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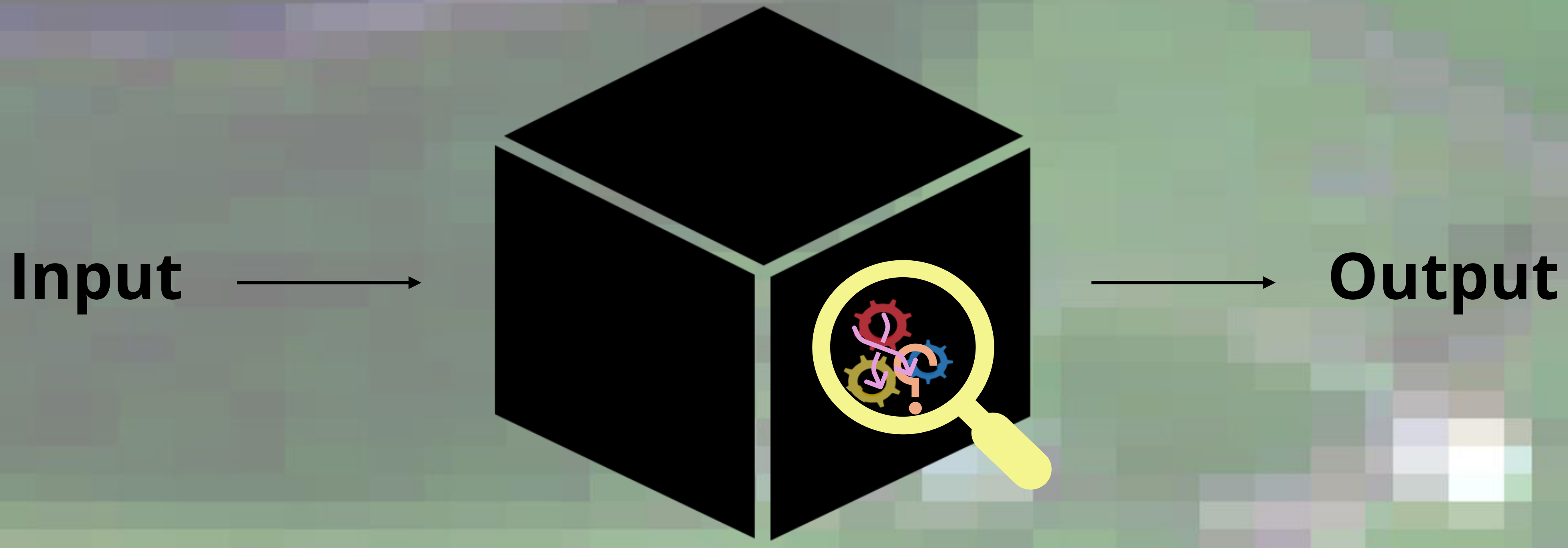


Why ML ≠ EO
From Black-Box to the Accuracy Paradox

Professor Karen Anderson & Brianna Pickstone

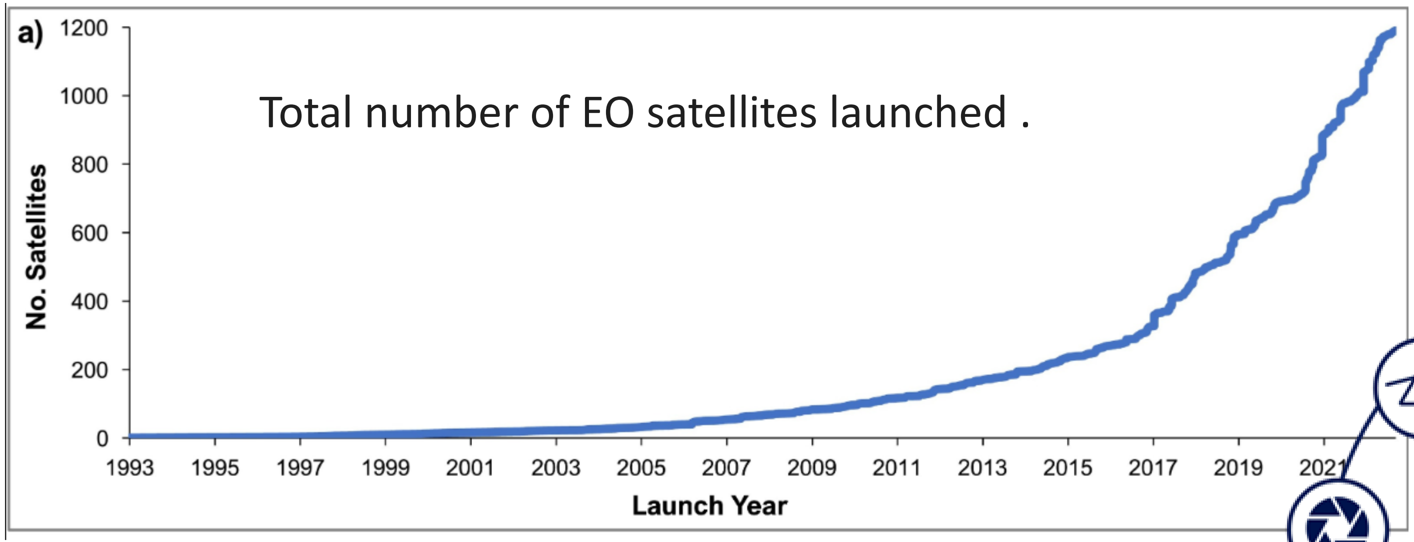
University of Exeter

Al Gore, 1998 – next generation digital Earth

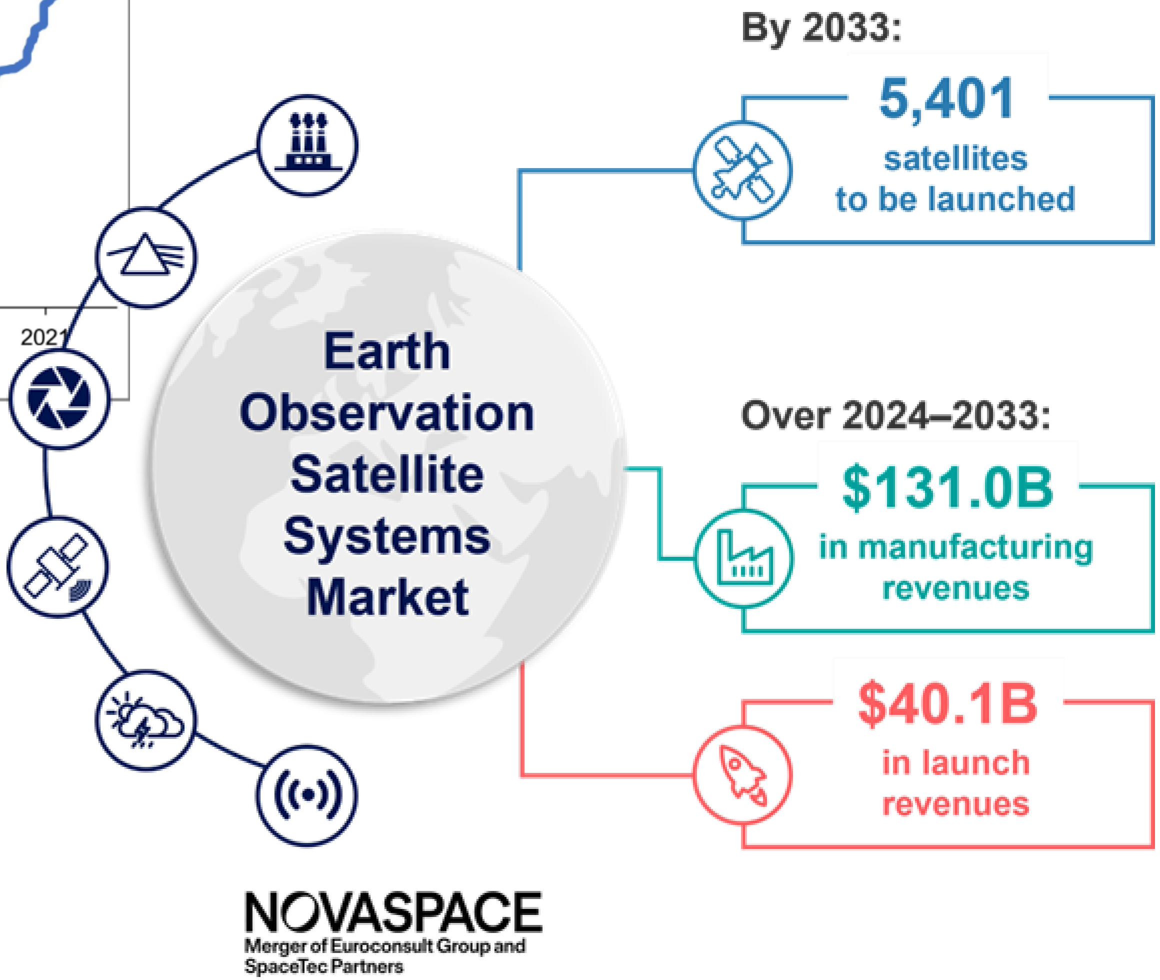
> In spite of the great need for that information, the vast majority of those images have never fired a single neuron in a single human brain.

Gore, A. The Digital Earth: Understanding our planet in the 21st century. Aust. Surv. **1999**, 43, 89–91.

Growth in EO data

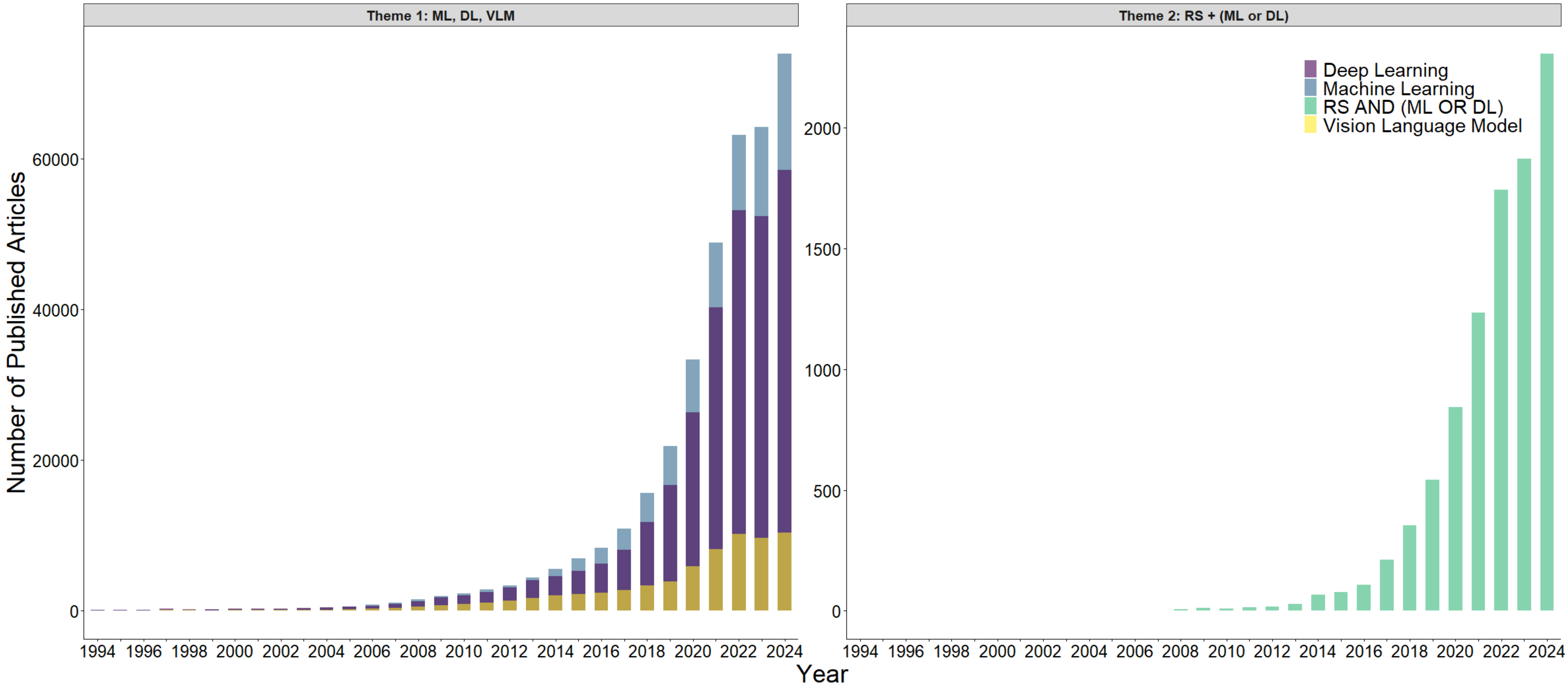


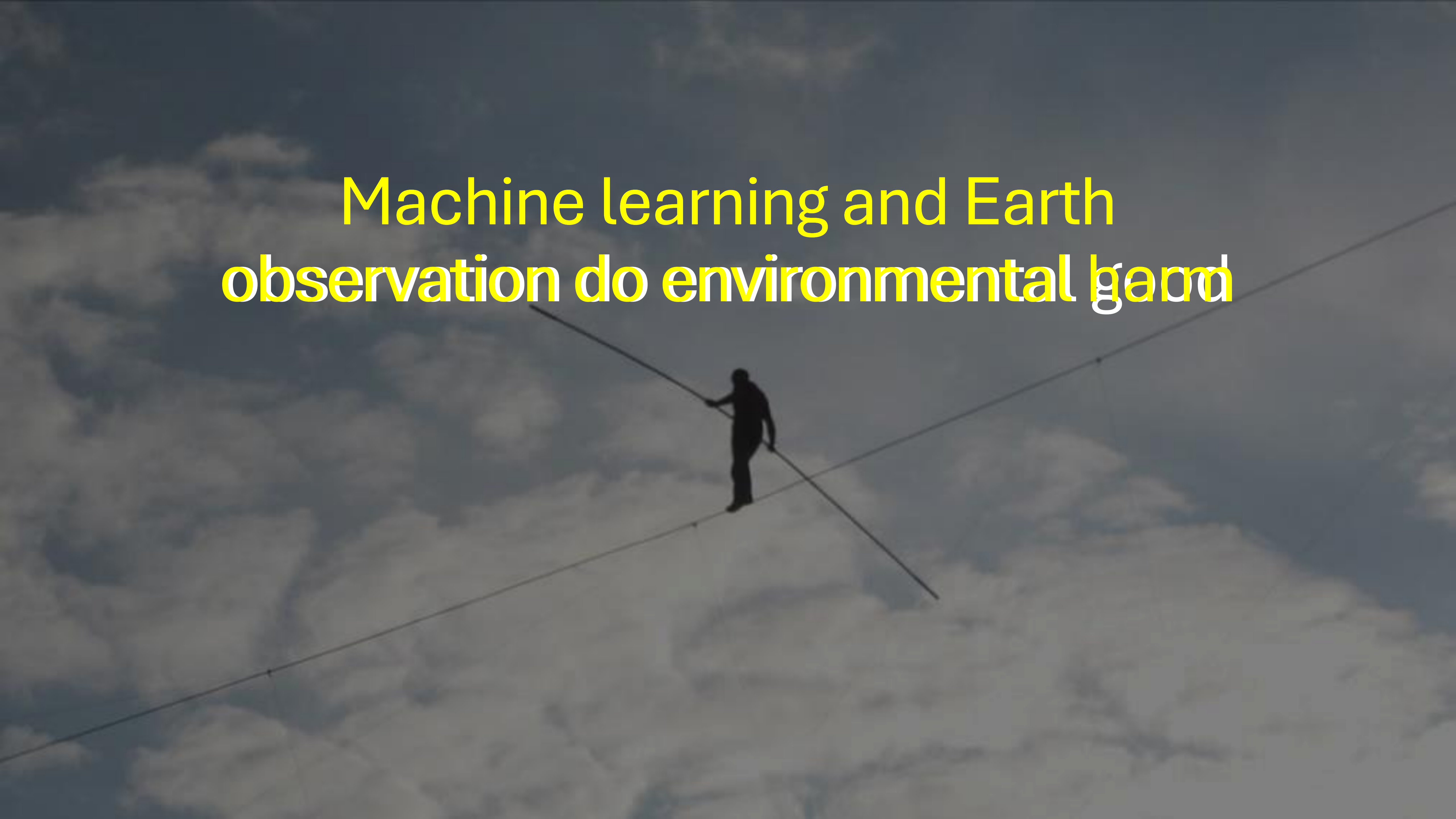
Numbers of EO satellites set to triple by 2033



Wilkinson, R., et al. 2024. Environmental impacts of earth observation data in the constellation and cloud computing era. *Science of The Total Environment*, *909*, p.168584.

