Land cover land use mapping with remote sensing and machine learning

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Content

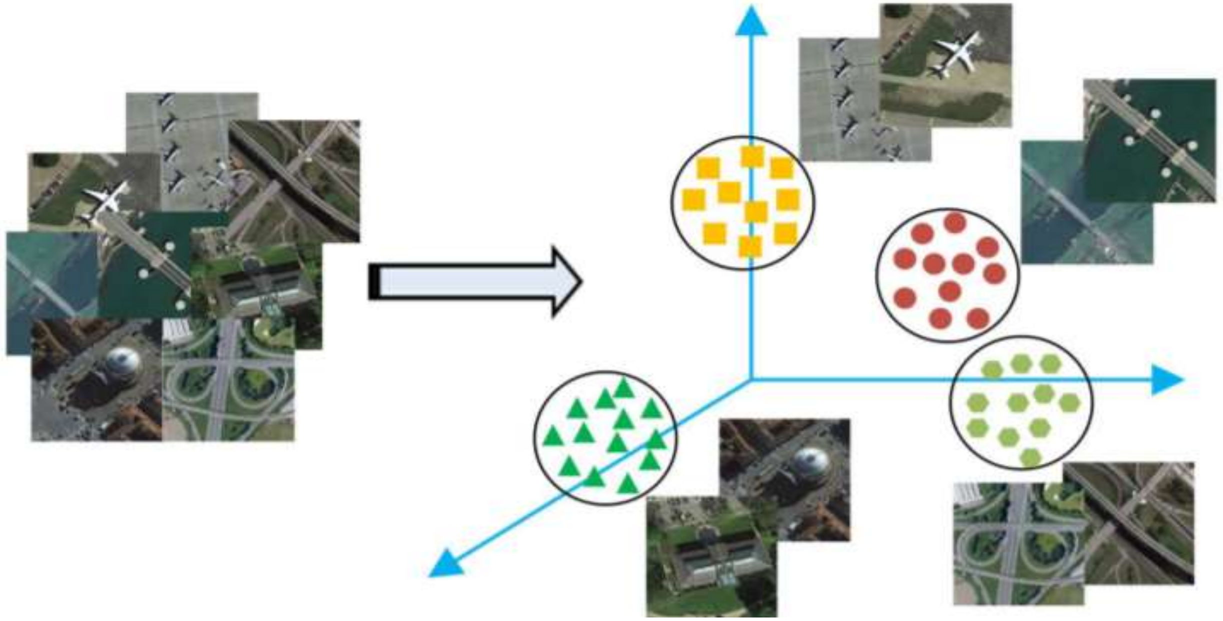
- **Earth observation perspective & machine learning**

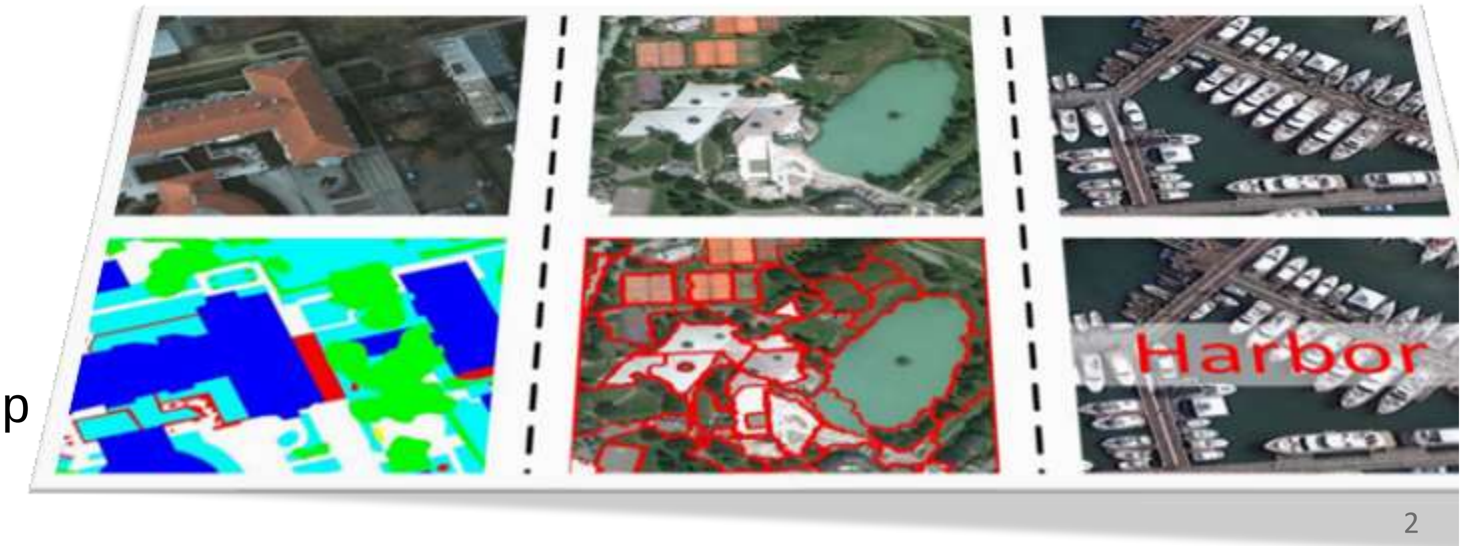
- **Case studies**
  - Forest & tree height mapping
  - Counting trees
  - Mapping artillery craters
  - Detection of man-made changes (constructions)

- **Open problems RS/ML**

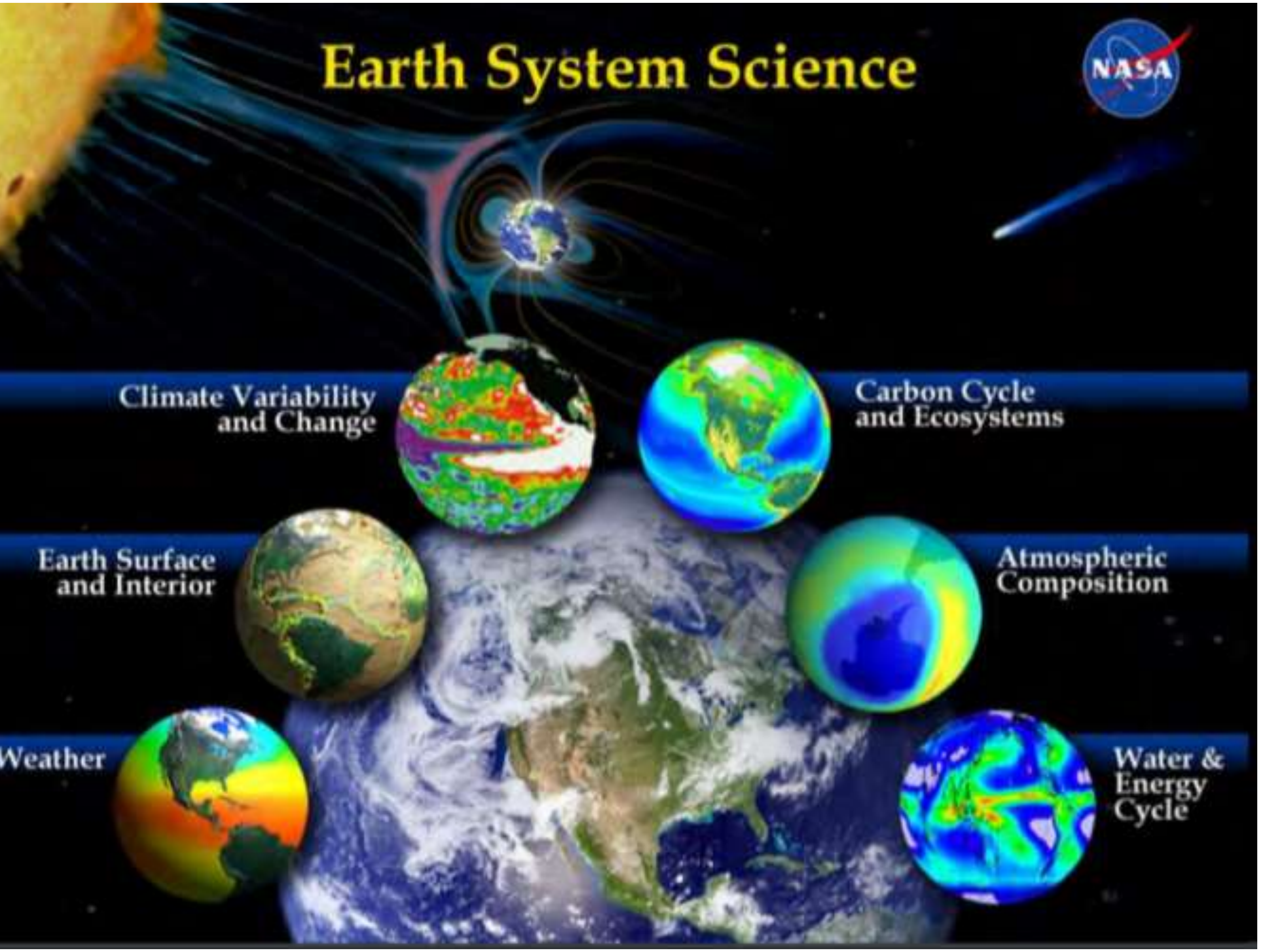
- **Showcase**:
  - Crater detection with DL and VHR

- **Practical session**:
  - Airborne images classification with deep learning





NASA Earth Science Division (ESD): Focus areas



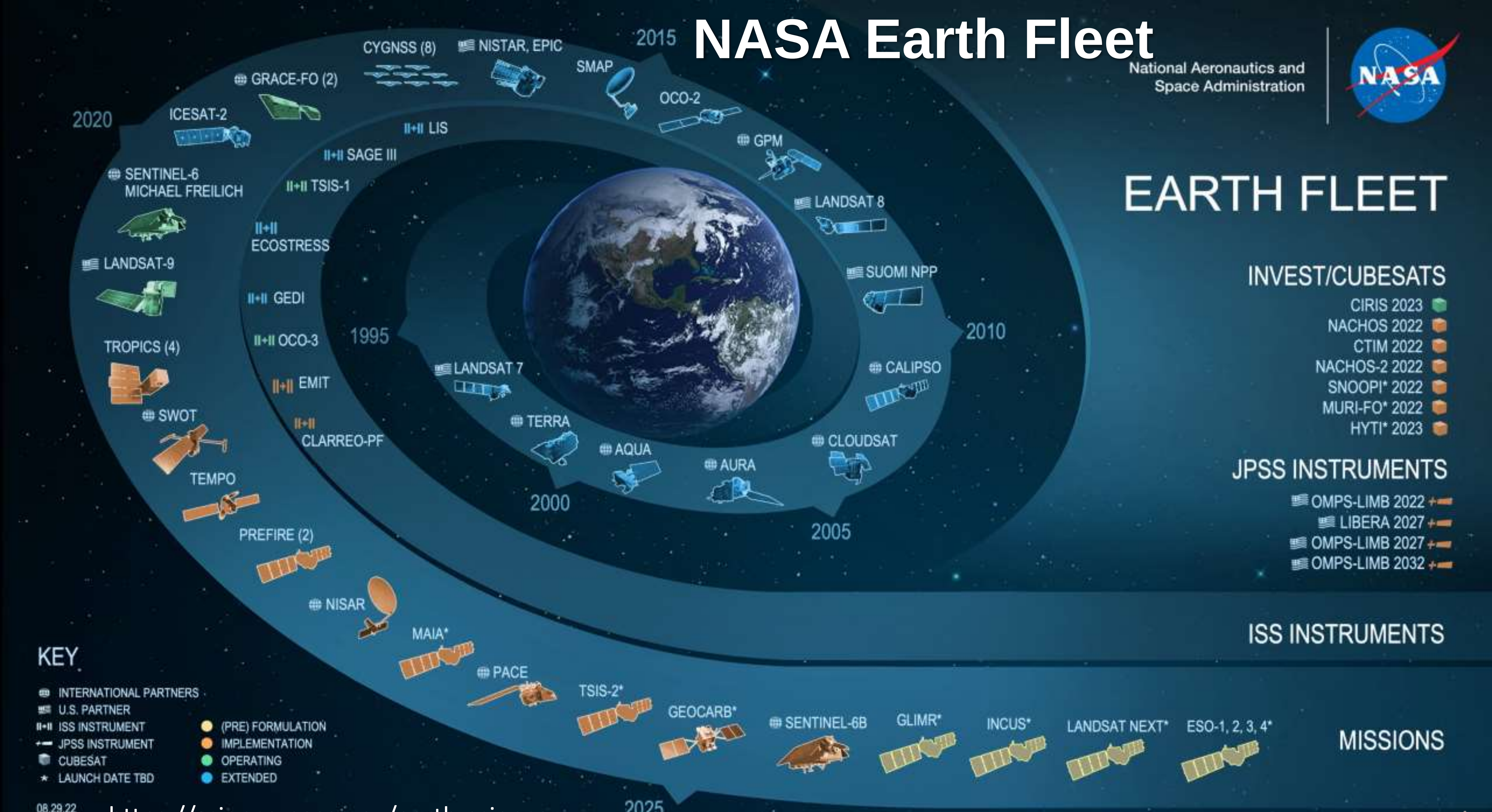
How is the global Earth system **changing**?

What **causes** these **changes** in the Earth system?

How will the Earth system **change in the future**?

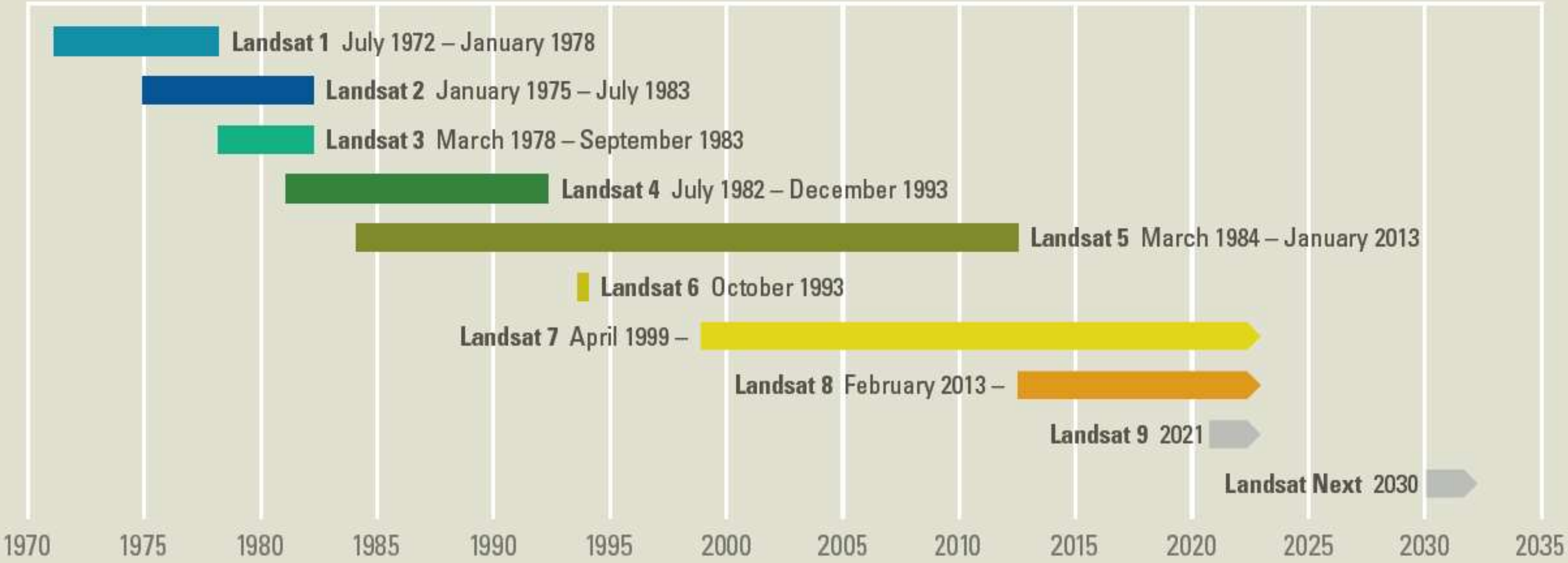
How can Earth system science provide **societal benefit**?

