Land cover land use mapping with remote sensing and machine learning

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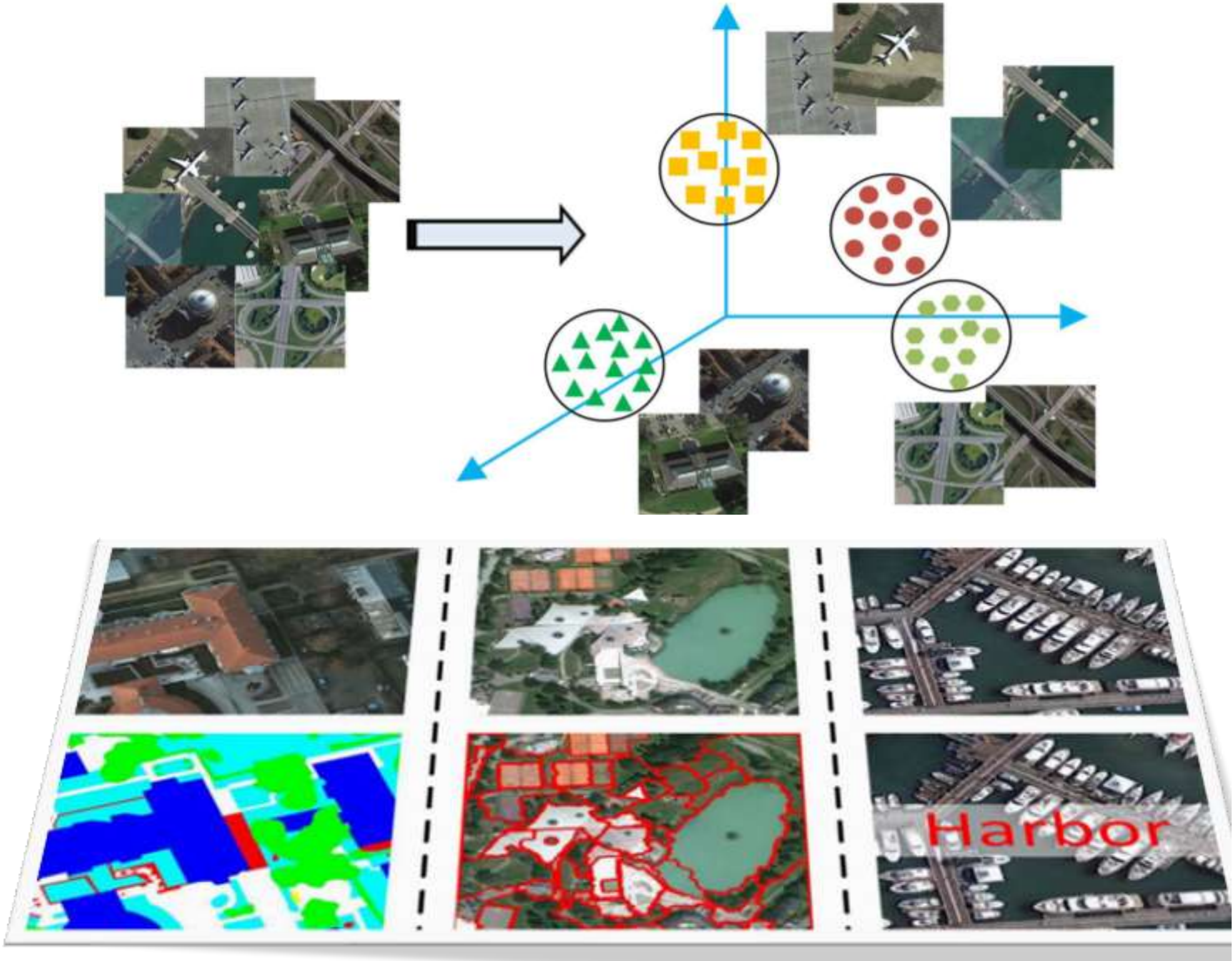
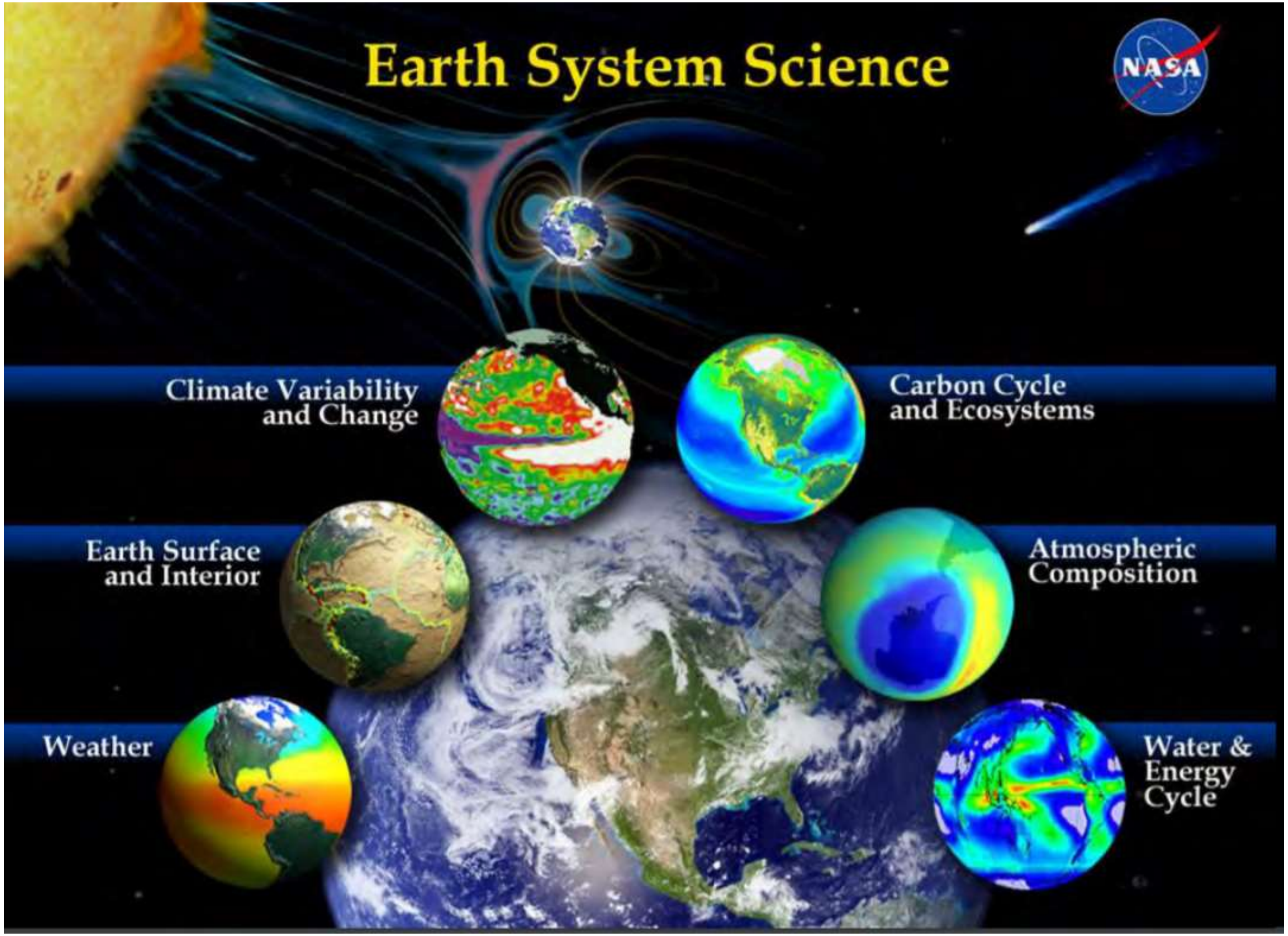
Content

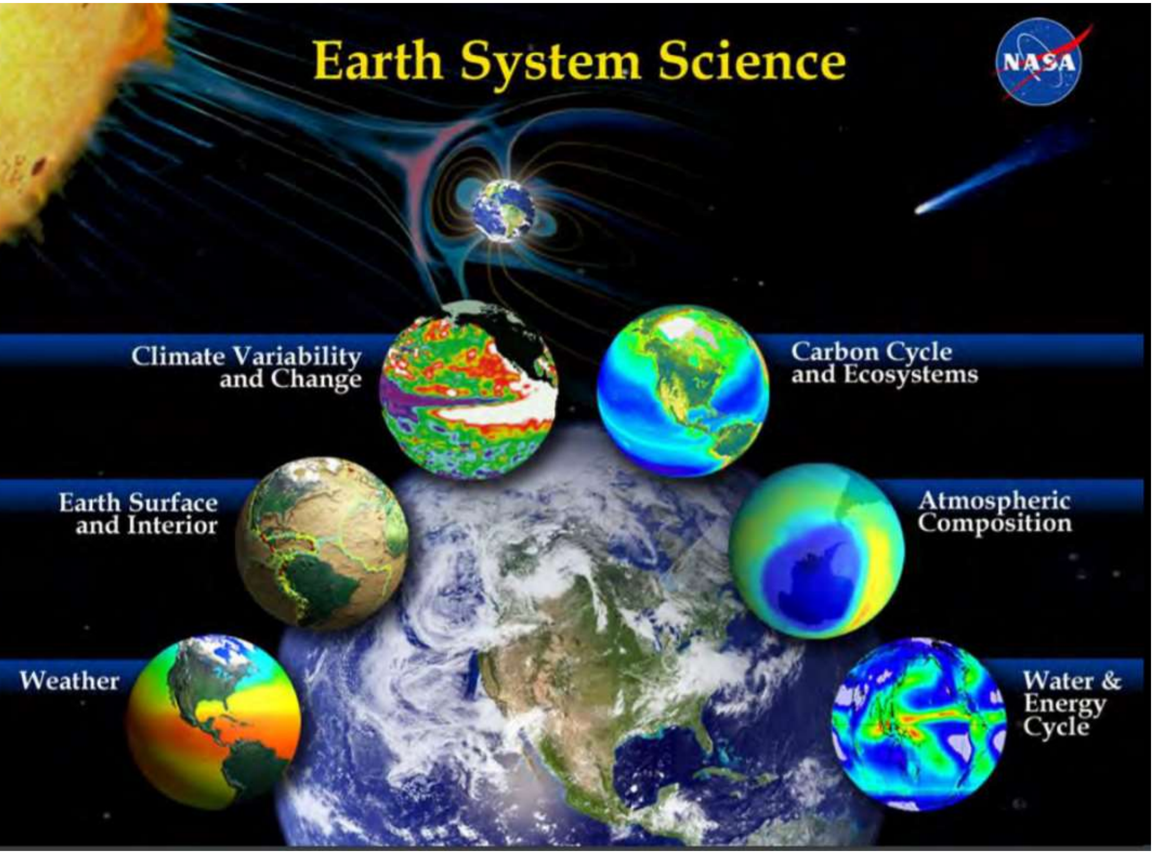
- **Earth observation perspective**
- **Machine learning**
- **Case studies**
  - e.g. winter crop mapping, forest & tree height mapping, counting trees, mapping artillery craters, detecting and counting elephants, etc
- **Open problems RS/ML**
- **Practical session**:
  - Airborne images classification with deep learning



NASA Earth Science Division (ESD): Focus areas

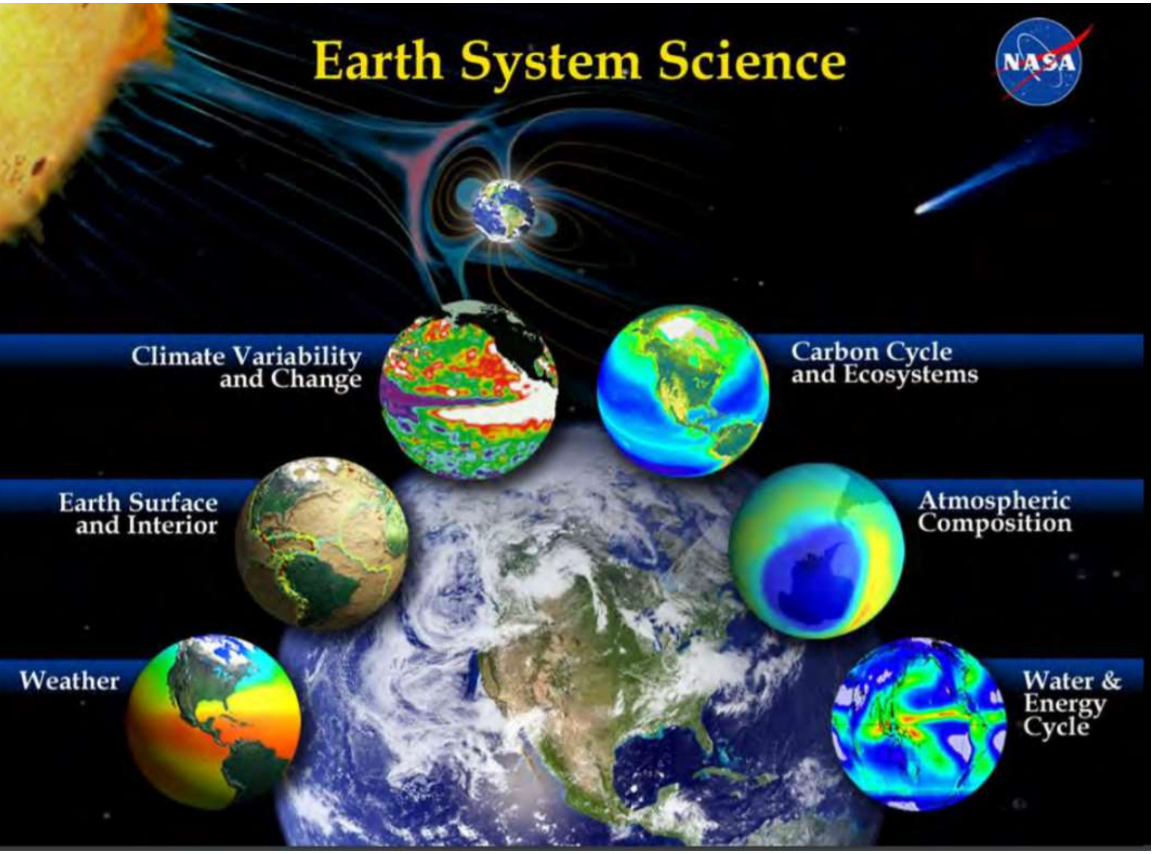


NASA Earth Science Division (ESD): Focus areas



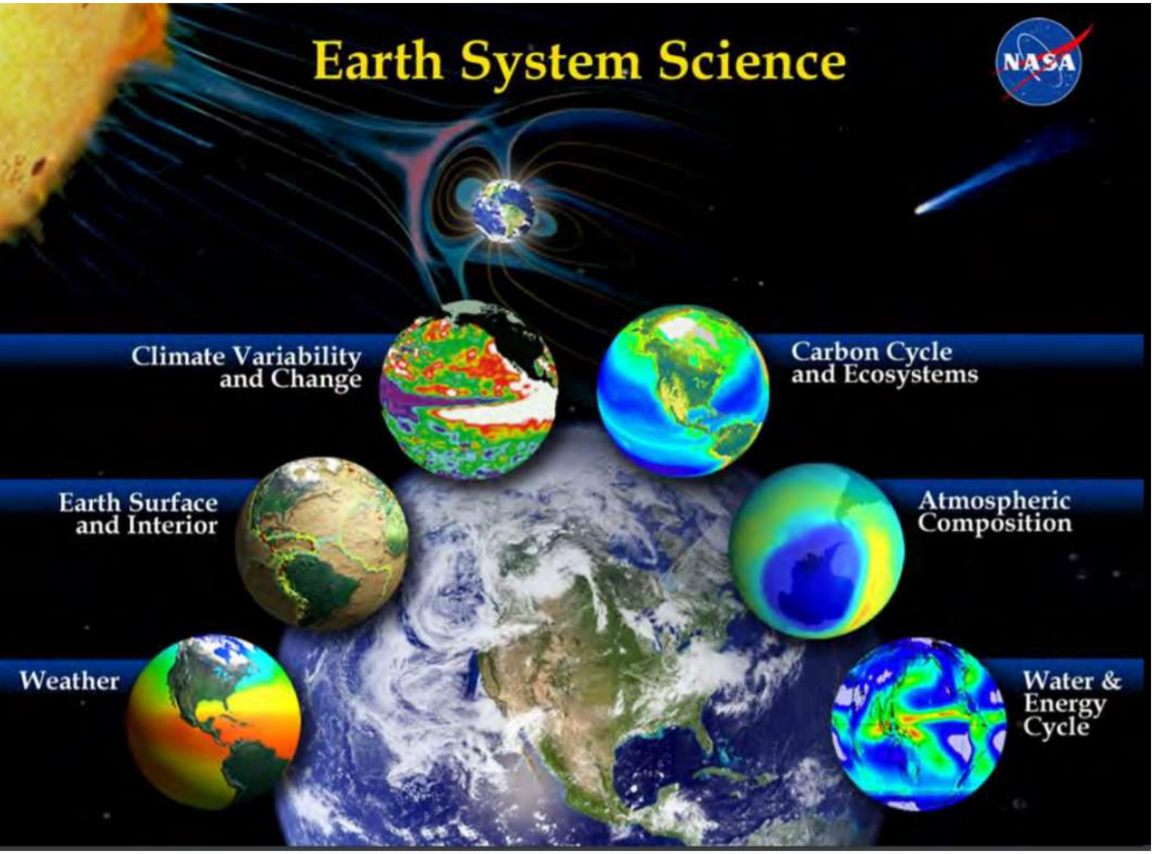
How is the global Earth system **changing**?

NASA Earth Science Division (ESD): Focus areas



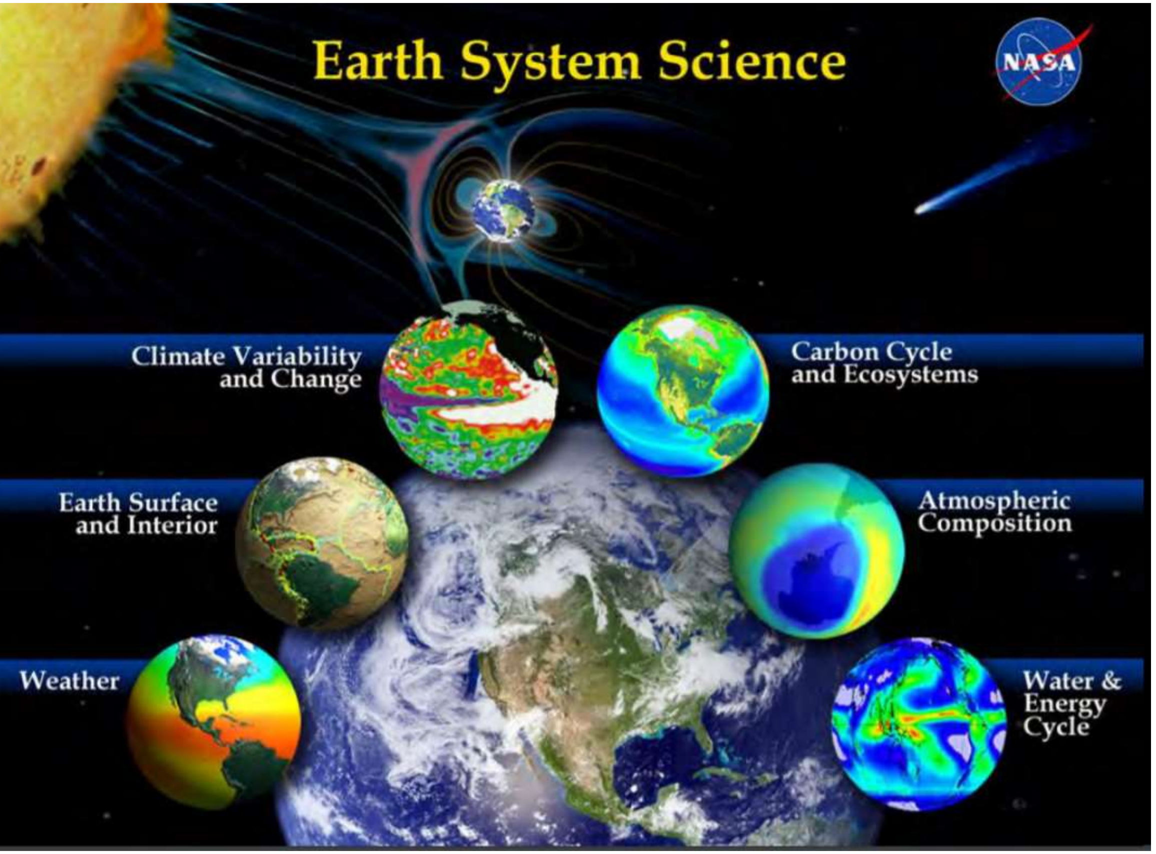
What **causes** these **changes** in the Earth system?

