Mapping peat thickness and carbon stocks of the central Congo Basin using field data

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The world’s largest tropical peatland complex is found in the central Congo Basin. However, there is a lack of in situ measurements to understand the peatland’s distribution and the amount of carbon stored in it. So far, peat in this region has been sampled only in largely rain-fed interfluvial basins in the north of the Republic of the Congo. Here we present the first extensive field surveys of peat in the Democratic Republic of the Congo, which covers two-thirds of the estimated peatland area, including from previously undocumented river-influenced settings. We use field data from both countries to compute the first spatial models of peat thickness (mean 1.7 ± 0.9 m; maximum 5.6 m) and peat carbon density (mean 1,712 ± 634 Mg C ha⁻¹; maximum 3,970 Mg C ha⁻¹) for the central Congo Basin. We show that the peatland complex covers 167,600 km², 36% of the world’s tropical peatland area, and that 29.0 Pg C is stored below ground in peat across the region (95% confidence interval, 26.3–32.2 Pg C). Our measurement-based constraints give high confidence of globally significant peat carbon stocks in the central Congo Basin, totalling approximately 28% of the world’s tropical peat carbon. Only 8% of this peat carbon lies within nationally protected areas, suggesting its vulnerability to future land-use change.

Peatlands cover just 3% of Earth’s land surface1, yet store an estimated 600 Pg carbon (PgC)2–4, approximately one-third of Earth’s soil carbon. While most peatlands are located in the temperate and boreal zones1, recent research is revealing the existence of tropical peatlands with high carbon densities2,2,5. Tropical peatlands are vulnerable to drainage and drying, with subsequent fires resulting in large carbon emissions from degraded peatlands, particularly in Southeast Asia3–5. In the central depression of the Congo Basin (the ‘Cuvette Centrale’), the only field-verified peatland map to date reported that peat underlies 145,500 km² of swamp forests, making this the world’s largest tropical peatland complex6. The field data used in this estimate are from northern Republic of the Congo (ROC), yet two-thirds of the central Congo Basin peatlands are predicted to be found in neighbouring Democratic Republic of the Congo (DRC)7, sometimes hundreds of kilometres from existing field data (Fig. 1a). Similarly, peat carbon stocks are estimated to be 30.6 Pg C, but the lower confidence interval is just 6 Pg C (ref. 8). Thus, it is unclear whether the central Congo peatlands are truly as extensive or deep as suggested, and it is unclear whether they store globally significant quantities of carbon.

Uncertainties are further compounded by a limited understanding of the processes that determine peat formation in central Congo, particularly hydrology9,10. Peat has been systematically documented only in interfluvial basins in ROC9,11, where an absence of annual flood waves9, modest domes12 and remotely sensed water-table depths13 all suggest peatlands are largely rain-fed and receive little river-water input. However, peat is also predicted in other hydro-geomorphological settings9, including what appear to be river-influenced regions close to the Congo River mainstem and dendritic-patterned valley floors along some of its left-bank tributaries9 (Fig. 1a). These areas of swamp forest are probably seasonally

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Fig. 1 | Maps of field-sampling locations and peat swamp forest predictions in the central Congo Basin. a, Map of field-sampling locations. Points indicate transects, coloured by region. The Congo and Ruki River regional groups appear to be in largely river-influenced peatlands, predominating in DRC, sampled for this study. The Likouala-aux-Herbes River and Ubangi River regional groups are in largely rain-fed interfluvial basins, predominating in ROC, from ref. 9. The base map, in green, shows the first-generation peat swamp forest map. Inset: location of the central Congo Basin peatlands. b, Predicted land-cover classes across the central Congo Basin from this study as the most likely class per pixel (>50%), using a legend identical to ref. 9 to facilitate comparison. In both panels, national boundaries are black lines; sub-national boundaries are grey lines; non-peat-forming forest includes both terra firme and non-peat-forming seasonally inundated forests. Panel a adapted from ref. 9, Springer Nature Limited.

Mapping peatland extent

We found peat along all ten hypothesis-testing transects in DRC that were predicted to be peatlands. Our new field data show that extensive carbon-rich peatlands are present in the forested wetlands of the DRC’s Cuvette Centrale, including in geomorphologically distinct river-influenced regions predicted as peatlands by ref. 9.

inundated14 to depths up to 1.5 m during the main wet season15, suggesting seasonal river flooding and/or upland run-off as key sources of water. Whether peat accumulates under these river-influenced conditions is currently unknown.

