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DeepGeoMap: A deep learning convolutional neural network architecture for geological hyperspectral classification and mapping

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Motivation

Image: Jean Beaufort

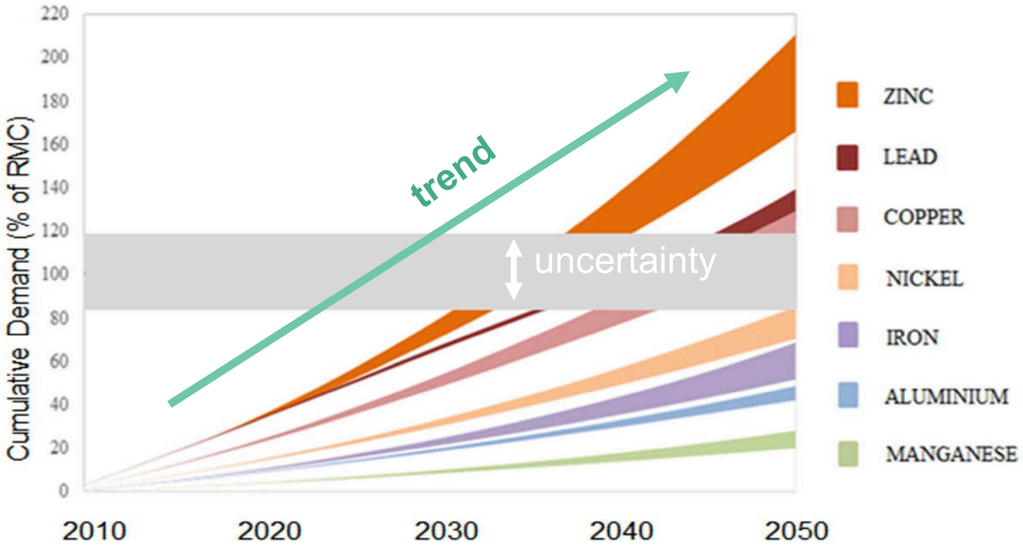
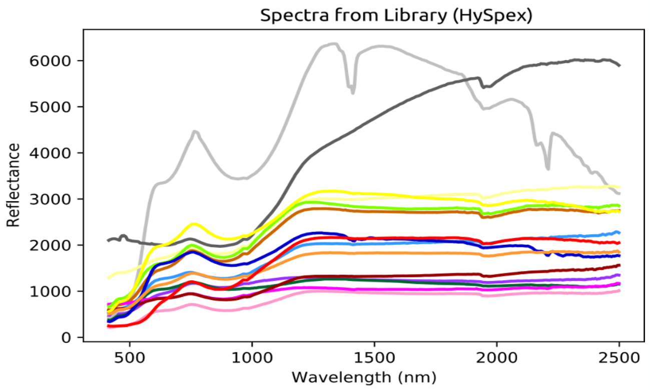


Image: Elshkaki et. al, 2018



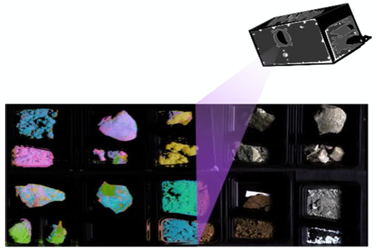
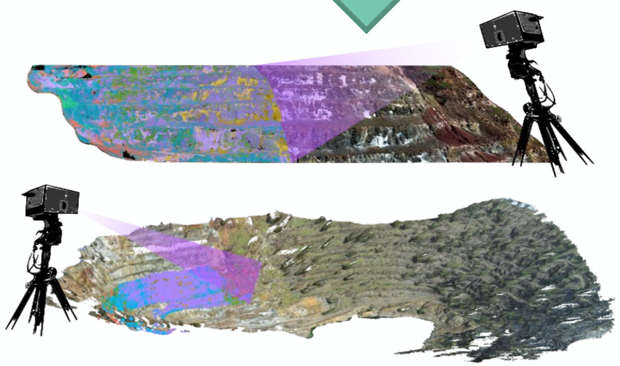
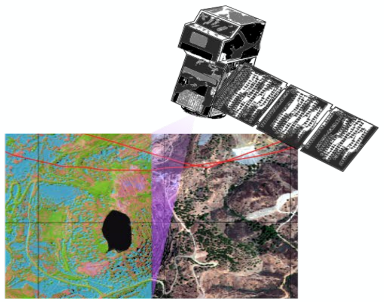


Image: Koerting (2021)





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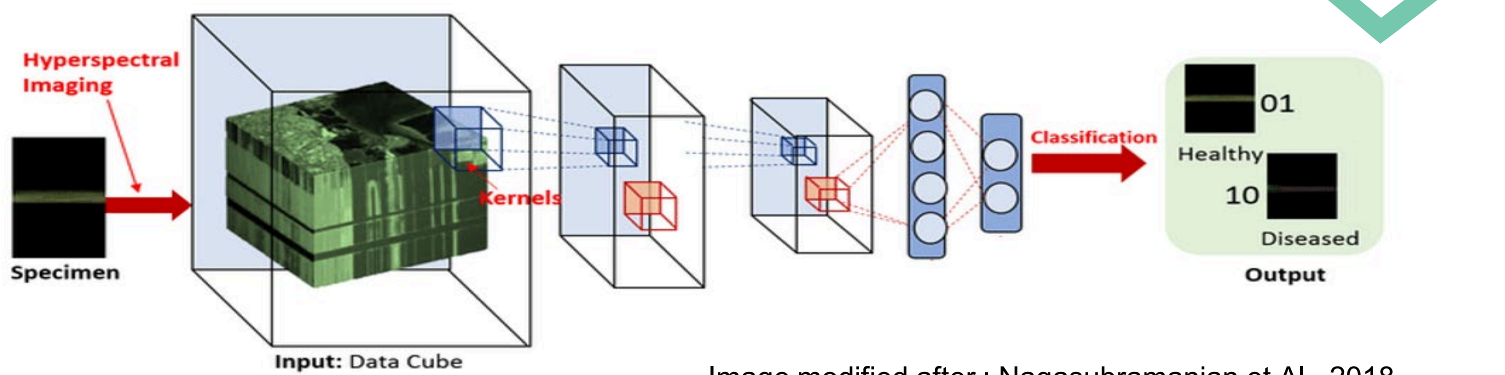


Image modified after : Nagasubramanian et Al., 2018

Image: Global Trade Team SDN BHD

- **Geological or soil patterns often spatially much more complex than objects in other image detection diciplines where 2D or 3D neural netwoks function well**
- **Shape of a rock is not necessarily indicative for the minerolgy of the rock but for larger geologial processes**

DeepGeoMap: Concept

- 1D deep learning convolutional neural network architecture for geological hyperspectral classification and mapping

- Spectrally focused, and spatial information independent

- Allows the models to be trained with spectral data from many different instruments (including point-spectrometers)
  - Requirement: same spectral region and number of bands

