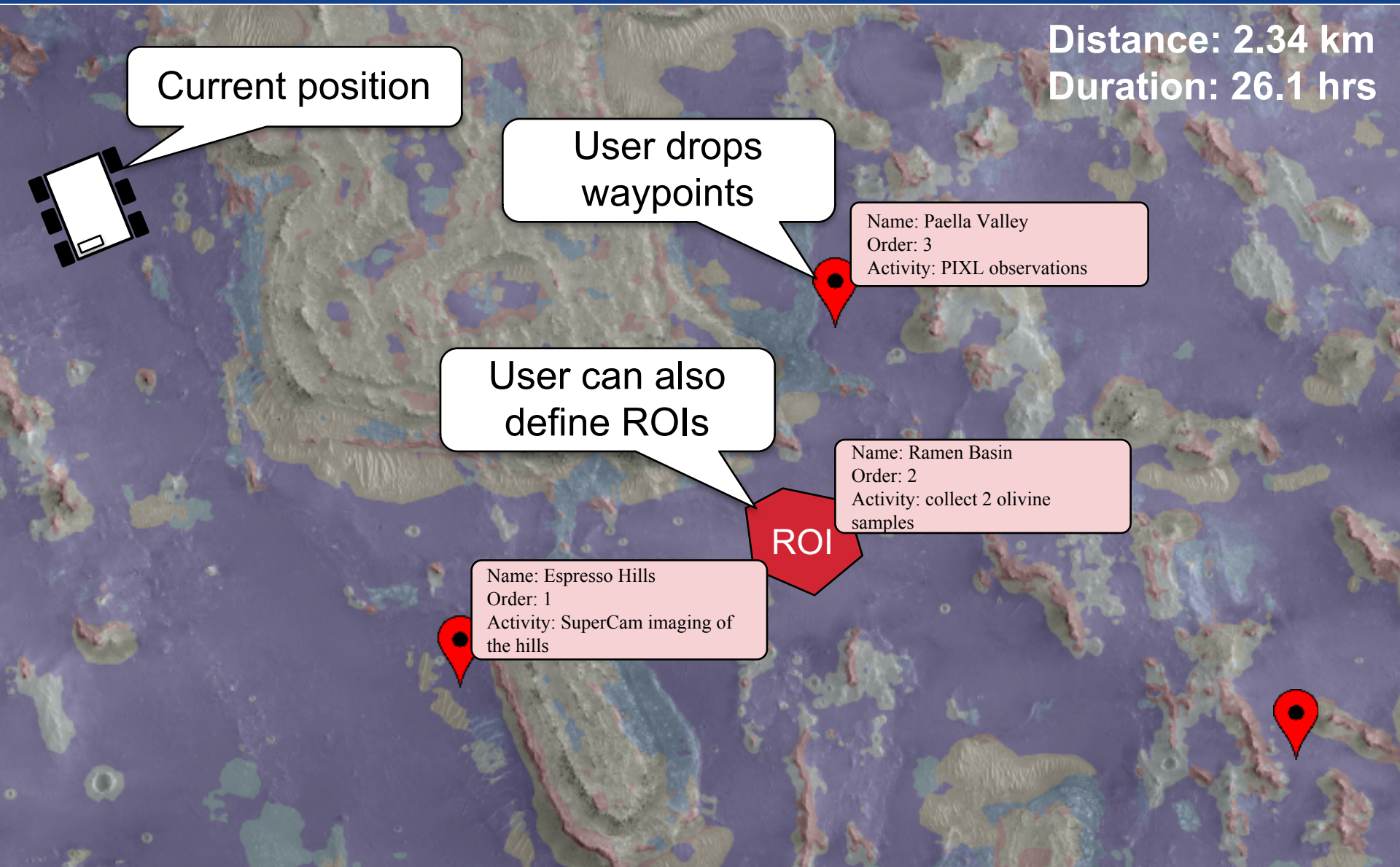
- Fast Autonav 80 m/hr
- Slow Autonav 60 m/hr
- Blind drive only 50 m/sol
- Untraversable

Pre-Decisional: For Planning and Discussion Purposes Only.