NASA Earth Science Division (ESD): Focus areas



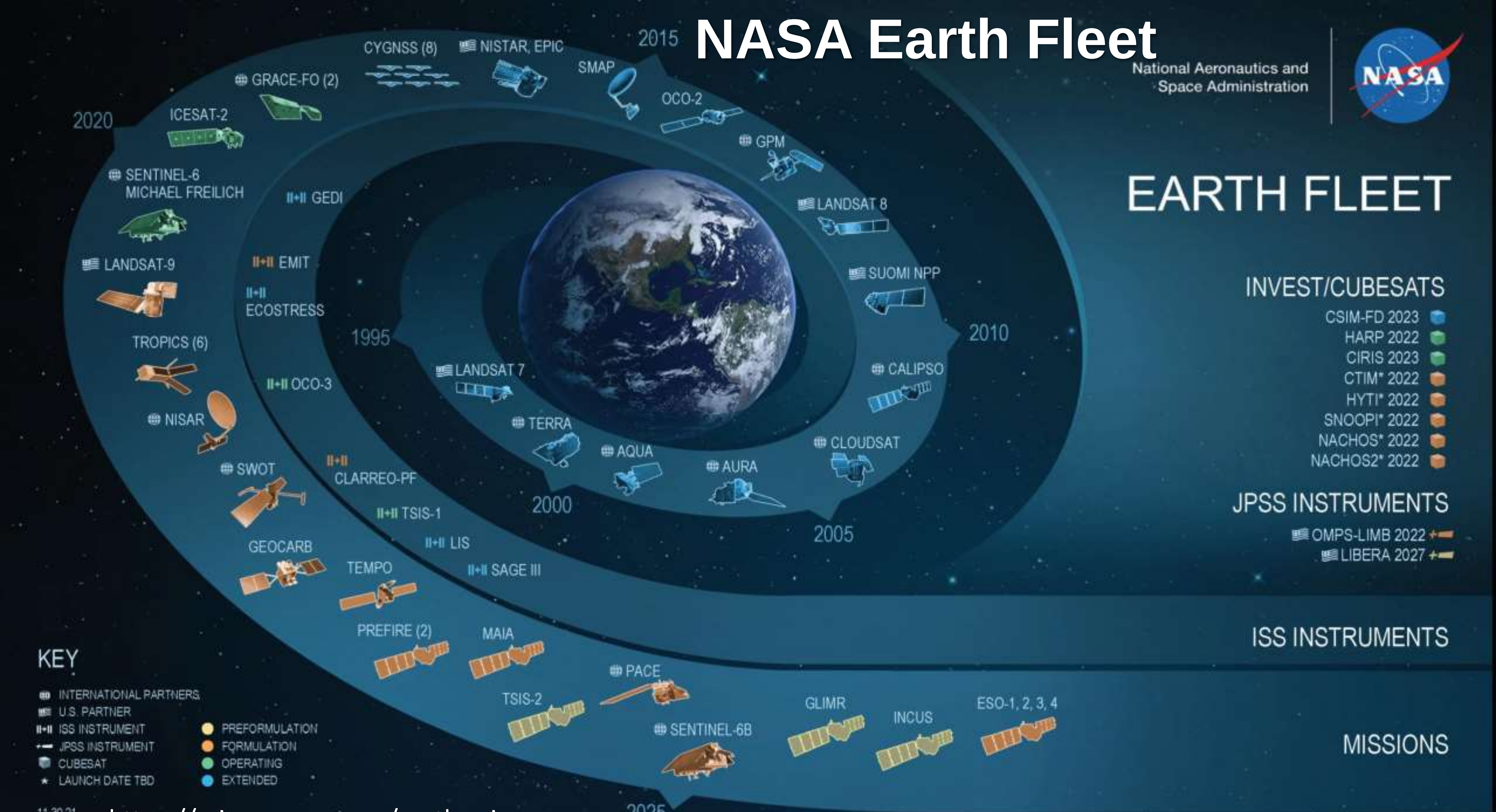
How will the Earth system **change in the future**?

NASA Earth Science Division (ESD): Focus areas



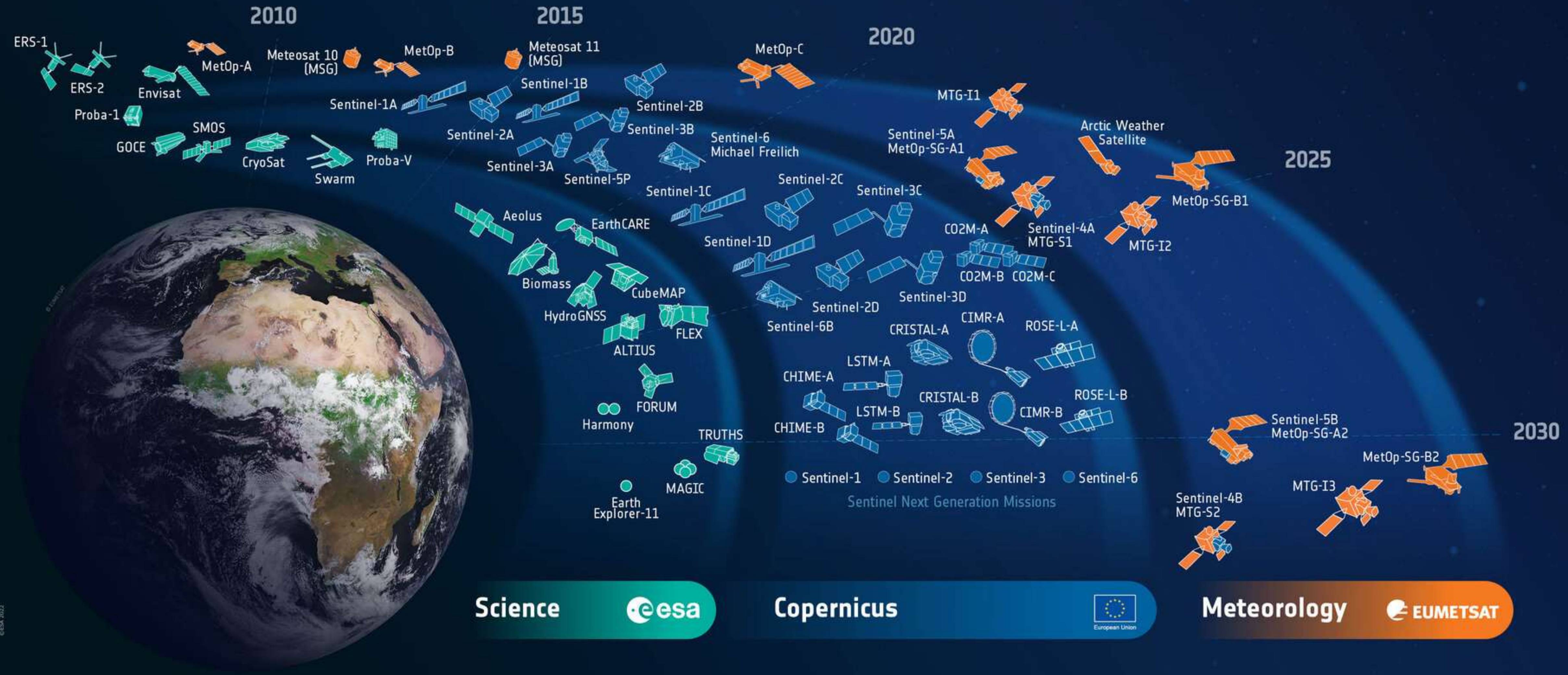
How can Earth system science provide **societal benefit**?

NASA Earth Fleet

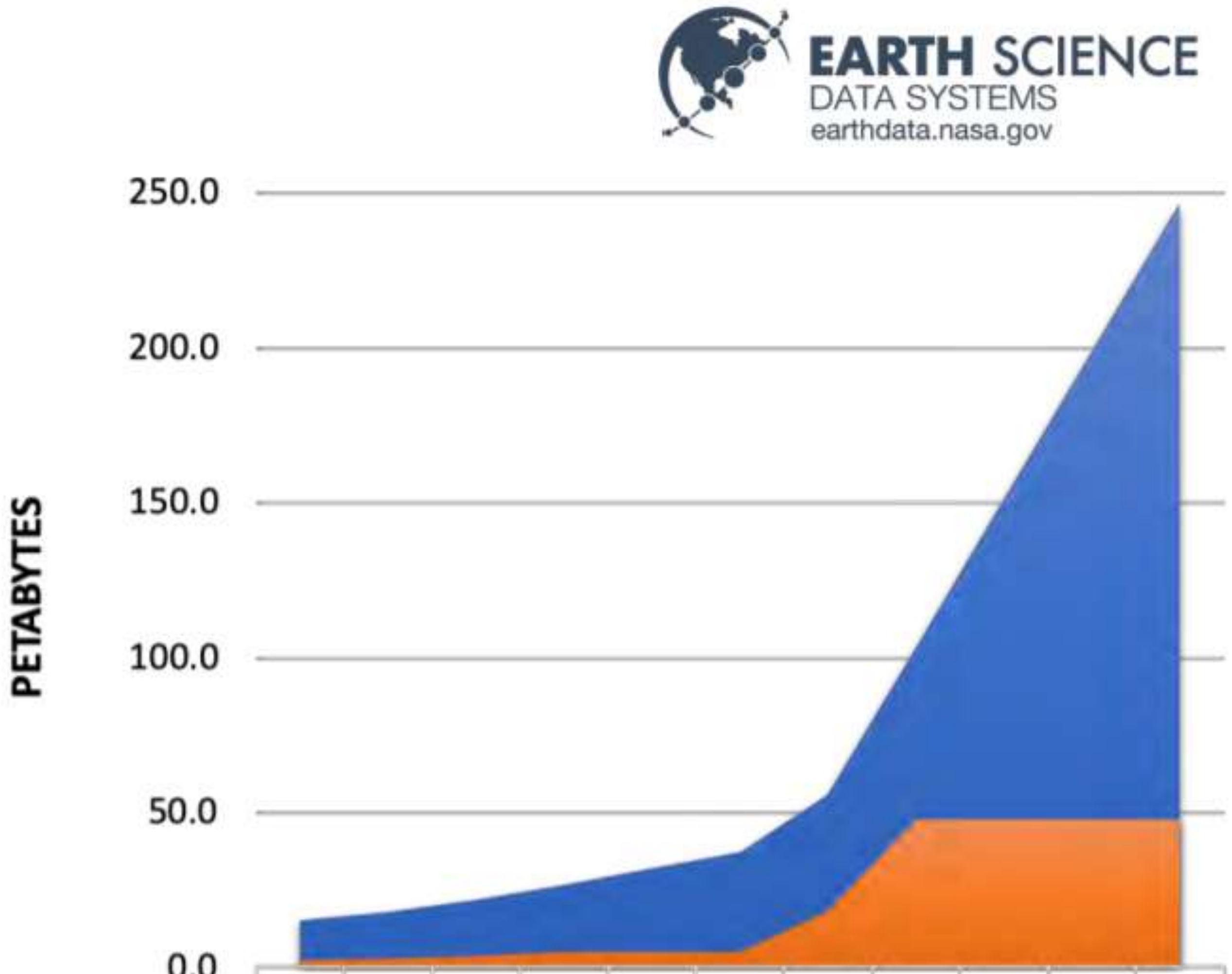


https://science.nasa.gov/earth-science

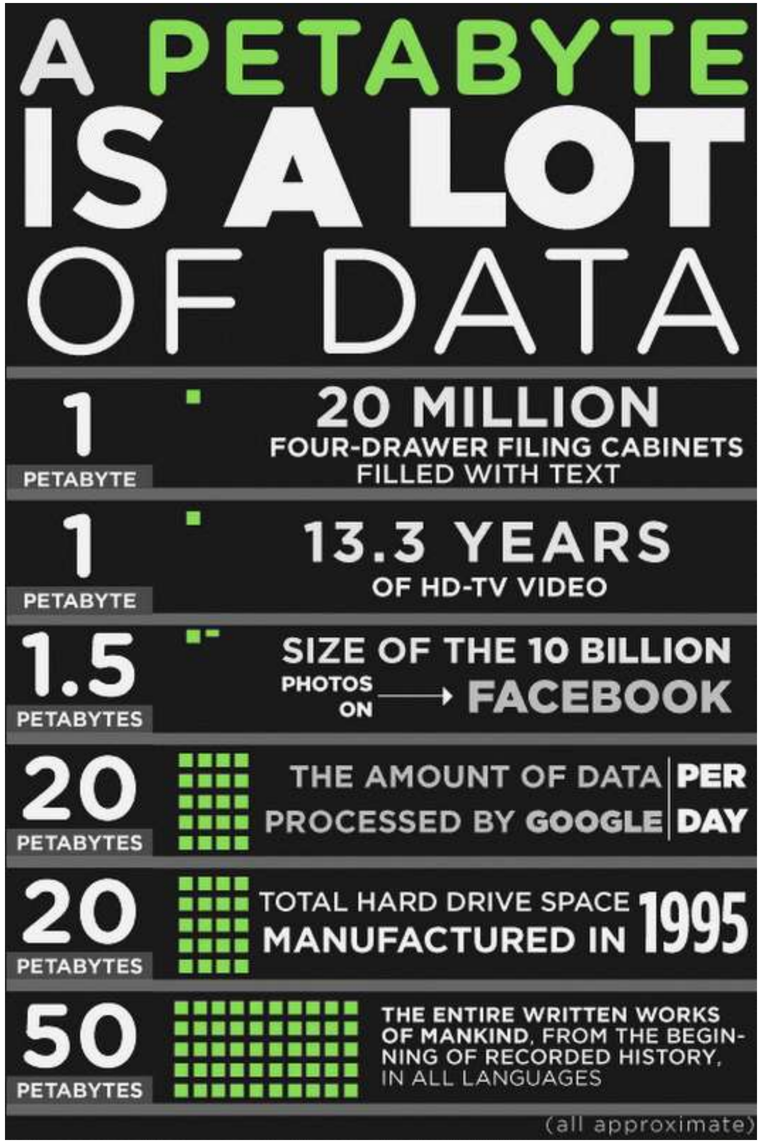
ESA-developed Earth observation missions



Big Data: Earth Science



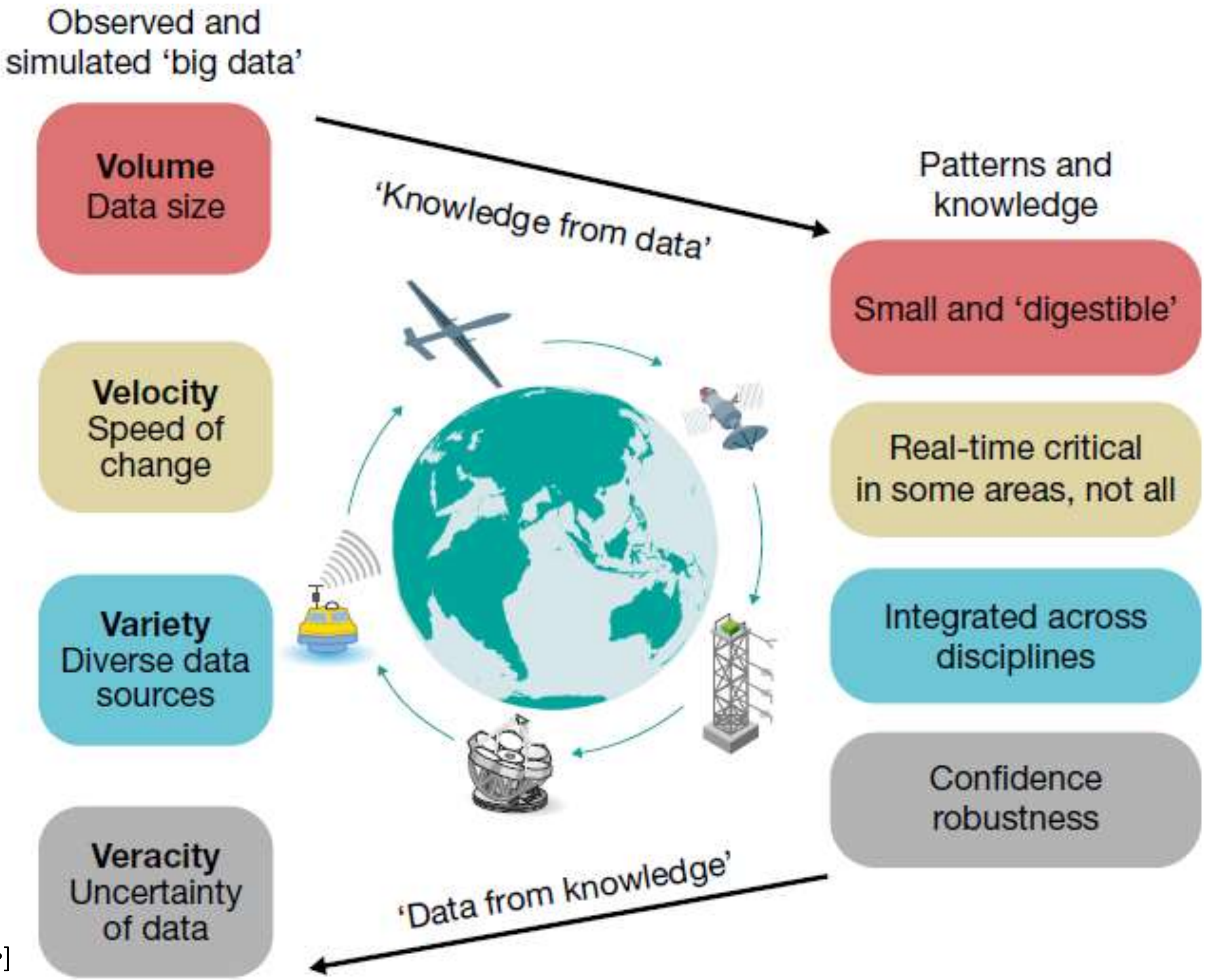
	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024	2025
Archive Size (PB)	15.0	17.7	21.6	26.8	32.0	37.2	55.6	103.4	151.1	198.9	246.6
Annual Growth (PB)	2.6	2.8	3.9	5.2	5.2	5.2	18.4	47.7	47.7	47.7	47.7



[*Courtesy of S. Cauffman, NASA*]

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

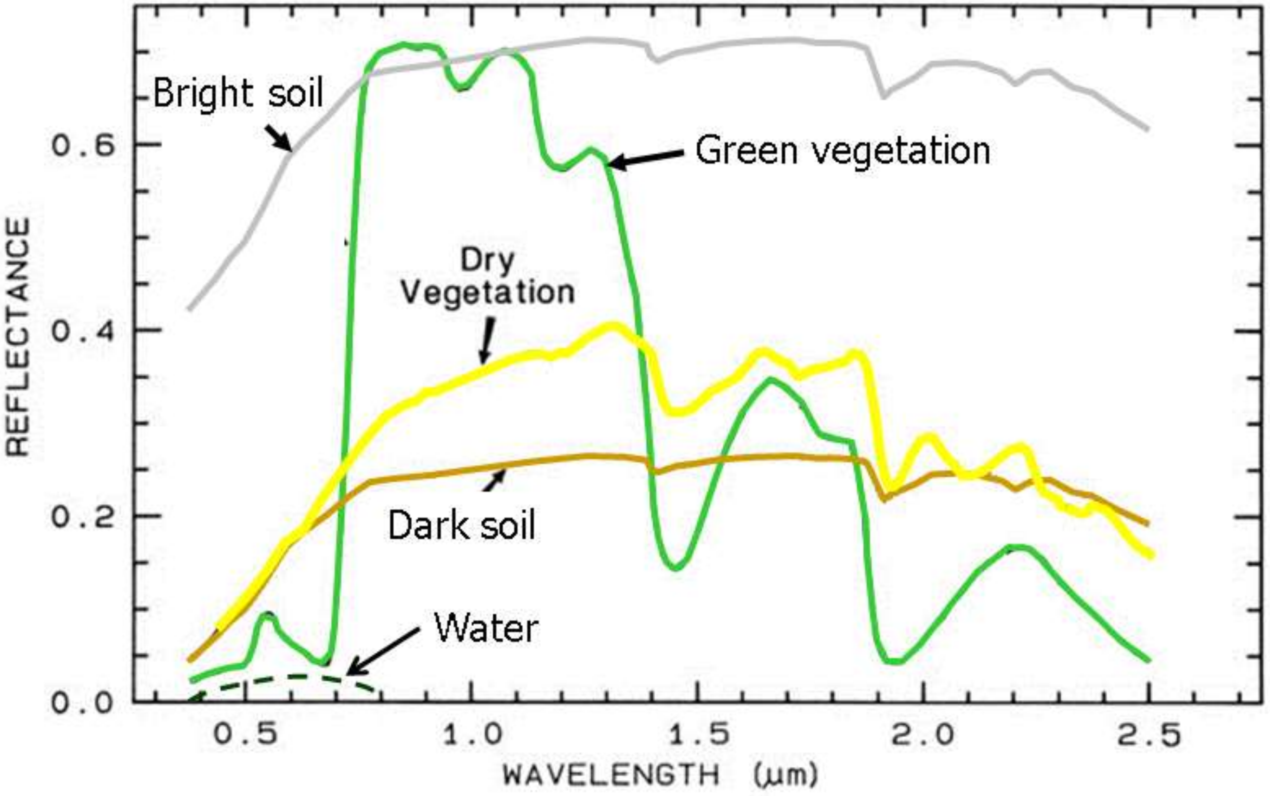
Big data challenges in the geoscientific context

