Nation-wide mapping of tree level carbon stocks in Rwanda

Maurice Mugabowindekwe
Københavns Universitet
Martin Brandt (martin.brandt@mailbox.org)
Københavns Universitet https://orcid.org/0000-0001-9531-1239
Jerome Chave
CNRS, Université Paul Sabatier https://orcid.org/0000-0002-7766-1347
Florian Reiner
Københavns Universitet
David Skole
Michigan State University https://orcid.org/0000-0002-8575-3540
Ankit Kariryaa
Københavns Universitet
Christian Igel
University of Copenhagen https://orcid.org/0000-0003-2868-0856
Pierre Hiernaux
Københavns Universitet
Philippe Ciais
Laboratoire des Sciences du Climat et de l'Environnement https://orcid.org/0000-0001-8560-4943
Ole Mertz
University of Copenhagen https://orcid.org/0000-0002-3876-6779
Xiaoye Tong
University of Copenhagen
Sizhuo Li
Københavns Universitet
Gaspard Rwanyiziri
University of Rwanda
Thaulin Dushimiyimana
Københavns Universitet
Alain Ndoli
International Union for Conservation of Nature
Valens Uwizeyimana
Department of Earth and Environmental Sciences https://orcid.org/0000-0003-0120-9837
Jens-Peter Lillesø

University of Copenhagen https://orcid.org/0000-0003-1418-3496
Fabian Gieseke
University of Münster
Compton Tucker
NASA
Sassan S Saatchi
University of California Los Angeles
Rasmus Fensholt
University of Copenhagen https://orcid.org/0000-0003-3067-4527

Article

Keywords:

Posted Date: June 1st, 2022

DOI: https://doi.org/10.21203/rs.3.rs-1536453/v1

Nation-wide mapping of tree level carbon stocks in Rwanda

Maurice Mugabowindekwe[1,2], Martin Brandt[1], Jérôme Chave[3], Florian Reiner[1], David L. Skole[4], Ankit Kariryaa[1,5], Christian Igel[5], Pierre Hiernaux[6], Phillippe Ciais[7], Ole Mertz[1], Xiaoye Tong[1], Sizhuo Li[1,8], Gaspard Rwanyiziri[2,9], Thaulin Dushimiyimana[1], Alain Ndoli[10], Valens Uwizeyimana[11,12], Jens-Peter Barnekow Lillesø[1], Fabian Gieseke[5,13], Compton J. Tucker[14], Sassan Saatchi[15], Rasmus Fensholt[1]

[1] Department of Geosciences and Natural Resource Management, University of Copenhagen, Copenhagen, Denmark
[2] Centre for Geographic Information Systems and Remote Sensing, College of Science and Technology, University of Rwanda, Kigali, Rwanda
[3] Laboratoire Evolution et Diversité Biologique, CNRS, UPS, IRD, Université Paul Sabatier, Toulouse, France
[4] Global Observatory for Ecosystem Services, Department of Forestry, Michigan State University, East Lansing, MI 48823, USA
[5] Department of Computer Science, University of Copenhagen, Copenhagen, Denmark
[6] Pastoralisme Conseil, Caylus, France
[7] Laboratoire des Sciences du Climat et de l'Environnement, CEA/CNRS/UVSQ/Université Paris Saclay, Gif-sur-Yvette, France
[8] Université Paris Saclay, Gif-sur-Yvette, France
[9] Department of Geography and Urban Planning, College of Science add Technology, University of Rwanda, Kigali, Rwanda
[10] International Union for Conservation of Nature, Kigali, Rwanda
[11] General Directorate of Land, Water, and Forestry, Ministry of Environment, Kigali, Rwanda
[12] Department of Earth and Environmental Sciences, Division of Forest, Nature and Landscape, KU Leuven. Celestijnenlaan 200E, B-3001, Leuven, Belgium
[13] Department of Information Systems, University of Münster, Münster, Germany
[14] Earth Sciences Division, NASA Goddard Space Flight Center, Greenbelt, MD 20771, USA
[15] Jet Propulsion Laboratory, California Institute of Technology, Pasadena, CA 91109, USA

Abstract

Trees sustain livelihoods and mitigate climate change, but a predominance of trees outside forests and limited resources make it difficult for many developing countries to conduct frequent nation-wide inventories. Here, we propose a rapid and accurate approach to map the carbon stock of each individual tree and shrub at the national scale of Rwanda using aerial imagery and deep learning. We show that 72% of the mapped trees are located in farmlands and savannas, and 15% in plantations. These non-forest trees account for 41% of the national carbon stocks. Natural forests cover 5% of the country and 11% of the total tree count, but comprise 59% of the national carbon stocks. The mapping of all trees facilitates any landscape stratification and is urgently needed for effective planning and monitoring of landscape restoration activities as well as for optimization of carbon sequestration, biodiversity and economic benefits of trees.

Introduction

Trees both inside and outside forests are the foundation of ecosystem structure and function (*1*). Individual tree traits such as size and spatial distribution are key determinants of ecosystem services such as carbon storage, climate regulation, food security, and fuel wood (*2,3*). Because of their strategic importance, countries across the globe regularly evaluate, quantify and monitor forests using field inventories as part of national forest monitoring systems (*4-6*). Forest inventories are the backbone to measurement, reporting and validation (MRV) for international climate change mitigation initiatives such as national level REDD+ (Reducing Emissions from Deforestation and Forest Degradation) (*5,6*), Sustainable Development Goals (SDGs) especially SDG no. 15 (*7*), the Paris Agreement (*8*), and the Bonn Challenge (*9*). In European countries, sample-based forest inventories are often accompanied by airborne

LiDAR campaigns, providing detailed information on the carbon stocks of forests. However, field inventories and LiDAR campaigns are expensive and labour-intensive (*4*), resulting in trade-offs between accuracy, reproducibility, and the frequency of reporting. In developing countries, financial and human resource constraints limit the coverage and frequency of the field inventories.

This is particularly problematic for many African countries, where LiDAR data are not available across a variety of landscape types, ranging from savannas, woodlands, sub-humid and humid forests, to highly fragmented, small scale agro-ecosystem mosaics. This complexity makes it difficult to scale from sparsely sampled plots to the national scale. Indeed, many of these landscapes are dominated by non-forest trees which are very difficult to map with traditional methods (*10,11*).

Inventories and existing large-scale tree cover maps (*12-14*) often omit an accurate accounting of trees growing outside forests, which is related to differences in forest definitions, mapping techniques, and the complexity of the environment (*15,16*). This leads to incomplete censuses of trees and their related benefits and services at a national scale (*16*). More specifically, these inaccuracies aggravate the existing uncertainties in estimates of both national carbon stocks and emission reference levels (*17,18*), and may confound the relative contributions of emissions attributed to forest degradation or deforestation (*19*). In turn, these inaccuracies in tree mapping hinder natural resource management and climate change decision-making and policy-formulation (*20*). These challenges are especially significant in the tropics, where a large number of important landscape restoration activities and projects have been initiated without fully functional monitoring systems in place (*21,22*).

In Africa, the alarming rate of tree cover loss has spurred both political and economic incentives for the restoration of tree-dominated landscapes (*14,23,24*). Ongoing initiatives include the African Forest Landscape Restoration Initiative (AFR100), with more than 30 African governments making commitments to restore at least 100 million hectares of land across the continent by 2030 (*21*), the African Resilient Landscapes Initiative (ARLI), the Africa Low Emissions Development Strategies (*25*), among others. However, there is currently no accurate and regularly updated monitoring platform to track the progress and biophysical impact of these initiatives (*26*). Here, we propose an approach to rapidly and accurately map individual trees and quantify their carbon stocks at national scale, and illustrate how some of the above-mentioned challenges can be addressed with efficient new monitoring tools, using Rwanda as a case study. The country has been selected based on two key criteria. First, it is a signatory to most of the above-mentioned global climate mitigation initiatives and regularly reports on their implementation. Rwanda had targeted at least 30% of the country to be covered by forests by the year 2020 (*27,28*), which was achieved in 2019 (*29*). Under the Bonn Challenge, the country has also committed to restore 2 million hectares by 2030, or 81% of the country's surface area (*30*). Second, although the country is small in size, it represents contrasting landscape types and land uses: drylands dominated by savannas and pastureland, plateaus dominated by agriculture, and humid highlands dominated by natural forests and protected areas, including tropical montane rainforest (*31, 32*).

Recently, (*15*) demonstrated that advanced machine learning techniques are able to map individual trees over large dryland areas. However, the analysis used costly commercial satellite images, was limited to isolated trees in savannas excluding small trees with a crown area below 3 m², and did not cover other complex and heterogeneous ecosystems such as woodlands and forests. Here, we use publicly available aerial images and map the crown size and carbon stock of each individual tree in Rwanda, regardless of ecosystem type. We suggest a rapid, reproducible and highly accurate way to upscale field inventory data collected at the level of individual trees to the entire country. This will allow tree inventory reports to be of unprecedented accuracy, and can support MRV of climate change mitigation initiatives. The repeated reporting at the level of individual trees also enables the distinction between tree harvest, deforestation and forest degradation, which can then be linked to land use and ownership, payment of ecosystem services, logging permit issuance and compliance, among other benefits.

Results

Comprehensive mapping of individual trees at national scale. Aerial images with a spatial resolution of 25x25 cm were acquired in 2008 covering the entire country (*33*). A deep learning model was trained using 97,574 hand-

labeled tree crowns and then used to map 357,437,805 trees with a crown size larger than 0.25 m^2. The crown area threshold was set based on visual inspection of the images, as trees of this size are still clearly visible (Fig. 1). To separate clumped crowns, we developed a post-processing method to determine the crown centers in the predictions, assuming that tree crowns have round shapes. The method then relabels the crown predictions based on weighted distances to the identified crown centers (see Methods).

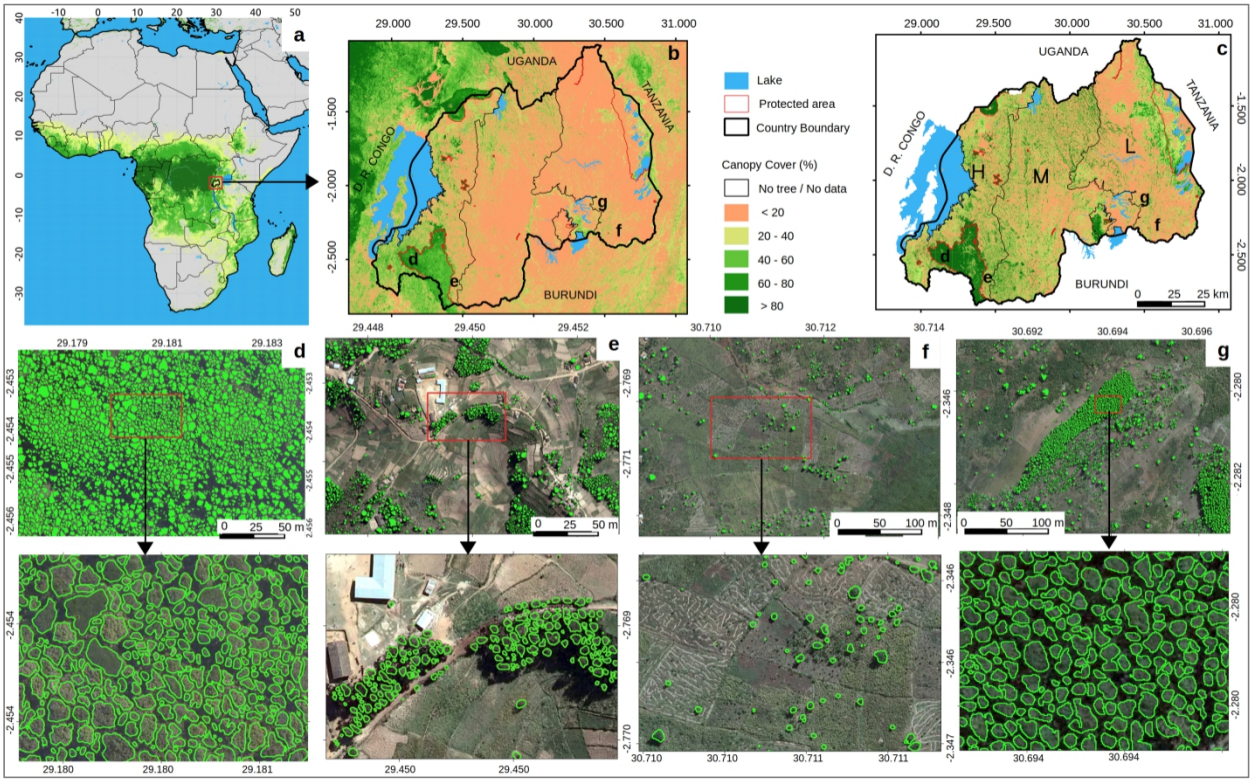


Fig. 1. Mapping of individual trees inside and outside of forests in Rwanda. **a,** Tree cover from a previously published global tree cover map using Landsat data (*12*) in Africa and **b,** in Rwanda. **c,** Country-wide tree cover estimated by deep learning from 0.25 m resolution aerial imagery from 2008 (L: Lowlands, M: Midlands, H: Highlands). **d-e,** Examples of individual tree crown mapping in **d,** tropical montane rainforest; **e,** *Eucalyptus* plantations; **f,** farmlands; and **g,** *Pinus* plantations. An example of previously published manual forest area delineations is shown in Extended Data | Fig. 1.