CDF (Time)

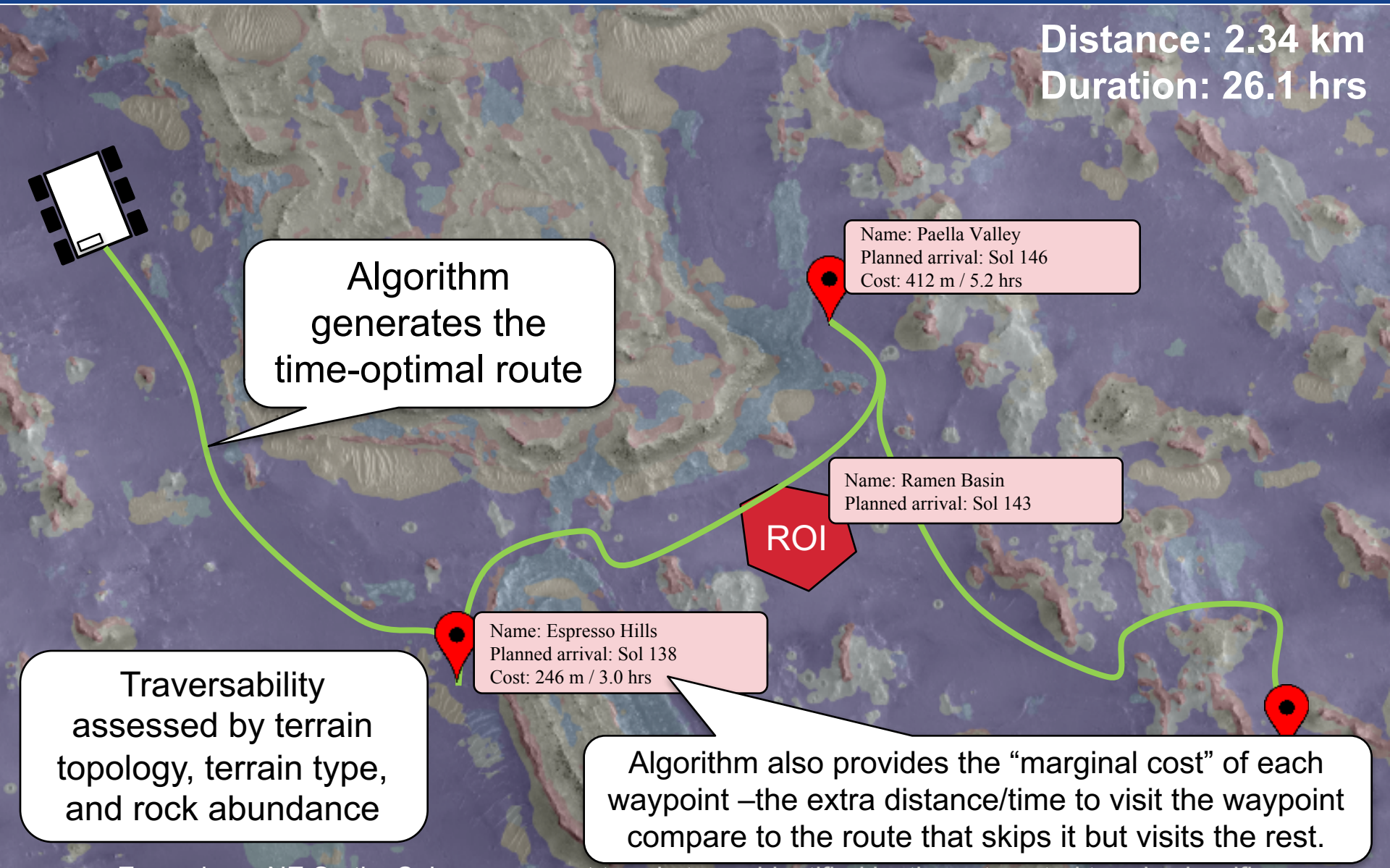

CurrentAutonav
Cumlative Probability
Driving time [sols]
85 sols
CLH
EBW
HOL
JEZ
MAW
NES
NIL
SWM
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
0
20
40
60
80
100
120
140
160
180
200

Strategic Planning Tool



Example on NE Syrtis. Colors represent terrain types identified by the automated terrain classifier.

