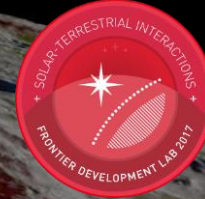


NASA-FDL: Artificial Intelligence in Planetary Science Lunar Resource Mission

D. Backes, E. Bohacek, A. Dobrovolskis, T. Seabrook
Sara Jennings, James Parr



UNIVERSITÉ DU
LUXEMBOURG



Agenda

Great Opportunity
for young Scientists

- Frontier Development Lab (FDL) – an applied research accelerator
- Deep Dive in Artificial Intelligence (AI), Machine Learning, Deep Learning Big Data
- The Lunar Resource Missions of FDL 2017

Maybe nice but
not enough time
for a 'Deep Dive'

Quick fly trough

Nasa Frontier Development Lab NASA-FDL

'FDL is an applied Artificial Intelligence research accelerator designed to enhance NASA's capabilities by combining the expertise of NASA, Academia, and the private research community.'

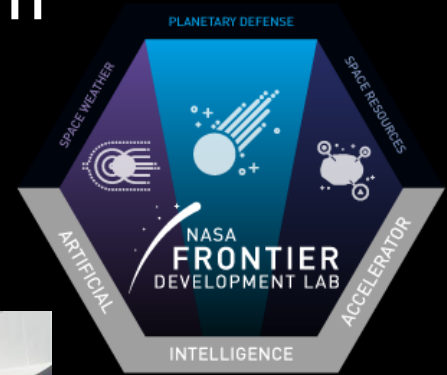
Novel Private Public Partnership which brings together:

- Young Planetary and Data Scientists
- Domain experts from NASA and the private sector



FDL, 6 Missions addressed by one team

- Planetary defence



- Planetary resources



- Space weather prediction

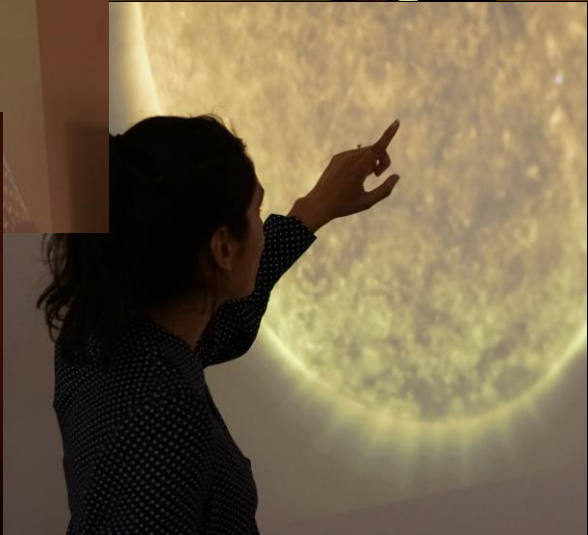
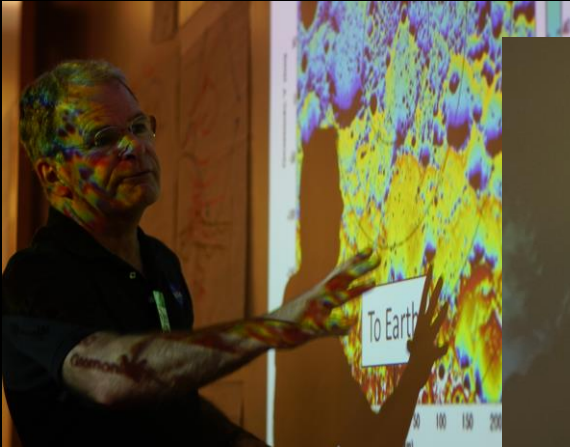
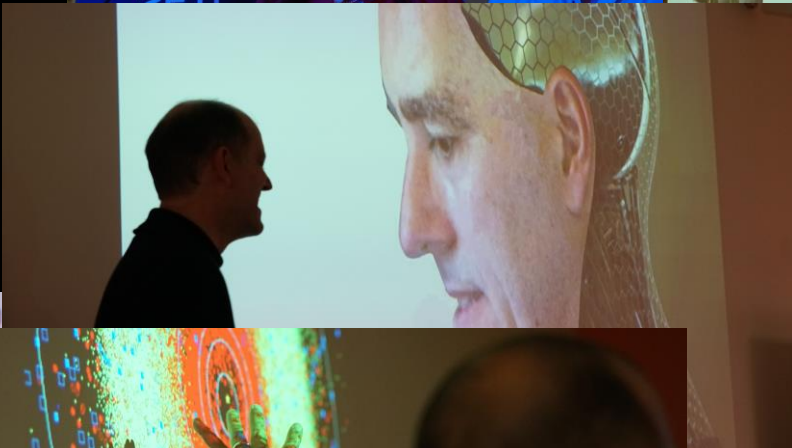
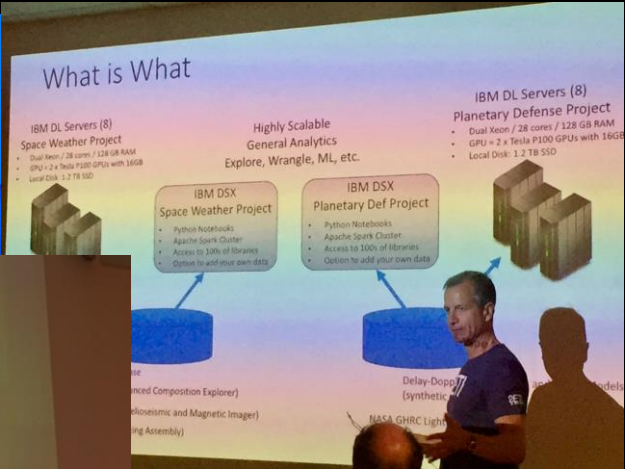


