Jet Propulsion Laboratory
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TU-Net and TDeepLab: Deep Learning-based Terrain Classification Robust to Illumination Changes, Combining Visible and Thermal Imagery

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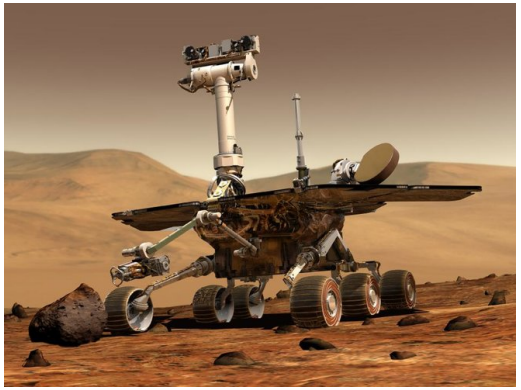
Terrain classification (TC)

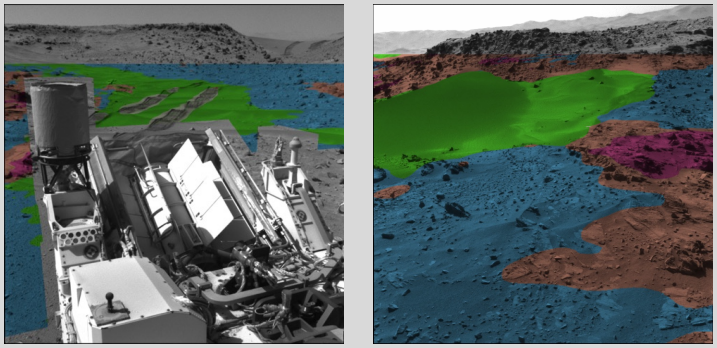
- Terrain classification (TC) is an essential component of a broader understanding of the terrain to be traversed by rovers



Spirit got stuck in a sand trap, 2010

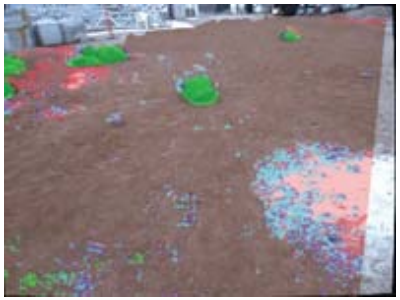
Wheels of Curiosity rover got damaged

Terrain classification from **visible** images



Sand Smooth Outcrop
Rocks Rocks on outcrop

- We have developed a TC system from visible images



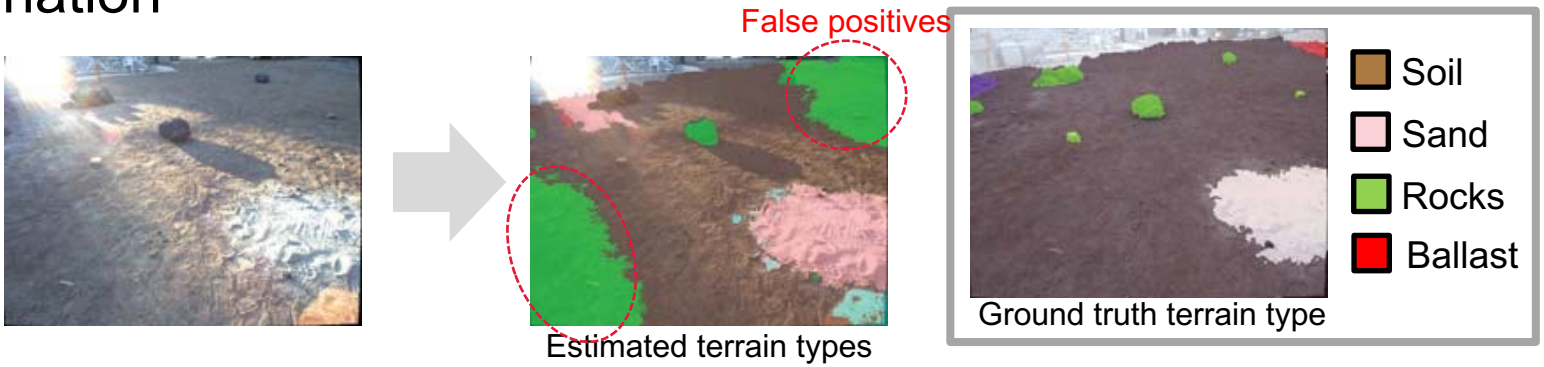
Estimated terrain type

Soil Rocks Rocky terrain
Ballast Bedrock Sand

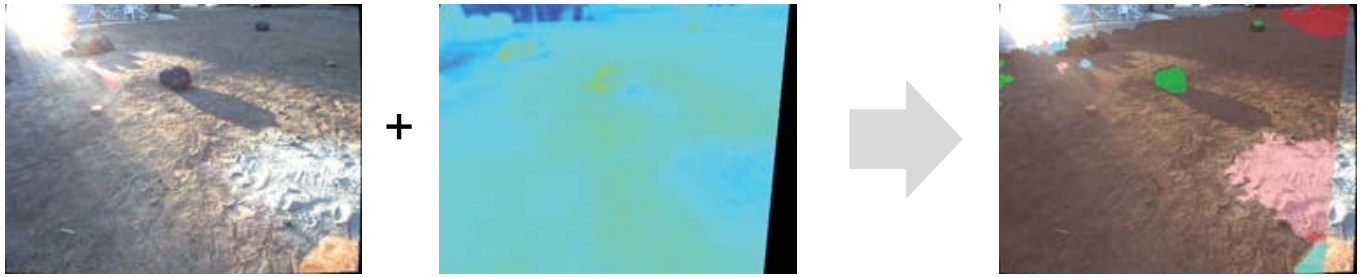
Ground truth

Terrain classification

- Terrain classification with visible information is challenging due to a variety of factors, of most importance being the changes in illumination



- The terrain classification can be aided by the fact that the temperature of various types of terrains depends on the thermal characteristics of the terrain