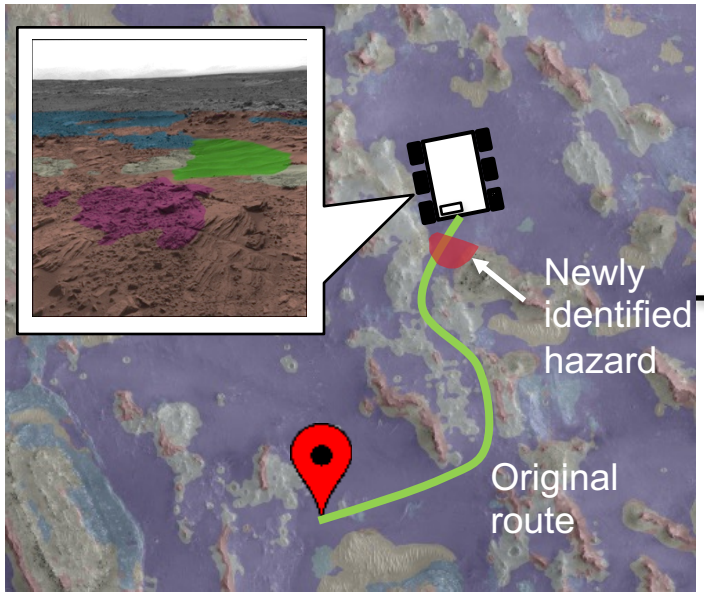
Strategic Planning Tool



Example on NE Syrtis. Colors represent terrain types identified by the automated terrain classifier.

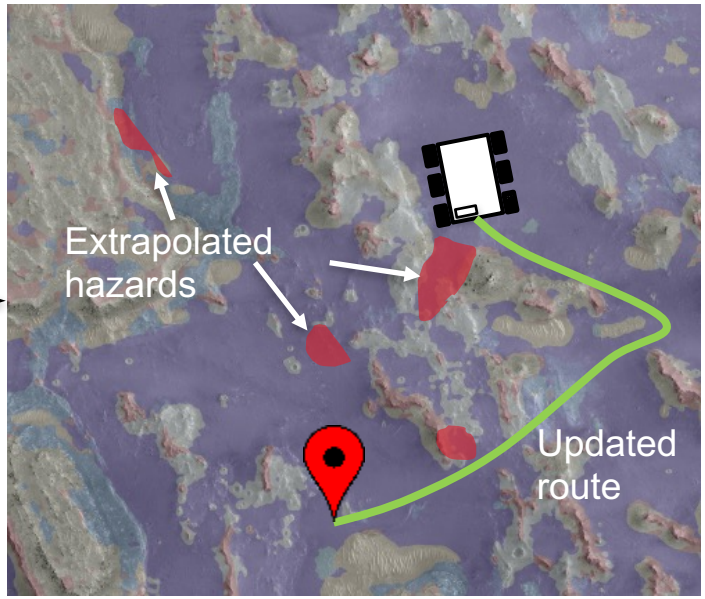
Constant Update of Traversability Assessment

- Adapts to new observations and updates traversability assessment throughout the surface operation
- Learn from local observation and apply the updated knowledge globally
  - E.g., If a new hazardous terrain type is observed from rover imageries, identify the regions that have similar terrain features on HiRISE and update the traversability assessment of the regions