- AI case study



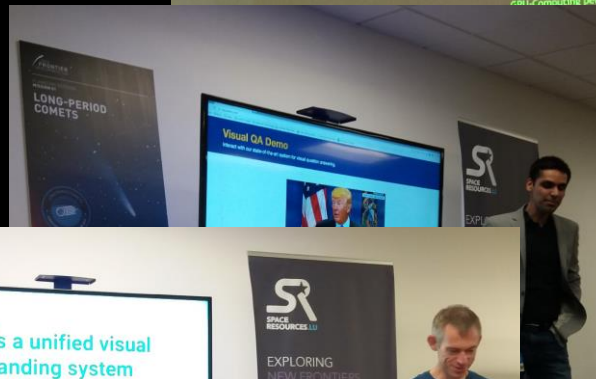
FDL Functions

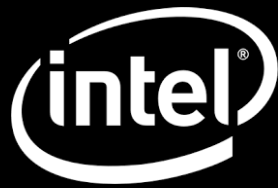
- Research Accelerator
- Research Incubator



FDL Functions

- Summer School
- Team building and interpersonal skills

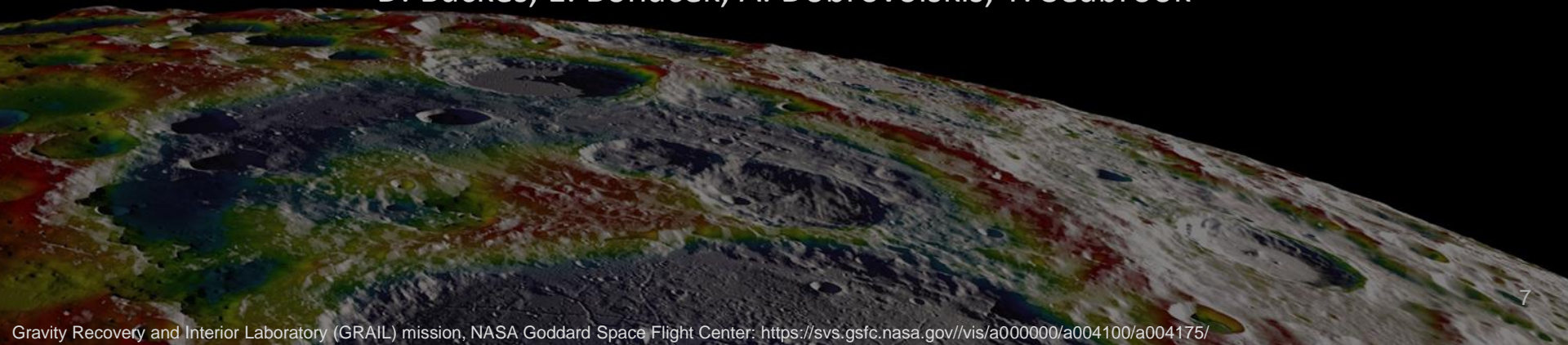




Automated Crater Detection Using Deep Learning

NASA FDL Lunar Volatiles Team

D. Backes, E. Bohacek, A. Dobrovolskis, T. Seabrook



FDL Space Resources Team



Dietmar Backes

Geoinformatics
Université du Luxembourg



Eleni Bohacek

Computer Vision
and Planetary Science
University College London



Tony Dobrovolskis

Planetologist
SETI Institute



Timothy Seabrook

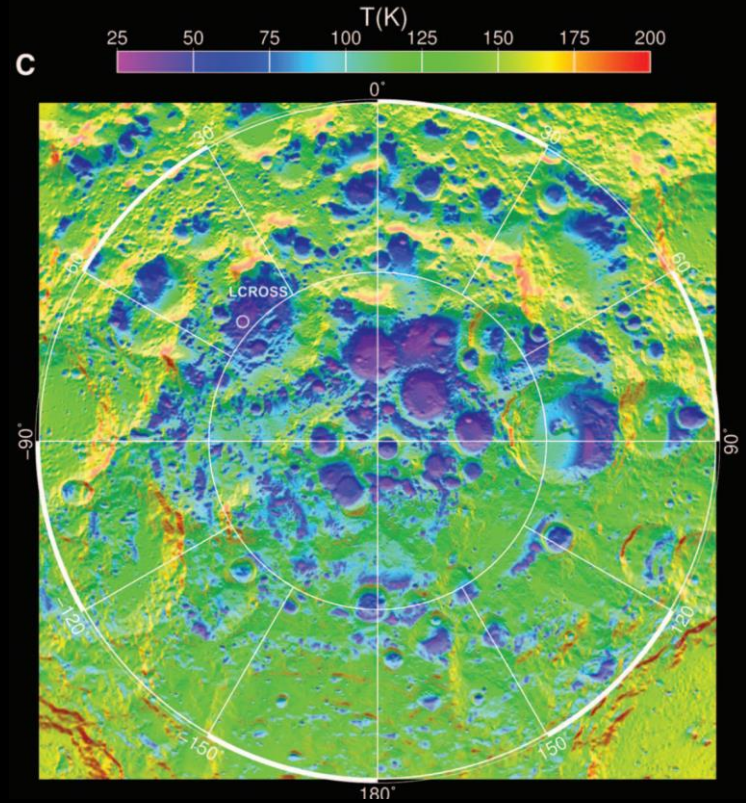
Autonomous Intelligent Machines
& Systems
University of Oxford