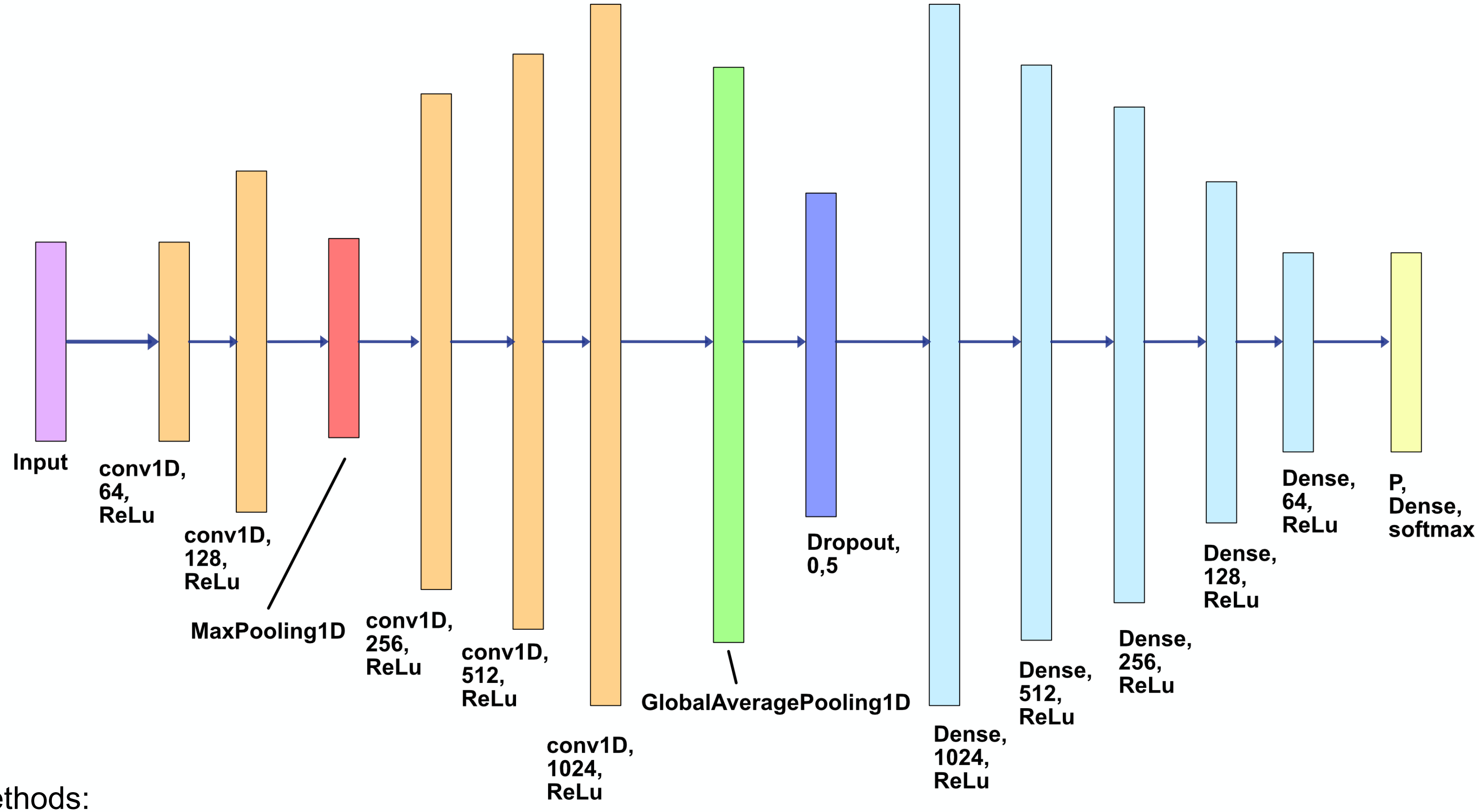
DeepGeoMap: Concept

- DeepGeoMaps architecture represents a signal analysis tool that can be used for any kind of signal data classification and categorisation

- One of the main ideas: train models with hyperspectral images of geochemically validated samples acquired under laboratory conditions

avoids or reduces the number of false positives due to mixed-spectra or falsely labelled training data/pixels in lower resolution airborne or satellite data

DeepGeoMap: Architecture



Backpropagation methods:

- *categorical crossentropy loss* function with an *Adam* gradient descent optimization

Data Input

Data is split 60/40 into training and test data and randomized beforehand

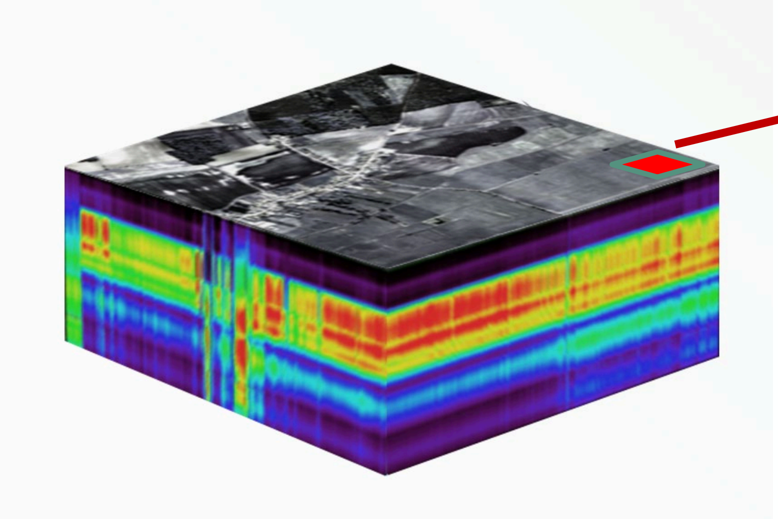
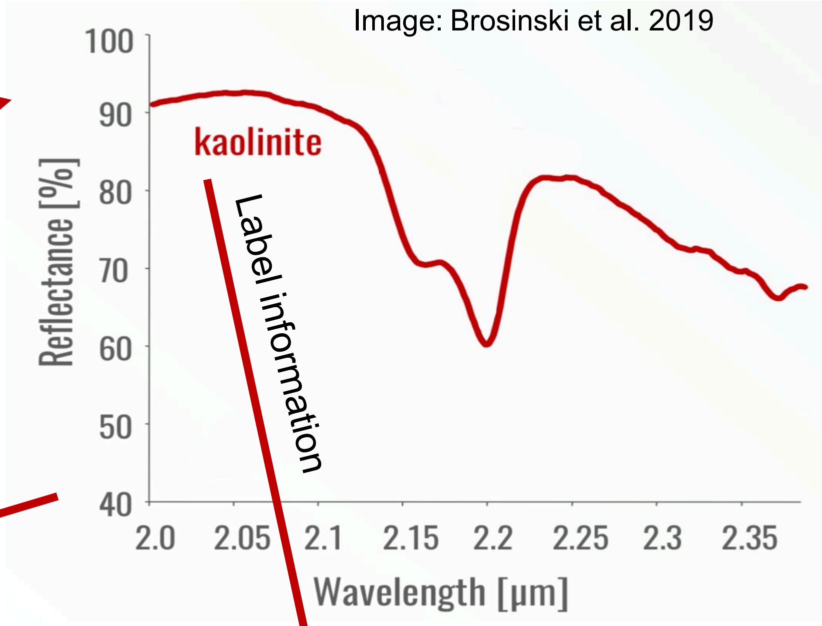