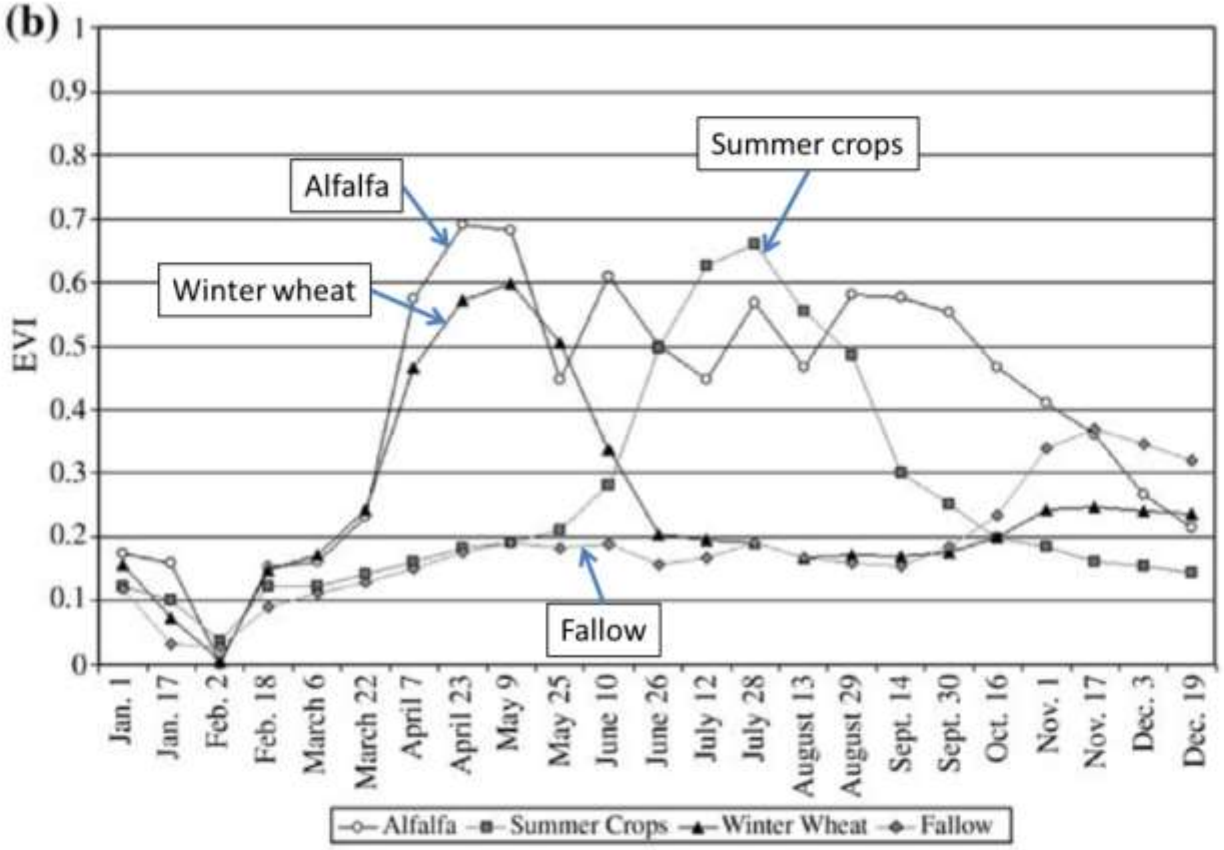


[Reichstein *et al.*, (2019). *Nature*]

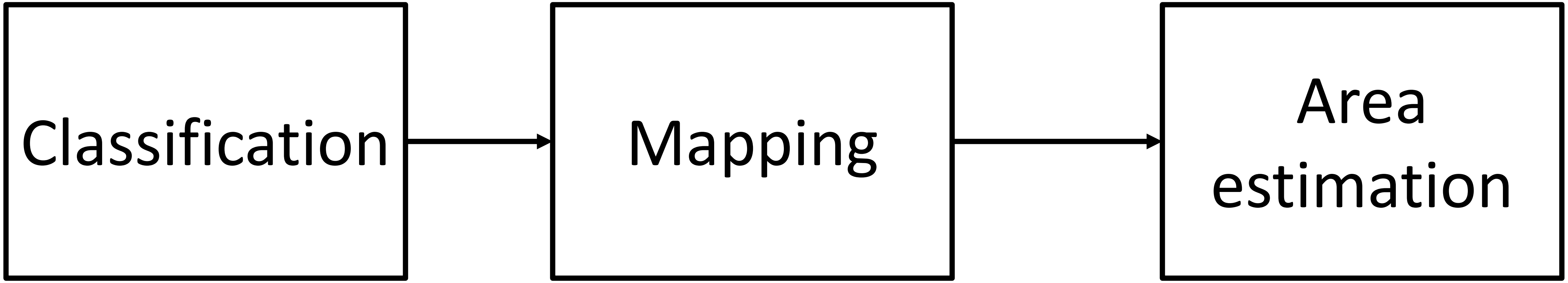
Classification: From Data to Labels

- **Feature**
  - an individual **measurable property** or **characteristic** of a phenomenon. Choosing informative, discriminating and independent features is a crucial element of effective algorithms in classification.
- Features in remote sensing: **Spectral**, **spatial**, **temporal**, **spatial unit** (pixels, objects)





Land cover / land use mapping and area estimation



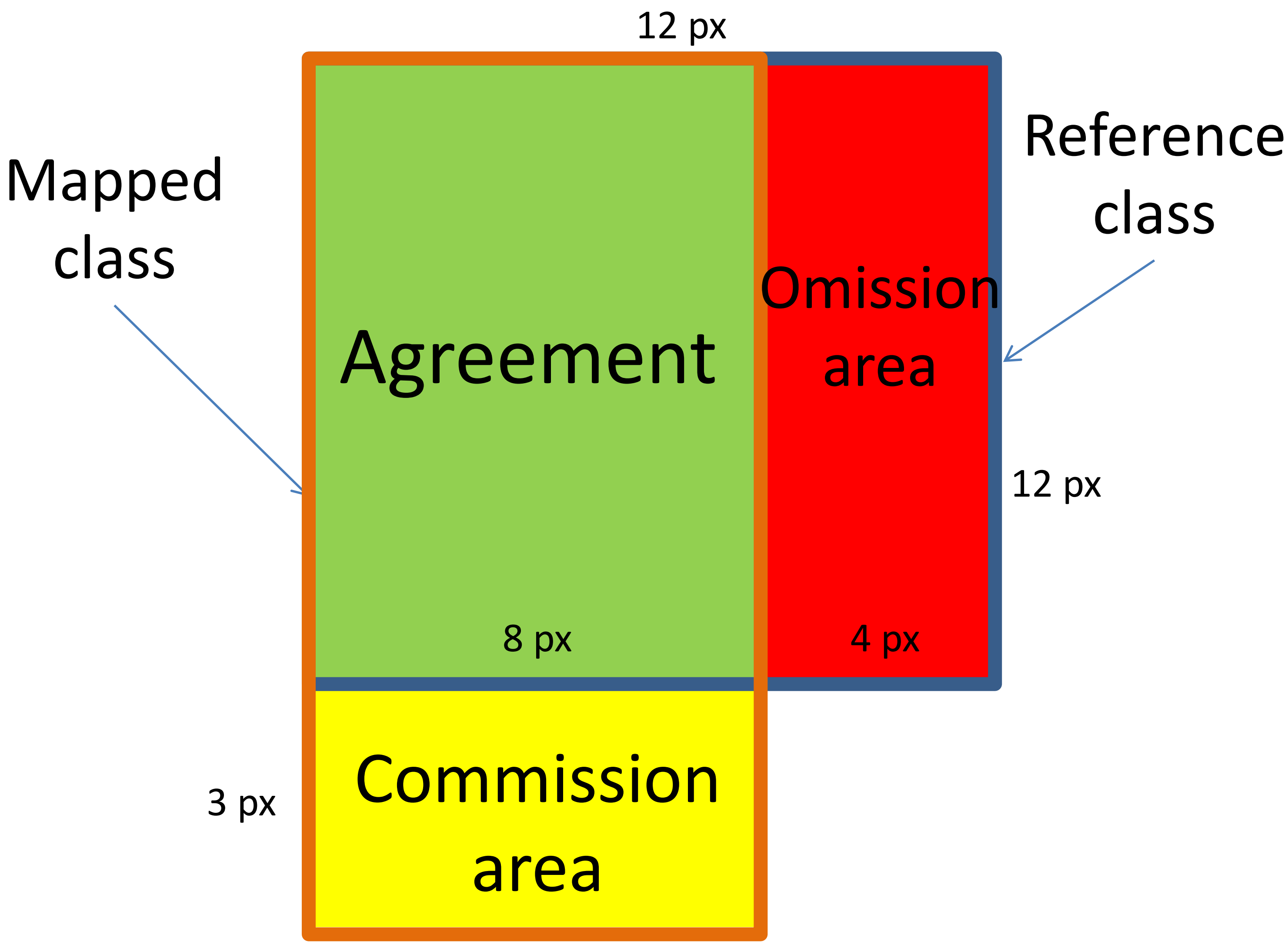
- Data
- Features
- Algorithms

- 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

ELSEVIER

Remote Sensing of Environment

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

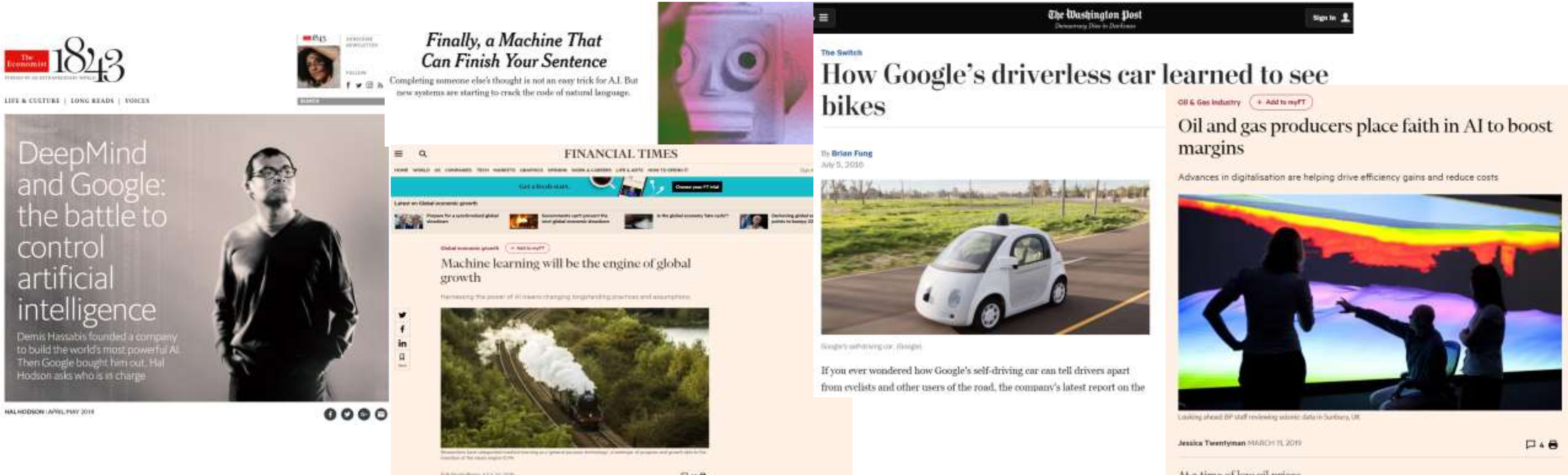
Review

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]

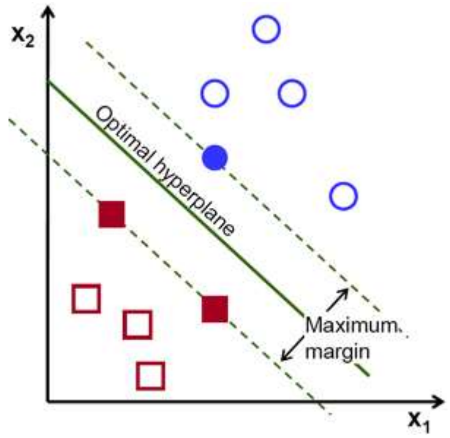
Machine learning

- 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**

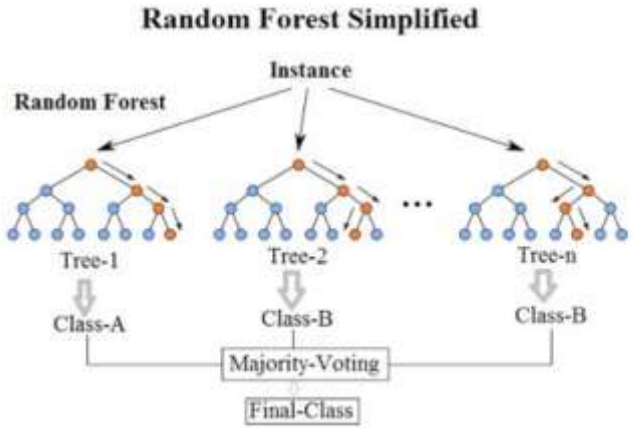


Machine learning: most popular in satellite data processing

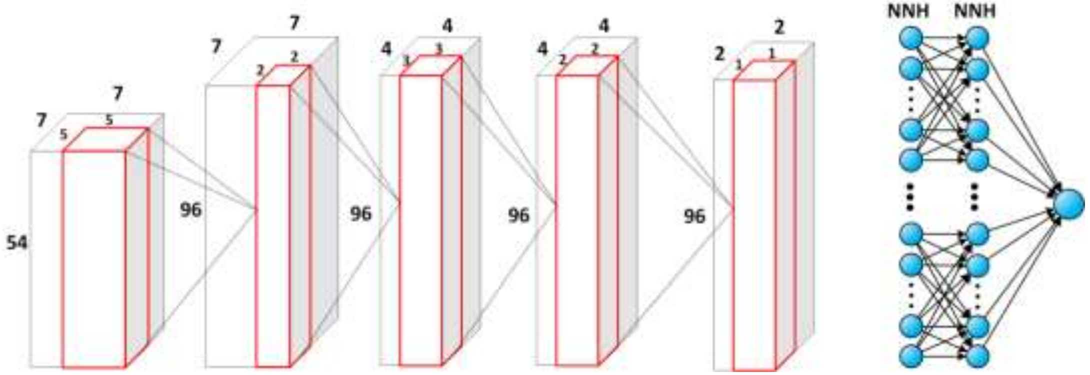
- **Support vector machine (SVM)**
  - Works well with small amount of data
  - Computational cost grows linearly with the number of classes
  - Several parameters to be optimized
  - Require feature engineering



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

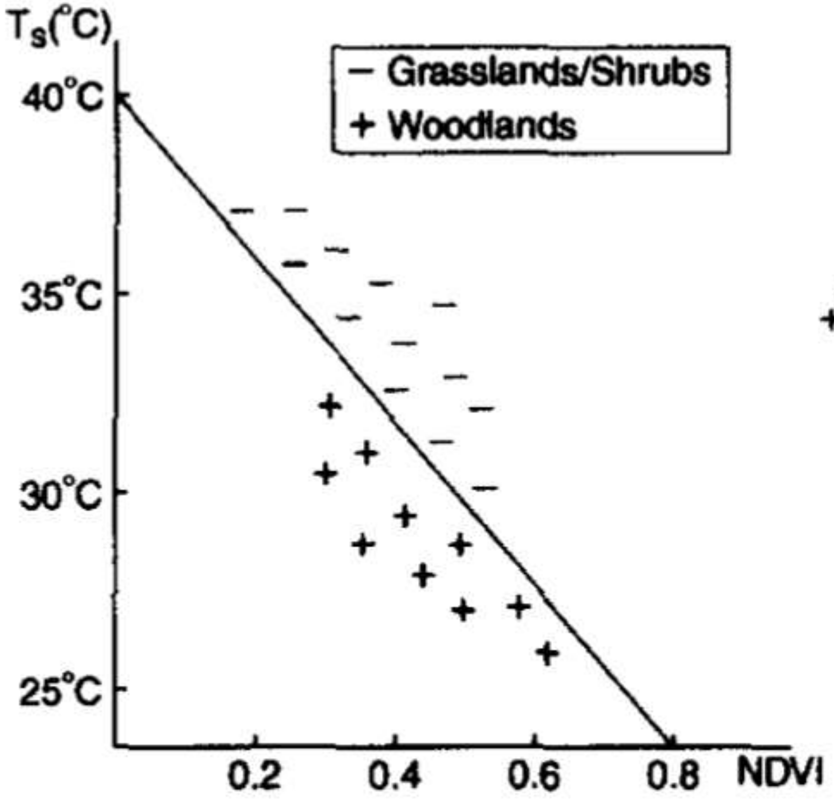


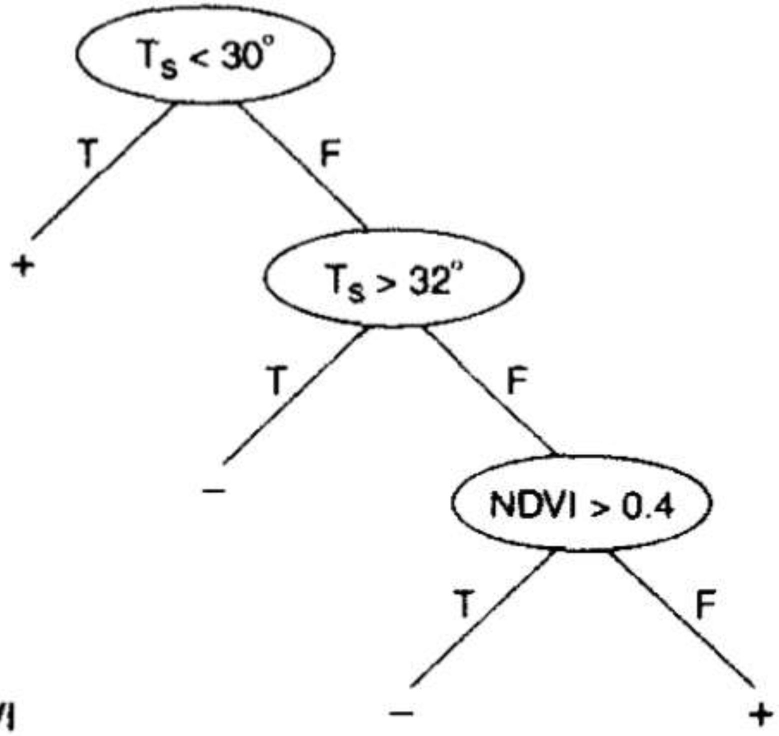
- **Artificial neural networks** (**ANN** or **NN**)
  - Difficult to train with a lot of parameters to tune
  - Require a lot of skills and expertise
  - No need for feature engineering: feature are learned by the network
  - Can learn very complex decision boundaries



