

Model selection criteria

- We did not even scratch the surface of available models...
 - List of models: https://scikit-learn.org/stable/supervised_learning.html
- Model selection:
 - Interpretability
 - Simpler models generally are mote interpretable
 - In memory vs out memory
 - Storage vs RAM
 - Number of features and examples
 - Small training dataset with few covariates = CART or KNN
 - Small training dataset with many covariates = SVM or gaussian
 - Large training dataset with many covariates = Neural networks and boosting
 - Categorical vs numerical features
 - Classification or regression?
 - Normality of data
 - Linear relationships or non-linear?
 - Training speed
 - More complex models generally take longer to train
 - Prediction speed
 - Important if real-time predictions are needed
 - https://medium.com/mlearning-ai/brief-guide-for-machine-learning-model-selection-a19a82f8bdcd

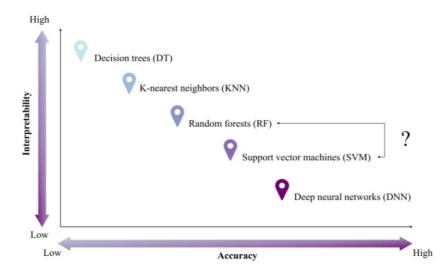
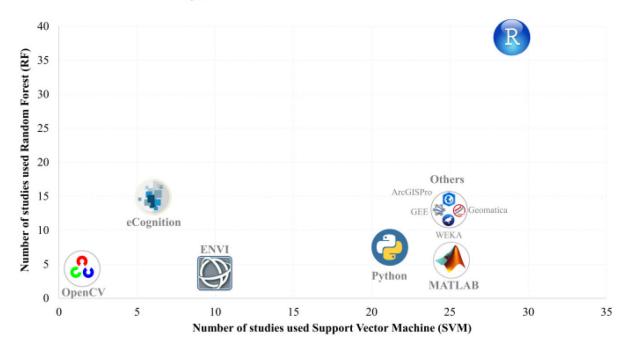
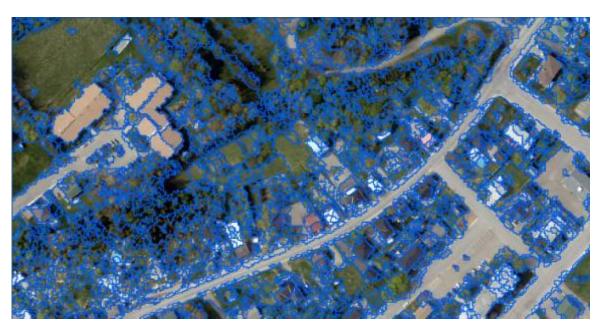


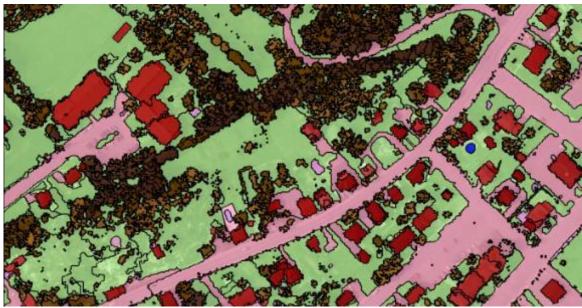
Fig. 1. Interpretability-accuracy tradeoff in machine learning classification algorithms.