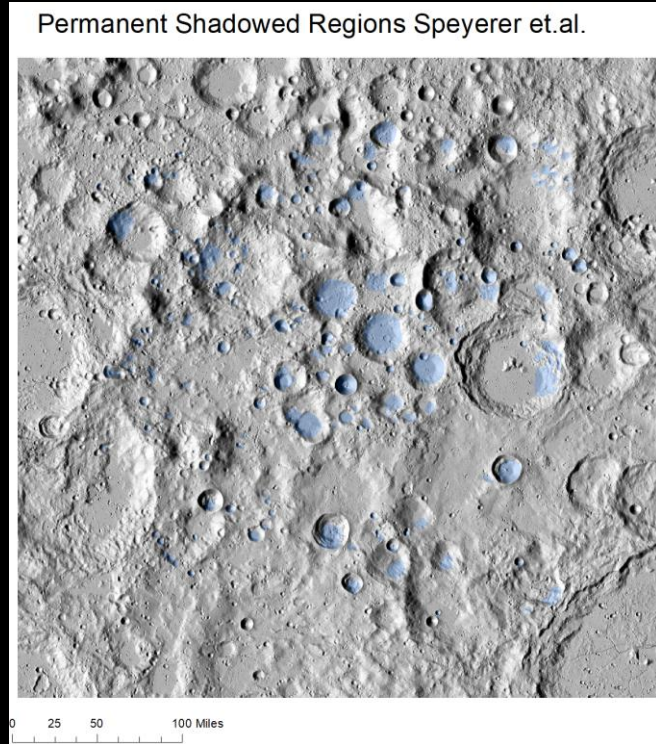
Where is water on the moon?

- Craters near the poles
- Some floors of these craters never see the sun
- Permanently Shadowed Regions (PSRs)



*Simulated annual average near-surface temperatures
Paige et al., Science 330 (2010); www.sciencemag.org*

Permanently Shadowed Regions



Missions are being planned for *In Situ* measurements



Credit: NASA

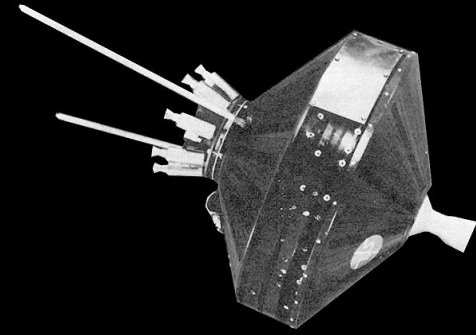
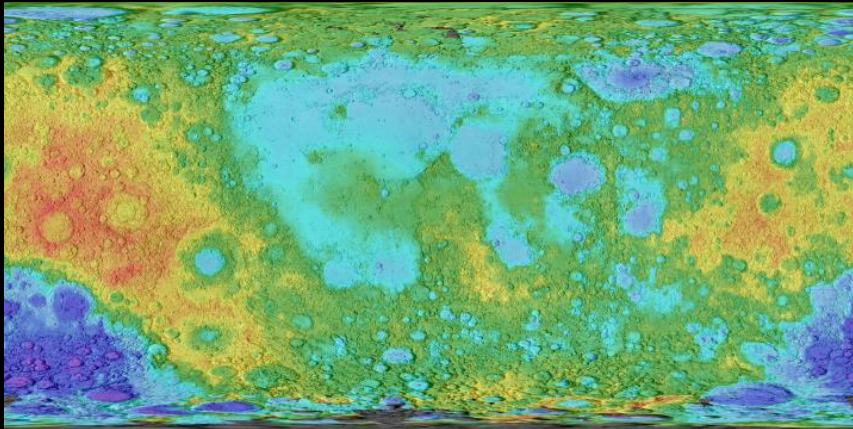
We learned that Mission Planners lack adequate maps.

