

Mapping every adult baobab (*Adansonia digitata* L.) across the Sahel to uncover the co-existence with rural livelihoods

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Abstract

The iconic baobab tree (*Adansonia digitata* L.) is an integral part of rural livelihoods throughout the African continent. However, the combined effects of climate change and increasing global demand for baobab products are currently exerting pressure on the sustainable utilization of these resources. Here we employ sub-meter resolution satellite imagery to identify the presence of nearly 2.8 ($\pm 27.1\%$) million baobab trees in the Sahel, a dryland region of 1.5 million km². This achievement is considered an essential step towards an improved management and monitoring system of valuable woody species. Using Senegal as a case country, we find that 94% of rural households have at least one baobab tree in their immediate surrounding, and that the abundance of baobabs is associated with a higher likelihood of people consuming a highly nutritious food group: dark green leafy vegetables. The generated database showcases the feasibility of mapping the location of single tree species at a sub-continental scale, providing vital information in times where human mismanagement and climate change cause the extinction of numerous tree species.

Main Text

Trees are a fundamental component of livelihoods in drylands and their use goes far beyond the provision of wood products. Dryland trees provide nutritious food and medicinal products, artifact material, cultural aspects and income to the local people, and a higher density of specific trees can improve the physical and economic wellbeing of local communities¹. Recent research found that tree cover has generally increased in drylands over the past decades, which is often related to changing management patterns or climatic conditions, such as changes in the rainfall patterns that favor woody over herbaceous species². However, not all woody species have high nutritional, ecological, cultural or economic value, and the encroachment of particular invasive species is, in some areas, considered as ecosystem degradation³. Yet, climatic changes, such as increased frequency of droughts, and human mismanagement can lead to a reduction in tree density and productivity as well as local extinction of high-value tree species^{4,5}, which can have profound consequences for local livelihoods. Examples include loss of valuable products from the trees, such as fruits, leaves, seeds, and bark- products that local people often use for food and medicinal purposes, and to generate income⁶.

A prominent example of a highly valuable tree is the baobab, which is an iconic landscape feature of most of the continent's drylands^{7,8,9}. While the bark, pulp extract and leaves are used in the treatment of fevers, dysentery, and sores, the fruits, seeds and leaves are known for being rich in Vitamin A and C and a source of iron, calcium and zinc^{8,10,11}. The baobab products are traditionally sold in local rural as well as urban markets. In recent years, an international demand for especially baobab fruit powder has increased, and foreign companies have started exporting baobab products, such as juice, cream and powder to global customers^{9,12,13}. The export of baobab fruit powder to Western and Asian markets has seen a remarkable increase, estimated at several hundred tons per year, compared to negligible quantities just two decades ago¹². Traditional trees like the baobab are key for local livelihoods and it is

therefore important to quantify their abundance at national scales¹⁴. This is particularly true in times where plantations of fast growing and easily marketed species, such as *Eucalyptus*^{15,16,17}, are promoted throughout the tropics, which often do not provide the same level of benefits, such as nutrition.

Our knowledge on the distribution of tree species in Africa is currently either derived from field surveys^{18,19,20,21}, drones²² or hyperspectral data²³, or the potential distribution is estimated from niche models^{21,23,25}. Only the latter allows for large-scale assessments, and uses variables defining the growing conditions, such as soil and rainfall, which are used to estimate the possible abundance of certain tree species. This method includes a high level of uncertainty, in particular for species that are closely related to human management, such as the baobab. Consequently, such maps are of limited use for management purposes, as they only provide potential suitable areas for a given species to grow. To effectively monitor tree population dynamics in relation to climate change and management, ensuring adequate regeneration and sustainable management of economic outputs, it is crucial to obtain precise information regarding the abundance of tree species.

Monitoring scattered dryland trees from satellite and aerial images has been challenging until recent times, thus making local field surveys and unmanned aerial vehicles (UAV)-based mapping the most commonly used monitoring tools^{26,27,28}. In the past years, several studies have shown that new methods and sub-meter resolution data can support a monitoring tool of trees at the level of individuals over large areas, thereby improving our knowledge on dryland trees and carbon stocks²⁹. However, such maps do not distinguish between an invasive shrub or a baobab, and merge every woody plant under the variable tree cover. Such tree cover maps are often used to proxy ecosystem services in a given area³⁰, although they are better suited to assess carbon stocks, climate change mitigation and wood products^{31,32}. The creation of maps that include information on specific tree species and their distribution represent a promising avenue for improving assessments of the ecosystem services provided by various trees as well as their contributions to local livelihoods³³.