Captured RGB image | Captured IR image | Estimated terrain types

Deep learning for terrain classification

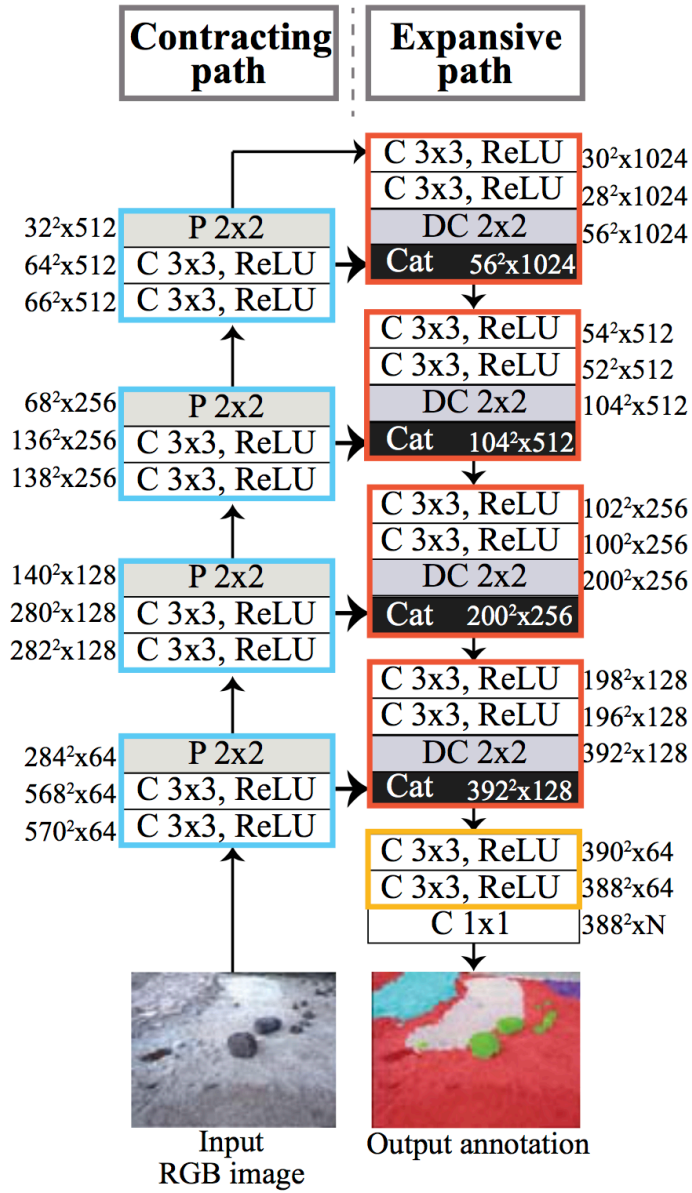
- Existing approaches
  1. Fully Convolutional Networks (FCN), such as DeepLab
     - In general it requires a huge dataset to train its parameters
       - If we do not have enough dataset to train FCN from scratch, finetune the parameters from pre-trained parameters
  2. U-Net
     - It has short-cut connections, which help a lot with parameter training even given a small number of dataset

- We propose two novel deep learning-based terrain classification methods based on U-Net and FCN (DeepLab), which combine visible and thermal IR images
  1. **TU-Net (Two U-Net)**
  2. **TDeepLab (Two Deeplab)**
- We also extend the proposed methods to Siamese-based approaches to realize robustness to illumination changes

U-Net for terrain classification from RGB images

U-Net architecture

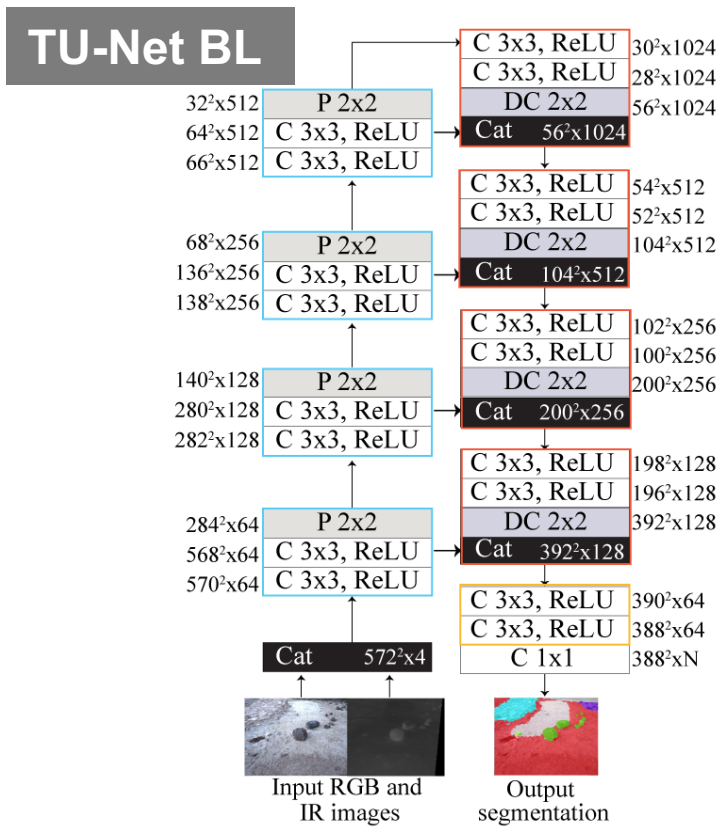
Cat: concatenate
C: convolution
ReLU: rectified linear unit
P: pooling
DC: deconvolution