Mapping on the Moon:

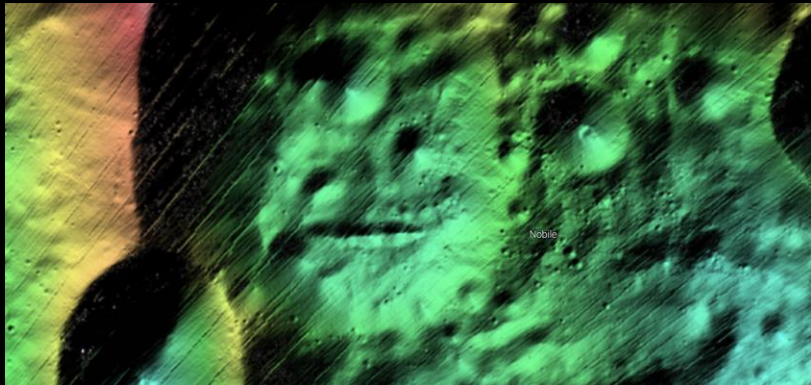
Reconnaissance Missions since late 1950's - 1960's

Plethora of Reconnaissance data

Lunar Reconnaissance Orbiter mission since 2009:



Mapping Quality

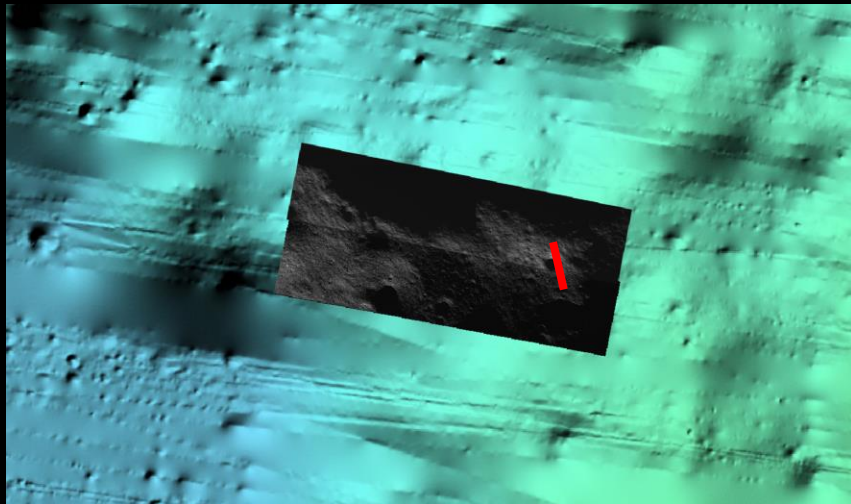


Lunar Orbiter Laser Altimeter
Digital Elevation Model (LOLA DEM), 20 m resolution



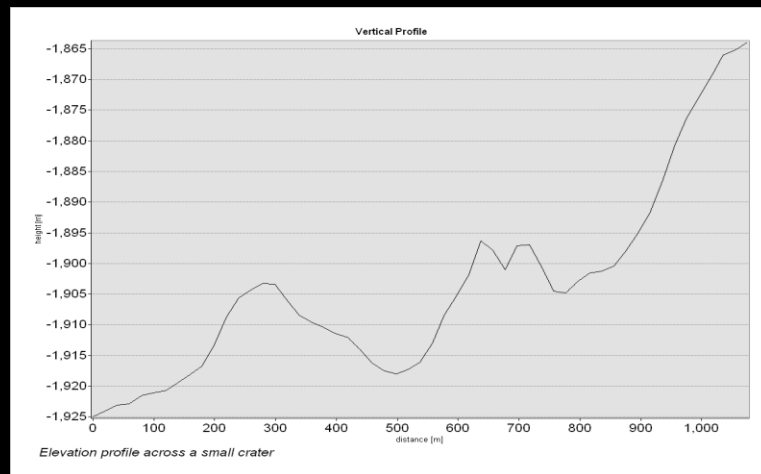
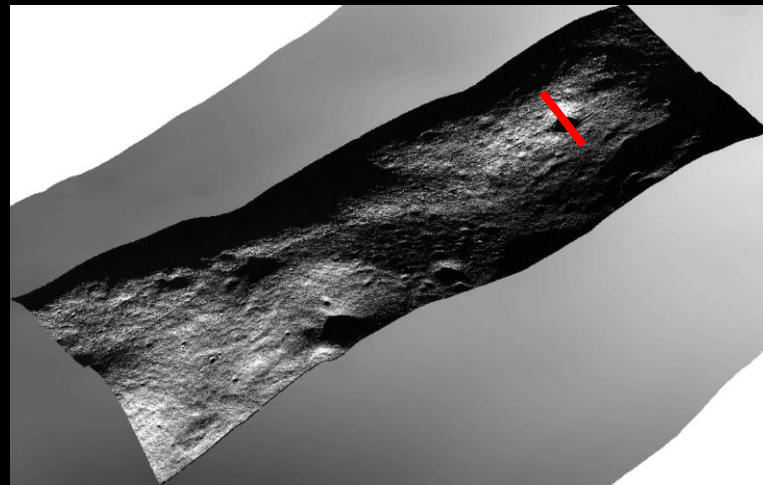
Narrow Angle Camera (NAC)
Optical images, 0.5 m resolution