NASA Earth Fleet



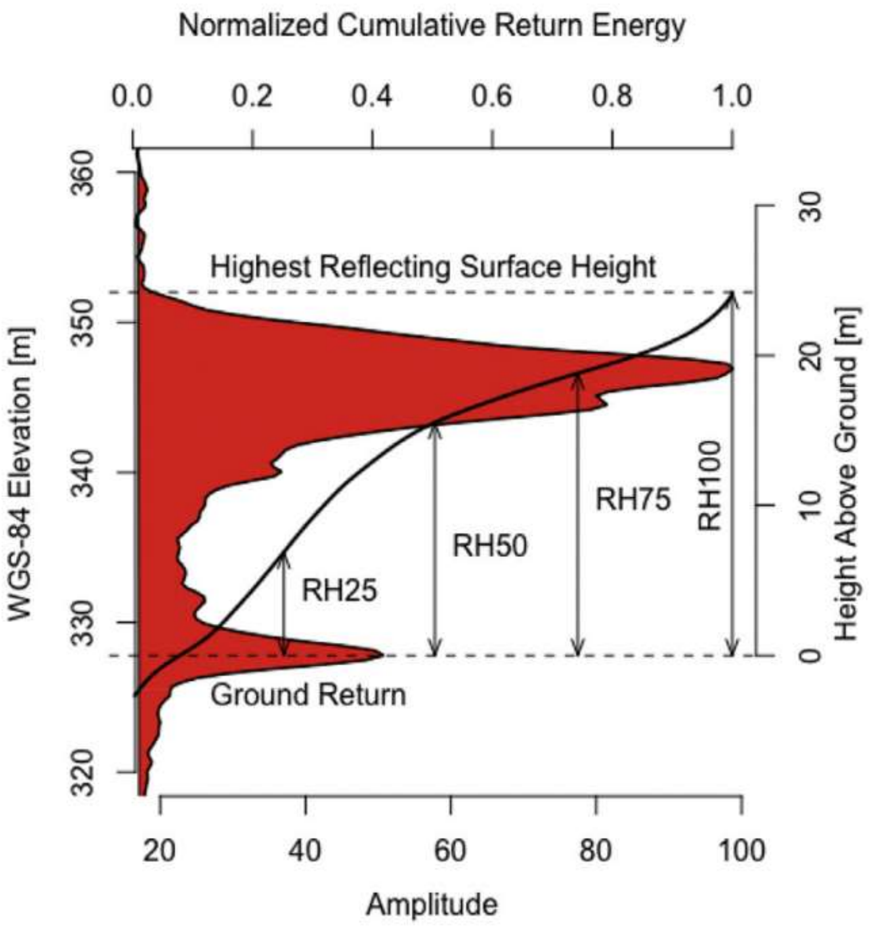
https://science.nasa.gov/earth-science

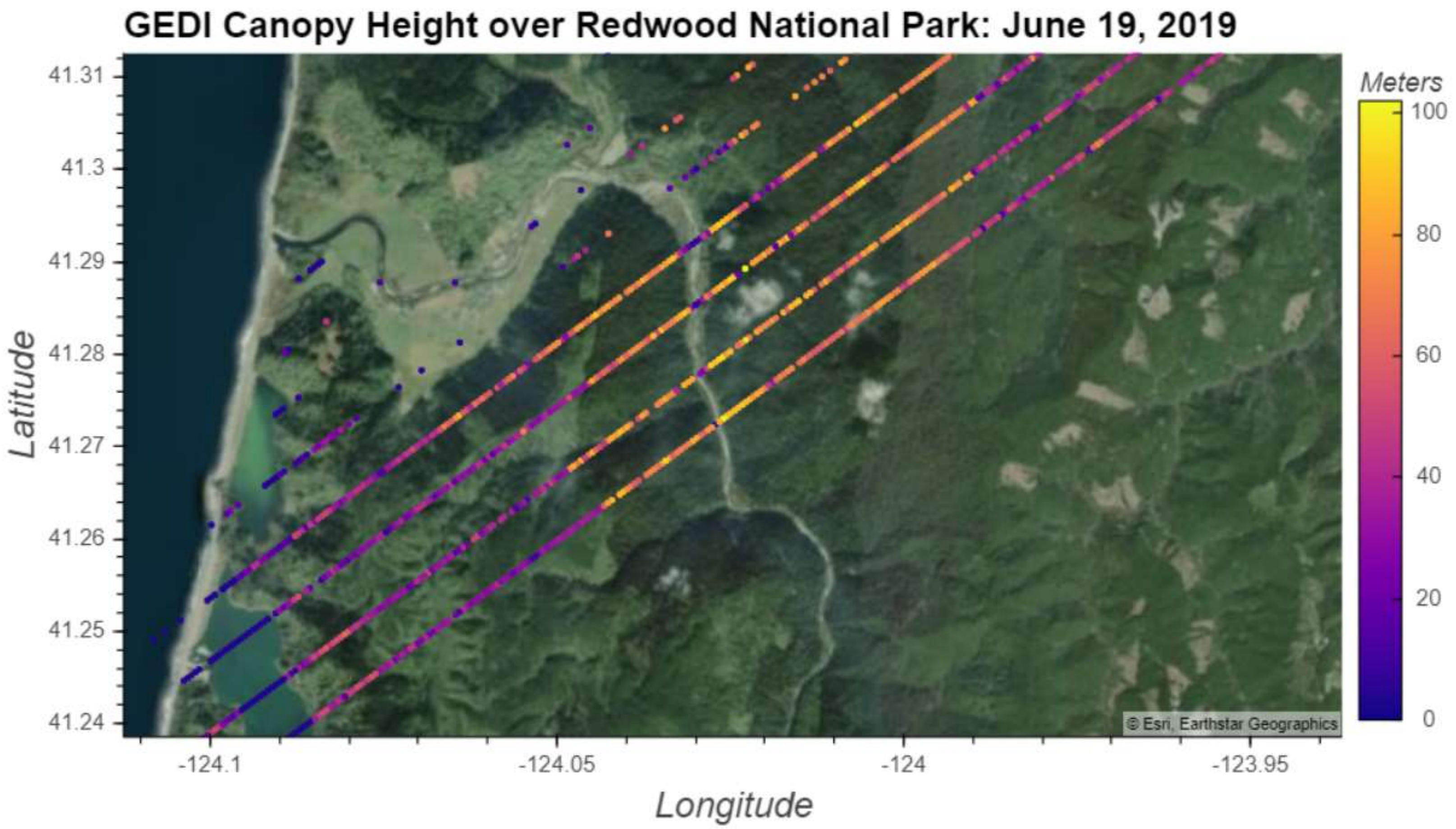
Landsat Missions: Imaging the Earth Since 1972



GEDI: Global Ecosystem Dynamics Investigation

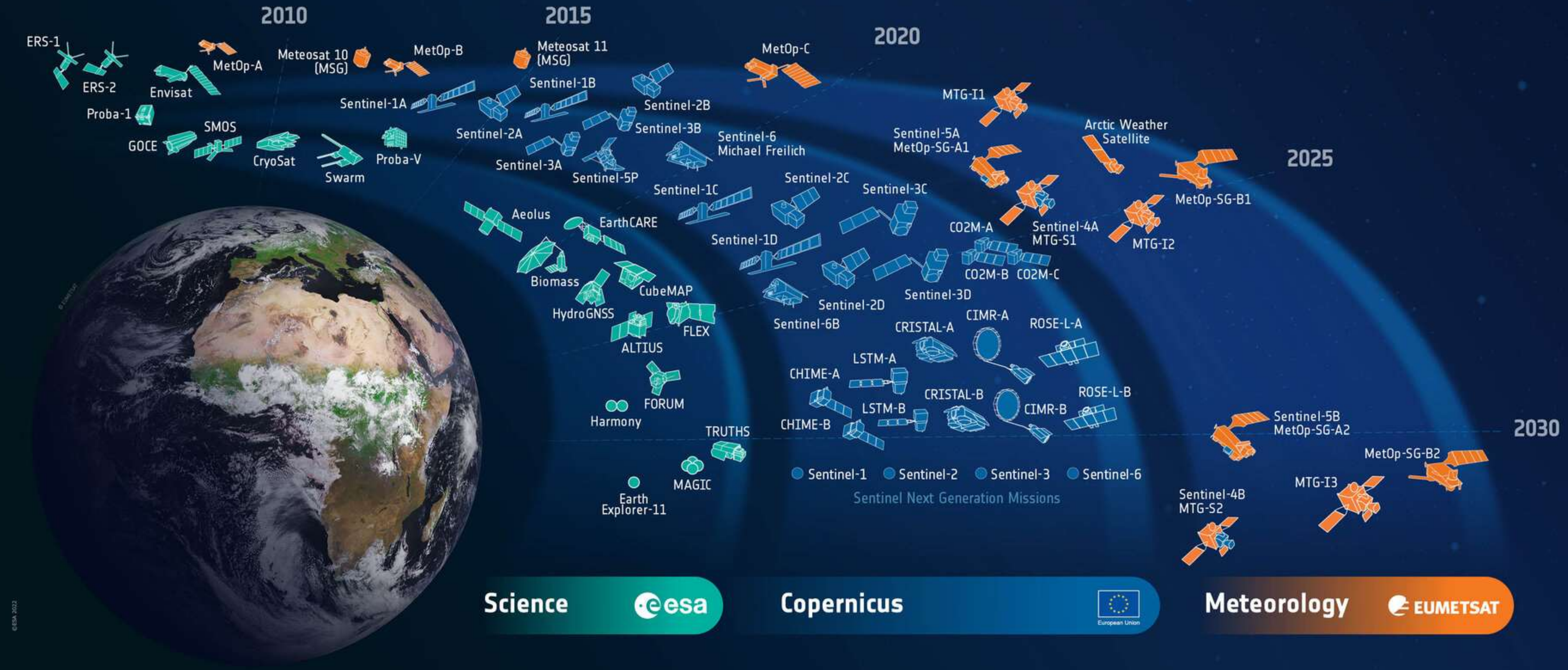
- ***May the Forest Be With You!***





https://doi.org/10.1016/j.srs.2020.100002

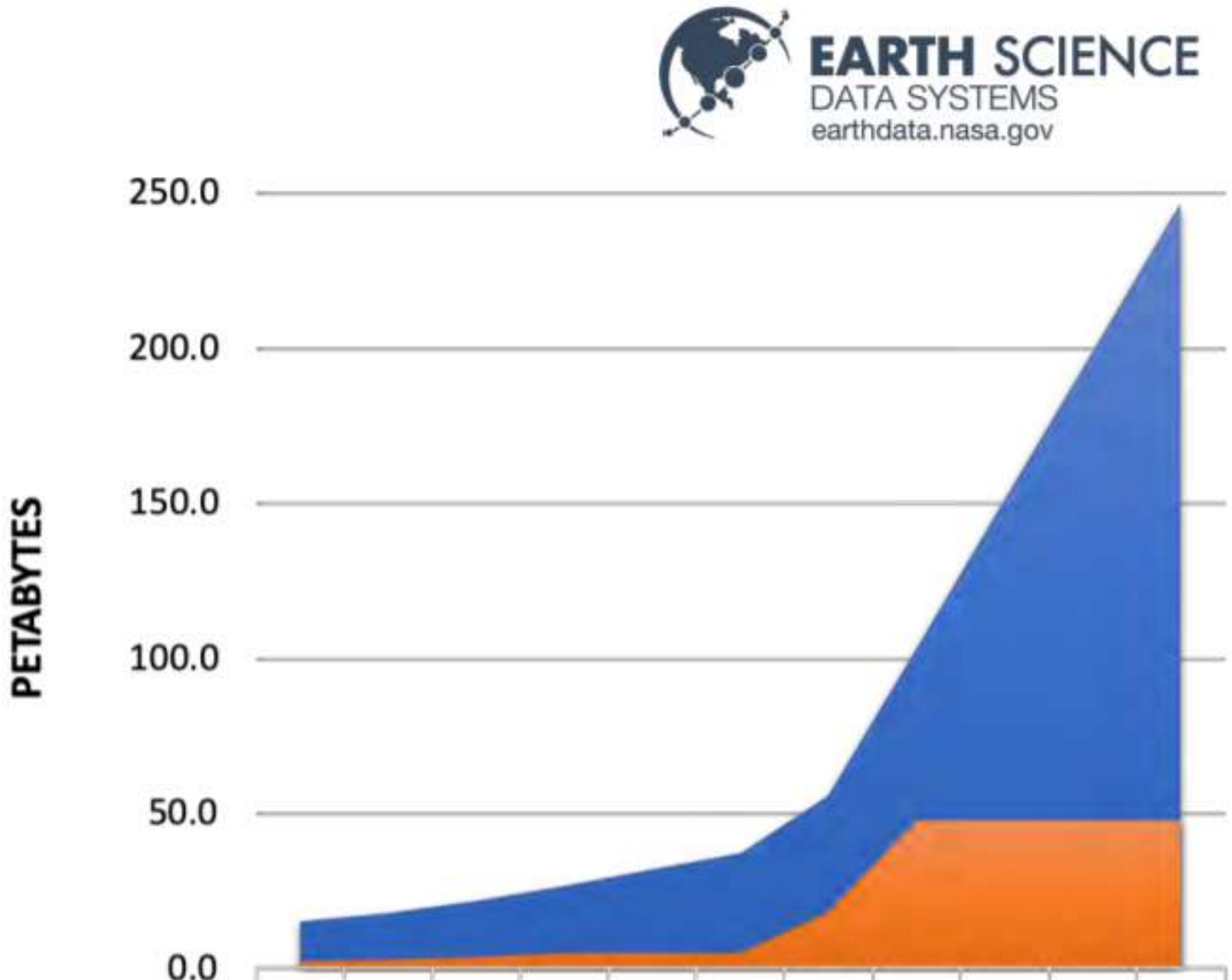
ESA-developed Earth observation missions



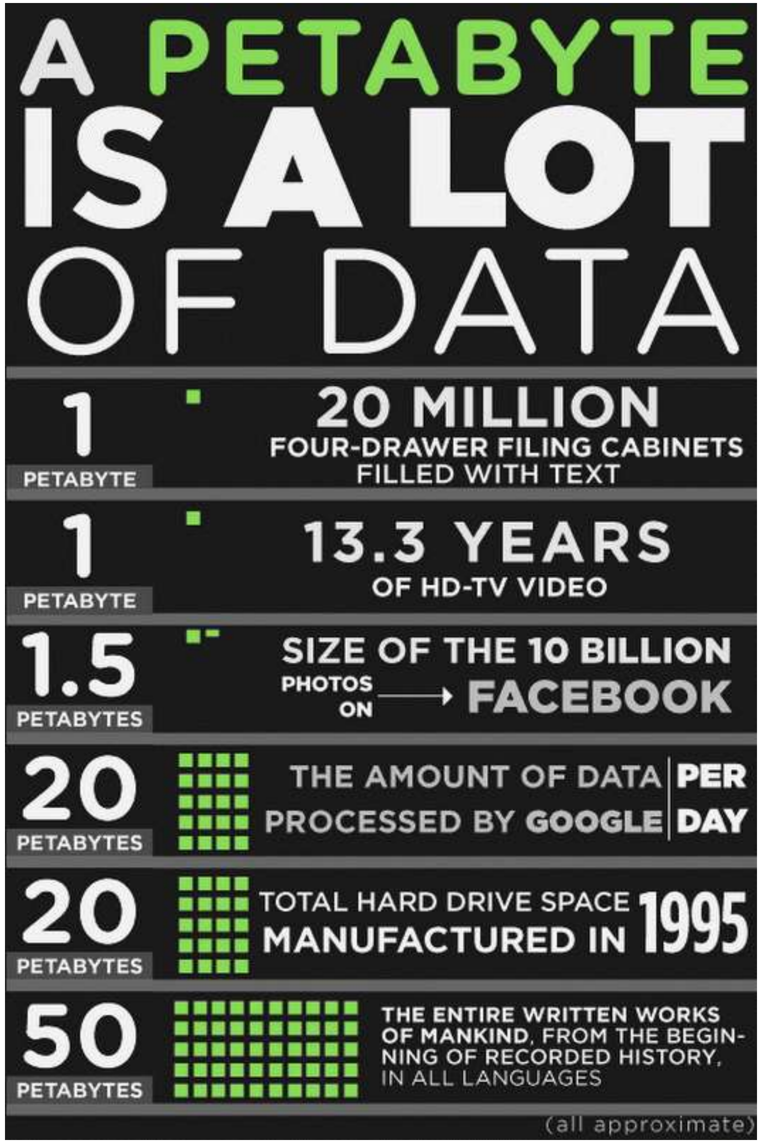
Copernicus Satellites

	**Sentinel 1** (A/B/C/D) **SAR Imaging**	All weather, day/night applications, interferometry
	**Sentinel 2** (A/B/C/D) **Multispectral Imaging**	Land applications: urban, forest, agriculture, … Continuity of Landsat, SPOT
	**Sentinel 3** (A/B/C/D) **Ocean & Global Land Monitoring**	Wide-swath ocean colour, vegetation, sea/land surface temperature, altimetry
	**Sentinel 4** (A/B) **Geostationary Atmospheric**	Atmospheric composition monitoring, pollution; instrument on MTG satellites
	**Sentinel 5** (A/B/C) & Precursor **Low-Orbit Atmospheric**	Atmospheric composition monitoring; instrument on MetOp-SG satellites
	**Sentinel 6** **Jason CS (A/B)**	Altimetry reference mission

Big Data: Earth Science



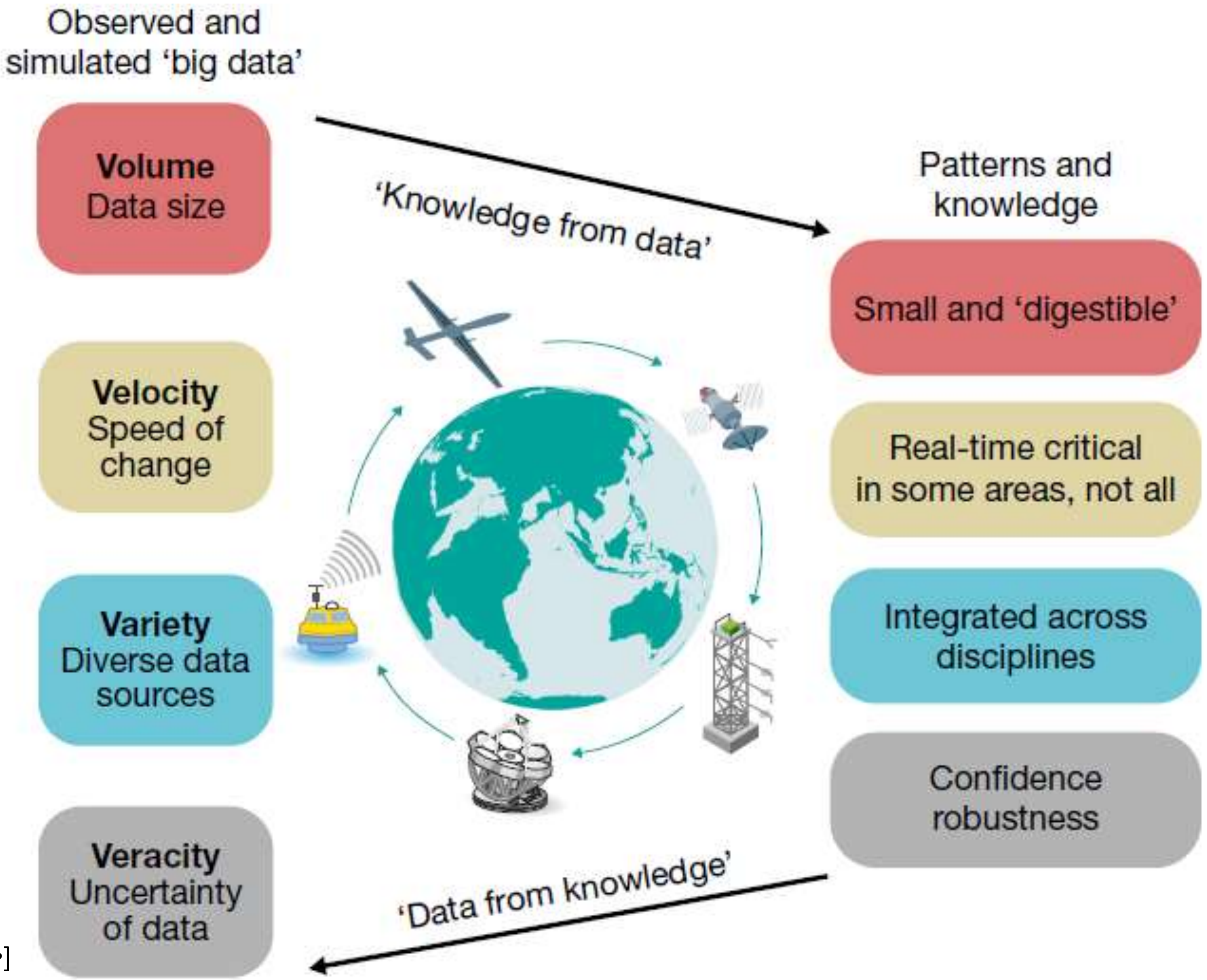
	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024	2025
Archive Size (PB)	15.0	17.7	21.6	26.8	32.0	37.2	55.6	103.4	151.1	198.9	246.6
Annual Growth (PB)	2.6	2.8	3.9	5.2	5.2	5.2	18.4	47.7	47.7	47.7	47.7