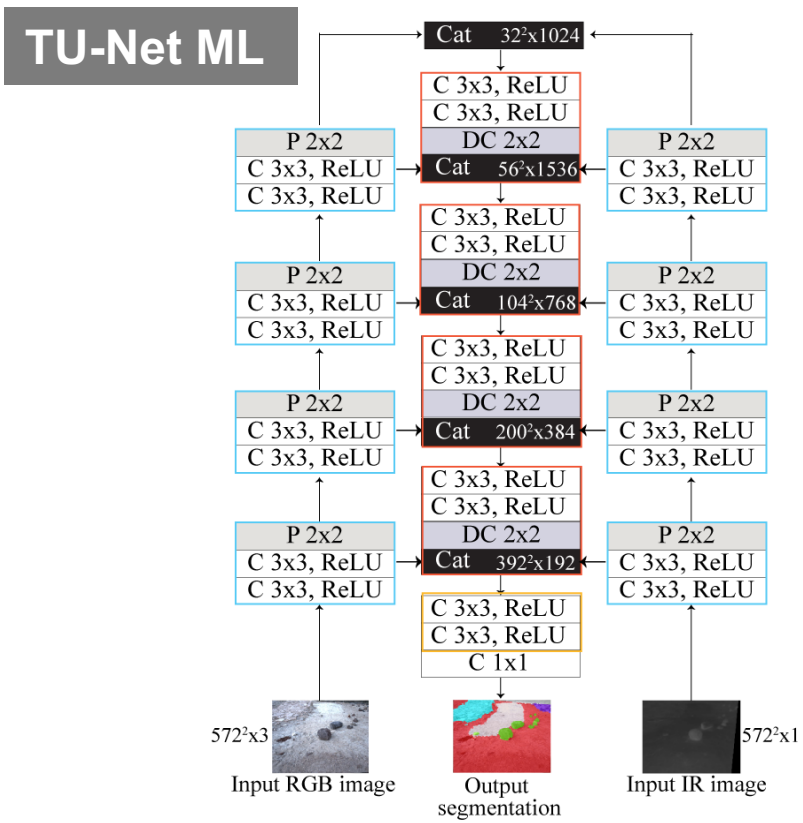


Loss function for terrain classification $\mathcal{L}_{CE}$:
Cross entropy **from annotation images**

TU-Net (Two U-Net)

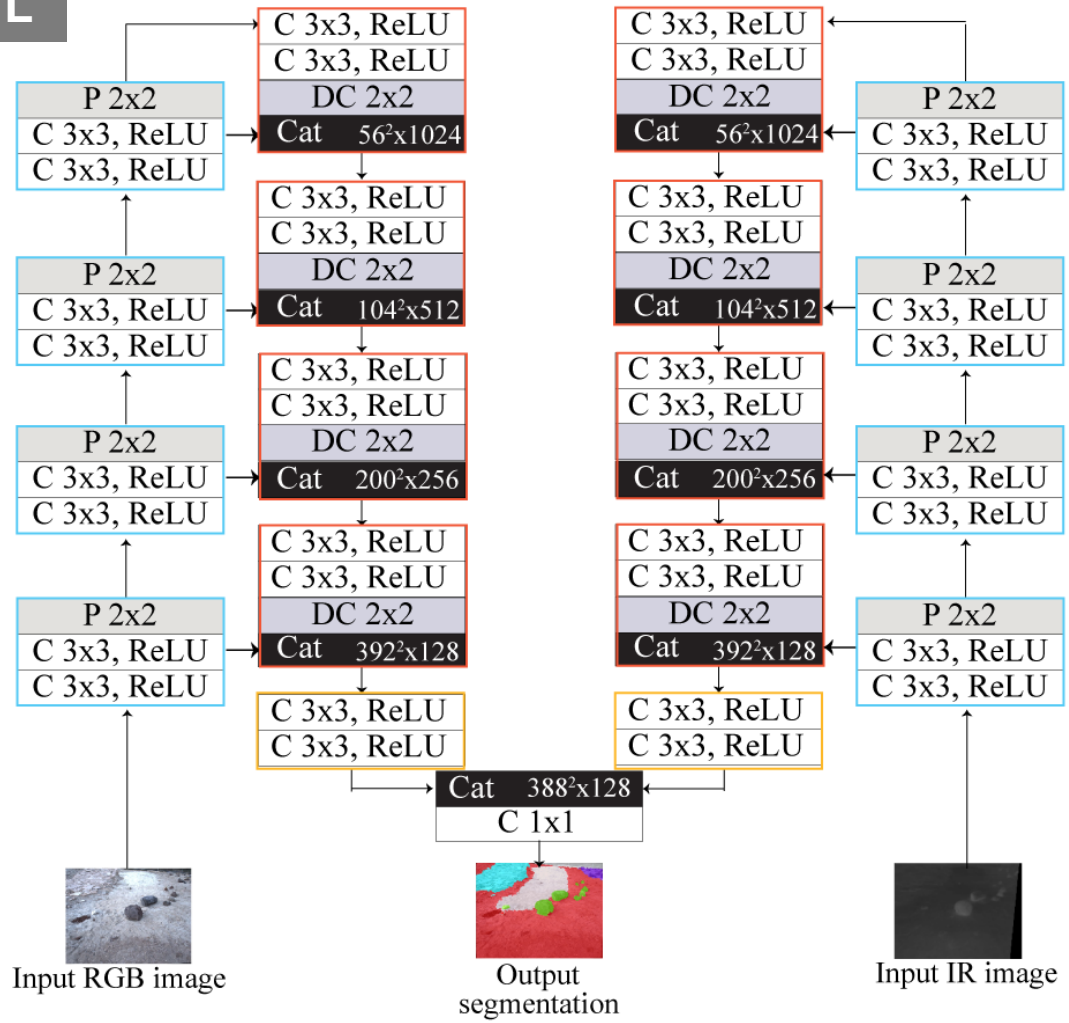
- Three different architectures: fusion of visible and thermal images at different level
  - **TU-Net BL (bottom layer): fusion of local information**
  - **TU-Net ML (middle layer): fusion of global information**
  - **TU-Net TL (top layer): fusion of feature-level information**





TU-Net (Two U-Net)

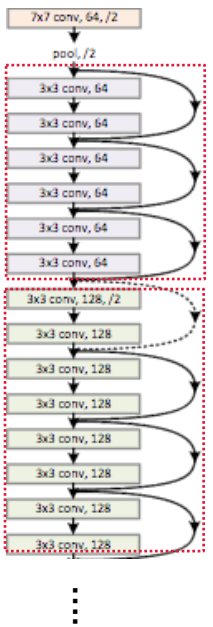
TU-Net TL



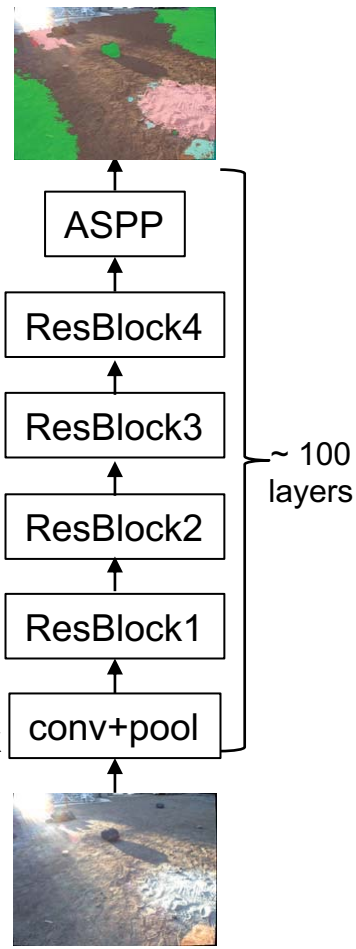
TDeepLab (Two DeepLab)