Mapping Quality



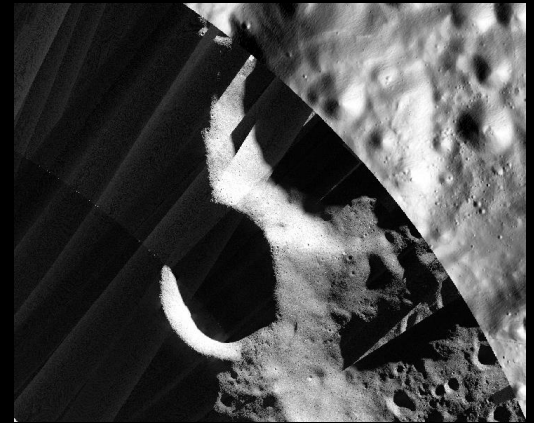
0 0.5 1 2 3 4 Kilometers

 Profile



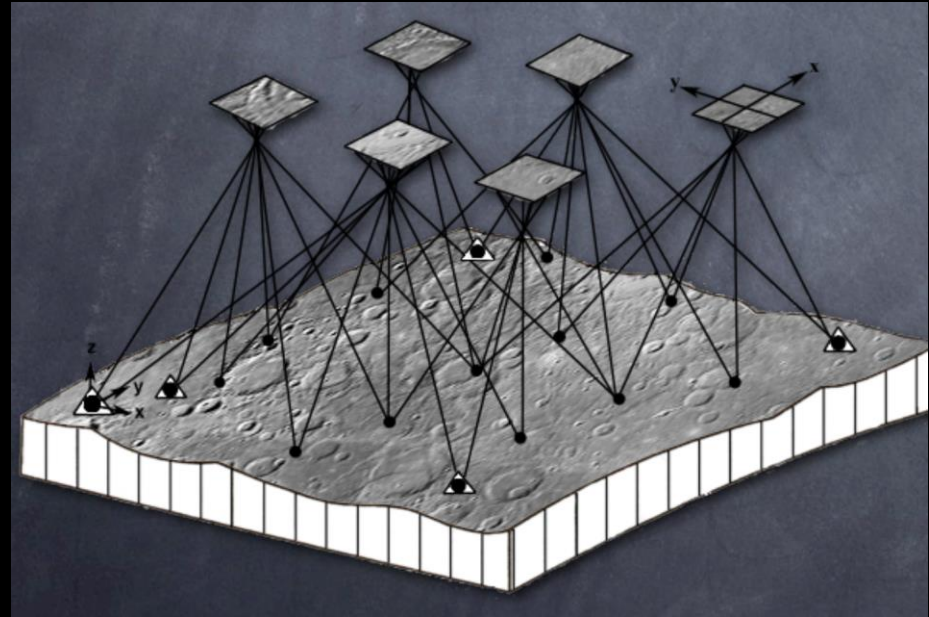
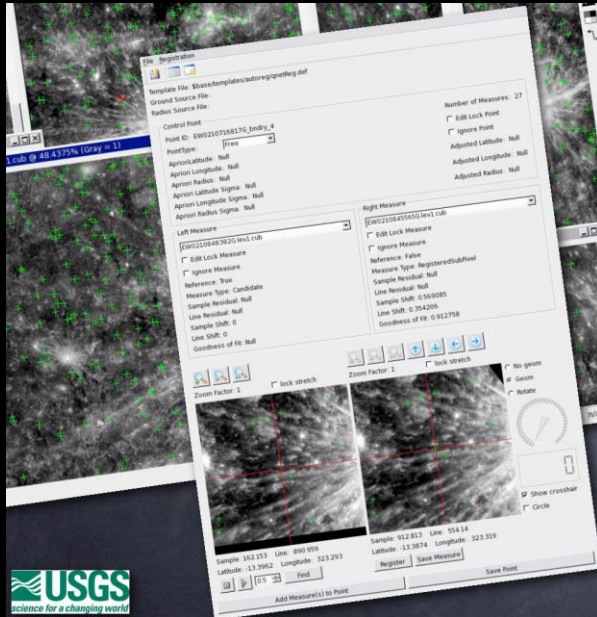
Problem Summary

- Most of lunar water is in PSRs at the poles
- Mapping at the poles is problematic
 - Co-registration issues
 - Artifacts
 - Image illumination
- Labour intensive data preparation is required before meaningful mission planning can be conducted

