

The background of the slide is a composite image. The top half shows a view of Earth from the Moon's surface, with the blue and white planet rising over a dark, cratered horizon. The bottom half shows a close-up, grayscale view of the Moon's surface, showing various craters and lunar maria.

**EPFL**

**Machine learning on the  
Earth System with  
remote sensing**

**towards machines that  
we can understand and  
interact with.**

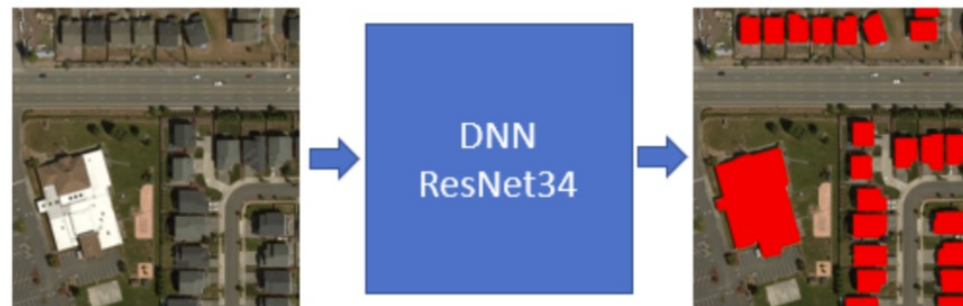
Devis Tuia  
ECEO lab  
EPFL

ESA/ECMWF

15.11.2021

# Applying deep learning with optical remote sensing data seems very easy

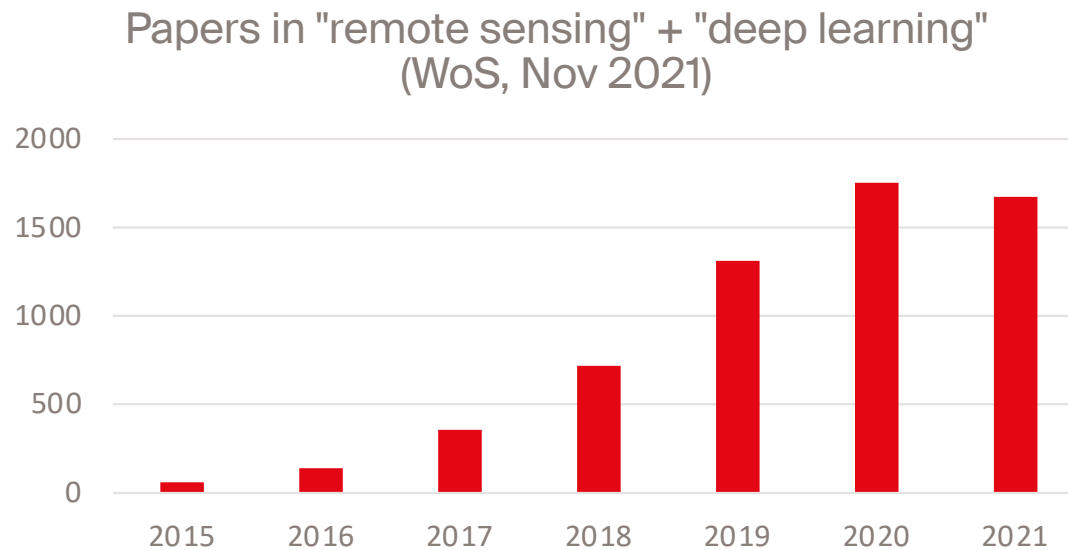
June 28th 2018: *Bing releases 125 million Building Footprints in the US as Open Data*  
How?



Apply ResNet [He et al., 2015] + smart postprocessing

# The low hanging fruit is a blessing...

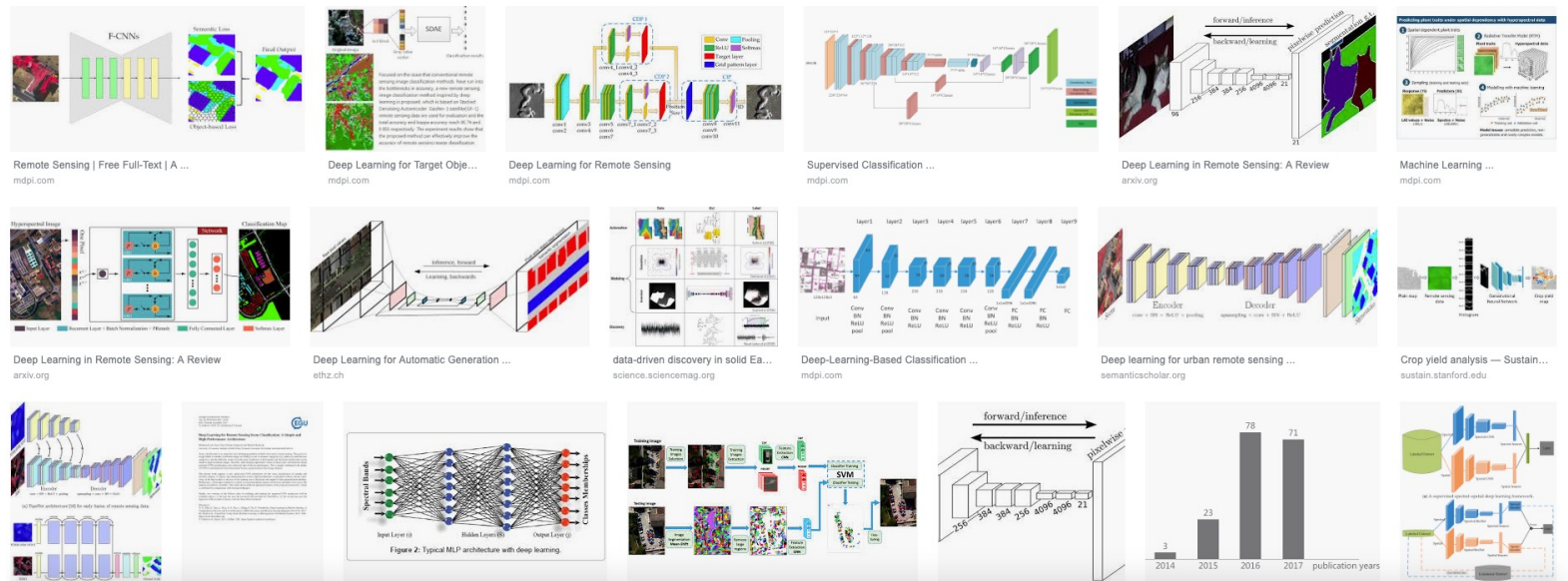
- We can advance several applications with this technology from CS
- Massive increase of “DL-in-RS” papers



Web of science, 4.11.2021

# The low hanging fruit is a blessing... in disguise

- We can advance several applications with this technology from CS
- Massive increase of “DL-in-RS” papers
- Kind of DL-winter already.



# So we started thinking on what is exciting in AI4EO...

arXiv.org > cs > arXiv:2104.05107

Search...

Help | Advance

Computer Science > Computer Vision and Pattern Recognition

[Submitted on 11 Apr 2021]

## Towards a Collective Agenda on AI for Earth Science Data Analysis

Devis Tuia, Ribana Roscher, Jan Dirk Wegner, Nathan Jacobs, Xiao Xiang Zhu, Gustau Camps-Valls

In the last years we have witnessed the fields of geosciences and remote sensing and artificial intelligence to become closer. Thanks to both the massive availability of observational data, improved simulations, and algorithmic advances, these disciplines have found common objectives and challenges to advance the modeling and understanding of the Earth system. Despite such great opportunities, we also observed a worrying tendency to remain in disciplinary comfort zones applying recent advances from artificial intelligence on well resolved remote sensing problems. Here we take a position on research directions where we think the interface between these fields will have the most impact and become potential game changers. In our declared agenda for AI on Earth sciences, we aim to inspire researchers, especially the younger generations, to tackle these challenges for a real advance of remote sensing and the geosciences.