Here we make use of a deep learning model being trained to identify the distinct crown shape of baobab trees in sub-meter resolution satellite imagery to create a database with the location and size of every adult baobab tree (crown size > 10 m²) across the arid and semi-arid Sahel (150–700 mm annual rainfall), from the Atlantic ocean to the red sea, an area spanning 11 countries and 1.5 million km². Using household survey data, we also document the associations between the presence of baobab trees and rural people's consumption of dark green leafy vegetables. Finally, we discuss the implications of establishing a publicly accessible database, containing such precise geospatial information on all individual baobab trees.

For this study we acquired satellite images covering the entire Sahel at 50 cm resolution during the early dry season³², a period where only *Adansonia digitata*, *Bombax costatum*, *Ceiba pentandra* and *Sterculia setigera* are large trees which have no or only few leaves. To avoid confusion between these species, we included the shadow of the distinctive branches in the training samples (Fig. 1c-d). We manually labeled

5013 trees used for training the model. The expert labeling was done in Senegal and Mali in regions visited by the authors, and guided by GPS-referenced field photos taken between 2010 and 2015. Only clear examples were trained. The model mapped ~ 2.8 million baobab trees over the entire study area (Fig. 1a). We used independent Skysat data (Fig. 1c-d) to count baobab trees in randomly selected areas, which was compared to our predictions and results in an underestimation bias of 27.1% (Fig. 2a). We subsequently split the mapped baobabs in three size classes (large > 150 m², medium > 70–150 m², and small 10–70 m²) and found that large trees can be mapped with a lower uncertainty (17.5%). High densities of baobabs are found in Senegal, Mali, and Sudan. The Kayes region in Mali had the highest density with up to 150 baobabs per km² (Fig. 1b), which was confirmed by local reports (Fig. S2).

Due to the high density of baobabs (Fig. 1b) and the availability of high quality auxiliary datasets, we selected Senegal to further study the distribution of baobab trees in more detail. We found 665,973 baobabs in Senegal of which 58.8% are small, 26.5% have a medium size, and 14.7% are large trees. Compared with a wall-to-wall assessment of all trees from all species²⁹, baobabs only account for 0.0009% of the number of trees in Senegal.

We then used household survey data from the DHS program (Demographic and Health Survey) from 387 rural household cluster records in Senegal to examine the relationship between rural people's consumption of dark green leafy vegetables, an important nutritious food group, and the abundance of baobabs. We used the consumption of dark green leafy vegetables (including also other leaves than baobab leaves) as an important sentinel food group, likely to be influenced by the abundance of baobab trees. The variables were recorded as a binary value (consumption/no consumption) in the past 24 hours for children (between 12 and 60 months). We found a significant positive association ($p < 0.01$) between the abundance of baobabs and the consumption of dark green leafy vegetables (Fig. 2b). No relationship was found if trees of all species were used²⁹, documenting that tree cover alone is not related to the consumption of dark green leafy vegetables in the Sahel.

By using the Google Open Building dataset that includes 8.4 million buildings in Senegal (Fig S3), we found that 78.5% of all rural households have at least one baobab tree within their immediate surroundings (1 km), and only 5.8% of households do not have baobab trees within a distance of 2 km (Fig. 2d). Moreover, most of the mapped baobabs grow in immediate distance to rural households (Fig. 2c) (here rural is defined as a settlement with less than 10,000 people).

We finally used a gradient boosted regression tree analysis to study the variables affecting the spatial distribution of baobabs (Fig. 3). With a total explanatory power of 79.8%, we found that climate factors dominate (62.1%), followed by proximity to rivers and human settlements, which may be interrelated (20.7%), and soil variables (17.2%). Note that climate factors are also interrelated with the presence of human settlements.

We acknowledge that a mapping at the 50 cm scale as presented here cannot currently be repeated on a frequent basis due to image cost and availability, thereby impeding the use of such work as a monitoring

tool. However, recent work has shown that cost efficient nanosatellites such as Planet or RapidEye are able to reliably map scattered dryland trees with a crown size $> 30 \text{ m}^2$ as individuals³⁴, which applies to most adult baobab trees (Fig. 4). Species information cannot be readily derived from those images, but a nanosatellite-based tree map can be combined with the benchmark baobab tree species map provided here to track the future status of known baobab trees. Removal, mortality, survival/recovery and even the health status of identified baobab trees can then be tracked in future times using low-cost images. The importance of a regular monitoring tool, not only for tree cover but single tree species, is highlighted by a recent study, which found a high death rate of old baobab trees in different African countries within the past decade³⁵.