Following a manual delineation, which is also based on the same aerial images as used here and includes forest patches down to a size of 0.25 ha (*34*; Extended Data | Fig. 1), we stratified the landscapes into natural forest, *Eucalyptus* plantations (excluding isolated *Eucalyptus* trees in farmlands and urban areas), non-*Eucalyptus* tree plantations, farmlands, urban areas (including all the built-up areas), as well as savannas and shrublands (see Methods). We further subdivided each class in protected and non-protected areas (*31*). Overall, our results show a dominance of trees with small crown sizes of 0.25-3 m^2 which account for 48.2% of the mapped trees, followed by crown sizes of 3-15 m^2 which account for 44.6% of the trees. Related to our land stratification, these two crown size ranges are dominant in farmlands and *Eucalyptus* plantations (Fig. 2a,b). Trees of the largest crown size class (crown sizes > 200 m^2) are very scarce and mainly found in natural forests which dominate areas under protection.

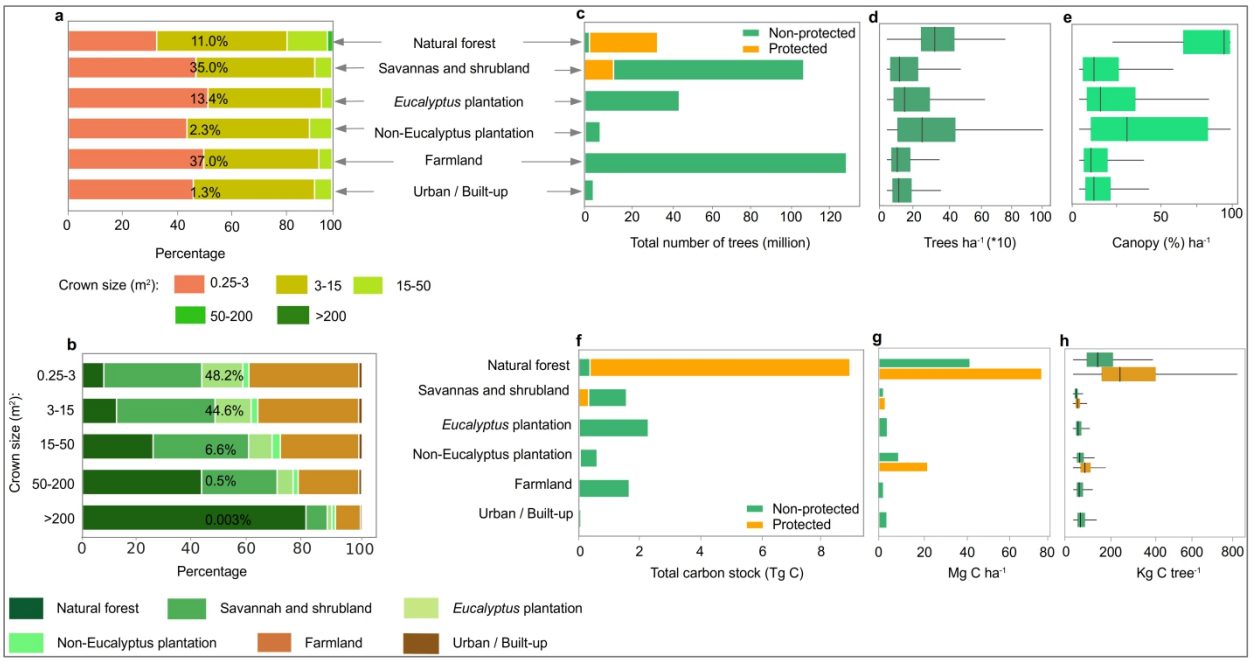


Fig. 2. Tree counts, crown areas and carbon stocks for different land cover/use types. a, Percentage covered by different crown sizes in each land cover/use type. The percent number shows the contribution of the land cover/use type to the total area. Crown sizes >200 m^2 comprise only 0.003% of the total tree count, making the class barely visible. **b,** Percentage covered by each land cover/use type in different crown size categories. **c,** Total count of trees by land cover/use. **d,** Boxplot showing the average number of trees per ha by land cover/use type. **e,** As **d** but for canopy cover. **f,** Total estimated carbon stock per land cover/use type (see Methods for uncertainties and error propagation), **g,** barplot showing the average carbon density per ha per land cover/use. **h,** Boxplots showing the average carbon stock per tree per land cover/use. Number of trees = 357,437,805.

Table 1. Tree counts in the major landscape types of Rwanda

Landscape type	Biophysical and climatic characteristics	Area and tree count (total & %)	Trees ha^{-1} - median (5^{th} - 95^{th})	Canopy cover (%) ha^{-1} - median (5^{th} - 95^{th})
Lowlands	- Elevation range: 900-1,500 m - Mean annual rainfall: 600 - 2000 mm - Mean annual temperature: 17 - 24°C - Dominant tree-dominated cover type: savanna and tree plantations	- Area: 984,575 ha (38.9%) - Tree count: 95,071,194 (26.6%)	53(0-350)	6.2(0-54.4)
Midlands	- Elevation range: 1500-2000 m - Mean annual rainfall: 1300-2200 - Mean annual temperature: 14 - 24°C - Dominant tree-dominated cover type: tree plantations	- Area: 1,084,908 ha (42.8%) - Tree count: 157,941,607 (44.2%)	86(8-478)	10.9(0.7-80.7)
Highlands	- Elevation range: 2000-4,507 m - Mean annual rainfall: 1800-2300 mm - Mean annual temperature: 8 - 21°C - Dominant tree-dominated cover type: tropical montane rainforest and forest plantations	- Area: 463,382 ha (18.3%) - Tree count: 104,425,004 (29.2%)	165(7-632)	20.4(0.3-100)

Tree counts and densities for different landscape types and land uses. Elevation and rainfall are key determinants of ecosystem structure in Rwanda (*31,32*) and are closely related with the distribution of trees (Table 1; Extended Data | Fig. 2). The highlands cover the smallest area of the country (18.3%) but have the highest tree density and canopy cover. They are also home to the largest tropical montane rainforest of the country, located inside a protected area, the Nyungwe National Park in the South-West. Protected forests in highlands account for 9.5% of the total mapped trees and 42.5% of the national carbon stock.

We show that 11% of the mapped trees are located inside natural forests, and the largest number of trees are located in farmland (37%). Specifically, natural forests have 39.3 million trees, with a median (5^{th}-95^{th} percentiles) density of 298 (42-580) trees ha^{-1}, and a median canopy cover of 96% (1.8-100%). Farmlands have a median tree density of 63 (4-411) trees ha^{-1} and a median canopy cover of 7.6% (0-57.4%). *Eucalyptus* plantations account for about 48 million trees (~13.4% of the total mapped trees), a median density of 109 (9-598) trees ha^{-1}, and median canopy cover of 13.9% (0.7-85.1%). The low canopy cover can be explained by the inclusion of bare areas manually delineated as plantation areas (Extended Data | Fig. 1). Non-*Eucalyptus* tree plantations have 8.3 million trees (~2.3% of the total mapped trees), a median density of 219 (11-670) trees ha^{-1} and a median canopy cover of 31.5% (0.9-100%). Urban areas have 4.5 million trees (~1.3% of the total mapped trees), and a median density of 72 (5-429) trees ha^{-1}. Savannas and shrublands account for 125.1 million trees (~35% of the total mapped trees), with a median density of 77 (0-478) trees ha^{-1} and a median canopy cover of 9.6% (0-72.7%). Overall, trees outside of natural forests cover 318.1 million trees, of which 41.6% are in farmlands. The quantification of non-forest trees depends on how forests are defined. If we would consider both natural forests and tree plantations as forest, 73.3% of the trees in Rwanda would be considered as trees outside forests. Using our own tree cover map and consider areas with canopy cover above 25% (10%) as forest, 53.9% (31.8%) would be trees outside forests.

The importance of protected areas for tree density and count is worthwhile to note. Although they cover only 9% of the country, they have 52.1 million trees (11% of the total mapped trees) with the highest median tree density of 206 (0-553) trees ha^{-1} and median canopy cover of 44.1% (0-100%). Overall, we show that 20.8% of Rwanda was covered by trees (canopy cover) in 2008. Note that understory trees are not visible in aerial/satellite images (see Methods).

Carbon stocks estimated for individual trees. We conducted a field campaign in December 2021 and measured 793 trees in the natural forest, and also used 10,591 measurements of non-forest trees from (*35*), as well as 952 non-forest trees from (*36*) to estimate the stem diameter from the mapped crown sizes via allometric equations. We then estimated the above-ground carbon stocks for each tree using existing equations (see Methods). We established biome specific relationships and report here the combined results from (*37*) for natural forest; (*38*) for *Eucalyptus* and non-*Eucalyptus* plantations, farmlands, and urban areas; and (*36*) for savannas and shrublands. For each biome, we validated the results with data from the Rwanda National Forest Inventory (NFI) from 2013/2014 as well as with field measurements from Kenya and Rwanda (see Methods). From these field data, we estimate an overall area weighted C stock uncertainty of 16.9% at national scale: 5.9% for farmlands, 18.9% for savannas and shrublands, 26% for natural forests, and 52.6% for plantations (see Methods for sources of uncertainties). The high uncertainty for plantations can be partly explained by the time difference between images and field data and the inaccuracies in the manual delineation of plantation areas (Extended Data | Fig. 1). We estimate a total of 34.9 Tg of dry matter content from stems, branches and leaves of the mapped trees across the country, which represents an equivalent of 16.4 Tg of above-ground carbon stocks. For areas outside the natural forests, we estimate 7.0 Tg C, which is 42.3% of the total national carbon stocks and slightly lower than NFI estimations (8.4 Tg C). Farmlands have a total estimate of 3.5 Tg C corresponding to 21.3% of the national C stock with a C density of 3.0 (0.1-9.1) Mg C ha^{-1}. Urban areas have 0.1 Tg C corresponding to 0.9% of the national C stock with a C density of 4.0 (0.2-11.8) Mg C ha^{-1}. *Eucalyptus* plantations comprise a total estimate of 1.1 Tg C corresponding to 6.8% of the national C stocks, with a C density of 4.2 (0.2-12.6) Mg C ha^{-1}. These low estimates can be explained by the fact that regular harvesting keeps the trees young (*39*) in addition to sparse tree planting practices in some cases (*40*). Non-*Eucalyptus* plantations have a total estimate of 0.3 Tg C corresponding to 1.9% of the national carbon stocks, with a C density of 10.0 (0.3-29.3) Mg C ha^{-1}. Savannas and shrublands have 1.9 Tg C corresponding to 11.7% of the national C stock with a C density of 2.4 (0.0-7.4) Mg C ha^{-1}. For natural forests, we estimate a mean C density of

102.8 Mg C ha^{-1} for areas where field data are available (i.e. Nyungwe tropical montane rainforest in South-west of Rwanda), which is lower than the field measurements of 139 Mg C ha^{-1} (*41,42*), possibly due to trees from lower layers not being visible from above. Overall, we estimate that 58.7% of the total national carbon stocks are in natural forests with a total estimate of 9.5 Tg C and a C density of 75.9 (3.6-142.1) Mg C ha^{-1}.

The highlands have an overall estimate of 8.7 Tg C with mean C density of 18.8 (0.1-102.8) Mg C ha^{-1}. The midlands have a total estimate of 5.3 Tg C with mean C density of 4.9 (0.2-10.8) Mg C ha^{-1}, while the lowlands contain a total estimate of about 2.4 Tg C with mean C density of 2.8 (0.0-8.6) Mg C ha^{-1}. Overall, our results show that carbon stocks highly increase with both increase in density and cover of large trees, compared to an increase in small trees (Extended Data | Fig. 2). Using our own tree cover map and considering areas with a canopy cover above 25% (10%) as forest, 28.9% (16.9%) of the national C stocks would be stored in trees outside forest.