Comments: In press at IEEE Geoscience and Remote Sensing Magazine

Subjects: **Computer Vision and Pattern Recognition (cs.CV)**; Signal Processing (eess.SP)

DOI: [10.1109/MGRS.2020.3043504](https://doi.org/10.1109/MGRS.2020.3043504)

Cite as: [arXiv:2104.05107](https://arxiv.org/abs/2104.05107) [cs.CV]

(or [arXiv:2104.05107v1](https://arxiv.org/abs/2104.05107v1) [cs.CV] for this version)

# Six exciting research directions



Reasoning, encoding  
spatial thinking



Massive multi-source  
(audio / video / social media)



Human machine interaction  
In natural language



Physics-based ML



Interpretable models



Discovering causal relations

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Reasoning, encoding  
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Massive multi-source  
(audio / video / social media)



Interpretable models



Human machine interaction  
In natural language



Discovering causal relations

# Two (out of six) questions to move forward



Understand what is going  
on within CNNs

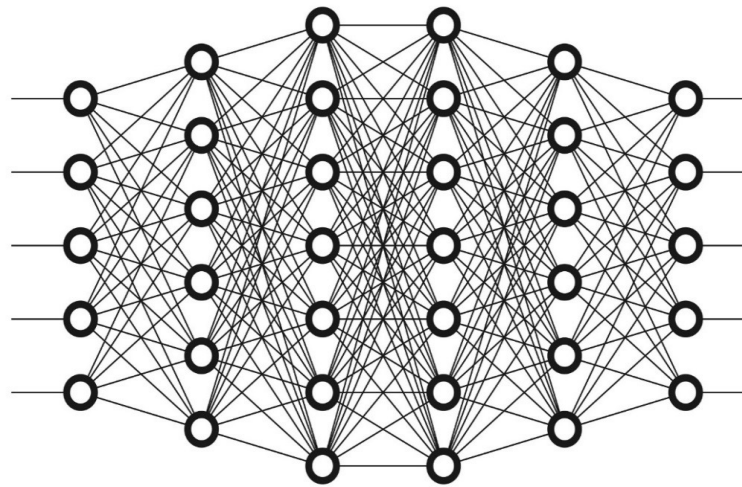
**XAI**



Make them accessible to anyone

**Interaction, NLP**

# What happens inside a CNN is a bit of a mystery...



0.74 Canal

0.23 River

0.02 Park

0.01 Station

0.01 Road

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0.74 Canal

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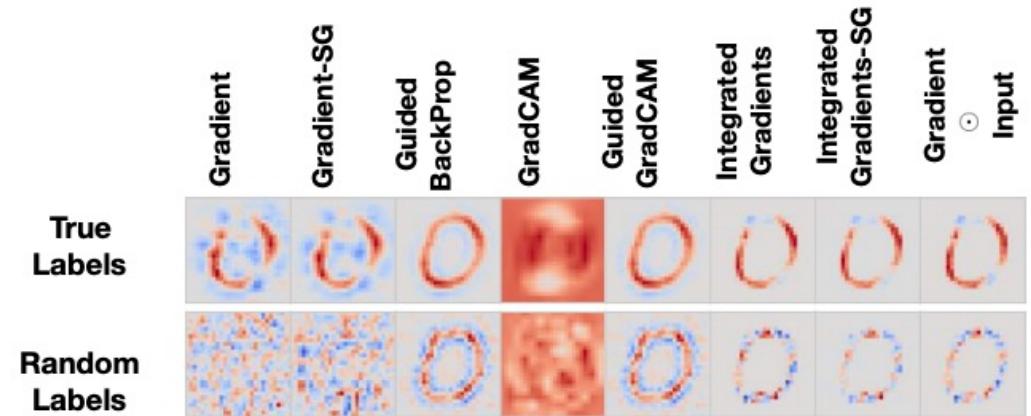


0.74 Canal  
0.23 River  
0.02 Park  
0.01 Station  
0.01 Road

Zhou, Bolei, et al. "Learning deep features for discriminative localization.", *CVPR*. 2016.

# Explaining what a neural network is doing is DIFFICULT

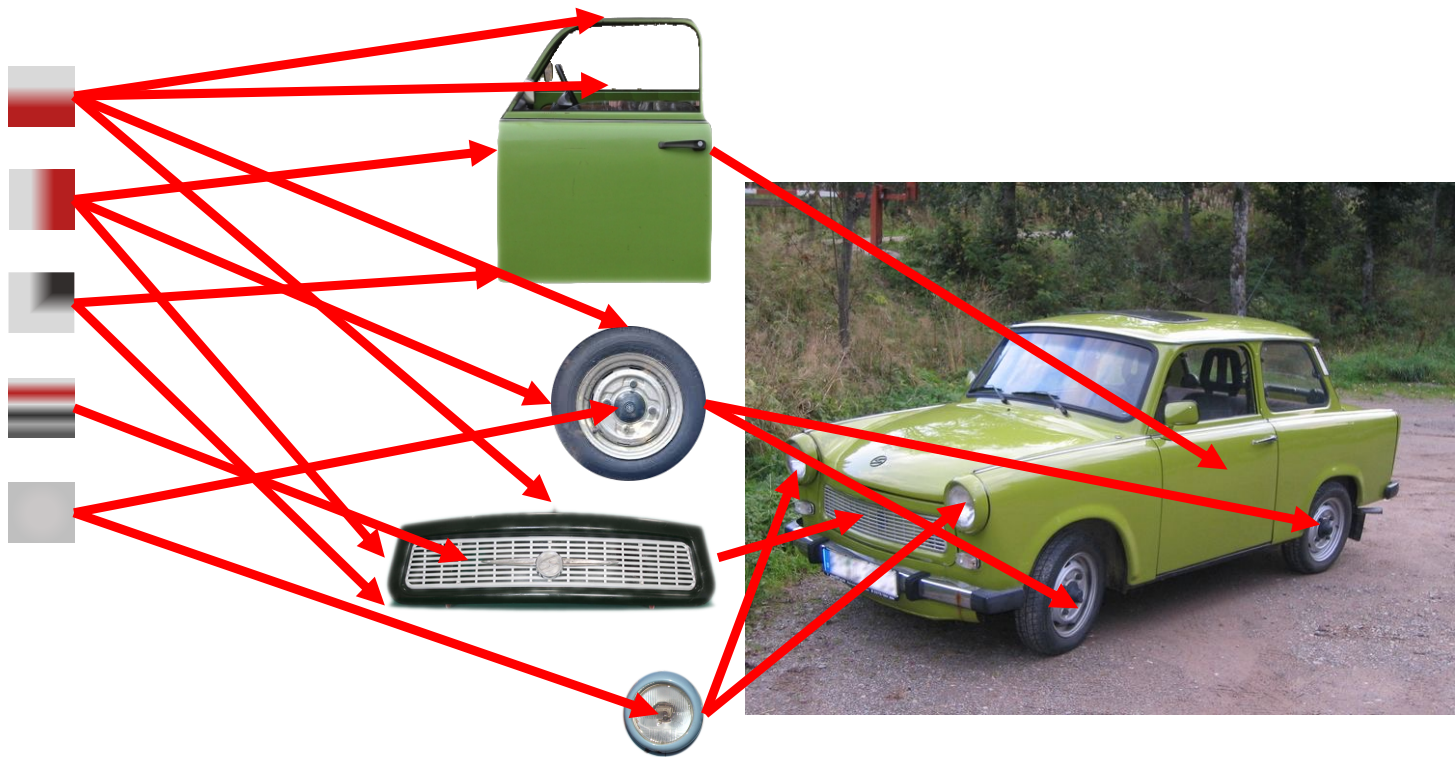
- Models can trick you by their capacity



[Adebayo et al., *Sanity checks for saliency maps*, NeurIPS 2017]

- There are many ways to get to the same result
- Don't forget, we optimize for accuracy, not interpretability!
- Can we use simpler primitives to ensure explainability?