In this Article, we present new in situ data on peat presence, thickness and carbon density (mass per unit area) from the central Congo Basin in DRC. We specifically investigated the river-influenced swamp forests along the Congo River and its Ruki, Busira and Iklemba tributaries in contrast to previous data collection from interfluvial basins2 (Fig. 1a). Every 250 m along 18 transects, we recorded vegetation characteristics, peat presence and peat thickness. We targeted a first group of ten transects in locations highly likely to contain peat, to help test hypotheses (detailed in Supplementary Table 1) about the role of vegetation, surface wetness, nutrient status and topography in peat accumulation. To improve mapping capabilities, we sampled a second group of eight transects specifically to test preliminary maps that gave conflicting results or suspected false predictions of peat presence (detailed in Supplementary Table 1). We combine these new field measurements from DRC with previous transect records in ROC using the same protocols8 and other ground-truth data (Supplementary Table 2) to produce (1) a second-generation map of peatland extent, (2) a first-generation map of peat thickness and (3) a first-generation map of below-ground peat carbon density for the central Congo Basin. These maps enable us to compute the first well-constrained estimate of total below-ground peat carbon stocks in the world’s largest tropical peatland complex.

Fig. 2 | Comparison of peat swamp predictions from this study with a previous map. Peat swamp forest predictions from this study and ref. 9 using the most likely class per pixel. White indicates peat in both studies; red indicates peat in this study only; blue indicates peat only in ref. 9. Open water is dark grey. National boundaries are black lines; sub-national boundaries are grey lines. Adapted from ref. 9, Springer Nature Limited.

The best-performing algorithm to map the peatlands was the maximum likelihood (ML) classifier, because of its ability to most accurately predict in regions with no training data (Methods). ML was run 1,000 times on nine remotely sensed datasets using a random two-thirds of 1,736 ground-truth data points each time (Extended Data Fig. 1), giving a median total peatland area for the central Congo Basin of 167,600 km² (95% confidence interval (CI),
### Table 1 | Field-measured and spatially modelled estimates of peat thickness, bulk density and carbon concentration in the central Congo Basin peatland complex

| Peatland Type | Median (m) | Minimum (m) | Maximum (m) | Mean (m) ± s.d. | Median (g cm⁻³) | Minimum (g cm⁻³) | Maximum (g cm⁻³) | Mean (g cm⁻³) ± s.d. | Median (%OC) | Minimum (%OC) | Maximum (%OC) | Mean (%OC) ± s.d. | Median (%C) | Minimum (%C) | Maximum (%C) | Mean (%C) ± s.d. |
|---------------|------------|-------------|-------------|----------------|----------------|----------------|----------------|-----------------|----------------|----------------|----------------|----------------|--------------|----------------|----------------|----------------|
| Interfluvial basin peatlands (ROC) | 0.2 | 0.0 | 0.5 | 0.3 ± 0.2 | 50 ± 50 | 10 | 100 | 50 ± 50 | 0.3 | 0.0 | 0.5 | 0.3 ± 0.2 | 50 ± 50 | 10 | 100 | 50 ± 50 |
| River-influenced peatlands (ROC) | 0.2 | 0.0 | 0.5 | 0.3 ± 0.2 | 50 ± 50 | 10 | 100 | 50 ± 50 | 0.3 | 0.0 | 0.5 | 0.3 ± 0.2 | 50 ± 50 | 10 | 100 | 50 ± 50 |
| Central Congo Basin peatlands (ROC + DRC) | 0.2 | 0.0 | 0.5 | 0.3 ± 0.2 | 50 ± 50 | 10 | 100 | 50 ± 50 | 0.3 | 0.0 | 0.5 | 0.3 ± 0.2 | 50 ± 50 | 10 | 100 | 50 ± 50 |

#### Field measurements
- Peat thickness: 238 locations in DRC (including 59 laboratory-verified measurements; Extended Data Fig. 3), finding a mean (±s.d.) thickness of 2.4 (±1.6) m and a maximum of 6.4 m.
- This shows that river-influenced peatlands can attain similar peat thickness as rain-fed interfluvial basins reported in ROC (Table 1).