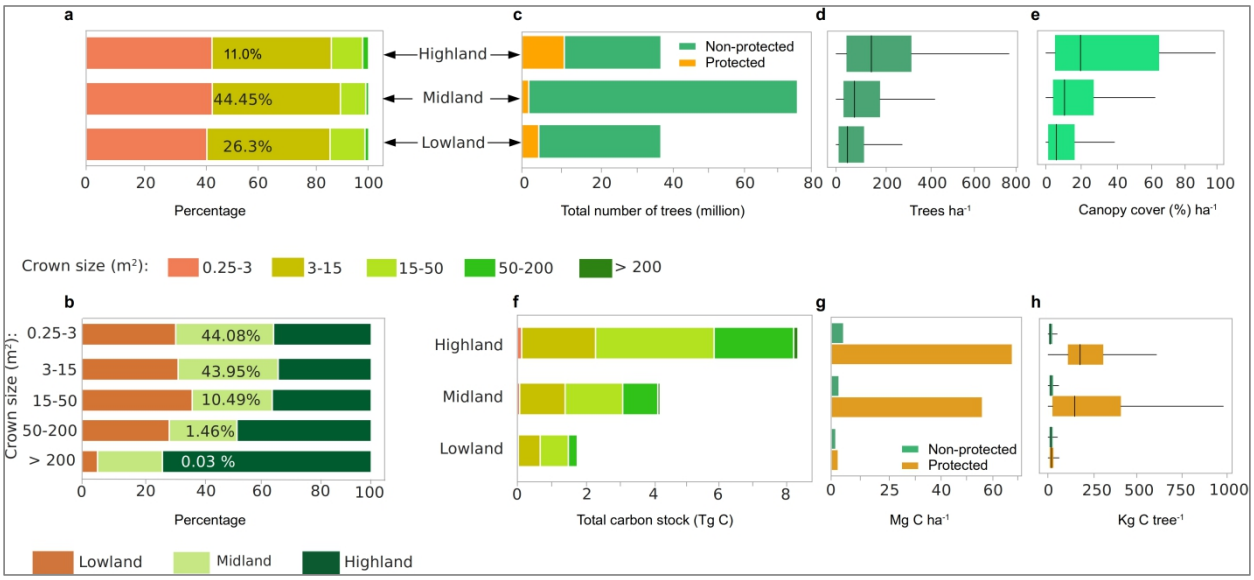


Fig. 3. Tree properties of different landscape types. a, Percentage covered by different crown sizes in each landscape type. The percent number shows the contribution of the landscape type to the total area. **b,** Percentage covered by each landscape type in different crown size categories. **c,** Total count of trees by landscape type. **d,** Boxplot showing the average number of trees per ha by landscape type. **e,** Same as **d** but for tree cover. **f,** Total estimated carbon stock per landscape type. **g,** Barplots showing the distribution of average carbon stock per ha per landscape type, and **h,** boxplots showing the average the carbon stock per tree per landscape type.

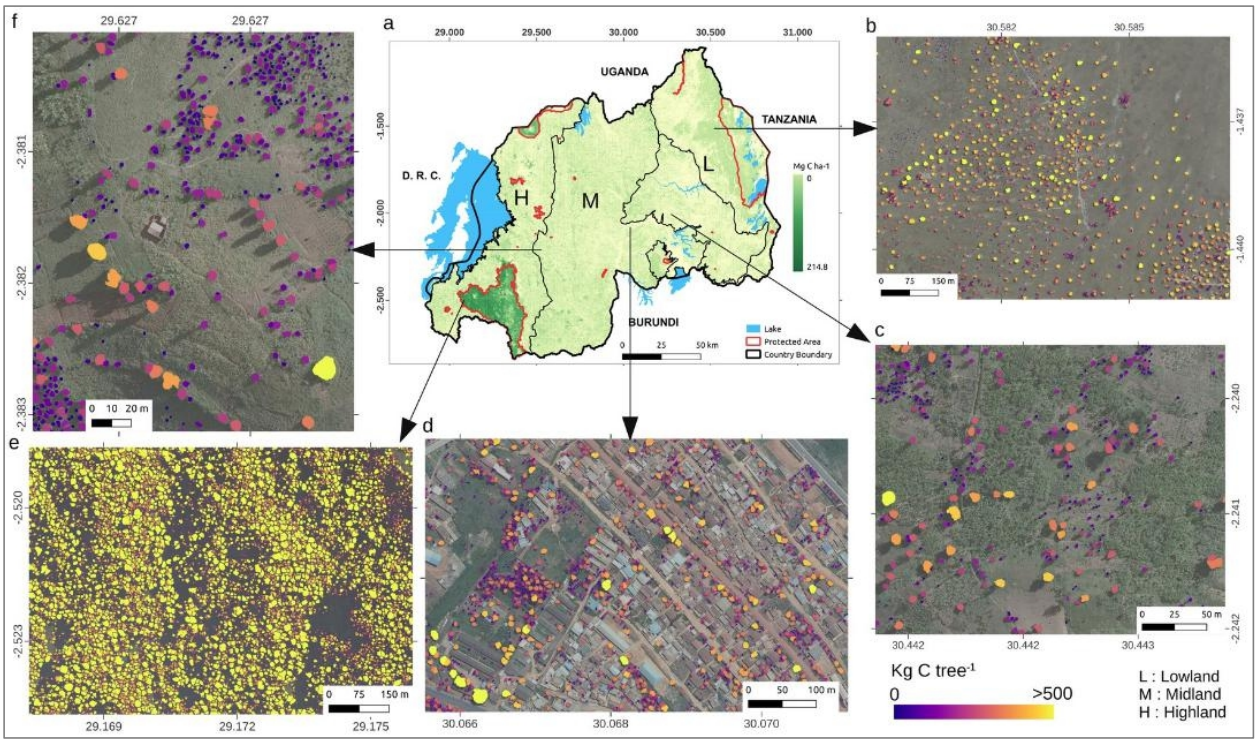


Fig. 4. Above-ground carbon stocks at tree level in Rwanda. a, Spatial distribution of the estimated carbon stock across the major landscape types. **b-f,** Examples of estimated carbon stock per individual tree in, **b,** wooded savanna, **c,** farmland, **d,** Kigali city, **e,** the tropical montane rainforest in the Nyungwe National Park, and **f,** in tree plantations.

Discussion

We report on a country-scale comprehensive mapping of individual trees both inside and outside forests for Rwanda, a country that spans a wide range of African landscapes: natural forest - including tropical montane rainforest, savannas and shrublands, tree plantations (including young plantations and coppices), agroforestry trees in farmlands, and isolated garden trees. Using aerial images and deep learning, we have demonstrated that we are able to quantify the spatial distribution and carbon stock of all trees and shrubs of the country, down to crown sizes as small as 0.25 m^2.

Assessments and reporting schemes of tree resources at country scale are limited by poor data quality and ambiguous or inconsistent definitions of land cover and land use types (*20,43*). Forests have been defined differently depending on location, measurement protocols, and landscape contexts. When forests are specified as continuous tree cover at a given mapping resolution, the underlying definition and the quality of the data product are essential to understand precisely what is being mapped. For instance, at medium spatial resolution, tree cover products may include only continuous clusters of trees of a certain size, and may exclude shrubs and isolated trees. Ambiguities and uncertainties also result from differences in the quality of the data (*12*). A previous work has overestimated the extent of forests by the inclusion of shrubs and bushes as forestland (*44*). Uncertainties in tree cover estimates propagate to estimations of carbon stocks, resulting in large uncertainties in existing biomass and carbon estimates and maps (*45*, Extended Data | Fig. 4).

This analysis presents an assessment of all trees, aside the assessment of their cover, density or land use, allowing for an accurate and independent quantification of the woody resources and carbon stocks. Thus, another major advance of the present study is that our carbon stocks are not merely proxy-based estimates per unit area, as it was the case of previous work. Rather, we map individual tree allometric parameters, especially tree crown area, and

calculate tree carbon stocks for each tree, an approach that previously was only possible with spatially limited field inventory or LiDAR data (*35*). Most of allometric scaling from a tree parameter to biomass or carbon involves non-linear relationships, where the size class distribution of trees matters for the final estimate of landscape carbon stocks. This large national-scale analysis provides the distribution of tree sizes and thereby is directly useful for application with standard or local allometric models.

Furthermore, the ability to map all trees makes our assessment independent of forest, tree cover and land use definitions. Reporting carbon stocks based on individual trees would solve important uncertainties caused by definitions, methods, data sources, and spatial resolution (*20*). Our example shows that even a very detailed manual forest delineation approach missed 38.2% of the isolated trees in Rwanda, which account for 22.2% of the national carbon stocks and likely a larger fraction of growing stocks. With results as presented here, management and conservation decision-making can be more targeted by discriminating various types of tree systems under specific conditions and in specific locations. Our approach therefore could support management of a broad array of tree-based systems such as agroforestry and farmer managed regeneration, as well as catalyze important cross-sector management strategies inclusive of Agriculture, Forestry and other Land Use (AFoLU). A focus on AFoLU provides a way to simultaneously manage both emission reductions and removals of greenhouse gases (*46*). Integrating non-forest trees along with trees inside forests in environmental conservation initiatives could be an opportunity to expand the scope of ongoing climate change mitigation and adaptation efforts, such as various approaches to REDD+ and the Bonn challenge for forest restoration by also accounting for trees not included in standard forest assessments (47). Our methods would also provide much more effective, accurate, and regular monitoring, though this will not solve the inherent problems in REDD+ of measuring emission reductions against forest reference levels and counter-factual business as usual scenarios (*17*).

We can draw on a common concrete example of the value of discriminating tree-system types by looking at activity data on forest area change. If only forest area or tree cover are reported, a cleared forest that is replaced by newly planted trees might readily be treated as no net change, ignoring the loss in carbon in these areas during their clearing. Interestingly, 54.2% of the mapped trees in Rwanda are plantations. Most of these trees were part of Rwanda's phased out vision 2020 (*28*) and currently part of the Bonn Challenge, but their frequent harvest and replanting keep their carbon stocks very low (3.4 Mg C ha^{-1}; 5.1 Tg C). This is contrasted by high numbers of natural forests (11% of national tree count) which make up only 4.9% of Rwanda but store 58.7% of the national carbon stocks (75.9 Mg C ha^{-1}; 9.5 Tg C, Extended Data | Fig. 8). While previous governmental programs aimed at maximizing tree cover, results like shown in this study with the ability to attribute individual trees to their respective land cover and use, can help to revise ongoing initiatives towards maximizing the sequestration of carbon.

Obtaining accurate individual tree maps depends on the availability of high-resolution satellite or aerial images. While these data exist for many African countries, they are often old, and have not been digitized. Sometimes also data access is restricted even for research (*48*), because images were acquired in the frame of sensitive information such as land tenure or construction planning, and the data access rights remain with custodian institutions. Here we show the benefits of such data for environmental applications, and how allocation of financial resources to their acquisition can efficiently serve landscape monitoring and restoration efforts by providing more and better information to support the monitoring, reporting and verification (MRV) efforts. In addition to directly supporting national climate change mitigation efforts, accurate tree maps promote better understanding of the spatial distribution and abundance of trees in relation to biophysical and climatic factors such as rainfall, temperature and elevation (Extended Data | Fig. 2). The value of this is that climate change mitigation and adaptation actions can be readily integrated into existing broad-based forest and sustainable land management plans and objectives.

We acknowledge that a satellite-based approach cannot resolve the full range of crown sizes in forests due to overlapping crowns, and also the conversion of crown area to carbon stocks includes uncertainty (*35,37,45*) (see Methods). However, our results are key to a better understanding of the structure and functioning of wooded ecosystems, and vital for the development of informed regulation and monitoring policies for site- and ecosystem-based interventions. To reduce uncertainty, future versions of the proposed method should include more localized field inventory databases that allow for more local biome-specific allometric conversions, as well as integrate tree

height estimations from field and airborne LiDAR surveys. Ideally, national inventories are coupled with results such as those presented here to identify systematic bias and optimize the upscaling from field plot information to country scale.

Analyses as presented here quantify existing tree resources, and provide an example of an approach that empowers countries to quantify carbon stocks at the level of individual trees (Fig. 4). Having this capability is important to a range of applications including monitoring of forest landscape restoration, tree plantation survival rate, forest demography: dynamics of mortality and recruitment, tree-dominated land ownership, payments for ecosystem services, issuance of concession permits and tracking compliance, among other benefits. Therefore, we emphasize the inclusion of funding for regular high resolution aerial/satellite imagery along with localized field inventory databases in development packages. We also highlight the relevance of all trees for conservation and protection efforts, and encourage that trees outside forests are considered as equally important as trees in forests.

Methods

Aerial images. We use publicly available aerial images of Rwanda at 0.25x0.25 m resolution, collected in June - August of 2008 and 2009. The images were acquired from 3000 meter altitude above ground level, initially with a mean ground resolution of 0.22x0.22 m pixel size, using a Vexcel UltraCam-X aerial digital photography camera (*33*). They include a red, green, and blue band stored under 8 bit unsigned integer format. The aerial images cover 96% of the country, and the remaining 4% were filled by satellite images from WorldView-2, Ikonos, Spot, and QuickBird satellite sensors which are part of the publicly available dataset.