[1] L. Chen, et al., “DeepLab: Semantic Image Segmentation with Deep Convolutional Nets, Atrous Convolution, and Fully Connected CRFs”, arXiv 2016

- TDeepLab is based on DeepLab v2 (Backbone is ResNet-101 v1)
  - 2 architectures: **TDeepLab BL and TDeepLab TL**

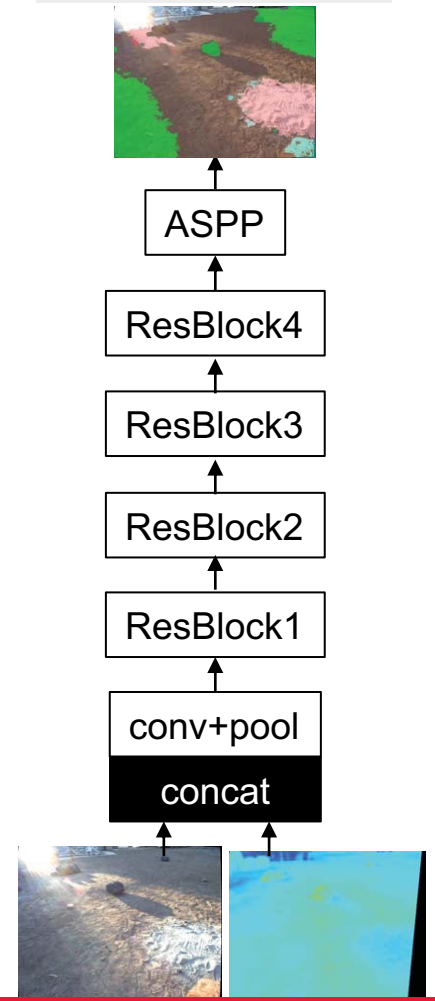


DeepLab (network for single modal)