#### Spatial model
- The RF model outperforms multiple linear regression with interactions using the same four variables (adjusted $R^2 = 93.4$%; RMSE = 0.42 m). The RF model outperforms multiple linear regression with interactions using the same four variables (adjusted $R^2 = 73.6$%, RMSE = 0.80 m; Extended Data Fig. 5).

Spatially, we predict thick peat deposits in the centres of the largest interfluvial basins (far from peatland margins), and in smaller, river-influenced valley-floor peatlands along the Ruki/Busira rivers (Fig. 3a). The river valleys’ thick deposits are probably driven by greater climatic water balance and lower precipitation seasonality in the eastern part of the Cuvette Centrale region (Extended Data Fig. 6), plus potentially greater water inputs from nearby higher ground, which offsets the shorter distances from peatland margins.
Our modelled results are consistent with our field data, as the two deepest peat cores are from the interfluval Centre transect in ROC (5.9 m) and the river-influenced Bondamba transect on the Busira River in DRC (6.4 m). Overall, mean (±s.d.) modelled peat thickness (1.7 ± 0.9 m) is lower than our field measurements (2.4 ± 1.5 m; Table 1), as expected given our linear transects, which oversample deeper peat at the centre relative to the periphery in approximately ovoid peatlands. Areas of high uncertainty in peat thickness occur where distance from the margin is uncertain (Fig. 3b). Our results contrast strongly with an ‘expert system approach’ that assigned peat-thickness values on the basis of hydrological terrain relief alone and estimated a mean thickness of 6.5 ± 3.5 m for the central Congo Basin peatlands\textsuperscript{17}, compared with our field-derived estimate of 1.7 ± 0.9 m (Fig. 3a).

After distance from the margin, precipitation seasonality and climatic water balance are the most important predictors of peat thickness in the RF model, reflecting the relative importance of rainfall inputs in peat accumulation in central Congo. This appears to differ from smaller-scale assessments in temperate\textsuperscript{18} or other tropical peatlands\textsuperscript{19}, where surface topography (elevation and slope) are primary predictors of peat thickness. However, this is potentially merely an artefact of the spatial scale of the studies,
as climate varies only over large scales. Alternatively, the relatively low rainfall in the central Congo Basin (~1,700 mm yr$^{-1}$), compared with other tropical peatland regions (for example, ~2,500–3,000 mm yr$^{-1}$ in Northwest Amazonia and Southeast Asia$^{1,2}$), may mean that peat thickness is more strongly related to climate in central Congo, as it implies greater exposure to (seasonal) drought conditions that may cross thresholds that negatively impact peat accumulation rates.

Peat bulk density measured across the central Congo Basin is $0.17 \pm 0.06$ g cm$^{-3}$ (mean ± s.d.; $n=80$ cores), and mean carbon concentration is $55.7 \pm 3.2$% ($n=80$; 56.6 ± 4.5% for the 22 well-sampled cores). While peat bulk density is significantly lower in largely river-influenced sites than in rain-fed interfluvial basins ($P<0.01$), no significant difference between these peatland types is found for either peat carbon concentration or carbon density (mass per unit area; Table 1).

We used the peat-thickness, bulk density and carbon concentration measurements to construct a linear peat-thickness–carbon-density regression (Extended Data Fig. 7). We applied this regression model to our peat-thickness map to spatially model carbon stocks per unit area (Fig. 4a). Modelled below-ground peat carbon density for the central Congo Basin is $1,712 \pm 634$ Mg C ha$^{-1}$, similar to the field-measured mean of $1,741 \pm 1,186$ Mg C ha$^{-1}$ (mean ± s.d., $n=80$; Table 1). This carbon density is approximately nine times the mean carbon stored in above-ground live tree biomass ($867$ Mg C ha$^{-1}$), the central Congo peatlands store almost twice as much carbon per hectare. Spatial patterns of peat carbon density (Fig. 4a) and uncertainty (Fig. 4b) follow similar patterns as peat thickness (Fig. 3a,b).

Estimating basin-wide peat carbon stocks

Median estimated total peat carbon stock in the central Congo Basin is 29.0 PgC (95% CI, 26.3–32.2; Extended Data Fig. 8a), based on bootstrapping the area estimate and peat-thickness–carbon-density regression. This is similar to the median 30.6 PgC reported by ref. $^4$, but their lower 95% CI was 6.3 PgC, which our study increases to 26.3 PgC. This constraint on the carbon-stock estimate is possible because our larger field-based dataset allows a spatial modelling approach so that we can sum carbon density across all peat pixels. Therefore, the possibility of low values of carbon storage in the central Congo peatlands can now confidently be discarded.