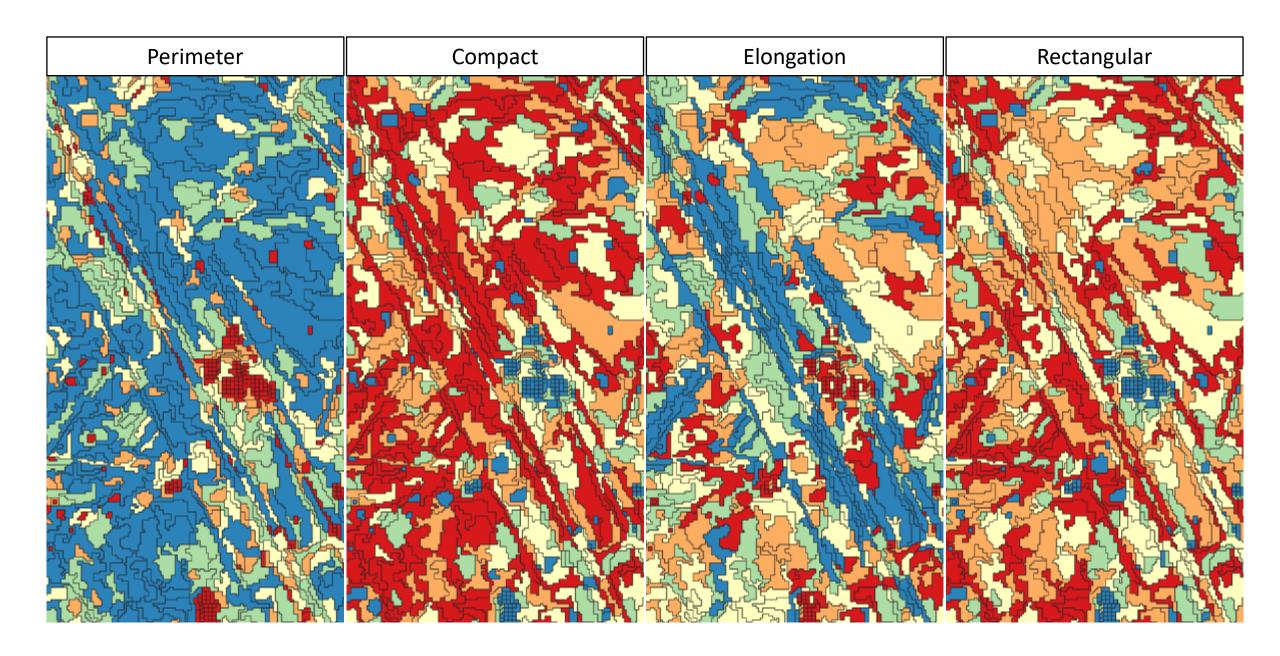


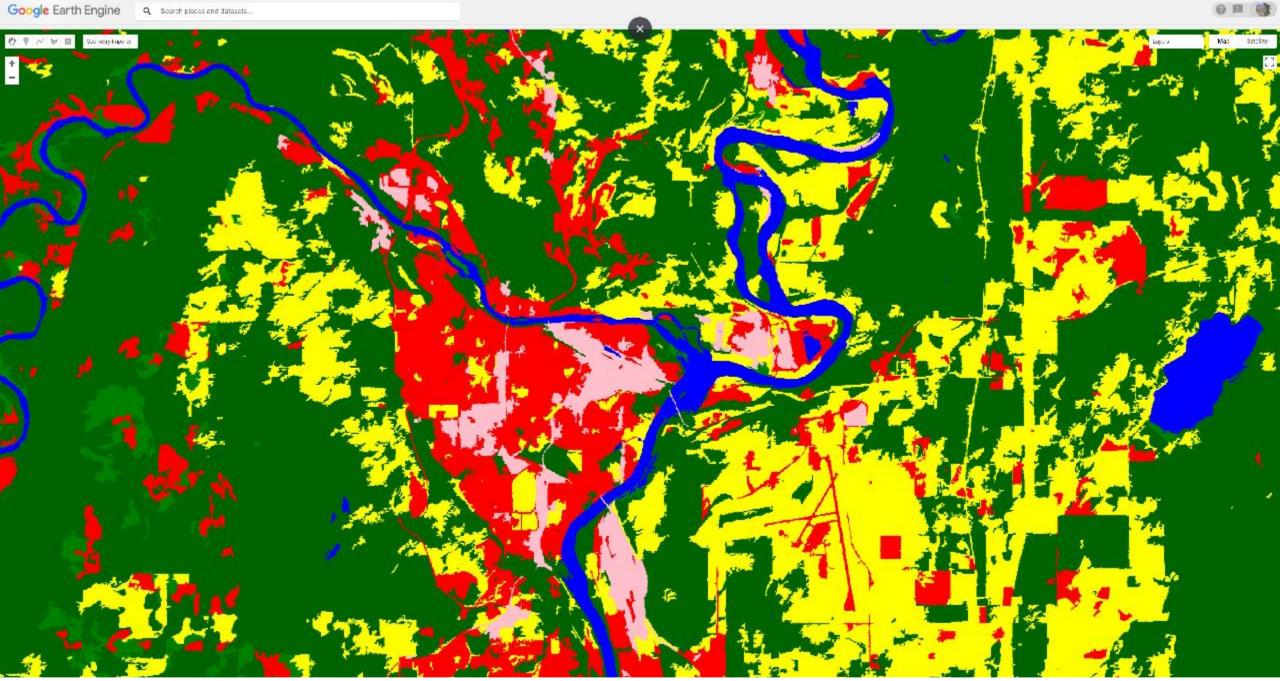
OBIA / Segmentation

- Image segmentation
 - Unsupervised segmentation of the image into similar polygons
 - Calculate shape attributes (length, width, area, perimeter, adjacency, etc.)
 - Algorithms have parameters: Input bands, scale, shape, compactness
- Classification of segments
 - Same as pixel-based (can be supervised or unsupervised) but uses spectral and geometrical polygon statistics
- Grew in popularity with high resolution satellite imagery
- Software
 - Commercial: E-cognition, ArcGIS, PCI
 - Open: GRASS, OrfeoToolbox, R-SuperPixels, Python-SciKit Learn, SAGA