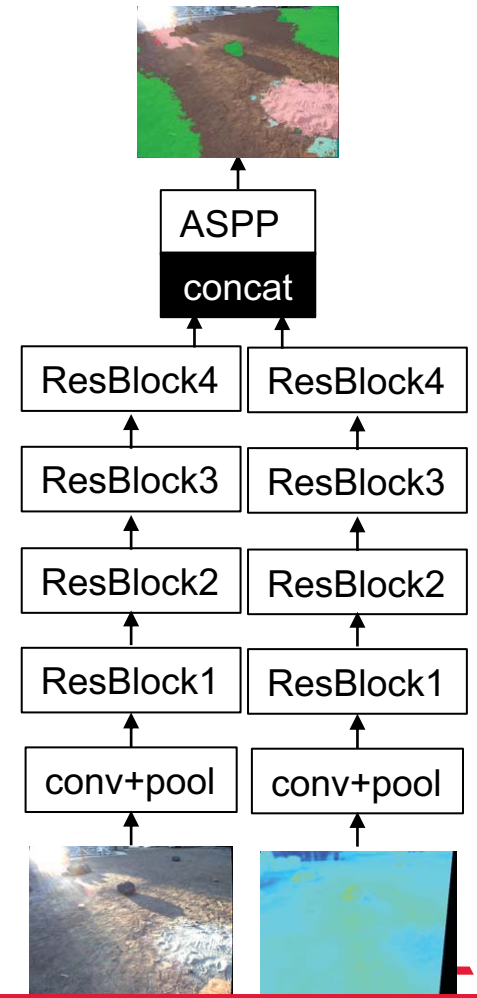


ResBlock: Residual Block
ASPP: Atrous Spatial Pyramid Pooling

TDeepLab BL



TDeepLab TL

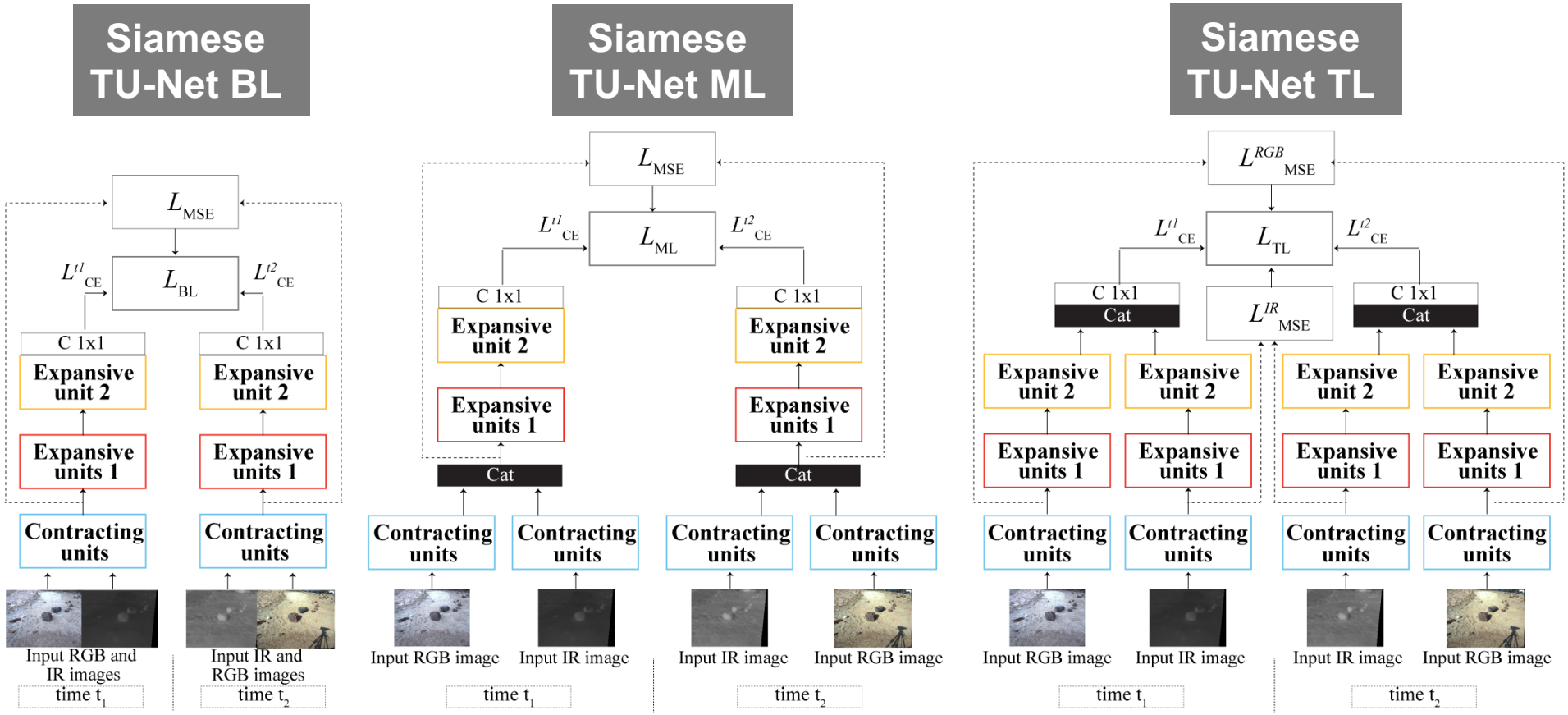


Siamese-based TU-Net and TDeepLab

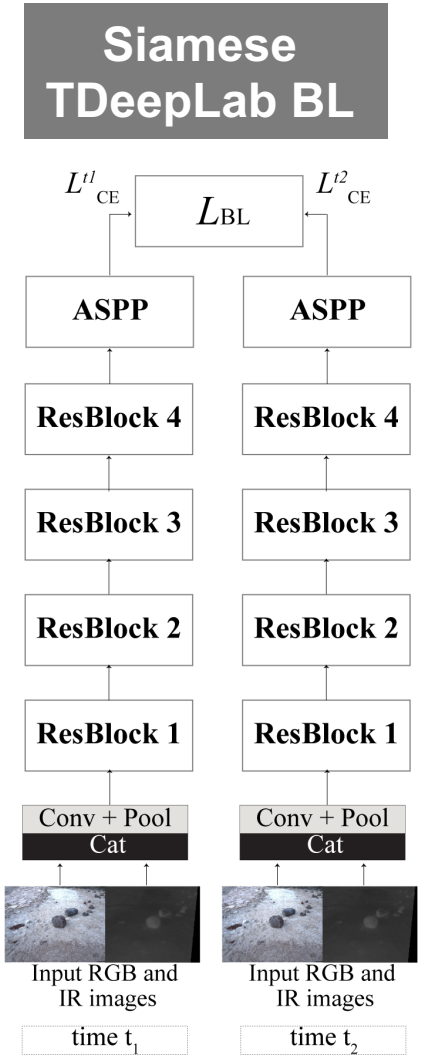
- TU-Net and TDeepLab can implicitly learn ***implicitly*** illumination changes with images captured at various time of a day

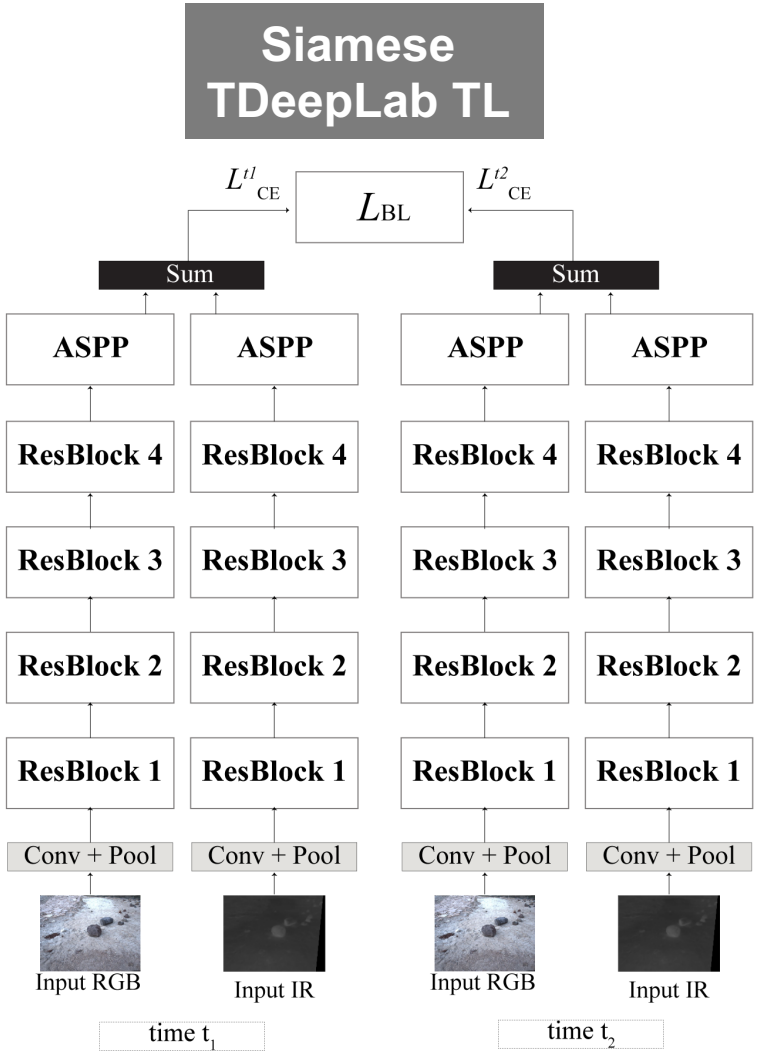
- To make it ***explicitly***, we integrate a Siamese approach into TU-Net and TDeepLab
  - 3 architectures of Siamese-based TU-Net
    - Siamese TU-Net BL, Siamese TU-Net ML, Siamese TU-Net TL
  - 2 architectures of Siamese-based TDeepLab
    - Siamese TDeepLab BL, Siamese TDeepLab TL