Our new results show that the central Congo Basin peatlands are a globally important carbon stock. About two-thirds of this peat carbon is in DRC (19.6 PgC; 95% CI, 17.9–21.9), and one-third in ROC (9.3 PgC; 95% CI, 8.4–10.2; Extended Data Fig. 2), which is equivalent to approximately 82% and 238% of each country’s above-ground forest carbon stock, respectively$^1$. The high peat carbon stocks are found across several administrative regions in both countries, with the largest stocks in DRC’s Equateur province (Extended Data Fig. 2). Sensitivity analysis shows that uncertainty in total peat carbon stock is now driven mostly by uncertainty in peatland area (Extended Data Fig. 8b).

Because the central Congo peatlands are relatively undisturbed$^{14,28}$, our new maps of peatland extent, thickness and carbon density form a baseline description for the decade 2000–2010, given the remotely sensed data used. Today the peatlands of the central Congo Basin are threatened by hydrocarbon exploration, logging, palm oil plantations, hydroelectric dams and climate change$^{29}$, While the peatlands are largely within a UN Ramsar Convention transboundary wetland designation, we estimate that only 2.4 Pg C in peat, just 8% of total stocks, currently lies within formal national-level protected areas (Extended Data Figs. 9 and 10). Meanwhile, logging, mining or palm oil concessions together overlie 7.4 Pg C in peat, or 26% of total stocks (Extended Data Figs. 9 and 10), while hydrocarbon concessions cover almost the entire peatland complex$^{24,26}$.

Our results show that the central Congo Basin peatlands cover approximately 36% of the world’s tropical peatland area, and store approximately 28% of the world’s tropical peat carbon$^1$. Therefore, keeping the central Congo Basin peatlands wet is vital to prevent peat carbon being released to the atmosphere. The identification of extensive river-influenced peatlands suggests that there is more than one geomorphological setting where peat is found in the central Congo Basin. Further work is required to understand both the sources and flows of water in these river-influenced peatlands, specifically the relative contributions of water from precipitation, riverbank overflow and run-off from higher ground to peat formation and maintenance. Given the current areas of formal protection of peatlands are largely centred around interfluvial basins, we suggest that additional protective measures will be needed to safeguard the newly identified river-influenced peatlands of the central Congo Basin. Keeping the central Congo peatlands free from disturbance would also help protect the rich biodiversity, including forest elephants, lowland gorillas, chimpanzees and bonobos$^{30,31}$, that form part of this globally important but threatened ecosystem.

Online content

Any methods, additional references, Nature Research reporting summaries, source data, extended data, supplementary information, acknowledgements, peer review information; details of author contributions and competing interests; and statements of data and code availability are available at https://doi.org/10.1038/s41561-022-00966-7.

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Field work was conducted in DRC between January 2018 and March 2020. Ten transects (4–11 km long) were installed, identical to the approach in ref. 9, in locations that were highly likely to be peatland. These were selected to help test hypotheses about the role of peatland, surface water, nutrient status and topography in peat accumulation (Fig. 1a and Supplementary Table 1). A further eight transects (0.5–3 km long) were installed to assess our peat mapping capabilities (Fig. 1a and Supplementary Table 1).

Every 250 m along each transect, land cover was classified as one of six classes: water, savanna, terra firme forest, non-peat-forming seasonally inundated forest, hardwood-dominated peat swamp forest or palm-dominated peat swamp forest. Peat swamp forest was classified as palm dominated when >50% of the canopy, estimated by eye, was palms (commonly Raphia laurentii or Raphia seae). In addition, several ground-truth points were collected at locations in the vicinity of each transect from the clearly identifiable land-cover classes, water, savanna and terra firme forest.

Peat presence/absence was recorded every 250 m along all transects, and peat thickness (if present) was measured by inserting metal poles into the ground until the poles were prevented from going any further by the underlying mineral layer, identical to the pole method of ref. 9. In addition, a core of the full peat profile was extracted every kilometre along the ten hypothesis-testing transects, if peat was present, with a Russian-type corer (52 mm stainless steel Eijkelkamp model); these 63 cores were sealed in plastic for laboratory analysis.