Image: Brosinski et al. 2019

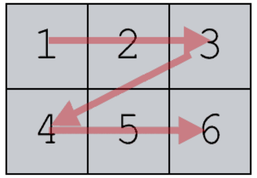
Spectral information



Spectral information

Conversion to binary numbers (one hot encoding):

Conversion to 1D Data (Array flatening):




```
array.flatten(order = 'C')
```

1	2	3	4	5	6

Image: Ebner et al. 2021

Input for Neural Net:

Spectral 1D array input (xTrain) + Label input e.g. 'Kaolinite' as binary (yTrain)

Methods: Example Data Apliki + Acquisition

Image: Google maps 2021

Outcrop mine face scan + sample measurements in Lab

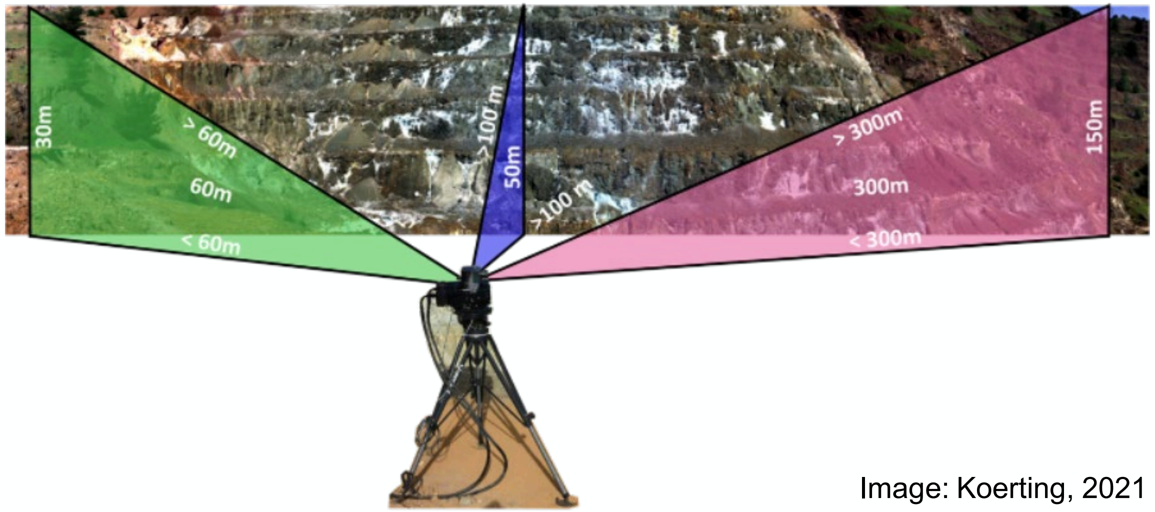


Image: Koerting, 2021

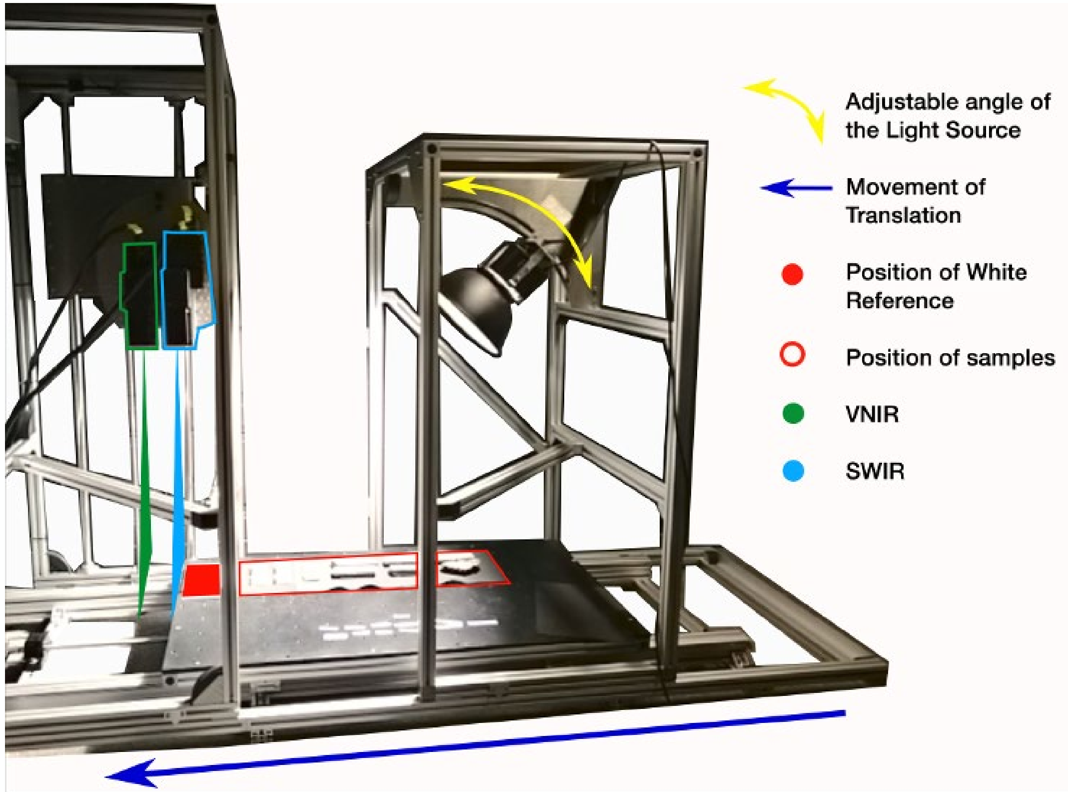
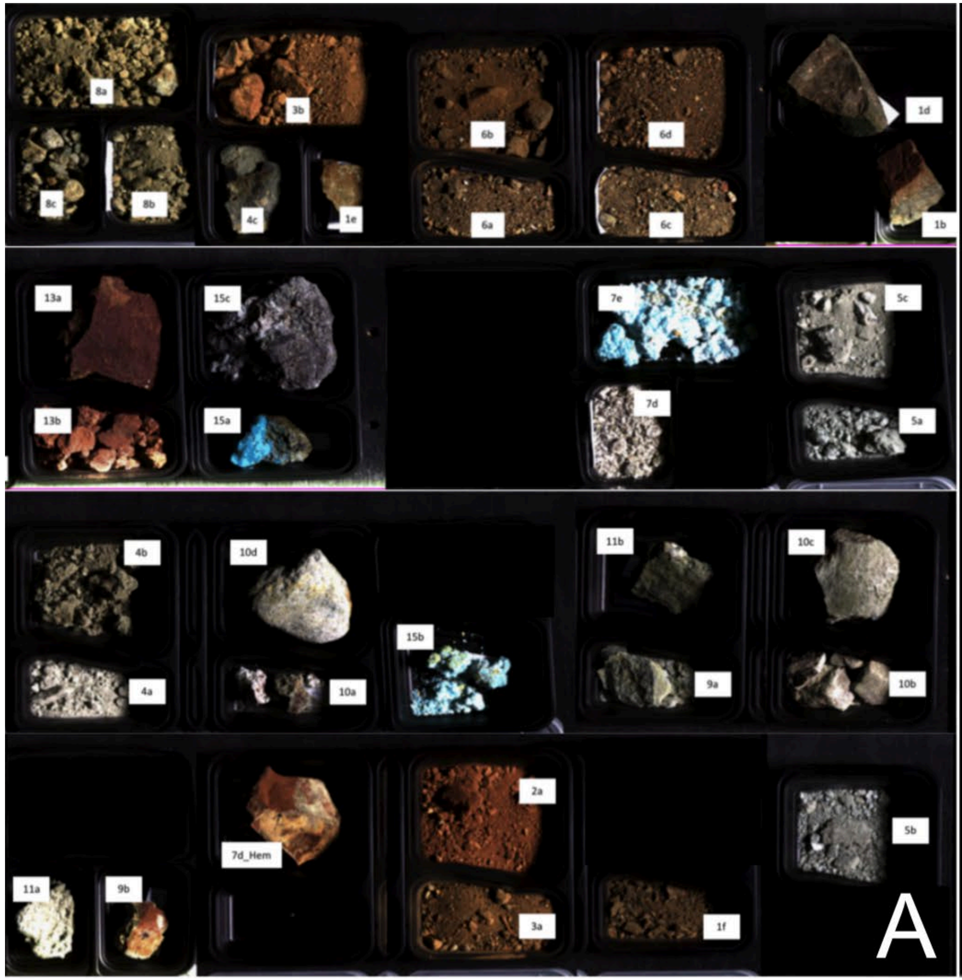