Our study demonstrates the feasibility of mapping the precise distribution of individual tree species at a subcontinental scale. This information is crucial in times where human mismanagement and climate change cause the extinction of numerous tree species^{34,35}. Mapping of individual tree species at large scale creates economic opportunities, but inevitably also involves a danger in relation to over-exploitation of local resources. This is in particular problematic for areas where local people strongly depend on the resources provided by trees, which is the case for baobabs in West Africa^{14,15,19,36,37}. Here, a better understanding of where to conserve and invest in long-term sustainable use can support the development of rural communities and promote value chains^{28,36,37,38}. Nevertheless, regardless of the baobab example, the precise mapping of individual tree species is sensitive towards unsustainable economic exploitation, which may then impose a threat to these trees. National and foreign companies interested in selling products derived from fruits and leaves, do not always create opportunities for local livelihoods, but may also lead to disadvantageous situations, such as over-exploitation of resources and by-passing of local markets. In extreme cases, rare tree species possessing valuable timber could be located, extracted, and exported⁴¹. This adds a challenge to the concept of open data, and it is important that data, such as the database produced and presented in this study, is responsibly managed by national and local authorities, and used to strengthen and develop rural communities.

Materials and Methods

Concept. We deployed deep learning and sub-meter satellite images to segment baobab trees over the entire Sahel (150–700 mm mean annual rainfall), an area of 1.5 million km^2 . Here we made use of the unique shape of the baobab tree, which can be identified by human eyes, and consequently also by a deep learning model developed in a previous study²⁹. We manually labeled baobab trees in areas known to the authors and applied the model over the entire Sahel.

Satellite imagery. We utilized Maxar panchromatic and pansharpened Normalized Difference Vegetation Index (NDVI) images from the QuickBird-2, GeoEye-1, WorldView-2, and WorldView-3 satellites collected from 2002 to 2020 between November and March, with priority for later years and the early dry season. Images were obtained by NASA through the NextView License from the National Geospatial Intelligence Agency. More information on the data source, such as image dates, can be found in^{29, 32}.

Mapping baobab trees with deep learning. We used a deep learning based framework developed by²⁹ with the difference that²⁹ trained and mapped all trees regardless of species, whereas we mapped only baobab trees in this study. The framework utilizes a U-Net architecture with a Tversky loss function, and we added attention blocks for this study. Hyperparameters were set as follows: alpha = 0.45, beta = 0.55, augmentation = flip, flop, affine and perspective transform. First, we manually delineated 5013 baobab trees mostly in Senegal and Mali based on the satellite images. The delineation of training data was done in areas known to the authors from field visits over the past 3 decades, and baobabs were only used for training if the species were properly identified. In addition, we used several thousands GPS-referenced field photos from Senegal and Mali (Fig. 1g). Two unique features characterize baobab trees: the shape of the branches, which is also reflected in the shadow casted by the tree, and the fact that baobabs have little (Fig. 1b) or no leaves (Fig. 1e) during the dry season (November to June)⁴², causing a low NDVI value. The combination of these two features enables the identification of even small trees in the satellite images (Fig. 1g). To improve the results, we included both the tree crown and the shadow in the preparation of the training data and predictions. This implies that the segmented area is not the real crown size, but was used to classify trees in three classes: large (> 150 m²), medium (> 70–150 m²), and small (10–70 m²). We then trained the U-Net model with 900 epochs with 700 steps and identified and segmented baobabs across 1.5 million km².

Evaluation. To evaluate results, we used two independent datasets that had not been used for any of the optimization procedures. First, we randomly selected areas in which we predicted baobabs and purchased 50 km² Skysat multispectral (NIR, R, G, B) dry season images at 50 cm resolution. The frames have different sizes, related to the Skysat raw scenes. A total of 2830 baobabs were manually identified in the Skysat images, supported by Google Earth and Bing maps, and we compared these with the model prediction results using the Maxar images to calculate the error, defined as:

$$bias = \frac{|\sum_N (Y_{obs} - Y_{pred})|}{|\sum_N Y_{obs}|}$$

Results are shown in Fig. 2a, and the bias indicates an underestimation of 27.1%. The relatively high error can be explained by the use of only 2 bands, panchromatic and NDVI, and may be improved in future versions using multispectral bands, which however implies a considerable increase in data amount and processing time. Second, we used 255 GPS-recorded baobab trees from the Global Biodiversity Information Facility (GBIF)⁴³ and Flotrop databases⁴⁴ in Senegal and Mali. We filtered the records to match the study period and checked if the baobabs were correctly mapped. Here the underestimation bias was 38.1%. The higher error from the database can be explained by uncertainty from both sides related to position errors, but also that the dates may not match, considering that our mosaics include a mix of images from different years. Another important source of error is the tree size, which is not clear from the databases, and very young or small trees cannot be identified in the satellite images.