Siamese-based TU-Net



Siamese-based TDeepLab



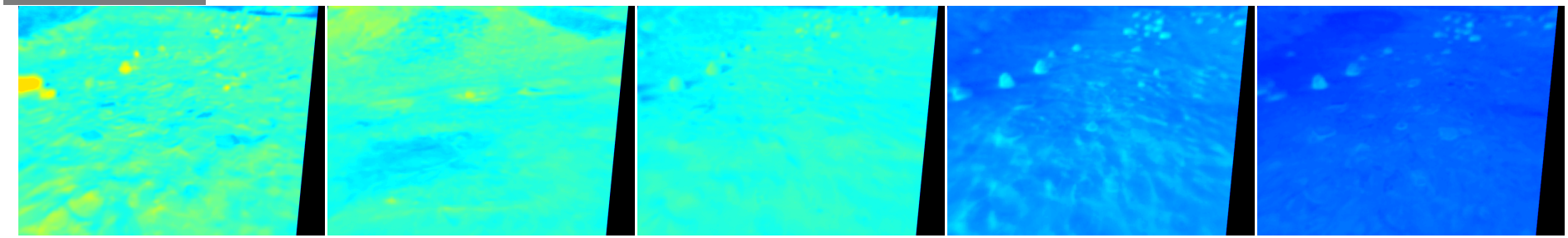


Experiment setting

- Dataset collection
  - Every 1 hour from 10 am till 5 pm on Nov 17th 2017, 52 images at each time
  - RGB camera (FLIR Grasshopper 5M) and thermal camera (FLIR AX65)
    - RGB images include challenging illumination changes

RGB images

IR images

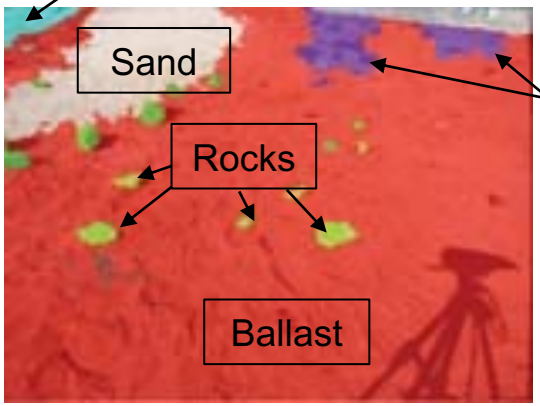


10 am | 12 pm | 2 pm | 4 pm | 5 pm

Experiment setting

- Manually annotated images into 6 categories
  - Sand, soil, rocks, bedrock, rocky terrain, and ballast

Captured RGB image



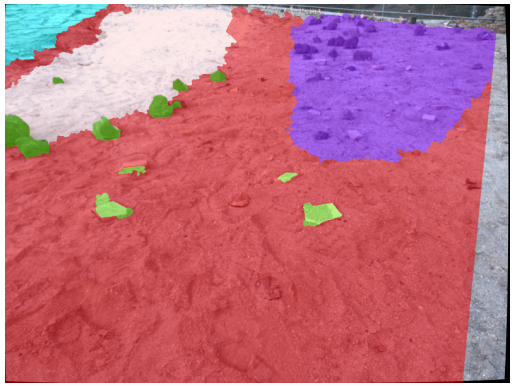
Ground truth annotated image

  - At each time 52 images are separated into 3 dataset
    - 50 % for training, 25 % for evaluation, and 25% for test dataset

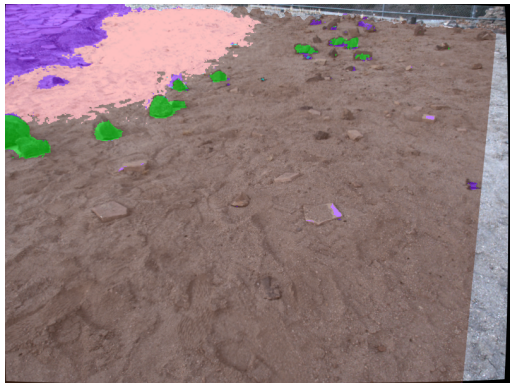
- Training a model
  - TU-Net is trained from a scratch
  - TDeepLab is finetuned (initial parameters are trained with COCO)

Exp 1. Train, evaluate, and test (all 5pm images)

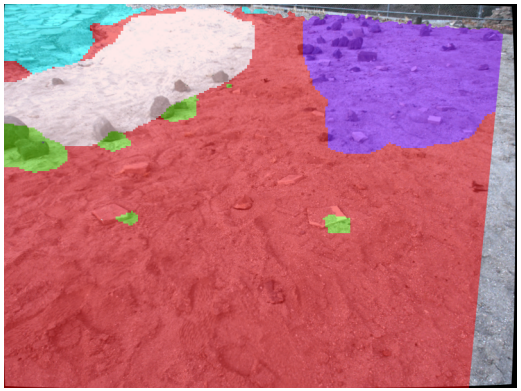
- Visualization of example results



Ground truth annotated image



Estimated result by TU-Net TL



Estimated result by TDeepLab TL

	Pixel accuracy	Mean accuracy	Mean IoU*	Frequency weighted IoU*
U-Net (RGB)	0.632	0.481	0.239	0.512
TU-Net BL (RGB + IR)	0.678	**0.529**	0.283	0.552
TU-Net ML (RGB + IR)	0.684	0.500	0.262	0.565
TU-Net TL (RGB + IR)	**0.727**	0.497	**0.304**	**0.592**
DeepLab (RGB)	0.871	0.708	0.599	0.781
TDeepLab BL (RGB+IR)	0.859	0.772	0.610	0.792
TDeepLab TL (RGB+IR)	**0.911**	**0.820**	**0.679**	**0.848**

*IoU (Intersection over Union)