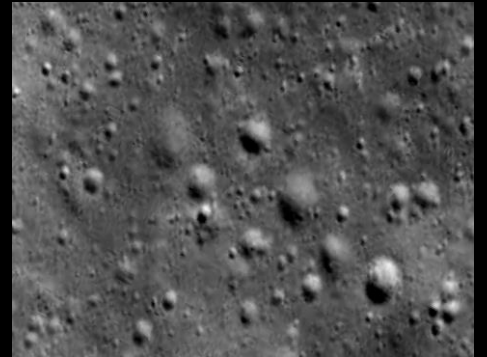
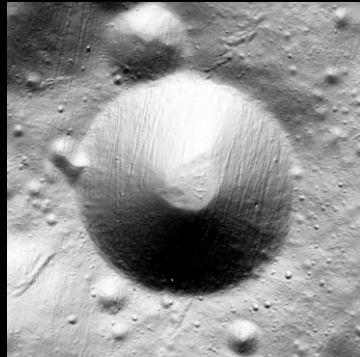
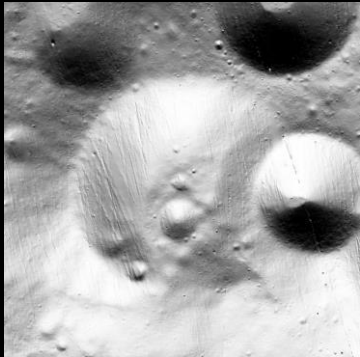
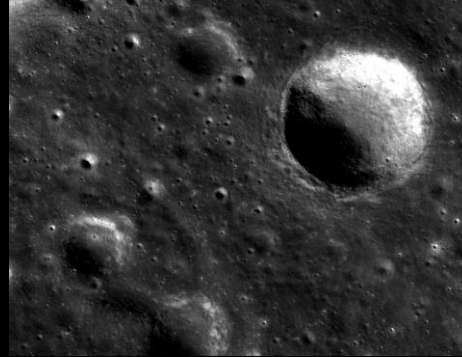


Nobile Crater: optical image mosaic overlaid over DEM

Improving Maps Conventionally, how do we solve co-registration and artifacts?

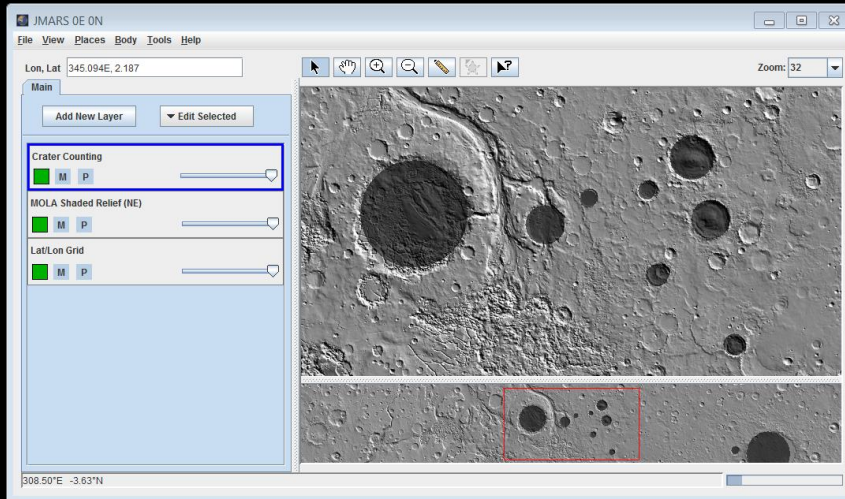


Common features are Craters



Crater Detection at Present

- ~77 crater detection algorithms published as of 2011 (Salamunićcar et al.)
- Rarely adopted by larger community
- Nearly all crater ID done by hand



Automatic Crater Detection Using Convex Grouping and Convolutional Neural Networks

Ebrahim Emami¹, George Bebis^{1(CS)}, Ara Nefian², and Terry Fong²

Available online at www.sciencedirect.com
ScienceDirect
 Advances in Space Research 54 (2014) 2419–2429

ELSEVIER

ADVANCES IN SPACE RESEARCH
 (a COSPAR publication)
www.elsevier.com/locate/ast

A machine learning approach to crater detection from topographic data

Kaichang Di^a, Wei Li^{a,b}, Zongyu Yue^{a,*}, Yiwei Sun^{a,b}, Yiliang Liu^{a,b}

^aState Key Laboratory of Remote Sensing Science, Institute of Remote Sensing and Digital Earth, Chinese Academy of

Hybrid Method for Detection of Lunar Craters Based on Topography Reconstruction from Optical Images

G. Salamunićcar^{1,2}, S. Lončarić², A. Grumpe³, C. Wöhler³
¹AVL-AST d.o.o., Av. Dubrovnik 10/II, HR-10020 Zagreb-Novki Zagreb, Croatia, gsc@icee.org
²Faculty of Electrical Engineering and Computing, University of Zagreb, Unska 3, HR-10000 Zagreb, Croatia, sven.koncic@fer.hr
³Faculty of Electrical Engineering and Information Technology, Dortmund University of Technology, Otto-Hahn-Str. 4, D-44227 Dortmund, Germany, ([@arne.grumpe](mailto:arne.grumpe@christian.woehler) | [@christian.woehler](mailto:christian.woehler))@tu-dortmund.de