Settlement and Demographic and Health Survey (DHS) household survey data. Settlement data were produced by Google⁴⁵ and include each single building in Senegal (n = 8.4 million). The mapping was done using deep learning and sub-meter resolution satellite data. The data are freely available as vector files delineating each building (Extended Data Fig. 2). To separate rural from urban buildings, we formed settlement clusters by merging all houses that have a maximum distance of 200 m between buildings. Clusters with more than 10,000 people (using Global Human Settlement population data, GHS-Pop)⁴⁶ were defined as urban and below 10,000 people as rural, resulting in a total of 4.3 million rural settlements in Senegal. We then created buffer areas with a 2 km radius around the rural cluster centers and counted the number of baobab trees within these areas.

The demographic and health survey (DHS) dataset provides information on a range of socio-economic and health variables at the household level in Senegal⁴⁷, including people's food consumption in the past 24 hours. Households are grouped in clusters and for each cluster (usually corresponding to a village or community) a georeferenced point is given. For confidentiality purposes, this point is randomly displaced by 0–5 km for 99% of the clusters, and up to 10 km for the remaining clusters. In total, 2,845 household records are used based on the survey of 135 communities/villages during 2014–2019 within the rural region of Senegal. To define the area where the households can access woody products, we created a buffer area with a 5 km radius around the cluster points. We then counted the number of adult baobab trees and all woody plants with a crown area $> 3 \text{ m}^2$ within this area. We examined the correlation between the number of baobab trees and the consumption of dark green leafy vegetables by children (1–5 years), with the consumption variable recorded as a binary yes/no consumption of any dark green leafy vegetables within the last 24 hours. Here we split the total number of communities (or DHS clusters; n = 387) into two almost equal parts, reflecting communities where less than 10% of the surveyed households (n = 197) reported consumption of dark green leaves, vs. more than 10% (n = 190) reported consumption of dark green leaves.

Variables influencing the spatial distribution of baobab trees. We used a gradient boosted regression tree analysis to study the variables affecting the spatial distribution of baobabs. All variables were resampled to a common spatial resolution ($5 \times 5 \text{ km}$) and we used only grids with at least one baobab tree occurring. We used annual rainfall⁴⁸, annual average temperature⁴⁹, soil property from HWSD (The Harmonized World Soil Database)⁵⁰ and proximity to rivers and households as the potential environmental driving variable, to explain the distribution of baobab density across the Sahel. Soil property includes the soil silt content, sand content, pH in both the topsoil layer and subsoil layer. The information on proximity to river was generated as buffers along rivers. The proximity to human settlements was calculated as the average distance to the nearest human settlement inside each $5 \times 5 \text{ km}$ grid. The occurrence of human settlements was calculated by the number of settlements inside each $5 \times 5 \text{ km}$ grid. The total explanatory power of the model was 79.8%. The contribution of each variable to the total explanatory power provides information on the importance of factors determining the spatial occurrence of baobabs.

Declarations

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Author Contributions. KH, MB and RF conceptualized the project. CT, JS and SS prepared the satellite data. KH and PH identified the trees used for training the model. The codes were done by KH, AK, SL, FR, MM. KH and MB conducted the analyses and performed the visualization. BB and LR prepared the DHS survey data. MB and KH prepared the manuscript with support from all authors.

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Competing interest. The authors declare no competing interests.

Code availability. The tree detection framework based on U-Net is publicly available at <https://doi.org/10.5281/zenodo.3978185>. The R script for spatial analysing, boosted regression tree model and visualization can be found in GitHub. Please contact KH (ke.huang@ign.ku.dk) or AK (a k@di.ku.dk) for support and more information.