The current age: rapid growth in ML + DL




Machine learning and Earth
observation do environmental harm
good

Haraway's (1985) cyborg manifesto

Late twentieth-century machines have made thoroughly ambiguous the difference between natural and artificial, mind and body, self-developing and externally designed, and many other distinctions that used to apply to organisms and machines.

Our machines are disturbingly lively, and we ourselves frighteningly inert.

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Haraway's 'god trick'

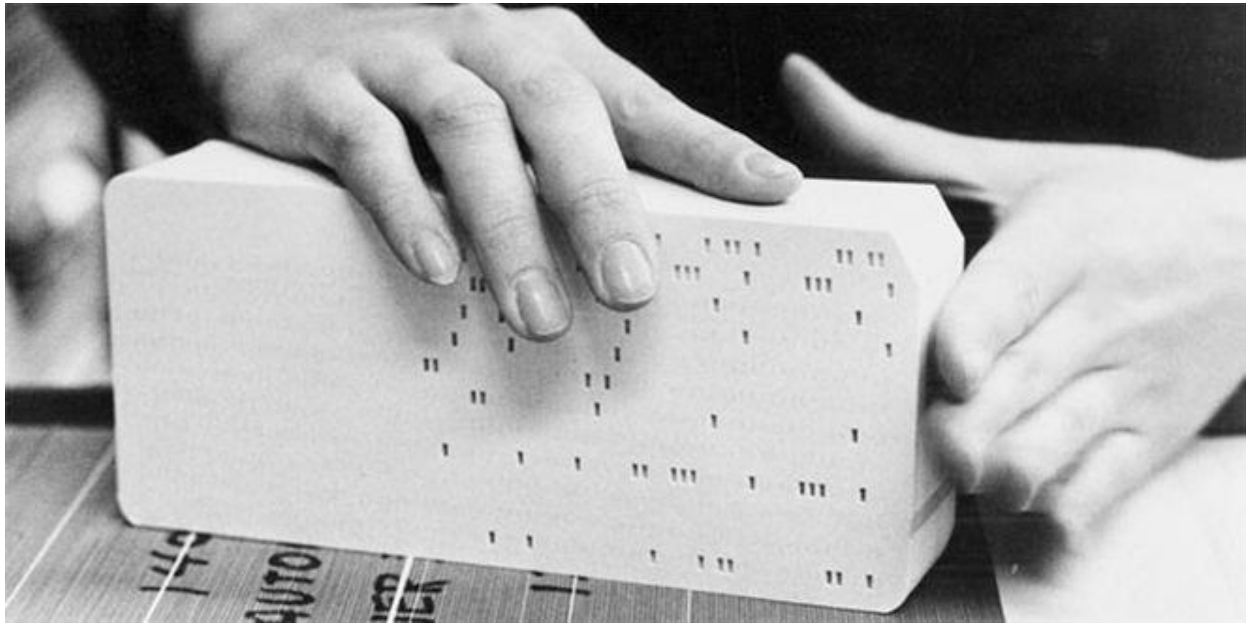
Vision in this technological feast becomes **unregulated gluttony**

This makes '**techno-monsters**'

The eye of an ordinary primate is endlessly enhanced by satellite surveillance systems

Haraway, D., 2013. Situated knowledges: The science question in feminism and the privilege of partial perspective 1. In *Women, science, and technology* (pp. 455-472). Routledge.

Early days of remote sensing were data- and computation-poor



Led to many fundamental questions about data quality, utility and efficiency.

Finer resolution data ≠ better information?

REMOTE SENSING OF ENVIRONMENT 21:311–332 (1987)

The Factor of Scale in Remote Sensing

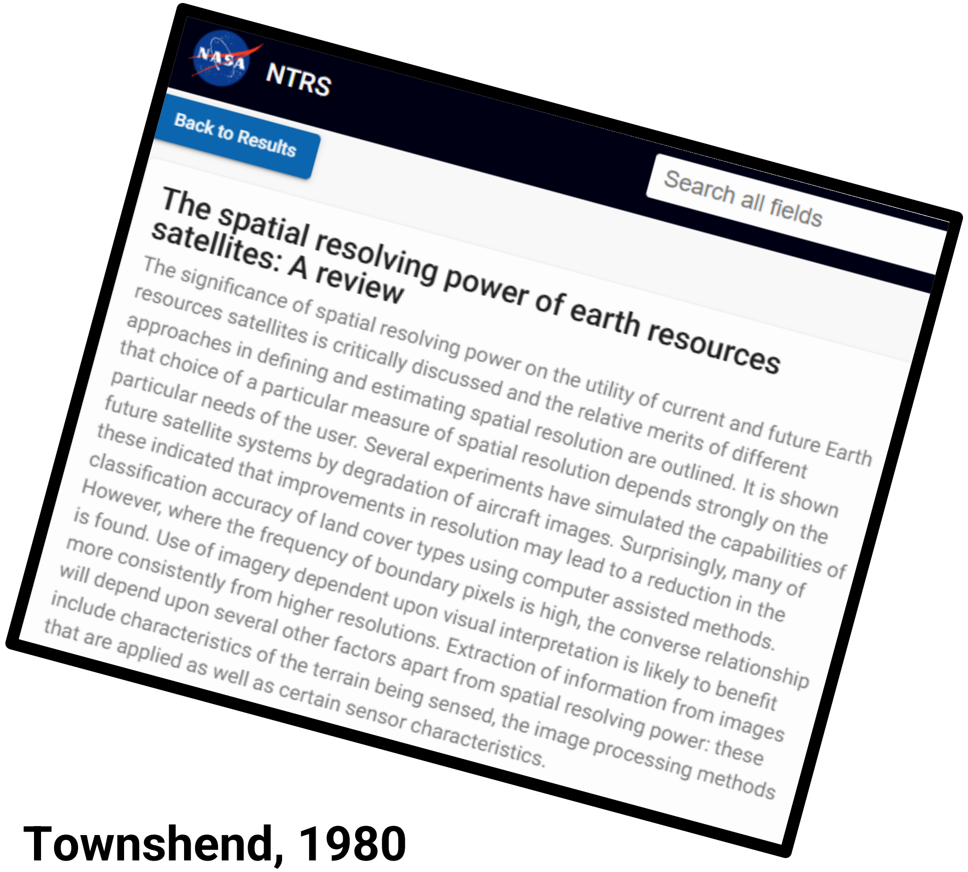
CURTIS E. WOODCOCK
Department of Geography and Center for Remote Sensing, Boston University, Boston, Massachusetts 02215

ALAN H. STRAHLER
Department of Geology and Geography, Hunter College, City University of New York, New York, New York 10021

Thanks to such second- and third-generation sensor systems as Thematic Mapper, SPOT, and AVHRR, a user of digital satellite imagery for remote sensing of the earth's surface now has a choice of image scales ranging from 10 m to 1 km. The choice of an appropriate scale, or spatial resolution, for a particular application depends on several factors. These include the information desired about the ground scene, the analysis methods to be used to extract the information, and the spatial structure of the scene itself. A graph showing how the local variance of a digital image for a scene changes as the resolution-cell size changes can help in selecting an appropriate image scale. Such graphs are obtained by imaging the scene at fine resolution and then collapsing the image to successively coarser resolutions while calculating a measure of local variance. The local variance/resolution graphs for the forested, agricultural, and urban/suburban environments examined in this paper reveal the spatial structure of each type of scene, which is a function of the sizes and spatial relationships of the objects the scene contains. At the spatial resolutions of SPOT and Thematic Mapper imagery, local image variance is relatively high for forested and urban/suburban environments, suggesting that information-extracting techniques utilizing texture, context, and mixture modeling are appropriate for these sensor systems. In agricultural environments, local variance is low, and the more traditional classifiers are appropriate.

Woodcock and Strahler, 1987

"the factor of scale plays an increasingly important role in the planning of remote sensing investigations"


NTRS

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The spatial resolving power of earth resources satellites: A review

The significance of spatial resolving power on the utility of current and future Earth resources satellites is critically discussed and the relative merits of different approaches in defining and estimating spatial resolution are outlined. It is shown that choice of a particular measure of spatial resolution depends strongly on the particular needs of the user. Several experiments have simulated the capabilities of future satellite systems by degradation of aircraft images. Surprisingly, many of these indicated that improvements in resolution may lead to a reduction in the classification accuracy of land cover types using computer assisted methods. However, where the frequency of boundary pixels is high, the converse relationship is found. Use of imagery dependent upon visual interpretation is likely to benefit more consistently from higher resolutions. Extraction of information from images will depend upon several other factors apart from spatial resolving power: these include characteristics of the terrain being sensed, the image processing methods that are applied as well as certain sensor characteristics.

Townshend, 1980

"improvements in resolution may sometimes lead to a reduction in the classification accuracy of land cover types using computer assisted methods."

The crises

We are amidst an age of rapid change where big data might hold some of the answers. But the question is how to get the answers.

The New York Times

Doomsday Clock Moves One Second Closer to Catastrophe

The Bulletin of the Atomic Scientists shifted the hands of the symbolic clock to 89 seconds to midnight, citing the threat of climate change, nuclear war and the misuse of artificial intelligence.

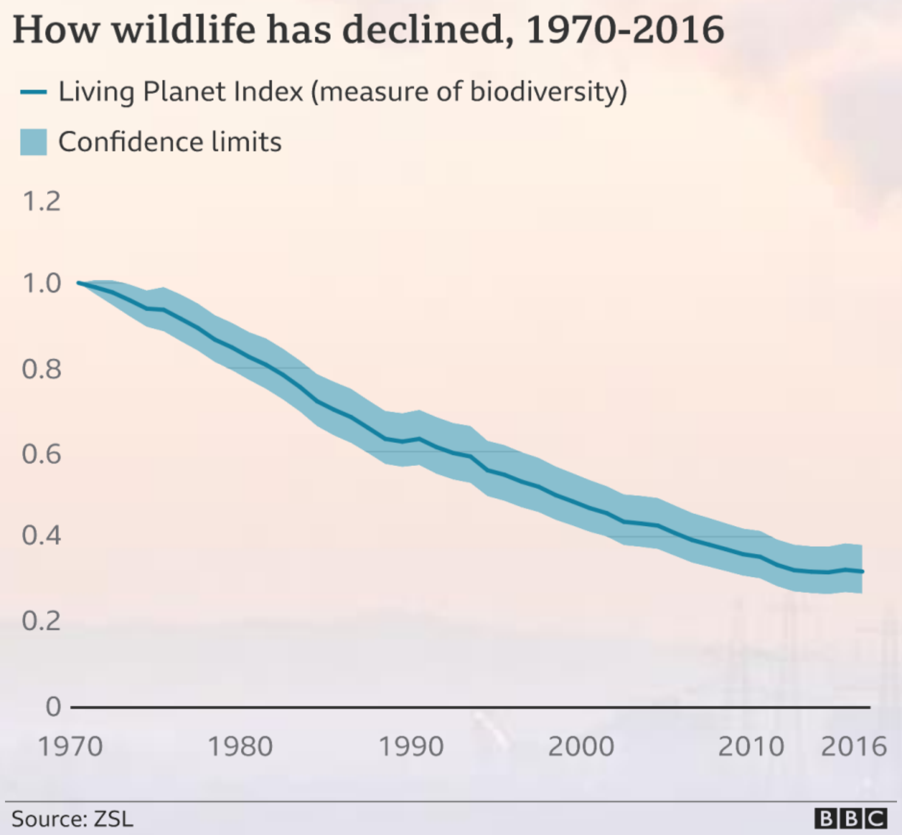
Listen to this article · 5:07 min Learn more

Share full article

Juan Manuel Santos, left, the former president of Colombia, and Robert Socolow, a professor emeritus in the Department of Mechanical and Aerospace Engineering at Princeton University, revealed the location of the minute hand on the Doomsday Clock at a news conference in Washington on Tuesday. Kevin Lamarque/Reuters

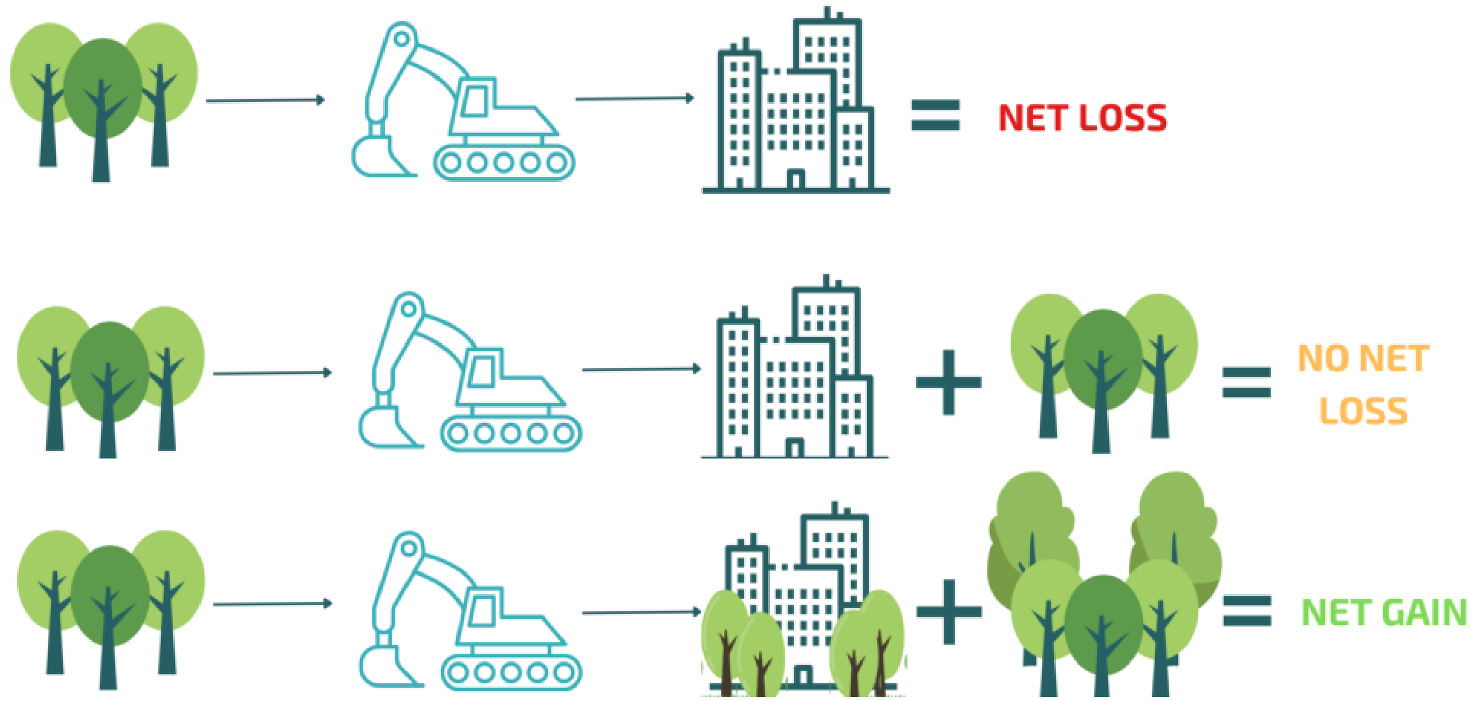
Biodiversity crisis

UK is one of the most nature-depleted countries in the world



source: State of Nature Report - ZSL (2023)

Bri’s project: Biodiversity Net Gain



Biodiversity Net Gain (BNG)