Environmental data. We use locally available climate data: mean annual rainfall, mean annual temperature, and elevation data (10x10 m resolution) to assess relationships between tree density, crown cover and environmental gradients. We also use land cover data to extract the spatial extent of plantations, forest, farmland, and urban areas, for our stratification. Climate data was obtained from the Rwanda Meteorological Agency as daily records from 1971 to 2017. The national forest map was manually created in 2012 using on-screen digitising techniques over the 2008 aerial images (*34*). A forest was defined as "a group of trees higher than 7 m and a tree cover of more than 10%, or trees able to reach these thresholds in situ on a land of about 0.25 ha or more" (*49*). A shrub was defined as "a group of perennial trees smaller than 7 m at maturity and a canopy cover of more than 10% on a land of about 0.25 ha or more". The forest dataset was composed of 105,690 forest polygons, classified as either natural forest (i.e. closed natural forest, degraded natural forest, bamboo stand, wooded savanna, and shrubland), or "forest plantations" (i.e. *Eucalyptus spp*. - Eucalyptus, *Pinus spp*. - pine, *Callitris spp.* - callitris, *Cupressus spp*. - cypress, *Acacia mearnsii spp.* - black wattle, *Acacia melanoxylon* - melanoxylon, *Grevillea robusta* - grevillea, *Maesopsis eminii* - maesopsis, *Alnus acuminata* - alnus, *Jacaranda mimosifolia* - jacaranda, mixed species - mixed, and others (Extended Data | Fig. 9). We separate shrubland from natural forest and merged it with savanna into the class "savannas and shrublands". We further separated tree plantations and grouped them into *Eucalyptus* and non-*Eucalyptus* plantations. Then, a farmland map was acquired from the Rwanda Land Management and Use Authority (RLMUA) (*50*), and overlaid with the 2012 forest cover map as a reference to clean the overlapping parts, under an assumption that the overlap is due to land use dynamics. Finally, a layer marking urban areas was acquired from RLMUA as well, and the same pre-processing step as done for farmlands was applied. The combination of the land cover datasets resulted in our stratification scheme with 6 classes: natural forests, savannas and shrublands, *Eucalyptus* plantations, non-*Eucalyptus* plantations, farmland, and urban / built-up.

Mapping of individual trees using deep learning. We used the open-source framework developed by *ref. 15* to map individual tree crowns. The framework uses a deep neural network based on the UNet architecture (*51,52*). We trained the network using 97,574 manually delineated tree crowns spread over 103 areas/bounding boxes representing the full range of biogeographical conditions found across Rwanda. To cope with the challenge of separating touching tree crowns, we used a higher weight for boundary areas between crowns, as suggested in *ref 15* and *ref. 51*. Crown sizes in the predictions were found to be 27% smaller as compared to the manual delineations within the 103 training areas, which is caused by the applied boundary weight that emphasizes gaps between tree crowns. Therefore, to calculate the real canopy cover, we extended each predicted tree crown by 27% and dissolved

the touching crowns into continuous features. Furthermore, we developed a post-processing method that separates clumped tree crowns and fills any gap inside a single crown (Extended data | Fig. 7). Our post-processing method determines the crown centers in the model predictions assuming that tree crowns have a round shape. The method then relabels the model predictions based on weighted distances to the identified crown centers. We counted single tree crowns for each hectare presented here as tree density, and the percentage of each hectare covered by the extended tree crowns as canopy cover.

Allometry for biomass and carbon stock estimation. Generally, allometric equations define a statistical relationship between structural properties of a tree and its biomass (*53, 54*). In our case, we assume a relationship between the crown area and AGB, which varies between biomes (*35*). Since destructive AGB measurements are rare, we established biome specific relationships between crown diameter (CD) derived from the crown area (CD = 2*√(Crown area /π)) and stem diameter at breast height (DBH) (E1,E4). DBH has been shown to be highly correlated with AGB (*36,37,45,53,54*). We then used established relationships from literature to derive AGB from DBH for savannas and shrublands (E2), tree plantations (E3), and natural forests (E5). AGB was predicted for each tree and summed for 1 ha grids to derive AGB in the unit Mg per ha. Values were multiplied by 0.47 (*55,56*) to derive above-ground carbon (AGC). Summed numbers over land cover classes are considered as carbon stocks. The bias as reported here was calculated following the approach from *ref. 35* reporting relative absolute values.

For trees outside natural forests, we used the database from *ref. 35* including 10,591 field-measured trees from woodlands and savanna plus 952 samples from agroforestry landscapes in Kenya (*36*) to establish a linear relationship between CD and DBH (Extended Data | Fig. 3a). A major axis regression (average of 4 runs each 50% of the data) leads to equation E1:

$DBH_{predicted}$ in cm = -4.665 + 5.102 * CD (E1)

E1 shows a reasonable performance with a very low bias (average of 4 runs on the 50% not used to establish E1: r^2 = 0.71; slope = 0.95; RMSE = 6.2 cm = 42%; bias = 1%). We tested E1 on an independent data set from Kenya consisting of 93 trees where AGB was destructively measured (Fig. 3b). On these 93 trees, DBH can be predicted reasonably well from CD using E1 (r^2 = 0.84; slope = 0.86; RMSE = 8 cm = 25%; bias = 6%). We then applied an allometric equation from literature (*36*) established for non forest trees in East Africa to estimate AGB from $DBH_{predicted}$ and compared the predicted AGB with the destructively measured AGB (r^2 = 0.81; RMSE = 511 kg = 55%; bias = 25%) showing an acceptable performance (Extended Data | Fig. 3c) but indicating a systematic bias, which will be further tested with biome specific field data (next section). We apply equation (E2) to estimate AGB for trees outside forests in Rwanda in savannas and shrublands:

$AGB_{predicted}$ in kg = 0.091 * $DBH_{predicted}^{2.472}$ (E2)

Given the different structure of trees in farmlands, urban areas and plantations as compared to trees in natural forests and in natural non-forest areas, we used a different equation for trees in these areas. It was established in Rwanda using destructive samples from tree plantations (38):

$AGB_{predicted}$ in kg = 0.202 * $DBH_{predicted}^{2.447}$ (E3)

A different CD-DBH relationship was established for natural forests. Here we conducted a field campaign in December 2021 sampling 793 overstory trees in Rwanda's protected natural forest. We measured both CD and DBH and established a logarithmic major axis regression model with a Baskerville correction (*57*) between the two variables to predict DBH from CD (Extended Data | Fig. 3d). We did 4 runs each using 50% of the data to establish E4 (average of the 4 runs) and the other 50% to test the performance also averaged over the 4 runs (r^2 = 0.71; slope = 0.99; RMSE = 13 cm = 45%; bias = 19%). Note that CD is extended by 27% to account for underestimations of touching crowns in dense forests (see previous section):

$DBH_{predicted}$ in cm = (exp(1.154+1.248*ln(CD*1.27)) * (exp(0.3315^2/2))) (E4)

We then used a state-of-the-art allometric equation established for tropical forests (37) to predict AGB from DBH for natural forests in Rwanda:

$$AGB_{predicted} \text{ in kg} = \exp[1.803 - 0.976E + 0.976 \ln(\rho) + 2.673 \ln(DBH) - 0.0299[\ln(D)]^2] \quad (E5)$$

Where E measures the environmental stress (*37*; a gridded layer is accessible via https://chave.ups-tlse.fr/pantropical_allometry.htm), and ρ is the wood density which we set to 0.7 (*58*). No destructive AGB measurements were found that showed a similar CD-DBH relationship as we measured during the field trip in Rwanda's forest. We could thus not evaluate the performance for natural forests at tree level but had to rely on plot level comparisons (next section).

Evaluation and uncertainties of the allometry. Biomass estimations without direct measurements of height or DBH inevitably include a relatively high level of uncertainty at tree level (*36,45,59*). Uncertainty does not only originate from the CD to DBH conversion but also the equation converting DBH to AGB. As shown in the previous section, no strong systematic bias could be detected for the CD to DBH conversion, but the evaluation of the CD based AGB prediction with an independent data set from destructively measured AGB revealed a bias of 25%. However, this comparison (Extended Data | Fig. 3c) may not be representative for an entire country having a variety of landscapes and tree species, so a systematic propagation is unlikely. We also did not have sufficient field data to evaluate the conversions in natural forests. Here, we use data from 15 forest plots with 6,161 trees published by *ref. 41* and *ref. 42* and directly compared the summed biomass of the trees we predicted over their plots. The mean measured biomass for the plots is 139 Mg C ha^{-1} and we predict a mean biomass of 102 MgC ha^{-1} (plot based RMSE = 54%; bias = 11%; bias on summed plots = 26%). The overall underestimation by our prediction is not necessarily a model bias but may be partly explained by the contribution of the understory trees, which cannot be captured by aerial images. This number matches well with previously estimated contributions of understory to tropical intact forests AGB (*60*). Interestingly, our AGC estimates are in the same range of magnitude as global forest biomass products: (*61,62,63,64,65*) (Extended Data | Fig. 4), indicating that overstory tree level carbon stock assessments are possible from optical very high resolution images, even in tropical forests. Interestingly, especially older global products overestimated biomass for non-forest areas, which is likely because they rely more on optical data that cannot distinguish between herbaceous and woody vegetation. The most recent product of ref. *65* makes use of spaceborne GEDI Lidar and provides values which are much closer to our estimations.

We further use NFI data from 2014 to evaluate if systematic differences between AGB predictions and field assessments can be found for different land cover classes (Extended Data | Table 1). For the NFI data, a total of 373 plots with 2,415 trees were measured and species-specific allometric equations applied (66). Since the exact locations of the plots were unknown, we extracted averaged values for areas close to the plots from our predictions and calculated statistics on averages over all plots. Interestingly, our predictions for farmlands only show a bias of 5.9%: we estimate on average 2.46 Mg C ha^{-1} and the inventories measure 2.37 Mg C ha^{-1} on their 150 plots. For savanna and shrublands, we estimate 4.16 Mg C ha^{-1} while inventories measure 3.31 Mg C ha^{-1} (bias = 18.9%). For plantations, we estimate lower values (8.16 compared to 16.79 Mg C ha^{-1}; bias = 52.6%). To calculate the total uncertainty on countrywide C stock estimates, we weighted the bias from the different classes according to their relative area. We estimate a total bias of 16.9% at the national scale. (Extended Data | Table 1).

We found a very low bias for estimated C density in farmlands (5.9% bias) which make up most of the areas outside natural forests in Rwanda (Extended Data | Table 1). The high bias for plantations can be explained by 3 factors: large bare areas considered part of plantations (Extended Data | Table 1) by the manual delineation of plantation areas; regular harvesting and continual thinning which keep many plantation trees young and small (3*9*); and the fact that our aerial images are from 2008, and plantation trees have grown rapidly until 2014 with a few new NFI plots initiated after 2008. The bias in savannas and shrublands can be explained by the following factors: the presence of multi-stemed trees with large crowns such as *acacia spp*, *ficus spp*, among others; the fact that a crown-based method overestimates C stocks of shrubs with a small height; and presence of shrub trees with both small height and small (multiple) stems. If tree level based carbon stock assessments derived from crown diameter as presented here should become standard to complement national inventories, a database with sufficient samples to

evaluate for systematic errors needs to be established for each biome, and inventory and satellite/aerial image based methods need to be further harmonized.

To further quantify the error propagation of the CD to DBH conversion for our application, we established 4 equations each randomly using 50% of the dataset, and predicted the carbon stock for each tree in Rwanda with each equation. We did this separately for natural forests and trees outside natural forests. We calculated the RMSE between the aggregated carbon stocks for each hectare. We averaged the RMSE for each land cover class and show that the uncertainty for all classes does not exceed 5% (Extended Data | Table 2).

Evaluation and uncertainties of tree crown mapping. We create an independent test dataset after the deep learning model was finalized. This way, the test set was never seen during training and it was also not used to optimize hyper-parameters. The test set consists of 153 random plots each 1 ha in size with a total of 6,591 manually labeled trees (Extended Data | Fig. 6). The plot level comparison yielded very high correlations between the predictions and the labels and is shown in Extended Data | Fig. 5. We also calculated a confusion matrix showing an overall per pixel accuracy of 96.2%, a true positive rate of 79.6% and a false positive rate of 6.8% (Extended Data | Table 3). Trees outside natural forests are easy to spot and count for the human eye, so we have confidence in the plot based evaluation. However, it is often challenging in natural forests. Here we used again the field measurements from 15 plots including 6,161 trees (*41,42*). We find that we underestimate the total tree count by 22.6%, which may, at least partly, be explained by understory trees hidden by overstory trees and therefore not visible in our images. Here, new field campaigns are needed to better understand and calibrate our results and possibly correct for systematic bias.