We used nine remote-sensing products to map peat-associated vegetation (Supplementary Fig. 1). Eight of these are identical to those used by ref. 9: three optical products (Landsat 7 ETM + bands 5 (SWIR 1), 4 (NIR) and 3 (Red)); three L-band synthetic-aperture radar products (AOLS PALSAR HV, HH and HV/HH); and two topographic products (SRTM DEM (digital elevation model) void-filled with ASTER GDEM v.2 data and slope; acquisition date 2000). To this, we added a HAND-index (height above nearest drainage point), which significantly improved model performance compared with ASTER GDEM v.2 data and slope; acquisition date 2000). We used the Landsat bands and the HAND-index to derive a new peat index that is robust to low vegetation coverage and provides higher detection power for deep peats. We used an unsupervised classification method to identify potential peatland regions, and used a supervised classification approach to discriminate between land covers. The peat index was then used in a logistic regression model with HAND to map peat-associated vegetation across the basin.

To estimate peat carbon from modelled peat thickness across the basin, we developed a regression model between peat thickness and per-unit area carbon density using the 80 sampled cores. We compared linear regressions for normal, logarithmic- and square-root-transformed peat thickness, selecting the model with the highest adjusted Akaike information criterion (AICc). A linear model with square-root-transformed peat thickness was found to provide the best fit (R² = 0.86; P < 0.001; Extended Data Fig. 7). Bootstrapping was applied (boot package in R, version 1.3–2) to assess uncertainty around the regression.

Carbon-density estimates. To calculate carbon density (mass per unit area), estimates of carbon storage in each 0.1-m-thick peat sample (thickness × bulk density × carbon concentration) were summed to provide an estimate of total carbon storage in 0.1-m-thick peat samples. The pole method used to estimate peat thickness in the field was calibrated against thin-sections taken from each peat core. Linear interpolation was used to estimate carbon density for the remaining 58 cores, following ref. 9. We used segmented regression on the 22 sampled cores (segmented package in R, version 1.3–1) to parameterize the three sections of the core, using the means of these relationships to interpolate the carbon concentrations for the remaining 58 samples, following ref. 9.

To estimate carbon density from modelled peat thickness across the basin, we developed a regression model between peat thickness and per-unit area carbon density using the 80 sampled cores. We compared linear regressions for normal, logarithmic- and square-root-transformed peat thickness, selecting the model with the highest adjusted Akaike information criterion (AICc). A linear model with square-root-transformed peat thickness was found to provide the best fit (R² = 0.86; P < 0.001; Extended Data Fig. 7). Bootstrapping was applied (boot package in R, version 1.3–2) to assess uncertainty around the regression.
classifier using both a random and spatial cross-validation (CV) approach\textsuperscript{44–46}. Random CV was implemented using stratified two-thirds Monte Carlo selection, whereby 1,000 times, we randomly selected two-thirds of all data points per class as training data, to be evaluated against the remaining one-third per class as testing data.

Spatial CV was implemented by grouping all transects data points in four distinct hydro-geomorphological regions: (1) transects perpendicular to the black-water Likouala-aux-Herbes River (\(n = 179\) data points); (2) transects perpendicular to the white-water Ubangi River (\(n = 113\)); (3) transects perpendicular to the Congo River, intermediate between black and white water (\(n = 123\)); and (4) transects perpendicular to the black-water Ruki, Busira and Ikélémba rivers, plus nearby transects (collectively named the Ruki group; \(n = 258\)). To each group we added ground-truth data points from other non-transect data sources (Supplementary Table 2) that belonged to the same map region (\(n = 27, 20, 113\), respectively). We then calculated how well each classifier performs in each of the four regions when trained only on a stratified two-thirds Monte Carlo selection of the remaining data points (data points from the three other regional transect groups) plus ground-truth data points not associated with or near any transect group (\(n = 821\); for example, the Savannah and terra firme forest data points in Lomami National Park in DRC, which are far (>300 km) from any transect group).

Model performance was based on MCC for binary peat/non-peat predictions (hardwood- and palm-dominated peat swamp forest classes combined into one peat class; water, savanna and non-peat-forming forest combined into one non-peat class). We compared MCC, rather than popular metrics such as Cohen's kappa, F1 score or accuracy, because it is thought to be the most reliable evaluation metric for binary classifications\textsuperscript{45,46}. We also computed BA from random CV to compare with the first-generation map. While less robust than MCC, BA is independent of imbalances in the prevalence of positives/negatives in the data, thus allowing better comparison between classifiers trained on different datasets\textsuperscript{7}. The best estimates of each accuracy metric or area estimate per model or region is the median value of 1,000 runs, along with a 95% CI.