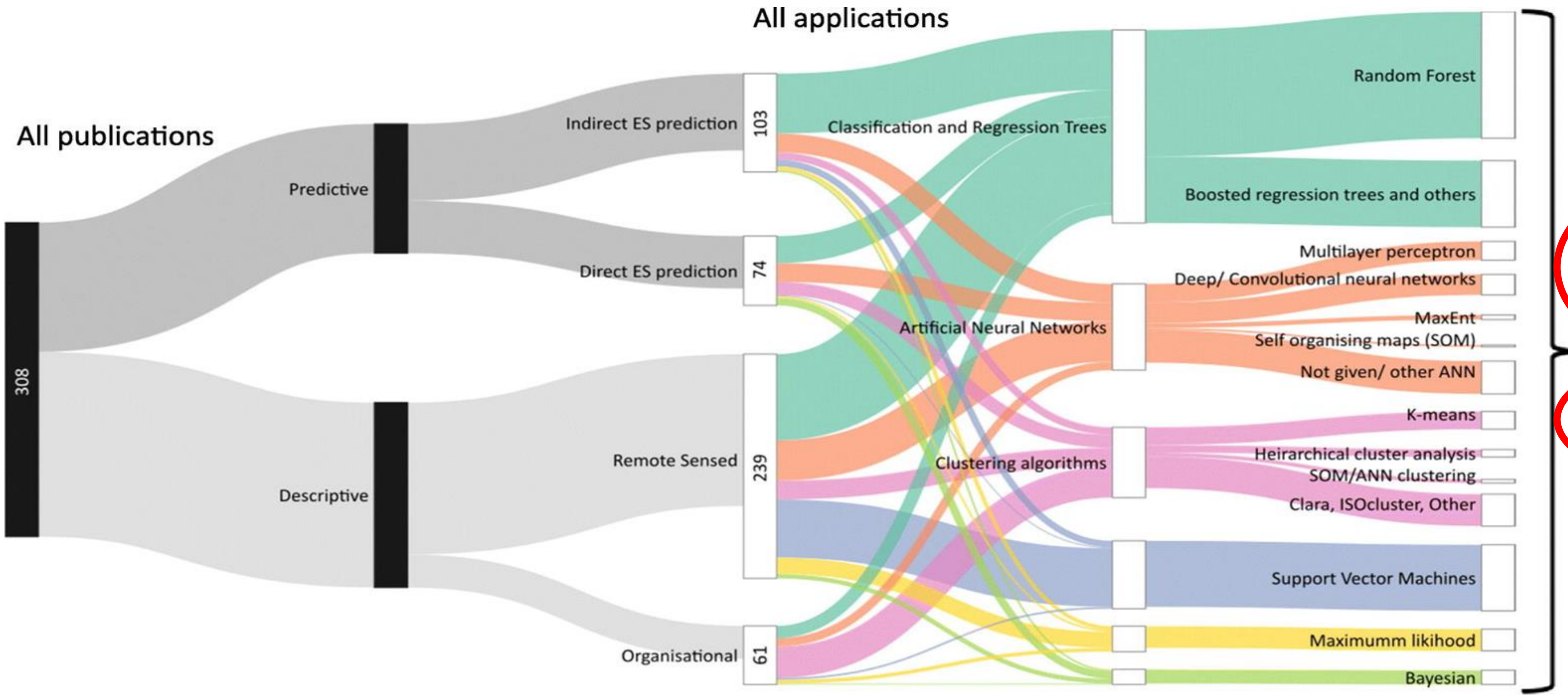
source: MGISS (2024)

MANDATORY IN ENGLAND – FEBRUARY 2024

SUSTAINABILITY-FOCUSED DEVELOPMENT

NET GAIN OF 10%

Unregulated gluttony? A techno-monster?



67% do not report any hyperparameter tuning

59 % do not report testing the generalisability of the model

43 % fail to report any model settings

28 % do not show software used

1138 medium number of data points

Overview of 308 publications within ecosystem services and how machine learning was used and reported. This overview demonstrates that many ecosystem service (ES) studies lack rigour in how ML is used

Scowen, M., Athanasiadis, I.N., Bullock, J.M., Eigenbrod, F. and Willcock, S., 2021. *Science of the Total Environment*, *799*, p.149263.

A landscape of gaps: inconsistent reporting across BNG tools

"Our scientific programme makes it much, much more accurate"

"AI Technology"

"Configurable quality checks ensuring data accuracy"

"high-res RS imagery and other data sources"

- ~13 companies offering some solution for BNG

We are cyborgs (hybrid machines and biological organisms)

Wilkinson, R., et al. 2024. Environmental impacts of earth observation data in the constellation and cloud computing era. *Science of The Total Environment*, *909*, p.168584.

Anderson, K., et al. 2024. The dark side of Earth observation. *Nature Sustainability*, *7*(3), pp.224-227.

The trick of the pixel part 1

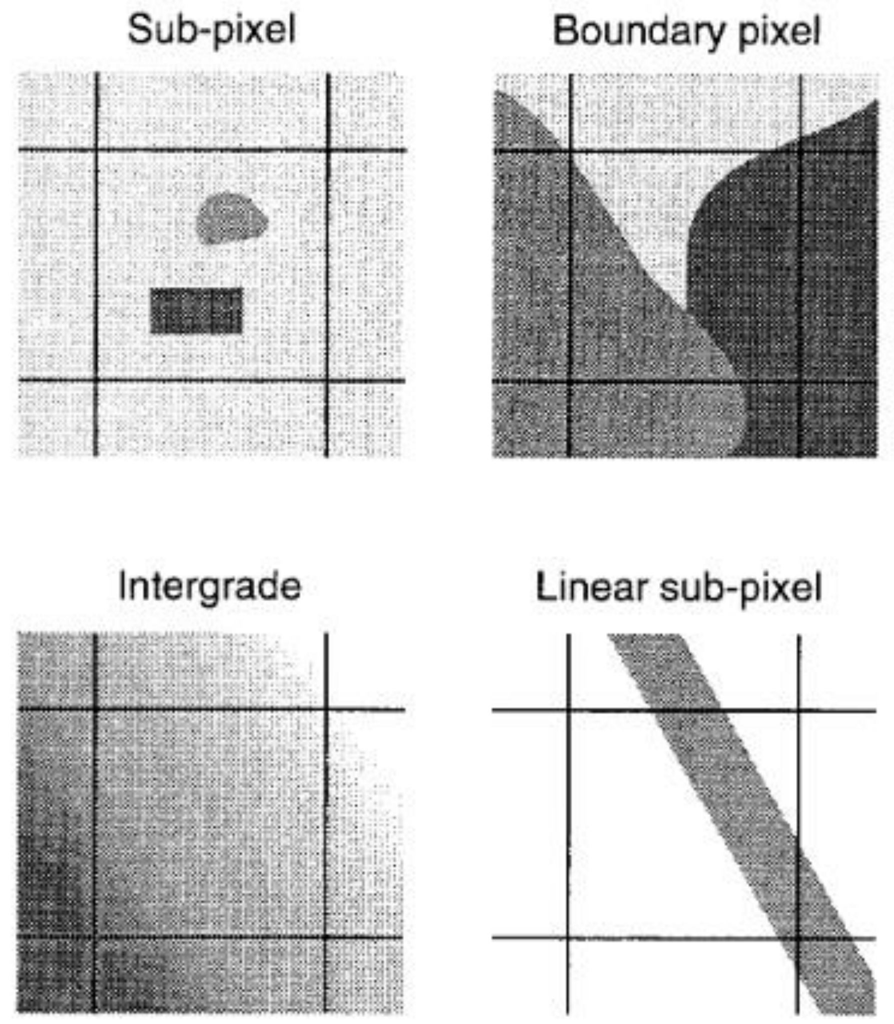


Figure 3. Four causes of mixed pixels.

Peter Fisher, 1997

It is my contention that the pixel, the elementary unit of analysis in remote sensing is a delusion which may become a snare for the unwary given the way in which it is treated in most modern software.

Fisher, P., 1997. The pixel: a snare and a delusion. *International Journal of remote sensing*, *18*(3), pp.679-685.

The trick of the pixel part 2 – point spread function (PSF)

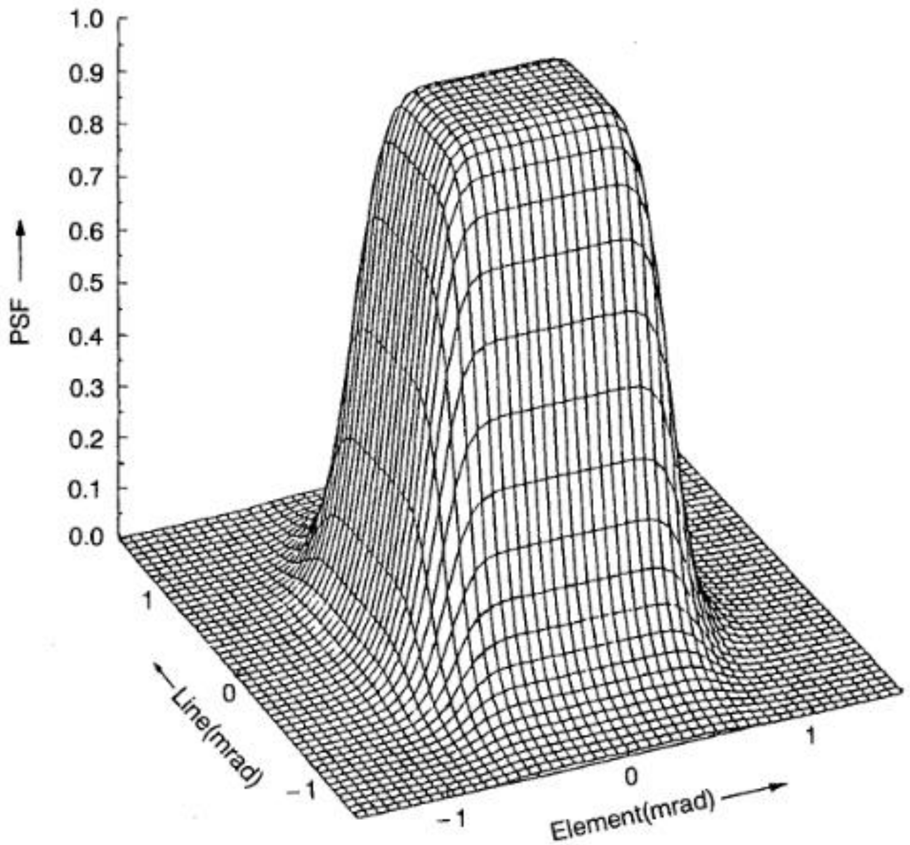
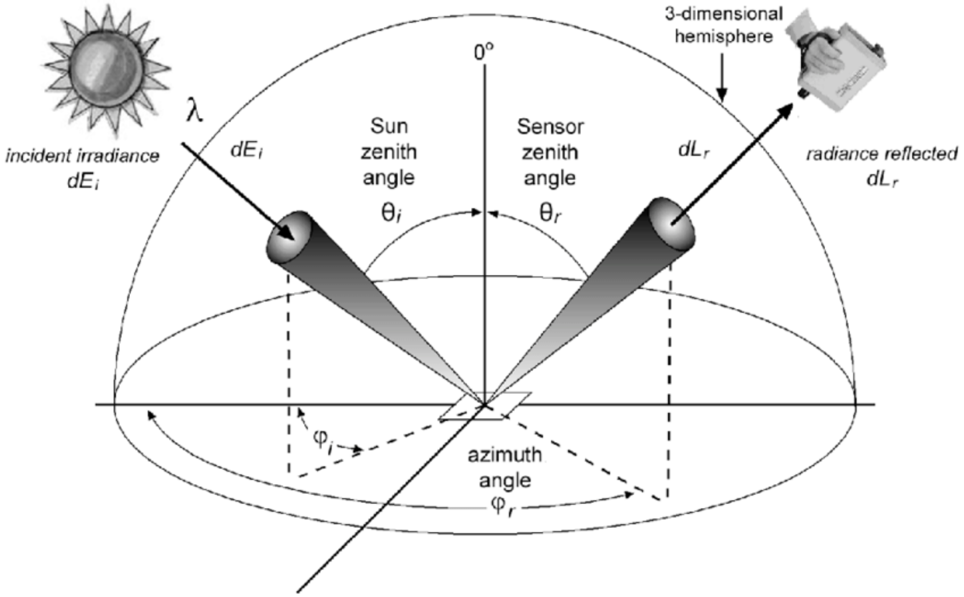


Figure 6. Sketch of point spread function for the AVHRR (Mannstein and Gesell 1991).

Cracknell, A.P., 1998. Review article Synergy in remote sensing-what's in a pixel?. *International Journal of Remote Sensing*, *19*(11), pp.2025-2047.

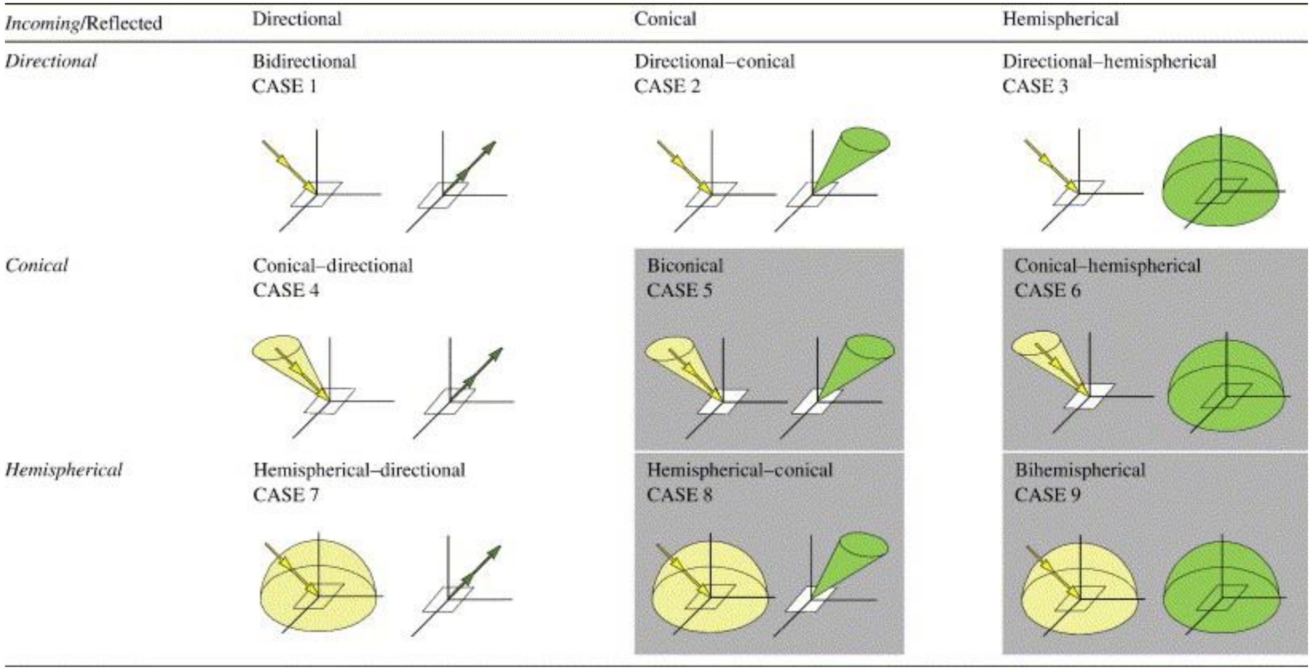
The trick of the light (manifested in pixel signal)

The same surface measured/illuminated from different angles will exhibit different apparent reflectance properties



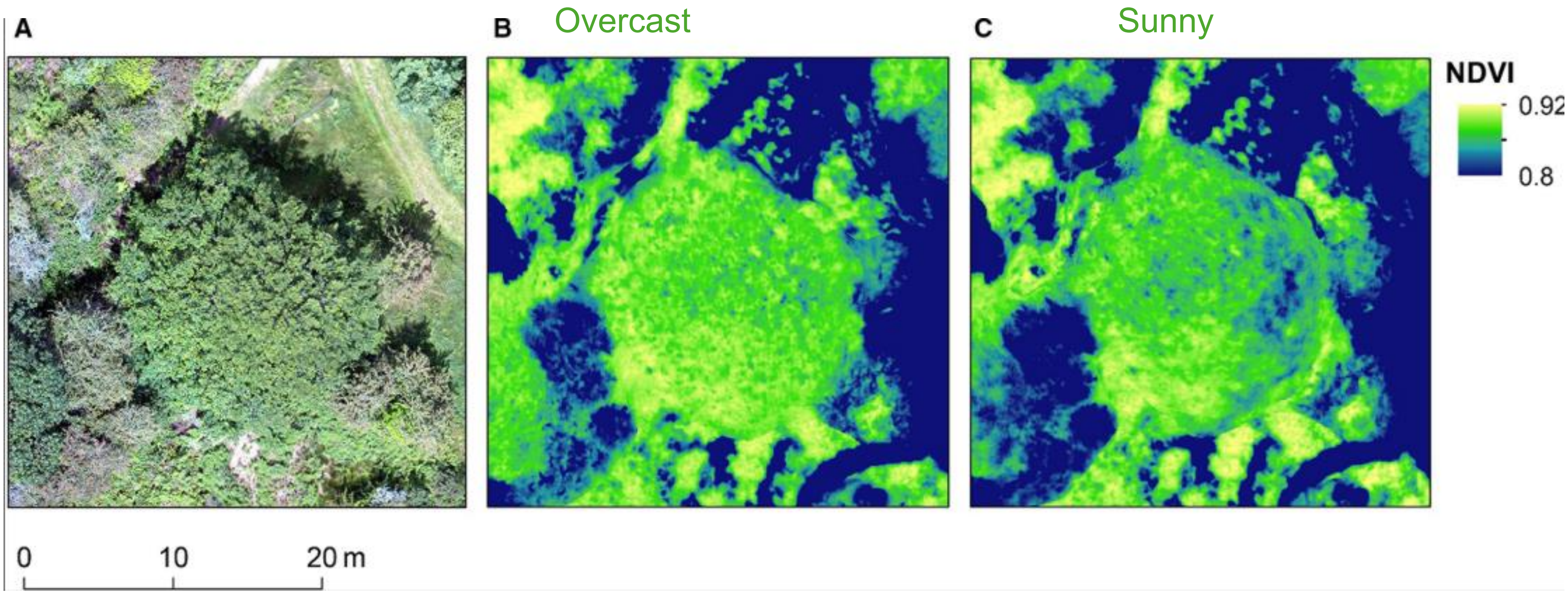
F.E. Nicodemus, *et al.* (1977) Geometrical considerations and nomenclature for reflectance, National Bureau of Standards, US Department of Commerce, Washington, DC

There are many different ways of measuring reflected light, each delivering different answers about 'reflectance'.