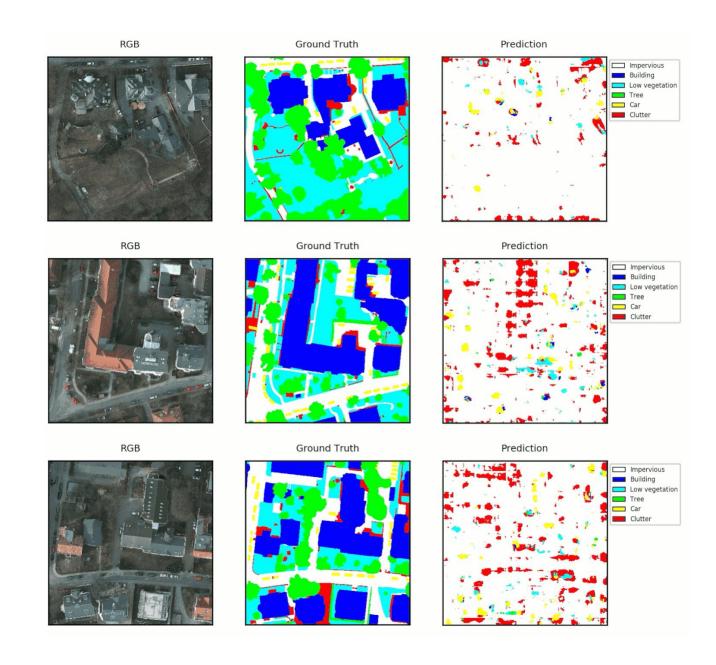




https://code.earthengine.google.com/018f25cf7c7f66041f0168a3e47d32ba

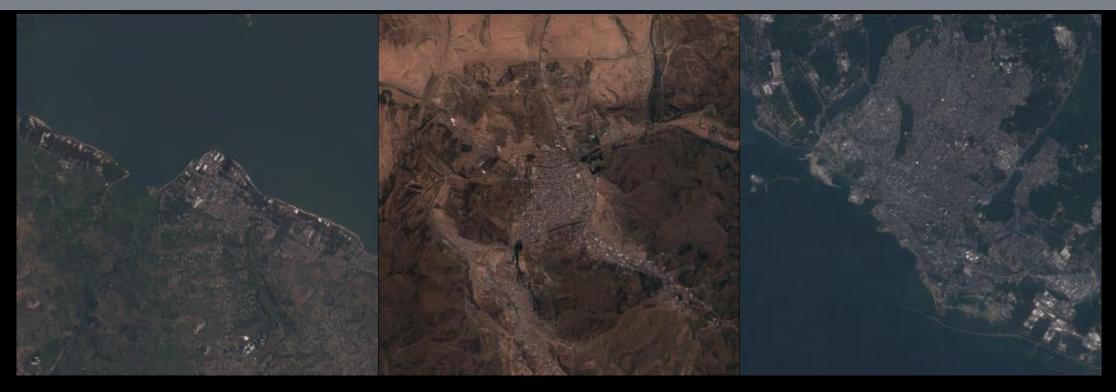
Next steps

- Steps to improve accuracy
 - Reducing dimensionality,
 - Adding terrain and derivatives,
 - Spectral indices,
 - Texture and edges,
 - SAR,
 - Seasons, ...
- Other methods
 - Time series classification
 - Spectral unmixing
 - Semantic segmentation
 - Deep learning / Al
- Recent advances
 - Pre-labeled training data <u>https://bigearth.net/#downloads</u>
 - Pre-trained models https://github.com/tchambon/DeepSentinel



Machine Learning in Remote Sensing

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Why ML and RS?

- Many pixels / bands
 - E.g. Sentinel-2 images (100 x 100 km) for 13 bands (4x10m, 6x20m, 3x60m) = 558,333,333 data points = 750 MB
- Multiple data types
 - Terrain, lidar, hyperspectral, SAR
- Multi-temporal data
 - Timeseries, change detection, seasonal changes
- Large areas
 - · Provincial, National, Global

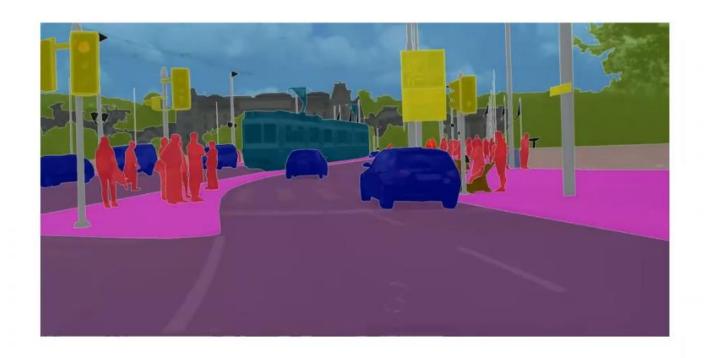
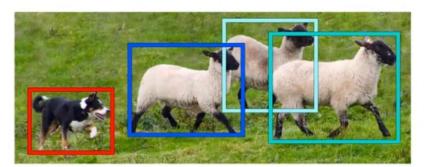
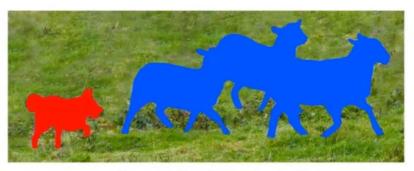