# We would like something like

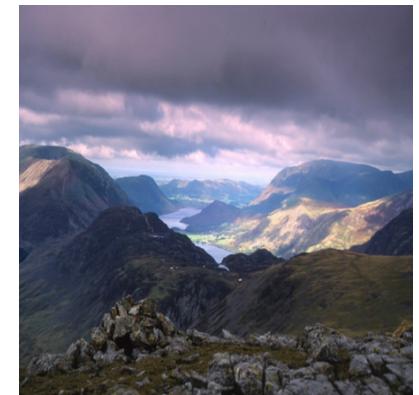


# Understanding landscape beauty (a quite subjective matter)

- Not all places are equally attractive
- Beauty is really subjective!
- However, there must be some kind of consensus

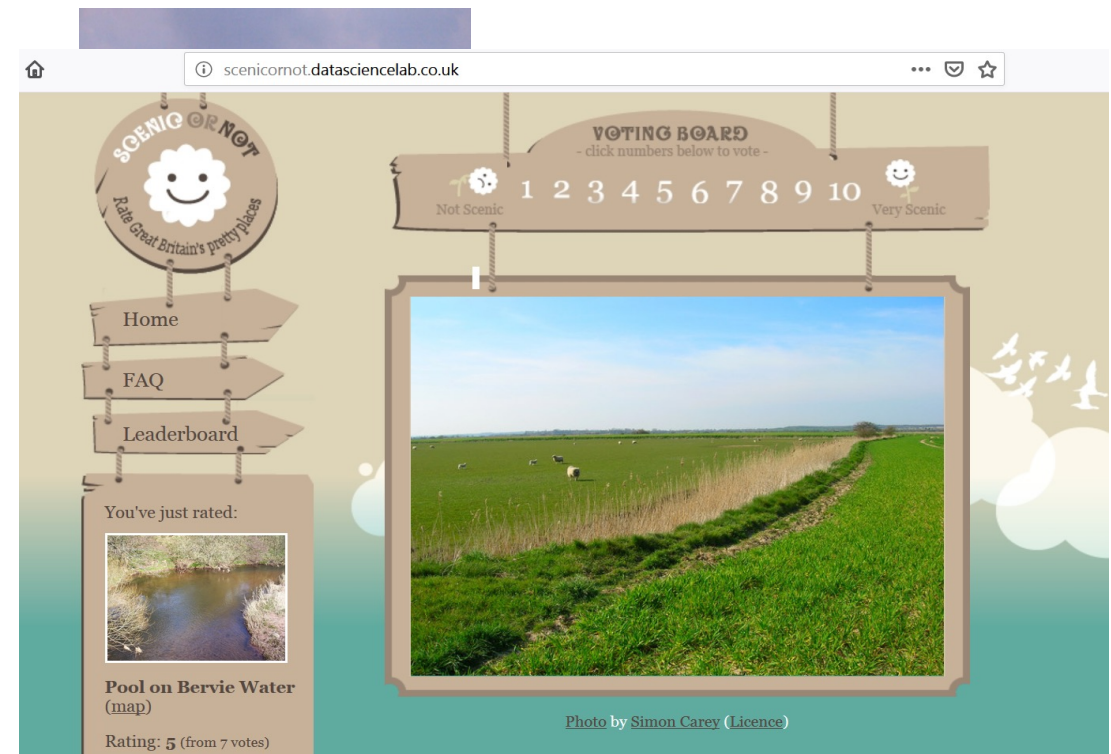


VS



# Understanding landscape beauty (a quite subjective matter)

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- Let's **crowdsource** that and understand factors related to beauty



# Understanding landscape beauty (a quite subjective matter)

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Photos © [Sonse](#), [Alex Healing](#), [Tim Green](#), [Jeremy Segrott](#) ([cc-by/2.0](#)).

# What are we aiming at

We want to go beyond saliency. We want to predict what makes a landscape scenic.

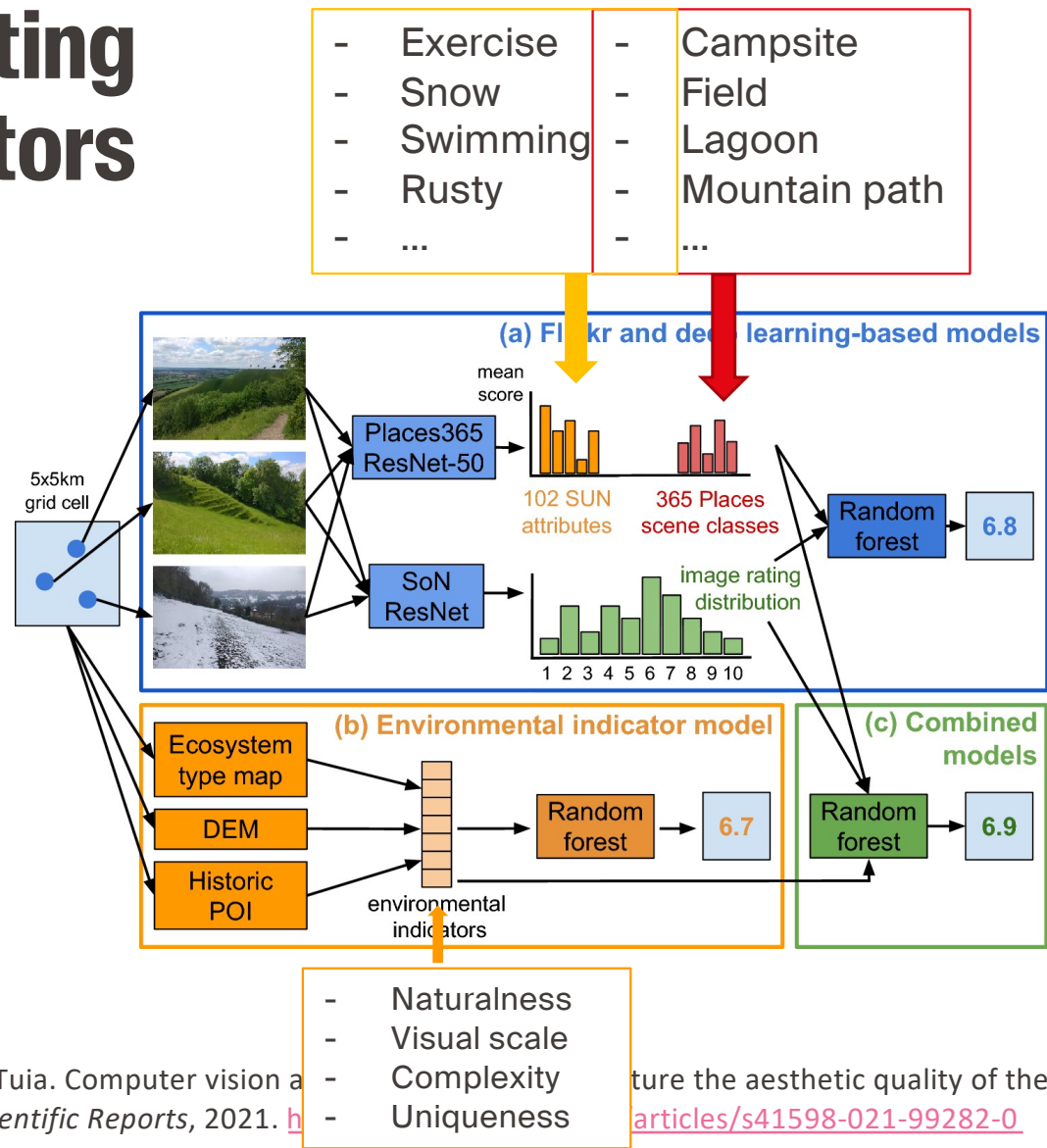


Scenic because of open fields

Not scenic because there are road signs

# Extracting interesting compositional factors

- Object and scene characteristics from social media
- Indicators from remote sensing
- Fuse with random forest

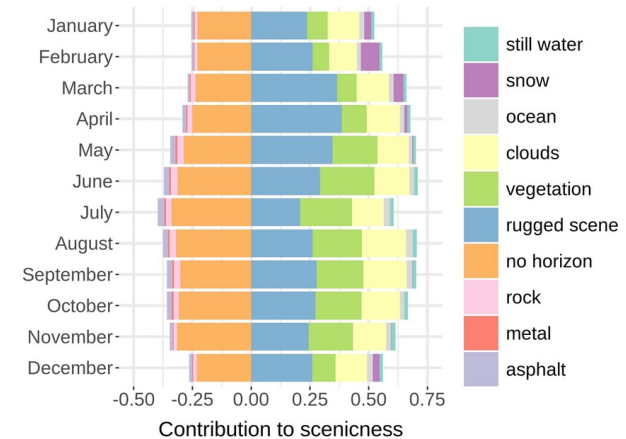
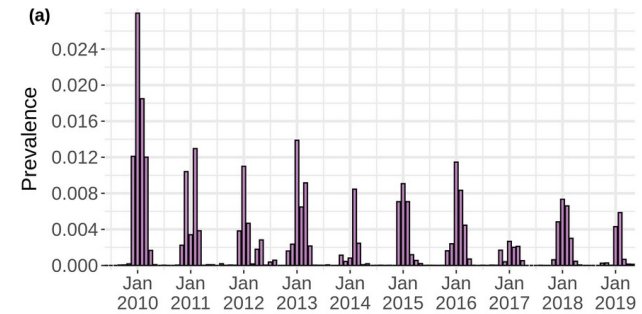