Image: Koerting, 2021

Methods: Data Samples - Apliki mine



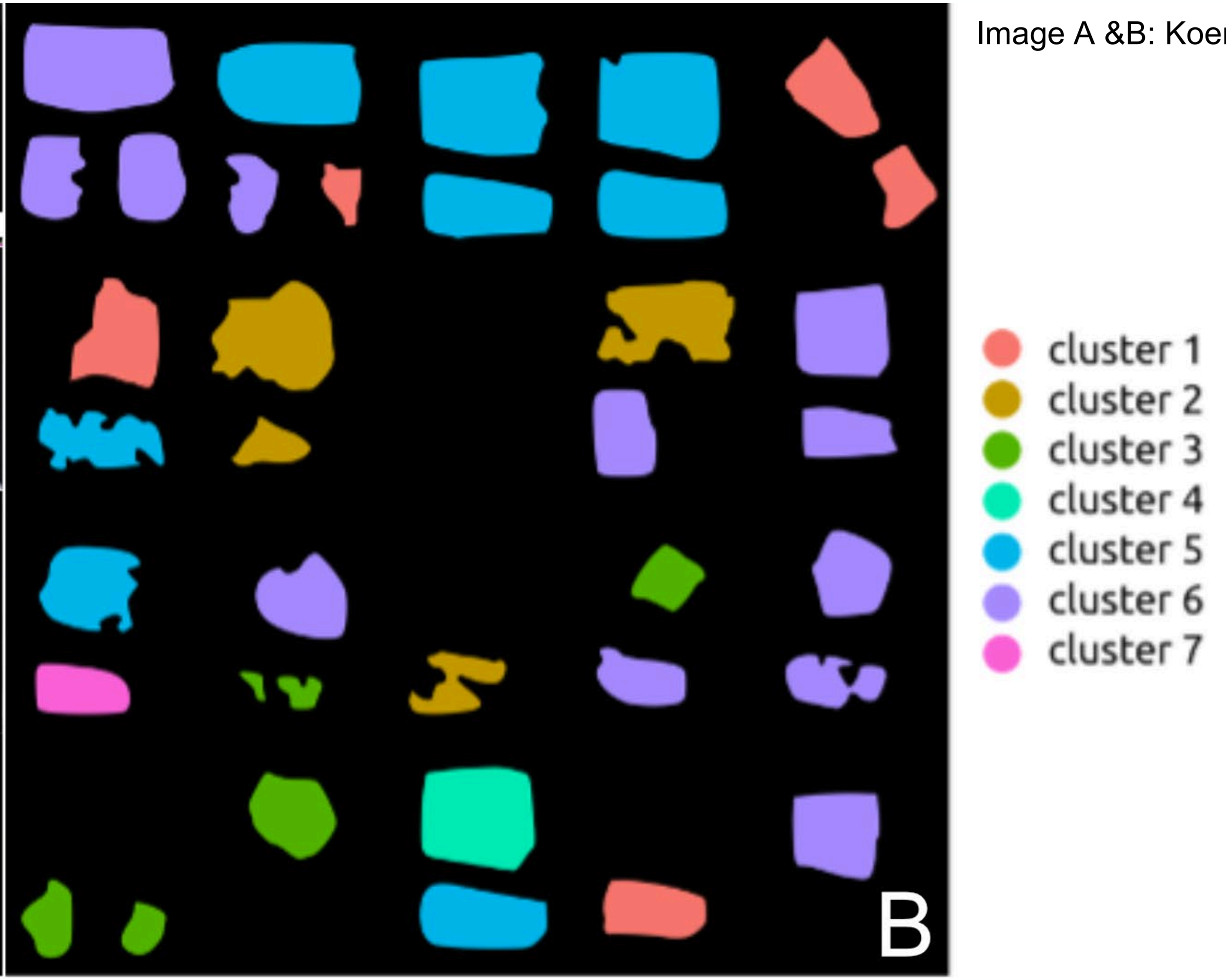


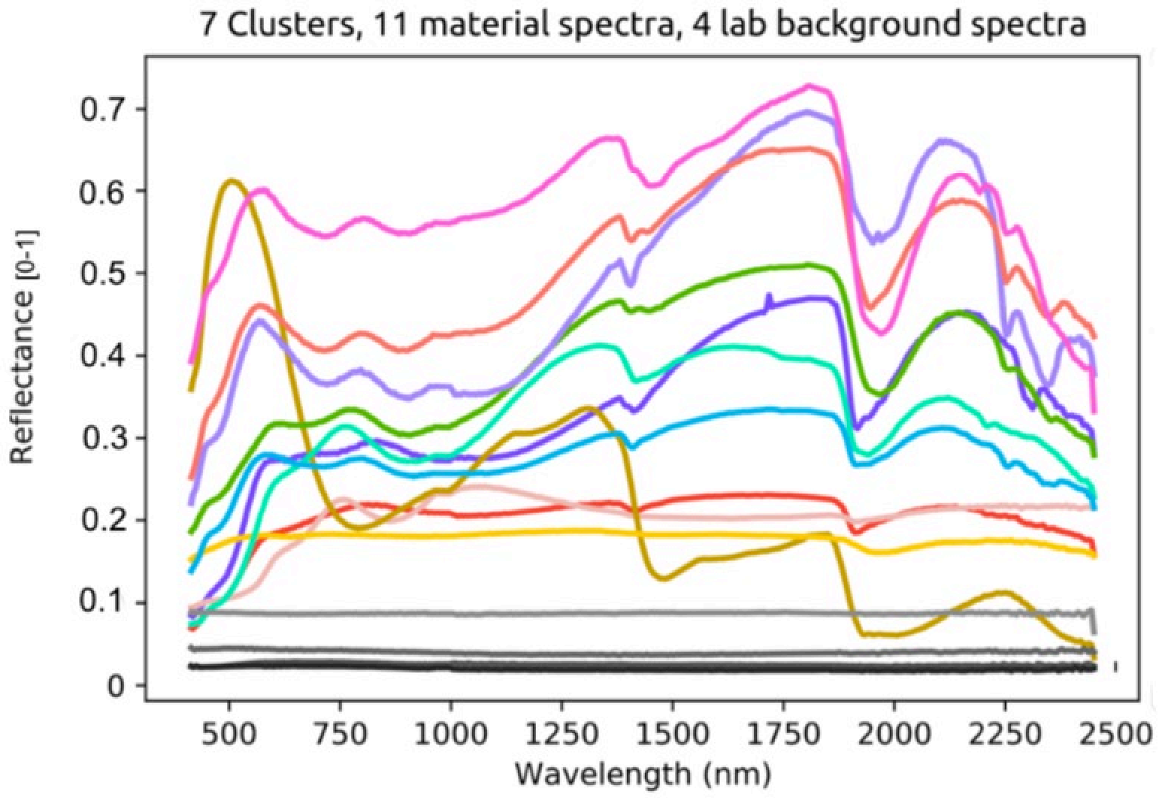
Image A &B: Koerting, 2021

A: Apliki samples in RGB color

B: Clustering based on geochemistry

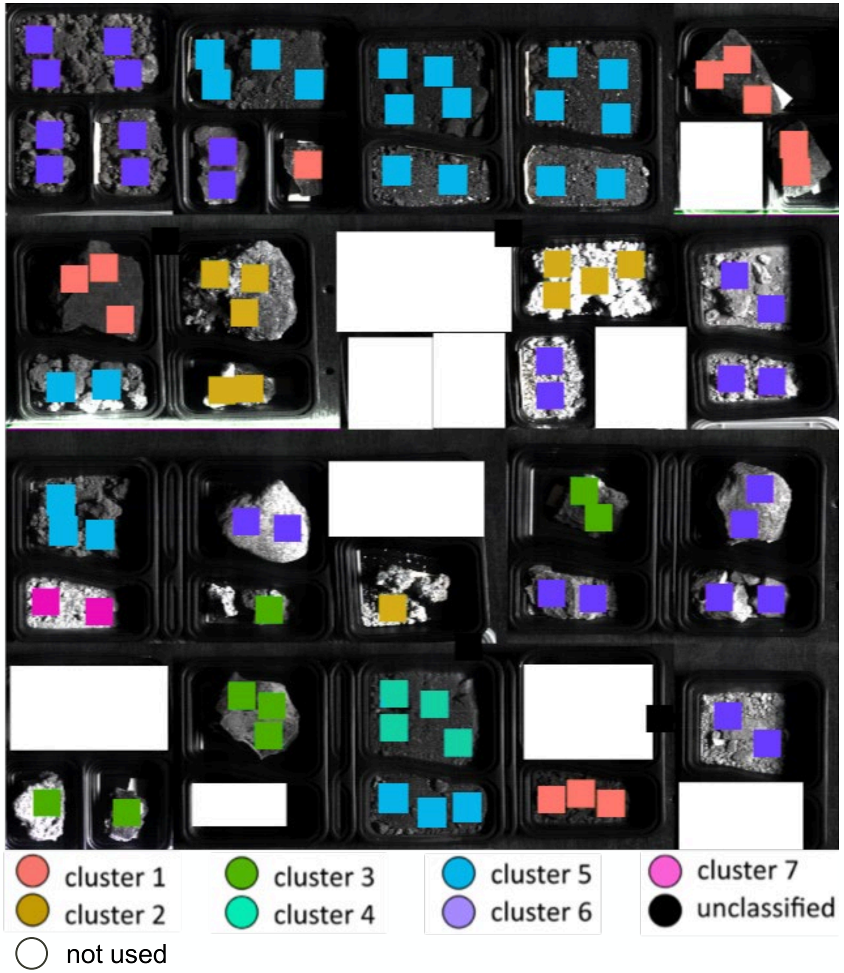
Methods: Data Samples - Apliki mine

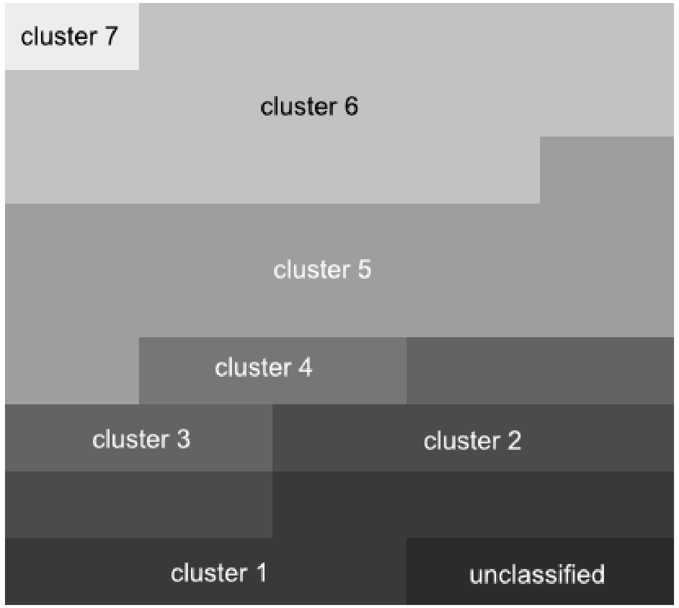
Cluster	Samples	Cluster Mineralogy
01	1b, 1d, 1e, 1f, 13a	Quartz, **Plagioclase Feldspar** (Andesine, Anorthite), **Pyroxene** (Diopside), **Smectite-group:** Montmorillonite, **Fe-Oxide:** Magnetite, **Sulfide:** (Pyrite (Fe, one sample only)); Dominated by: Plagioclase and Montmorillonite.
02	15c, 15a, 15b, 7e	Quartz, **Fe-Oxide:** Goethite, **Sulfides** (Cu, Fe, CuFe): Covellite, Pyrite, Chalcopyrite, **Sulfates** (Cu, Fe, Mn-Al, Mg): Chalcanthite, Ferrohexhydrite, Apjohnite, Rozenite, Pentahydrate (cuprian); Dominated by: Quartz, Sulfates and Sulfides, Fe-Hydrate (7e)