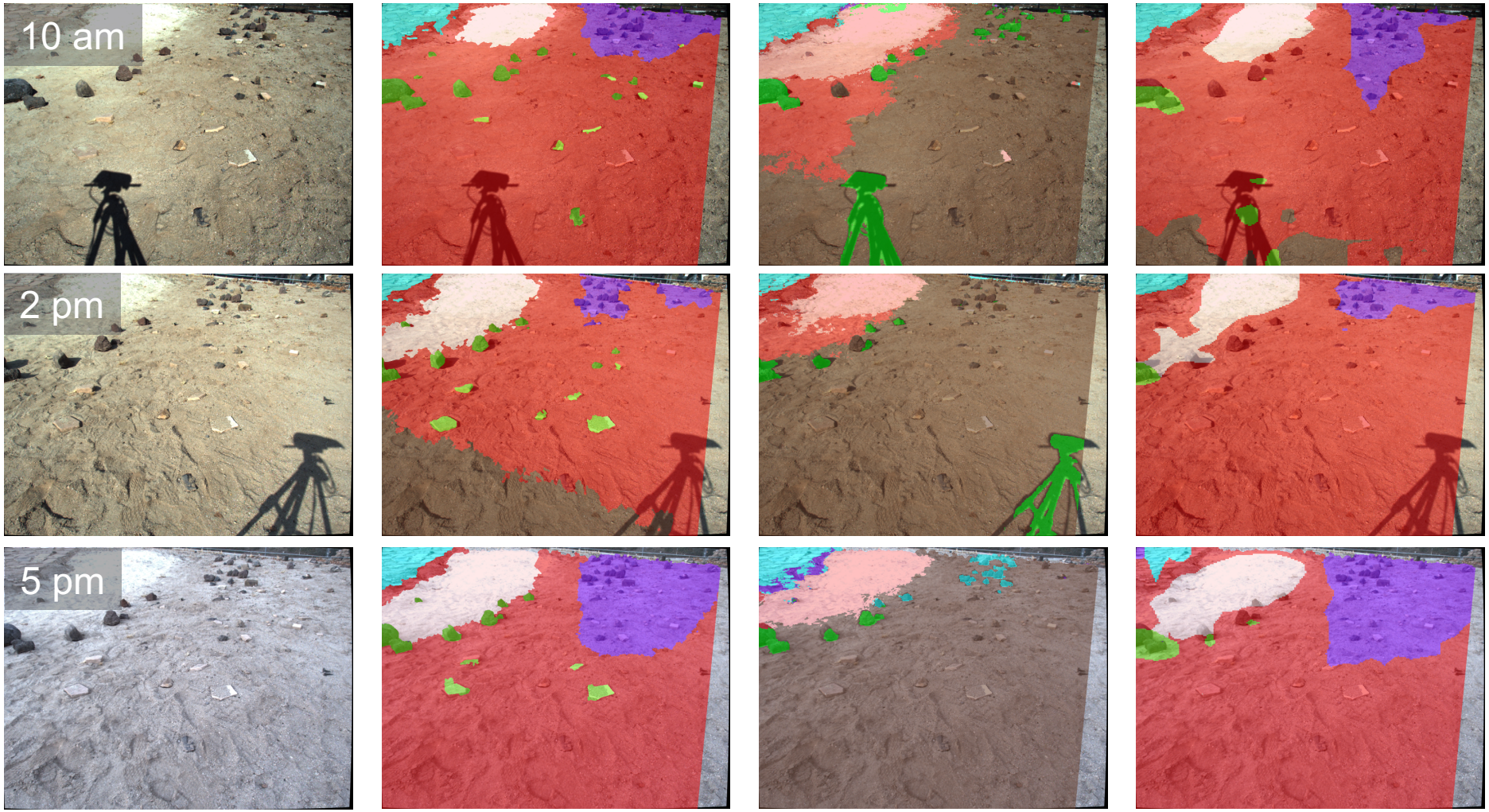
Exp 2. Train, evaluate, and test (all 10am-5pm images)

- Siamese-based TU-Net works better than TU-Net
  - Siamese TU-Net TL calculates a loss function of IR independently from the one of RGB
    - IR information without RGB shows some ambiguity
  - Both Siamese TU-Net BL and ML combines a loss function of IR and RGB
- On the other hand, Siamese-based TDeepLab is not effective
  - One of the reason might be over-trained

	Pixel accuracy	Mean accuracy	Mean IoU*	Frequency weighted IoU*
TU-Net TL	0.581	0.435	0.211	0.447
Siamese TU-Net BL	0.612	**0.542**	**0.307**	0.491
Siamese TU-Net ML	**0.620**	0.534	0.303	**0.505**
Siamese TU-Net TL	0.563	0.517	0.257	0.463
TDeepLab TL	**0.911**	**0.820**	**0.679**	**0.848**
Siamese TDeepLab BL	0.803	0.665	0.482	0.696
Siamese TDeepLab TL	0.864	0.731	0.600	0.771

Exp 3. Train and evaluate (2pm-5pm), and test (10am-1pm)

- Visualization of example results



Original image | Annotated image | Siamese TU-Net ML | TDeepLab TL

Exp 3. Train and evaluate (2pm-5pm), and test (10am-1pm)

- Results of Siamese TU-Net ML

Test data	Pixel accuracy	Mean accuracy	Mean IoU*	Frequency weighted IoU*
10am – 1pm	0.633	0.461	0.279	0.531
2pm – 5pm	0.687	0.529	0.374	0.559

- Results of TDeepLab TL

Test data	Pixel accuracy	Mean accuracy	Mean IoU*	Frequency weighted IoU*
10am – 1pm	0.861	0.816	0.625	0.772
2pm – 5pm	0.886	0.786	0.653	0.806

Conclusions

- We proposed novel deep learning-based terrain classification methods robust to illumination variations, called TU-Net and TDeepLab and those Siamese-based methods

- Future work
  - Compare the proposed approaches with AdapNet++
  - Integrate depth information

