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

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## 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-documented[3]. Here we map the crown size of each tree more than 3 $m^2$ in size over a land area that spans 1.3 million $km^2$ in the West African Sahara, Sahel and sub-humid zone, using submetre-resolution satellite imagery and deep learning[4]. We detected over 1.8 billion individual trees (13.4 trees per hectare), with a median crown size of 12 $m^2$, 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.





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## Data availability

Global tree cover maps are available at http://earthenginepartners.appspot.com/science-2013-global-forest. CHIRPS rainfall data are freely available at the Climate Hazard Group (https://www.chc.ucsb.edu/data/chirps). The Copernicus land-use map can be downloaded at https://land.copernicus.eu/global/. Commercial very-high-resolution satellite images were acquired by NASA, under a NextView Imagery End User Licence Agreement. The copyright remains with DigitalGlobe, and redistribution is not possible. However, the derived products produced in this Article are made publicly available at the Oak Ridge National Laboratory at https://doi.org/10.3334/ORNLDAAC/1832. Any further relevant data are available from the corresponding authors upon reasonable request.

## Code availability

The tree detection framework based on U-Net is publicly available at https://doi.org/10.5281/zenodo.3978185; support and more information are available from A.K. (kariryaa@uni-bremen.de or ankit.ky@gmail.com).



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### Contributions

M.B., C.J.T., R.F. and K.R. designed the study. C.J.T., J. Small, S.S., J.M., E.R., E.G. and K.M. prepared and processed the satellite data. M.B. selected the training data. A.K. wrote the code for the deep-learning framework, supported by S.L., J. Schöning, F.G., J.M. and C.I. M.B., C.A., A.K. and J.C. conducted the analyses. Interpretations were done by P.H., J.C., R.F., K.R., L.K., O.M., A.M. and A.A.D. M.D, C.A. and R.F. collected the field data. K.R., M.B. and L.V.R. wrote the first manuscript draft with contributions by all authors. M.B. designed the figures.

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## Ethics declarations

### Competing interests

The authors declare no competing interests.

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## Extended data figures and tables

### Extended Data Fig. 1 Predicting tree crowns.

This set of 256 × 256-pixel plots from the independent test dataset shows the capabilities of the convolutional neural network model to predict trees (right column) from panchromatic images (left column) and NDVI (central column) at 0.5-m resolution.

### Extended Data Fig. 2 Evaluation.

**a**, Manually labelled tree crowns from the independent test dataset are compared against predictions. The comparison is done for 100 random plots each having 256 × 256 pixels. Here, the canopy area (in $m^2$) of the trees in the plots is compared. **b**, As in **a**, but for the density (the number of labelled or predicted trees per plot). **c**, As in **a**, but for mean crown size per plot. **d**, The crown sizes of 102 in situ measured trees from 2 field campaigns in Senegal (Extended Data Fig. 4) are compared with the predicted ones. Extended Data Table 2 provides more details. $n = 100$ plots with 256 × 256-pixel size.

### Extended Data Fig. 3 Mapping individual tree crowns.

**a**, Before training the model, the spaces between labelled tree crowns (light blue) were filled (red) and given a higher weight. During training, the model was penalized more strongly for wrongly classifying gap pixels compared to other misclassifications. As a result, tree crowns that touch or are close to each other could be reliably separated. **b**, Examples of predicted trees (green), showing that most trees standing close to each other were mapped as individuals trees.

### Extended Data Fig. 4 Overview of training sites and study area.

The study area for the wall-to-wall mapping is the westernmost part of the Sahara and Sahel. It represents a typical north–south ecological and climatic gradient, starting in the Sahara Desert in hyper-arid areas (rainfall of 0–150 mm yr–[1]) with a sparse vegetation coverage, over arid (rainfall of 150–300 mm $yr^{-1}$) and semi-arid (rainfall of 300–600 mm $yr^{-1}$) Sahelian rangelands and croplands, up to sub-humid (rainfall of 600–1,000 mm $yr^{-1}$) Sudanian lands, where shrublands turn into forests. **a**, The locations of the manually drawn 89,899 tree crowns used for training the model are shown in red. CHIRPS rainfall[43] was used to delineate the rainfall zones. The land use for farmland and urban is from Copernicus Global Land[26]. In situ data were collected at the field sites around Widou and Dahra in Senegal. Areas of insufficient data quality and beyond rainfall of 1,000 mm $yr^{-1}$ were masked. **b**, The region was analysed for sandy (>70% sand content) and non-sandy areas[44].

## Extended Data Fig. 5 Variables mapped in this study.

**a**, The density of trees with a crown size larger 3 $m^2$ per hectare. **b**, The canopy cover. **c**, Mean crown size. All variables were mapped by 100 × 100-m (1-ha) grids. Rainfall isohyets of 150, 300, 600 and 1,000 mm $yr^{-1}$ are also shown.

## Extended Data Fig. 6 Tree density classes.

**a**–**d**, The tree density per hectare is shown for different crown size classes: 3–15 $m^2$ (**a**), 15–50 $m^2$ (**b**), 50–200 $m^2$ (**c**), and >200 $m^2$ (**d**). Trees in the class >200 $m^2$ typically do not represent individual tree crowns, but instead reflect closed-canopy areas. Trees <3 $m^2$ are not shown, owing high uncertainty in this class.

## Extended Data Fig. 7 Comparisons with other datasets.

**a**, Canopy cover of the study area from ref. [8]. **b**, Field-measured crown diameter (derived from crown size 3–200 $m^2$) of 811 individual trees measured in situ in the Ferlo of Senegal[21]. The *y*-axis has been log-transformed. **c**, As in **b**, but for the crown size and without log transformation. **d**, Woody cover derived from individual trees differs from the current state-of-the-art tree cover map from ref.[19]. $n = 4{,}017$ grids; $r^2 = 0.28$.

## Extended Data Fig. 8 Overview of satellite images.

We used 11,128 multispectral images from the QuickBird-2, GeoEye-1, WorldView-2 and WorldView-3 satellites, acquired from November to March of 2005–2018. Priority was set to images from the early dry season (starting in November), and an off-nadir angle of <25°. Although the model has been trained and validated to work for late-dry season images, the uncertainty is higher in February and March. **a**, Image acquisition months. **b**, Sun azimuth at the image acquisition time. **c**, Off-nadir angle shown for each image.

**Extended Data Table 1 Performance in relation to image quality**

**Extended Data Table 2 Evaluation**

## Supplementary information

### Supplementary Information

This file contains Supplementary Figures 1-4 and Supplementary Table 1.

### Reporting Summary

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