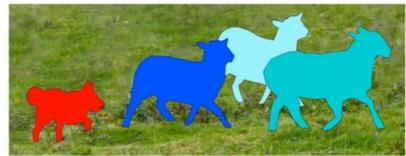
Image Recognition



Object Detection



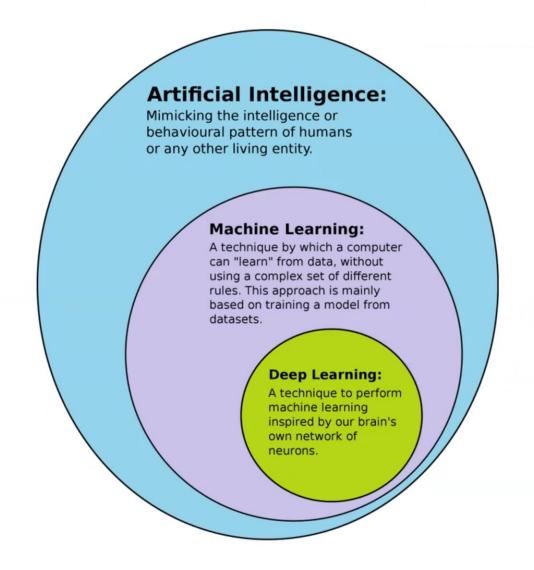
Semantic Segmentation



Instance Segmentation

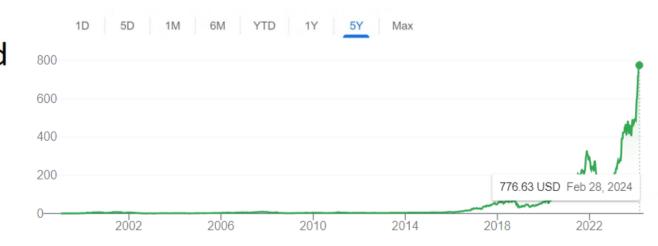
Deep Learning

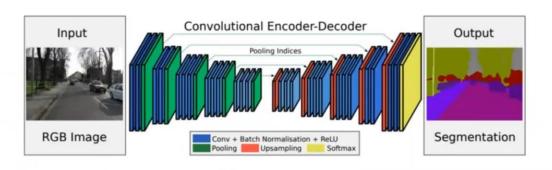
- Extract patterns from data with learning algorithms
- Typically with the optimization of neural networks
- Challenge:
 - Training data!
 - Sensible questions!



Why now

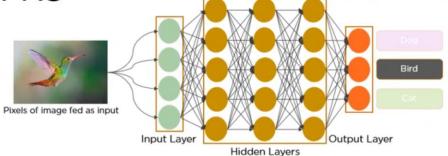
- We've always wanted to understand intelligence and create Al
- Problems are digital
- Moore's law
 - NDVIA shares
 - High performance computing
- Open tools
 - GitHub
 - TensorFlow, Python and pyTorch
- Many models, non-expert usage
 - Convolutional neural network (CNN)
 - Multi-task learning technology (MTL)
 - Transfer learning technology (TL)

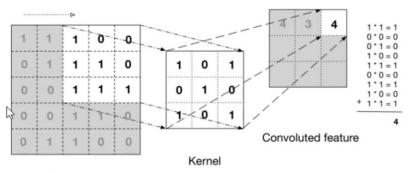




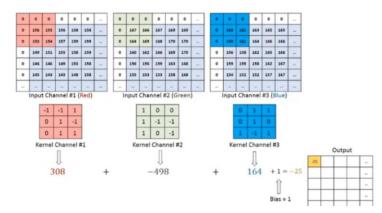
Convolutional neural networks

- Good for detecting patterns in images
- Model has convolutional (or hidden) layers
- CNNs reduce images so that they are easier to process
- Each layer receives input from previous layer, transforms them with filters/kernels, and outputs to next layer
- Convolutional layers can have 1 or more filters.
 User can specify the # of filters, the size of each filter (3x3, 12x12, 1x100), and the type of filter.
- Filter is moved around the entire image, or "convolved", and calculate the dot/scalar products
 - First filters typically detect geometric attributes: edges, corners, circles, rectangles.
 - Deeper filters can detect specific objects (houses, roads, forest) and
 - Even deeper filters can understand complex land covers (airports, schools, hydroelectric dams).