Backup

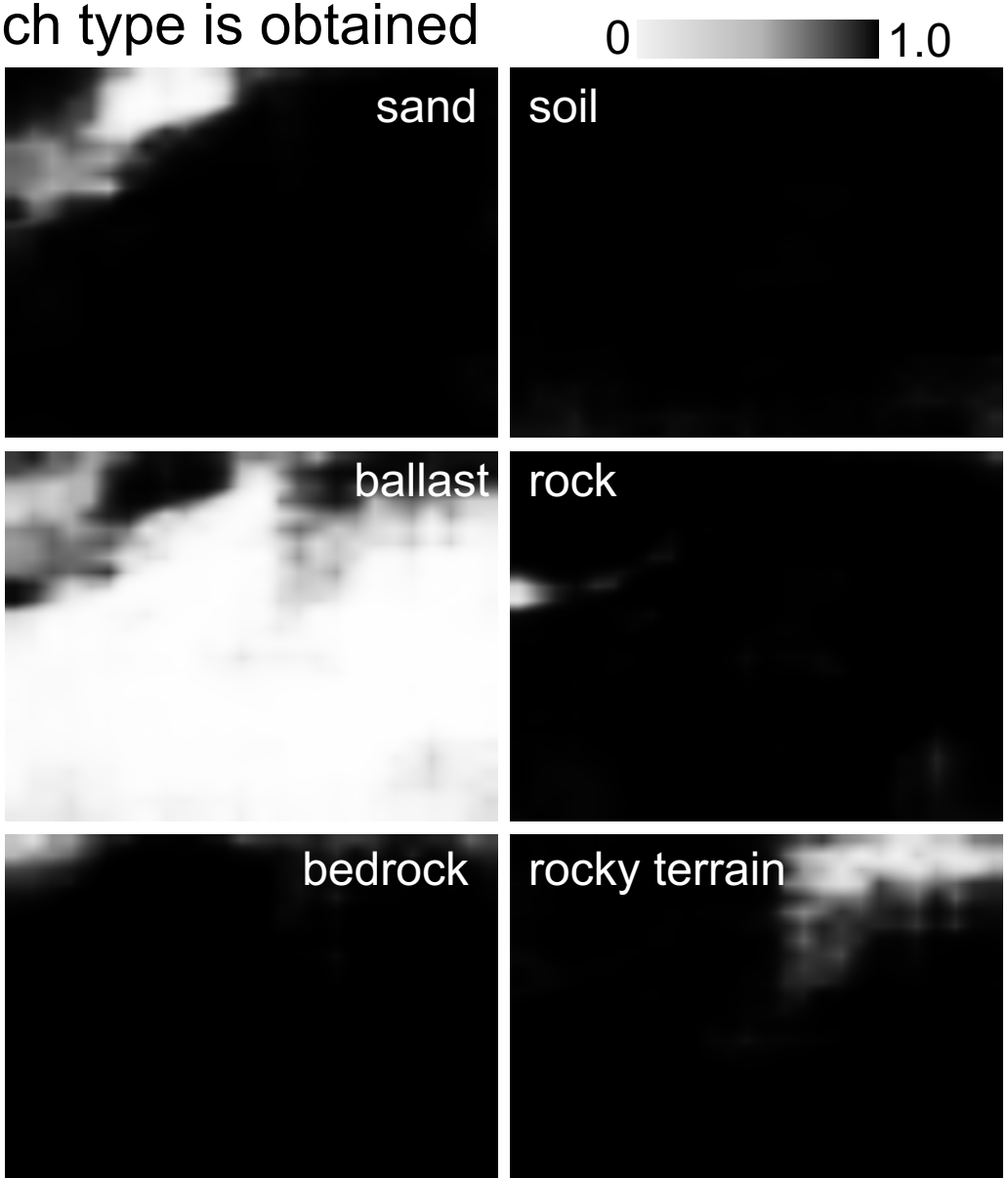
TDeepLab

- Probability of each type is obtained

Result by TDeepLab

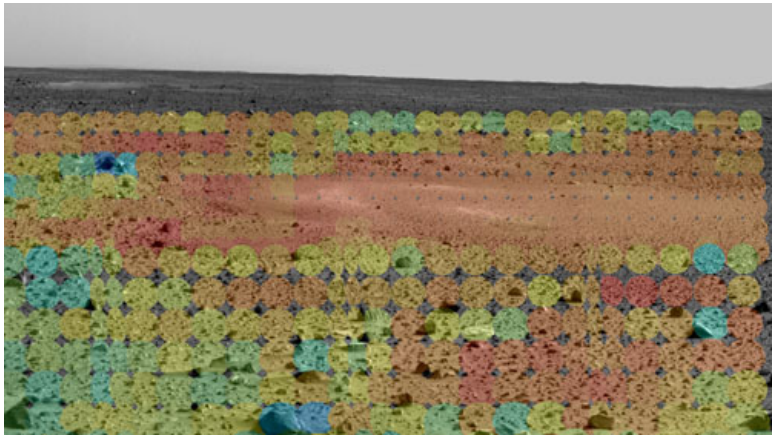
Probabilities
sand: 0.35
ballast: 0.65

It can estimate how many types / the proportion of terrain types



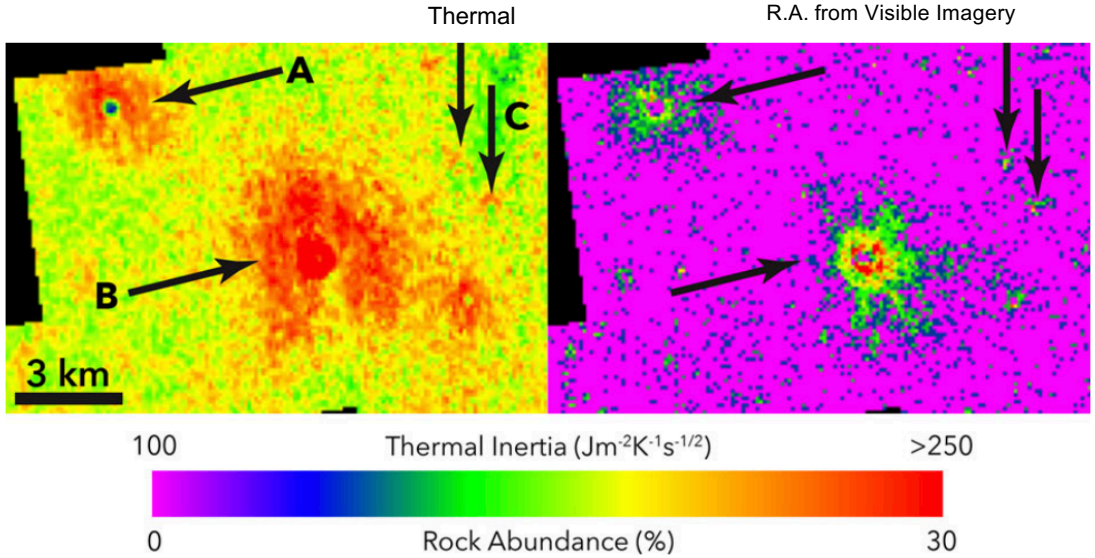
Benefits of IR images

- Remote measurements of mineralogy and thermophysical properties of the scene



Colorized mini-TES image (Spirit). The different colored circles show a spectrum of soil and rock temperatures

- Estimate rock size from orbiters
  - Useful for future landing site selection



Golombek et al. 2018