Unexpected terrain observed by rover

- Re-train classifier
- Update traversability assessment
- Update route

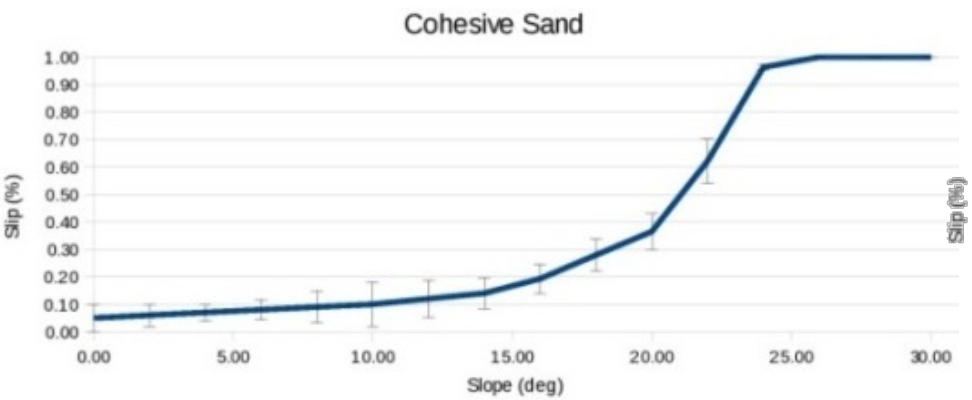


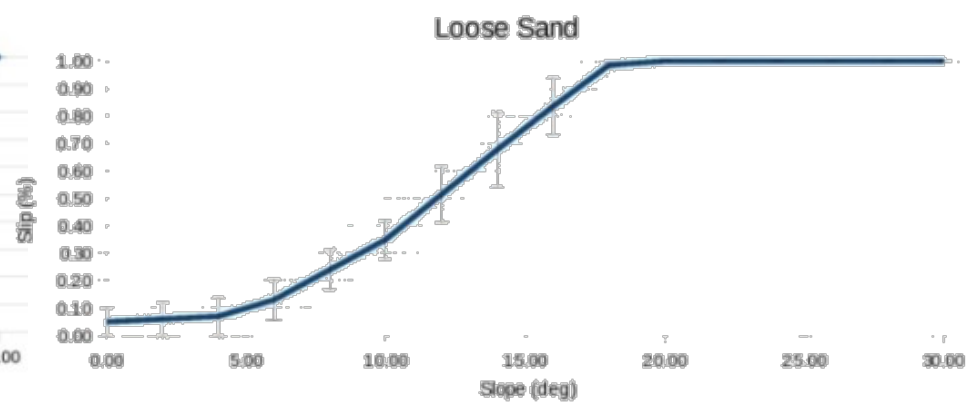
Updated strategic route

MSL Slip Analysis & Prediction

Backgrounds

- Slip model used in RSVP is extrapolated from Earth-based experiments
  - The model consists of slip curves for three terrain types
- There are ~8,000 slip data of Curiosity in EVR but have not been used for statistical analysis because manually correlating them with terrain is time consuming
- Question: How well the Earth-based slip model extrapolates to Mars





Objective/Approach

Objective:

- Statistically obtain slip curves from the EVR data
- Compare with the Earth-based model

Approach:

- From EVR, extract a VO arc on which both slope and slip are recoded
  - Find the NAVCAM image that best captures the terrain at the arc
  - Run the terrain classifier on the NAVCAM image to identify terrain type
- For each terrain type, run regression between slope and slip