References

1. Gamfeldt, L., Snäll, T., Bagchi, R. et al. Higher levels of multiple ecosystem services are found in forests with more tree species. Nat Commun 4, 1340 (2013). https://doi.org/10.1038/ncomms2328
2. Morin, X., Fahse, L., Jactel, H. et al. Long-term response of forest productivity to climate change is mostly driven by change in tree species composition. Sci Rep 8, 5627 (2018). https://doi.org/10.1038/s41598-018-23763-y
3. Tong, X., Brandt, M., Yue, Y. et al. Forest management in southern China generates short term extensive carbon sequestration. Nat Commun 11, 129 (2020). https://doi.org/10.1038/s41467-019-13798-8
4. Tomppo, E., Gschwantner, Th., Lawrence, M., McRoberts, R.E. (Eds.) (2010). National Forest Inventories Pathways for Common Reporting. Springer, 2010th edition
5. FAO. National Forest Monitoring Systems: Monitoring and Measurement, Reporting and Verification (M & MRV) in the context of REDD+ Activities. Forest Assessment, Management and Conservation Division (2013), Rome.
6. FAO. Voluntary Guidelines on National Forest Monitoring. Food and Agriculture Organization of the United Nations (2017), Rome
7. UN. The Global Forest Goals Report 2021. United Nations Department of Economic and Social Affairs, United Nations Forum on Forests Secretariat (2021). New York
8. UNFCCC. Report of the Conference of the Parties on its twenty-first session, held in Paris from 30 November to 13 December 2015. 2016. Bonn
9. Stanturf, J.A., Kleine, M., Mansourian, S. et al. Implementing forest landscape restoration under the Bonn Challenge: a systematic approach. Annals of Forest Science 76, 50 (2019). https://doi.org/10.1007/s13595-019-0833-z
10. Aleman, J., Blarquez, O., Gourlet-Fleury, S. et al. Tree cover in Central Africa: determinants and sensitivity under contrasted scenarios of global change. Sci Rep 7, 41393 (2017). https://doi.org/10.1038/srep41393
11. Félix, G. F., Diedhiou, I., Le Graff, M., et al. Use and management of biodiversity by smallholder farmers in semi-arid West Africa. Glob. Food Sec 18, 76-85 (2018). https://doi.org/10.1016/j.gfs.2018.08.005
12. Hansen, M. C., Potapo, P. V., Moore, R., et al. High-resolution global maps of 21st-century forest cover change. Science 342, 850–853 (2013). https://doi.org/10.1126/science.1244693
13. Crowther, T., Glick, H., Covey, K. et al. Mapping tree density at a global scale. Nature 525, 201–205 (2015). https://doi.org/10.1038/nature14967
14. Vancutsem, C., Achard, F., Pekel, J.F., Vieilledent, G., Carboni, S., Simonetti, D., Gallego, J., Aragão, L.E.O.C., Nasi, R. Long-term (1990–2019) monitoring of forest cover changes in the humid tropics. Science Advances 7(10), (2021), eabe1603. https://doi.org/10.1126/sciadv.abe1603
15. Brandt, M., Tucker, C.J., Kariryaa, A. et al. An unexpectedly large count of trees in the West African Sahara and Sahel. Nature 587, 78–82 (2020). https://doi.org/10.1038/s41586-020-2824-5
16. Schnell, S., Kleinn, C. & Ståhl, G. Monitoring trees outside forests: a review. Environ Monit Assess 187, 600 (2015). https://doi.org/10.1007/s10661-015-4817-7
17. Mertz, O.; Grogan, K.; Pflugmacher, D.; Lestrelin, G.; Castella, J.-C.; Vongvisouk, T.; Hett, C.; Fensholt, R.; Sun, Z.; Berry, N.; et al. Uncertainty in establishing forest reference levels and predicting future forest-based carbon stocks for REDD+. J. Land Use Sci. 13, 1–15 (2018)
18. Rinaldi, F. & Johnson, R. Accounting for uncertainty in forest management models. For. Ecol. Manag. 468, 118186 (2020). https://doi.org/10.1016/j.foreco.2020.118186
19. Qin, Y., Xiao, X., Wigneron, JP. et al. Carbon loss from forest degradation exceeds that from deforestation in the Brazilian Amazon. Nat. Clim. Chang. (2021). https://doi.org/10.1038/s41558-021-01026-5
20. Gross, D., Achad, F., Dubois, G., et al. Uncertainties in tree cover maps of Sub-Saharan Africa and their implications for measuring progress towards CBD Aichi Targets. Remote sens ecol con. 4(2), 94-112 (2018). https://doi.org/10.1002/rse2.52

21. Diakhite, M. AFR100 (the African Forest Landscape Restoration Initiative) is a country-led effort to bring 100 million hectares of land in Africa into restoration by 2030. African Union Development Agency-NEPAD. Accessed on 11th June 2021. Available online: https://afr100.org/
22. FAO. From reference levels to results reporting: REDD+ under the United Nations Framework Convention on Climate Change – 2020 update. (2020). Rome, FAO. https://doi.org/10.4060/cb1635en
23. Hansen, A.J., Burns, P., Ervin, J. et al. A policy-driven framework for conserving the best of Earth's remaining moist tropical forests. Nat Ecol Evol 4, 1377–1384 (2020). https://doi.org/10.1038/s41559-020-1274-7
24. Aleman, J.C., Jarzyna, M.A. & Staver, A.C. Forest extent and deforestation in tropical Africa since 1900. Nat Ecol Evol 2, 26–33 (2018). https://doi.org/10.1038/s41559-017-0406-1
25. Benioff, R., Bazilian, M., Cox, S., Uriarte, C., Kecman, A., De Simone, G., Kitaoka, K., Ploutakhina, M. & Radka, M. Low Emission Development Strategies: The Role of Networks and Knowledge Platforms. National laboratory of the U.S. Department of Energy, Office of Energy Efficiency & Renewable Energy, NREL/TP-6A00-55343, Denver West Parkway, Golden
26. Niang, I., Ruppel, O.C, Abdrabo, M.A. et al. Africa. In: Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part B: Regional Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Barros, V.R., C.B. Field, D.J. Dokken, M.D. Mastrandrea, K.J. Mach, T.E. Bilir, M. Chatterjee, K.L. Ebi, Y.O. Estrada, R.C. Genova, B. Girma, E.S. Kissel, A.N. Levy, S. MacCracken, P.R. Mastrandrea, and L.L.White (eds.)]. Cambridge University Press (2014), Cambridge, United Kingdom and New York, NY, USA, 1199-1265.
27. Dave, R., Saint-Laurent, C., Moraes, M., Simonit, S., Raes, L., Karangwa, C. Bonn Challenge Barometer of Progress: Spotlight Report 2017, (2017). Gland, Switzerland: IUCN, 36ppSDGs
28. Republic of Rwanda. Rwanda Vision 2020 – Revised in 2012. The Republic of Rwanda, Ministry of Finance and Economic Planning, Kigali (2012).
29. Nkurunziza, M. Rwanda reaches 30% forest cover target. The New Times, November 02, 2019. Accessed on 25th January 2021. Available online: https://www.newtimes.co.rw/news/rwanda-reaches-30-forest-cover-target
30. Stanturf, J.A., Kleine, M., Mansourian, S. et al. Implementing forest landscape restoration under the Bonn Challenge: a systematic approach. Annals of Forest Science 76, 50 (2019). https://doi.org/10.1007/s13595-019-0833-z
31. REMA. State of the Environment and Outlook Report - Rwanda. Rwanda Environment Management Authority, Kigali (2015)
32. Rwanyiziri, G. Relief and Hydrography. In D. Ben Yahmed and N. Houstin (Eds.), Africa Atlases. Rwanda, Les Éditions du Jaguar, Paris, 7677 (2013)
33. Swedesurvey. Rwanda National Land Use and Development Master Plan - Report for Production of orthophoto in Rwanda. Swedesurvey, Lantmäterigatan 2A, 802 64 Gävle (2010)
34. Nduwamungu, J., Nyandwi, E., Mazimpaka, J. D., Mugiraneza, T., Mukashema, A., Rwanyiziri, G., Nzabanita, V. Rwanda forest cover mapping using high resolution aerial photographs. The Global Geospatial Conference (2013), Addis Ababa, Ethiopia
35. Jucker, T., Caspersen,J., Chave, J. et al. Allometric equations for integrating remote sensing imagery into forest monitoring programmes, Global Change Biology, 23(1), 177-190. https://doi.org/10.1111/gcb.13388
36. Kuyah, S., Dietz., J., Muthuri, C., et al. Allometric equations for estimating biomass in agricultural landscapes: I. Aboveground biomass. Agric. Ecosyst. Environ. 158, 216– 224 (2012). http://dx.doi.org/10.1016/j.agee.2012.05.011
37. Chave, J. et al. Improved allometric models to estimate the aboveground biomass of tropical trees. Glob. Change Biol. 20, 3177–3190 (2014). https://doi.org/10.1111/gcb.12629
38. Mukuralinda, A., Kuyah, S., Ruzibiza, M. Allometric equations, wood density and partitioning of aboveground biomass in the arboretum of Ruhande, Rwanda. Trees, Forests and People 3, 100050 (2021). https://doi.org/10.1016/j.tfp.2020.100050
39. Mugunga, C. P. The use of Eucalyptus in agroforestry systems of southern Rwanda: to integrate of segregate? PhD thesis, Wageningen University, Wageningen, NL (2016)

40. Ndayambaje, J.D., Heijman, W.J.M. & Mohren, G.M.J. Farm woodlots in rural Rwanda: purposes and determinants. Agroforest Syst 87, 797–814 (2013). https://doi.org/10.1007/s10457-013-9597-x
41. Nyirambangutse, B., Zibera, E., Uwizeye, F. K., Nsabimana, D., Bizuru, E., Pleijel, H., Uddling, J., and Wallin, G. Carbon stocks and dynamics at different successional stages in an Afromontane tropical forest, Biogeosciences, 14, 1285–1303(2017). https://doi.org/10.5194/bg-14-1285-2017.
42. Cuni-Sanchez, A., Sullivan, M.J.P., Platts, P.J. et al. High aboveground carbon stock of African tropical montane forests. Nature 596, 536–542 (2021). https://doi.org/10.1038/s41586-021-03728-4
43. Castilla, G. and Hay, G. J. Uncertainties in land use data. Hydrol. Earth Syst. Sci., 11, 1857–1868 (2007). https://doi.org/10.5194/hess-11-1857-2007
44. Bastin, J-F., Finegold, Y., Garcia, C. The global tree restoration potential. Science, 365(6448), (2019). https://doi.org/10.1126/science.aax0848
45. Skole, D.L., Samek, J.H., Dieng, M., & Mbow, C. The contribution of trees outside of forests to landscape carbon and climate change mitigation in west africa. Forests 12, 1652 (2021). https://doi.org/10.3390/f12121652
46. Romijn, E., De Sy, V., Herold, M., et al. Independent data for transparent monitoring of greenhouse gas emissions from the land use sector – What do stakeholders think and need? Environ Sci Policy 85, 101-112 (2018). https://doi.org/10.1016/j.envsci.2018.03.016
47. Skole, D.L., Mbow, C., Mugabowindekwe, M. et al. Trees outside of forests as natural climate solutions. Nat. Clim. Chang. 11, 1013–1016 (2021). https://doi.org/10.1038/s41558-021-01230-3
48. Sayre, R., Roca. E., Sedaghatkish, G. et al. Nature in focus - rapid ecological assessment. The nature conservancy, Island press, Washington (2000)
49. CGIS. Rwanda forest cover mapping using high resolution aerial photographs. The "Programme d'Appui à la Reforestation - Component funded by the Netherland (PAREF NL)", Rwanda Natural Resources Authority (2012)
50. Republic of Rwanda. Presidential Order establishing the National Land Use and Development Master Plan, N° 058/01 of 23/04/2021. Official Gazette n° 15 bis of 26/04/2021. Republic of Rwanda (2021).
51. Ronneberger, O., Fischer P. & Brox, T. U-net: convolutional networks for biomedical image segmentation. In International Conference on Medical Image Computing and Computer-Assisted Intervention (eds. Navab, N. et al.) 234–241, (Springer, 2015).
52. Koch, T., Perslev, M., Igel, C. & Brandt, S. Accurate segmentation of dental panoramic radiographs with U-nets. In Proc. IEEE International Symposium on Biomedical Imaging (ISBI) (eds Davis, L. et al.) 15–19 (IEEE Computer Society, 2019).
53. Brown, S., Gillespie, A. J. R. & Lugo, A. E. Biomass estimation methods for tropical forests and the application to forest inventory data. Forest Science 35(4), 881-902 (1989)
54. Chave, J., Andalo, C., Brown, S. et al. Tree allometry and improved estimation of carbon stocks and balance in tropical forests. Oecologia 145, 87–99 (2005). https://doi.org/10.1007/s00442-005-0100-x
55. IPCC. IPCC Guidelines for national greenhouse gas inventories, Prepared by the National Greenhouse Gas Inventories Programme (2006), IGES, Japan
56. Martin, A.R., Doraisami, M. & Thomas, S.C. Global patterns in wood carbon concentration across the world's trees and forests. Nature Geosci 11, 915–920 (2018). https://doi.org/10.1038/s41561-018-0246-x
57. Baskerville, G. L. Use of logarithmic regression in the estimation of plant biomass. Can. J. Forest Res. 2, 49-53 (1972)
58. Bastin, J-F., Fayolle, A., Tareken, Y., et al. Wood specific gravity variations and biomass of central african tree species: The simple choice of the outer wood. PLOS ONE, 10(11), e0142146 (2015). https://doi.org/10.1371/journal.pone.0142146
59. Djomo, A. N., & Chimi, C. D. (2017). Tree allometric equations for estimation of above, below and total biomass in a tropical moist forest: Case Study with Application to Remote Sensing. Forest Ecology and Management, 381, 184-193. https://doi.org/10.1016/j.foreco.2017.02.022