Decision tree

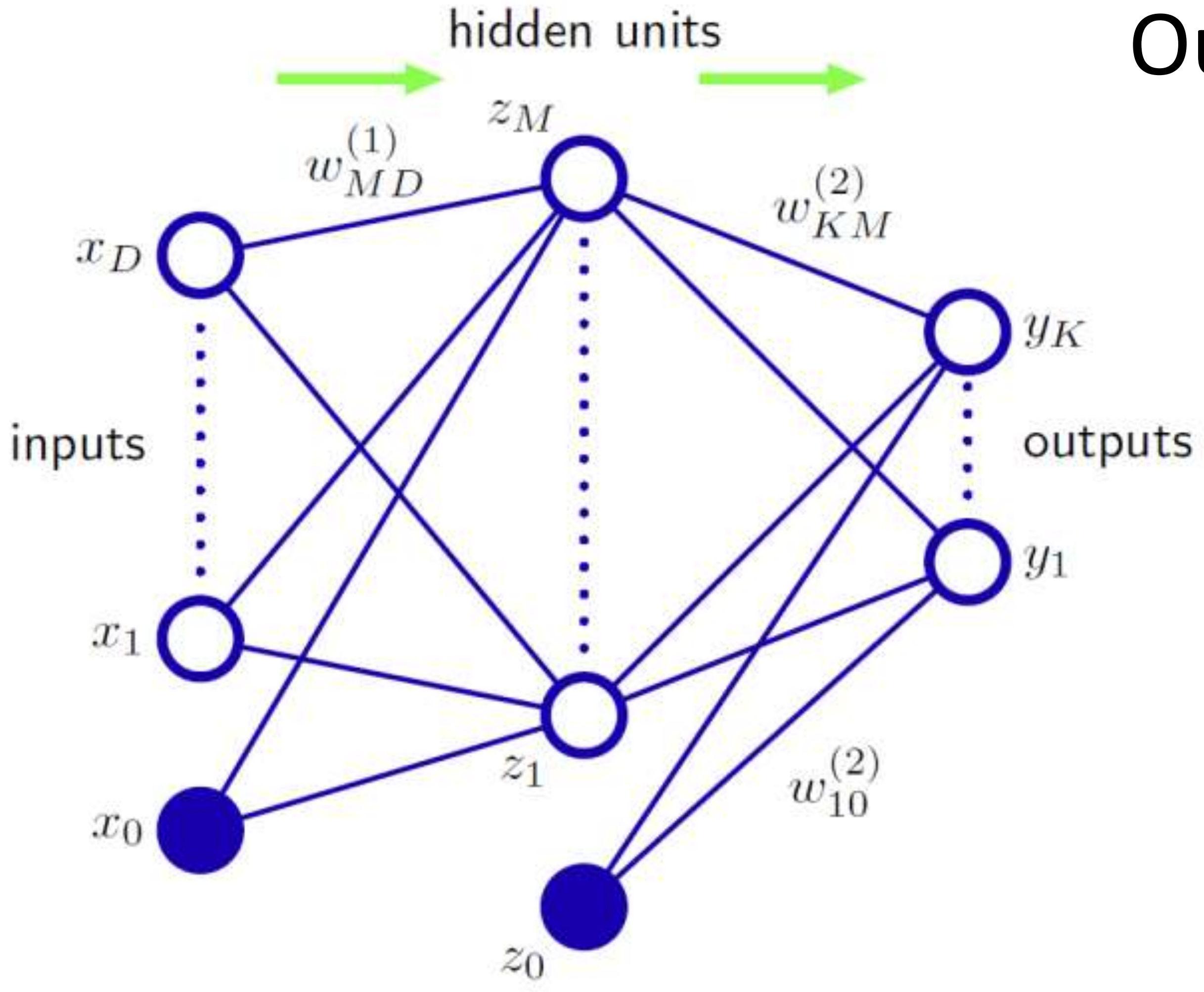
- Using the concept of **information entropy**
  - Level of “information”, “surprise”, or “uncertainty”
- Splitting data is based on the normalized **information gain**





[Friedl & Brodley, RSE 1997]

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***

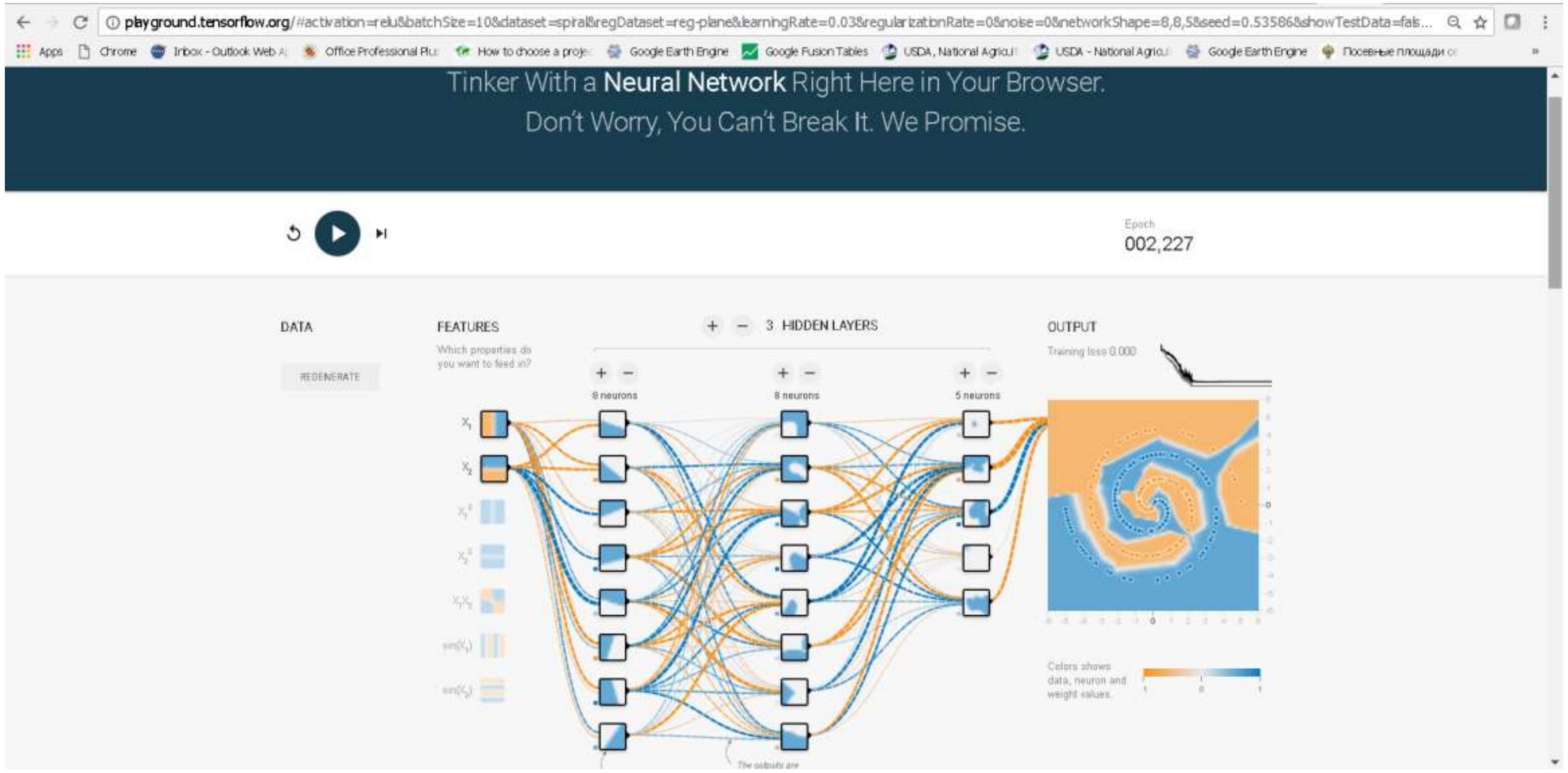
Weights ***w***

Universal approximators!

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

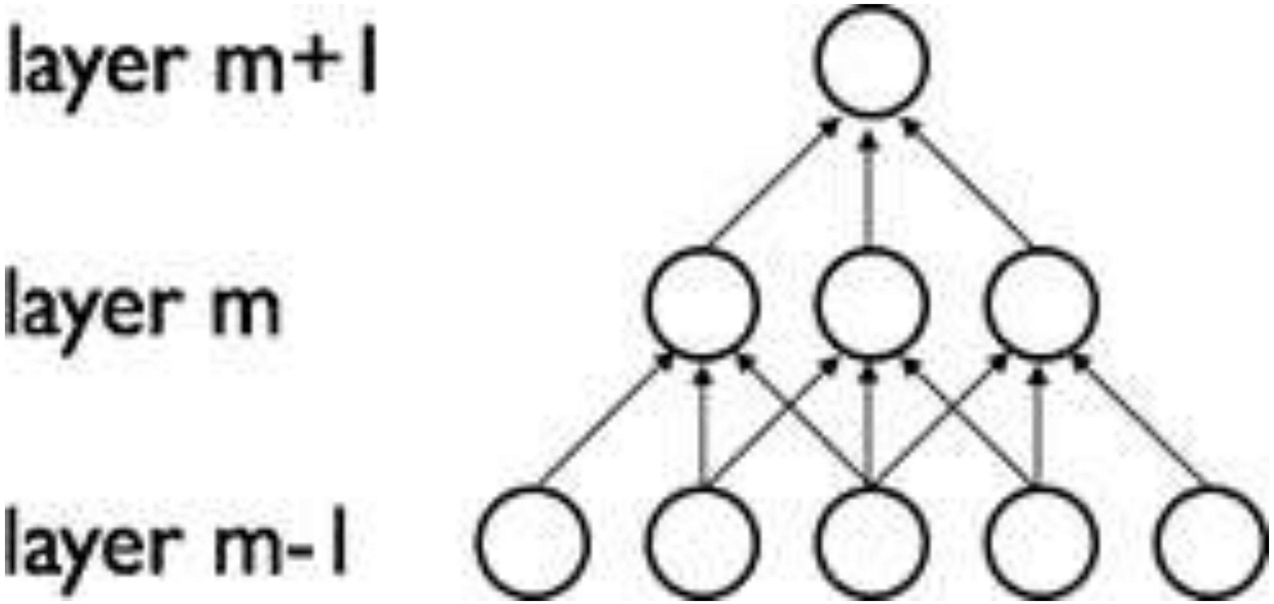
Multi-layer perceptron (MLP)

- http://playground.tensorflow.org
- http://playground.tensorflow.org/#activation=relu&batchSize=10&dataset=spiral&regDataset=reg-plane&learningRate=0.03&regularizationRate=0&noise=0&networkShape=8,8,5&seed=0.53586&showTestData=false&discretize=false&percTrainData=50&x=true&y=true&xTimesY=false&xSquared=false&ySquared=false&cosX=false&sinX=false&cosY=false&sinY=false&collectStats=false&problem=classification&initZero=false&hideText=false&showTestData_hide=true&activation_hide=true&problem_hide=true&noise_hide=true&discretize_hide=true&regularization_hide=true&dataset_hide=true&batchSize_hide=true&learningRate_hide=true&regularizationRate_hide=true&percTrainData_hide=true&numHiddenLayers_hide=false



Convolutional neural networks (CNN)

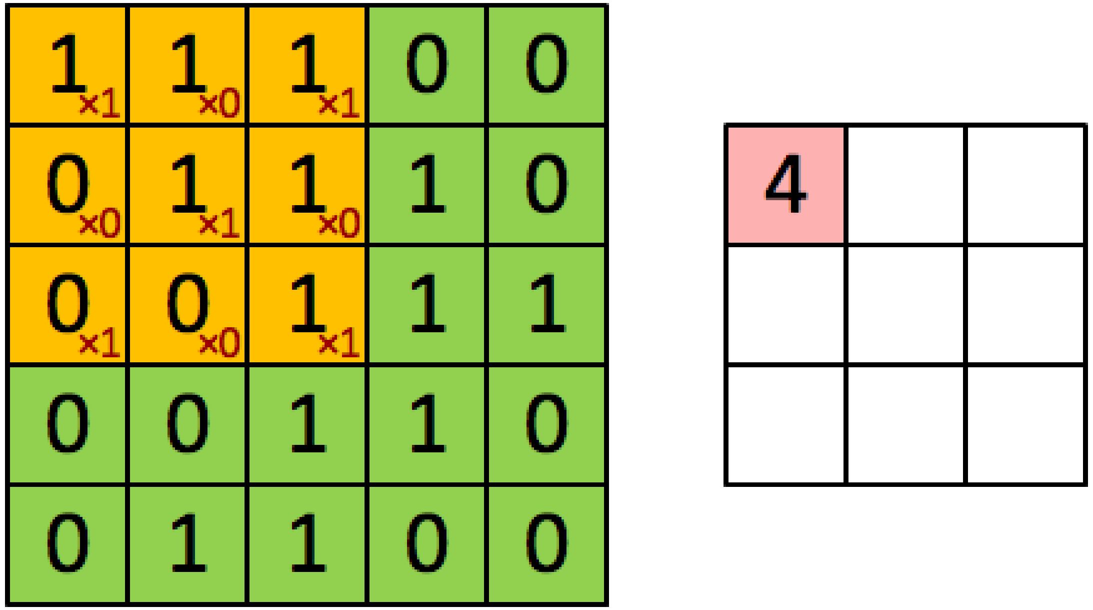
Sparse connectivity



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

Convolutional neural networks (CNN)

Convolution



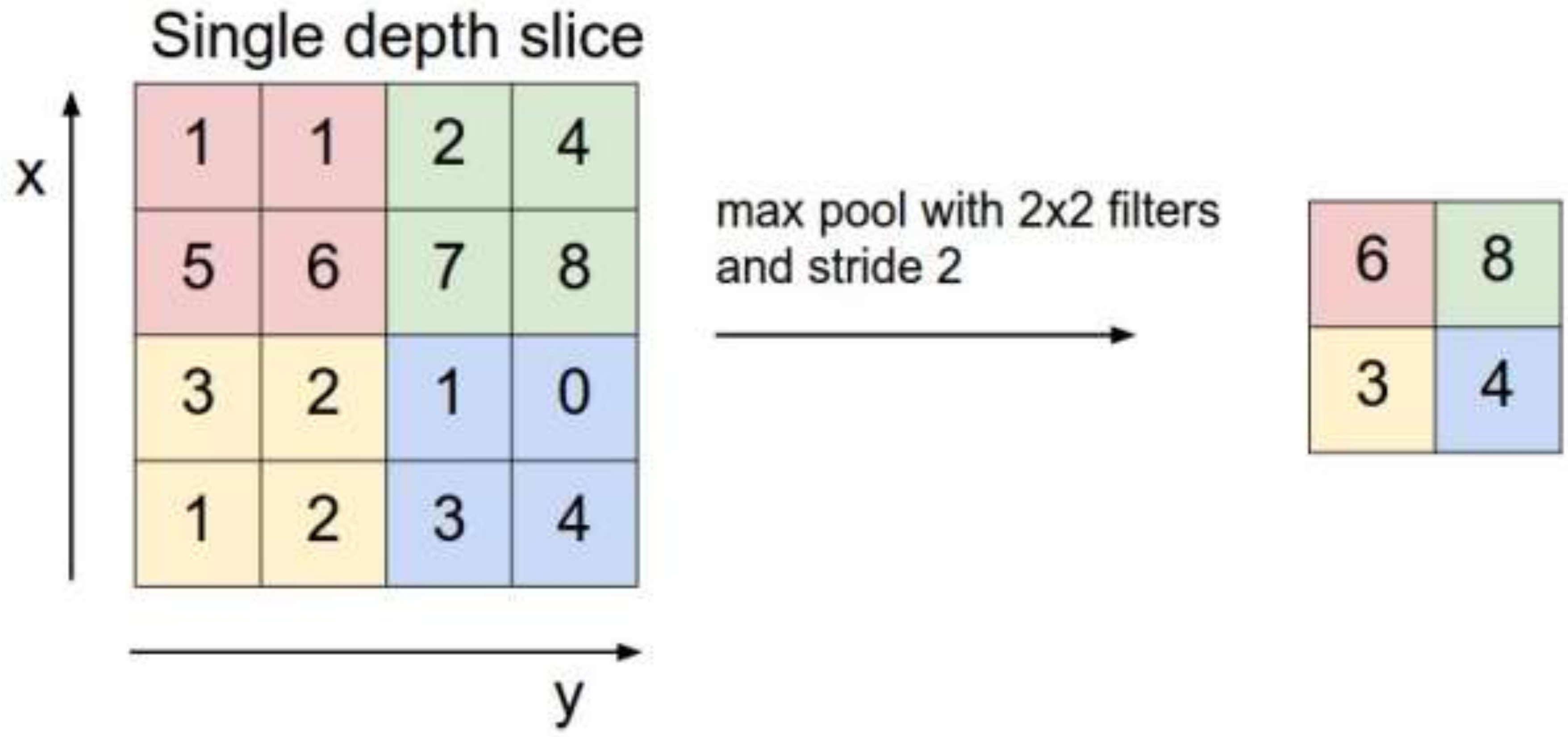
Image

Convolved Feature

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

Convolutional neural networks (CNN)

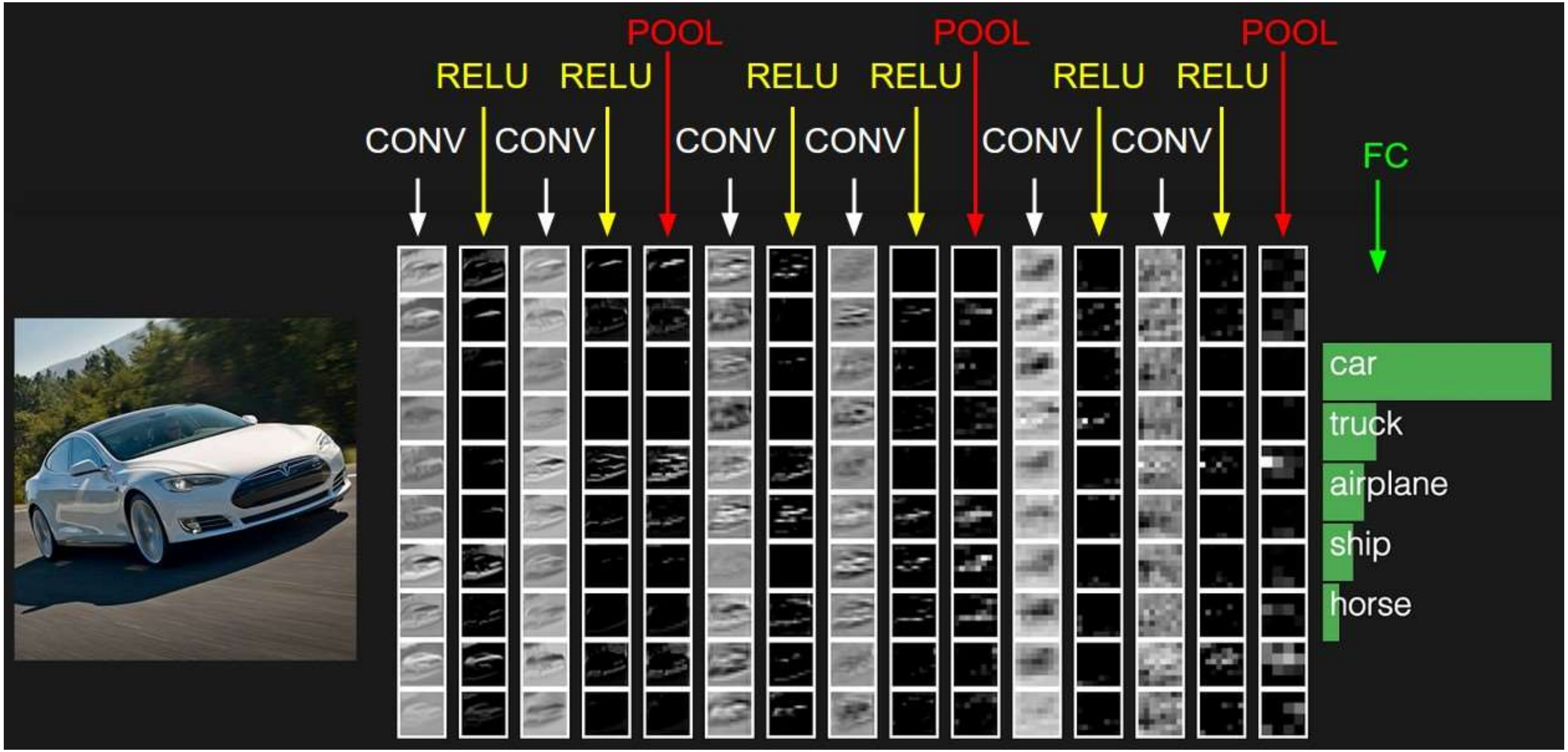
Pooling (sub-sampling)



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

Convolutional neural networks (CNN)