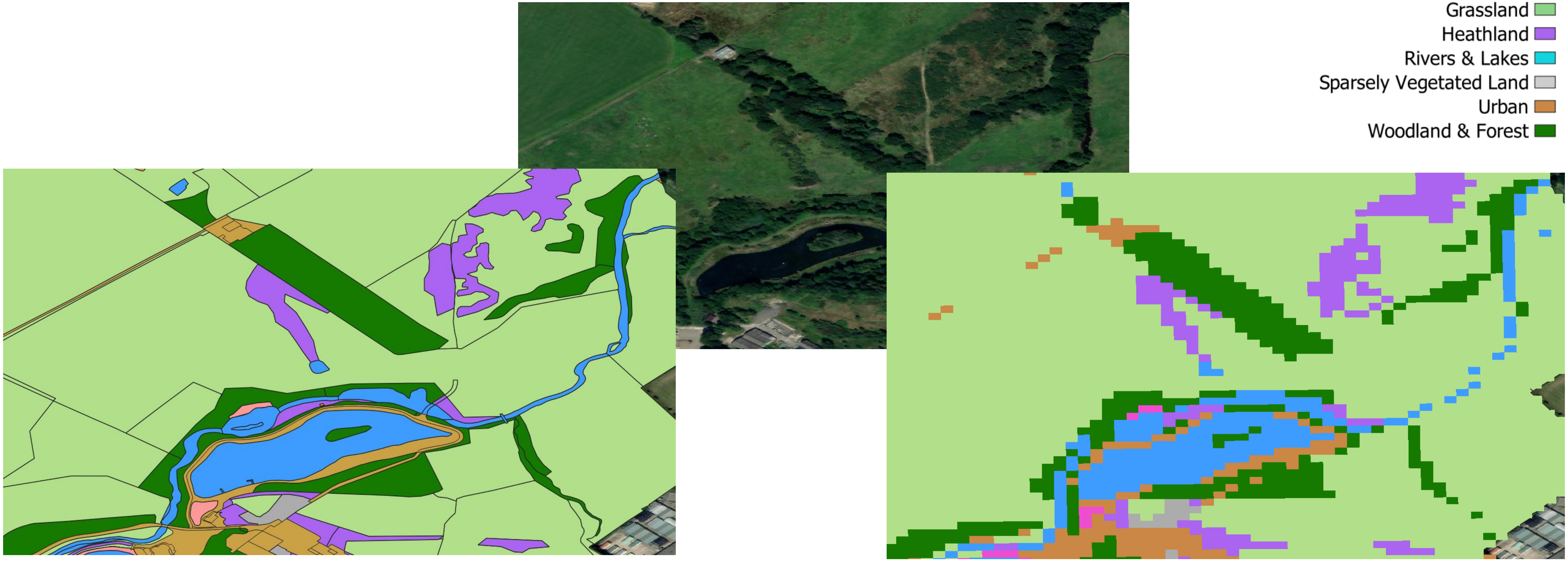
Schaepman-Strub, G., Schaepman, M.E., Painter, T.H., Dangel, S. and Martonchik, J.V., 2006. Reflectance quantities in optical remote sensing—Definitions and case studies. *Remote sensing of environment*, *103*(1), pp.27-42.

e.g. a tree crown measured in sunny and overcast conditions showing variations in NDVI

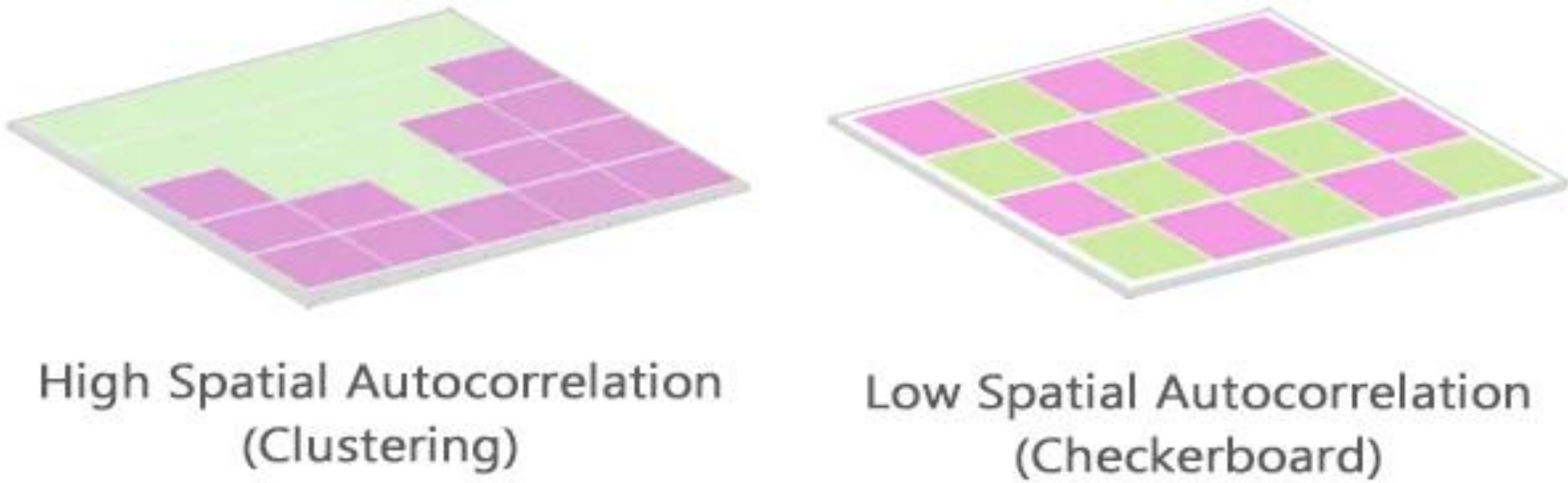


Fawcett, D., Bennie, J. and Anderson, K., 2021. Monitoring spring phenology of individual tree crowns using drone-acquired NDVI data. *Remote Sensing in Ecology and Conservation*, *7*(2), pp.227-244.

The abstraction chain:
Reality → Image →Vector → Raster



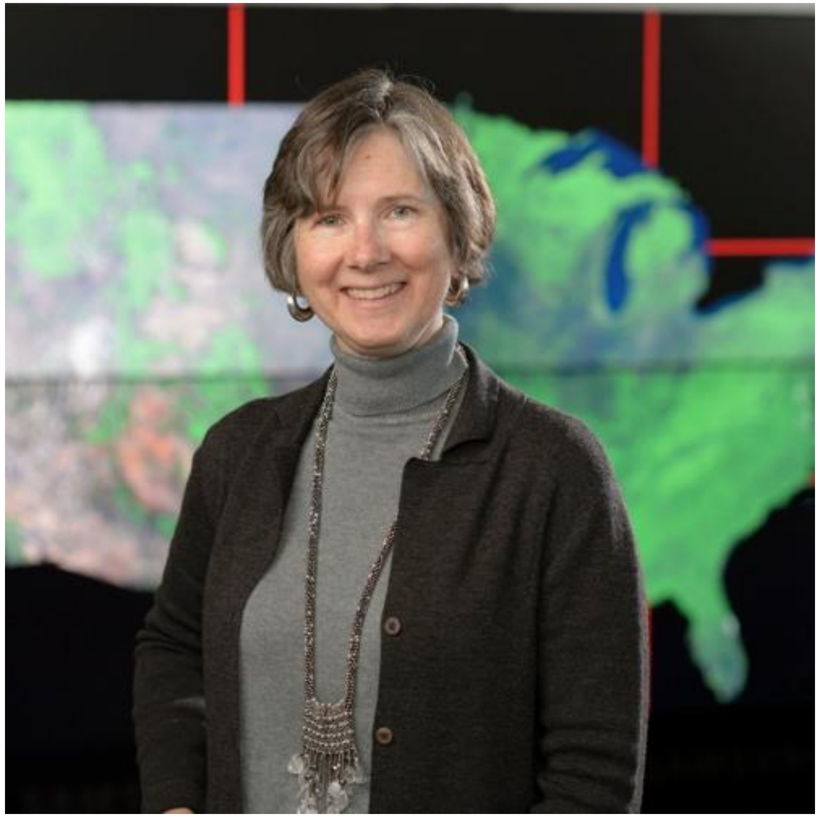
The trick of scale



Which spatial product to choose?

Dungan et al, 2002

When scales of observation or analysis change, that is, when the unit size, shape, spacing or extent are altered, statistical results are expected to change.



Dungan, J.L., et al. 2002. A balanced view of scale in spatial statistical analysis. *Ecography*, *25*(5), pp.626-640.

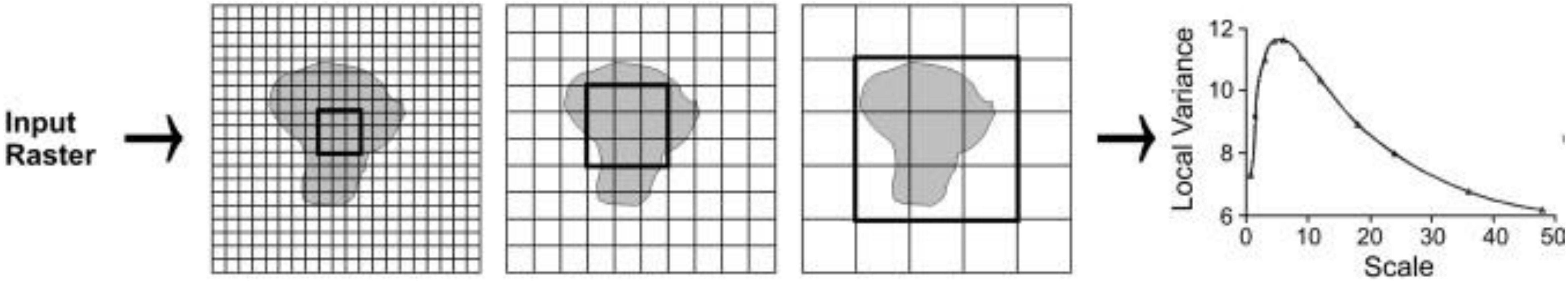
Which spatial product to choose?

Platform/sensor	Spatial Res (m)	Spatial scalar relative to Landsat
Landsat 8	30	1
Sentinel-2	10	9
PlanetScope	5	36
Drone	0.1	90,000

A crucial consideration is then:
What dataset (what spatial / spectral characteristics) to choose, and why?

Sentinel-2
10 m x 10 m

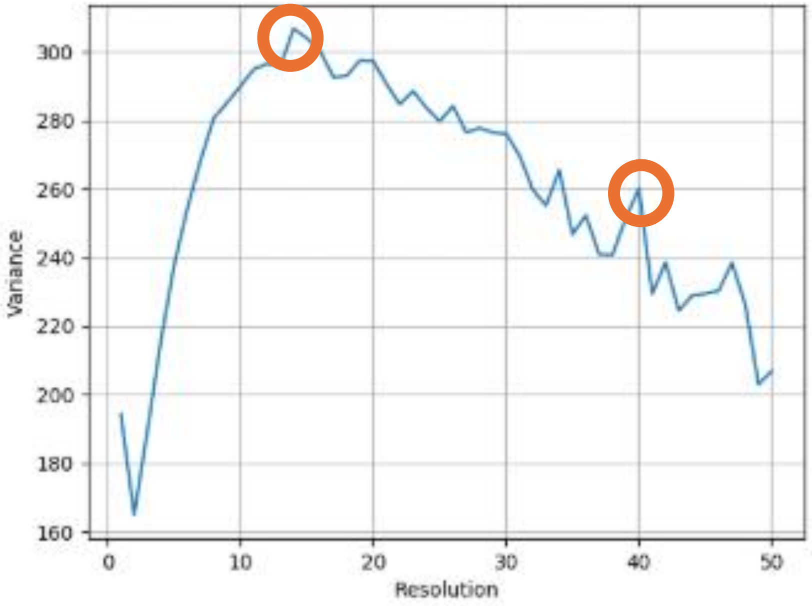
Woodcock and Strahler's local variance method



Peaks in the local variance graph at grains where objects aggregate.
→ Useful for exploring spatial phenomena in the scene
→ Useful for understanding spatial resolution considerations

Woodcock, C.E. and Strahler, A.H., 1987. *Remote sensing of Environment*, *21*(3), pp.311-332.

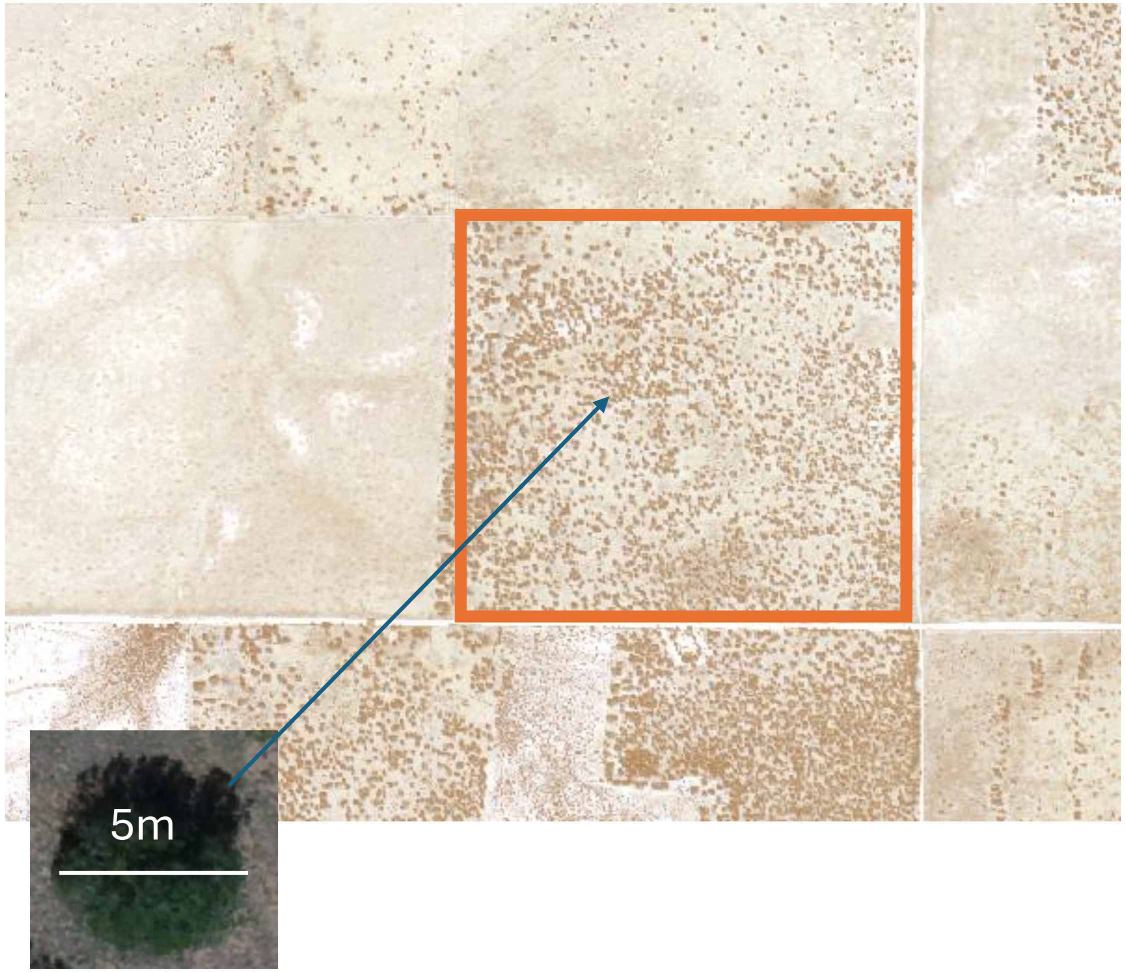
The golf course example



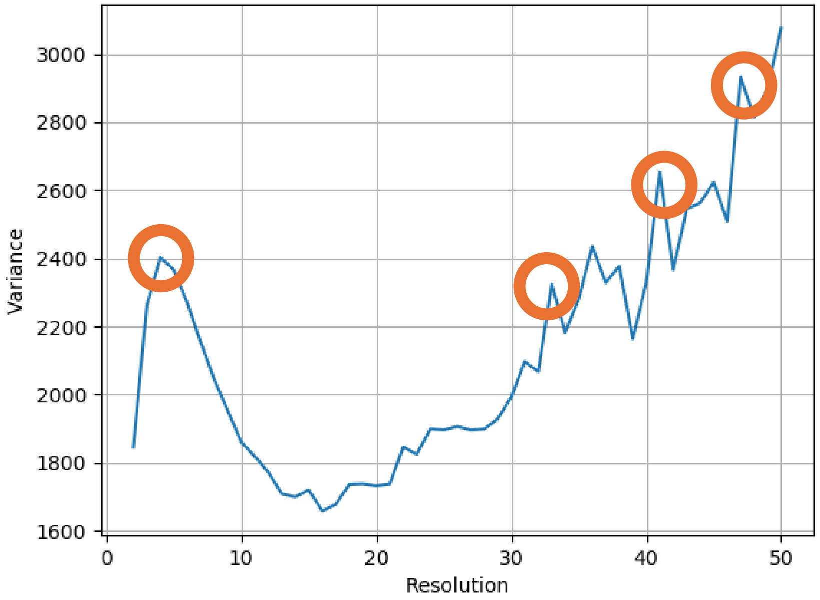
15 m = average distance between fairways