In the case of SVM and RF, random CV models were implemented in Google Earth Engine (GEE)\textsuperscript{47} using all nine remote-sensing products. However, because ML is currently not supported by GEE, random CV with this algorithm was implemented in IDL-ENVI software (version 8.7–5.5), using a principal component analysis to reduce the nine remote-sensing products to six uncorrelated principal components to reduce computation time. All spatial CV models were implemented in R (superClass function from the RStoolbox package, version 0.2.6), with principal component analysis also applied in the case of ML only. All RF models were trained using 500 trees, with three input products used at each split in the forest (the default, the square root of the number of variables). All SVM models were implemented with a radial basis function kernel, with all other parameters set to default values.

Comparison of the ML, SVM and RF models with the model performance of ref.\textsuperscript{1}, using balanced accuracy from random CV, shows improved results only in the case of the ML classifier (Supplementary Table 3). Comparing MCC using the spatial CV approach, we found that the ML algorithm is also more transferable to regions for which we lack training data. While RF gives slightly better MCC with spatial CV approach, we found that the ML algorithm is also most transferable to regions for which we lack training data. While RF gives slightly better MCC with random CV and performs worst of all three in the Congo region, RF seems to be the best algorithm for the Congo and Ruki regions when predicting peatland extent from 1,000 ML runs, each time trained only on the three other selected predictors (precipitation seasonality, climatic water balance and distance from the peatland margin) as input in an RF model to develop 100 different peat-thickness maps. For these model runs, we included all available thickness measurements (>0 m) that fell within each specific distance map. Each output map was masked to an area ≥0.3 m thickness, consistent with our peat definition. A map of median peat thickness (Fig. 4a) and relative uncertainty (±half the width of the 95% CI as percentage of the median; Fig. 4b) was then calculated for each pixel on the basis of the 100 available thickness estimates.

### Carbon-stock estimates

We mapped carbon density across the central Congo Basin in GEE by applying 20 bootstrapped thickness–carbon regressions that were normally distributed around the best fit (Extended Data Fig. 7) to the 100 peat-thickness maps from the RF regression model, generating a map of median carbon density out of 2,000 estimates; for area, thickness or carbon concentration. We thus obtained 2,000 peat-thickness maps from the RF regression model, generating a map of median carbon density out of 2,000 estimates (Fig. 4a), together with relative uncertainty (±half the width of the 95% CI as percentage of the median; Fig. 4b) was then calculated for each pixel on the basis of the 100 available thickness estimates.

Total peat carbon stocks were computed in GEE by summing carbon density (Mg ha\(^{-1}\)) over all 50 m grid squares defined as peat. To assess uncertainty around this estimate, we again combined the 100 peat-thickness maps (uncertainty from area and thickness) with 20 bootstrapped thickness–carbon regressions (uncertainty from carbon density, including bulk density and carbon concentration). We thus obtained 2,000 peat-carbon-stock estimates for the total central Congo Basin peatland complex, which were used to estimate the mean, median and 95% CI (Extended Data Fig. 8a).

Regional carbon-stock estimates were similarly obtained for each sub-national administrative region (department/communes in ROC and provinces in DRC; Extended Data Fig. 2), as well as national-level protected areas (national parks and nature/reserve/biosphere/community reserves)\textsuperscript{61} and logging\textsuperscript{62}, mining\textsuperscript{62} and palm oil\textsuperscript{63–65} concessions (Extended Data Figs. 9 and 10). As hydrocarbon concessions cover almost the whole peatlands area\textsuperscript{66–68}, they cover almost 100% of the central Congo peat carbon stocks.

Sensitivity analysis was performed by bootstrapping the area, thickness or carbon-density component, while keeping the others constant (Extended Data Fig. 8b). For area, we bootstrapped 100 randomly selected peatland area estimates; for thickness, 100 randomly selected two-thirds subsets of all thickness measurements; for carbon density, 20 normally distributed regression equations from the bootstrapped thickness–carbon relationship.