[*Courtesy of S. Cauffman, NASA*]

https://www.pecanstreet.org/2018/10/big-data-anyone/

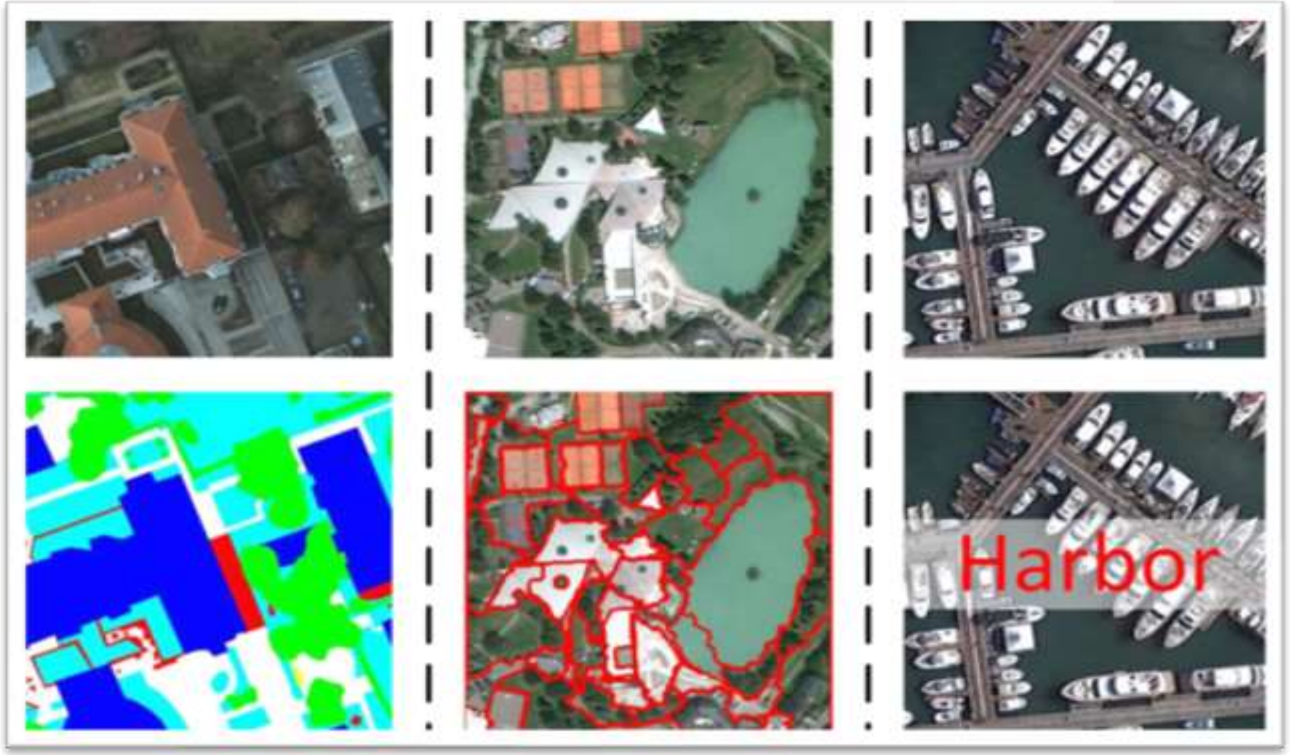
Big data challenges in the geoscientific context



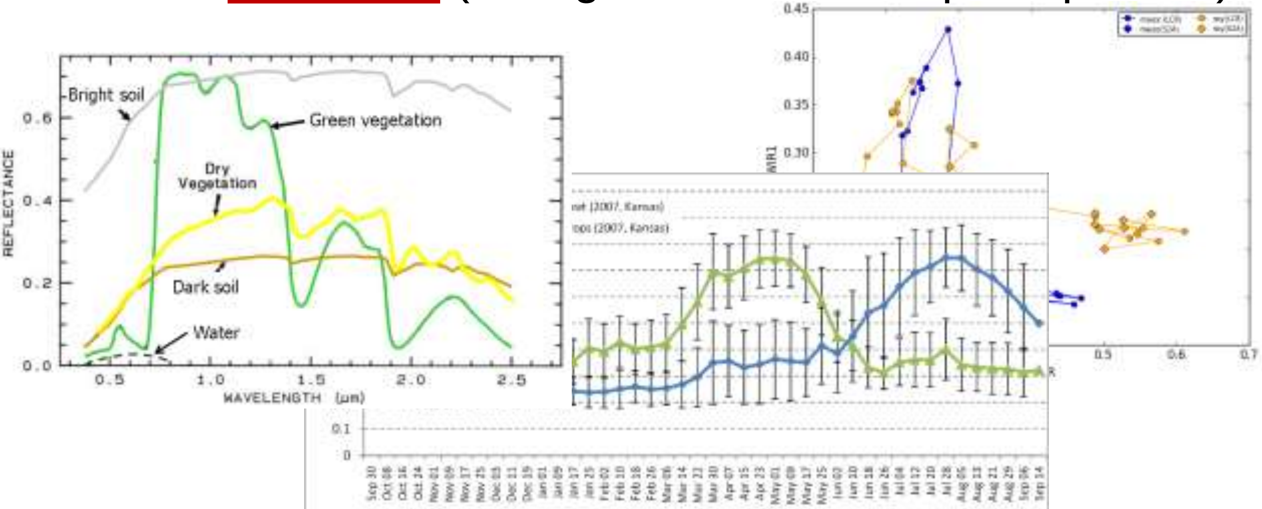
[Reichstein *et al.*, (2019). *Nature*]

Quantitative Analysis of Satellite Imagery: From Data to Labels

- **Classification**/**regression** is a mapping from measurements acquired by a remote sensing instrument to a **label**(s) (categorical/continuous) for each pixel that identifies it with what's on the ground
- Domains:
  - **Spatial** (e.g. textures, moving window, Fourier transformation etc.)
  - **Spectral** (e.g. spectral curvatures)
  - **Temporal** (change detection, temporal profiles)



Semantic labelling | Identifying objects | Scene-level labelling



Land cover / land use mapping and area estimation

Classification → Mapping → Area estimation

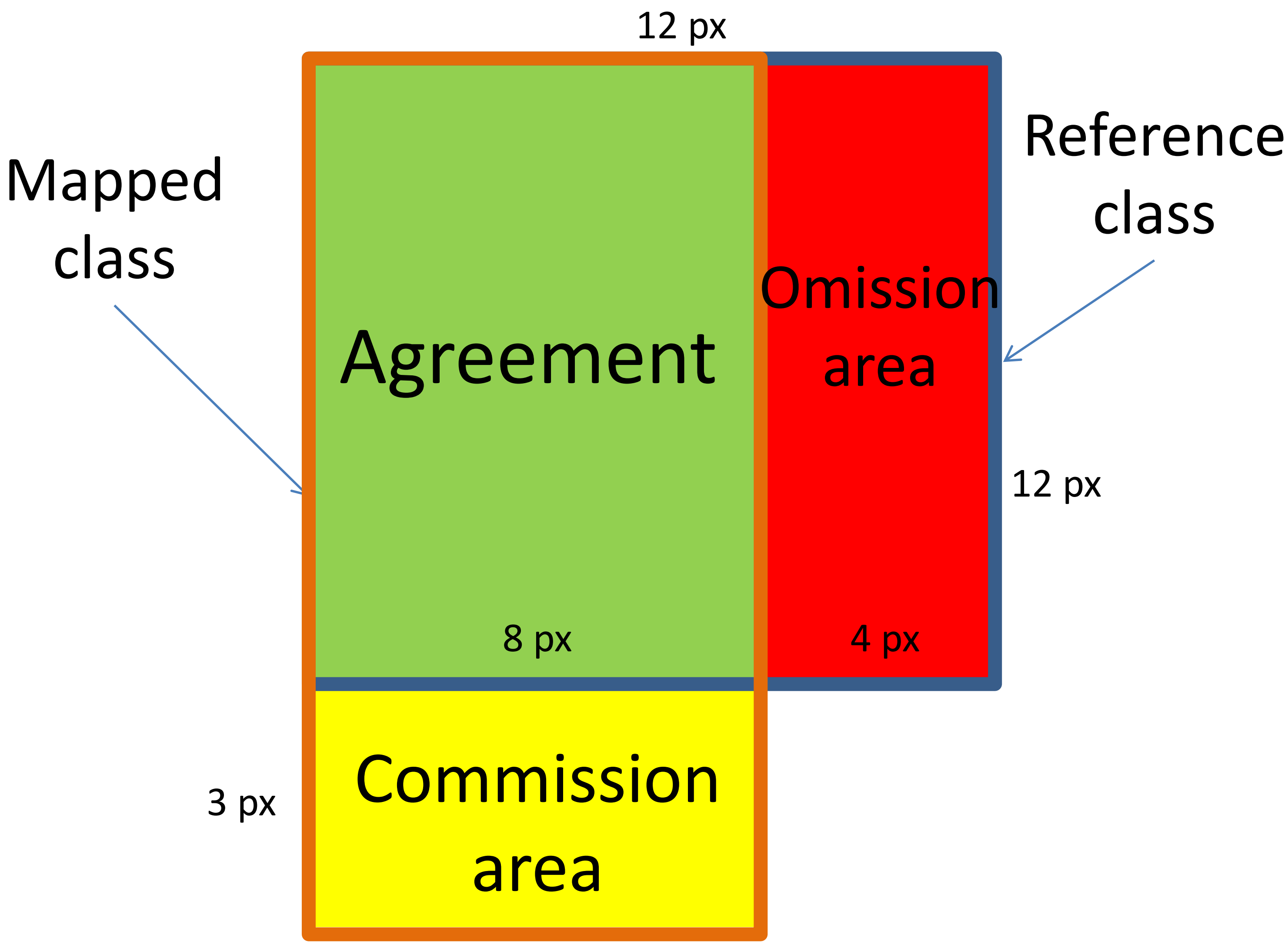
- Data
- Features
- Algorithms

- Spatial context

- Unbiased estimates with uncertainties

Land cover / land use mapping and area estimation

- Pixel counting is a biased estimator



Reference area:
12 x 12 = 144 px

Mapped area:
8 x 15 = 120 px (bias ~17%)

PA = 8 x 12 / (12 x 12) = 66.7%

UA = 8 x 12 / (8 x 15) = 80%

Land cover / land use mapping and area estimation

Remote Sensing of Environment 148 (2014) 42–57

Contents lists available at ScienceDirect

Remote Sensing of Environment

journal homepage: www.elsevier.com/locate/rse

Review

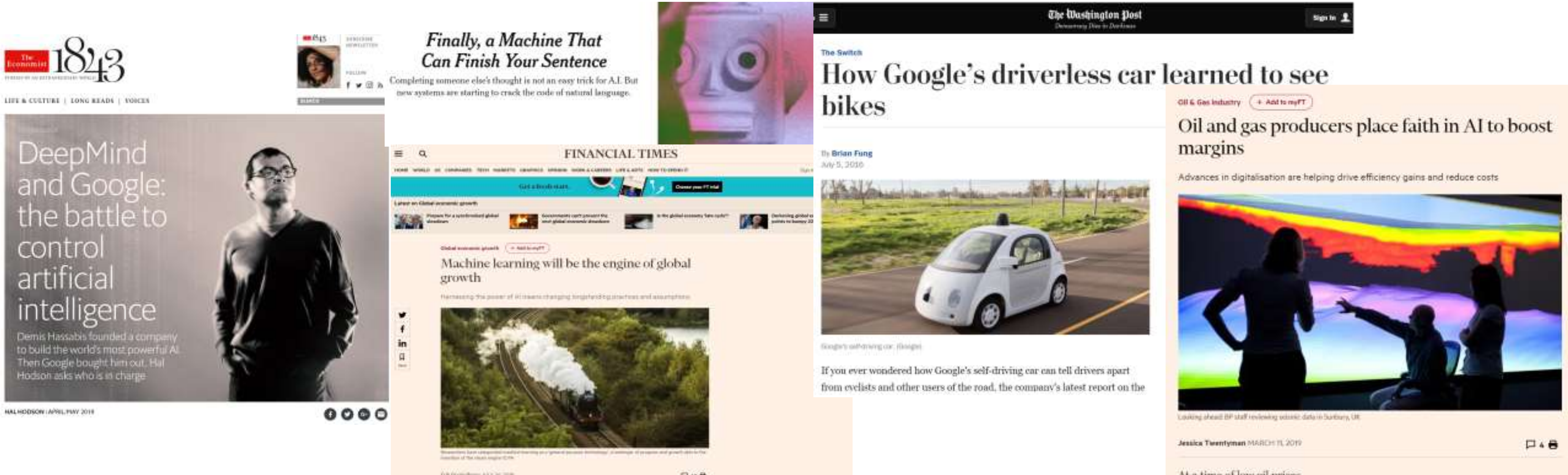
Good practices for estimating area and assessing accuracy of land change

Pontus Olofsson [a,*], Giles M. Foody [b], Martin Herold [c], Stephen V. Stehman [d], Curtis E. Woodcock [a], Michael A. Wulder [e]

Stratified random sampling, where strata are coming from maps

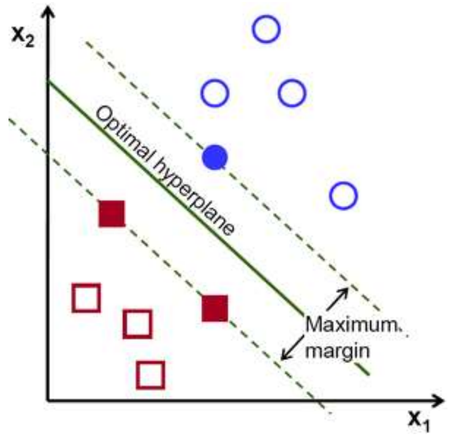
Machine learning

- ML is a field of computer science which gives "**computers the ability to learn without being explicitly programmed**" [Arthur Samuel (1959)]
- Machine learning explores the study and construction of **algorithms** that can **learn** from and make **predictions** on **data**

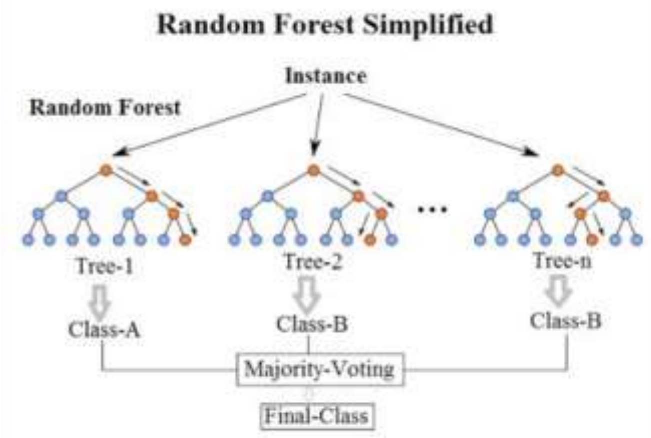


Machine learning: most popular in satellite data processing

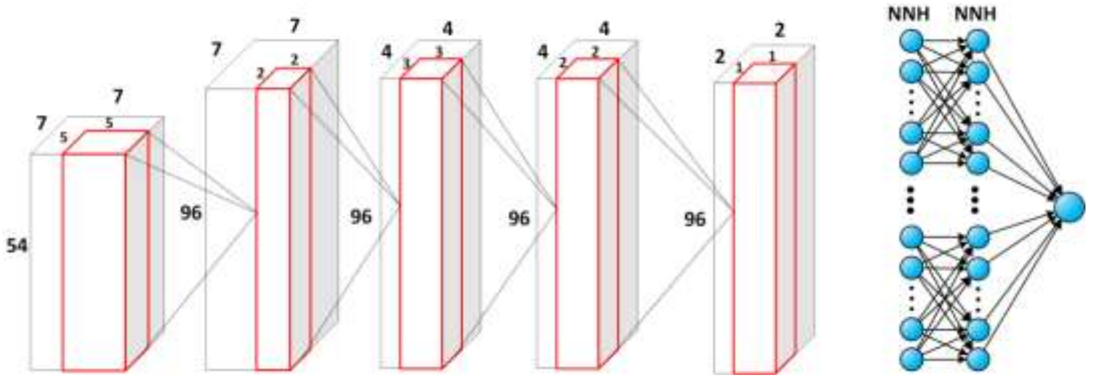
- **Support vector machine (SVM)**
  - Works well with small amount of data
  - Computational cost grows linearly with the number of classes
  - Several parameters to be optimized
  - Require feature engineering



- **Decision trees (DT)** / **Random forest (RF)**
  - Training is fast and simpler with small number of parameters to tune
  - Require feature engineering

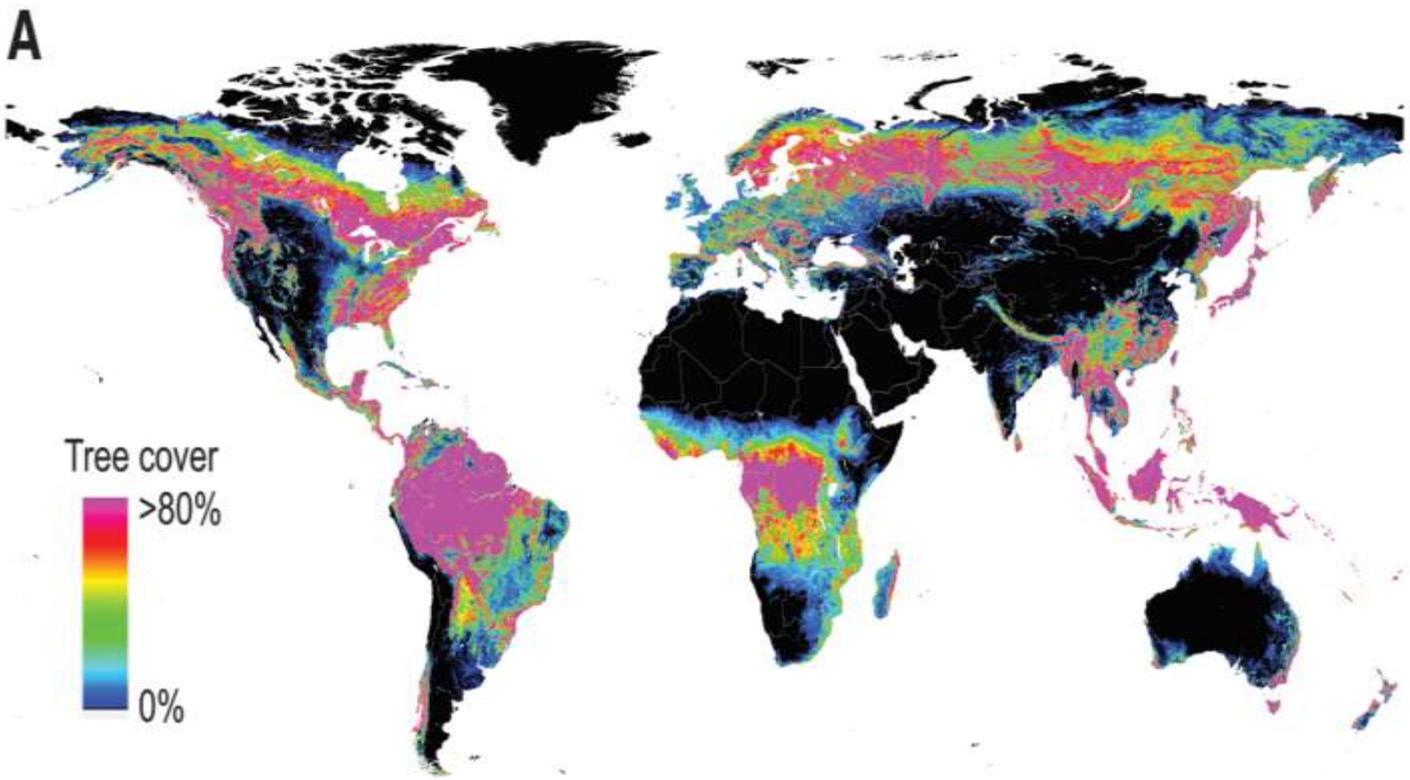


- **Artificial neural networks** (**ANN** or **NN**)
  - Difficult to train with a lot of parameters to tune
  - Require a lot of skills and expertise
  - No need for feature engineering: feature are learned by the network
  - Can learn very complex decision boundaries



Forest mapping

- High-Resolution Global Maps of 21st-Century Forest Cover Change
  - Satellite data
    - **Landsat 7** data at **30 m**
      - **654,178** Landsat 7 ETM+ analyzed or Google cloud
  - **Training data**
    - Image interpretation methods, including mapping of crown/no crown categories using very high spatial resolution data such as Quickbird imagery
  - Machine learning**:**
    - **Decision Trees**