03	11a, 11b, 10a, 7d_hem, 9b	Quartz; Fe-Oxide: Goethite; **Sulfides** (Cu): Pyrite; **Sulfates (Cu, Zn-Fe):** Gypsum, Bassanite, Sphalerite; **Chlorite group:** Clinochlore; Dominated by: Quartz (+ Chlorite-group (sample 11a, 11b))
04	2a	**Fe-Oxide:** Goethite; **Sulfate (K-Fe):** Jarosite-Natrojarosite; Quartz; **Plagioclase Feldspar** (Andesine); **Chlorite Group**: Clinochlore; Dominated by: Sulfates
05	13b, 3a, 3b, 4b, 6b, 6c, 6a, 6d	Quartz; **Plagioclase** (Andesine, Anorthite); Analcime; **Pyroxene** (Diopside); **Smectite-group:** Montmorillonite; **Fe-Oxide:** Goethite, Magnetite; **Sulfate (K-Fe, Ca):** Jarosite, Gypsum; **Chlorite-group:** Clinochlore; **Sulfide (Fe):** Pyrite; Dominated by: Clays, Smectite-chlorite group
06	4c, 5a, 5b, 5c, 8a, 8b, 8c, 9a, 10b, 10c, 10d, 7d	Chlorite-group: Clinochlore; Smectite-group: Montmorillonite; Sulfate (Ca, Mg): Gypsum, Hexahydrite; Quartz; Sulfide: Pyrite; Fe-Oxide: Goethite; Ajoite (minor copper ore, silicate hydroxide); Dominated by: Chlorite-group
07	4a	Sulfate (Ca, Fe): Gypsum, Rozenite; Quartz, Chlorite-group: Clinochlore; Dominated by: Gypsum