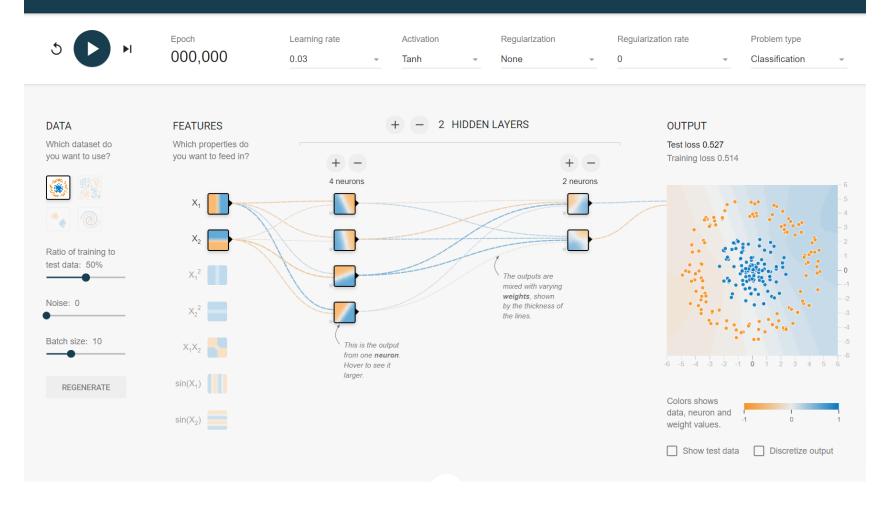


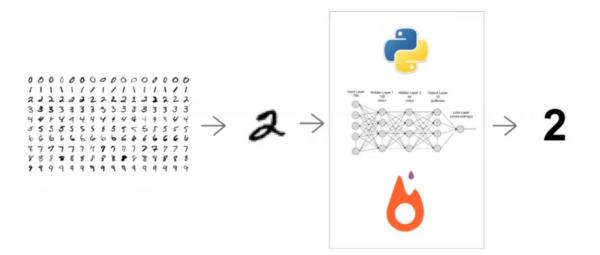
Input data





Tinker With a **Neural Network** Right Here in Your Browser. Don't Worry, You Can't Break It. We Promise.

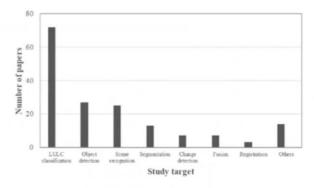




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Problems being worked on

- Land cover and <u>land use</u>
- Object detection
- Scene recognition
- Segmentation
- Change detection
- Fusion



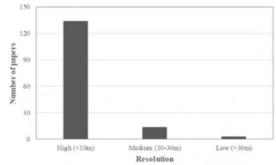


Fig. 2. Number of publications for different study targets.

4. Distribution of image spatial resolution used in the investigated cas-

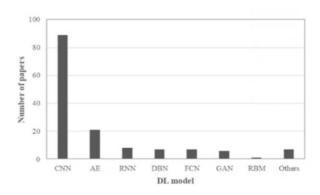


Fig. 3. Distribution of DL model used in the studies.

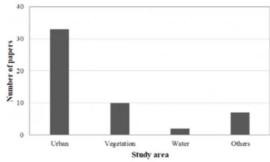
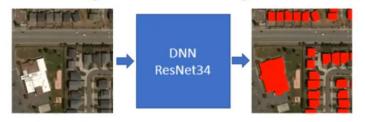
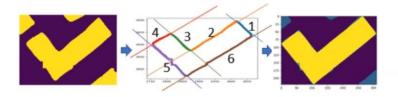


Fig. 5. Distribution of application area.

First Stage - Semantic Segmentation



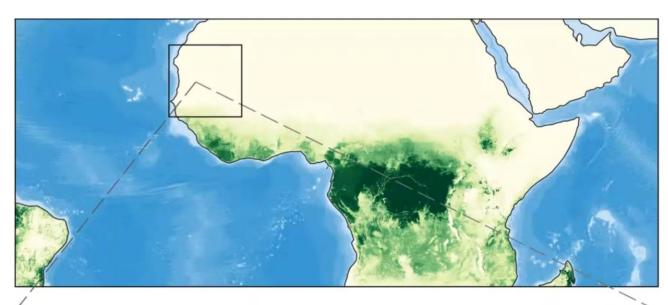
Second stage - Polygonization

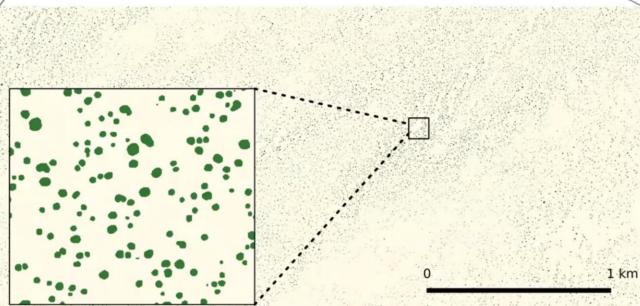


Province/Territory	Number of Buildings
Alberta	1,777,439
British Columbia	1,359,628
Manitoba	632,982
New Brunswick	350,989
Newfoundland and Labrador	255,568
Northwest Territories	13,161
Nova Scotia	402,358
Nunavut	2,875
Ontario	3,781,847
Prince Edward Island	76,590
Quebec	2,495,801
Saskatchewan	681,553
Yukon	11,395