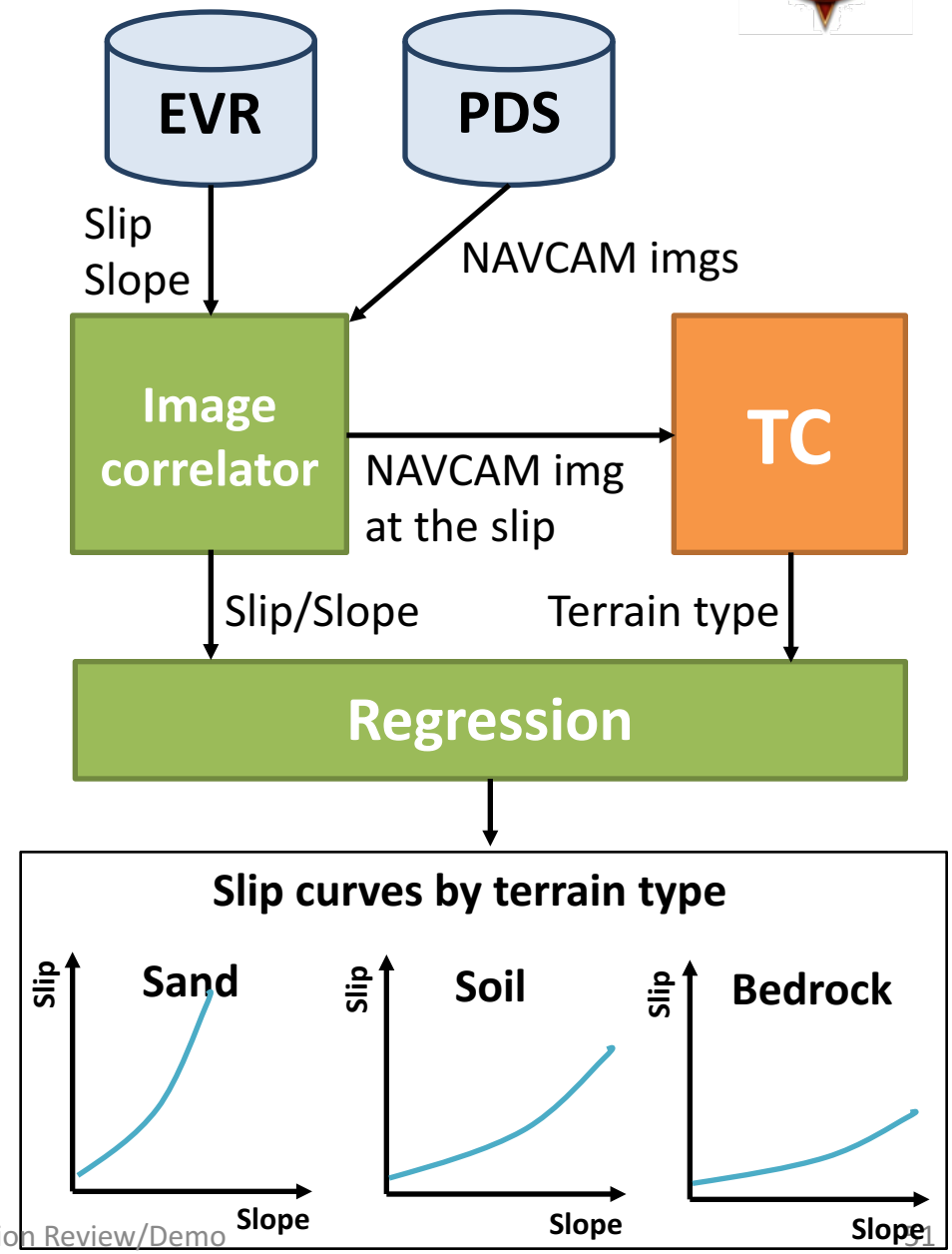
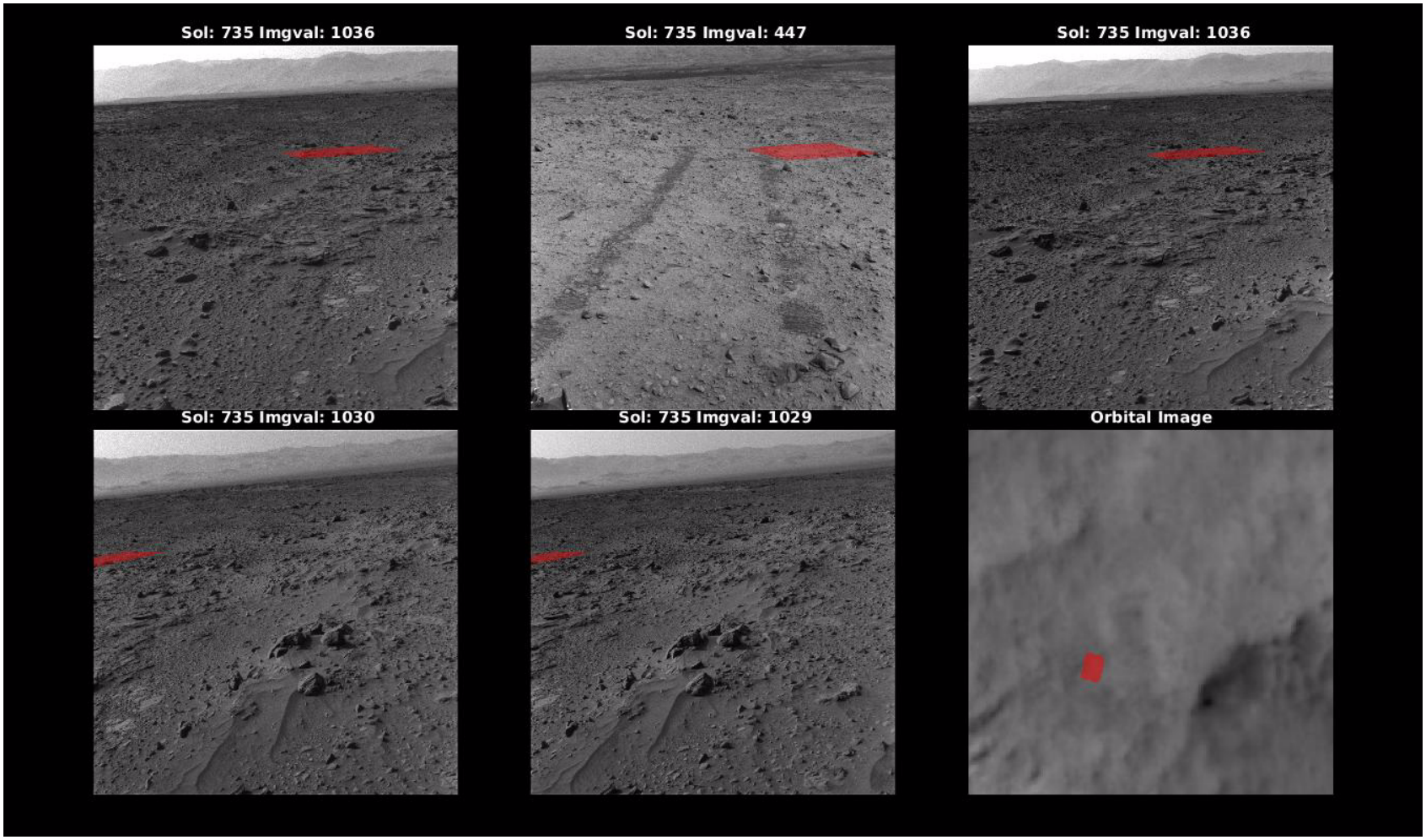
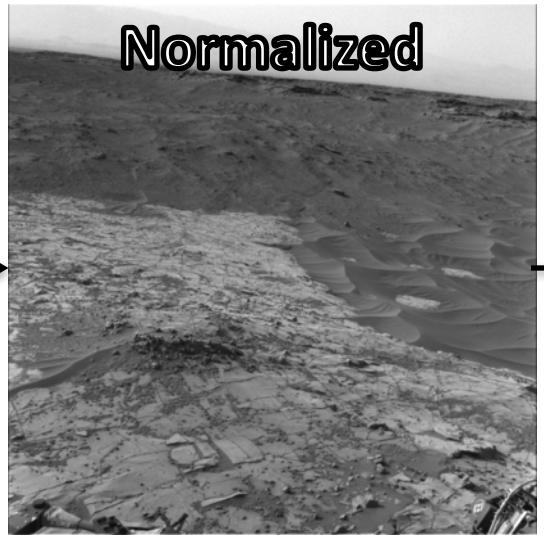