- Overall architecture

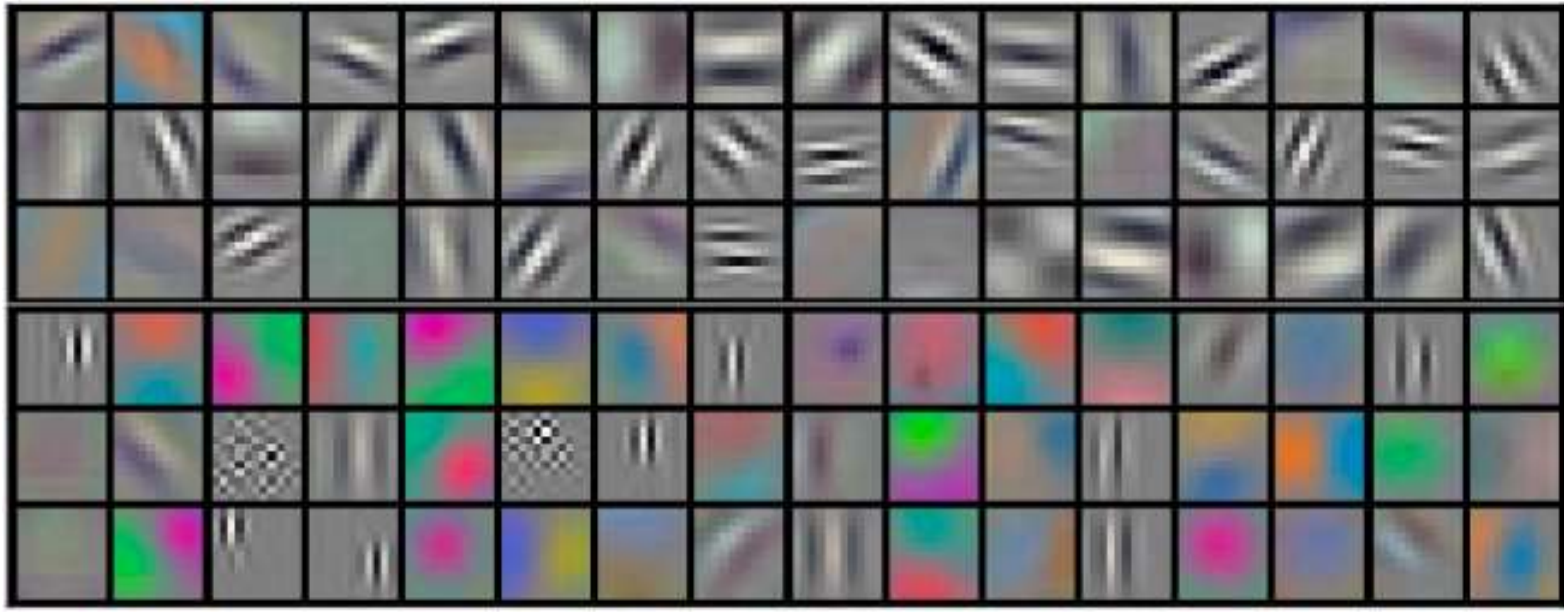


[Sources: http://cs231n.github.io/convolutional-networks]

Convolutional neural networks (CNN)

- Learned filters (Gabor-like)

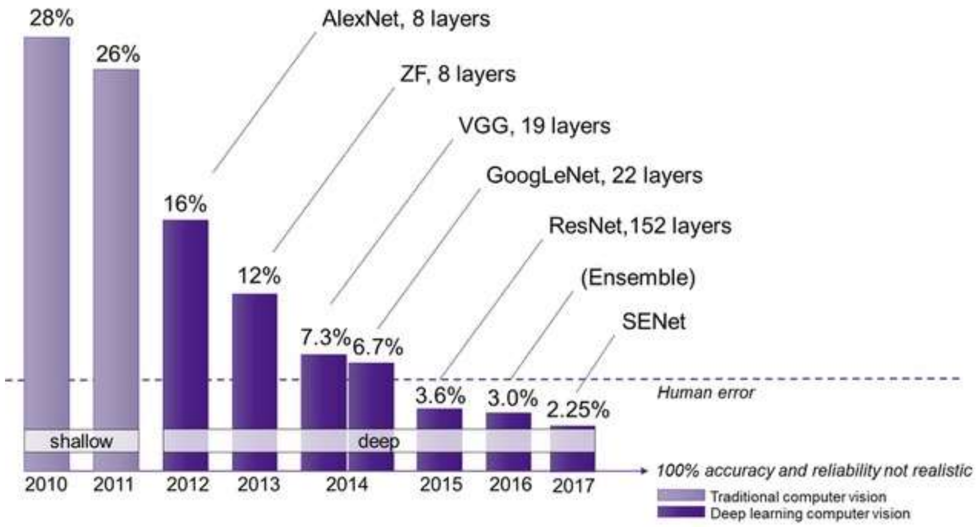
96 convolutional kernels of size 11×11×3 learned by the first convolutional layer on the 224×224×3 input natural images

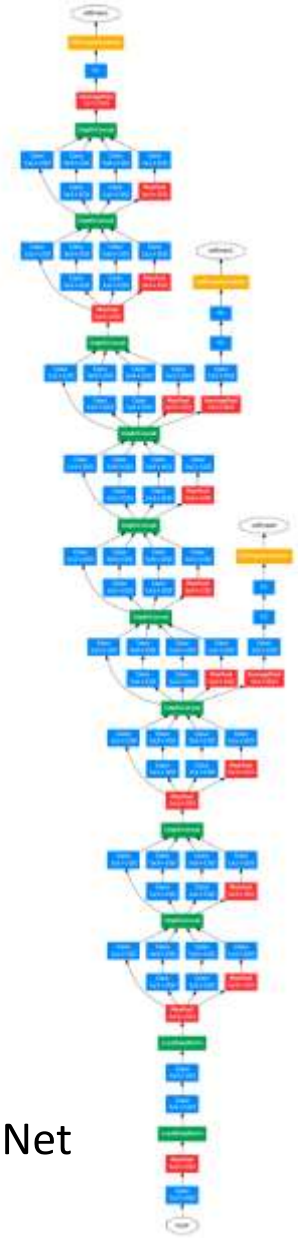


[Sources: Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). Imagenet classification with deep convolutional neural networks. In *Advances in neural information processing systems* (pp. 1097-1105)]

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

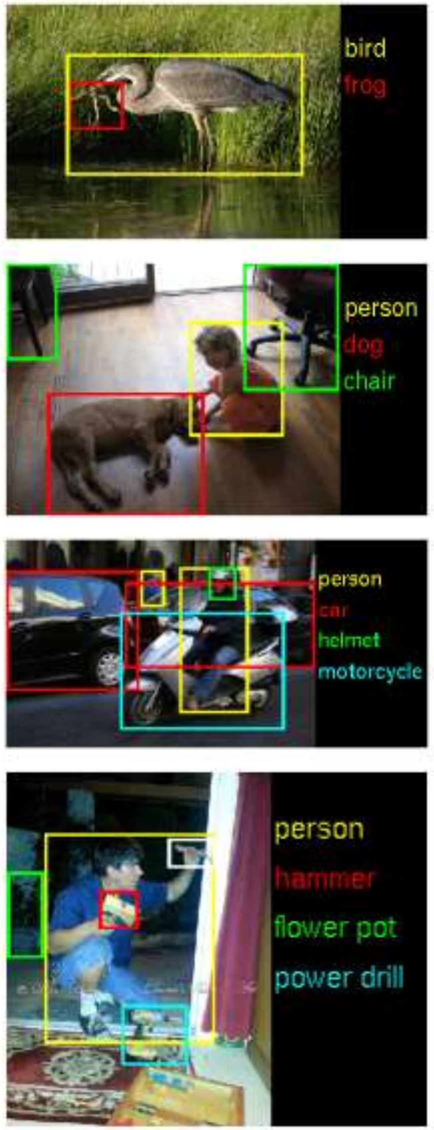
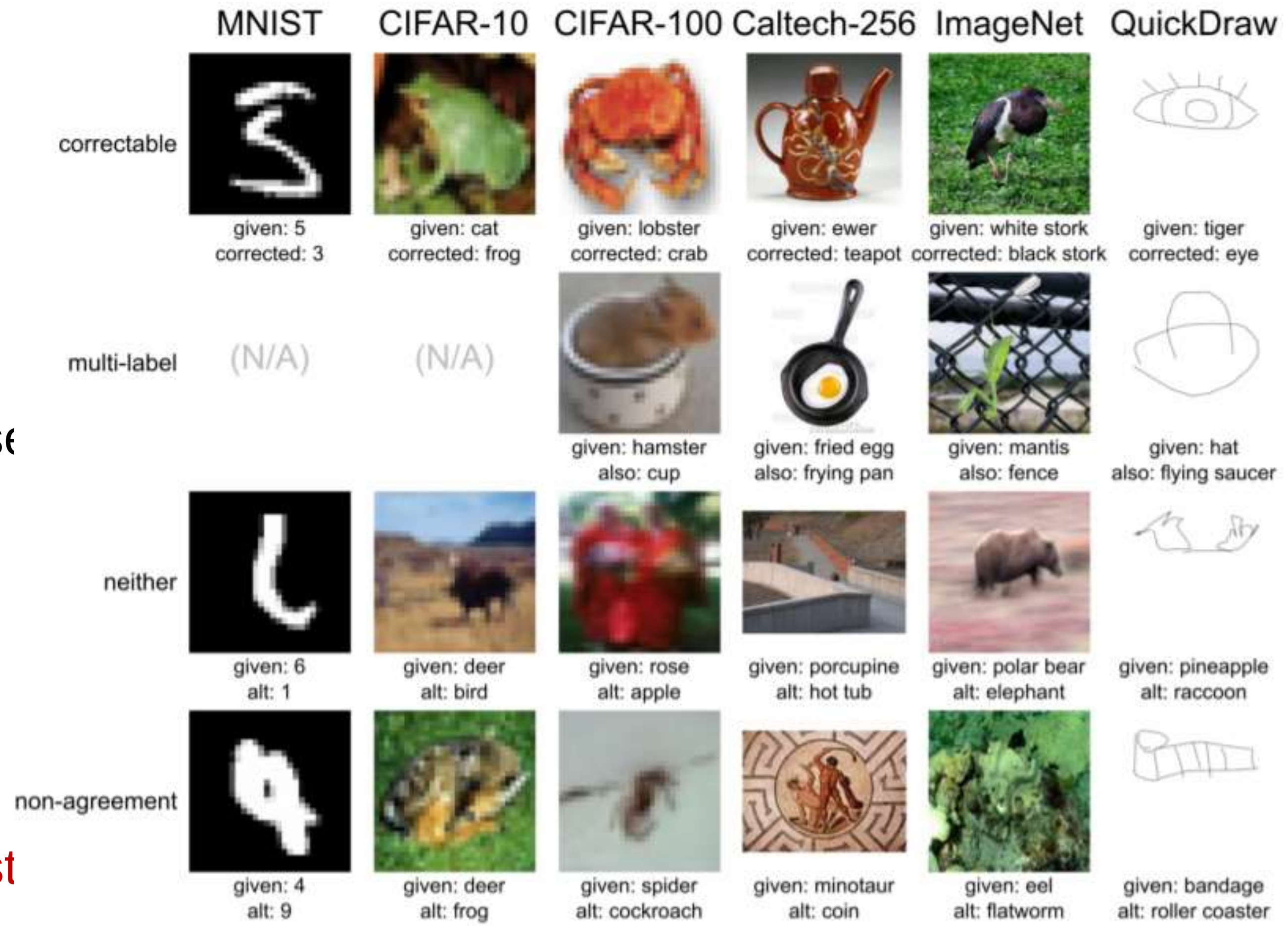


image-net.org

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

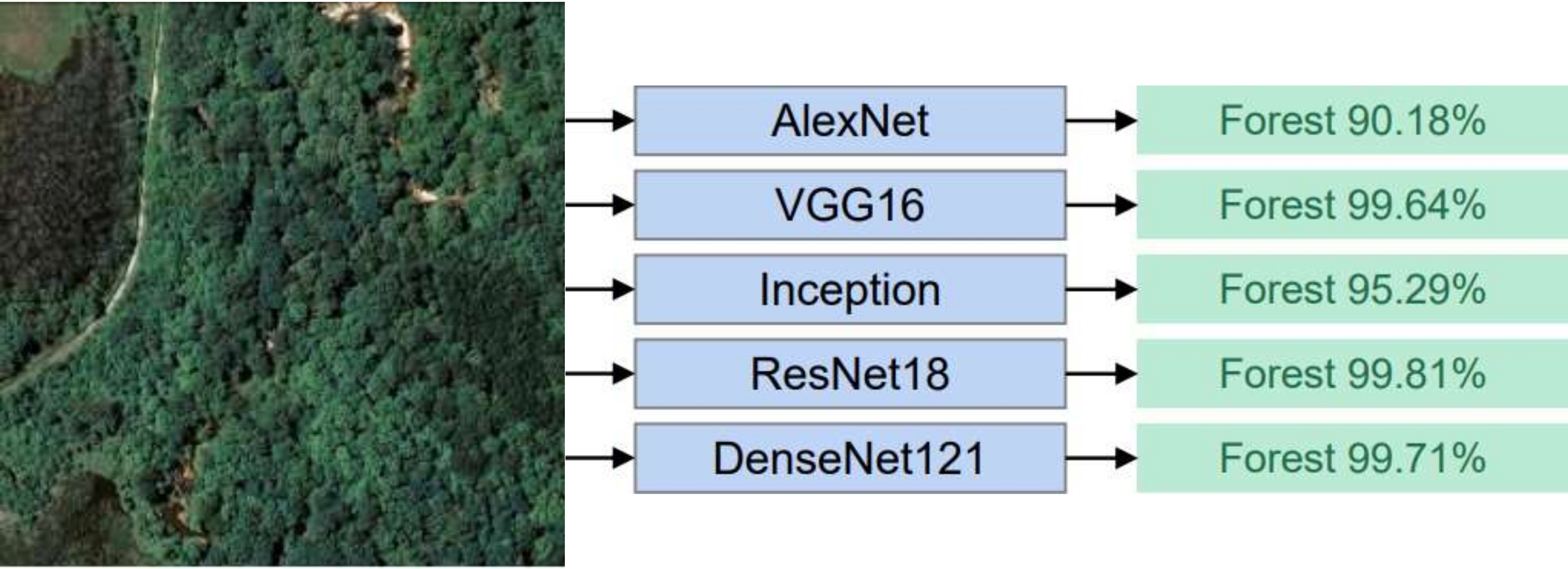
- Those deep learning models very **difficult to interpret**:
  - Fundamental question: **why the model makes a particular decision**?
  - Extremely important for many domains, including Earth observation (EO)

- A simple pitfall:
  - 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.**

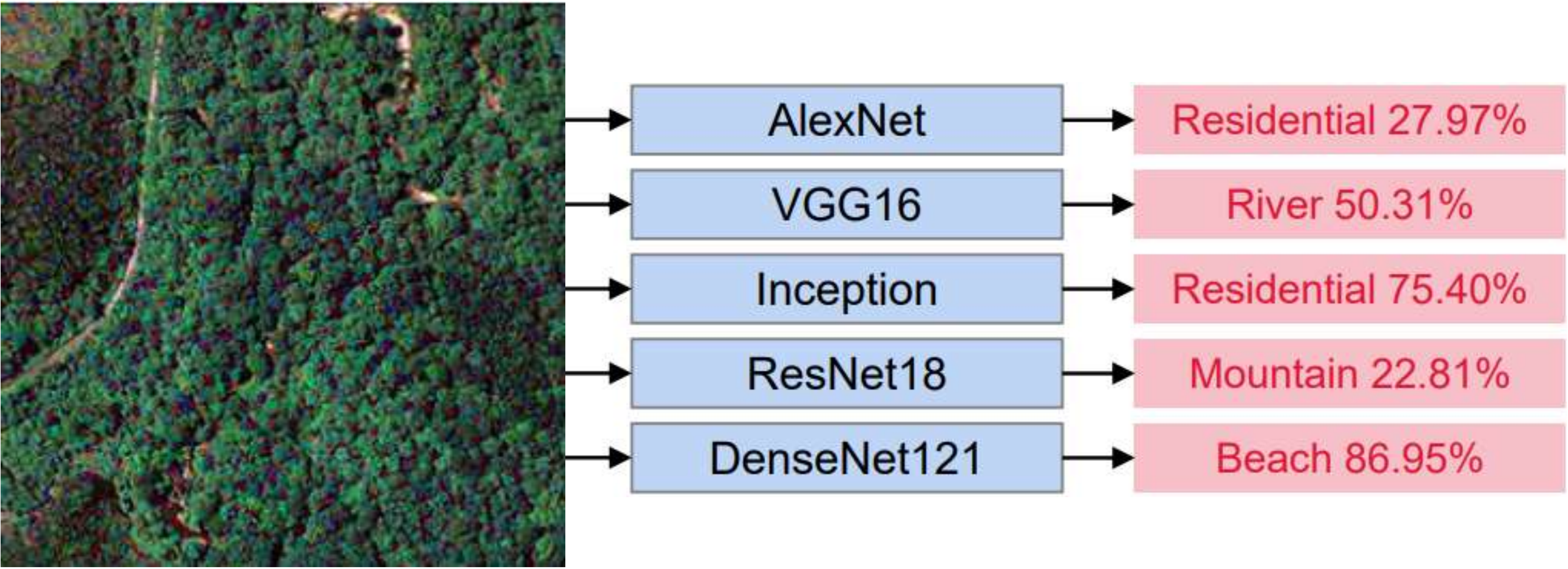
https://www.star.nesdis.noaa.gov/star/documents/seminardocs/2019/20190718_Kumler_and_Ebert-Uphoff.pdf

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



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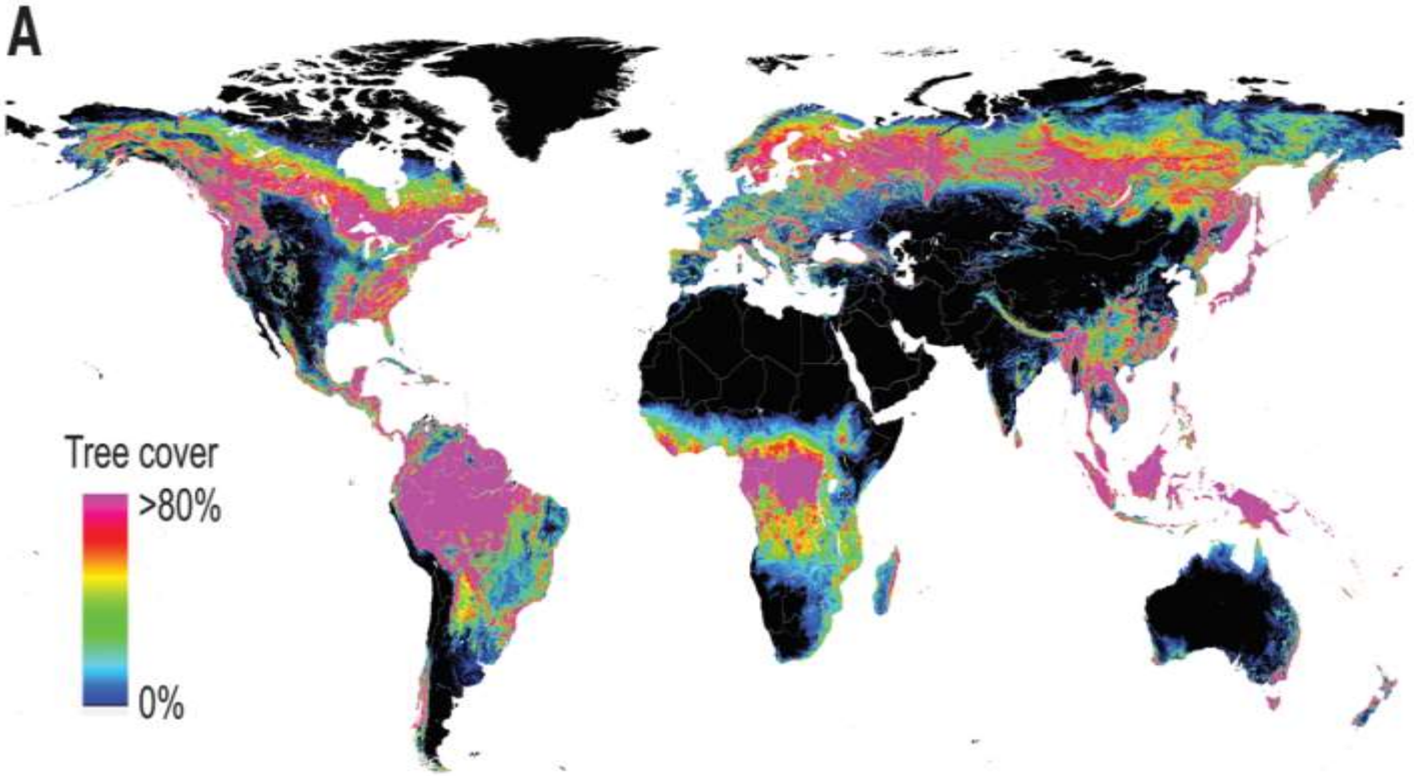
Case-studies

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 on 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**