40 m = average width of fairways

A high mountain desert with juniper trees



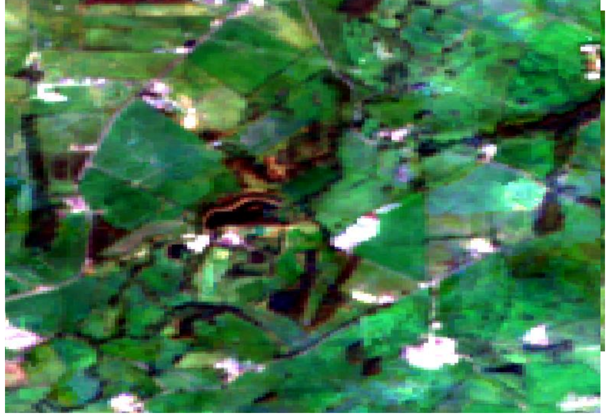
Worldview-2 blue band



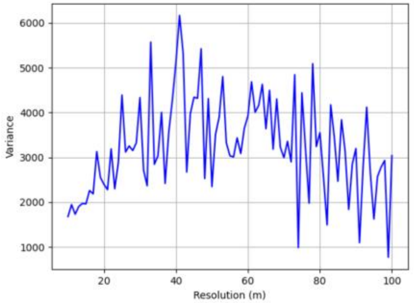
5 m = size of juniper tree crown

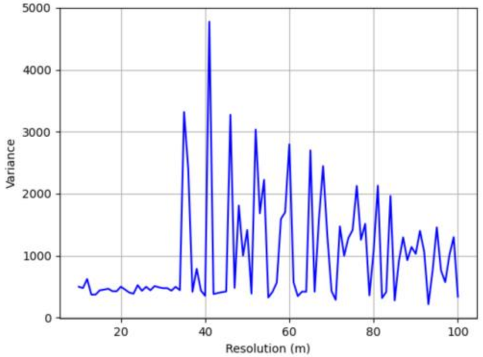
32, 41, 48 m = spacing between trees

LV in UK landscapes

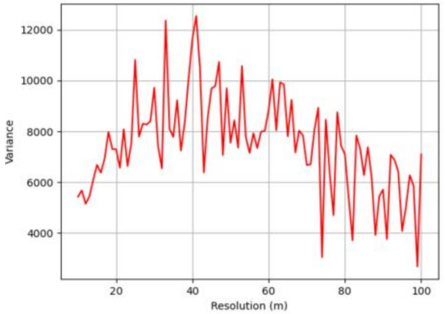


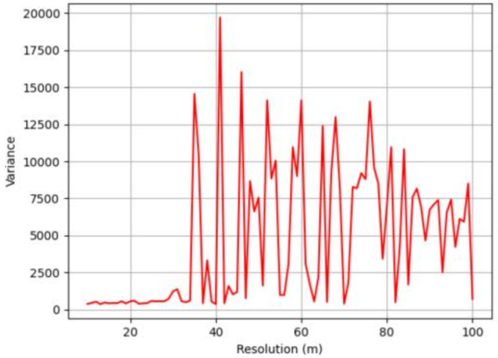
Blue



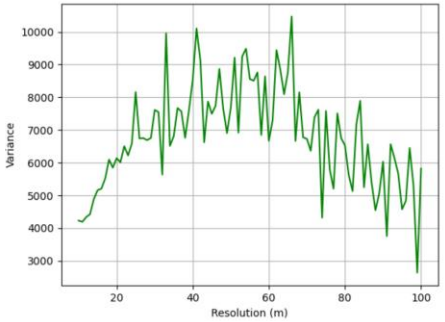


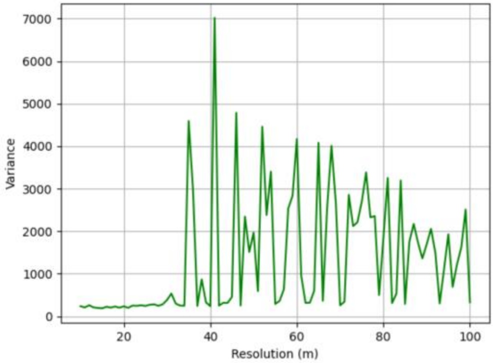
Red



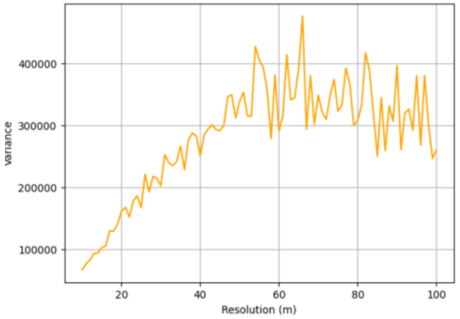


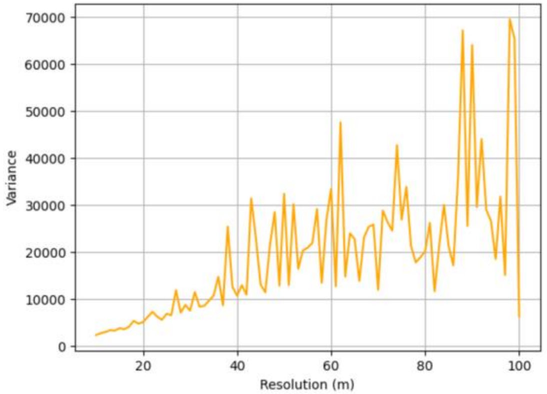
Green

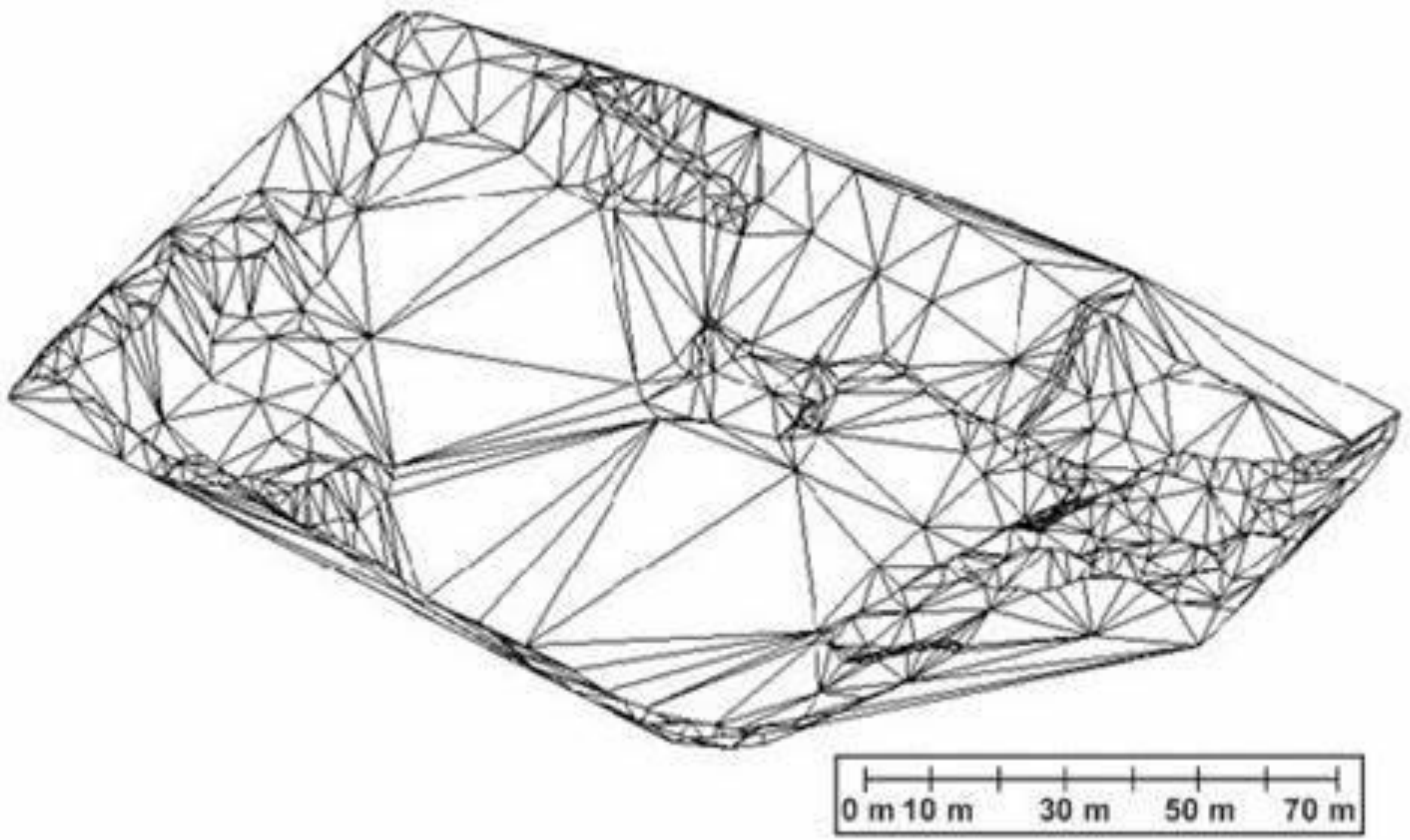


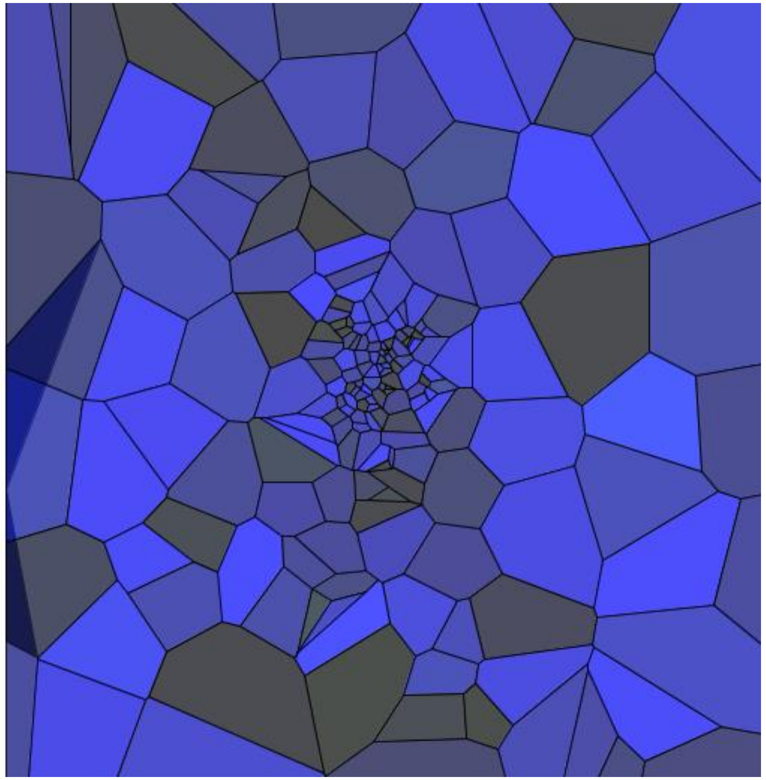


Red Edge 2

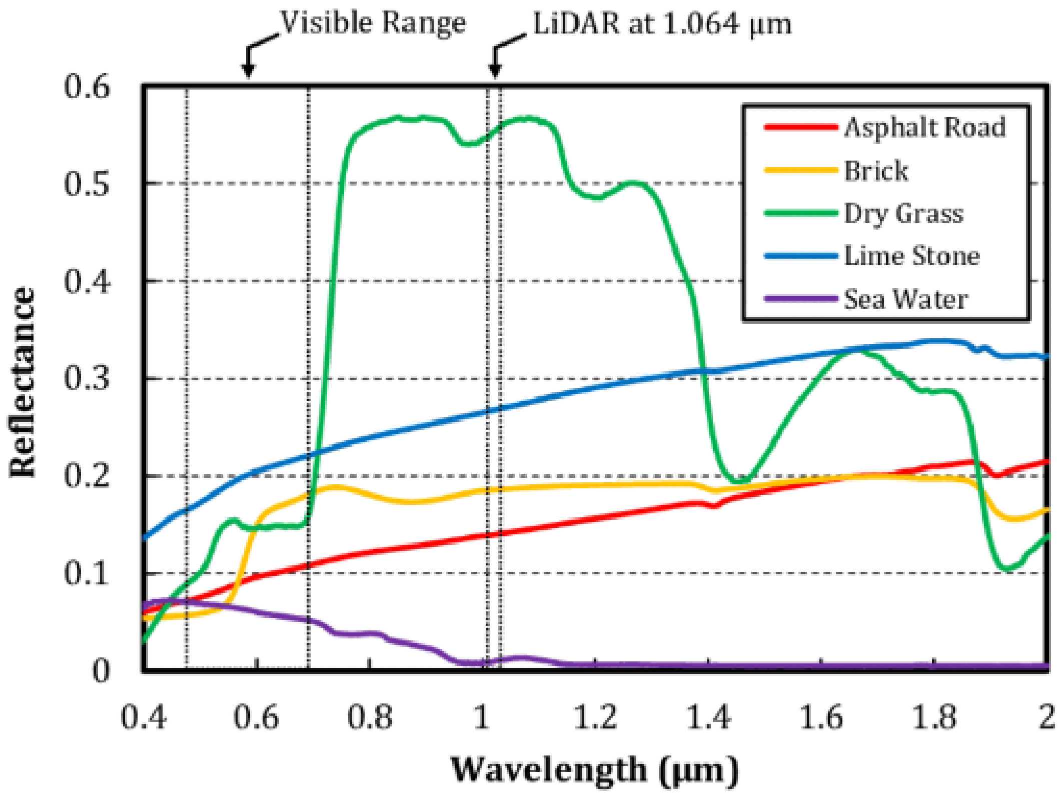




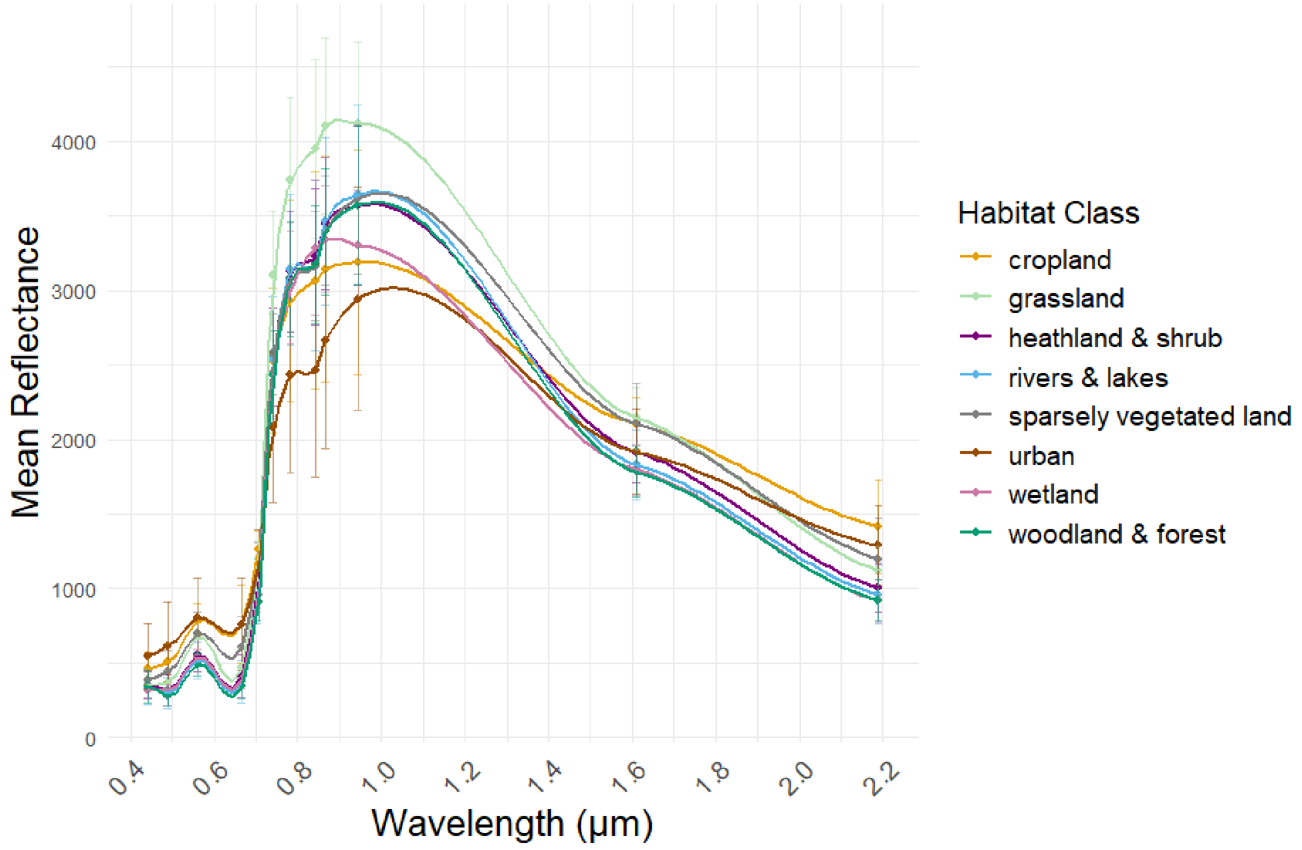

0 m 10 m 30 m 50 m 70 m



Spectral signatures



What textbooks tell us



The reality of scene-captured spectral signatures (Sentinel 2)

The trick of the data volume

:-) better opportunity for class discrimination (?)
:-(but at higher computational cost

More spectral bands
+ More data in temporal domain
= more dimensions to analyse
= sparser data spaces

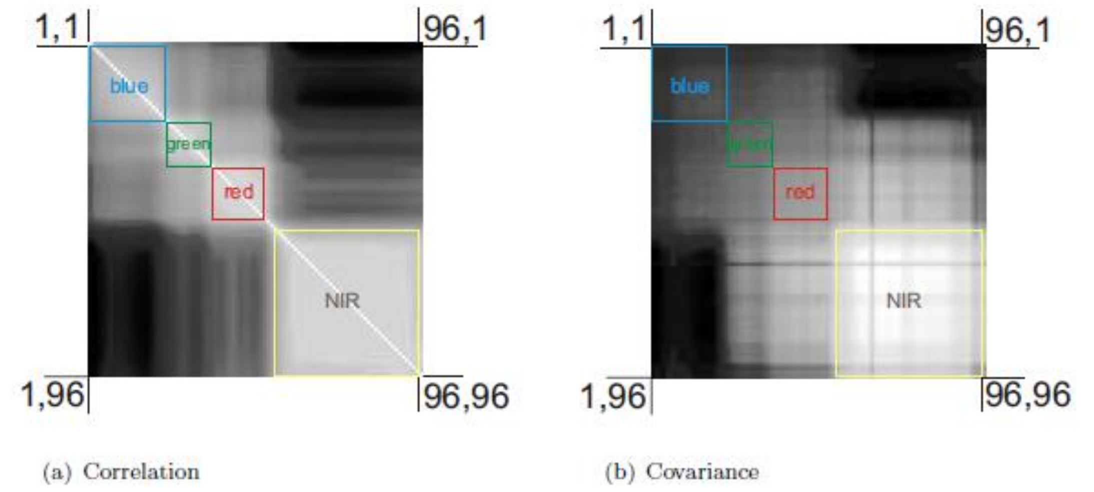
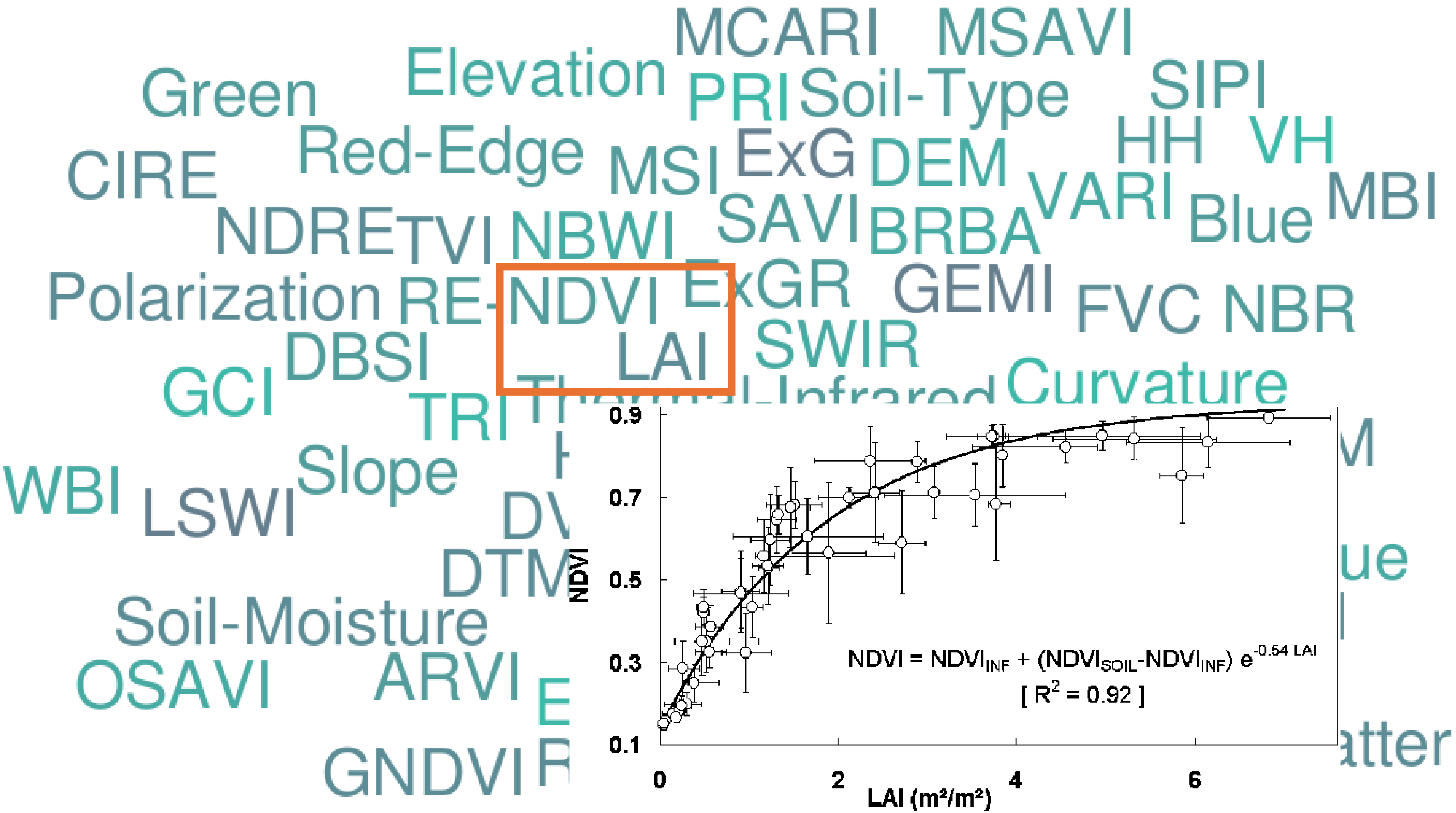


FIGURE 8.3: Correlation and covariance matrices for the 96 bands of the c106013a hyperspectral image, (main regions of the electromagnetic spectrum are highlighted).

Most of hyperspace is empty.



MCARI
MSAVI
Green
Elevation
PRI
Soil-Type
SIPI
CIRE
Red-Edge
MSI
ExG
DEM
HH
VH
MBI
VARI
Blue
NDRE
TVI
NBWI
SAVI
BRBA
Polarization