60. Pan, Y., Birdsey, R. A., Fang, J. A large and persistent carbon sink in the world's forests. Science 333(6045), 988-993 (2011). https://doi.org/DOI: 10.1126/science.1201609
61. Santoro, M.; Cartus, O. (2021): ESA Biomass Climate Change Initiative (Biomass_cci): Global datasets of forest above-ground biomass for the years 2010, 2017 and 2018, v2. Centre for Environmental Data Analysis, 17 March 2021. http://dx.doi.org/10.5285/84403d09cef3485883158f4df2989b0c
62. Baccini, A., Goetz, S., Walker, W. et al. Estimated carbon dioxide emissions from tropical deforestation improved by carbon-density maps. Nature Clim Change 2, 182–185 (2012). https://doi.org/10.1038/nclimate13
63. Bouvet, A., Mermoz, S., Le Toan, T. et al (2018). An above-ground biomass map of African savannahs and woodlands at 25m resolution derived from ALOS PALSAR. Remote Sens. Environ. 206, 156-173. https://doi.org/10.1016/j.rse.2017.12.030
64. Hanan, N.P., L. Prihodko, C.W. Ross, G. Bucini, and A.T. Tredennick. 2020. Gridded Estimates of Woody Cover and Biomass across Sub-Saharan Africa, 2000-2004. ORNL DAAC, Oak Ridge, Tennessee, USA. https://doi.org/10.3334/ORNLDAAC/1777
65. Xu, L., Saatchi, S., Yang, Y., et al. Changes in global terrestrial live biomass over the 21st century. *Science Advances*, 7(27). https:/doi.org/10.1126/sciadv.abe9829
66. RNRA. Execution of a National Forest Inventory - Technical report No. 8: Detailed Results Monitoring System for Forests and Measuring Tree Growth. Rwanda Natural Resources Authority, Kigali (2016)
67. Hazel, D. & Bardon, R. Conversion factors for bioenergy - NC Woody biomass. Oak Ridge National Laboratory, 2008. https://content.ces.ncsu.edu/conversion-factors-for-bioenergy

Acknowledgments

We thank the University of Rwanda for providing the very high resolution aerial imagery for the study. We also acknowledge the support from the University of Copenhagen, University of Rwanda, Wildlife Conservation Society of Rwanda, and IPRC Kitabi for the organization and supervision of the fieldwork. We also thank African Parks and Nyungwe Management Company for issuing the permit to conduct field data collection in Nyungwe Afromontane tropical rainforest.

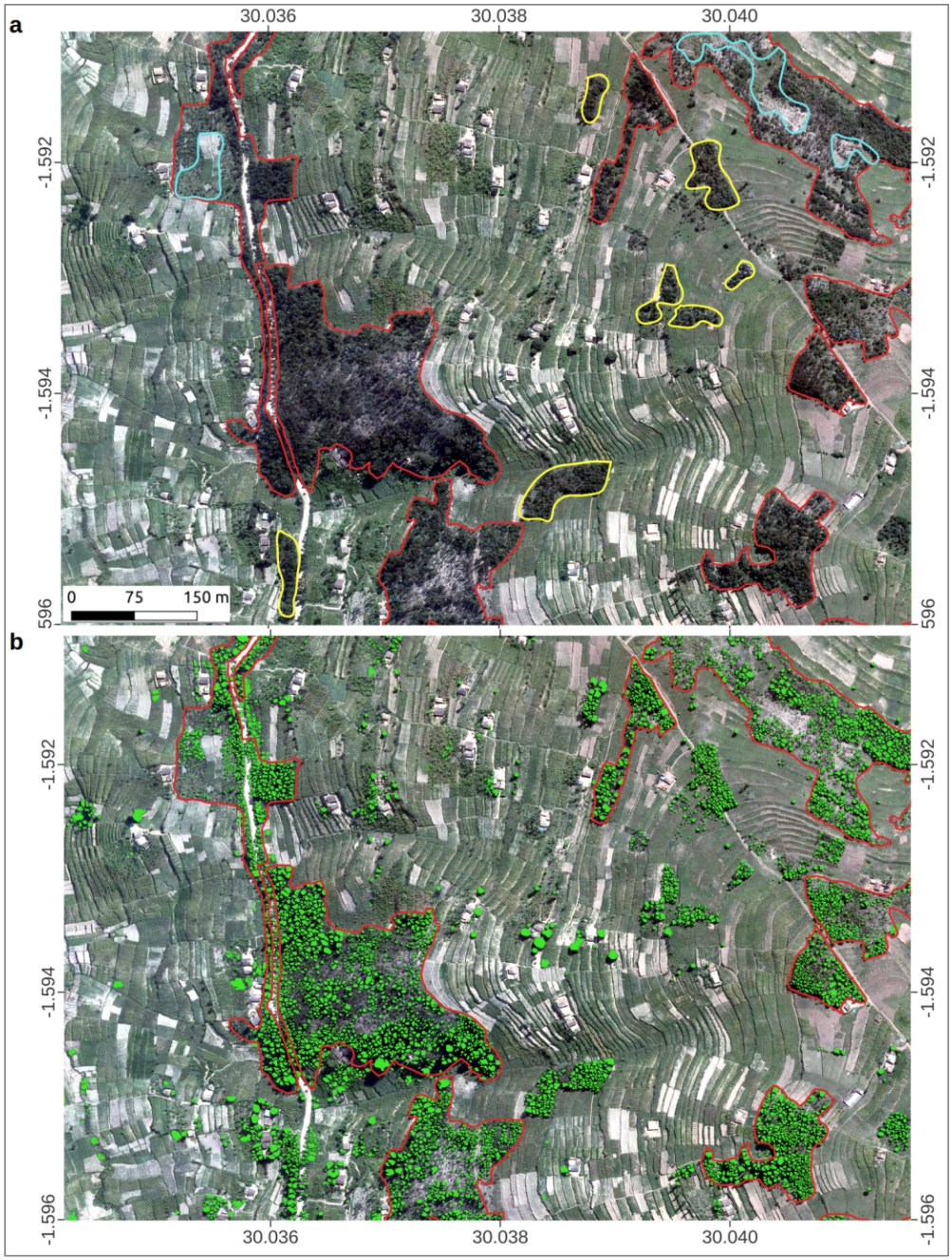
Funding: This work was funded by the European Research Council (ERC) under the European Union's Horizon 2020 Research and Innovation Programme (grant agreement no. 947757 TOFDRY) and DFF Sapere Aude (grant no. 9064–00049B). R.F., C.I., and A.K. acknowledge support by the Villum Foundation through the project Deep Learning and Remote Sensing for Unlocking Global Ecosystem Resource Dynamics (DeReEco). C.I. acknowledges support by the Pioneer Centre for AI, DNRF grant number P1.. J.C. acknowledges grants from "*Investissement d'Avenir*" (CEBA, ref. ANR-10-LABX-25-01; TULIP, ref. ANR-10-LABX-0041), ESA CCI-Biomass and CNES". D.S. acknowledges support by NASA, grant no. 80NSSC21K0315 from the Land Cover and Land Use Change Program. A.N. and V.U. acknowledge support by the European Union through the project Development of Smart Innovation through Research in Agriculture (DeSiRa).

Author contributions: M.B., R.F. and M.M. designed the study. M.M. prepared and selected training and validation dataset. A.K., S.L., F.R. wrote the code for the deep-learning framework, supported by F.G. and C.I.. A.K. and C.I. wrote the code for post-processing framework to separate clumped trees. J.C. and D.S. prepared data from existing tree measurements databases for carbon stocks related analyses. G.R. prepared aerial images. D.T. and V.U. collected field data. A.N. and V.U. prepared NFI data. S.S. prepared the 2021 global estimates of above-ground carbon stocks. M.M., M.B., J.C. and D.S. conducted the analyses. M.M., M.B., J.C., D.S., P.H., P.C., O.M., X.T., S.L., G.R., A.N., J-P. B. L., F.G., C.J.T., S.S. and R.F. conducted the interpretations. M.M. and M.B. wrote the first manuscript draft with contributions by all authors. M.M. designed the figures.

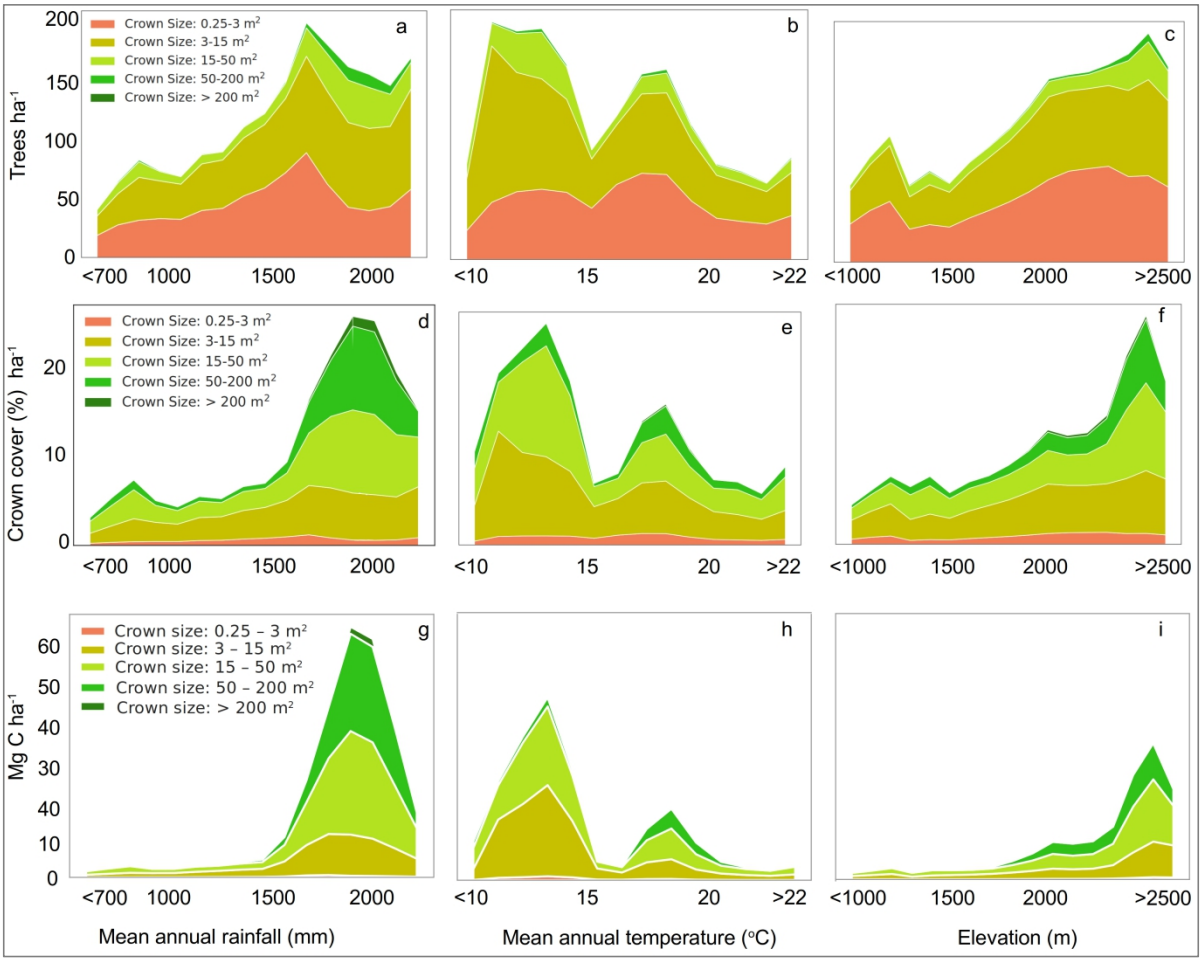
Competing interests: The authors declare no competing interests.

Data availability: Global tree cover maps are available at http://earthenginepartners.appspot.com/science-2013-global-forest. Climate data are freely accessible through online application to the Rwanda Meteorological Agency via http://mis.meteorwanda.gov.rw/. Aerial images, and land use and land cover data are freely available for research through formal application to the Rwanda Land Management and Use Authority: https://www.rlma.rw. Individual tree maps produced in this article will be made public upon acceptance of the manuscript. The global database with tree measurements including biomass is available from J.C.. Tree measurements from Kenya are available from D.S.. Tree measurements from Rwanda are available from M.M.. The code for 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. (ak@di.ku.dk or ankit.ky@gmail.com) or F.R. (flr@ign.ku.dk). The code for clumped trees separation framework is publicly available at https://github.com/ankitkariryaa/separate_instances; support and more information are available from A.K. or C.I. (igel@di.ku.dk). Any more relevant data can be availed upon reasonable request addressed to the corresponding authors.