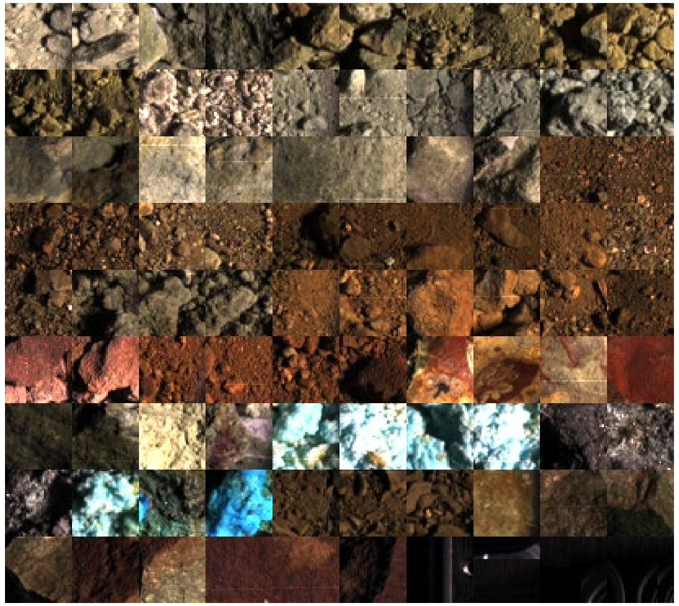


(Koerting, 2021)

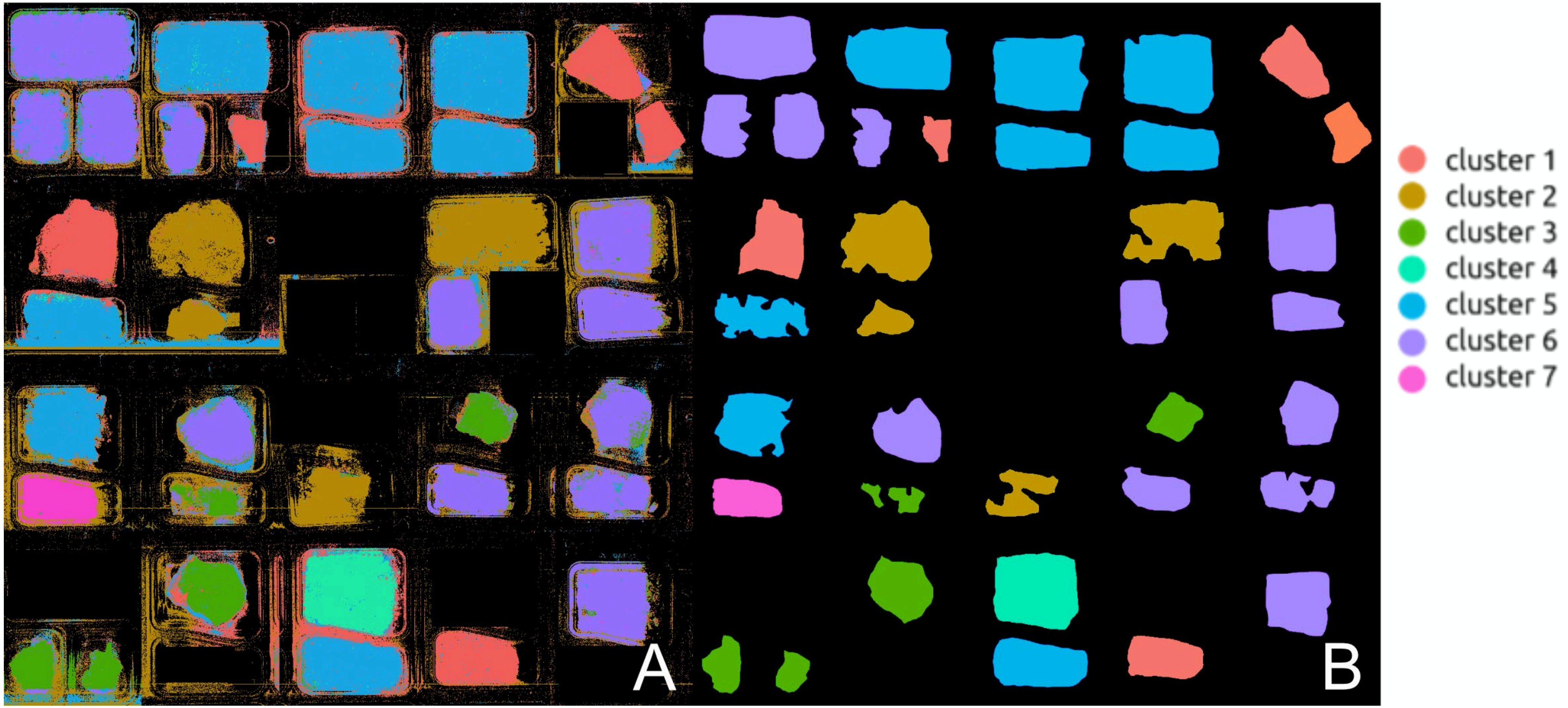
Methods: Data Pre-Processing Apliki mine