I. Havinga, D. Marcos, P. Bogaart, L. Hein, and D. Tuia. Computer vision a landscape for ecosystem service assessments. *Scientific Reports*, 2021. <https://doi.org/10.1038/s41598-021-99282-0>

# Extracting interesting compositional factors

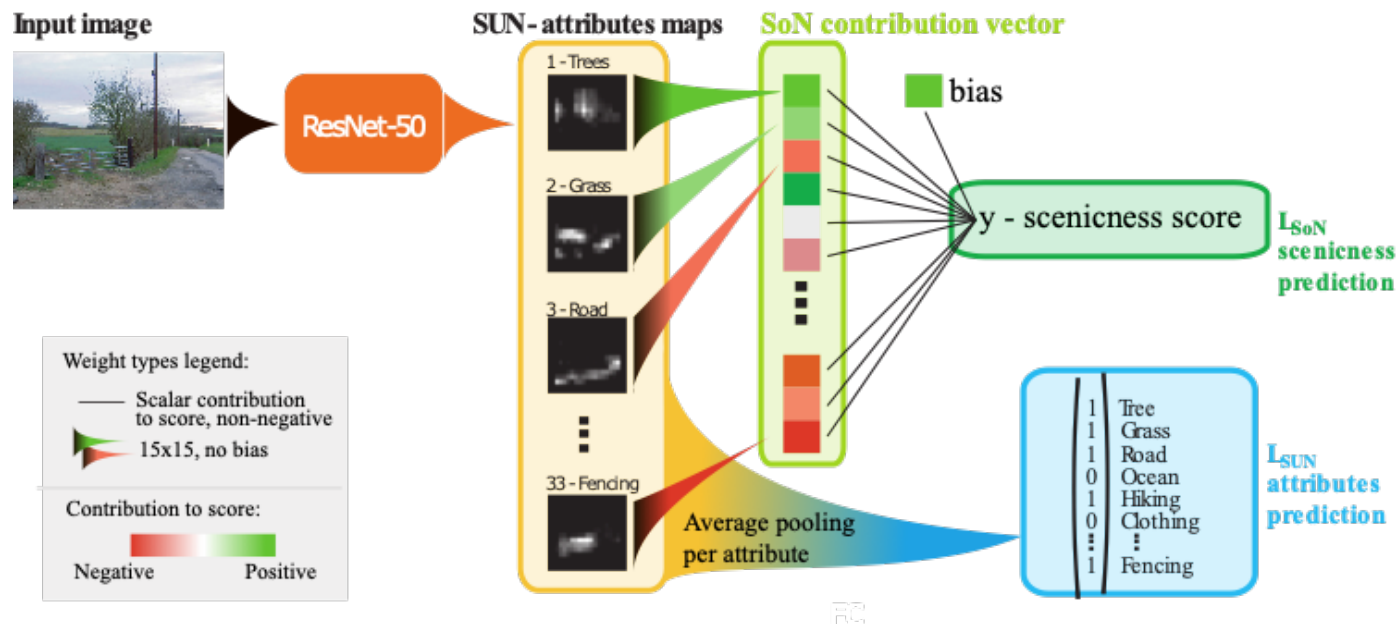
- Studying evolution in time, thanks to Flickr data
- Severeness of winters
- Concepts appearing at different times
- Different ecosystem services

flickr



I. Havinga, D. Marcos, P. Bogaart, L. Hein, and D. Tuia. Computer vision and social media data capture the aesthetic quality of the landscape for ecosystem service assessments. *Scientific Reports*, 2021. <https://www.nature.com/articles/s41598-021-99282-0>

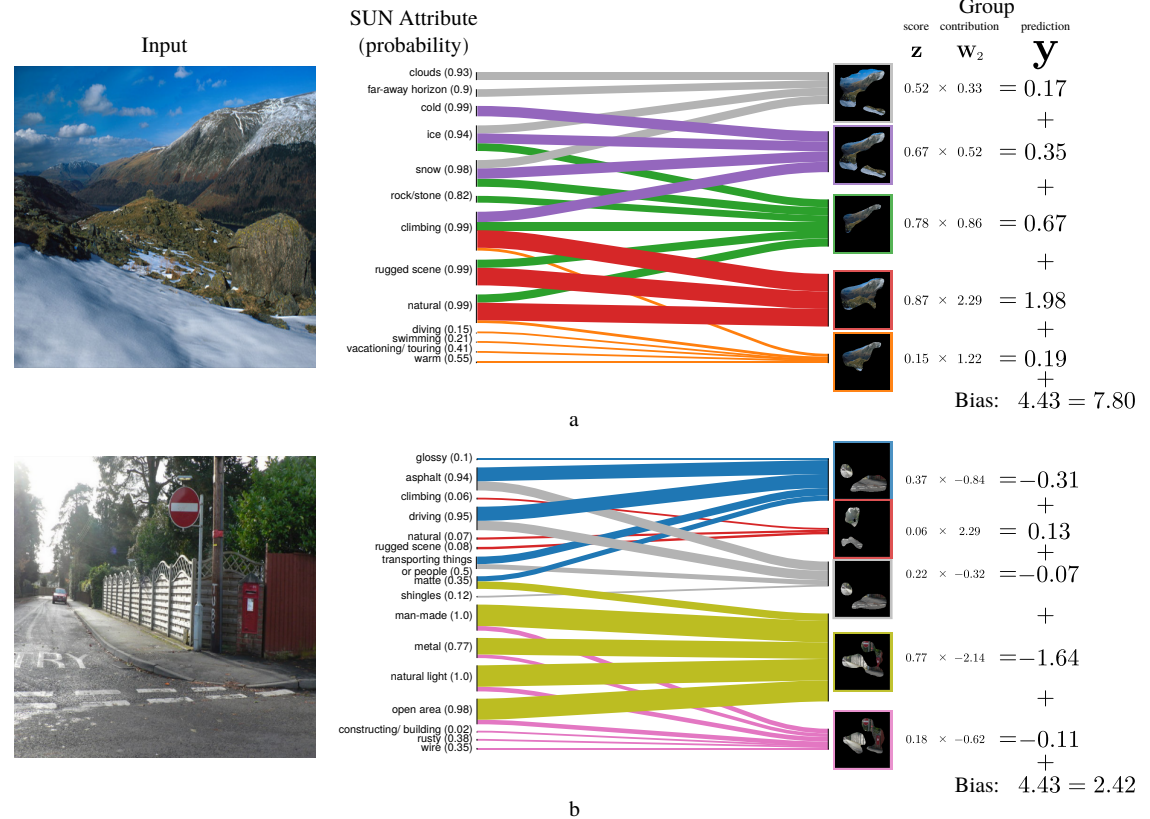
# Semantic bottleneck: explaining via learned semantic concepts



**Paper.** Marcos, Fong, Lobry, Flamary, Courty, Tuia, Contextual semantic interpretability, *ACCV 2020*  
<https://arxiv.org/abs/2009.08720>