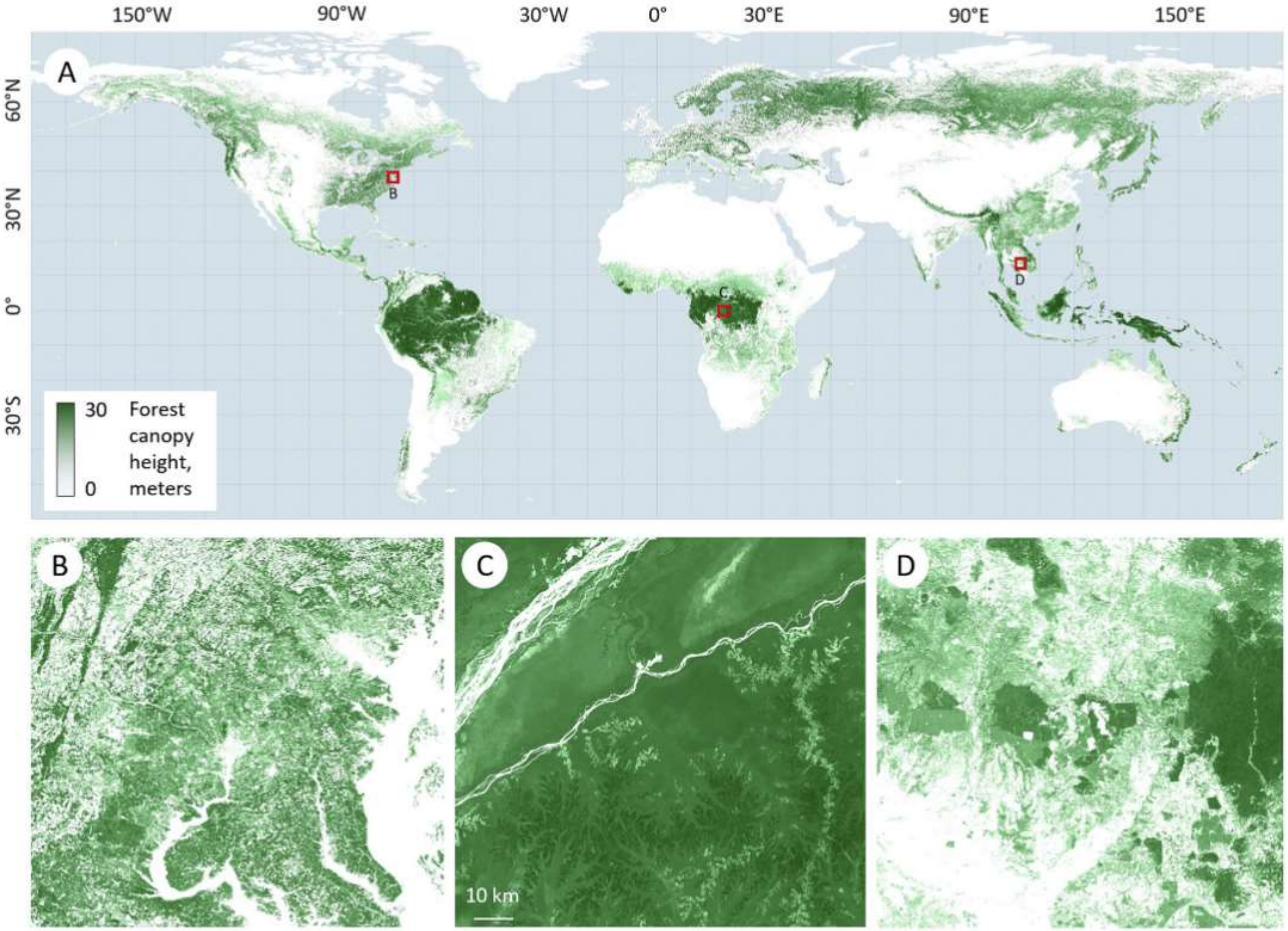


https://www.globalforestwatch.org/map/

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

Tree height mapping

- 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**

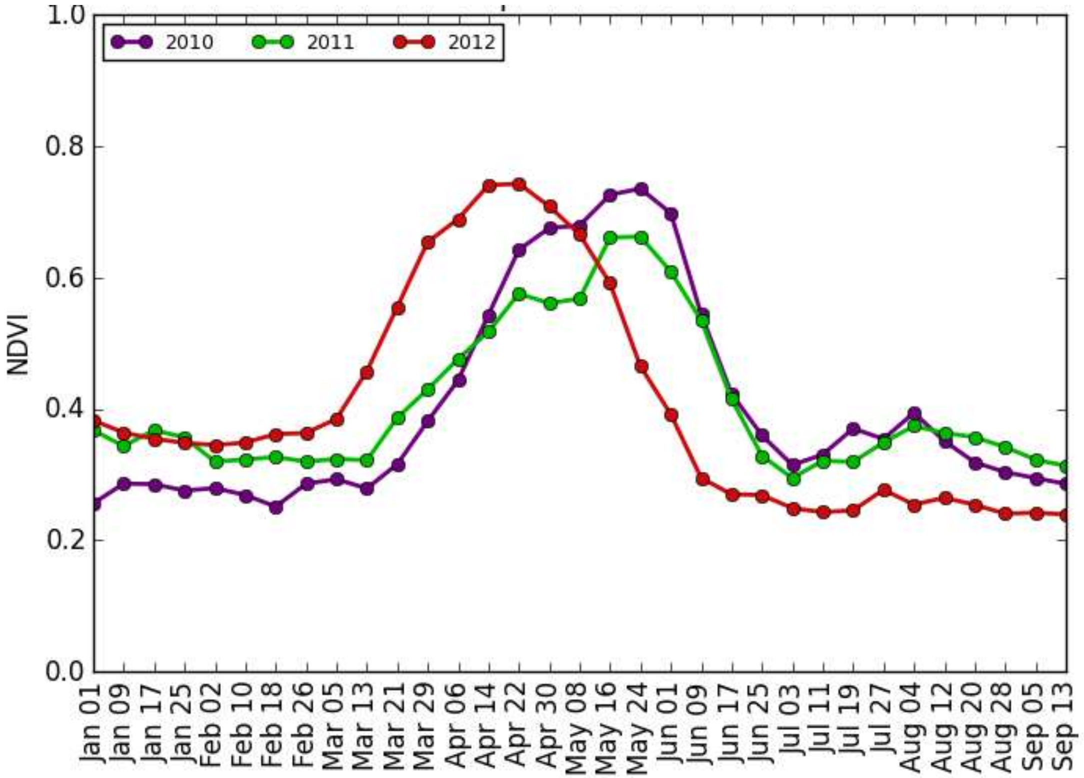


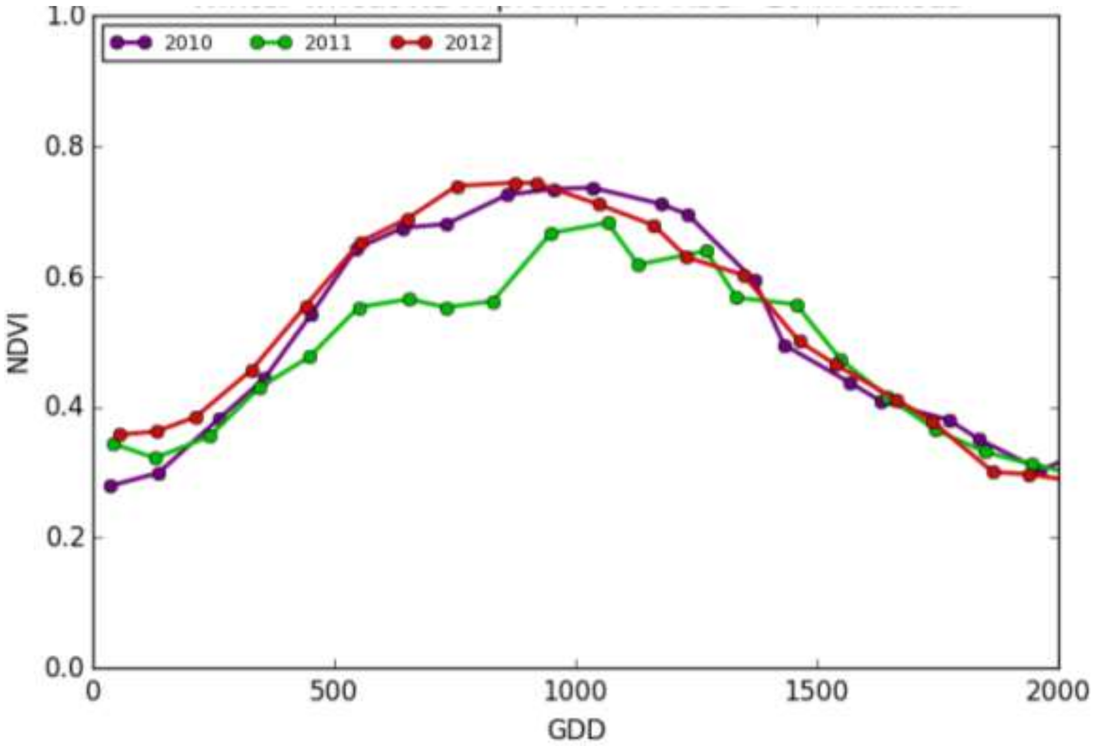
https://doi.org/10.1016/j.rse.2020.112165

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

Example: Winter crop mapping

- Automatic approach with MODIS data and growing degree days (GDD)



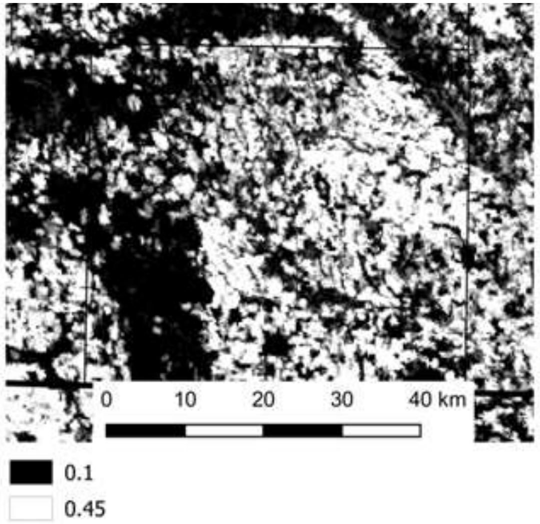


As winter crop development is temporally and spatially non-uniform due to the presence of different agro-climatic zones, GDD is used to account for such discrepancies

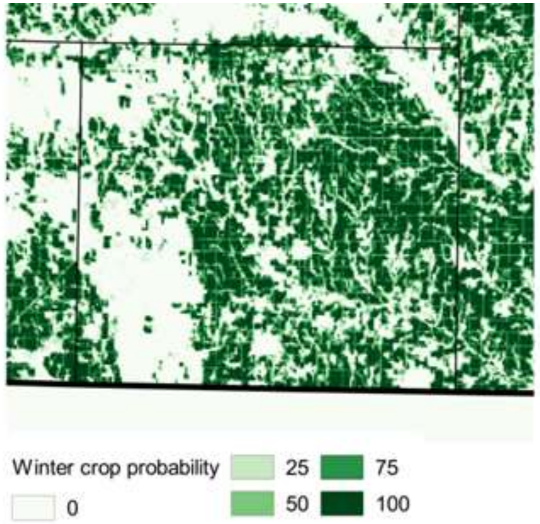
[Skakun, S., et al. (2017). Early season large-area winter crop mapping using MODIS NDVI data, growing degree days information and a Gaussian mixture model. ***Remote Sensing of Environment***, *195*, 244-258.]

Example: Winter crop mapping

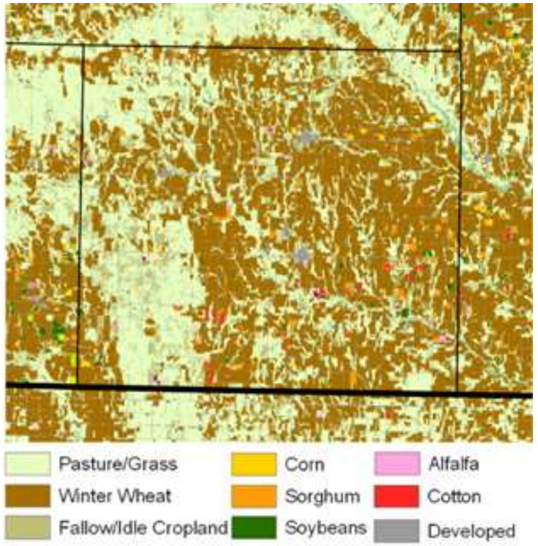
phenological metric

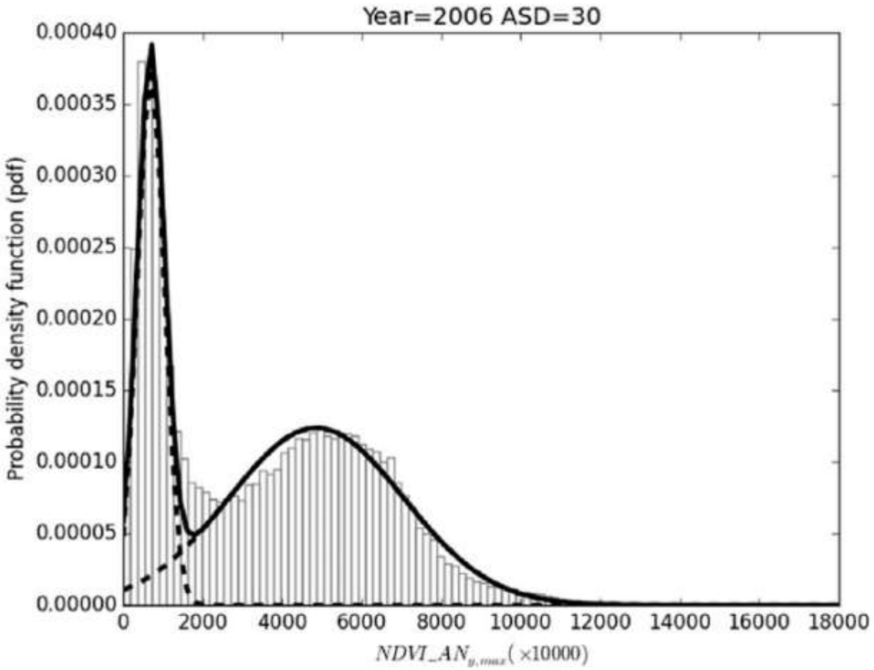


winter crop probability map



USDA Cropland Data Layer





Results for winter crop mapping for Harper County (Kansas, USA) in 2006 and its comparison to CDL map:
phenological metric (left);
winter crop probability map (center); and
USDA Cropland Data Layer map (right).

Discrimination between summer crops (left peak) with winter crops (right peak)

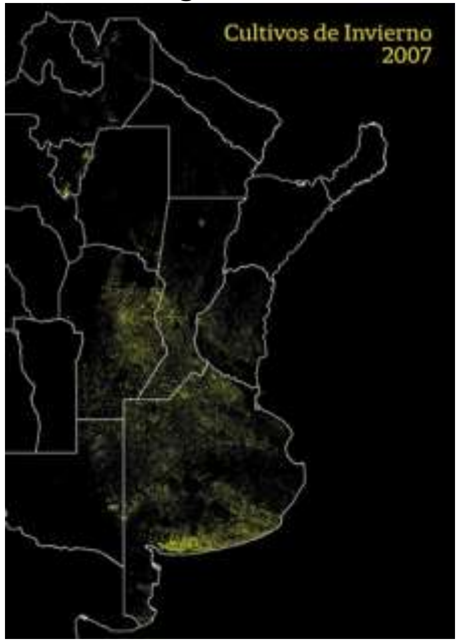
[Skakun, S., et al. (2017). Early season large-area winter crop mapping using MODIS NDVI data, growing degree days information and a Gaussian mixture model. ***Remote Sensing of Environment***, *195*, 244-258.]

Example: Winter crop type mapping (globally)

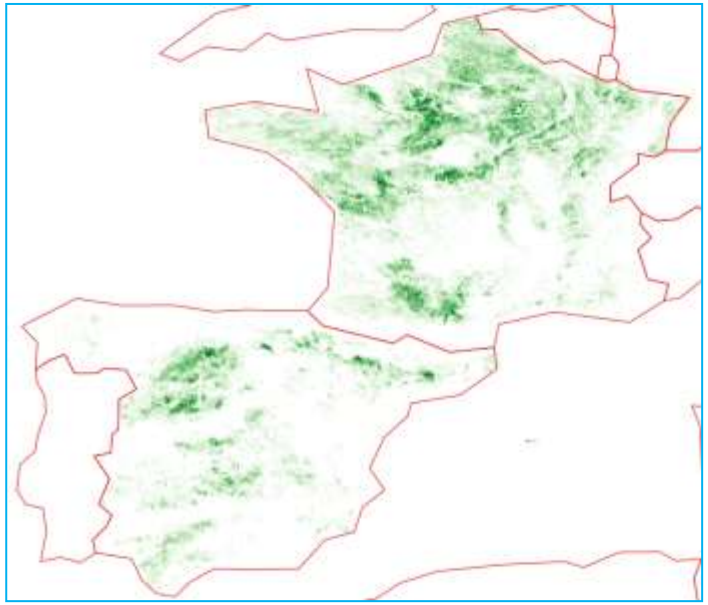
Ukraine

Russia

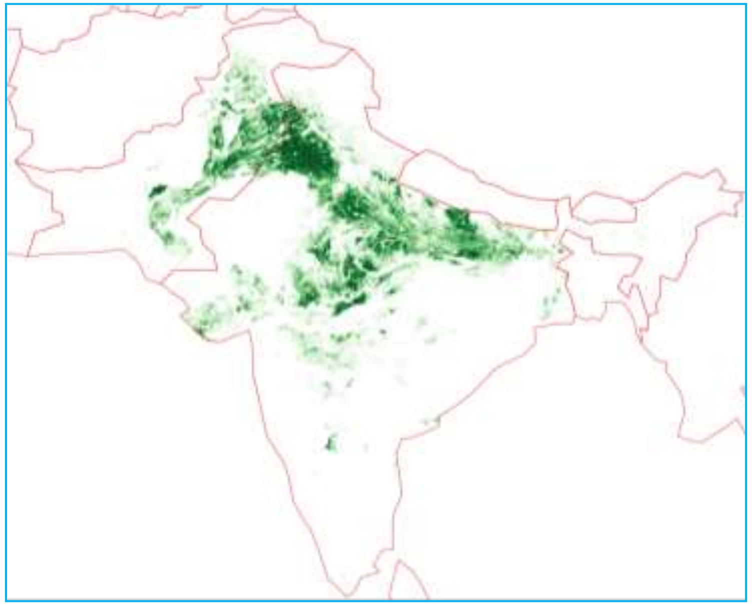
Argentina



France, Spain

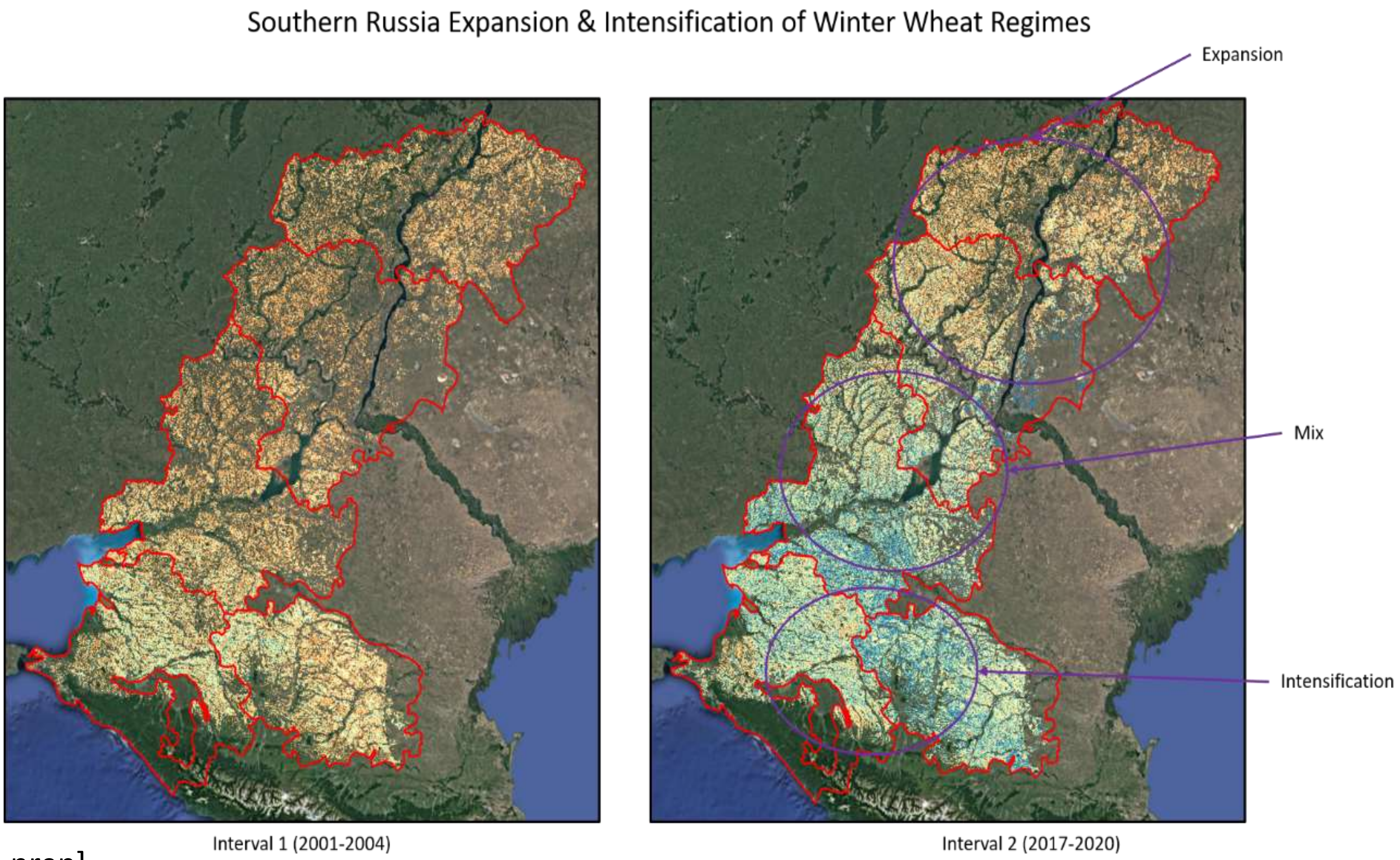


India, Pakistan



[Skakun, S., et al. (2017). Early season large-area winter crop mapping using MODIS NDVI data, growing degree days information and a Gaussian mixture model. ***Remote Sensing of Environment***, *195*, 244-258.]