Data availability. Commercial very high-resolution satellite images were acquired through the NASA under the NextView Imagery End User License Agreement. The copyright remains at Maxar Inc. and redistribution is not possible. The derived products produced by this study will be made available upon

acceptance of the manuscript, gridded at 1x1 km resolution. Skysat images were purchased from Planet Labs and cannot be distributed. Tree species data from the Flotrop database can be downloaded at <https://doi.org/10.15468/oxunf1>. GBIF data are available under <https://www.gbif.org>. The shapefile of Google building data are available from <https://www.sites.research.google/open-buildings/>. The GHS-pop dataset can be accessed via https://ghsl.jrc.ec.europa.eu/ghs_pop2023.php. DHS survey data are available from <https://dhsprogram.com/>. The Chirps rainfall data are freely available at <https://www.chc.ucsb.edu/data/chirps> at 0.05-degree. The temperature data at 0.1-degree are ERA5-Land version of land surface temperature, which is available at the Climate Data Store at <https://cds.climate.copernicus.eu/>. The river shapefile is provided by FAO and available at <https://data.apps.fao.org/catalog/iso/b891ca64-4cd4-4efd-a7ca-b386e98d52e8>. The boundary file of Senegal is available at <https://gadm.org/maps.html>. The gridded soil property at 0.05-degree spatial is available at https://daac.ornl.gov/cgi-bin/dsviewer.pl?ds_id=1247. Human settlement dataset used for the Sahel is the 2.8 arcsec spatial resolution Global Urban Footprint dataset, which is available at https://www.dlr.de/eoc/en/desktopdefault.aspx/tabid-9628/16557_read-40454/.