# Understand: explainable AI for subjective problems (and not only)

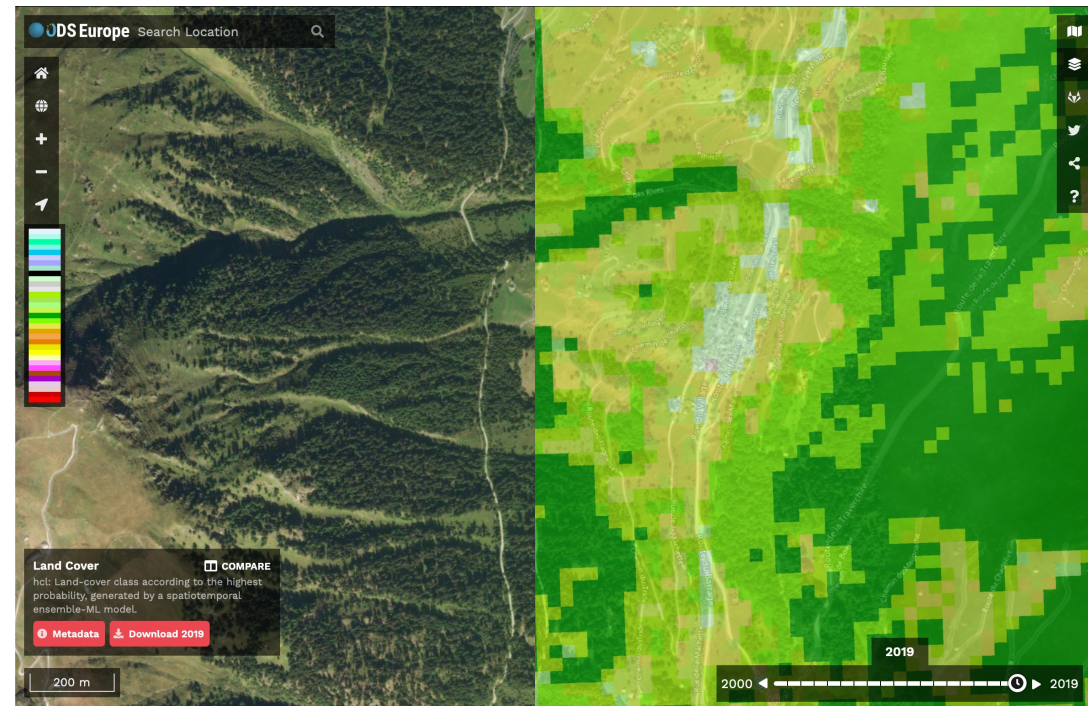
- We can now interpret scenicness in “*easy-to-understand and argue with*” terms



D. Marcos, S. Lobry, R. Fong, N. Courty, R. Flamary, and D. Tuia. Contextual semantic interpretability. In *Asian Conference on Computer Vision (ACCV)*, Kyoto, Kapan, 2020. <https://arxiv.org/abs/2009.08720>

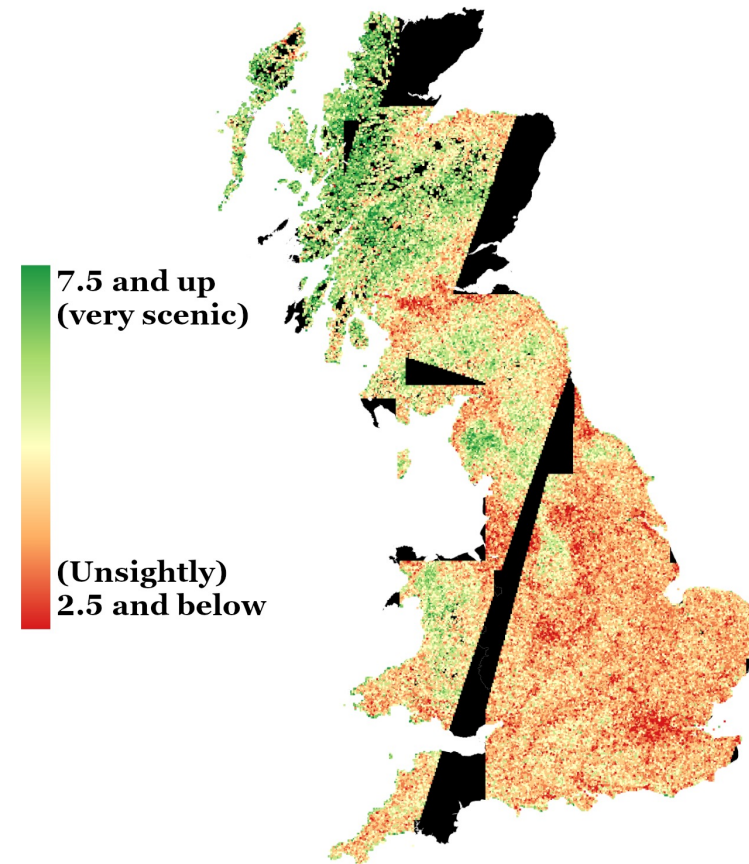
# Understand: explainable AI for subjective problems (and not only)

- We can study the same effects from satellite images
- And use land cover types as explanations
- For instance using Corine Land Cover
- Sentinel-2 images being available everywhere, we can scale findings!



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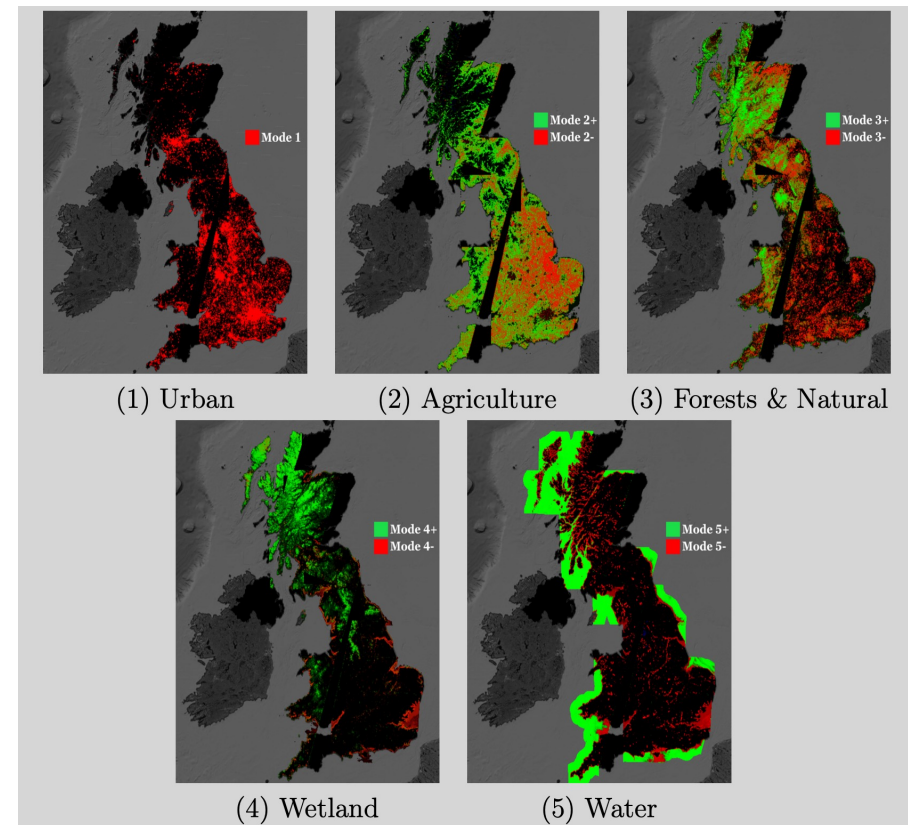
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A. Levering, D. Marcos, and D. Tuia. On the relation between landscape beauty and land cover: a case study in the U.K. at Sentinel-2 resolution with interpretable AI. *ISPRS J. Int. Soc. Photo. Remote Sens.*, 177:194–203, 2021. <https://www.sciencedirect.com/science/article/pii/S0924271621001234>