Supplementary Information



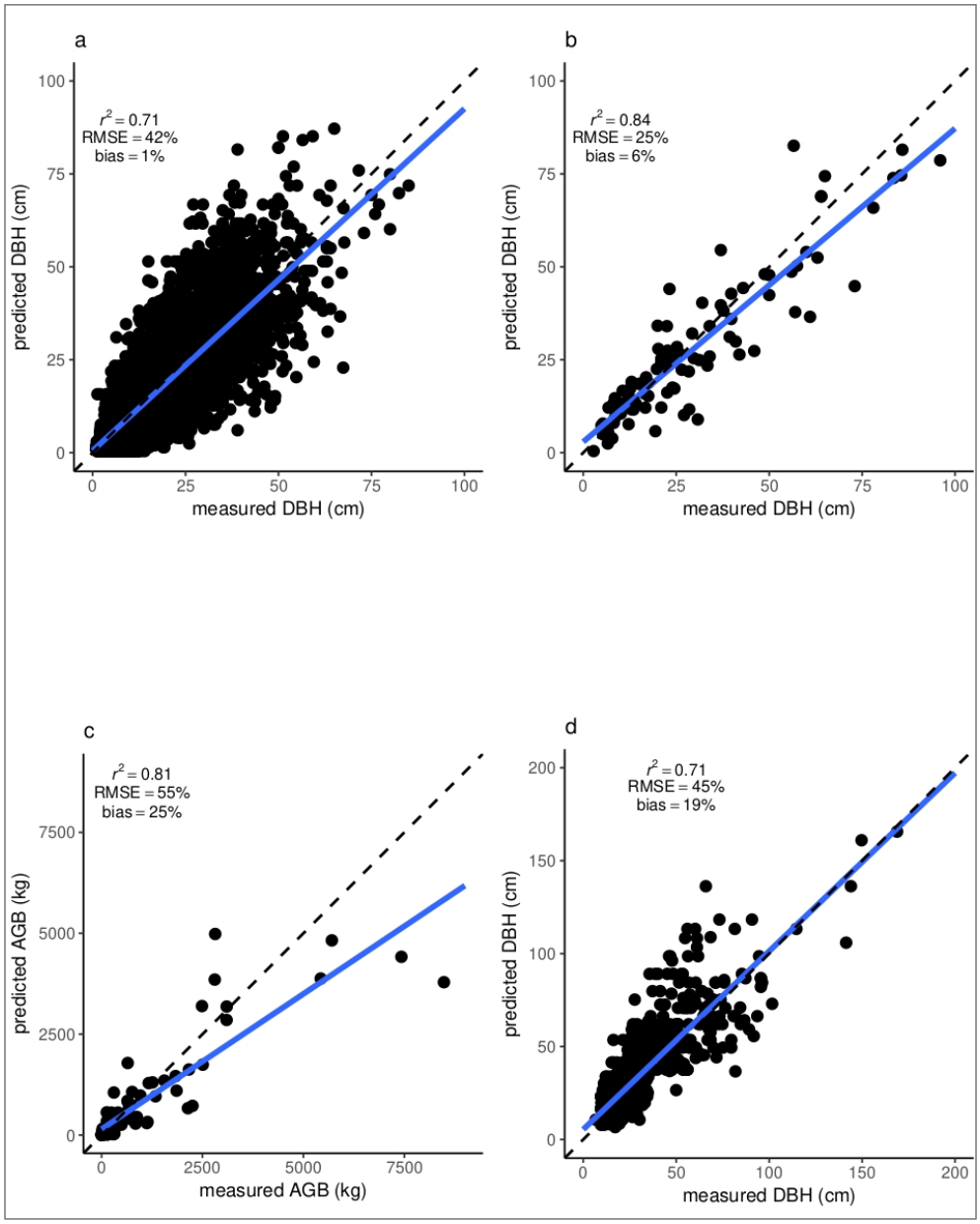
Extended Data | Fig. 1. An example showing previous manual forest delineations. The red lines are manually labeled forest boundary from the Rwanda national forest map of 2012 (*49*). **a,** Several patches which would qualify for the used forest definition were missed by the manual delineation (yellow lines). Also, some bare areas inside forest patches (cyan line) were considered as part of forests. **b,** Our results are shown in green, highlighting the improvements over the previous method.



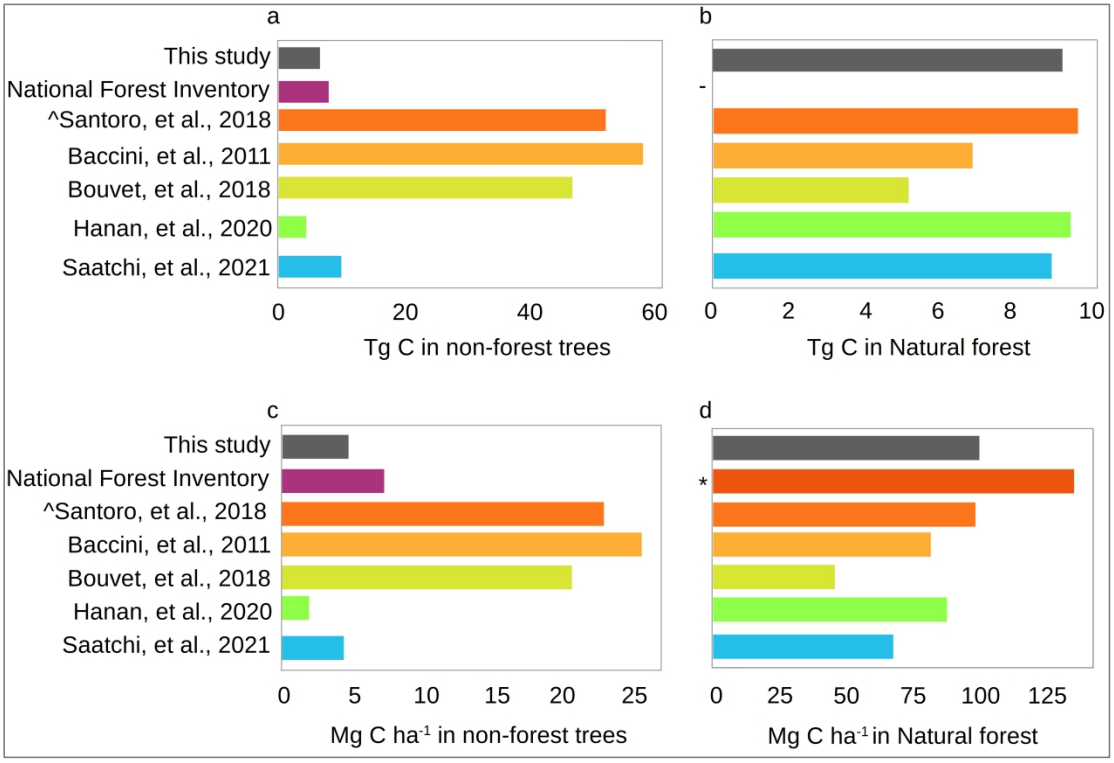
633

634 **Extended Data | Fig. 2. Tree characteristics related to different environmental factors.** The variation of
635 different crown sizes and their contribution to the total canopy cover along gradients of **a,** rainfall, **b,** temperature,
636 and **c,** elevation. **d, e, f,** are the same as **a, b, c**, but for the mean crown cover. **g, h, i,** are the same as **a, b, c,** but for
637 mean carbon stock ha^{-1}.

638



Extended Data | Fig. 3. Tree crown allometry. a, DBH is predicted from CD using a total of 11,593 samples from a global database (*35*). The plot compares the predicted against the measured DBH. **b,** DBH is predicted for an independent dataset of 93 trees from Kenya using the equation derived from (a). **c,** We used an allometric equation from literature (*36*) to calculate AGB from the CD predicted DBH shown in (b). Predicted AGB is here compared with destructively measured AGB. **d,** While samples shown in a-c are all outside forests, (d) shows 793 field measured trees from Rwanda's natural forest. As in (a), DBH was predicted from CD.

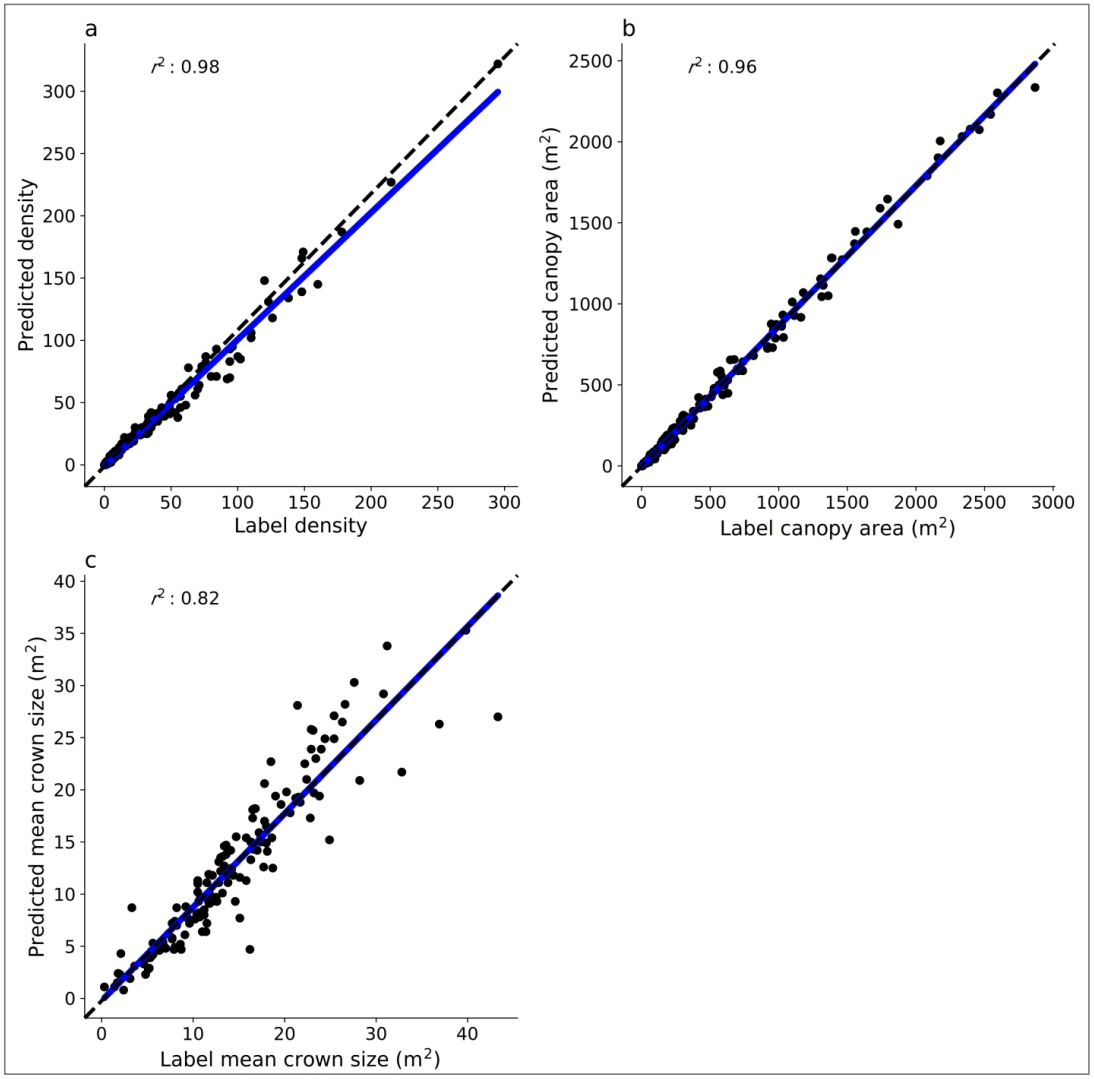


^ We selected the 2010 version

\- Natural forest is not considered as part of the NFI

* Source: (*20,21*)

Extended Data | Fig. 4. Comparison of above-ground carbon estimations at country scale. a, Comparison of predicted total above-ground carbon stocks by this study, NFI and existing global products for non-forest areas. **b,** Same as (a) but for natural forests. **c,** Comparison of predicted above-ground carbon density by this study, NFI, and existing global products for non-forest areas. **d,** Same as (c) but for natural forests.



Extended Data | Fig. 5. Tree crown model evaluation at plot level. We manually labeled 6,591 trees in 153 plots and compared predictions and labeled trees at plot level. **a,** Tree density, **b,** canopy area, **c,** mean crown size. Each point represents one 1 ha plot.

Extended Data | Table 1. Evaluation with field data. We compared our tree level carbon stock estimates aggregated to 1 ha grids with field data from different sources. The exact location of the NFI plots was unknown, so we used averages of the areas close by. The statistics were then calculated for averages per class, except for natural forests where exact plot coordinates were available and comparisons could also be done per plot. We then weighted the bias according to the relative area at the national scale to derive a nation-wide uncertainty of 16.9%.