NDVI
ExGR
GEMI
FVC
NBR
DBSI
LAI
SWIR
GCI
Curvature
TRI
WBI
LSWI
Slope
DTM
Soil-Moisture
OSAVI
ARVI
GNDVI
0.9
0.7
0.5
0.3
0.1
NDVI
0
2
4
6
LAI (m²/m²)
$NDVI = NDVI_{INF} + (NDVI_{SOIL} - NDVI_{INF})\ e^{-0.54\ LAI}$
[R^2 = 0.92]

The semantic trick

Semantics can be highly uncertain yet are very important particularly in the policy context of BNG

Comber et al, 2005
“Land-cover information is inherently subject to indeterminacy and relativism.”

Many aspects can influence derived land-cover information. The work of the biologist determines how abstract conceptualisations of land cover are specified within classified image data: **the ontology of land cover.**

Comber, A., Fisher, P. and Wadsworth, R., 2005. What is land cover?. *Environment and Planning B: Planning and Design*, *32*(2), pp.199-209.

Share three words you would use to describe a forest

Join at menti.com | Use vote code **8955 2765**

In the Eye of the Definer

In its broadest sense, a forest is an area covered by trees. So what is a tree? Generally, a tree is a woody perennial with a single stem. However, that is not the only definition that exists. We found 69 definitions of *tree* in such “societal” works as glossaries and dictionaries, plus five definitions used by international organizations.

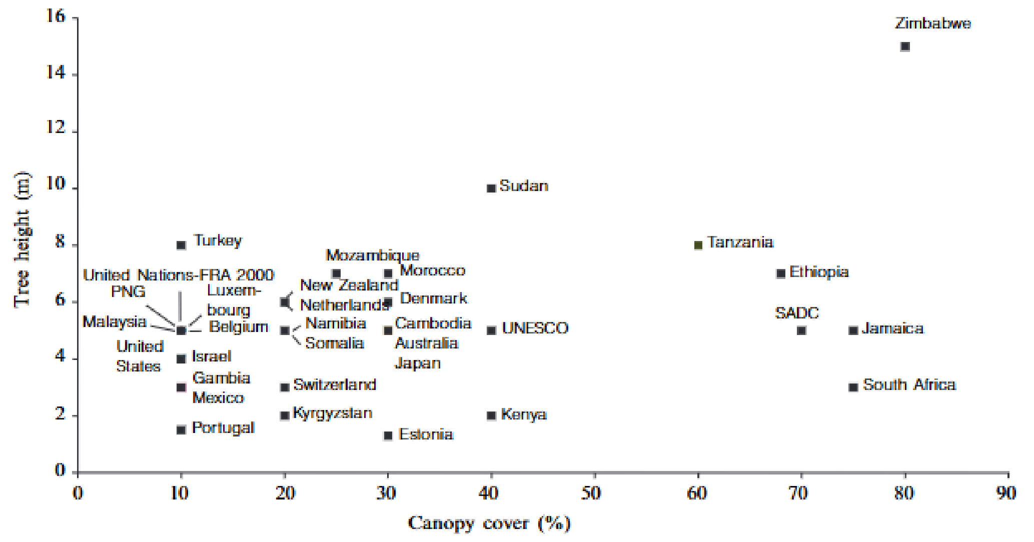
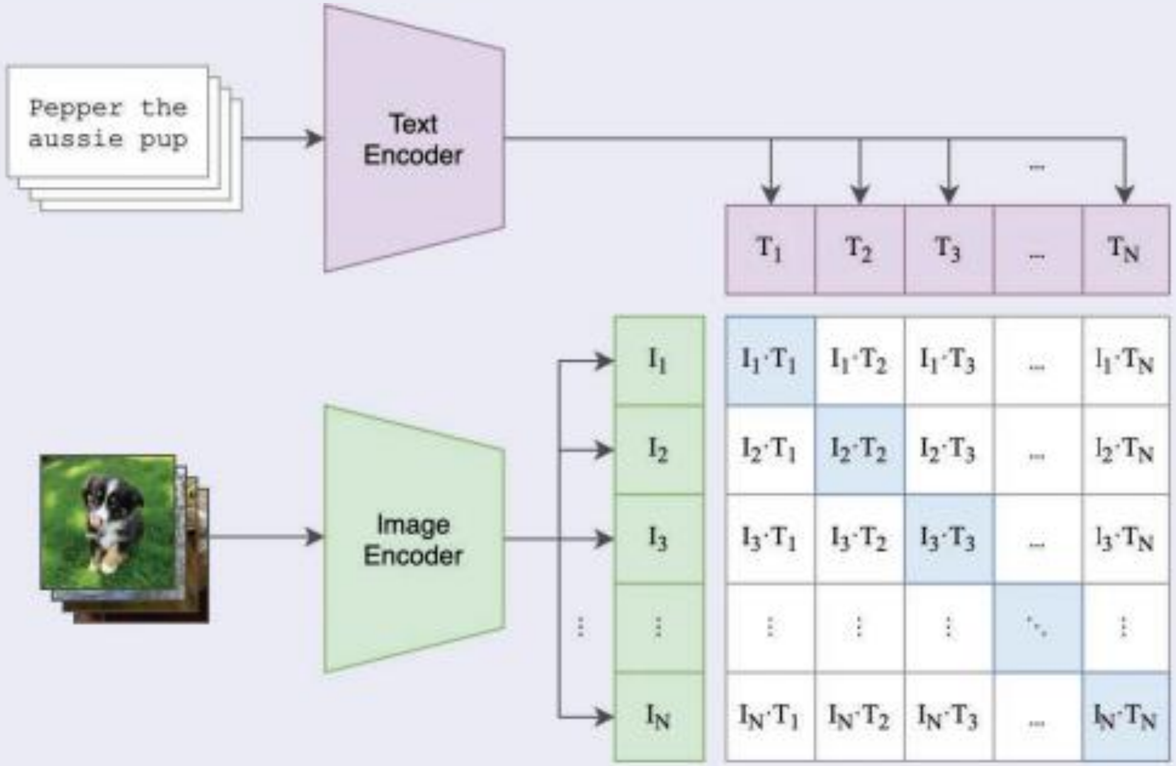


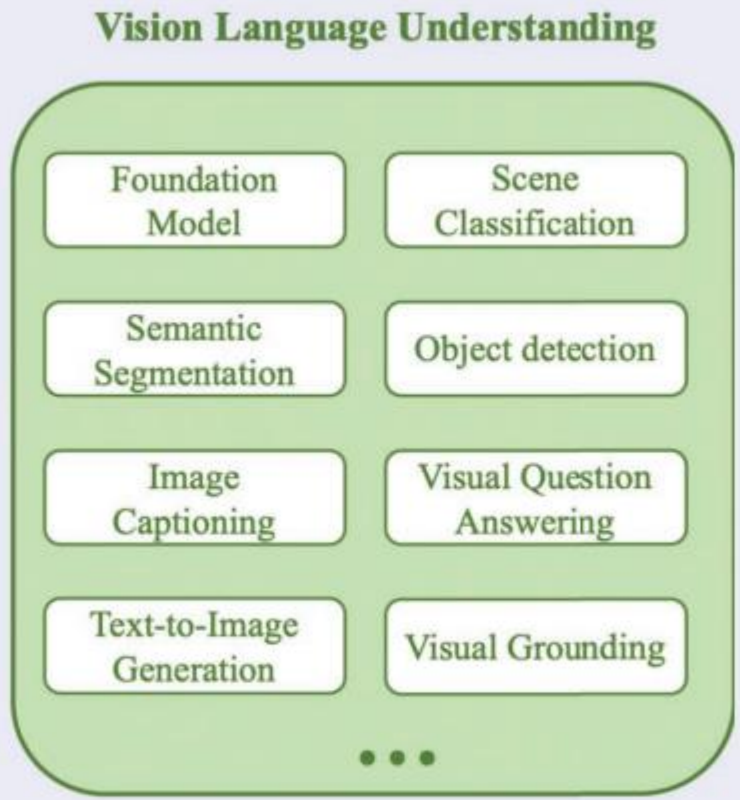
Figure 1. Minimum physical requirements of a ‘forest’ (data from Lund, 2004). Note most countries do not actually define their forests in this way.