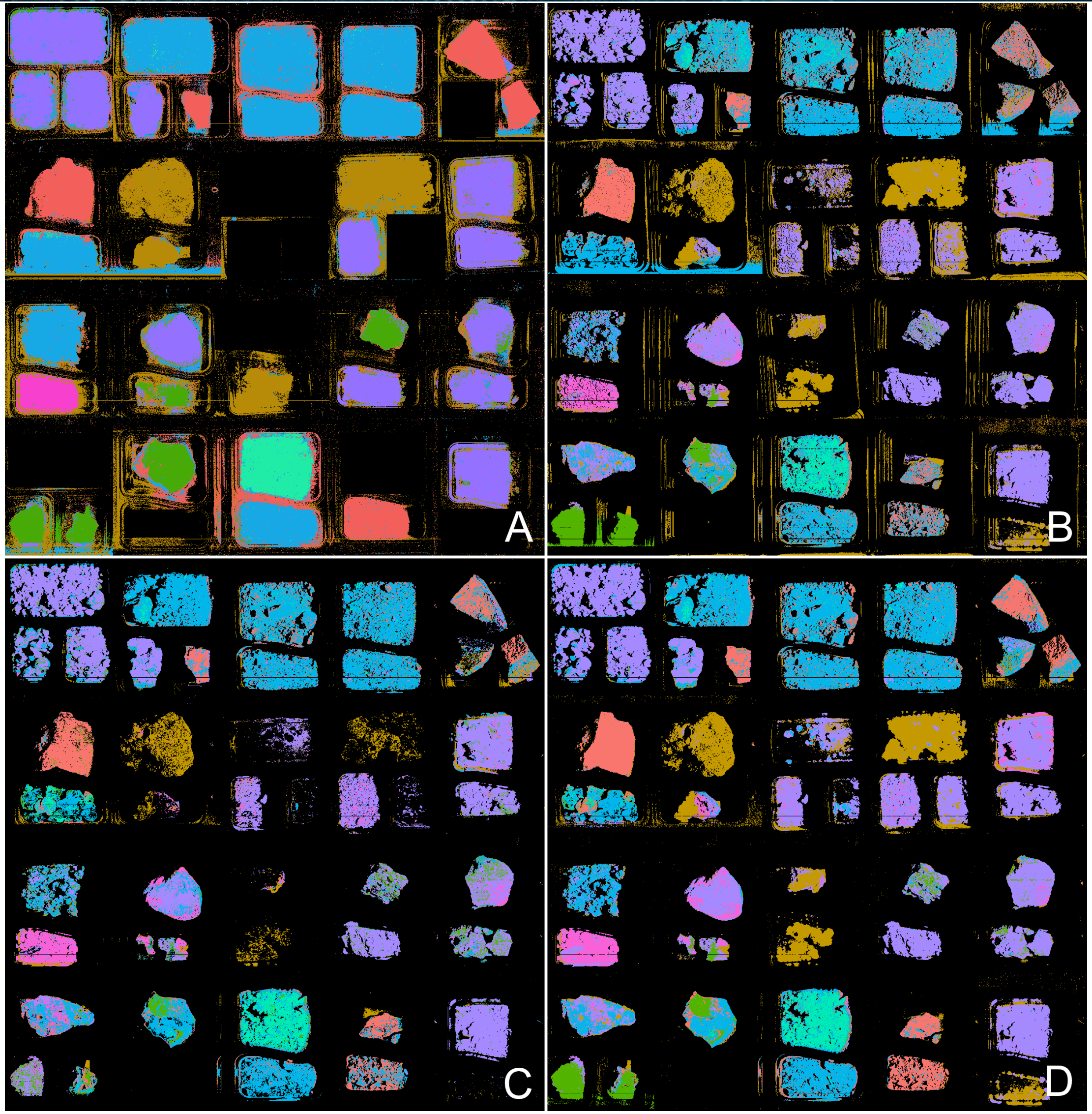
Results: Apliki Samples



A: DeepGeoMap Classification:
Validation Accuracy: 98.83%

B: Cluster/class validation

Results and Discussion: Apliki Samples



A: DeepGeoMap Classification:
- 400 bands
- Accuracy: 98.83% (including shadows)

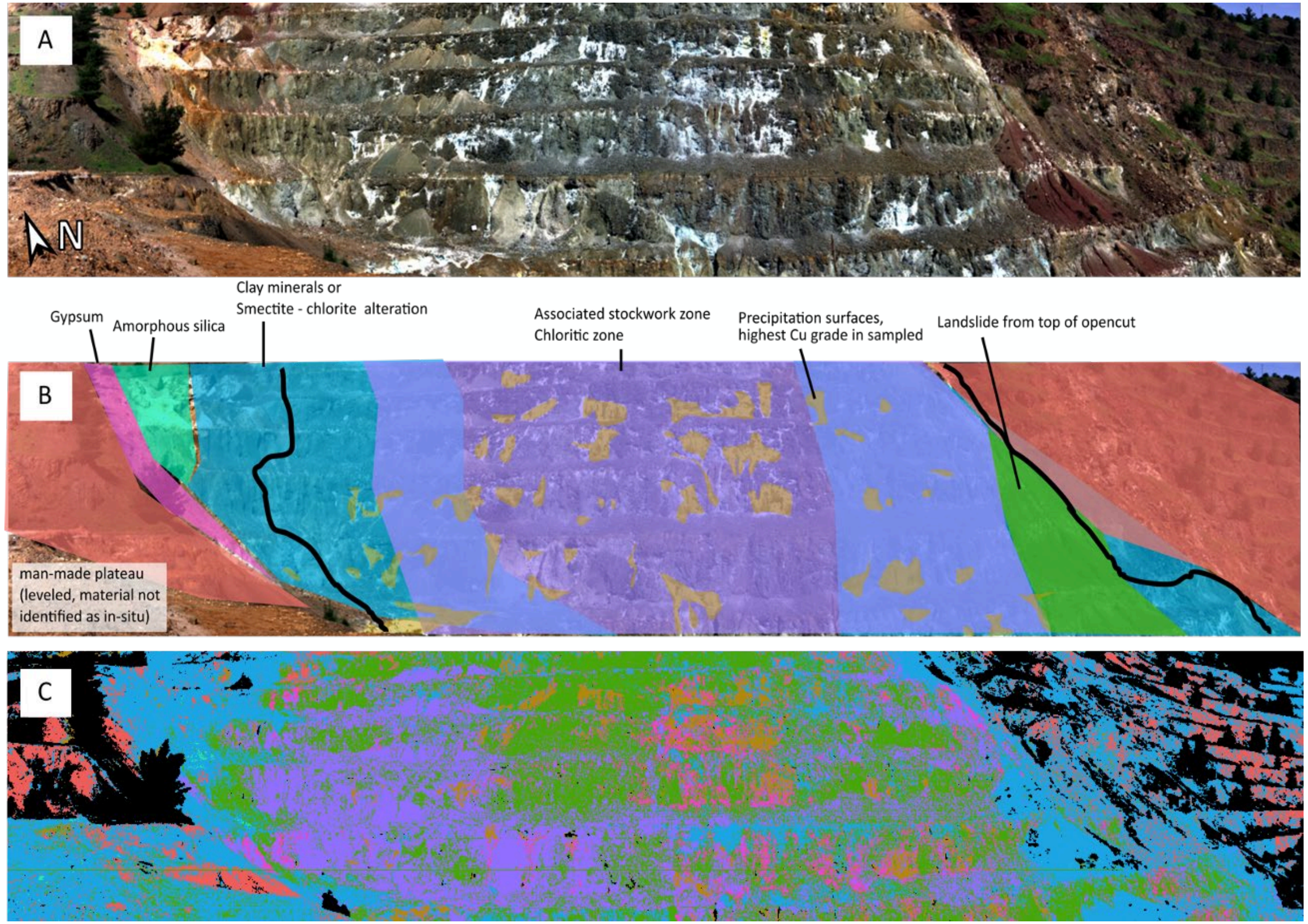
B: Binary Feature Fitting (BFF):
- 400 bands
- Accuracy: 81.39% (excluding shadows)

C: ENVI Spectral Angle Mapper (SAM):
- 400 bands
- Accuracy: 85.13% (excluding shadows)

D: Binary Feature Fitting (BFF):
- downsampled to 70 bands
- Accuracy: 85.6% (excluding shadows)