	Field data Mg C ha^{-1}	**This study Mg C ha^{-1}**	**bias**	**Plots**	**Source**	**Relative area at national scale**
Plantations	16.8	8.2	52.6%	106	NFI*	12%
Savanna and shrubland	3.3	4.2	18.9%	116	NFI*	33%
Farmland	2.4	2.5	5.9%	150	NFI*	48%
Natural forest	139	102	plots 11% sum 26%	15	Nyirambangutse, et al., 2017; Cuni-Sanchez, et al. (2021)	5%

* Note: The overall weighted national bias between NFI measurements and this study is 16.9% (NFI total C in TOF: 8.35 Tg C; this study estimates 6.95 Tg C)

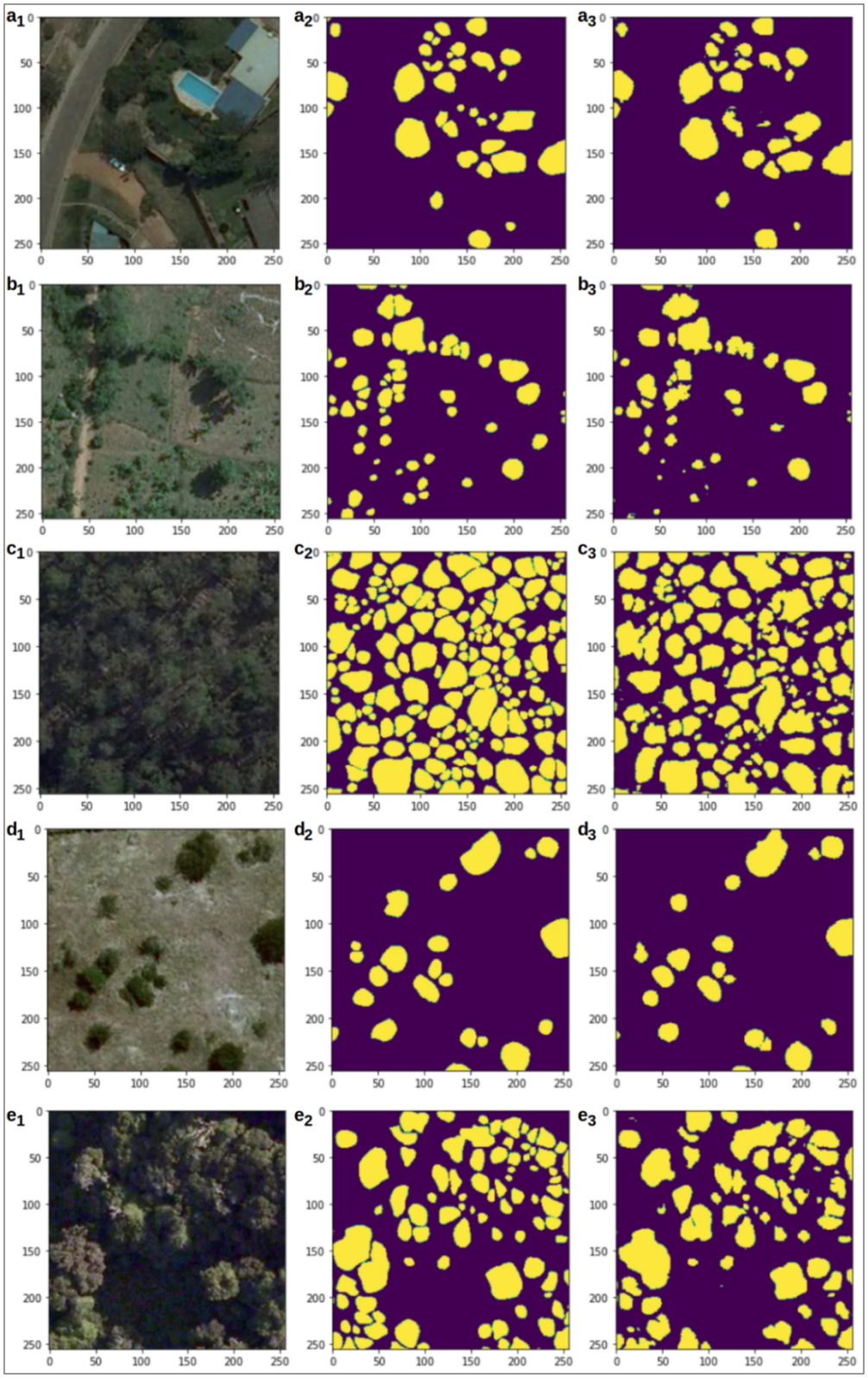
* The NFI original measurements are the above-ground biomass expressed in volume (m^3). We have converted them in weight (metric tonnes) using the conversion rate: 1 m^3 = 0.714 tonne (67) which assumes an overall average wood density of 0.714 g/cm^3 per tree, and multiply by the AGB-to-AGC conversion factor: 0.47 (*55,56*) to get the C equivalent.

Extended Data | Table 2. Evaluation of the crown diameter to stem diameter conversion. Four CD-DBH equations were established, each using a random subset of 50% of the data. Tree biomass was predicted with each equation and aggregated to the hectare level. We then calculated the RMSE and bias between the 4 predictions for each 1 ha grid. Results shown here are aggregated over land cover classes.

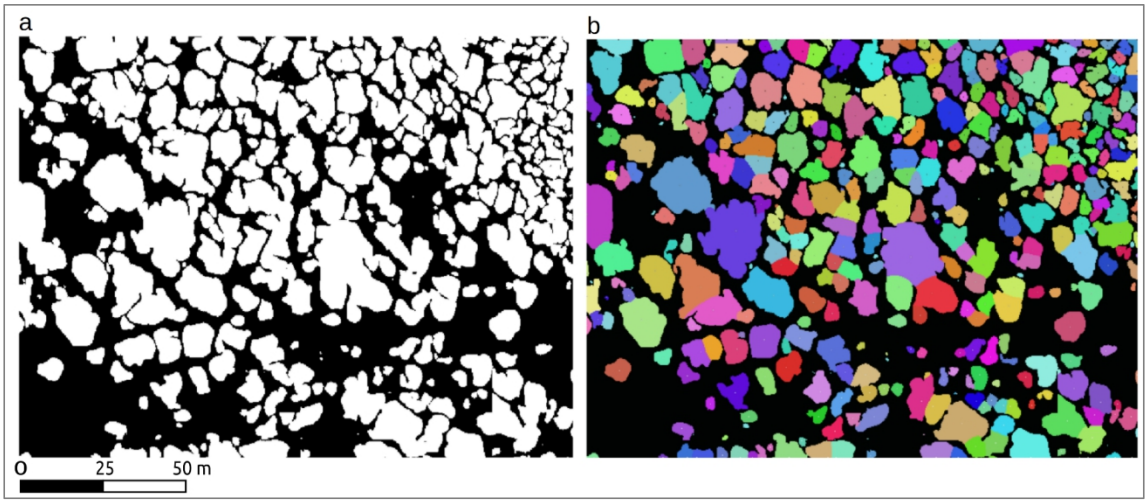
	RMSE (Mg C/ha)	Bias (%)
Farmland	0.08 (5%)	5.9
Savanna and shrubland	0.1 (5%)	5.1
Plantations (Eucalyptus)	0.2 (2%)	6.2
Plantations (non-Eucalyptus)	0.4 (2%)	3.9
Natural forest	1.7 (2%)	2.3

Extended Data | Table 3. Tree crown model evaluation at pixel level. Confusion matrix with 153 plots of 1 ha size and 6,591 manually labeled trees. These data are independent and were not used to establish or validate the model and the results.

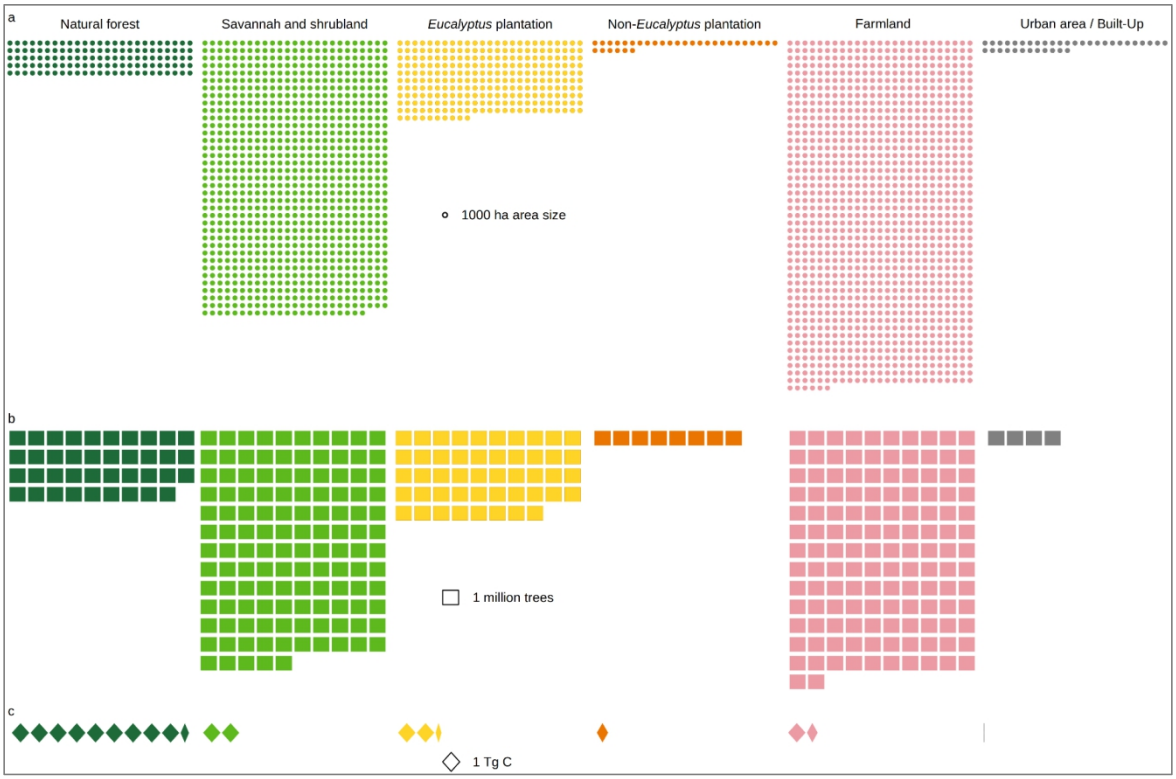
	Tree detected	**No tree detected**
Tree label exists	TP = 79.6%	FN = 20.4%
No tree label	FP = 6.8%	TN = 99.0%



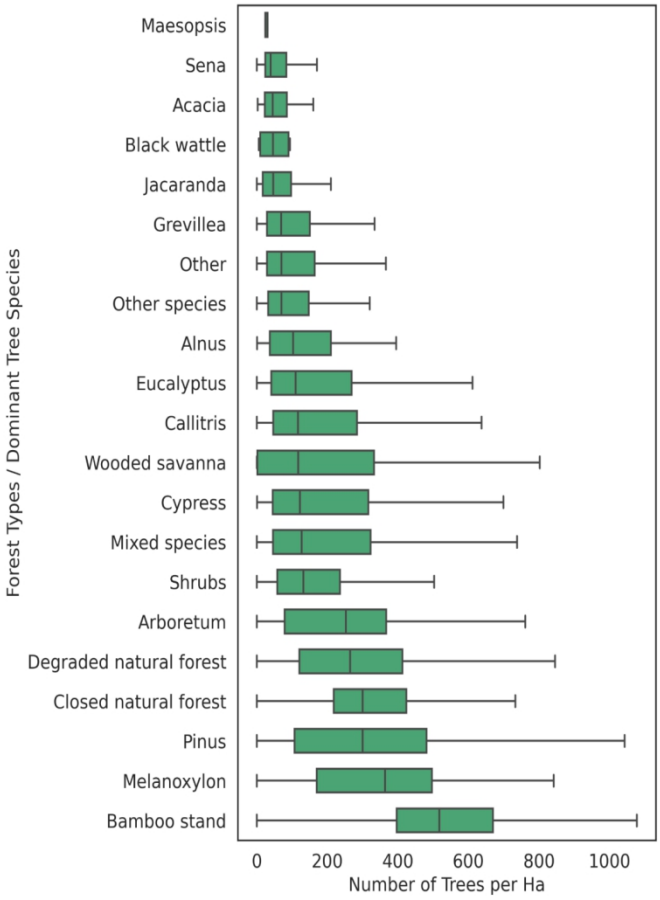
Extended Data | Fig. 6. Illustration of sample independent plots for evaluating the deep learning model performance. a, Sample plot ina urban area, **b-e,** as in **(a)** but for **b,** farmlands, **c,** plantations, **d,** savanna and shrublands, **e,** natural forest. **1,** original image, **2,** manual tree crown labeling, **3,** deep learning model predictions.



Extended Data | Fig. 7. Examples from the post-processing algorithm separating clumped trees. a, Example of predicted tree crowns in the rainforest, with many trees being predicted as clumped objects. **b,** Results after the post-processing algorithm separated the clumped crowns. The algorithm first finds the object centers, and then relabels the image based on weighted distances to the identified centers. Thus, blobs containing multiple centers are divided into various instances accordingly. The algorithm adds a large penalty for not-in-sight centers, and additionally performs a majority filtering to remove the lone-pixels.



Extended Data | Fig. 8. Visual illustration of tree count and carbon stock per land cover type in Rwanda. a, Area size (1000 ha) covered by different land cover types, and **b,** tree count per land cover type (million trees), and **c,** carbon stocks per land cover type (Tg C). Although natural forests cover a small portion of land, they are home to a remarkable number of trees with the largest C stocks of the country



699
700 **Extended Data | Fig. 9. Average tree density per tree species in Rwanda.** Species data are from Rwanda national
701 forest map of 2012 (49)
702
703