Lund, H.G., 2002. When is a forest not a forest? *Journal of Forestry*, *100*(8), pp.21-28.

Semantics within ML

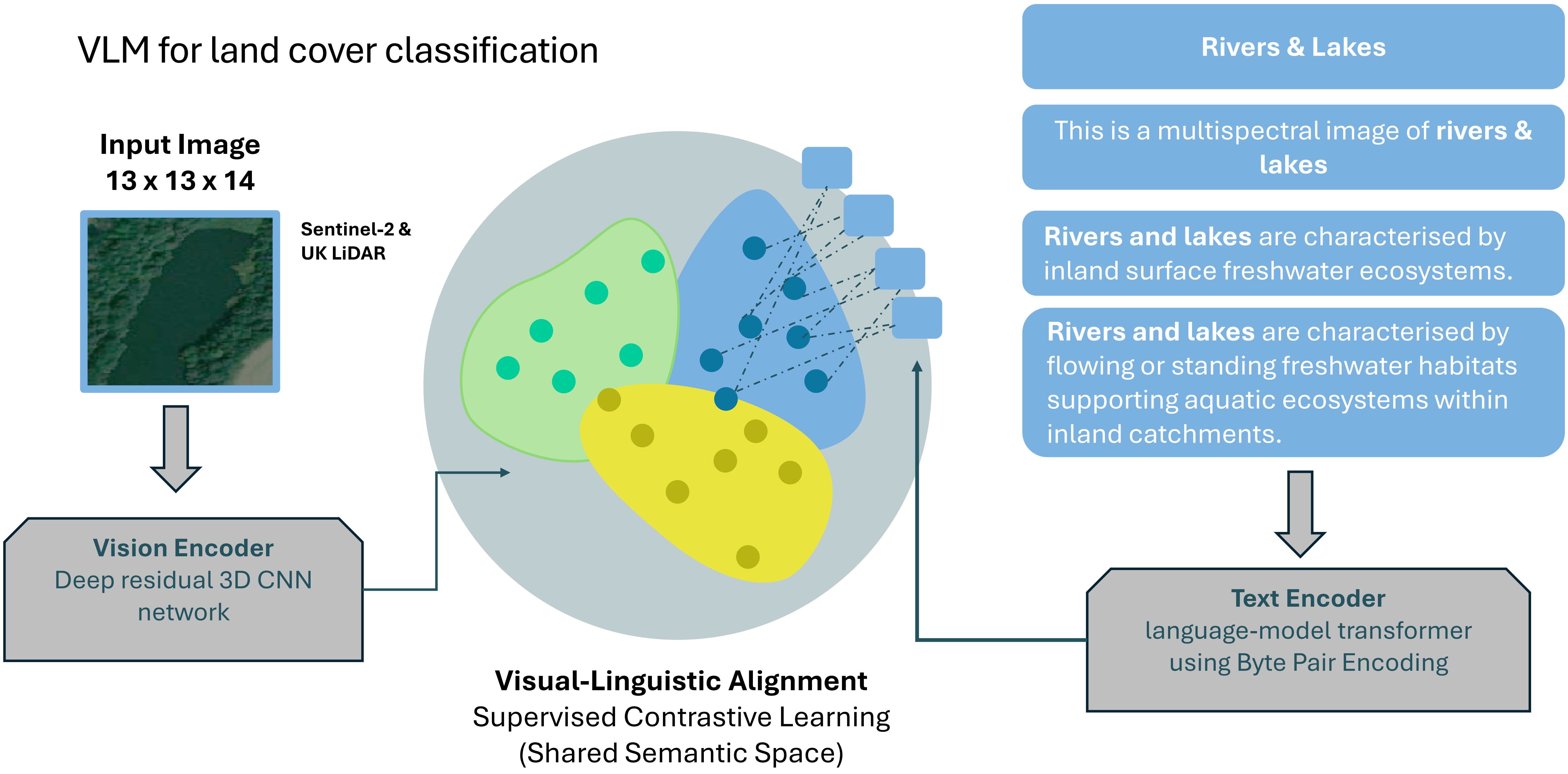


A. Radford et al., “Learning transferable visual models from natural language supervision,” in Proc. Int. Conf. Mach. Learn., PMLR, 2021, pp. 8748–8763.



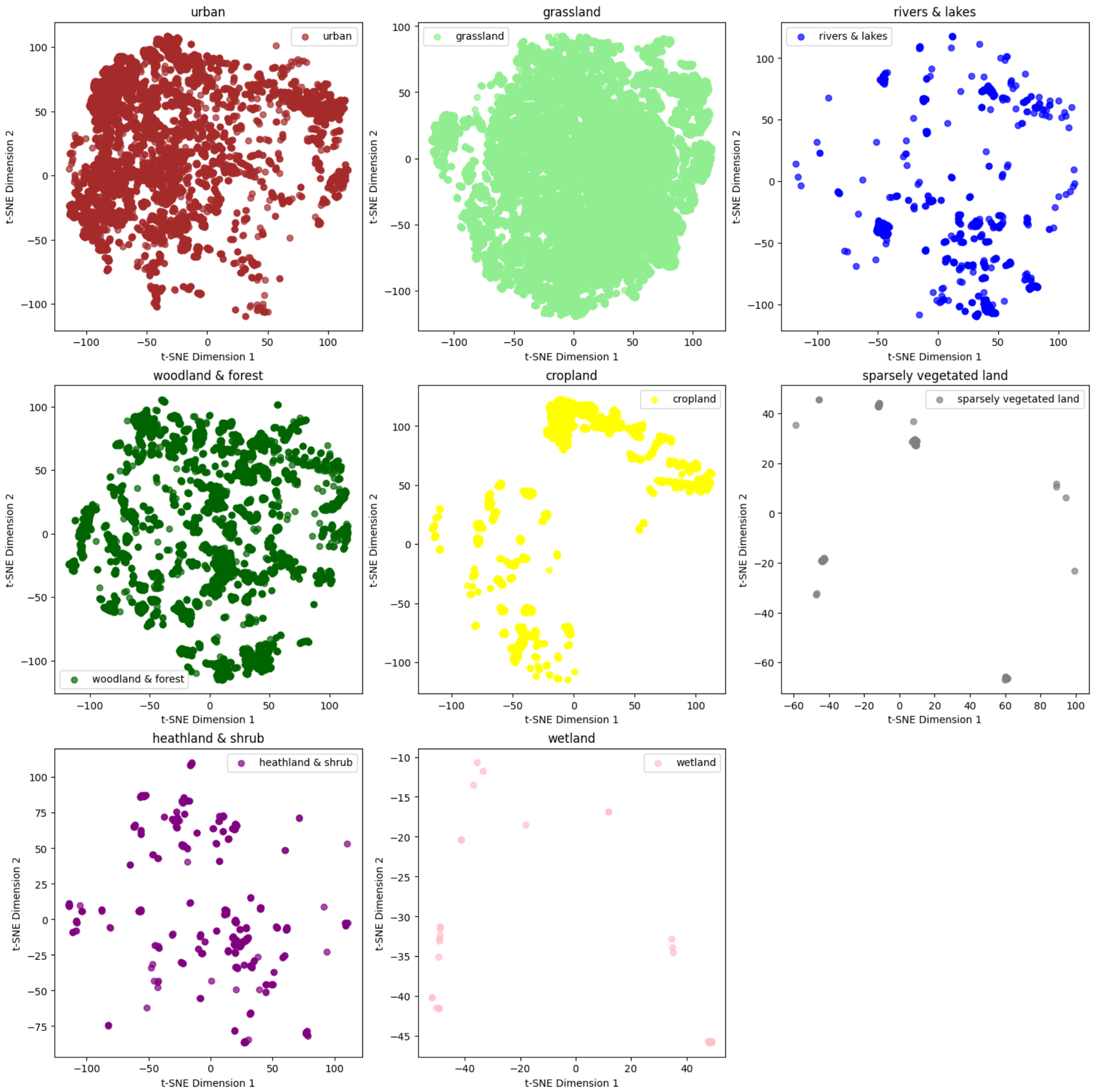
Li, X., Wen, C., Hu, Y., Yuan, Z. and Zhu, X.X., 2024. Vision-language models in remote sensing: Current progress and future trends. IEEE Geoscience and Remote Sensing Magazine.

VLM for land cover classification

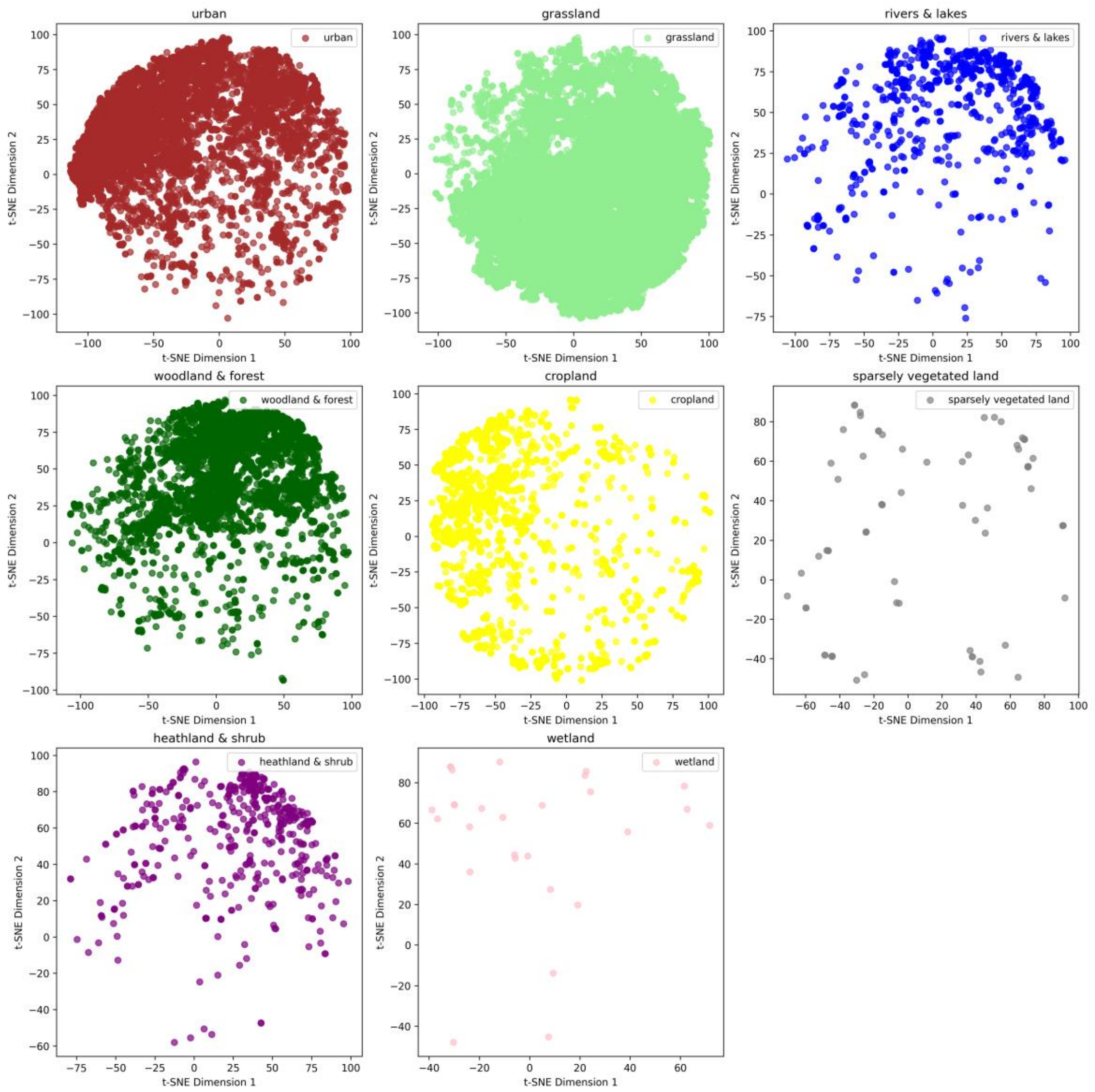


Adapted LDGnet Model (Zhang et al. 2023)

t-SNE plot Before VLM



t-SNE plot After VLM



The trick of accuracy

Foody (2020):

- No universal measure of accuracy
- Different applications demand different accuracy metrics
- Reporting the confusion matrix + querying overall accuracy is helpful.

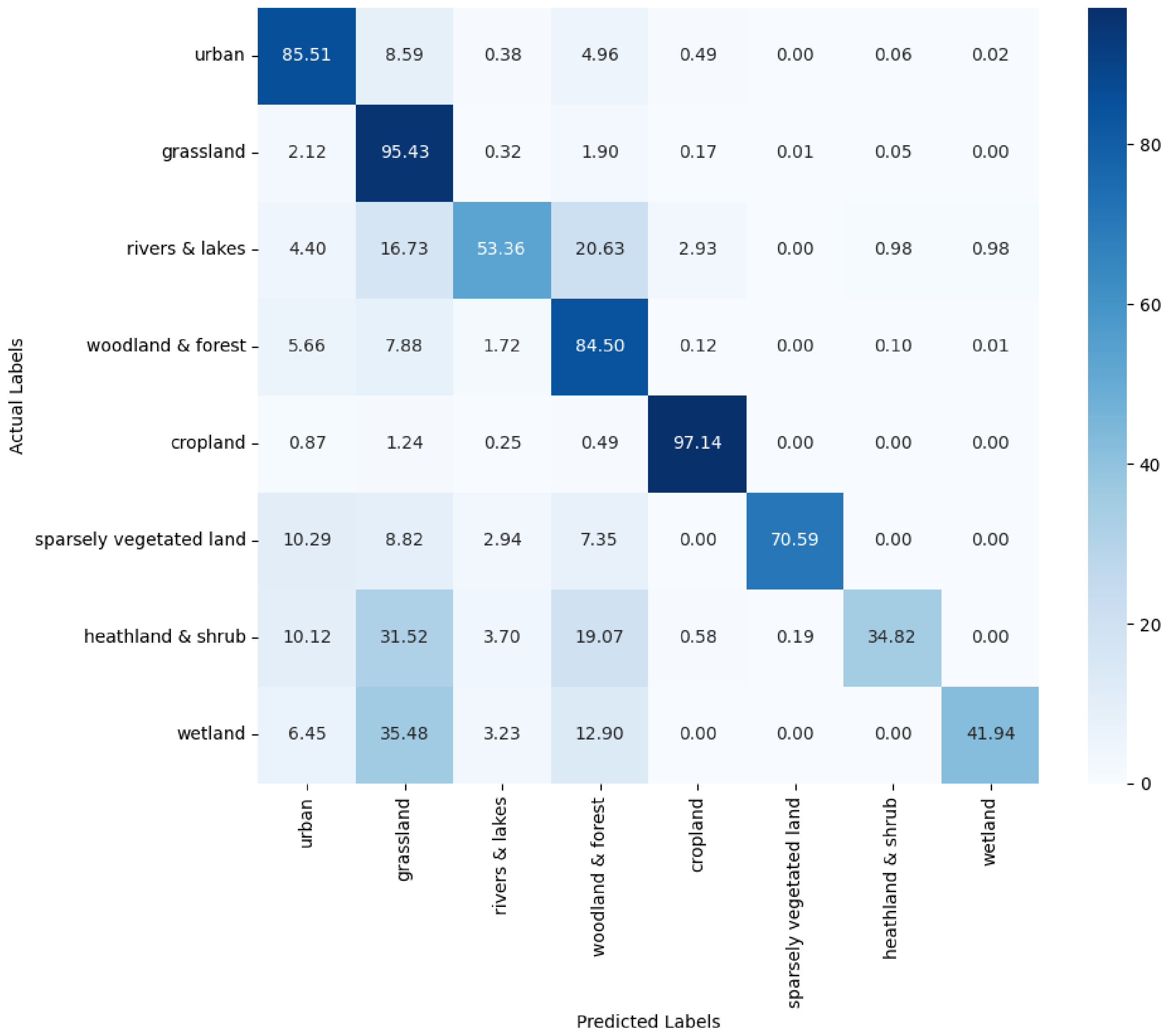
Braun (2021):

- Trying to maximize accuracy unthoughtfully is a way of incautious treatment
- Low accuracy values do not necessarily reflect poor technical setups, but the very ecological or environmental problem at hand.