Article Published: 14 October 2020

An unexpectedly large count of trees in the west African Sahara and Sahel

Martin Brandt ☑, Compton J. Tucker ☑, Ankit Kariryaa, Kjeld Rasmussen, Christin Abel, Jennifer Small, Jerome Chave, Laura Vang Rasmussen, Pierre Hiernaux, Abdoul Aziz Diouf, Laurent Kergoat, Ole Mertz, Christian Igel, Fabian Gieseke, Johannes Schöning, Sizhuo Li, Katherine Melocik, Jesse Meyer, Scott Sinno, Eric Romero, Erin Glennie, Amandine Montagu, Morgane Dendoncker & Rasmus Fensholt

<u>Nature</u> **587**, 78–82 (2020) Cite this article **18k** Accesses **62** Citations **921** Altmetric Metrics

Abstract

A large proportion of dryland trees and shrubs (hereafter referred to collectively as trees) grow in isolation, without canopy closure. These non-forest trees have a crucial role in biodiversity, and provide ecosystem services such as carbon storage, food resources and shelter for humans and animals 1.2. However, most public interest relating to trees is devoted to forests, and trees outside of forests are not well-documented³. Here we map the crown size of each tree more than 3 m2 in size over a land area that spans 1.3 million km2 in the West African Sahara, Sahel and sub-humid zone, using submetre-resolution satellite imagery and deep learning⁴. We detected over 1.8 billion individual trees (13.4 trees per hectare), with a median crown size of 12 m², along a rainfall gradient from 0 to 1,000 mm per year. The canopy cover increases from 0.1% (0.7 trees per hectare) in hyper-arid areas, through 1.6% (9.9 trees per hectare) in arid and 5.6% (30.1 trees per hectare) in semi-arid zones, to 13.3% (47 trees per hectare) in sub-humid areas. Although the overall canopy cover is low, the relatively high density of isolated trees challenges prevailing narratives about dryland desertification 5.6.7, and even the desert shows a surprisingly high tree density. Our assessment suggests a way to monitor trees outside of forests globally, and to explore their role in mitigating degradation, climate change and poverty.

Manual work still happens

 This study, published in 2024 manually classifies 26,000 2x2 km plots

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TECHNICAL NOTE

OPEN ACCESS Check for upday

Human Impact Land Use Layer from the Canadian Forest Service National Forest Inventory

Couche d'utilisation des terres par les humains de l'Inventaire forestier national du Service canadien des forêts

David A. Hill (19)

Canadian Forest Service, Pacific Forestry Centre, Natural Resources Canada, 506 West Burnside Road, Victoria, British Columbia, V8Z 1M5. Canada

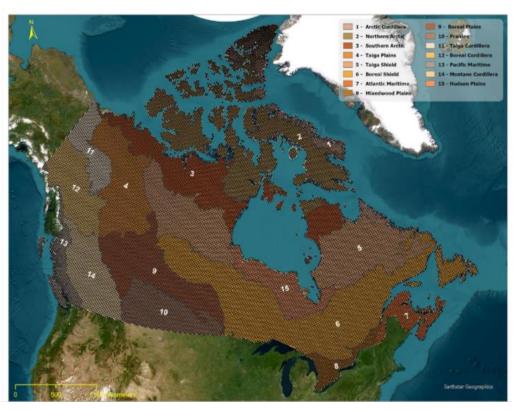




Figure 5. Seismic Lines: Left, Seismic line within 500 meters of each other, Right, Seismic lines greater than 500 m apart.