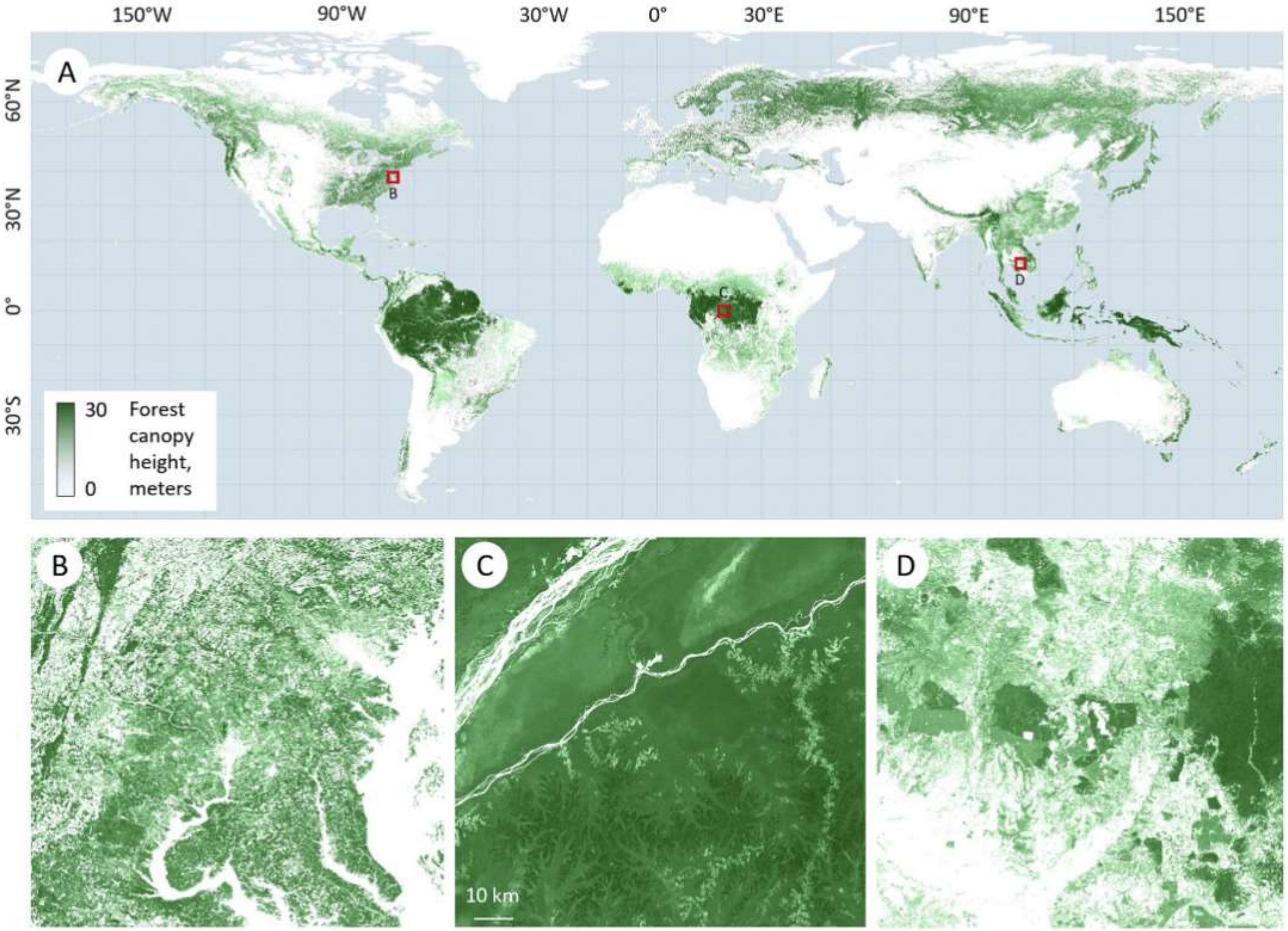


https://www.globalforestwatch.org/map/

[Source: Hansen *et al.*, Science 2015]

Tree height mapping: fusion Landsat + GEDI

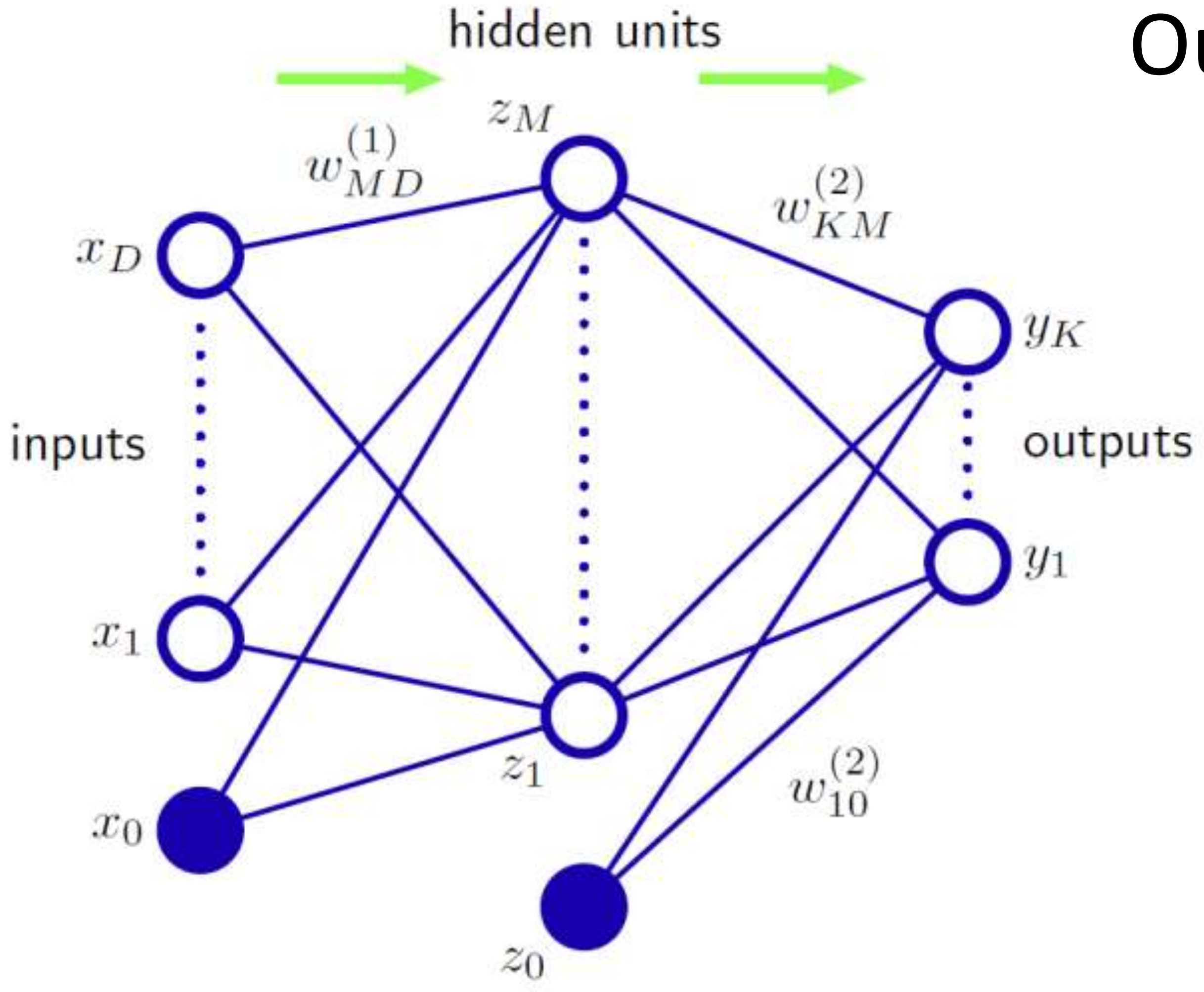
- Satellite data
  - **Landsat** + **GEDI** (Lidar)
  - Integration of **heterogenous** data
- Training data
  - GEDI-derived three canopy height
- Machine leaning
  - **Decision Tree** regression
- Performance
  - **RMSE ~ 6.6 m**



https://doi.org/10.1016/j.rse.2020.112165

https://glad.earthengine.app/view/global-forest-canopy-height-2019

Multi-layer perceptron (MLP)



Output ***y***

Input ***x***

$$y_k(\mathbf{x}, \mathbf{w}) = \sigma\left(\sum_{j=1}^{M} w_{kj}^{(2)} h\left(\sum_{i=1}^{D} w_{ji}^{(1)} x_i + w_{j0}^{(1)}\right) + w_{k0}^{(2)}\right)$$

Activation functions ***σ***, ***h***

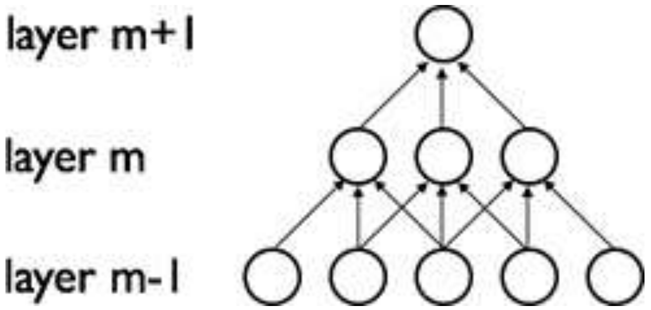
Weights ***w***

Universal approximators!

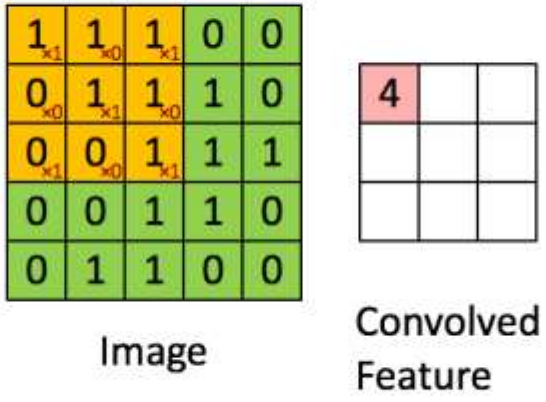
[Hornik, K., M. Stinchcombe, and H. White (1989). Multilayer feedforward networks are universal approximators. *Neural Networks* 2(5), 359–366.]

Convolutional neural networks (CNN)

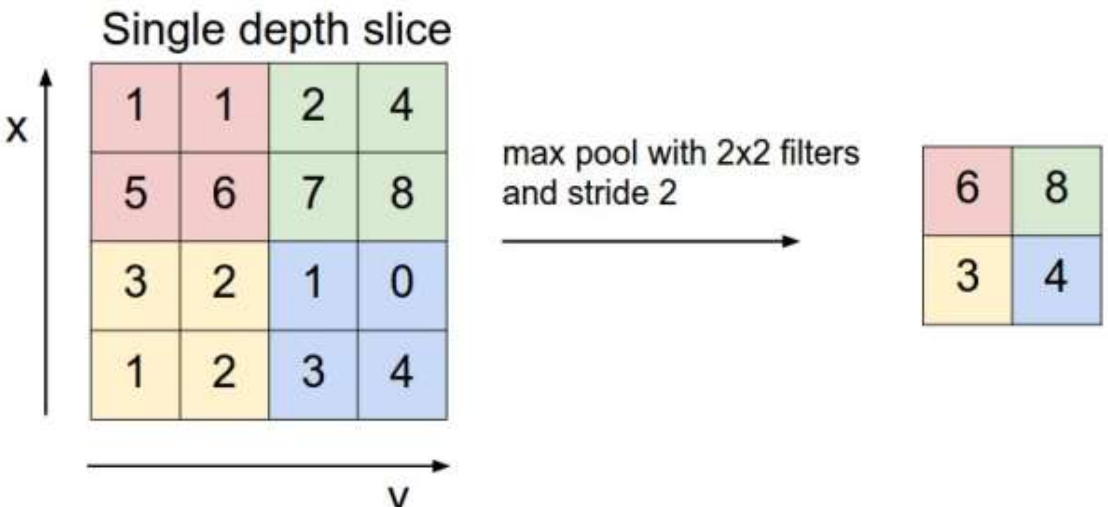
Sparse connectivity



Convolution



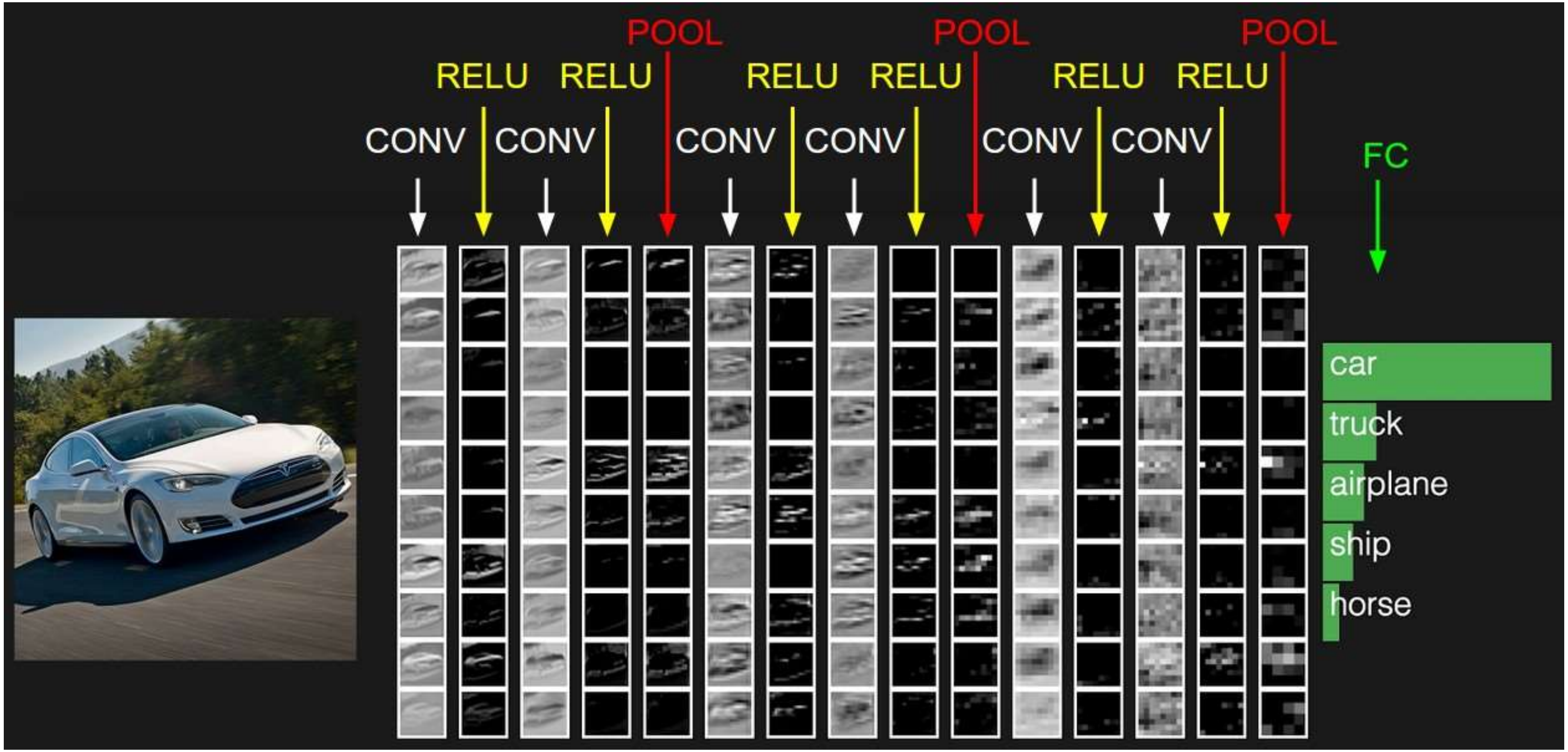
Pooling (sub-sampling)



[Sources: http://cs231n.github.io/convolutional-networks; http://deeplearning.stanford.edu]

Convolutional neural networks (CNN)

- Overall architecture

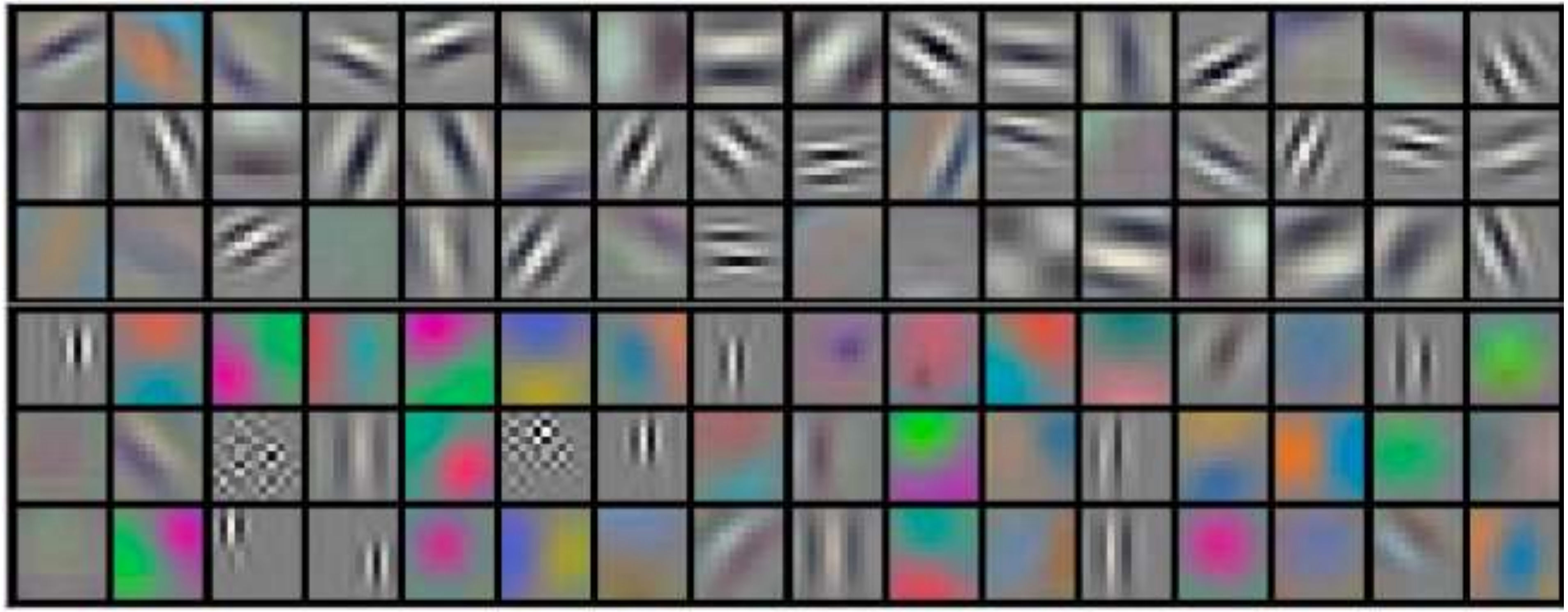


[Sources: http://cs231n.github.io/convolutional-networks]

Convolutional neural networks (CNN)

- Learned filters (Gabor-like)

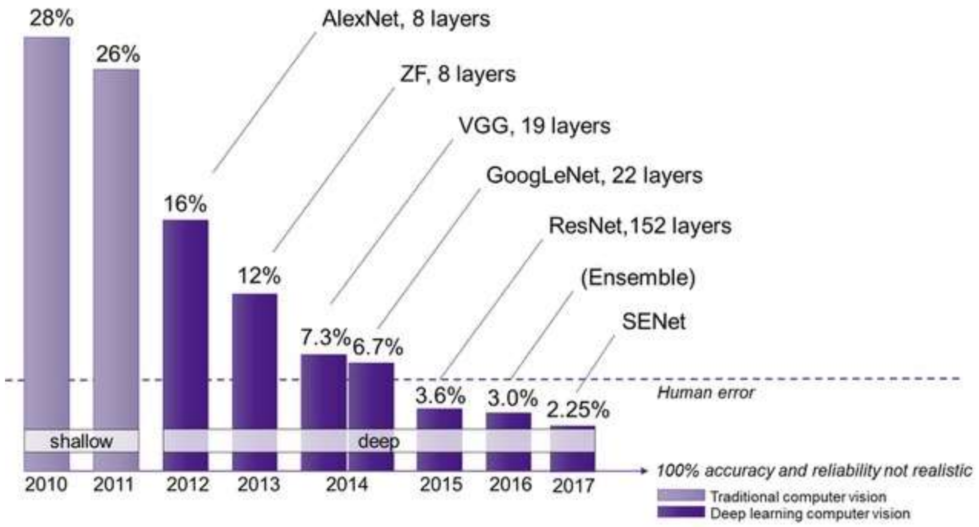
96 convolutional kernels of size 11×11×3 learned by the first convolutional layer on the 224×224×3 input natural images