Winter crop area increase in Russia

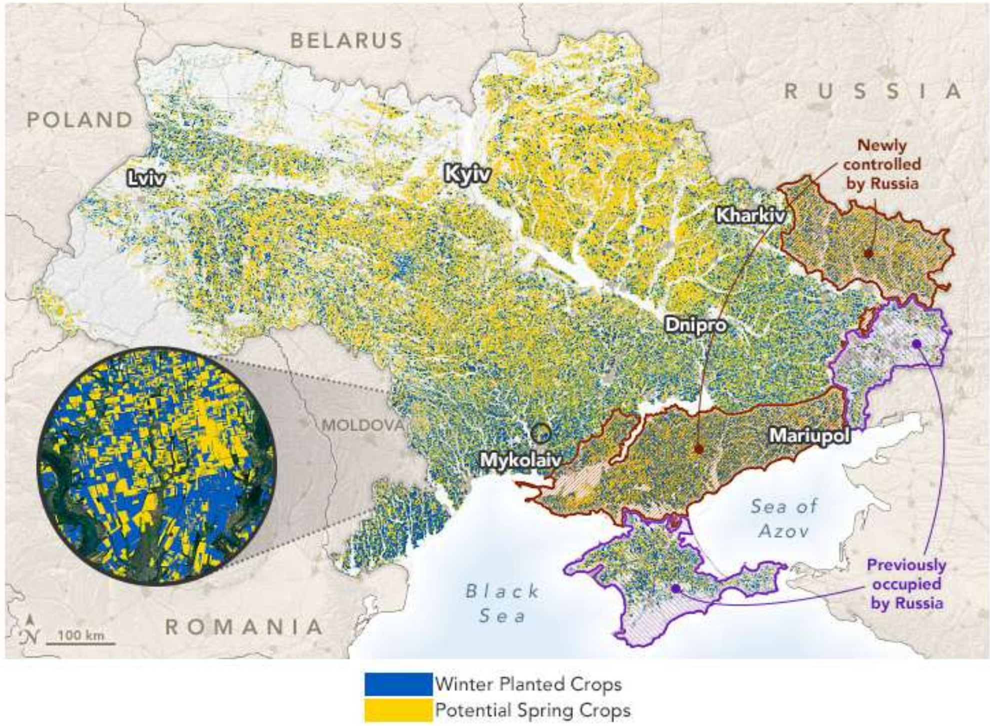


[Abys, C., et al., in prep]

earthobservatory.nasa.gov/images/150025/measuring-wars-effect-on-a-global-breadbasket

Images | Global Maps | Articles | Blogs | NASA earth observatory | EO Explorer | Topics

Measuring War's Effect on a Global Breadbasket



2022

JPEG

View this area in EO Explorer

NASA Harvest researchers are using satellite observations and economic data to track how the Russia-Ukraine conflict is disrupting the global food system.

Image of the Day for July 1, 2022

Instruments:
In situ Measurement
Landsat 8 — OLI
Photograph
Planet Labs — Cubesat

Appears in this Collection:
Applied Sciences

https://earthobservatory.nasa.gov/images/150025/measuring-wars-effect-on-a-global-breadbasket planet.com/pulse/nasa-harvest-tracks-frontline-agriculture-patterns-with-planets-satellite-data/

NASA Harvest Tracks Frontline Agriculture Patterns With Planet's Satellite Data

Megan Zaroda | September 7, 2022

AUTHOR PROFILE

MEGAN ZARODA

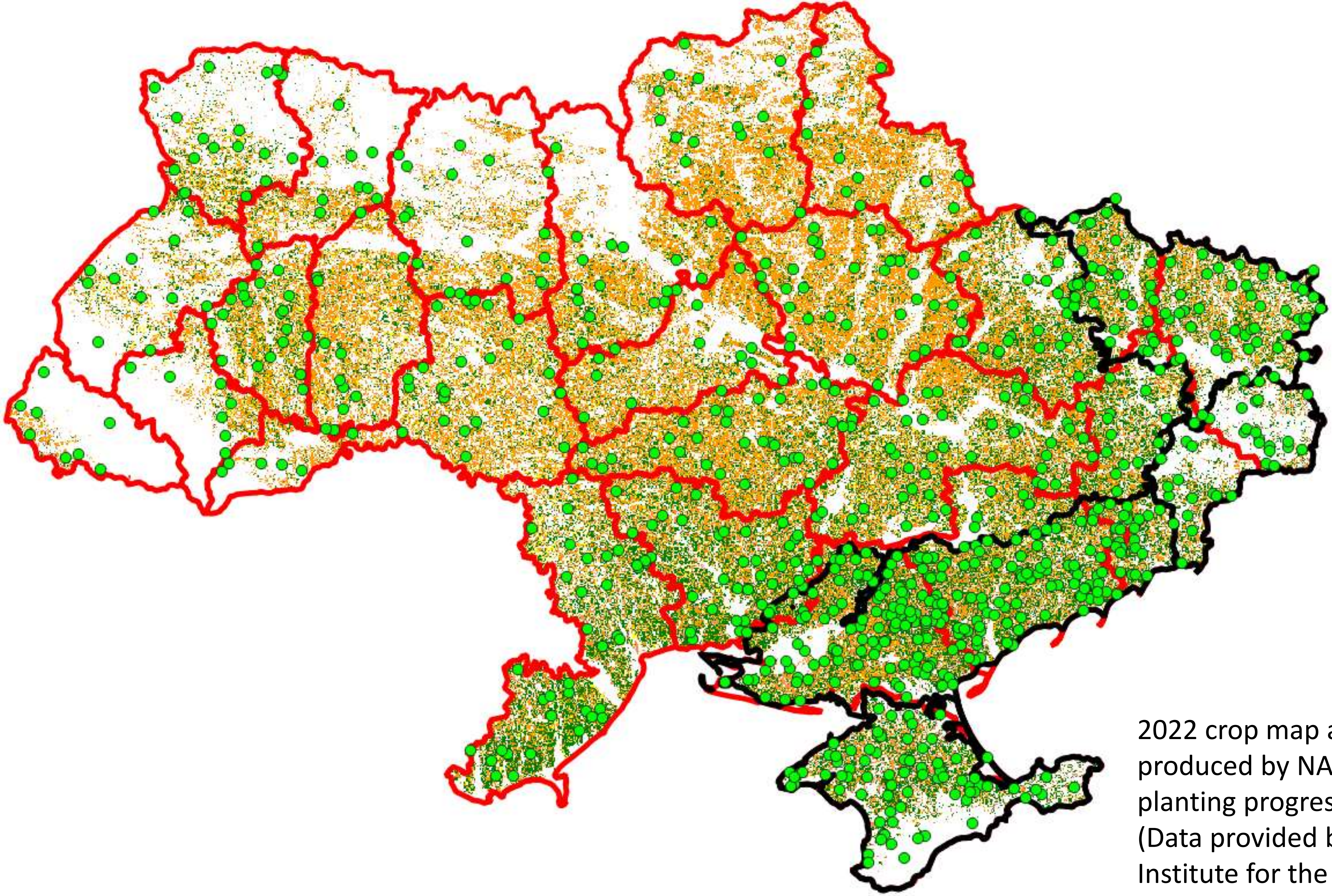
Curious Planeteer working to make the Earth's changes visible, accessible and actionable.

Pulse Home > Stories > **NASA Harvest tracks frontline agriculture patterns with Planet's satellite data**

STORIES

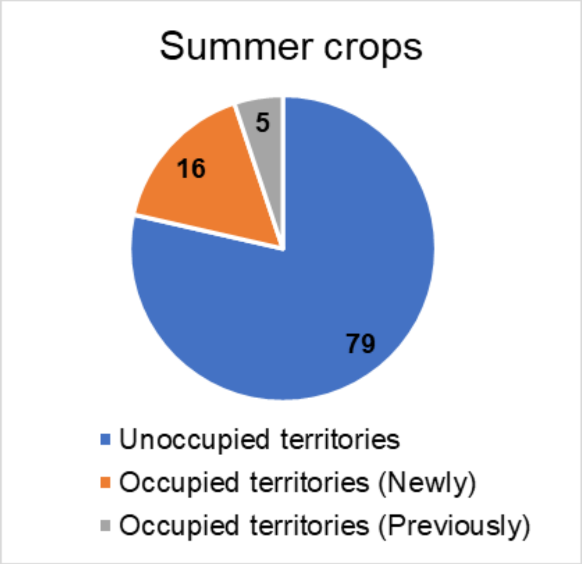
In the midst of the Russo-Ukrainian war, more cropland than was initially expected has been both harvested and planted along both the Russian-occupied and Ukrainian-held territories, according to NASA Harvest research.

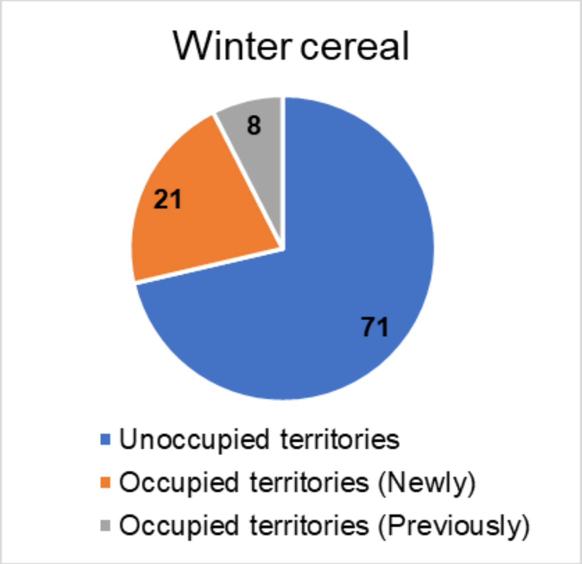
https://www.planet.com/pulse/nasa-harvest-tracks-frontline-agriculture-patterns-with-planets-satellite-data/

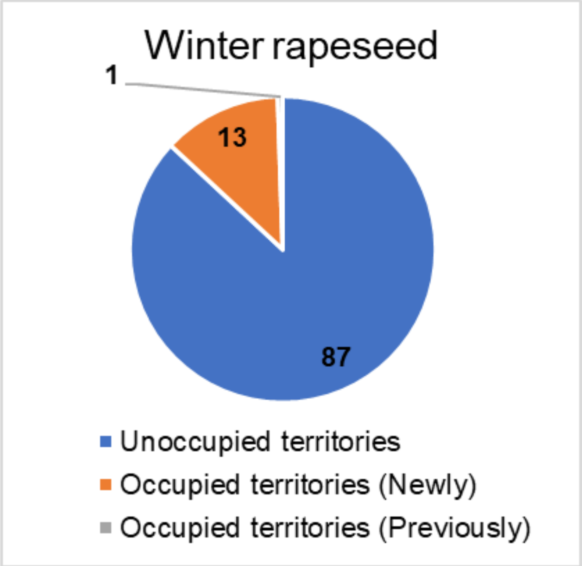


2022 crop map at 3 meter resolution produced by NASA Harvest showing planting progress across Ukraine. (Data provided by: Planet Labs PBC, Institute for the Study of War, NASA)

Harvest's Rapid Assessment Team based at the University of Maryland and University of Strasburg have delineated and mapped all agriculture fields across the country's 25 oblasts. Their latest findings from August 2022 show that 29% of winter cereals, 21% of summer/spring crops, and 13% of rapeseed are now under Russian occupation. However, across both sides (including the temporarily Russian-occupied territories), most of the winter crops like wheat and rapeseed, which would have been planted in the fall of 2021, have still been harvested. As for the spring planting, which includes commodity crops like corn and sunflower, NASA Harvest's results also found that while there is a higher proportion of unplanted areas in the Russian-occupied regions, planting and harvesting is still occurring on both geographical sides of the conflict. In fact, NASA Harvest is currently estimating a higher production out of the region than other publicly-sourced estimates.





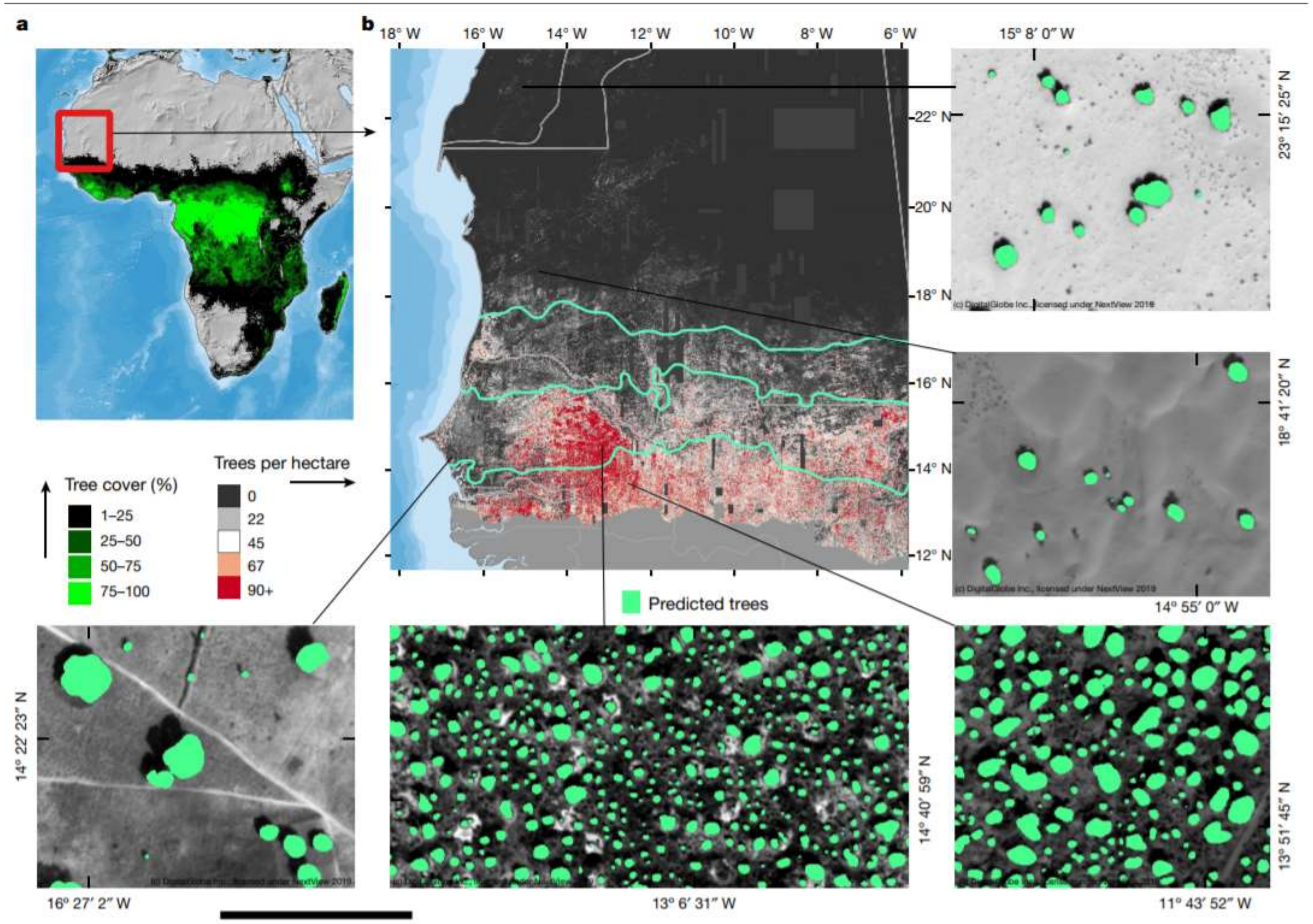


https://www.planet.com/pulse/nasa-harvest-tracks-frontline-agriculture-patterns-with-planets-satellite-data/

Deep learning-based

Counting trees 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

Detecting Artillery and Missile Craters

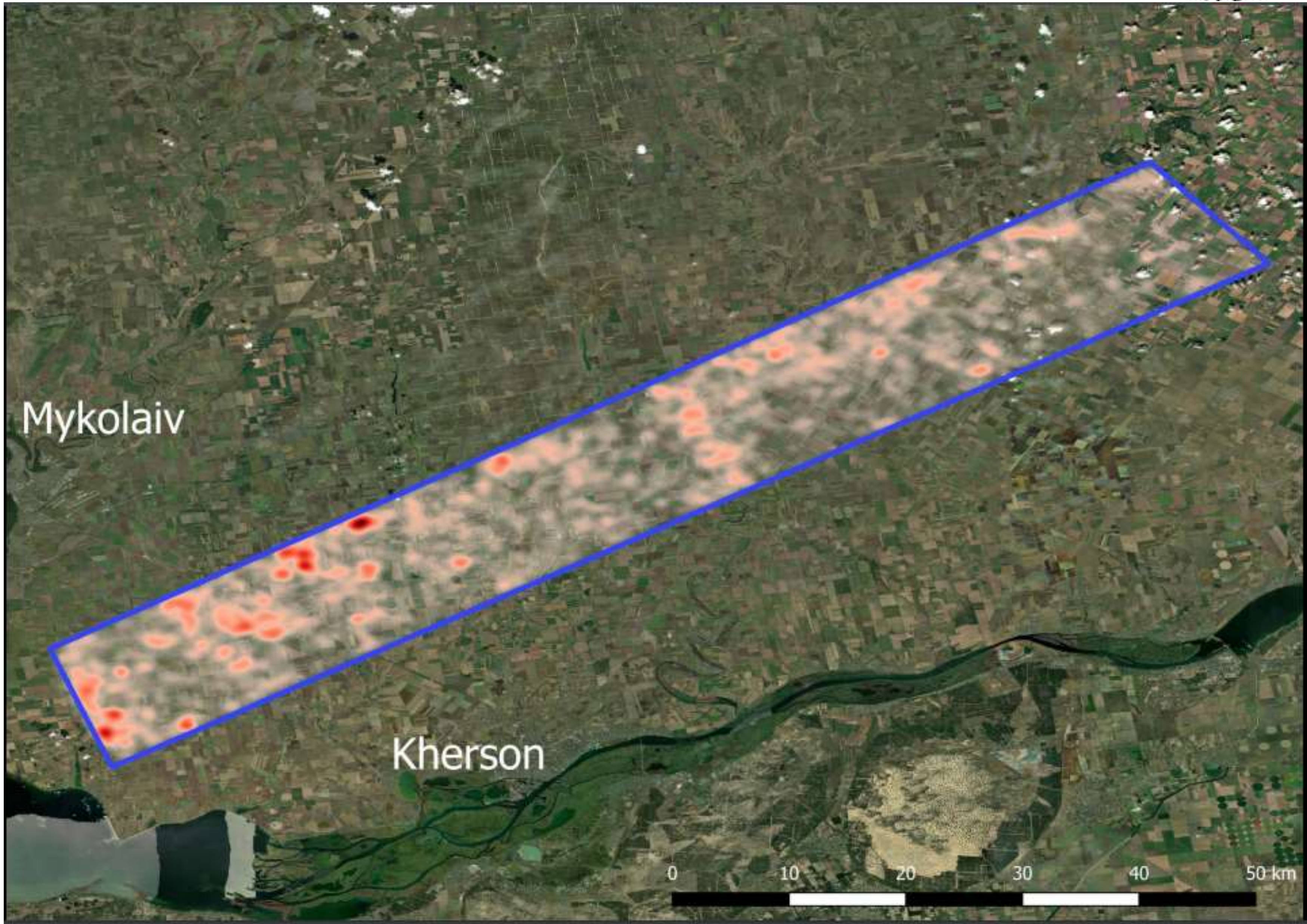
- Detecting of craters from rockets, bombs and Unexploded Ordnance
  - Eastern Ukraine, 2014
- Satellite data
  - WorldView-2 and -3 @0.5 m
- Machine learning
  - **Deep learning** (Unet-style network)
- Performance
  - ~60% (performance depends on crater size)

Source: Google Earth, Maxar Technologies

1: BM-21 rocket artillery system 2: Result of rocket artillery shelling 3: Side by side comparison of manually marked craters and UNet detected craters (blue) 4: A kernel density map showing intensity of artillery and rocket shelling across a landscape