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Figures

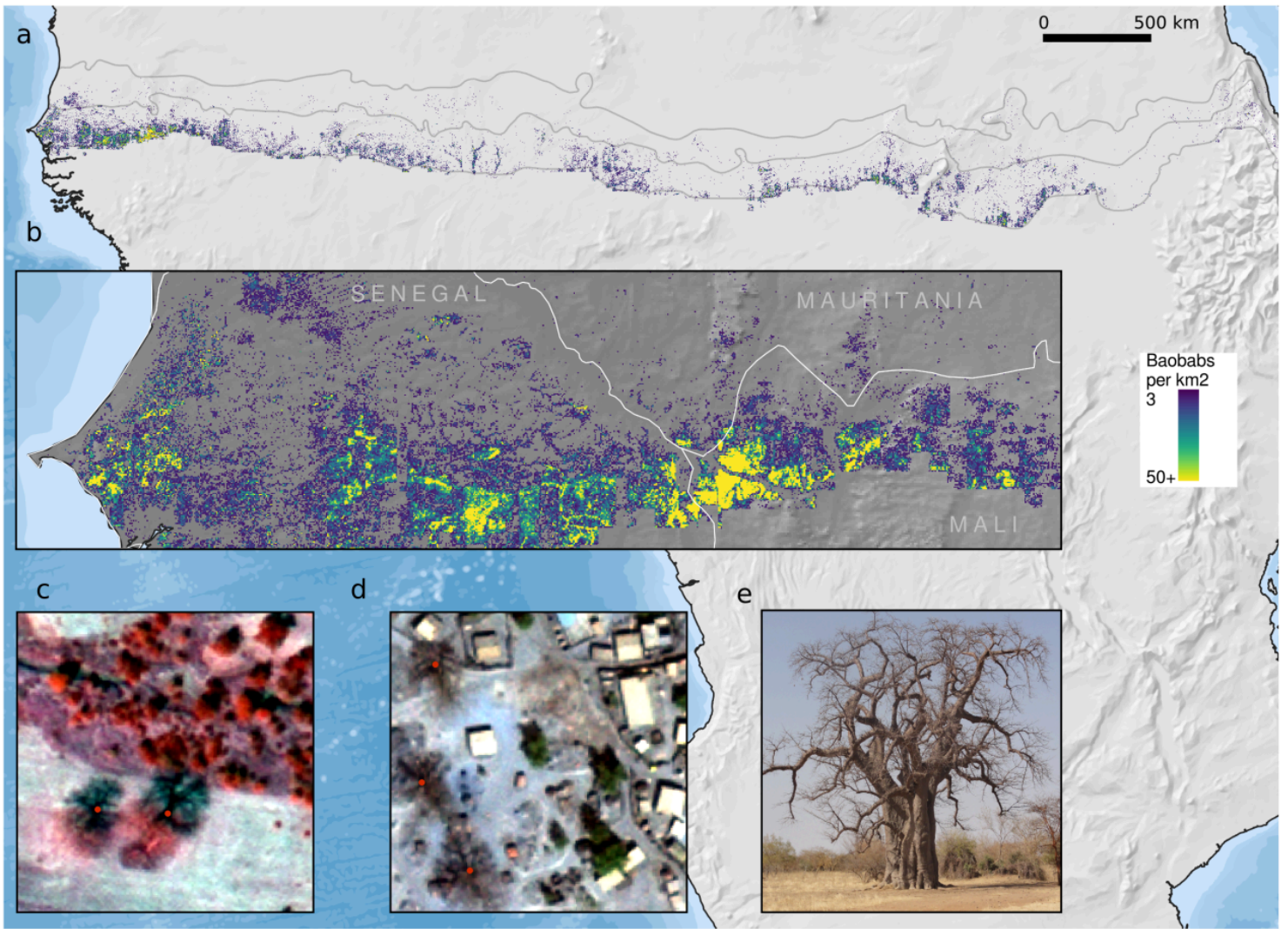


Figure 1

A wall-to-wall map of baobab trees in the Sahel. **a**, The map shows the numbers of mapped baobabs aggregated to 1×1 km scale ($n = 2,822,862$). The isohyets mark the 150, 300, and 700 mm year⁻¹ rainfall zones (from north to south), representing our study area. **b**, The zoom-in area shows high baobab densities in Senegal and Mali. **c**, The close-ups show baobabs in 50-cm Skysat images in false color (NIR, G, B) and **d**, true color (R, G, B). **e**, A photo of a baobab tree during the dry season taken in Senegal in 2012. The examples illustrate that baobabs have little or no leaves in the early dry season, and their branches have a distinct shape, which becomes even clearer from their shadows. Both features make baobabs distinguishable from other trees. See Fig. S1 for more examples.