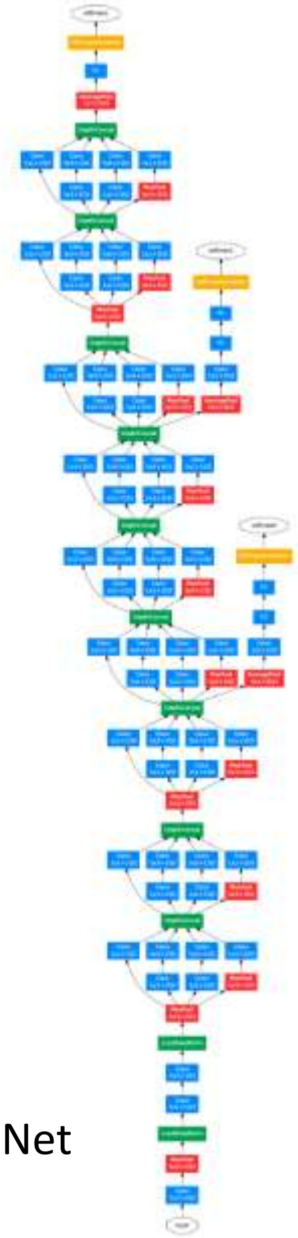


[Sources: Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). Imagenet classification with deep convolutional neural networks. In *Advances in neural information processing systems* (pp. 1097-1105)]

Modern neural networks

- Modern architectures, e.g.:
  - Szegedy, C., Liu, W., Jia, Y., Sermanet, P., Reed, S., Anguelov, D., ... & Rabinovich, A. (2015). Going deeper with convolutions. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 1-9).
  - Achieves **top-5 accuracy of 93.33% (error 6.67%)** ImageNet Large Scale Visual Recognition Competition 2014 (ILSVRC)
  - Human performance: **error ~5.1%**





GoogLeNet

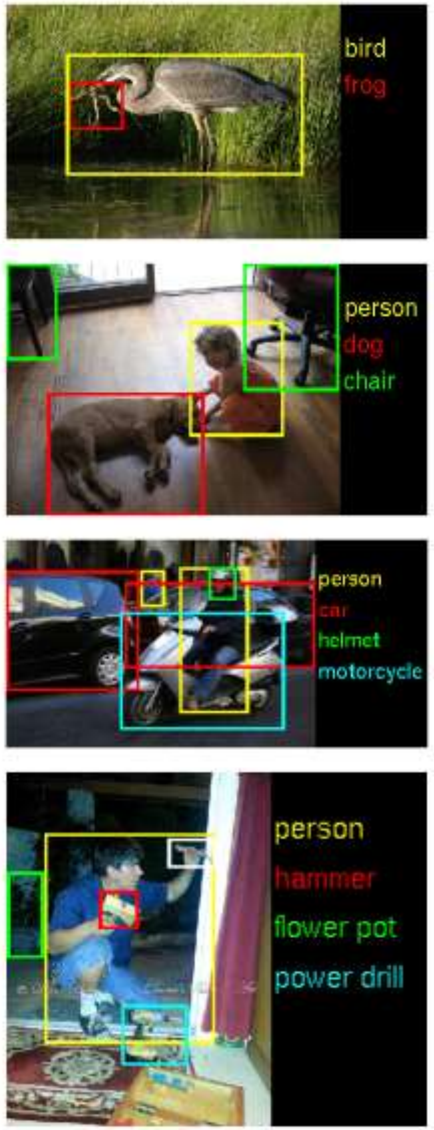
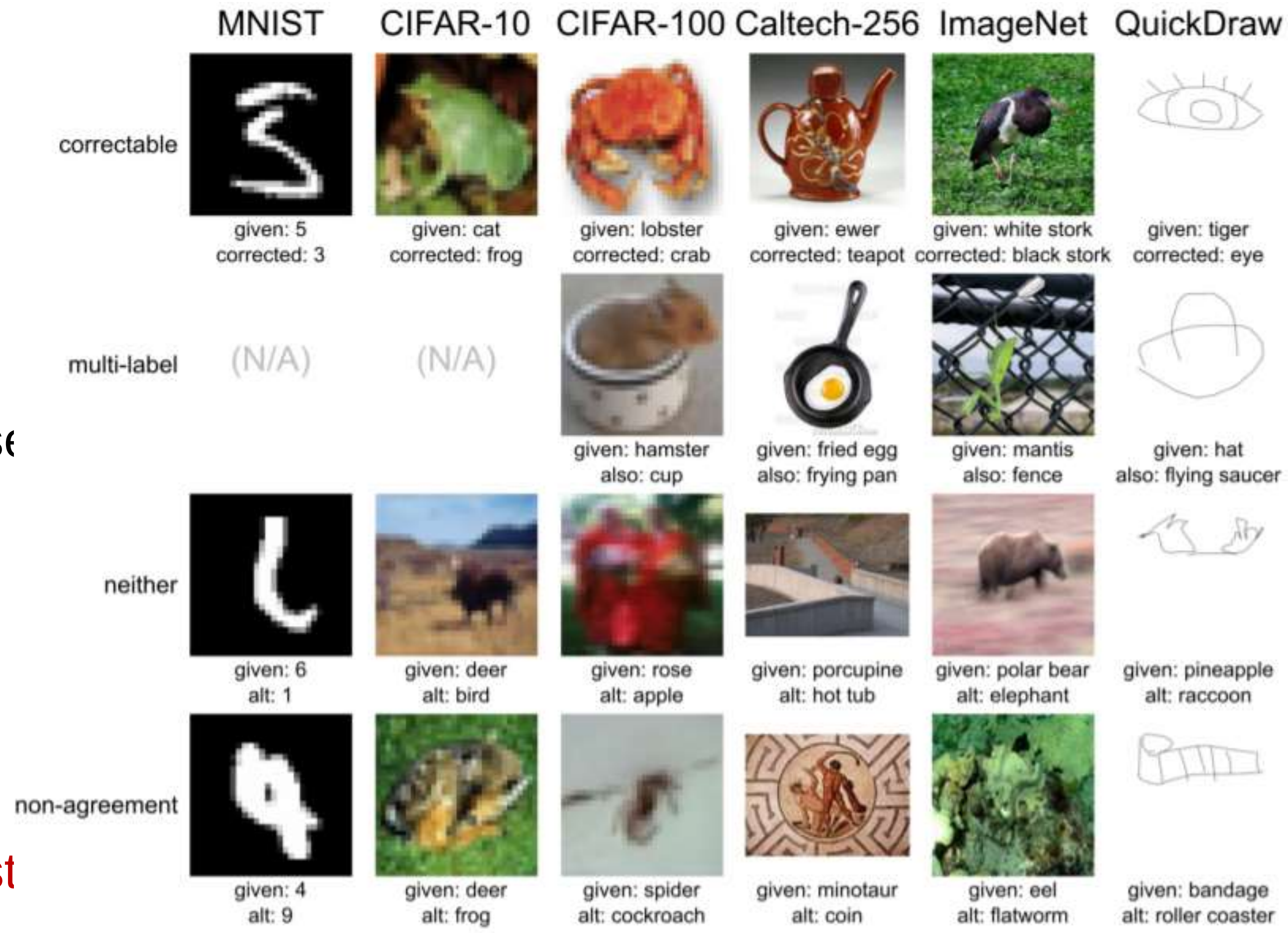


image-net.org

A catch #1: Wrong Labels

- **Label errors** in the **test sets of 10** of the most commonly-used computer vision, natural language, and audio datasets
- An average of **3.4% errors** across the 10 datasets,
  - where for example 2,916 label errors comprise 6% of the ImageNet validation set
- Judging models over correctly labeled test sets may be more useful
  - models that didn't perform so well on the original *incorrect* labels were some of the best performers after the labels were corrected



C.G. Northcutt, A. Athalye, J. Mueller. Pervasive Label Errors in Test Sets Destabilize Machine Learning Benchmarks, https://arxiv.org/pdf/2103.14749.pdf

A catch #2: Interpretation of results

- Those deep learning models very **difficult to interpret**:
  - Fundamental question: **why the model makes a particular decision**?
  - Extremely important for many domains, including Earth observation (EO)

- A simple pitfall:
  - **Application: ML applied to Skin cancer detection**
  - **Task: Given image of skin lesion, classify whether benign or malignant**
  - **On first try:** Method had *amazing* success rate - whenever the doctors thought it was benign/malignant, the ML method came to the same conclusion!
  - Almost *too good* to be true.
    - Scientists wanted to know: How did the algorithm figure it out?
    - Applied visualization tool to learn about method's reasoning.
  - Scientists found that …

https://www.star.nesdis.noaa.gov/star/documents/seminardocs/2019/20190718_Kumler_and_Ebert-Uphoff.pdf

A catch #2: Interpretation of results

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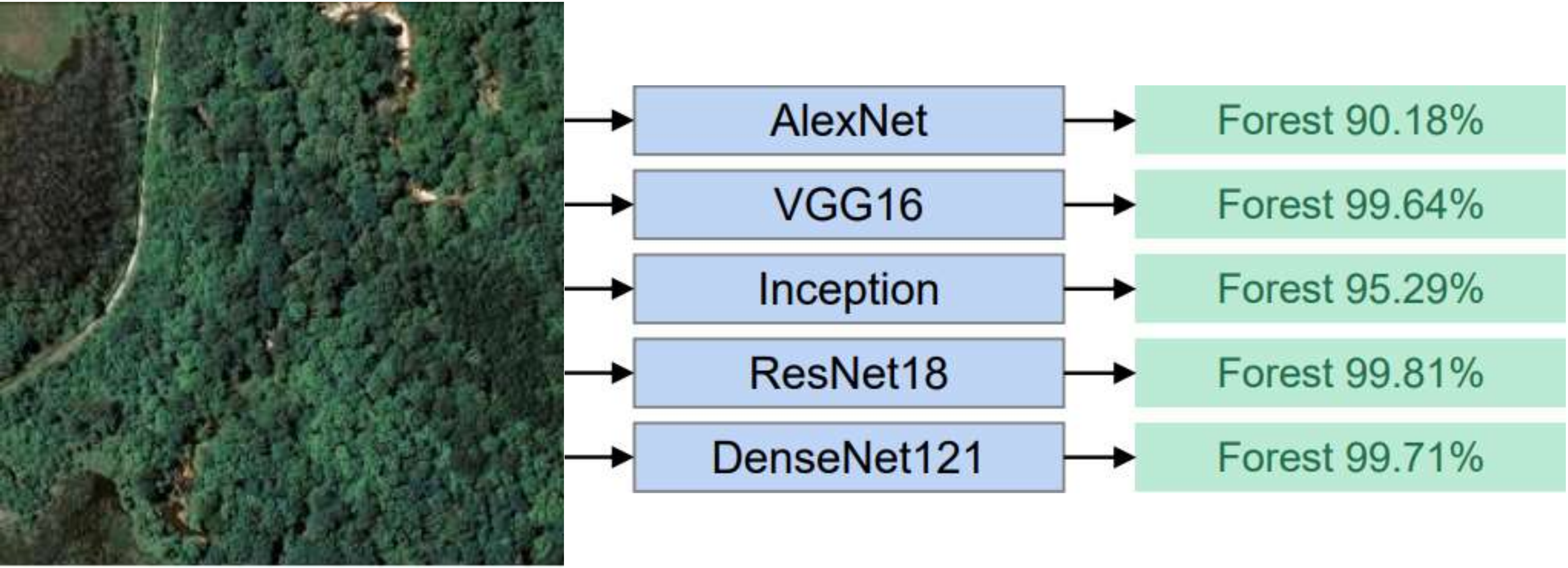
  - Fundamental question: **why the model makes a particular decision**?
  - Extremely important for many domains, including Earth observation (EO)

- A simple pitfall:
  - Scientists found that … doctors had placed a ruler into the image whenever they thought it was malignant.

  - The algorithm detected the ruler, then concluded that the growth was malignant. **That's not what folks had intended for the algorithm to do! Found problem early thanks to transparency tools.**

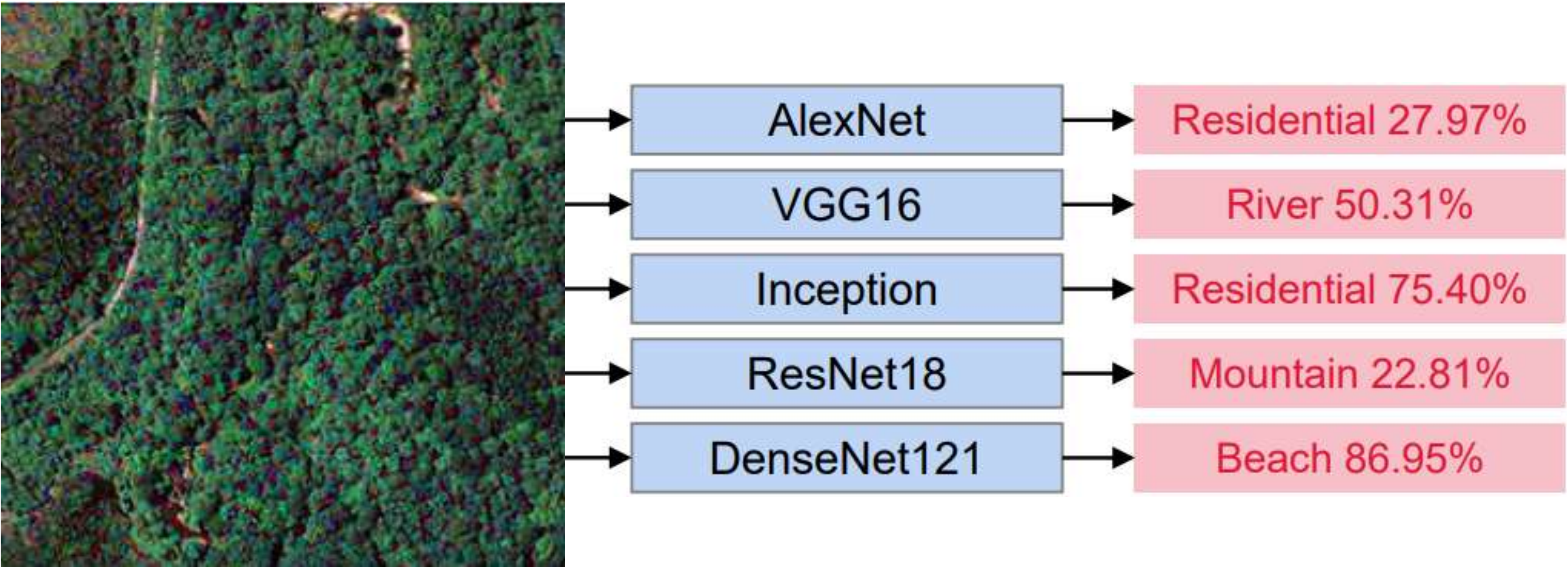
https://www.star.nesdis.noaa.gov/star/documents/seminardocs/2019/20190718_Kumler_and_Ebert-Uphoff.pdf

A catch #3: Fooling the model



Xu, Y., & Ghamisi, P. (2022). Universal Adversarial Examples in Remote Sensing: Methodology and Benchmark. *IEEE Transactions on Geoscience and Remote Sensing*. https://doi.org/10.1109/TGRS.2022.3156392

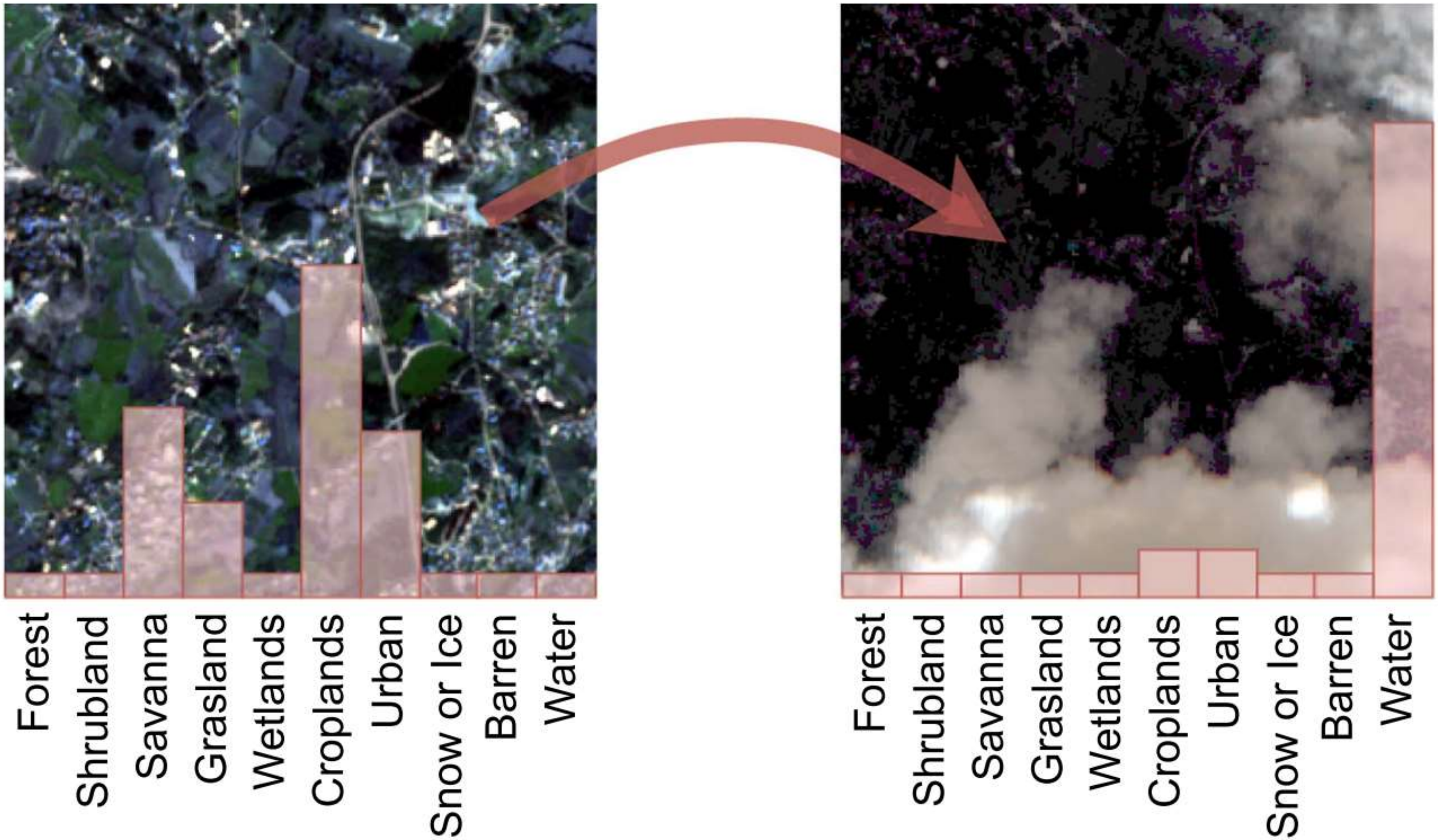
A catch #3: Fooling the model



Xu, Y., & Ghamisi, P. (2022). Universal Adversarial Examples in Remote Sensing: Methodology and Benchmark. *IEEE Transactions on Geoscience and Remote Sensing*. https://doi.org/10.1109/TGRS.2022.3156392