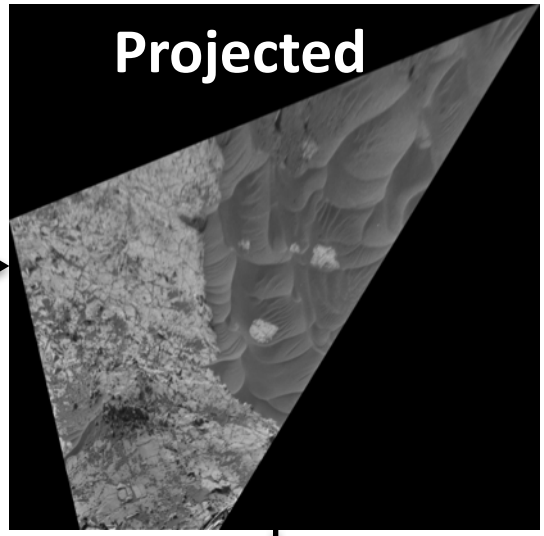
Image Correlator

- For a given arc, estimates the footprint on the ground
- Automatically finds the best NAVCAM image from PDR that best captures the footprint



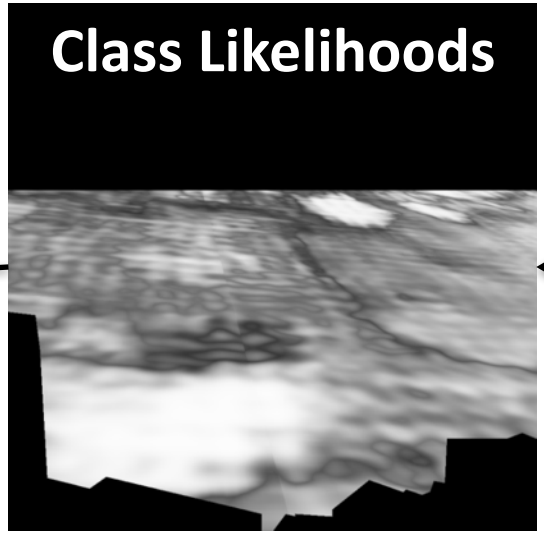
Visual Classifier

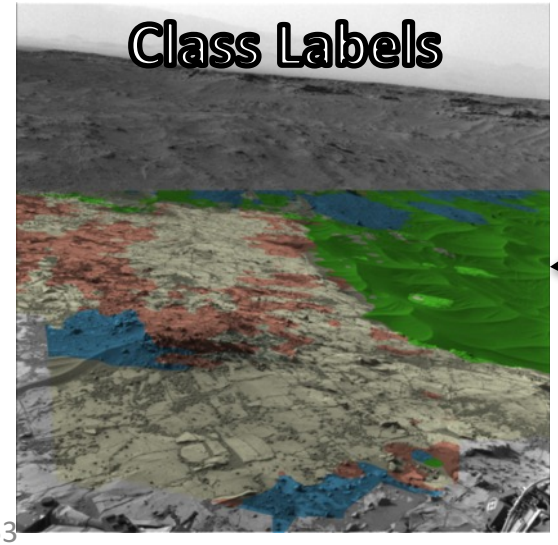




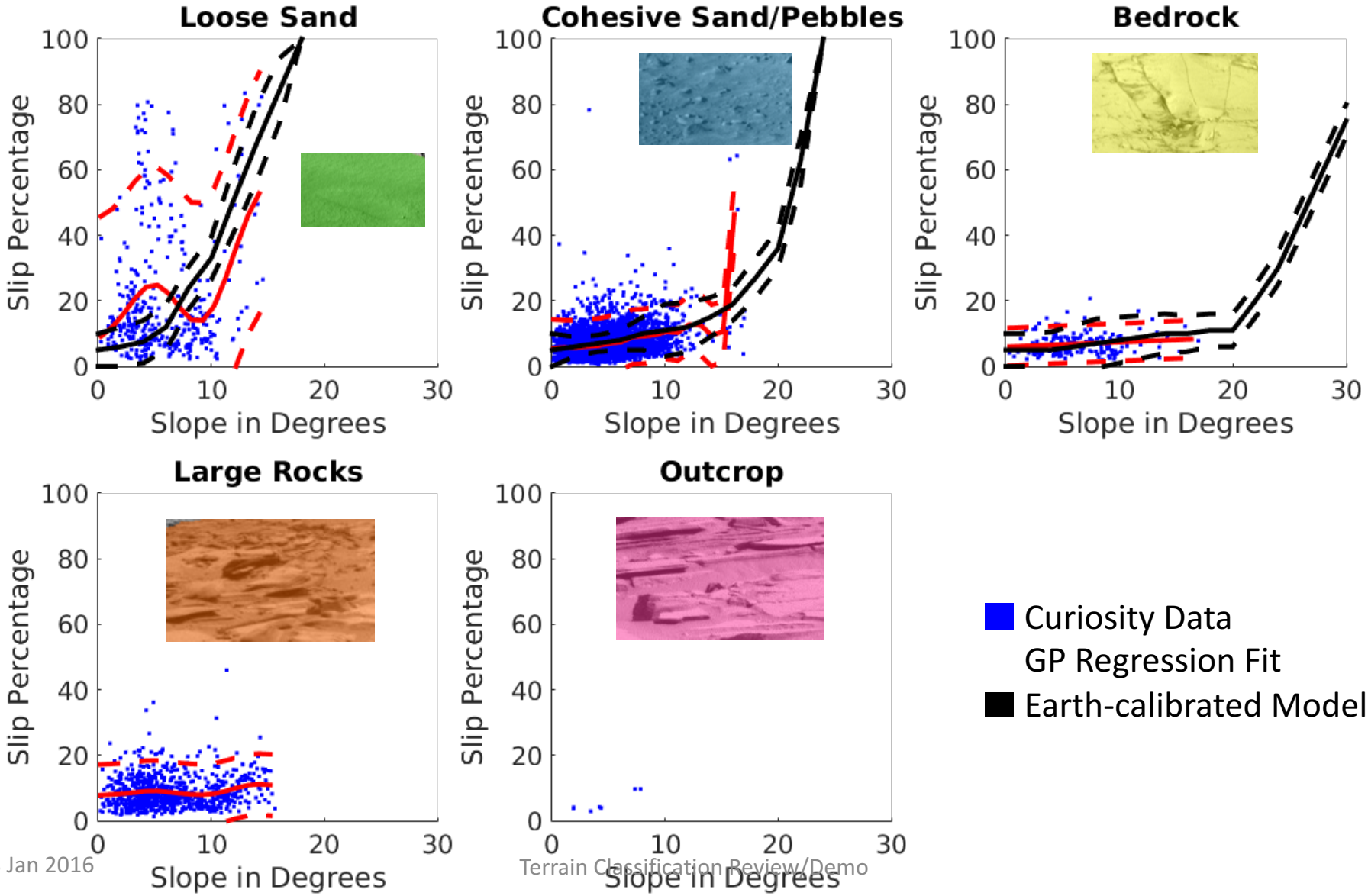
"DeepLab" Convolutional Neural Network

[Chen,2015]



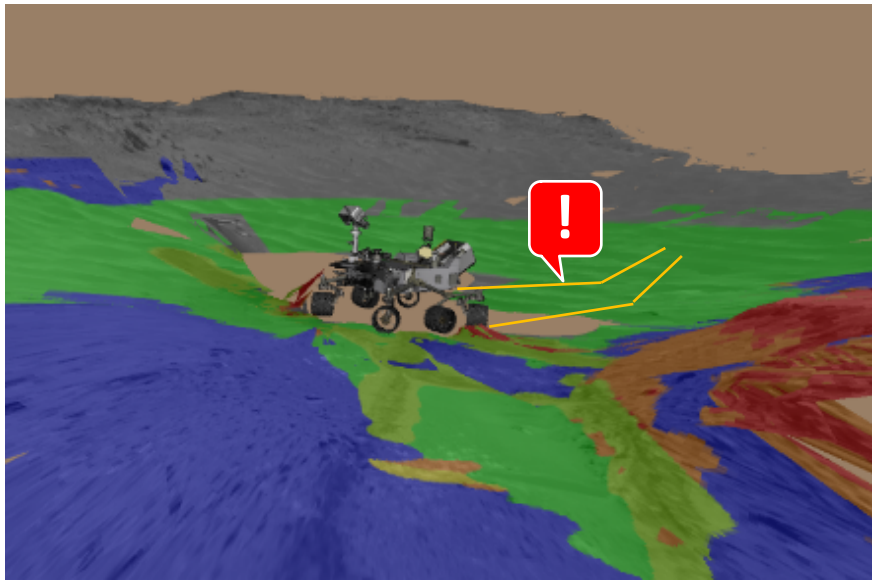


Slip Regression



RSVP Slip Checker

- Predicts slip of planned paths based on terrain type and slope
- Provides a warning if planned path may result in excessive slip
- Replaces current slip checker in RSVP that requires choosing terrain type manually



Conclusions

- Developed CNN-based terrain classifier that works on
  - Full-resolution HiRISE images
  - NAVCAM images
- Used by the M2020 project for landing site analysis and selection
- Will be deployed on MSL operation in late March
- On-board version is being developed
- Aiming for on-board infusion

LLAP