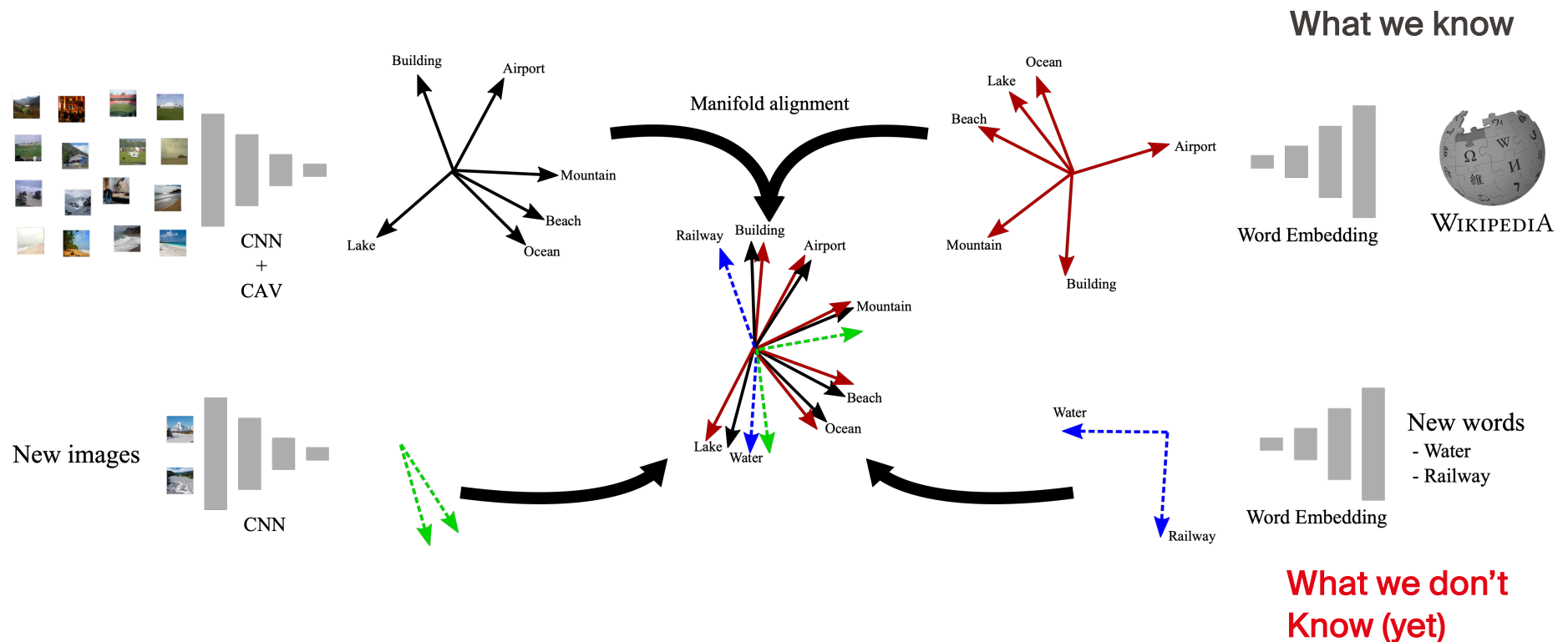
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# Moving forward: textual, open set interpretations



P. Arendsen, D. Marcos, and D. Tuia. Concept discovery for the interpretation of landscape scenicity. *Mach. Learn. Knowledge Extraction*, 2(4):397–413, 2020. <https://www.mdpi.com/2504-4990/2/4/22>

# Two (out of six) questions to move forward



Understand what is going  
on within CNNs



Make them accessible to anyone

**Interaction, NLP**



What do you want to know?





Where is it?

An aerial photograph of a university campus. In the upper left, a red speech bubble contains the text 'Where is it?'. Below the speech bubble, a small rectangular inset shows a portrait of a smiling man with short dark hair and a beard, wearing a dark shirt. The campus features various buildings, green spaces, and a large rectangular area with several circular features in the lower right.

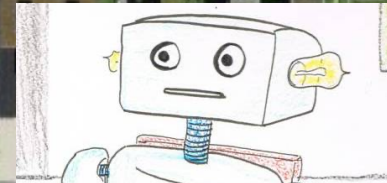
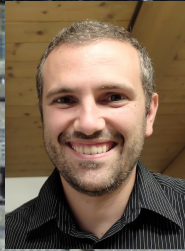
What do you want to know?




A horizontal strip showing a portion of the aerial campus view, featuring a road, green fields, and some buildings.

Where is it?

It is EPFL,  
Lausanne

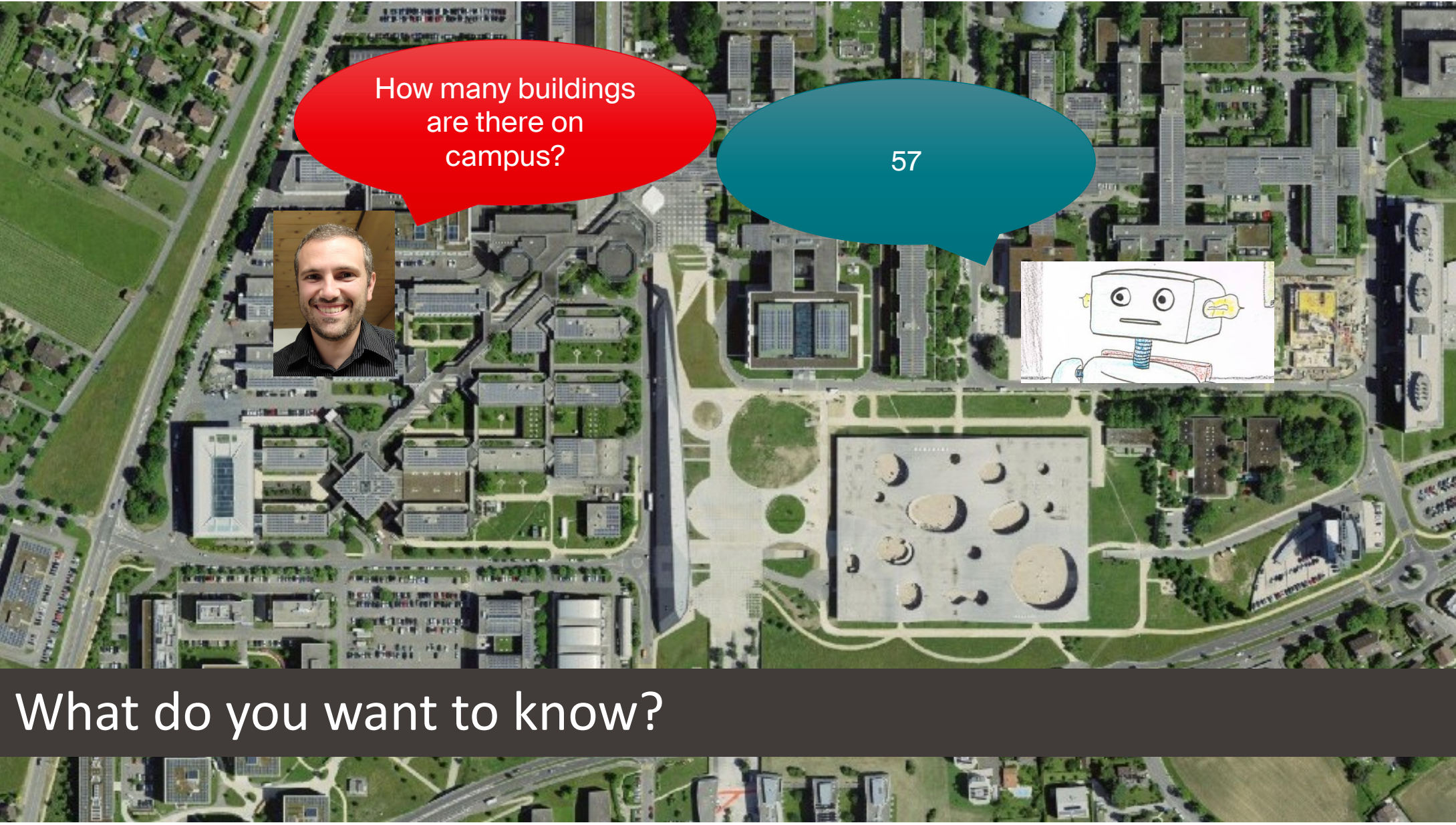


What do you want to know?

An aerial photograph of a university campus. A red speech bubble is overlaid on the image, containing the text "How many buildings are there on campus?". To the left of the speech bubble is a small, square portrait of a smiling man with short dark hair and a beard, wearing a dark shirt. The campus features numerous buildings, green spaces, and a large circular plaza with several circular structures in the center.