Approaches to Detecting Impact Craters in Planetary Images

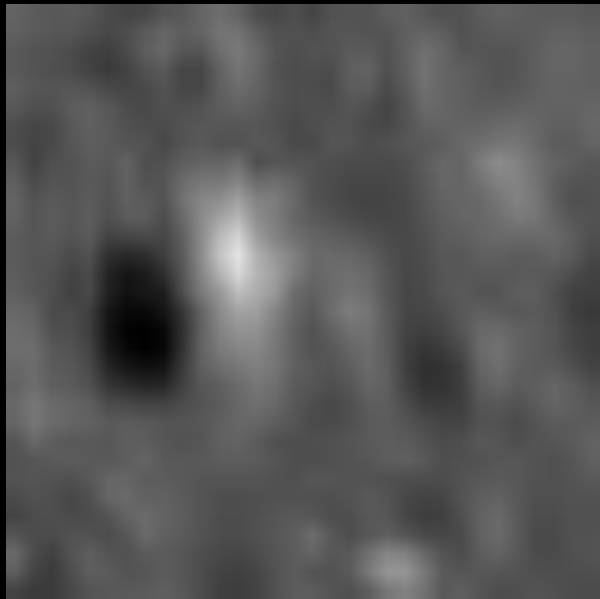
T. F. Stepinski¹, Wei Ding², R. Vilalta³
¹Dept. of Geography, Univ. of Cincinnati, OH 45221, USA. ²Dept. of Computer Science, Univ. of Massachusetts Boston, 100 Morrissey Blvd. Boston, MA 02125-339, USA. ³Dept. of Computer Science, University of Houston, 4800 Calhoun Rd., Houston, TX 77204, USA.

AUTOMATIC CRATER RECOGNITION USING MACHINE LEARNING WITH DIFFERENT FEATURES AND THEIR COMBINATION. A. Boukercha¹, A. Al-Tameemi¹, A. Grumpe¹ and C. Wöhler¹; ¹Image Analysis Group, TU Dortmund University, D-44227 Dortmund, Germany; [@arne.grumpe](mailto:anis.boukercha@atheer.altamimi@arne.grumpe@christian.woehler) | [@tu-dortmund.de](mailto:christian.woehler).



Breakthrough Solution

Crater Extractor
for Polar and Equatorial Regions



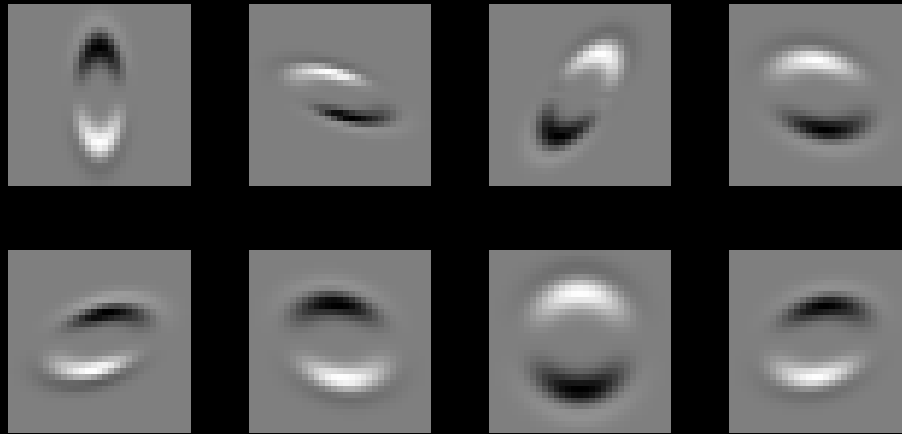
Crater?

Vs.



No Crater?

Adaptive Convolution Filter



Represents a formulated baseline approach to crater detection.



1. A NEW Features Dataset

18000 Labelled DEM Tiles

16000 Labelled Polar NAC Tiles

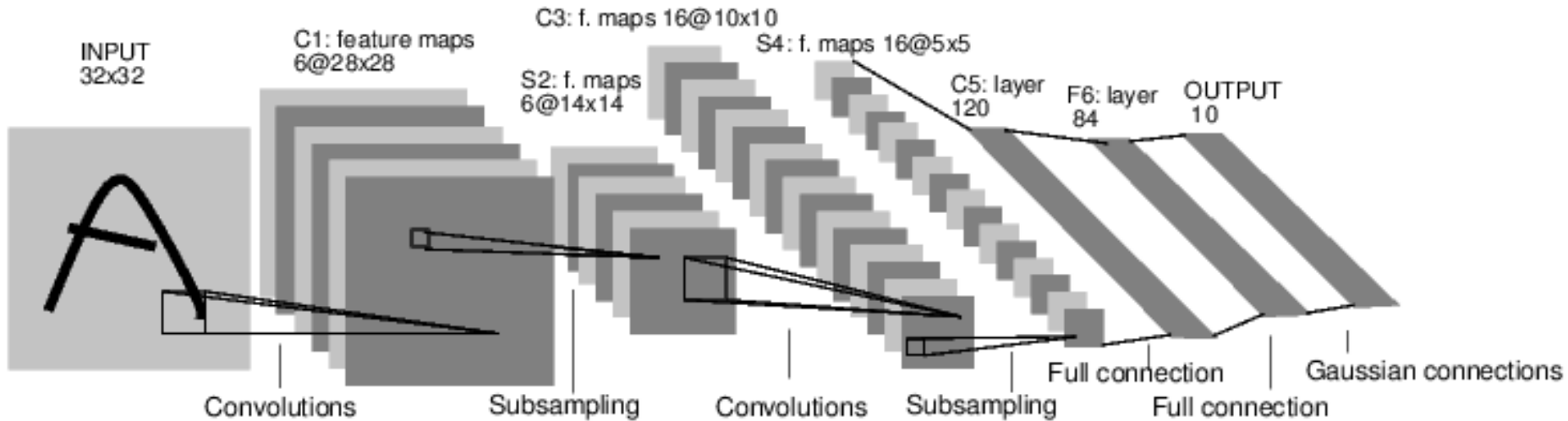
6000 Labelled Equatorial NAC Tiles

2800 Annotated DEM craters

450 Annotated NAC craters

And many tens of thousands unlabelled...