A catch #4: Unexpected outcomes

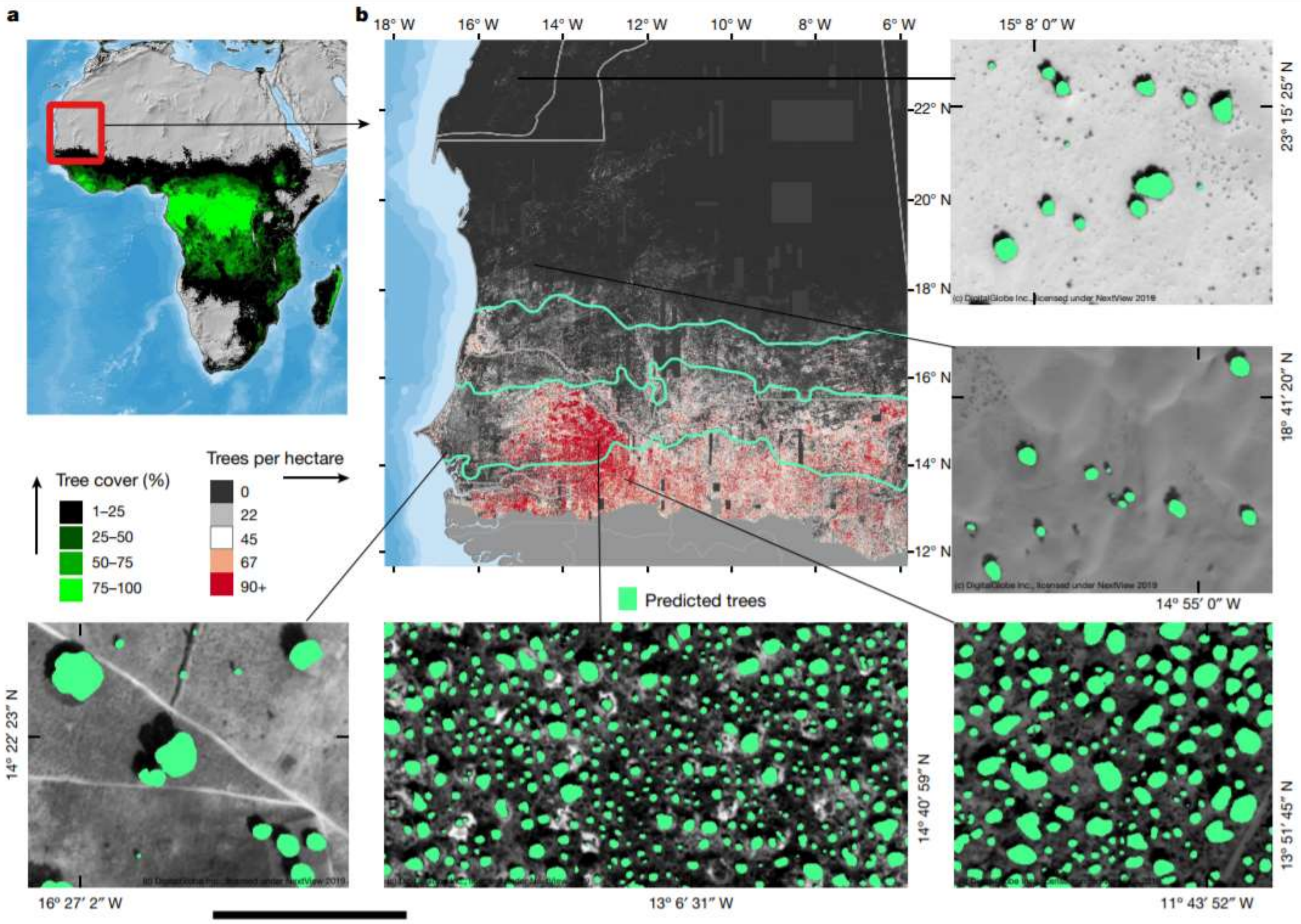
- The effect of clouds on image scene classification



https://ieeexplore.ieee.org/abstract/document/9956865

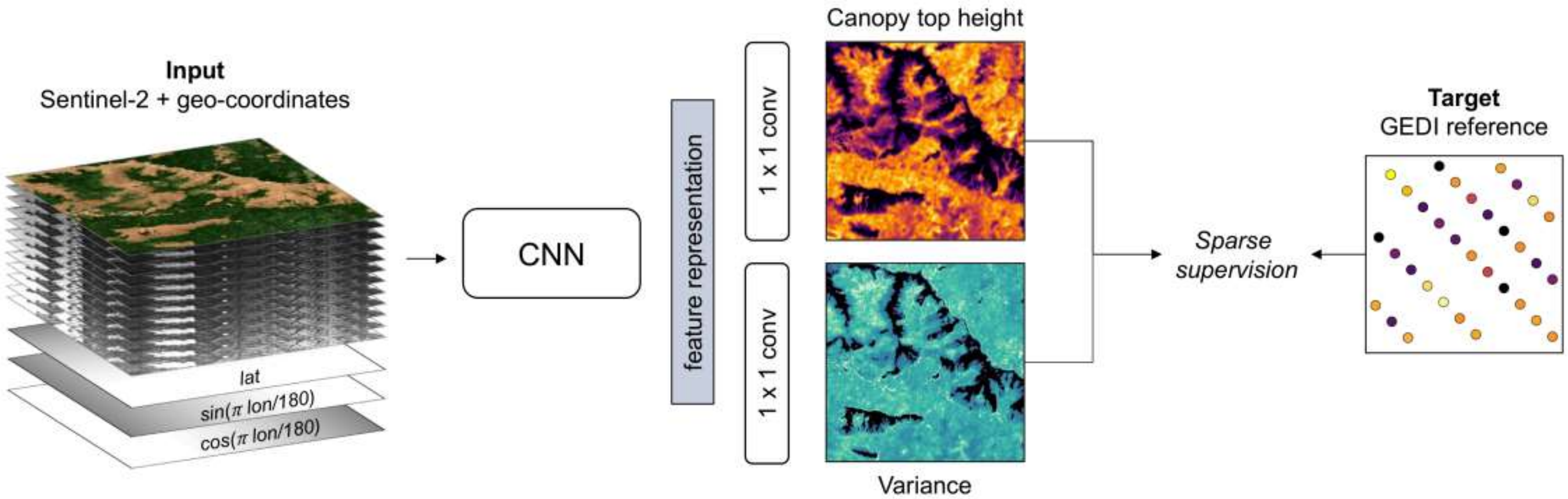
Counting trees in in the West African Sahara and Sahel

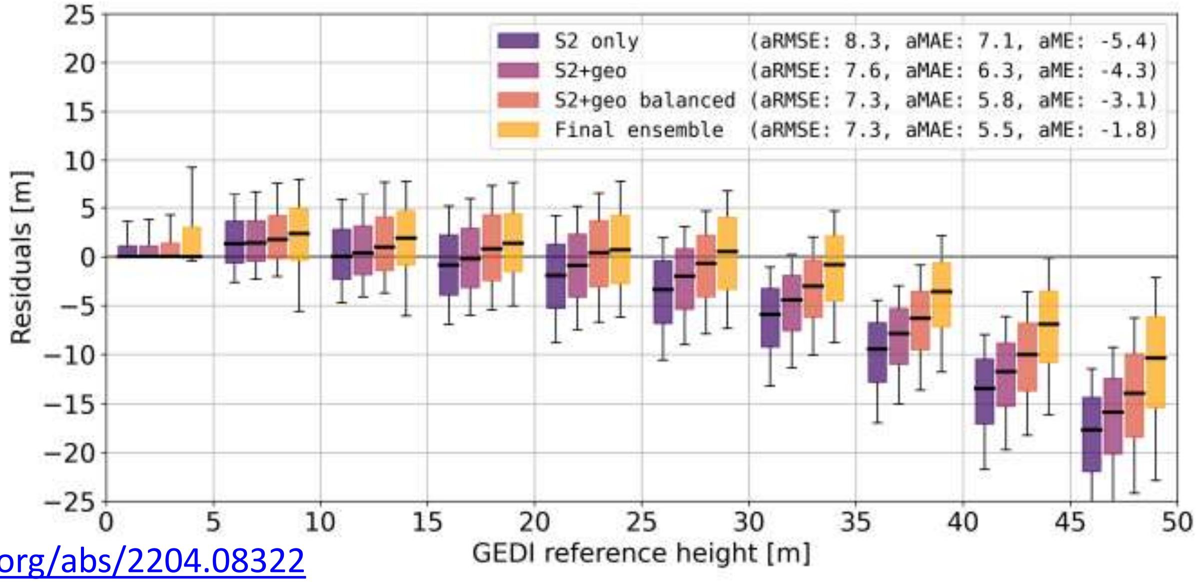
- Mapping crown size of each tree more than 3m^2 in size over a land area that spans 1.3 million km^2
  - detected **>1.8 billion individual trees** (13.4 trees per hectare), with a median crown size of 12 m^2
- Satellite data
  - 50,000 DigitalGlobe (Maxar) multispectral images from the **QuickBird-2, GeoEye-1, WorldView-2 and WorldView-3** satellites, collected from 2005–2018
  - @ 0.5 m resolution
- Machine learning
  - **Deep learning** (Unet-style network)
- Performance
  - **# of trees missed 5%**
  - **Area of trees missed 25%**

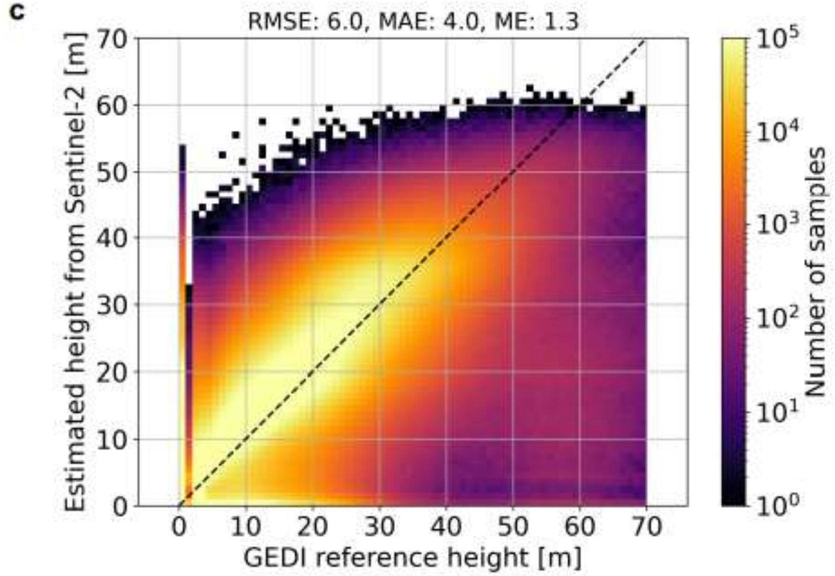


https://doi.org/10.1038/s41586-020-2824-5

10-m global canopy height: fusion of S2 + GEDI







https://arxiv.org/abs/2204.08322

Massive use of heavy weaponry

M-46 130mm field gun

~ Using 110,000 shells per month
~ Asking for 250,000 shells per month

~ Estimated 5,000,000 shells fired
~ Up to 60,000 per day in July, 2022

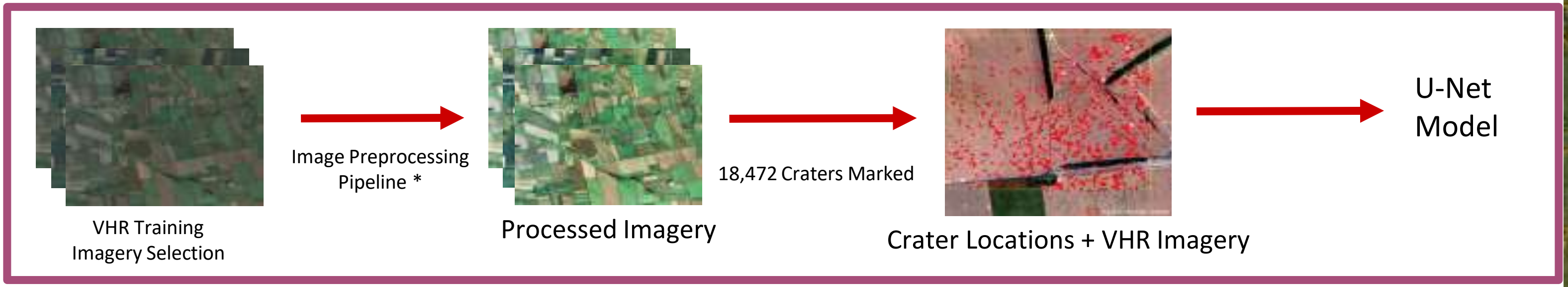
BM-21 Grad

Majority of Artillery shelling is **un-guided**

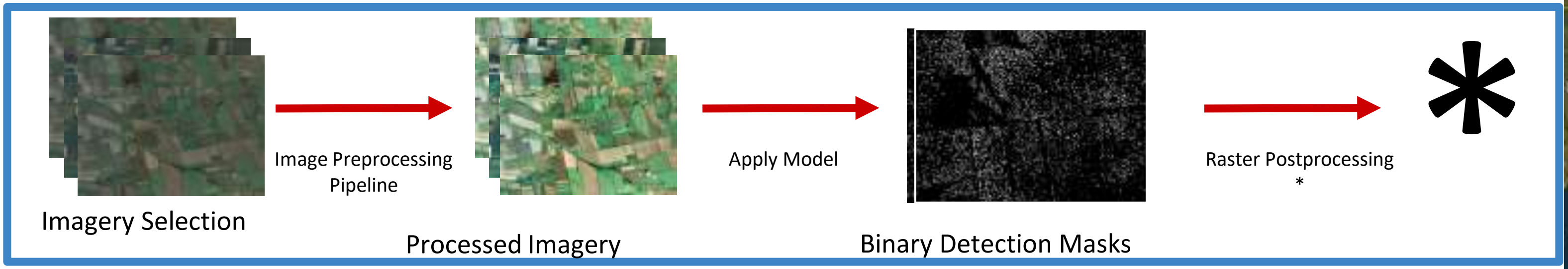
- Using the U-Net Segmentation model for crater detection
- Created VHR imagery processing pipeline for multi-terabytes of data
- Detecting on a per-crater level
- Using crater locations, we can scale up into hazard maps
- Agricultural, de-mining, and environmental products can be developed from crater dispersal

Crater Density Reference

Training A Crater Detection Model, with 2022 Imagery



Mapping With Trained Model



Artillery Crater Mapping Status

Artillery and Rocket Crater Detection and Monitoring with VHR Satellite Imagery

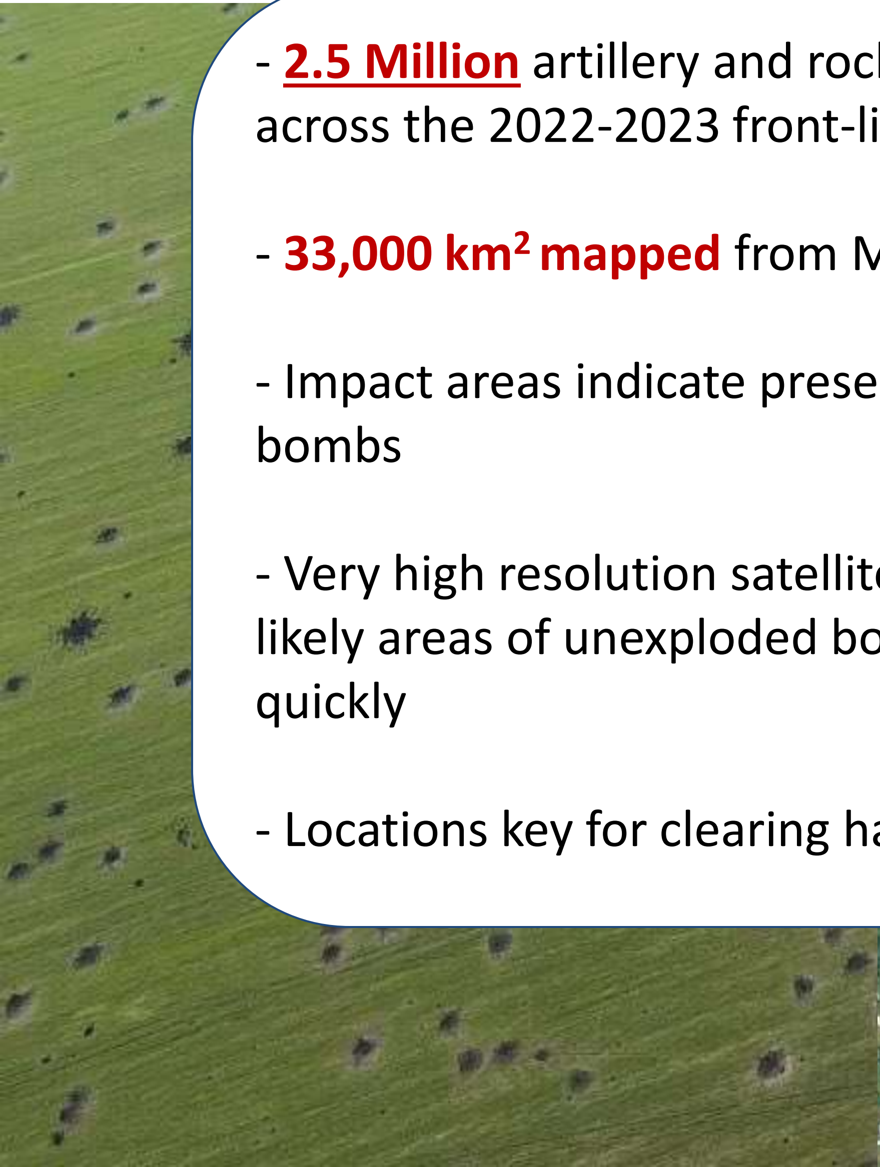
- **2.5 Million** artillery and rocket impacts mapped across the 2022-2023 front-lines