Image B , C, and D: Koerting, 2021

Results: Apliki Mine Face Scan



- Cluster 1 - Apliki pillow lavas, dominated by plagioclase and montmorillonite
- Cluster 2 - Disseminated and weathered sulfide ore, dominated by quartz, sulfides, sulfates
- Cluster 3 - Areas of higher silicification, Jasper, quartz (+ chlorite-group minerals)
- Cluster 4 - Veins of massive mineralization, dominated by sulfates
- Cluster 5 - Weather pillow lavas, smectitic alteration, dominated by clay, smecite-chlorite-group minerals
- Cluster 6 - Chloritic stockwork; dominated by chlorite-group minerals
- Cluster 7 - Gypsum mineralization

- DeepGeoMap model was trained with the sample scans
- Classification time of mine face scene ~30s

Image: A Koerting, 2021 ; B: Antivachis, 2015

Conclusion

- Generally good classification accuracies for this type of network, surpassing the accuracies of classical algorithms and some other neural networks for some specific geological data sets
- DeepGeoMap models can be trained with large amounts of geochemically validated sample data and hence unmixed (or knowledgeably mixed) pixels
- Models trained with laboratory data can classify larger scale mine face, arial, or satellite imagery
- High amount of training data is required in comparison to classical algorithms like EnGeoMAP or Binary Feature Fitting (e.g. more than 20.000 spectra vs. 15 library spectra)

Conclusion

- 1D DeepGeoMap architecture also allows models to be trained with beforehand acquired ground truth point-spectrometer data and/or laboratory image sample data (e.g. of rocks, powders, soil samples)

- Trained models can rapidly classify any kind of hyperspectral target image (classification times of few seconds to a few minutes depending on image size + computational power)

↳ Useful for classification of large image collections with the same target classes

- Spatially independent classification makes position-dependent ground truthing less important

↳ Similar to spectral library based classifications of classical algorithms (such as EnGeoMap)

DeepGeoMap (published as thesis)

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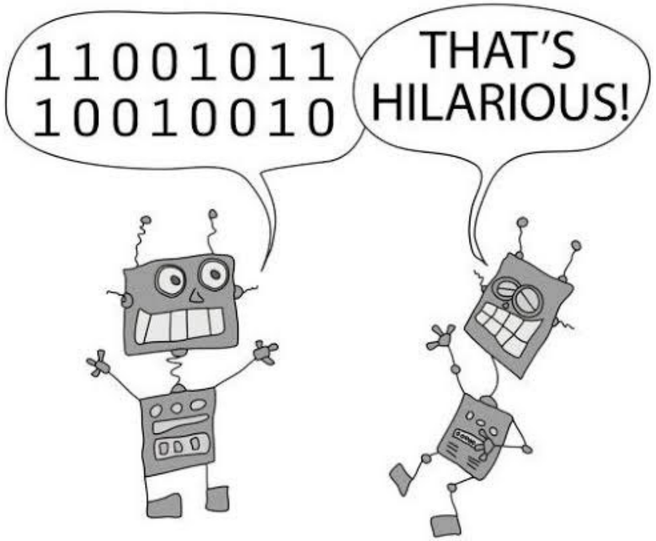
URN:

urn:nbn:de:kobv:517-opus4-520575

Also accessible via researchgate or google.

Thank you for your attention!



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- Cyprus Geological Survey

Outlook

- Training of DeepGeoMap models with **point spectrometer data** and then classify satellite scences (EnMAP) with these models

- Use DeepGeoMap for the classification of secondary iron mineral differentiation and classification
  - e.g. hematite, goethite and jarosite

- Create a user interface (UI) for DeepGeoMap

Results and Discussion: Apliki Mine Face Scan

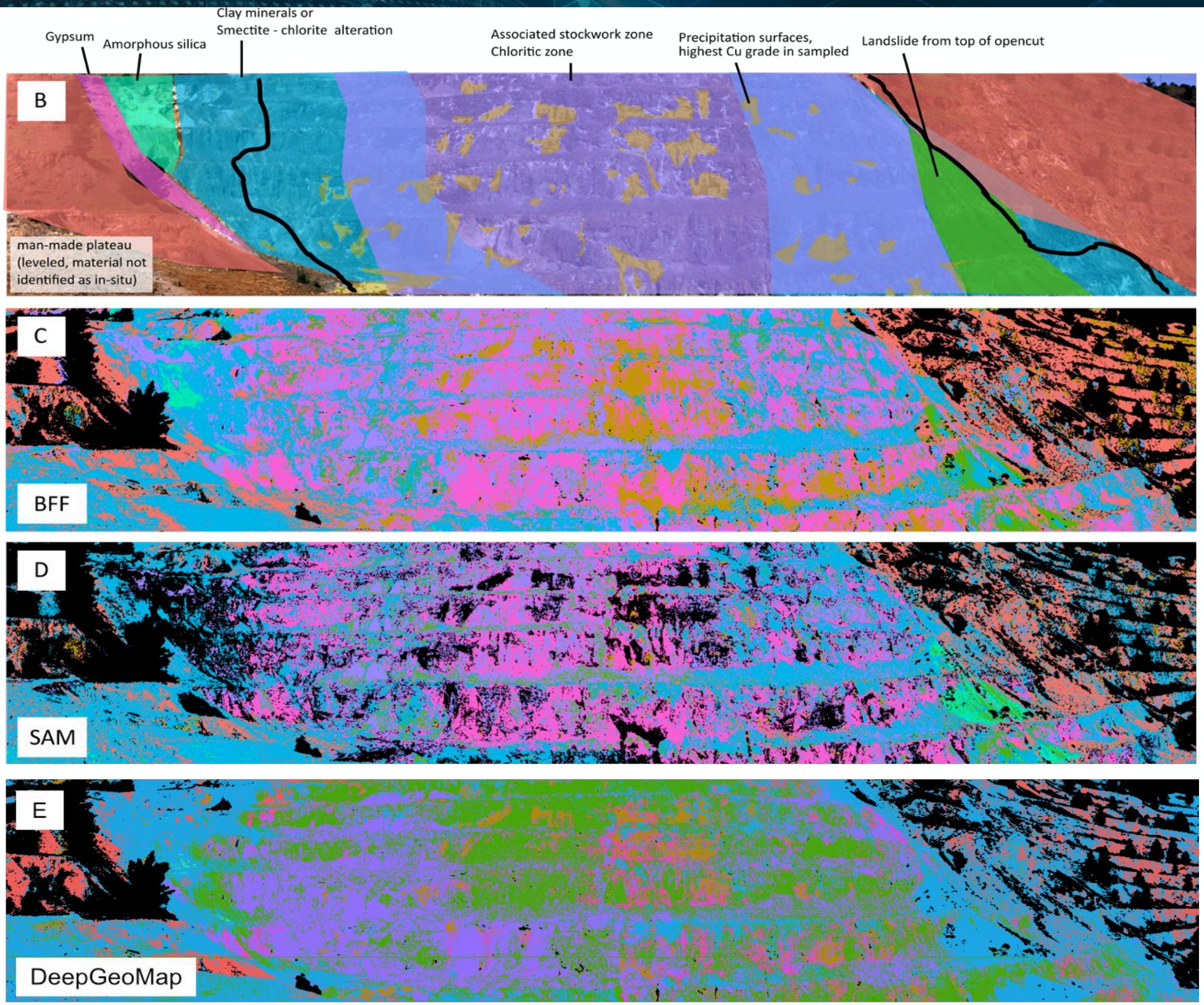

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Image B , C &D: Koerting, 2021