2. Deep Learning Classifier



Automated Crater Detection

Accuracy Compared with Previous Work

Group	Vijayan et al.	Di et al.	Emani et al.	FDL
Year	2013	2014	2015	2017
Method	Pattern recognition	Pattern recognition	CNN	CNN
Precision (%) (Accuracy)	91	87	86	98
Error Rate (%)	9	13	14	2

The Importance of Being Polar

Dataset	Test Region	Error Rate (%)
Equatorial	Equatorial	5.05
Equatorial	Polar	9.68
Polar	Polar	2.02
Both	Polar	1.61

Timing Comparison of Our Techniques

Group	Human	Single-Layer	CNN
Accuracy	-	Poor	98.4%
Time (1000 Images)	1-3 hours	10 hours	1 minute
Person-hours	1-3 hours	-	-

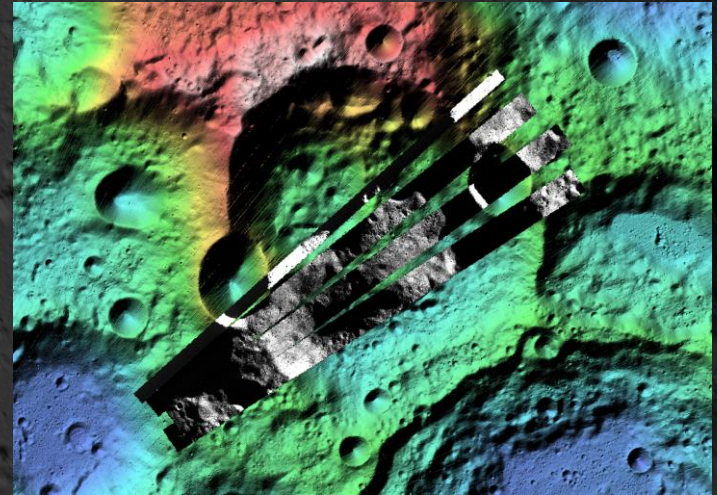
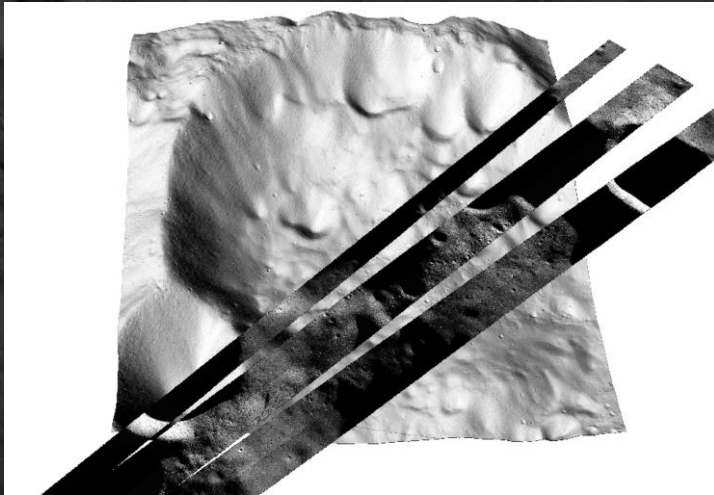
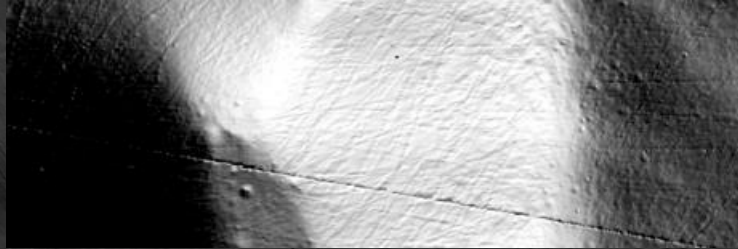
We need more training data: <http://www.frontierdevelopmentlab.org/ai-lunar-mapping/moonshot.html#>



Search for water at the lunar poles

Reach for the Stars!

Future Opportunities



Acknowledgements



Yarin Gal, Chedy Raissi, Phil Metzger, Brad Blair, Rick Elphic, Nader Moussa, Casey Handmer



Shashi Jain, Ravi Panchumarthy, Nagib Hakim, Pallab Paul, Gabe Sutherland, Tasnia Kabir



Take away:

FDL:

- Great opportunity for young Scientists
- Call for FDL 2018 is open: <http://frontierdevelopmentlab.org/#/apply>



Lunar Resource Missions & Artificial Intelligence:

- FDL2017 defined a project and set up early prototypes
- The mission will continue in 2018: intel.ly/fdl

AI will have a considerable impact to EO and RS





Thank You