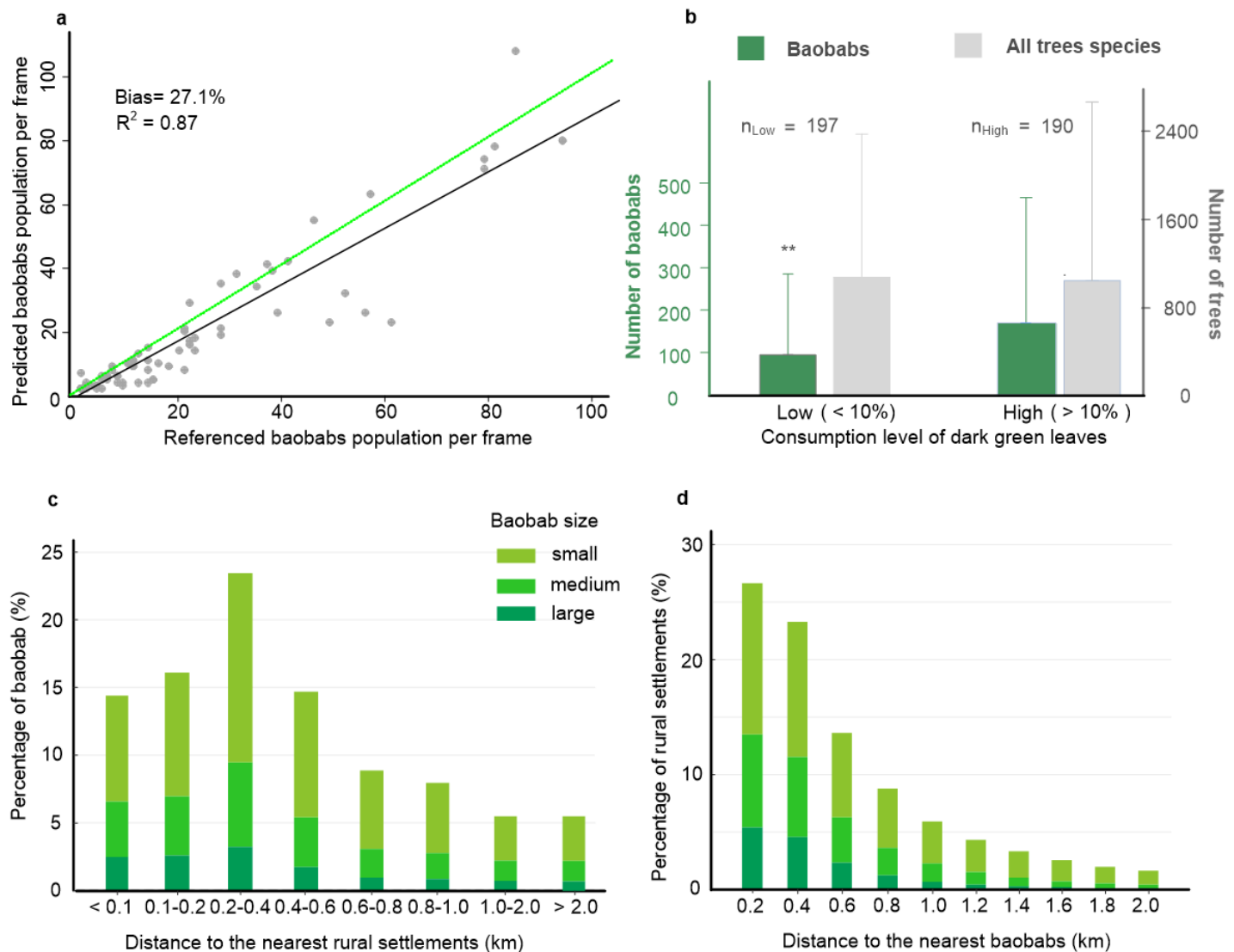


Figure 2

Mapping evaluation and relationships with rural households. **a**, The model predictions were evaluated by purchasing Skysat images in randomly selected areas of baobab predictions. We marked all baobabs ($n = 2698$) in 157 random frames and compared the number with the predicted baobab trees (see Methods). Each point represents a frame, and the x and y-axes show the number of counted and predicted baobabs per frame. The green line is the 1:1 line. **b**, DHS data on 387 rural household clusters in Senegal were split into two classes with an almost equal number of household clusters, reflecting clusters with high ($n = 190$) and low ($n = 197$) consumption levels of dark green leafy vegetables. The number of baobab trees in the surrounding areas of the surveyed DHS clusters (5 km radius) and also the number of all trees regardless of species from ref. 26 was compared across clusters with high vs low consumption of dark green leafy vegetables. The upper horizontal lines represent 75th percentiles of the data distribution and the filled bars denote the mean value. Significant ($p < 0.01$) differences from the t-test are marked with **. **c**, The percentage of baobabs that are within 2 km distance from rural settlements ($n = 4.3$ million) are shown as a function of distance. **d**, The percentage of settlements that

have baobabs within a 2 km distance is shown as a function of distance. The different colors in the bars reflect the contributions of the sizes of the trees, grouped into large, medium and small trees (see Methods).