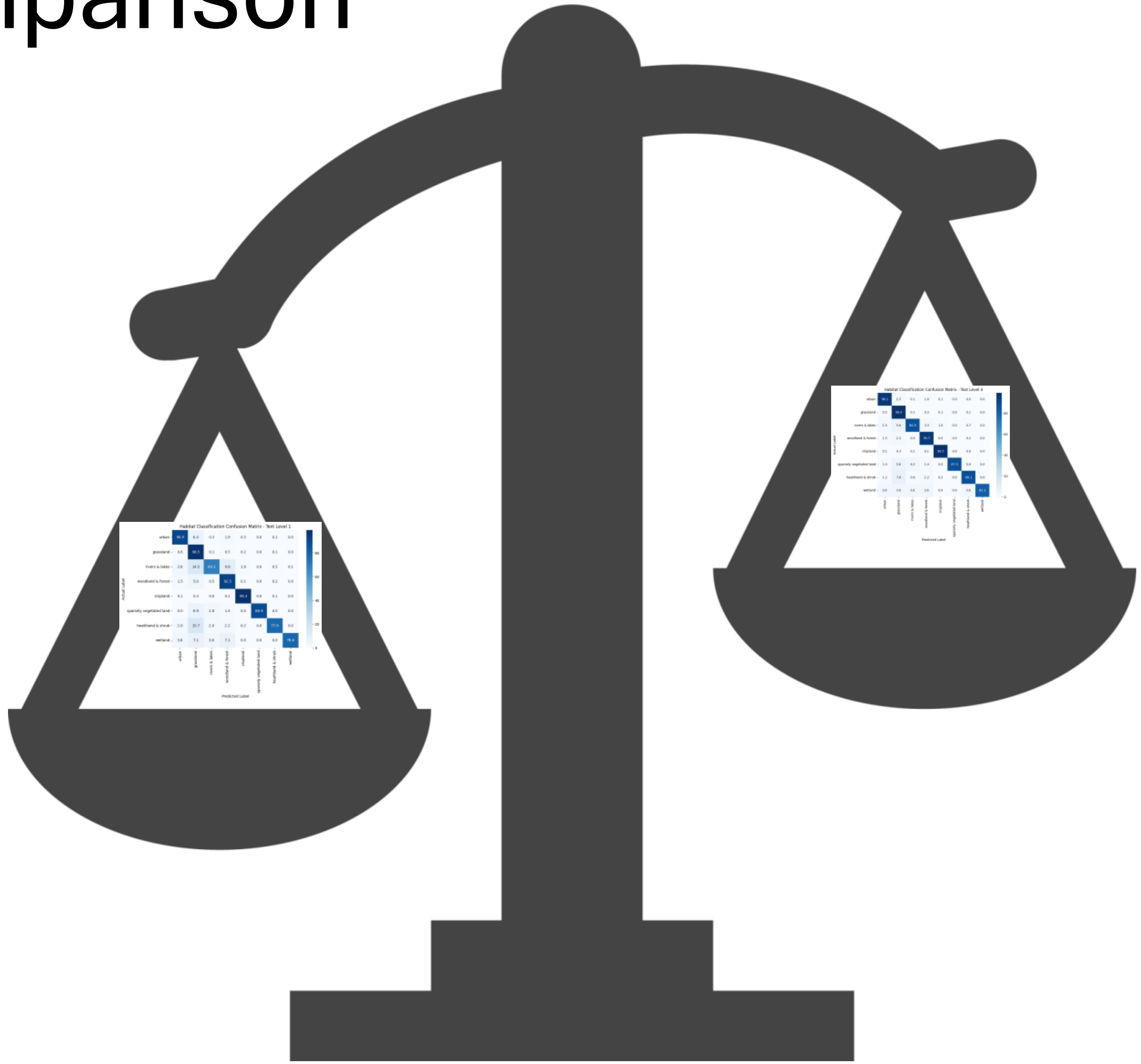
Foody, G.M., 2020. *Remote sensing of environment*, *239*, p.111630.
Braun, A.C., 2021. *Progress in Physical Geography: Earth and Environment*, *45*(5), pp.706-735.

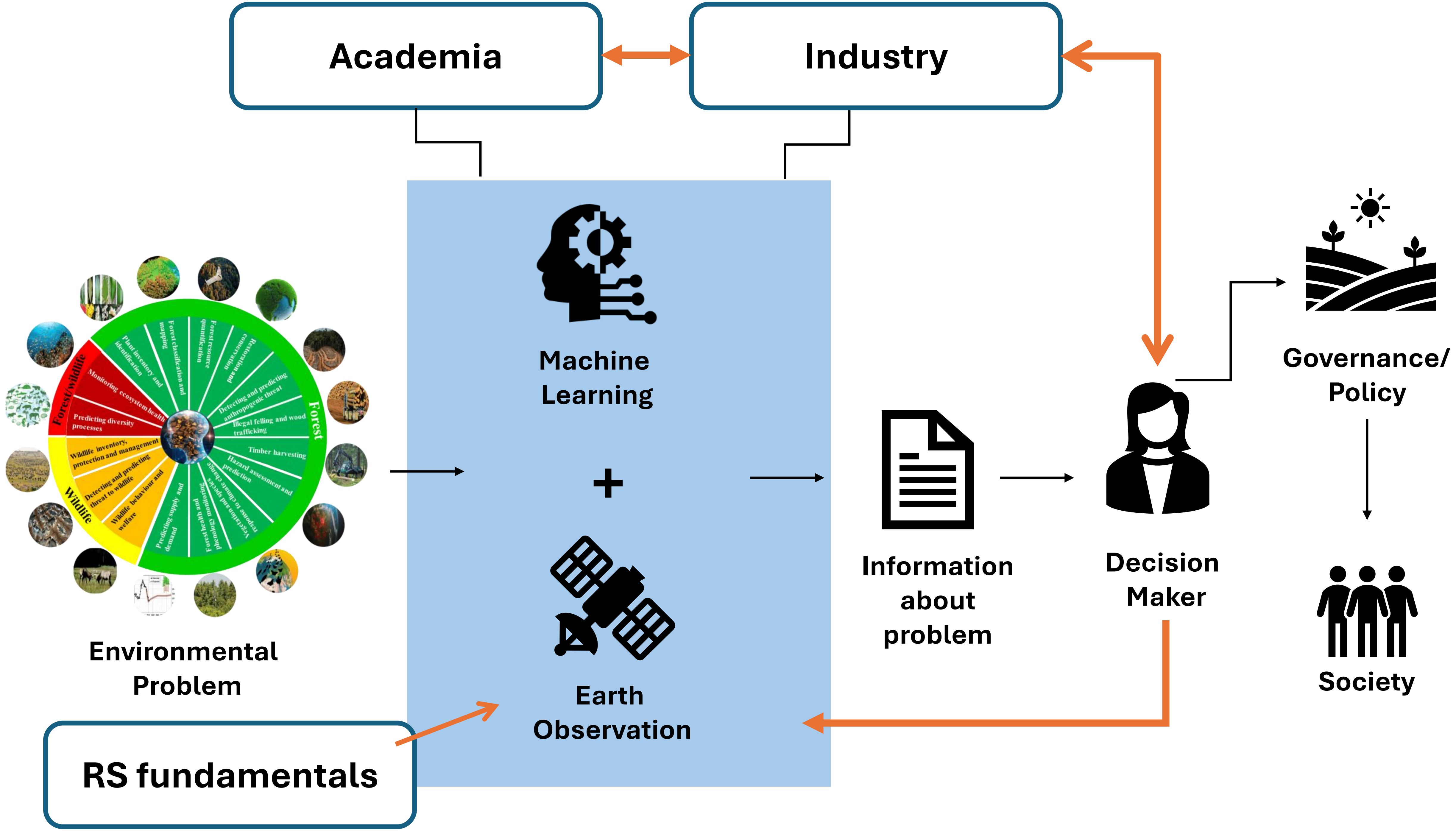
The trick of accuracy

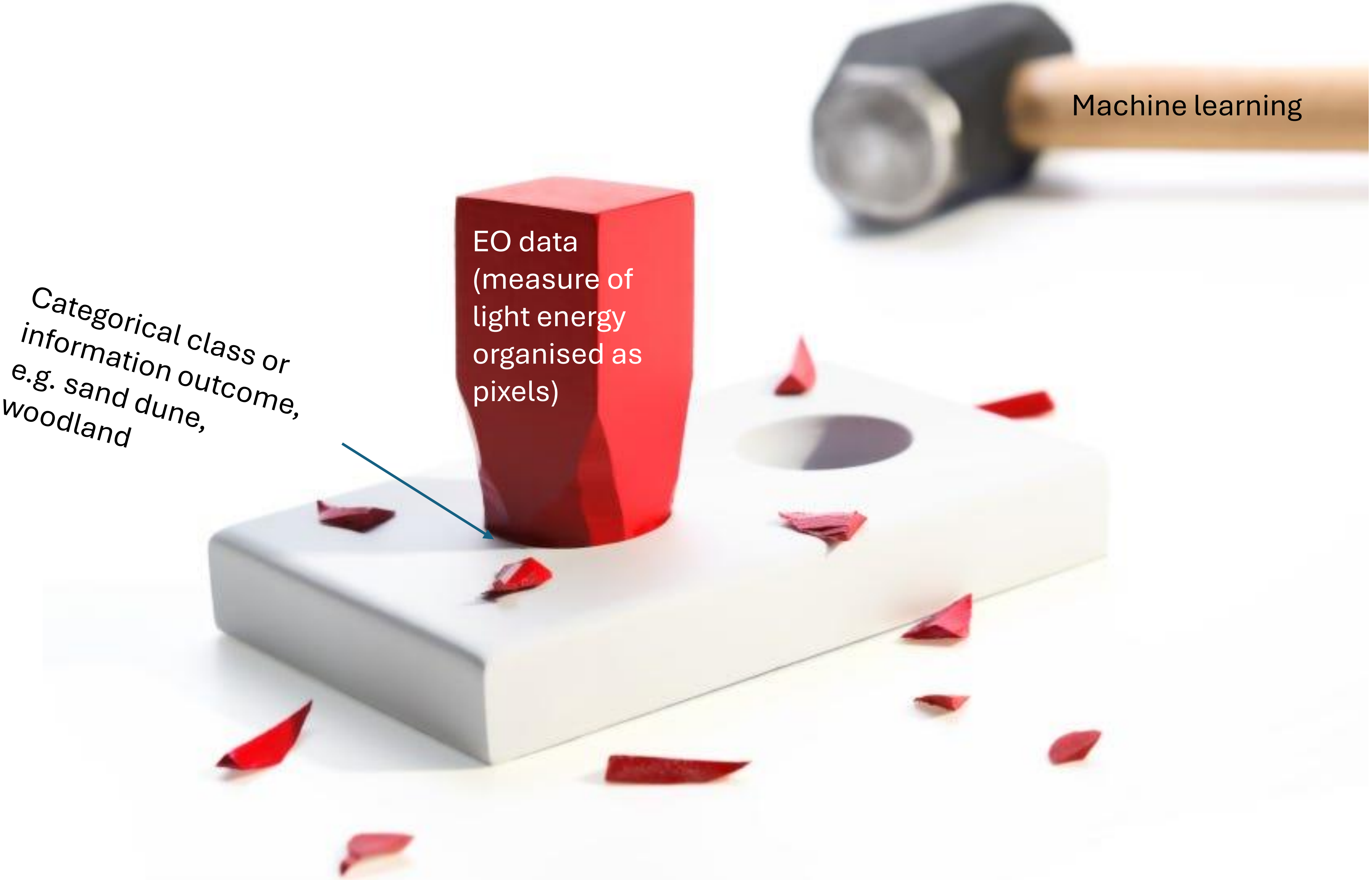
- Overall Accuracy = 92%

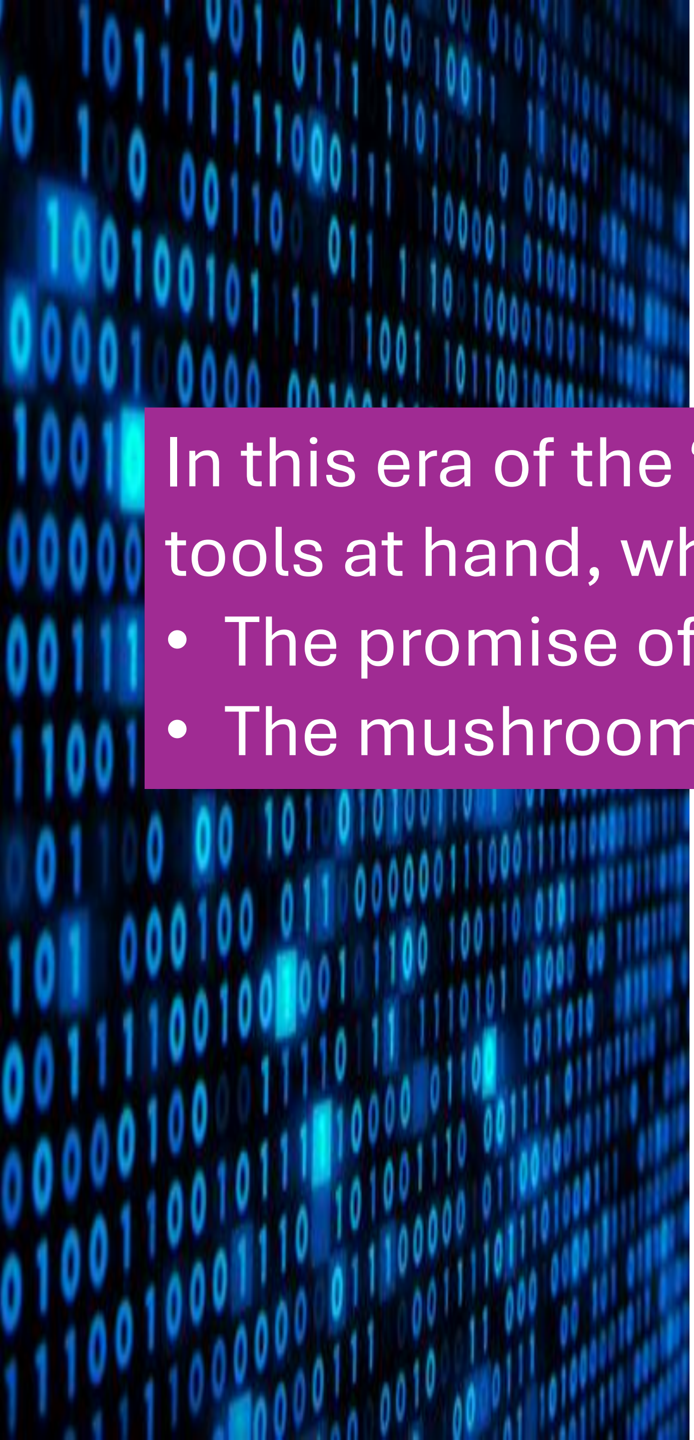


Model Comparison




Academia
Industry
Machine Learning
+
Earth Observation
Information about problem
Decision Maker
Governance/ Policy
Society
Environmental Problem
RS fundamentals
Forest
Wildlife
Forest/wildlife
Monitoring ecosystem health
Predicting diversity processes
Illegal felling and wood trafficking
Detecting and predicting anthropogenic threat
Timber harvesting


Machine learning
EO data (measure of light energy organised as pixels)
Categorical class or information outcome, e.g. sand dune, woodland



The rise of machines does not absolve us of the need to consider critically the core (physical, semantic, ontological) remote sensing factors

In this era of the ‘technological feast’ how do we best use the data and tools at hand, whilst avoiding the “unregulated gluttony” that

- The promise of ML presents
- The mushrooming data volume offers

…We need to remain alert to *machine vision* which can generate a disconnect with real world processes

= The techno-monster?

i.e. We should not overlook the importance of *situated knowledge*