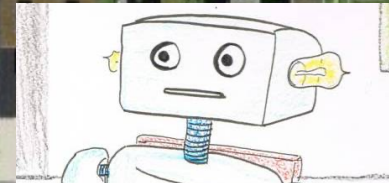
How many buildings  
are there on  
campus?

What do you want to know?



How many buildings  
are there on  
campus?

57




What do you want to know?

# This has great potential, but

- Non-experts are ... **non technical** experts.
- Non-experts want answers to **specific questions**.
- Non-experts want to formulate questions as **sentences**.

# What do we need?

- For web-search it works a bit like that.

Gmail Images  Sign In



deforestation



Google Search

I'm Feeling Lucky

Google offered in: [Nederlands](#) [Frysk](#)

Netherlands

[Advertising](#) [Business](#) [About](#) [How Search works](#)

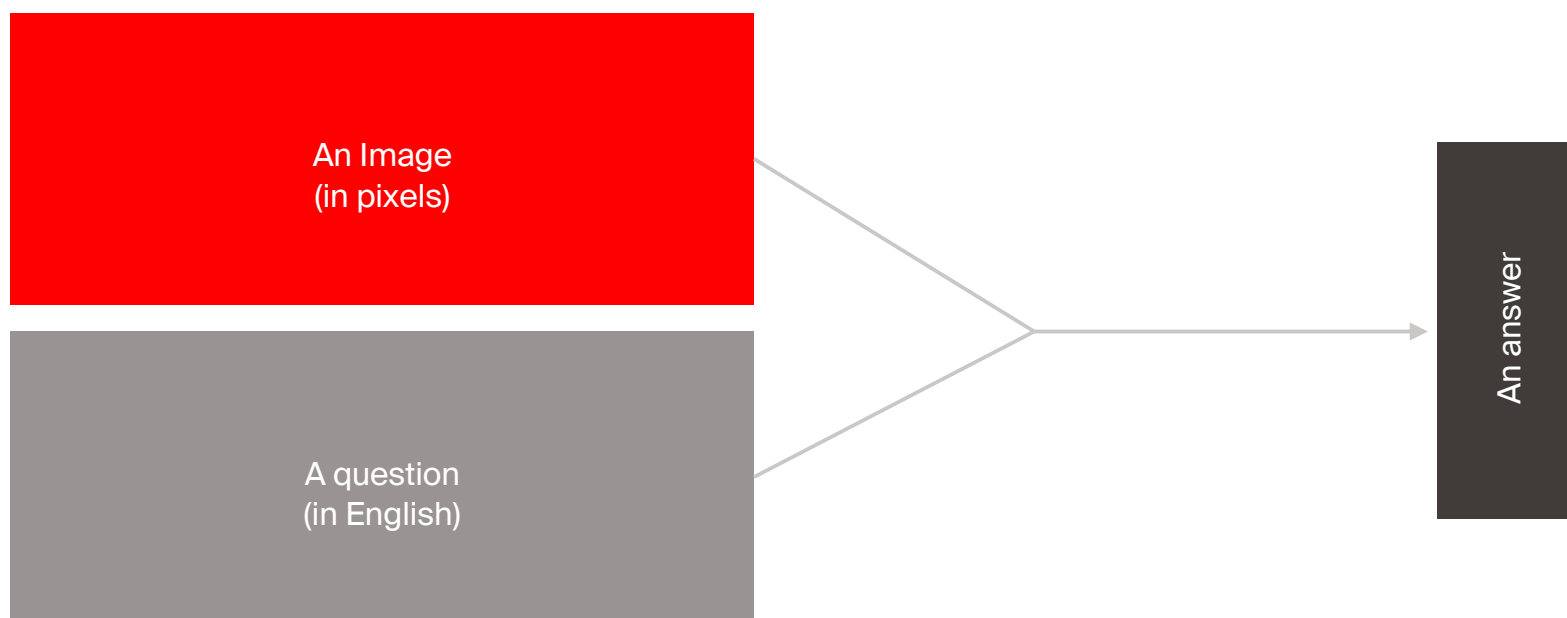
[Privacy](#) [Terms](#) [Settings](#)

# What do we need?

- For web-search it works a bit like that.
- With satellite images it just doesn't work (it's normal. It wasn't built for that)

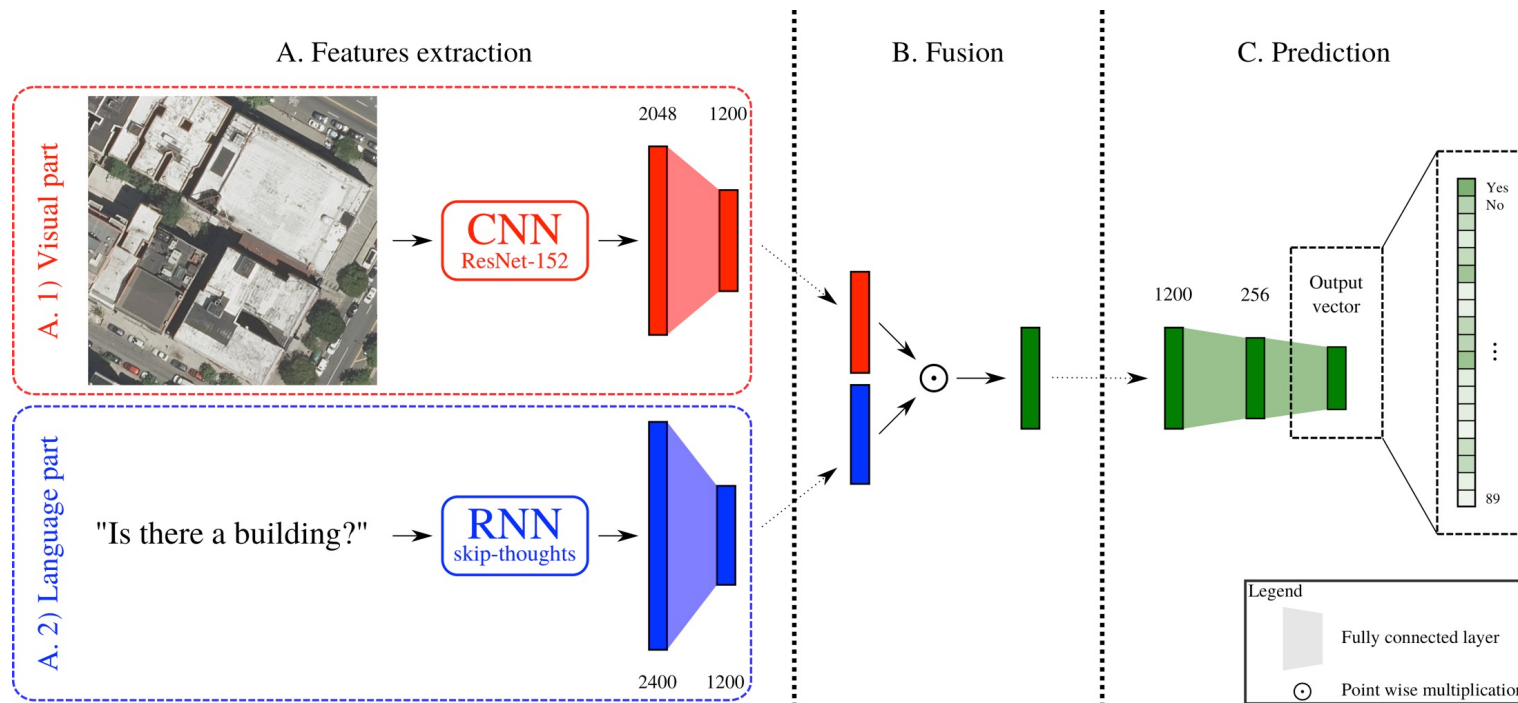


# Remote sensing visual question answering (RSVQA)



S. Lobry, D. Marcos, J. Murray, and **D. Tuia**. RSVQA: visual question answering for remote sensing data. *IEEE Trans. Geosci. Remote Sens.*, 58(12):8555–8566, 2020. <https://arxiv.org/abs/2003.07333>

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IMAGE



QUESTION  
Is there a  
cult place?

ANSWER  
Yes!