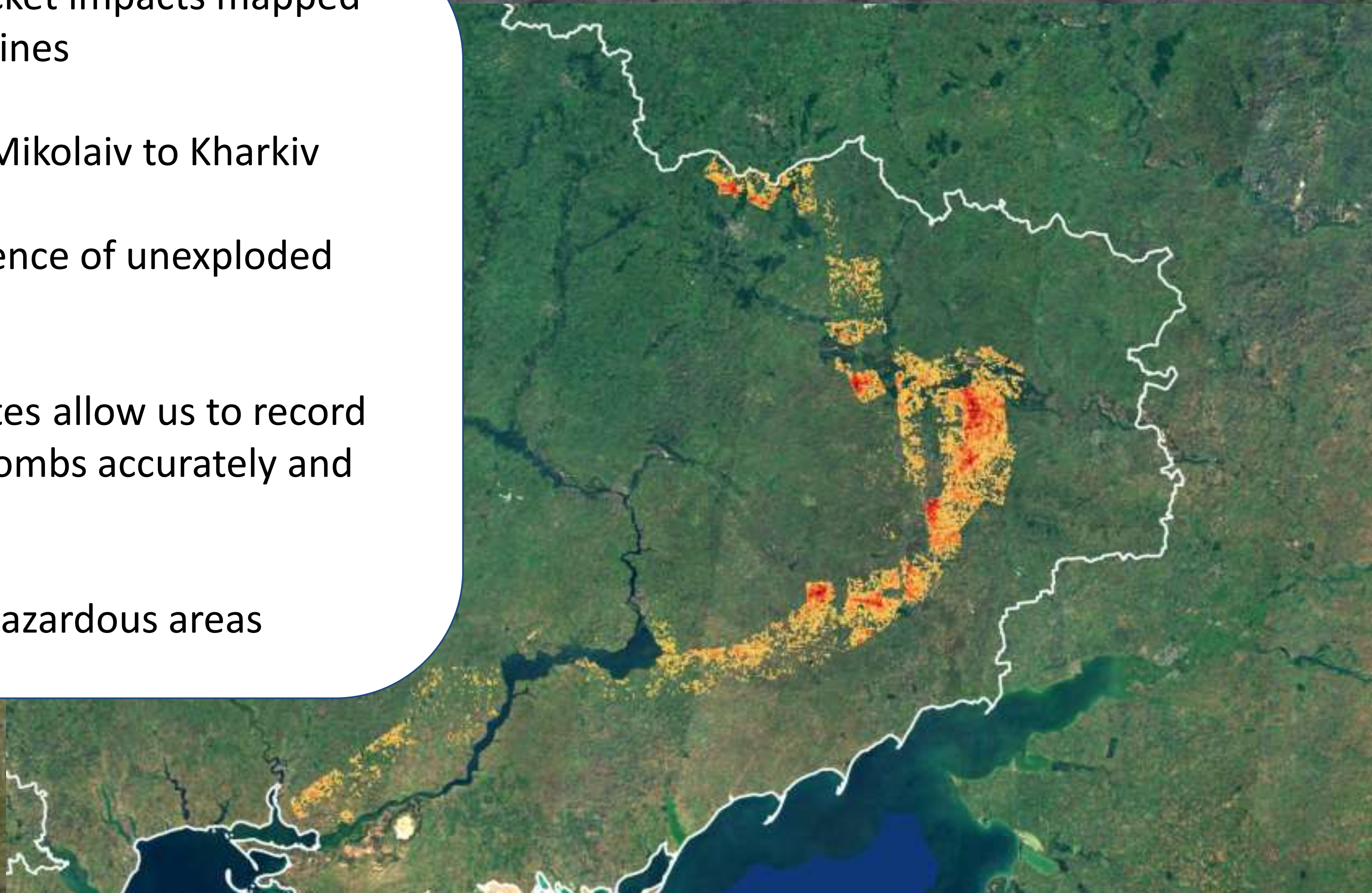
- **33,000 km^2 mapped** from Mikolaiv to Kharkiv

- Impact areas indicate presence of unexploded bombs

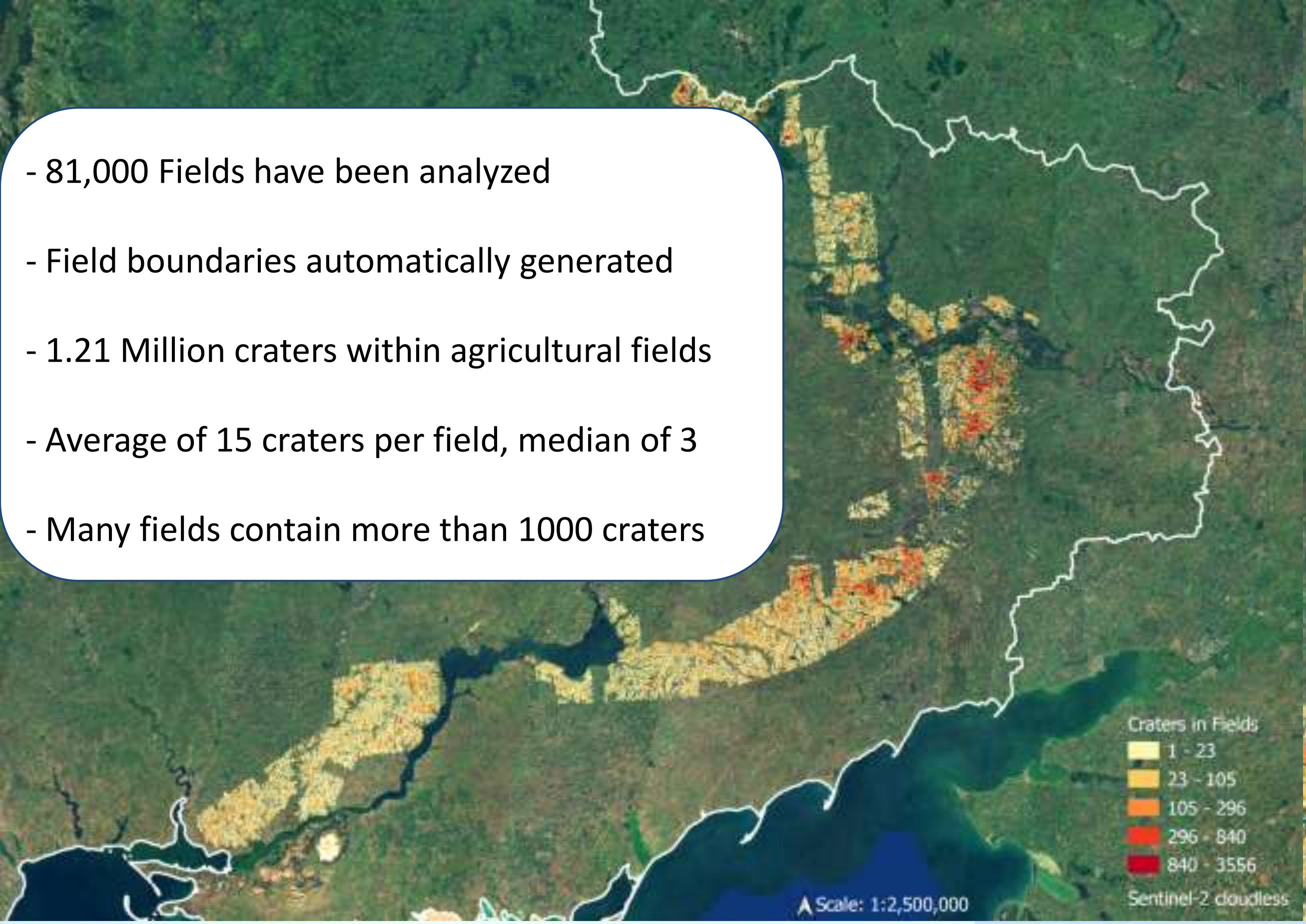
- Very high resolution satellites allow us to record likely areas of unexploded bombs accurately and quickly

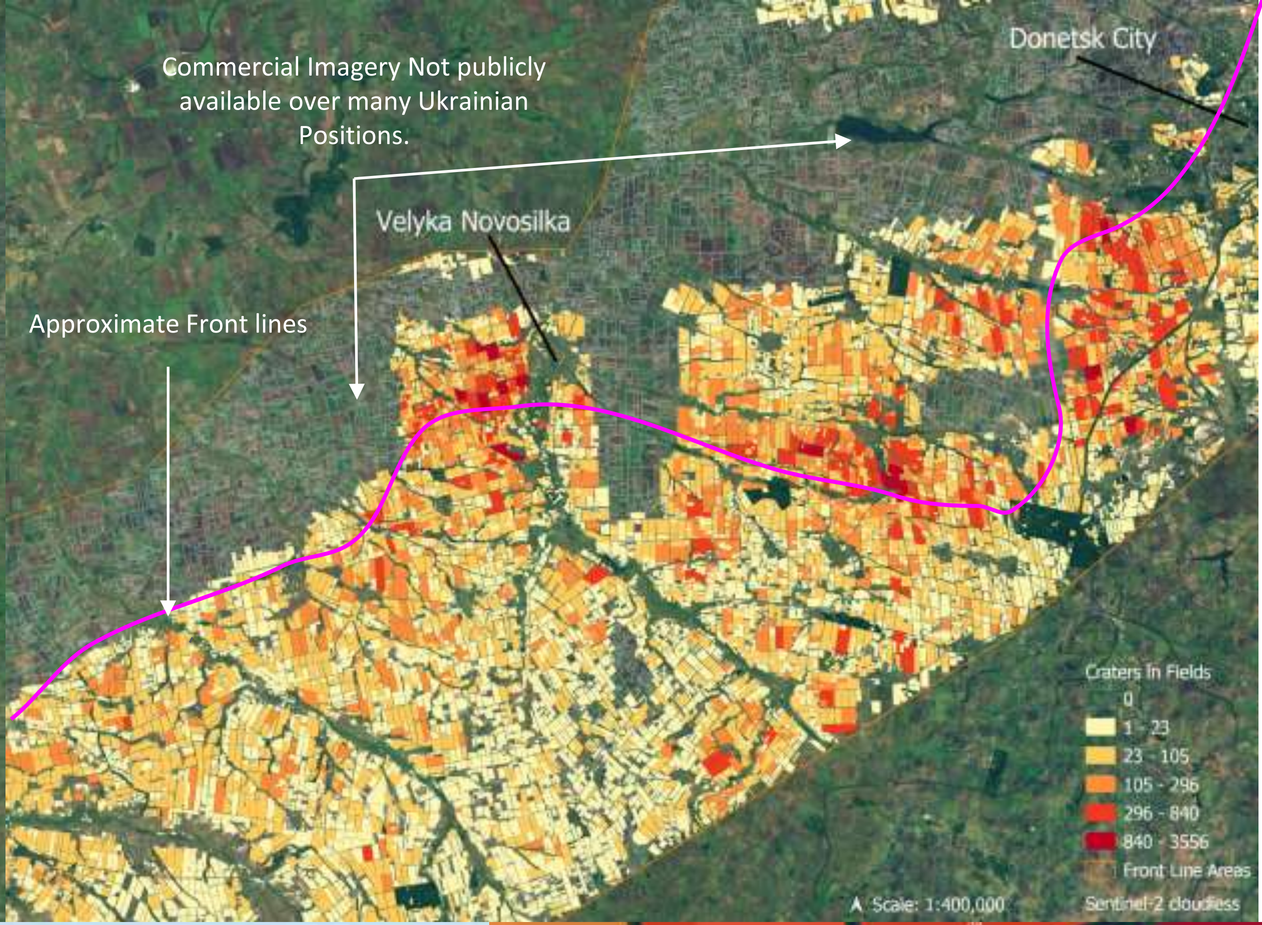
- Locations key for clearing hazardous areas

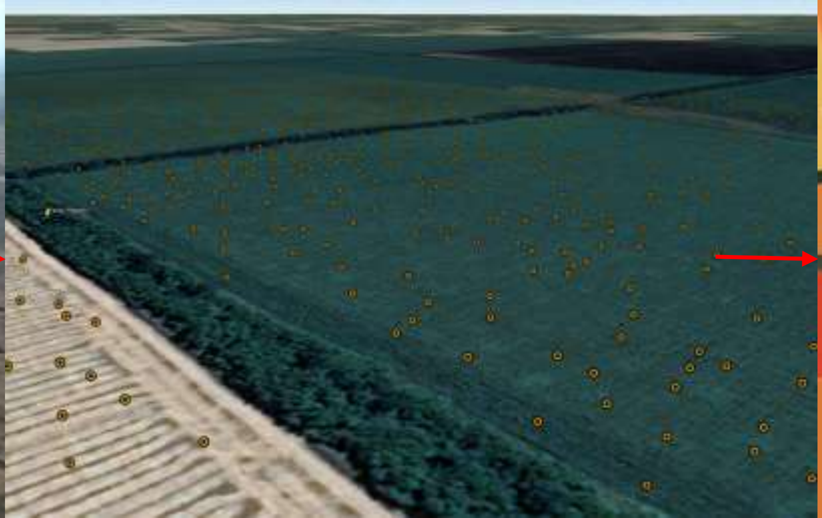


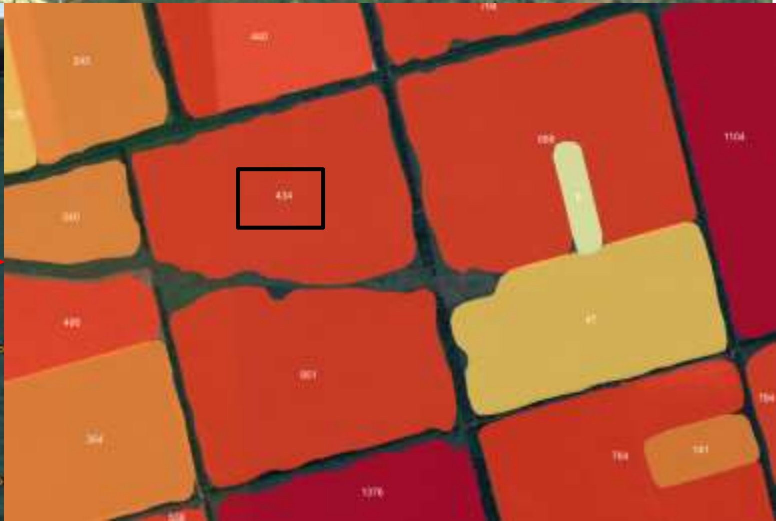


- 81,000 Fields have been analyzed
- Field boundaries automatically generated
- 1.21 Million craters within agricultural fields
- Average of 15 craters per field, median of 3
- Many fields contain more than 1000 craters



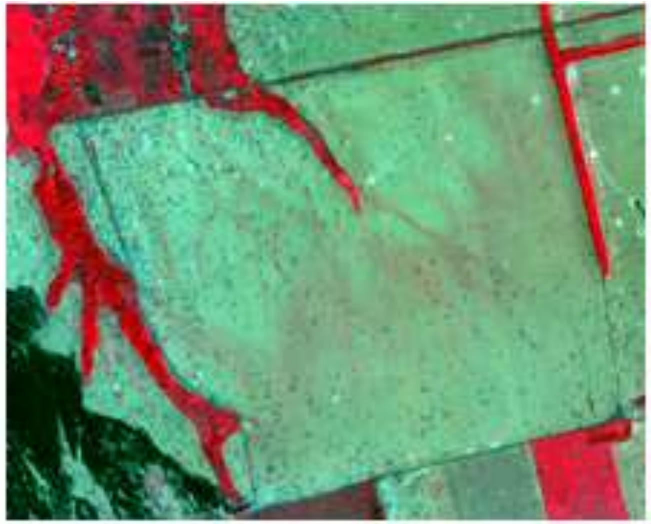




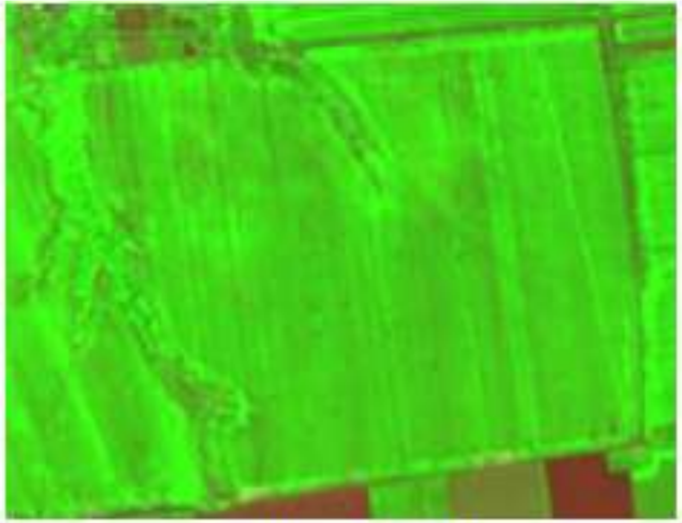



True color SkySat, 50 cm

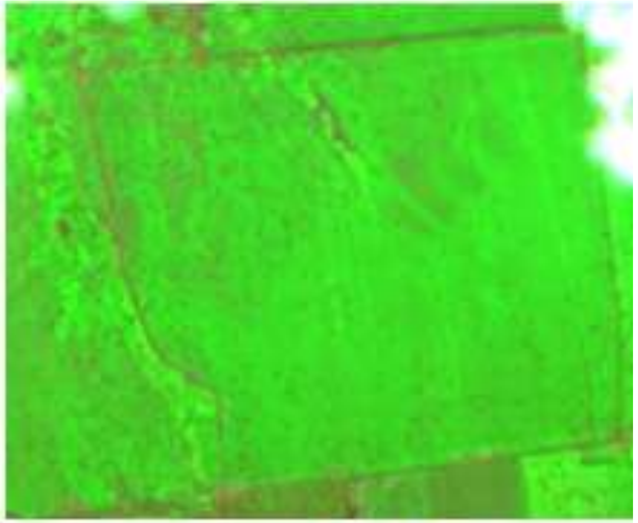
Example: unharvested field



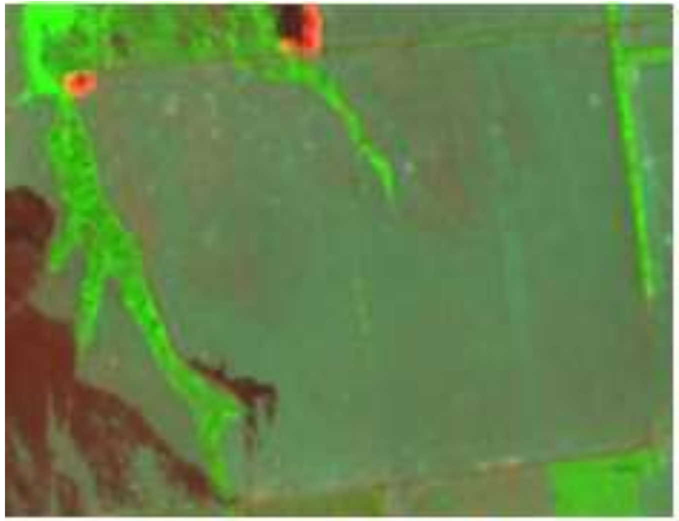
(a) 2022-07-02



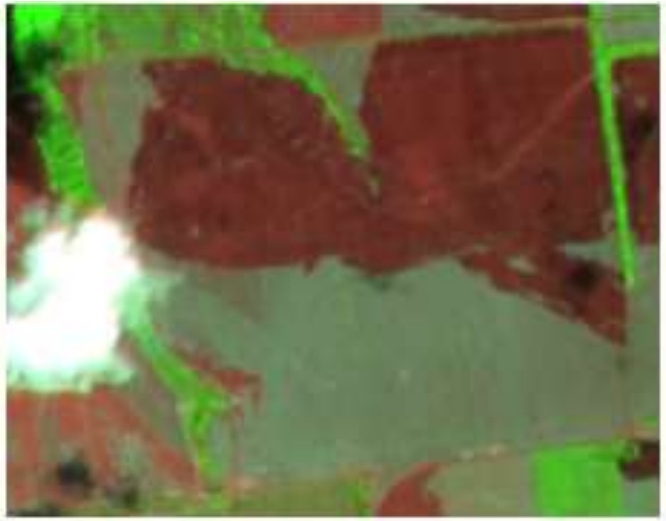
(b) 2022-05-08



(c) 2022-06-12



(d) 2022-07-07



(e) 2022-07-17

(a) SkySat false color (NIR-red-green) image. (b)-(e) Sentinel-2 false color (SWIR1-NIR-red). In Early May (b) the field was in very good condition; however, shelling occurred mid-June as seen by both Sentinel-2 (c) and SkySat (a). Fire onset is seen in (d) and the field is seen burned in (e).