[Duncan, E., et al., in prep]

Detecting Artillery and Missile Craters



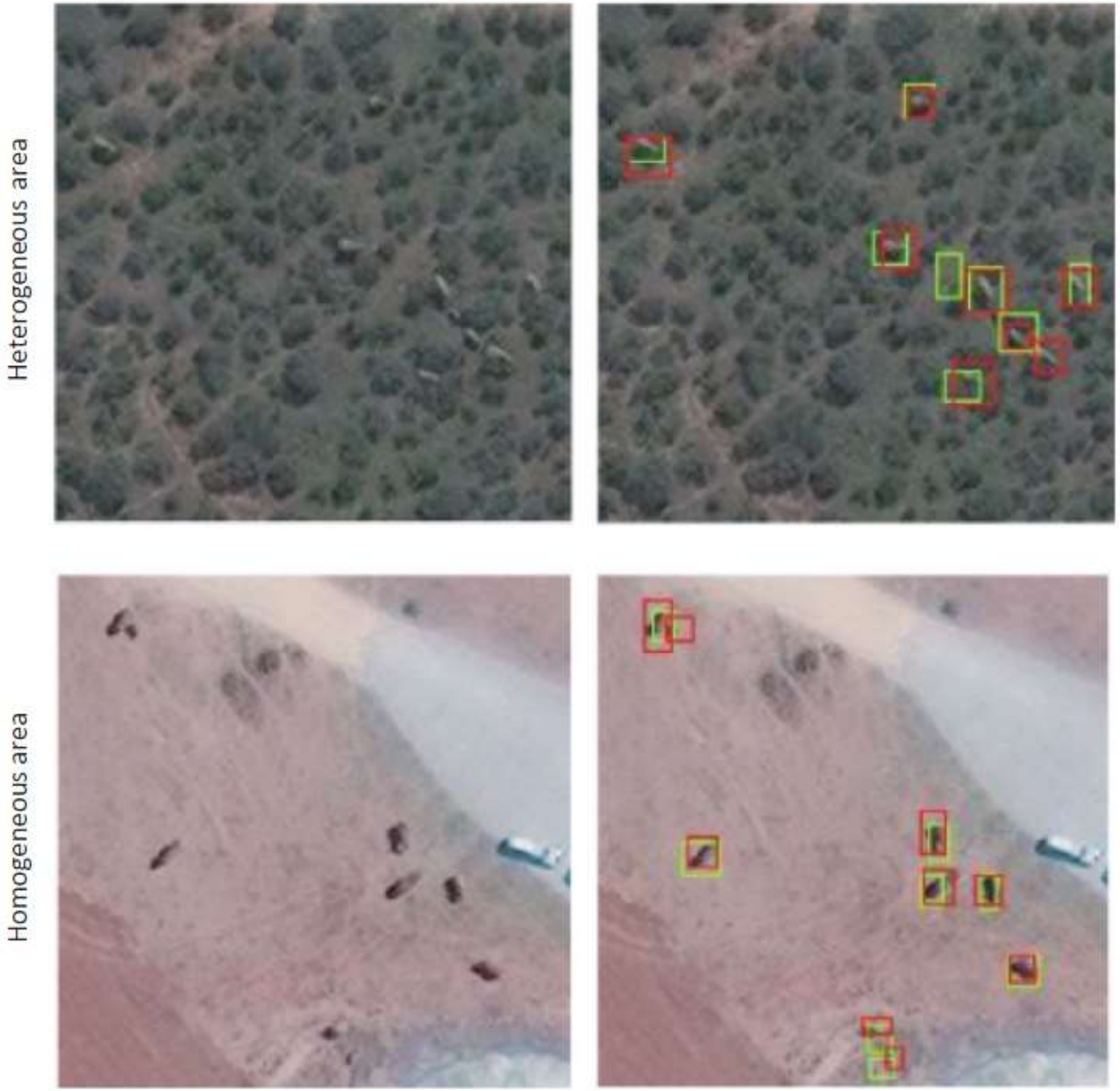
Detecting and counting elephants from satellite imagery

- Detecting and counting **elephants** in the Addo Elephant National Park in South Africa

- Satellite data
  – WorldView-3 and -4 @0.3-0.5 m

- Machine learning
  – **Deep Learning** (convolutional neural networks)

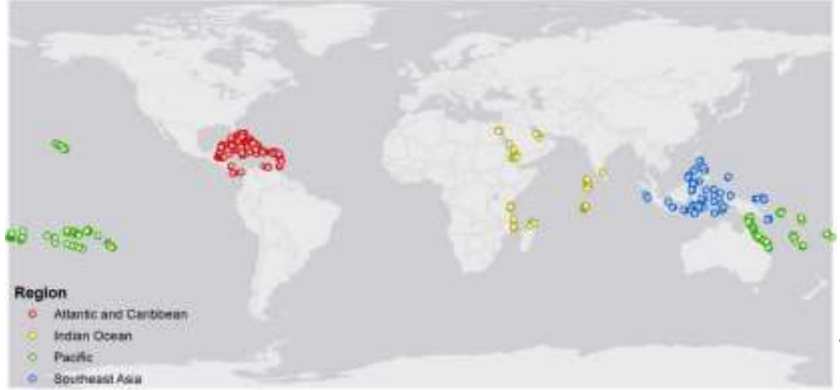
- Performance
  – **~78% accuracy**



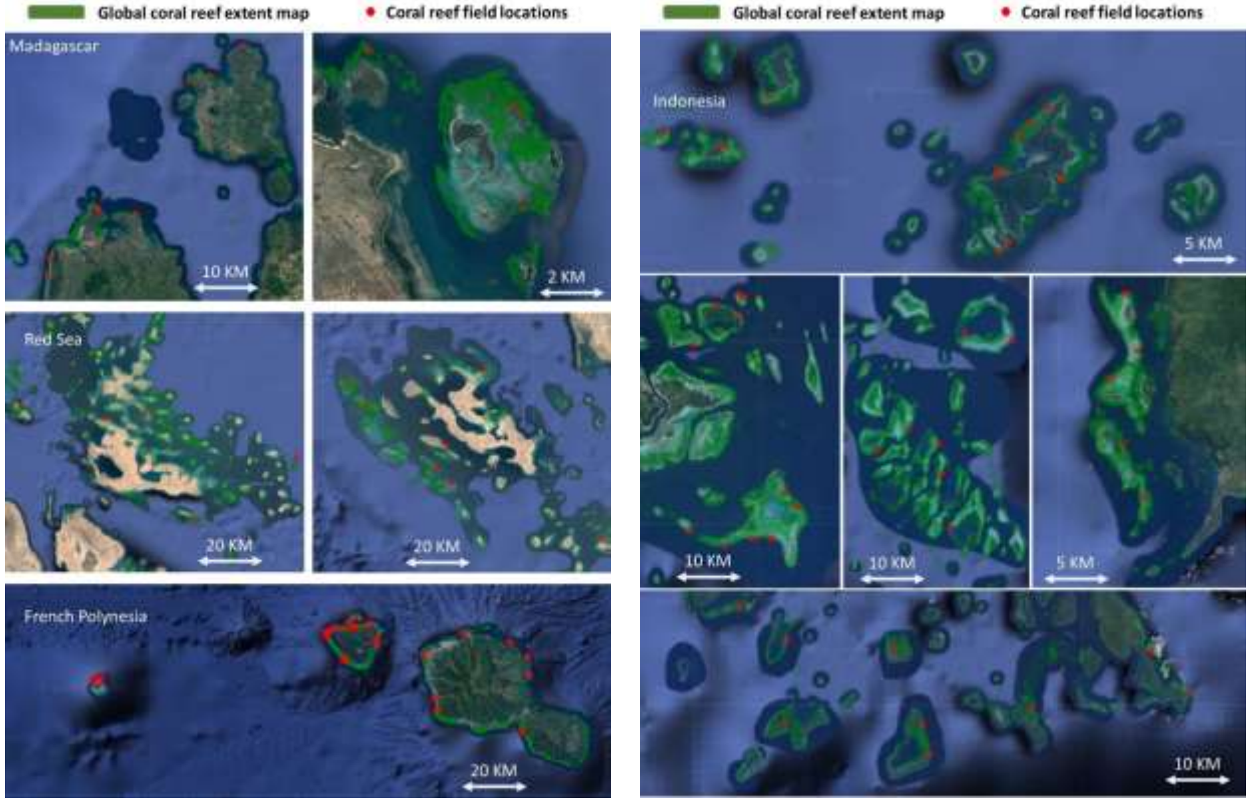
https://doi.org/10.1002/rse2.195

Coral reef mapping

- Global **coral reef** probability map
- Satellite data
  - Planet @ 3 m
- Machine learning
  - **Deep Learning** (convolutional neural networks)
- Performance
  - **~88% accuracy**



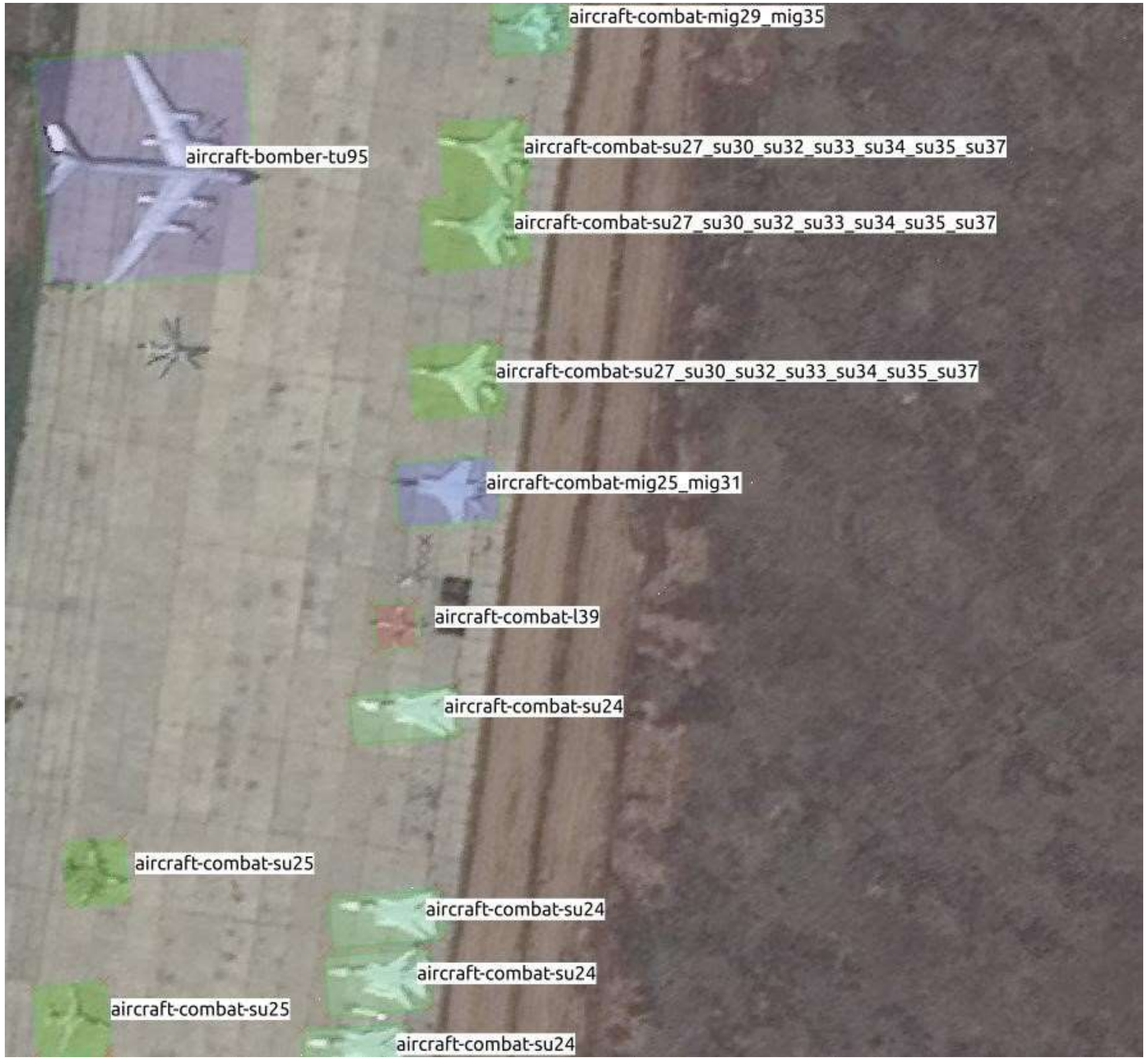
Global coral reef field locations



https://doi.org/10.1007/s00338-020-02005-6

Maxar Secure Watch

- Enabling AI/ML for GEOINT
- Satellite data
  - Very high-resolution WorldView-series



Automatic detection and identification of the aircraft in this Maxar WorldView-2 image collected in July 2019.

https://blog.maxar.com/earth-intelligence/2020/earthcube-leverages-securewatch-to-train-its-ai-models

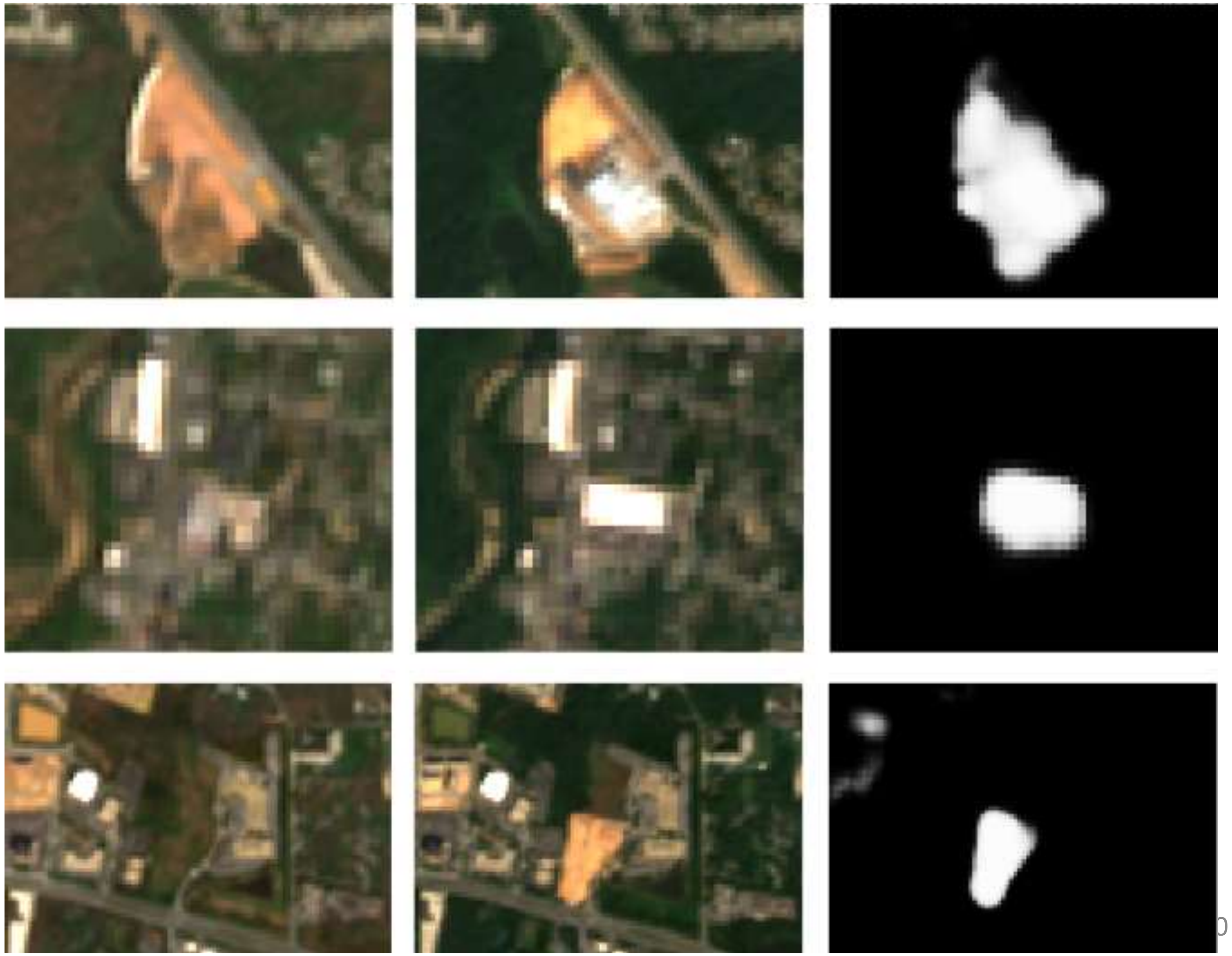
Change detection: construction detection

- 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%

https://doi.org/10.1080/17538947.2022.2094001

Validation on DC area

2018, April | 2019, August | Unet



Commercial

2018/04 2019/08

Detected changes

Residential

2018/04 2019/08

Detected changes

Construction of a new school

2018/04 2019/08

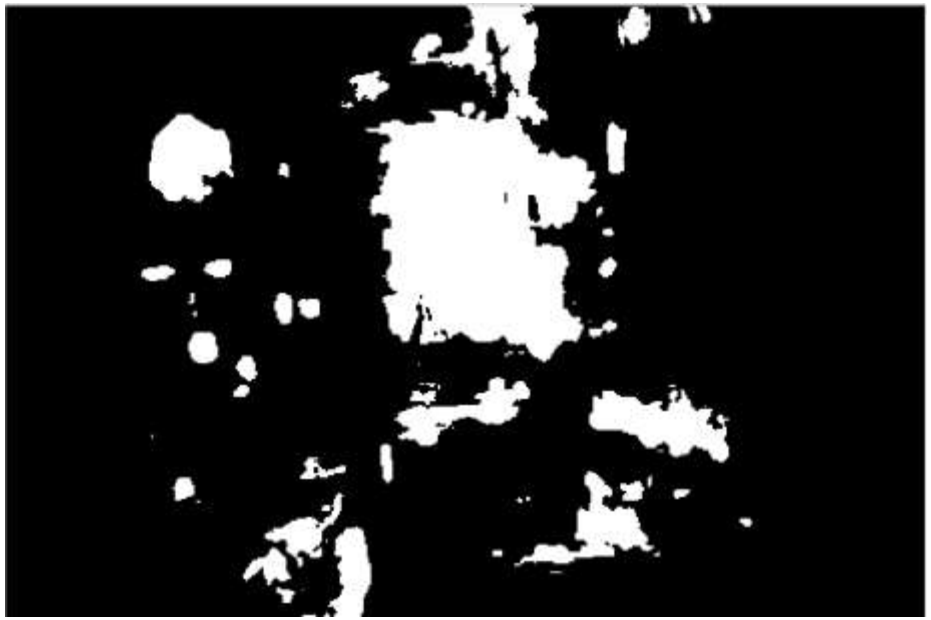
Detected changes

Portables (schools)

2018/04 2019/08 Detected changes

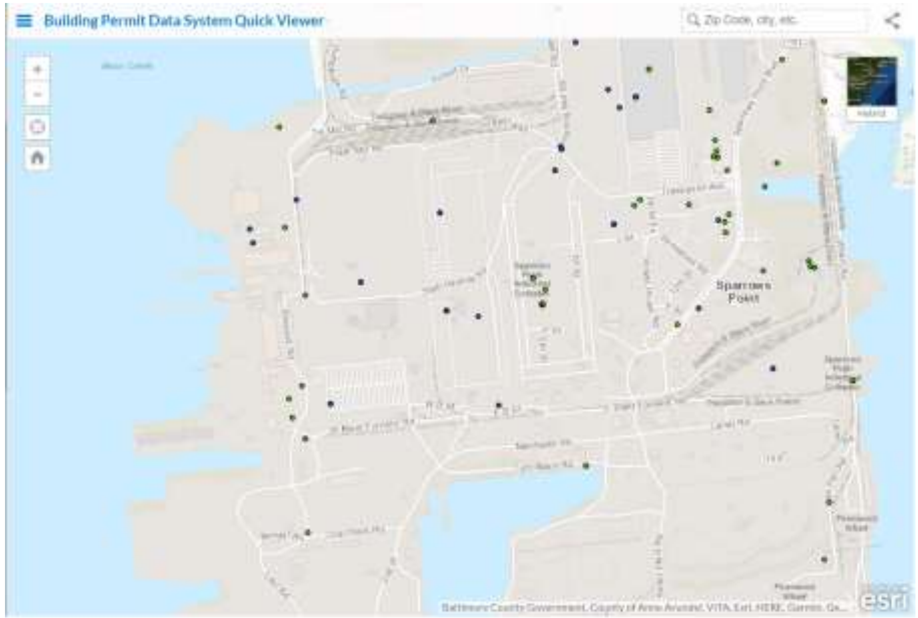
2018

Change detection



2019

Construction permits



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
- **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!**

Further readings

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