# How do we train a model like this?

We created two datasets:

- Sentinel-2 images (RGB)

Entire Netherlands

9 scenes

772 image tiles

77'200 triplets

- Aerial images (15cm)

New York and Philadelphia

11'000 tiles (6000 m<sup>2</sup> each)

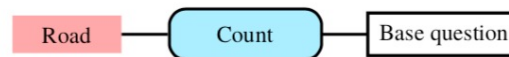
1'110'000 triplets

# Generating text inputs / outputs

- We generated {image, **question**, answer} triplets with OSM



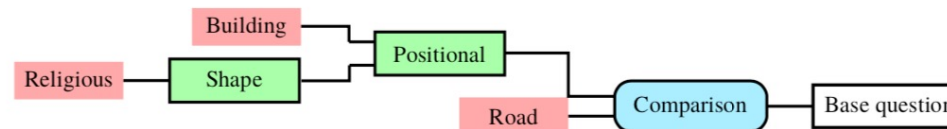
"How many roads are present in the image?"



"Is there a small retail place?"

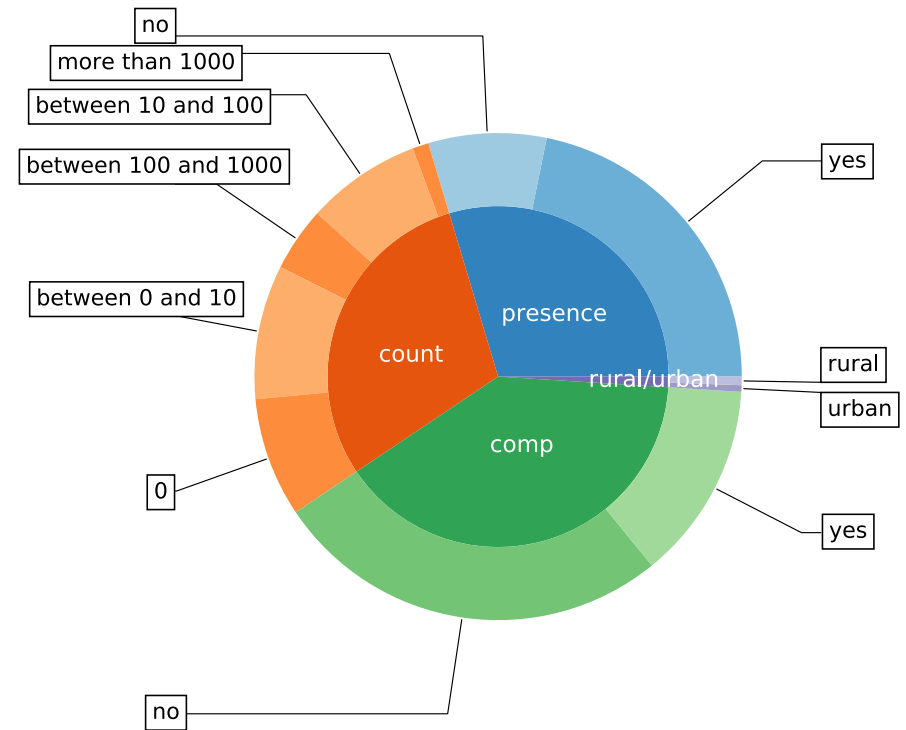


"Is there more buildings at the top of a circular religious place than roads in the image?"



# Generating text inputs / outputs

- We generated {image, question, **answer**} triplets
- We again use OSM



# Results

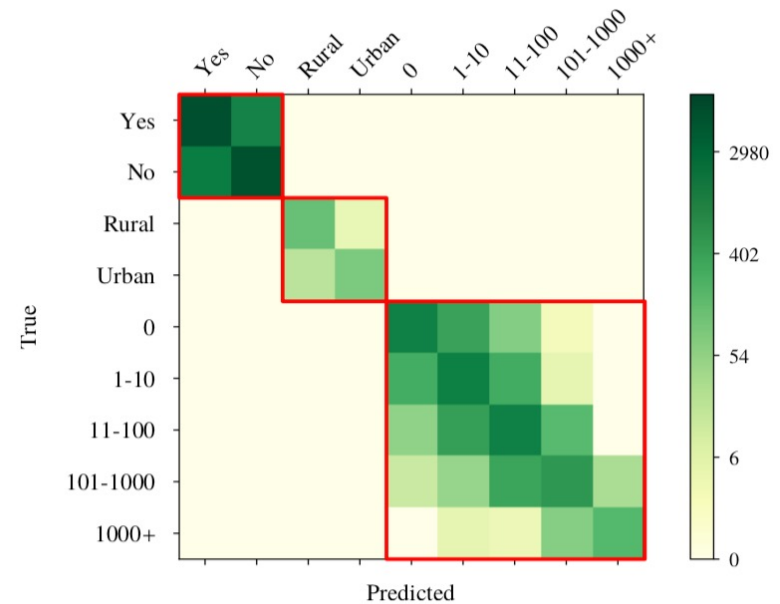
79% overall accuracy

73% if randomizing the image part

Count questions less accurate

Type	Accuracy
Count	67.01% (0.59%)
Presence	87.46% (0.06%)
Comparison	81.50% (0.03%)
Rural/Urban	90.00% (1.41%)
AA	81.49% (0.49%)
OA	79.08% (0.20%)

The model can make a good distinction between types of questions



# Some results



Building  
surface?

0 m<sup>2</sup>!



Building  
surface?

100 m<sup>2</sup>!



Is there a  
cult place?

Yes!

# Some results



How many  
buildings?

0!



How many  
bulidings?

1!



## Get data and codes!

<https://rsvqa.sylvainlobry.com/>

### DATASET

Very high resolution dataset

10659

Images

Low resolution dataset

955664

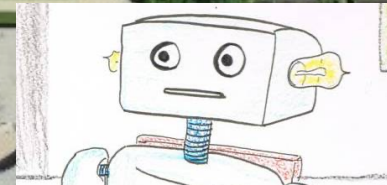
Questions

We have created a database using USGS' high resolution (15.24cm) orthorectified images and questions and answers derived from OSM. You can explore a subset of 50 images from this dataset [here](#).

# Moving forward (actually, backwards) : time

Which buildings are new?

mmm... let me check...



C. Chappuis PhD thesis, EPFL

**EPFL**

 **Université  
de Paris**

 **esa**

# In summary

EPFL

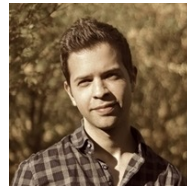
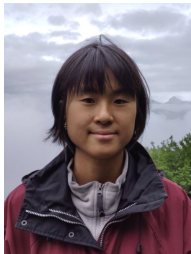


Earth observation and machine learning / computer vision are a match made in heaven.

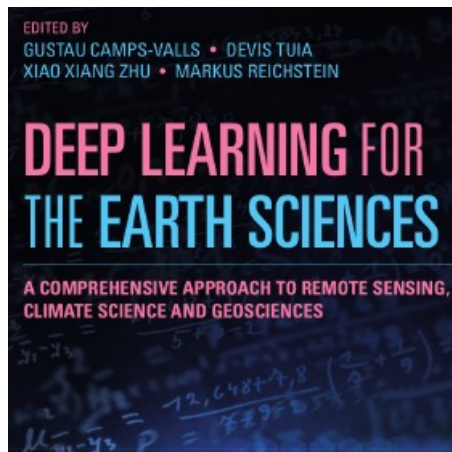
- There are many unsolved challenges for vision
- There is a lot of data out there
- and waaaaaaaay more importantly:

**Making a difference with EO means making a difference for the future of our planet  
For our air, water, food, biodiversity.**

[devis.tuia@epfl.ch](mailto:devis.tuia@epfl.ch), [eceo.epfl.ch](http://eceo.epfl.ch), @devistuia



## The book



## The paper

arXiv.org > cs > arXiv:2104.05107

Computer Science > Computer Vision and Pattern Recognition

[Submitted on 11 Apr 2021]

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DOI: 10.1109/MGRS.2020.3043504

Cite as: arXiv:2104.05107 [cs.CV]  
(or arXiv:2104.05107v1 [cs.CV] for this version)

## The network



European Laboratory for Learning and Intelligent Systems  
Program "ML for Earth and Climate Science"