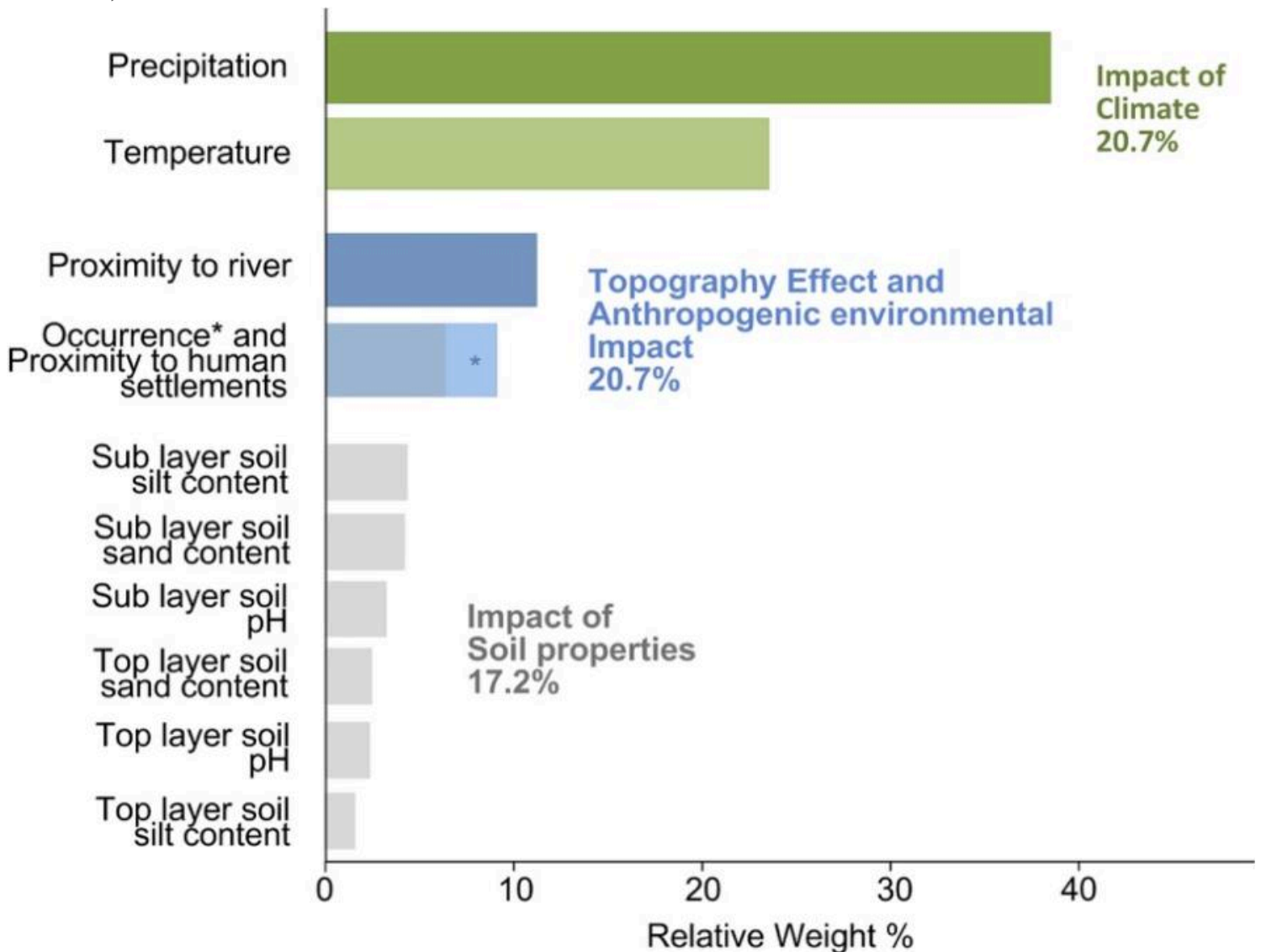


Figure 3

Variables affecting the baobab distribution. We used a gradient boosted regression tree to study how different variables impact the spatial distribution of baobabs; the total explanatory power was 79.8%. The variables were aggregated/resampled to 5×5 km grids ($n = 24,543$); only grids with at least one baobab were included. Precipitation is the annual mean, and temperature the mean of the daily values.

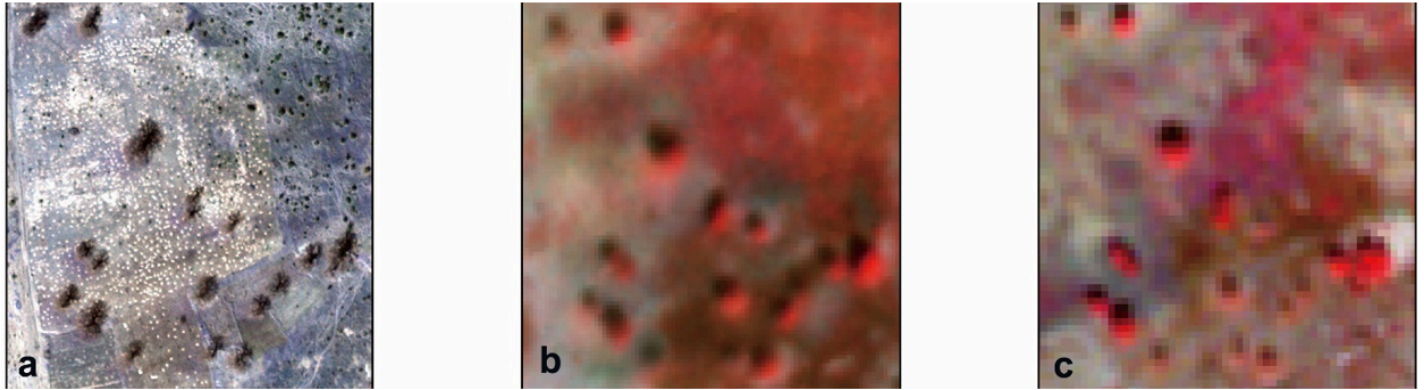


Figure 4

Baobab mapping with nanosatellites. **a**, A Skysat image at 50 cm resolution from 2020 shows the distinct pattern of baobab trees. **b**, The PlanetScope image at 3 m resolution from 2019 can be used to identify the trees, but the spatial resolution impairs species recognition. **c**, Same as (b) but for RapidEye at 5 m resolution from 2010. This comparison shows that this group of baobab trees has remained intact during 2010-2019. Skysat (image taken in January) is shown in true colors (R,G,B) and PlanetScope (taken in December) and RapidEye (taken in December) in false colors (NIR, G, B).

Supplementary Files

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