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Detection and mapping of artillery craters with very high spatial resolution satellite imagery and deep learning

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Change detection: construction detection

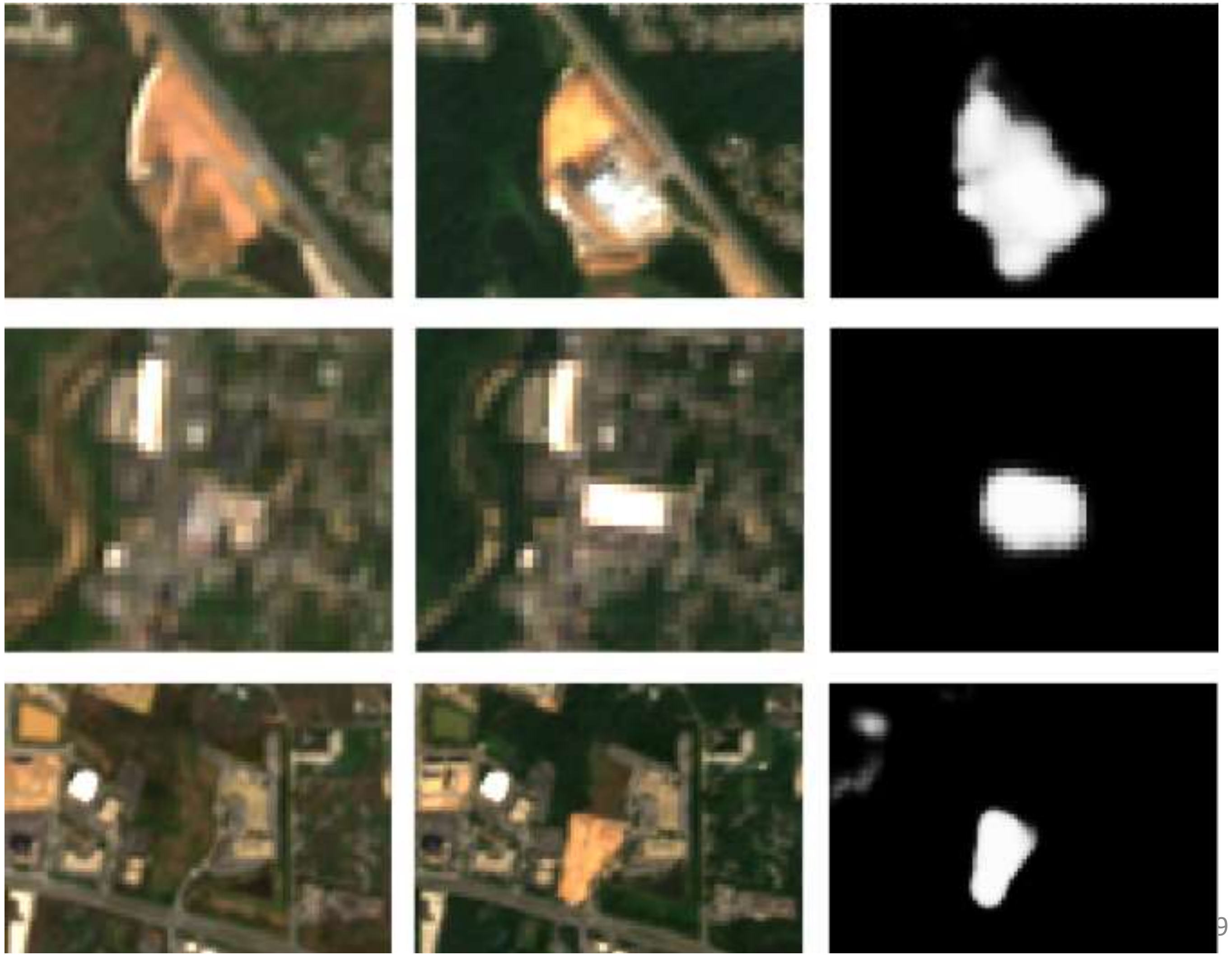
- Onera benchmark dataset [Daudt et al., IGARSS 2018]
  - Includes 24 location over cities
  - Changes between 2015 and 2018
  - Transitions between land use classes
    - Green urban areas → commercial use
    - Industrial -> residential use

- Machine learning
  - **Deep learning** (Unet)

- Performance
  - ~50-70%

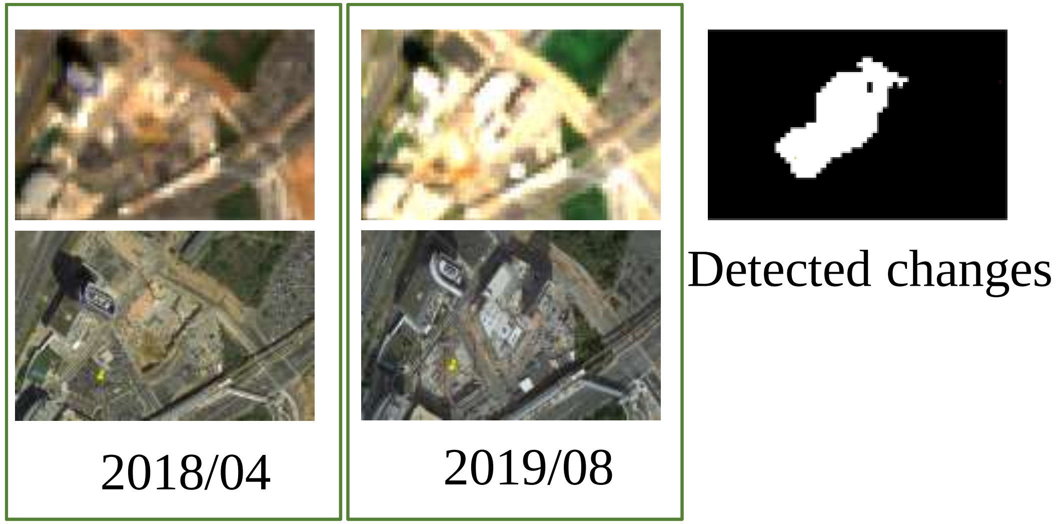
Validation on DC area

2018, April | 2019, August | Unet

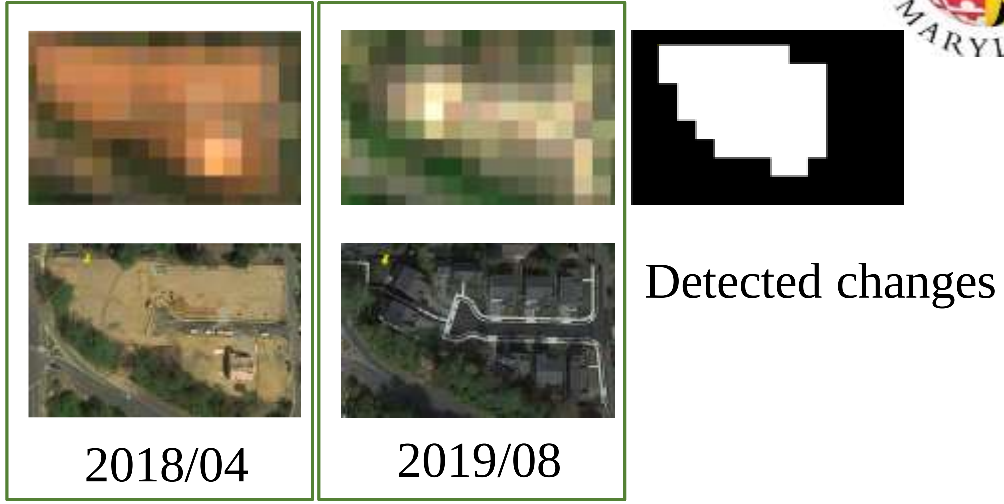


https://doi.org/10.1080/17538947.2022.2094001

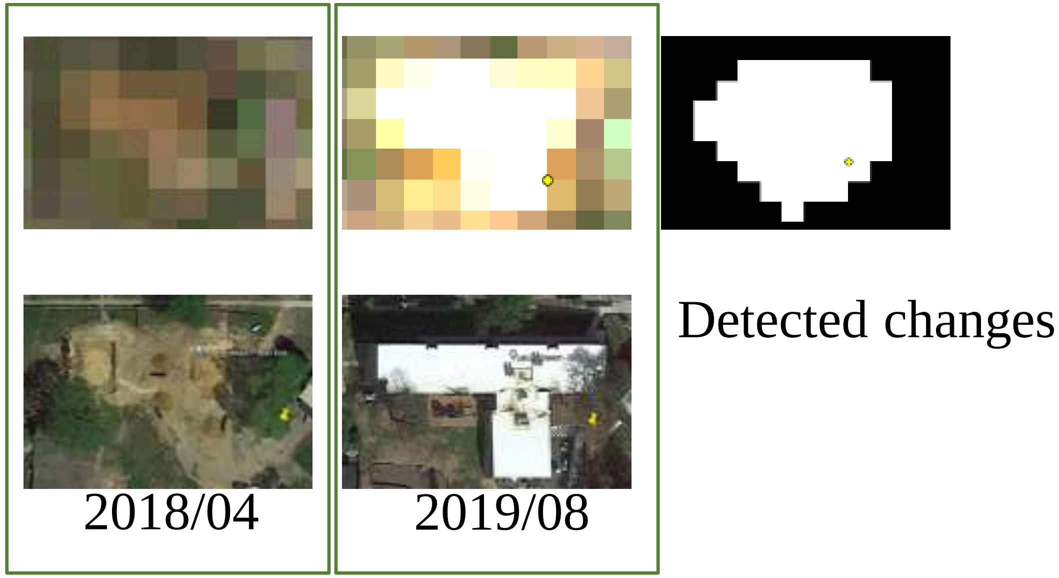
Commercial



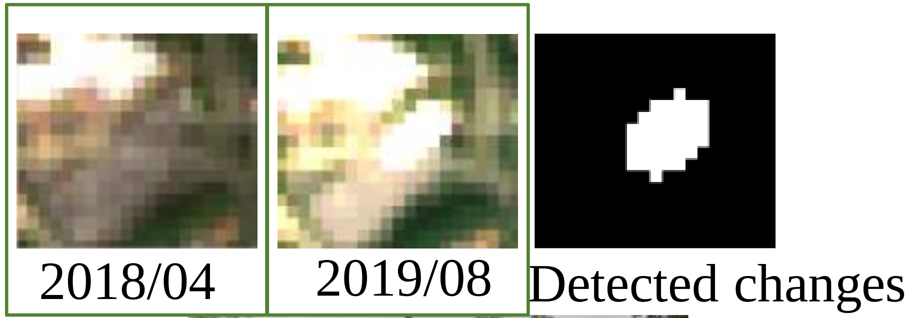
Residential



Construction of a new school

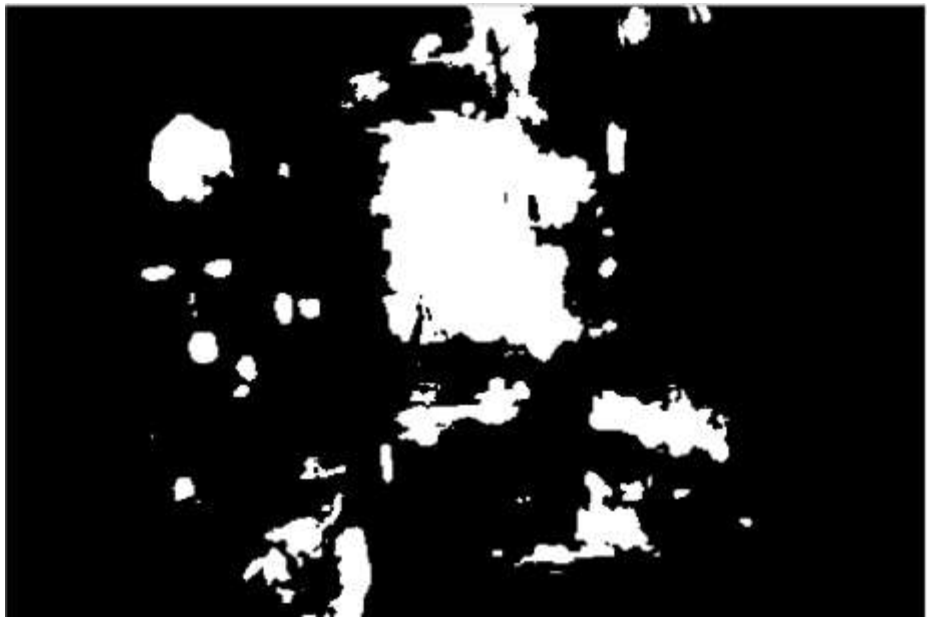


Portables (schools)



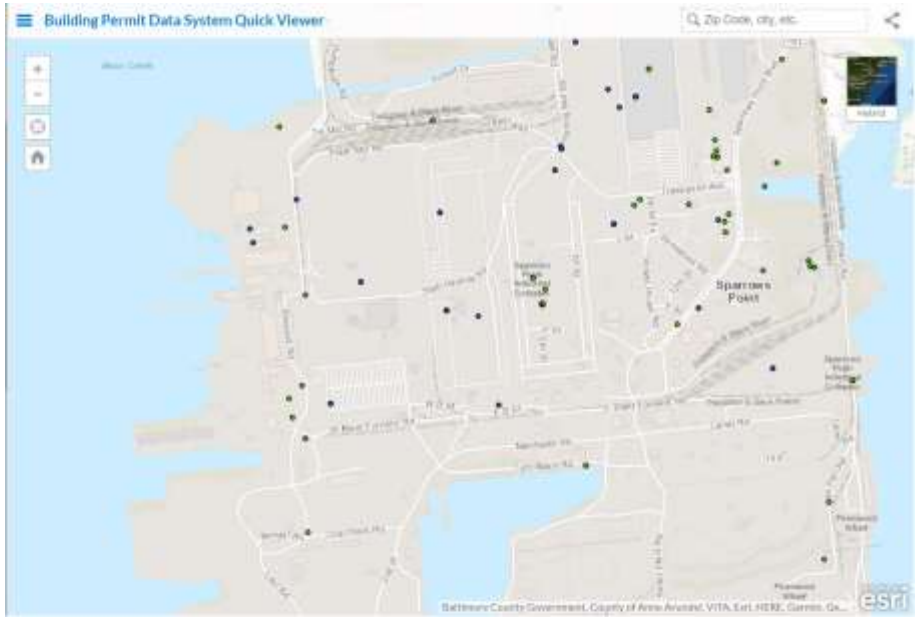
2018

Change detection



2019

Construction permits



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https://doi.org/10.1080/17538947.2022.2094001

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Leveraging the use of labeled benchmark datasets for urban area change mapping and area estimation: a case study of the Washington DC–Baltimore region

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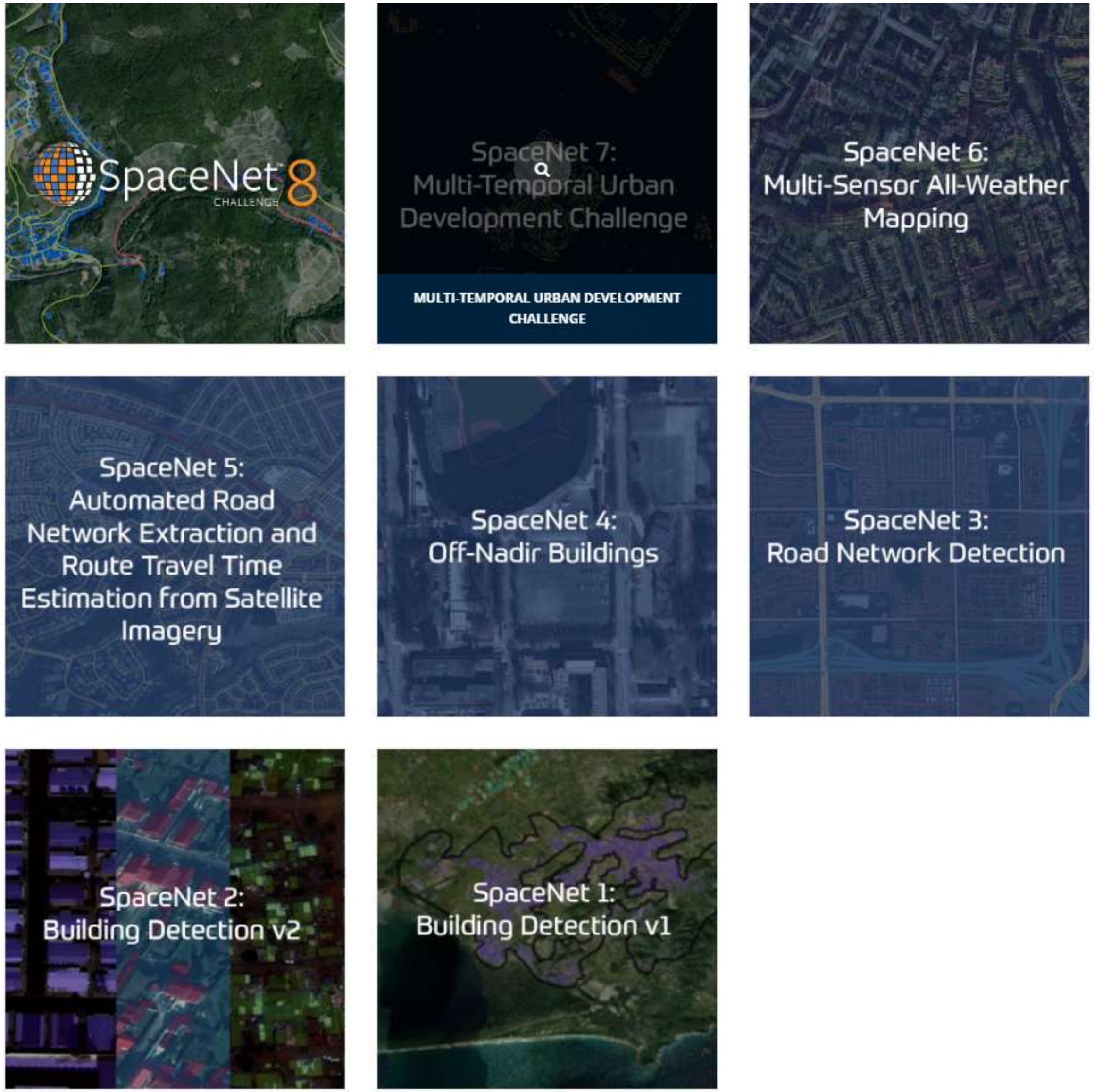
SpaceNet Challenges

- https://spacenet.ai/
  – SpaceNet, launched in August 2016 as an open innovation project offering a [repository](#) of freely available imagery with co-registered map features.



Open problems: AI/ML in RS

- **A lot of unlabeled data and few labeled data**
  - How to better deal with it? Can we build a general framework, which can be fine-tuned for specific problems? (Transfer learning)
  - Non-stationarity of labels
  - Increasing labeled data through crowdsourcing:
    - Perception that it is easy to do --- it's NOT!!!
    - It cannot be done for any classes, e.g. crop specific, biodiversity, etc.

- **Missing data, non-uniform coverage**
  - E.g. due to clouds/shadows in optical imagery

- **Heterogeneous data sources**
  - Multiple scales (spatial resolutions), temporal (time-series), multiple spectral bands, continuous and point-based coverage

Open problems: AI/ML in RS (cont')

- **How to incorporate domain knowledge into ML models?**
  - Fusing physics-based models and ML models
  - E.g. meteorology into crop mapping, shape in objects, …

- **From feature engineering to model engineering**
  - Complexity of optimizing ML models
  - Still need understanding

- **Need to provide QA/uncertainty!**
  - E.g., to avoid situations with misclassification with clouds

Further readings

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