Data availability

All map results from this study are available for download as raster files from https://congopeat.net/maps/. The supporting ground-truth data, peat-thickness...
measurements and carbon-density measurements are available from https://github.com/CongoPeat/Peatland-mapping.git. The remote-sensing datasets are available for download from https://www.esrich.jaxa.jp/ALOS/en/dataset/fnf_e.htm (ALOS PALSAR and ALOS-2 PALSAR 2.25 m HV and HH data), http://osfac.net/ (OSFAC ROC and DRC 60 m Landsat ETM+ bands S, 4, and 3 mosaics) and http://earthexplorer.usgs.gov/ (SRTM DEM 1-arc second and ASTER GDEM v2 1-arc second data).

Code availability

The IDL-ENVi script to run the maximum likelihood peatland-extent model is available from https://github.com/CongoPeat/Peatland-mapping.git. The scripts to run the peat-thickness model and carbon-stock calculations are available on Google Earth Engine: https://code.earthengine.google.com/?accept_repo=users/gnych/Central_Congo_Peatslands_2022. All R code is available from the corresponding author upon request.

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Author contributions

S.L.L., E.T.A.M., I.T.L., G.C.D. and S.E.P. conceived the study; B.C., G.C.D., S.L.L., E.T.A.M., I.T.L., S.E.P., S.A.I., C.E.N.E. and T.R.B. developed the study; B.C., G.C.D., S.L.L., C.E.N.E., O.E.B., P.B., I.K.T., N.T.G. and J.-B.N. organized and conducted the fieldwork; Y.E.B., S.A.I., W.H., D.S., R.B., G.I., A.C.-S., C.A.K., J.L. and H.-P.W. provided additional data; B.C., G.C.D., A.B. and H.B. performed laboratory analyses; B.C. and E.T.A.M. analysed the remote-sensing data and developed the models; B.C., G.C.D., A.B., J.I.B., T.R.B., P.I.M. and C.A.K. evaluated the results. B.C. and S.L.L. wrote the paper, with input from all co-authors.

Competing interests

The authors declare no competing interests.

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Extended Data Fig. 1 | Spatial overview of 1,736 ground-truth datapoints across the central Congo basin study area, grouped by six landcover classes. Only the palm-dominated and hardwood-dominated peat swamp forest classes (e, f) are associated with the presence of peat. *Terra firme* forest (c) and non-peat forming seasonally inundated forest (d) are combined into a single non-peat forming forest class when running classification models. The RGB baselayer of Landsat ETM+ 7 (SWIR 1, NIR and Red bands) reflects different forest types (shades of green), open savannah (pink), agricultural land (yellow) and open water (blue).
Extended Data Fig. 2 | Estimated peatland area, peat thickness, carbon density and carbon stocks per administrative region. All values are regional means (± s.d.) of the median peat thickness and carbon density maps; or median estimates (with 95% confidence interval in parentheses) for total peatland area and peat carbon stock. For regional area estimates without confidence interval, the median peatland map (> 50% probability) was used. Sub-national administrative regions are provinces (DRC) or departments (ROC). Marginal peat predictions in other administrative regions (Kasaï, Tshopo, Kwilu, Nord-Ubangi in DRC; Cuvette-Ouest in ROC) are included in total country estimates, but not listed separately.
Extended Data Fig. 3 | Relationship between peat thickness estimated using the pole-method and laboratory-verified peat thickness using Loss-On-Ignition (LOI) across four regional transect groups. Mean pole-method offset is significantly higher in the largely river-influenced transects in DRC (0.94 m, red line) than in the mostly interfluvial basin transects in ROC (0.48 m, blue line; P < 0.001). No significant differences were found between either the Likouala-aux-Herbes and Ubangi transects in ROC, or between the Congo and Ruki transects in DRC. Best-fitting line: corrected peat thickness = $-0.1760 + 0.8626 \times$ (pole-method thickness) $- 0.3284 \times$ (country); n = 93, adj-$R^2 = 0.95; P < 0.001$. Country is dummy coded as: ROC (0) and DRC (1). Shaded grey shows 95% confidence intervals. Outliers (n = 3) with $> 4x$ the mean Cook’s distance are excluded from the analysis.
Extended Data Fig. 4 | Relationships between field-measured peat thickness (LOI + corrected pole-method measurements) and distance from the peatland margin. Distance from the peatland margin is calculated as the shortest distance to a non-peat pixel in any direction, based on a smoothed median Maximum Likelihood map of peatland extent (> 50% peat probability threshold). Transects are ordered by increasing regression slope (in m km⁻¹; upper left corner of each panel), with colours indicating the four transect regions. Note that the horizontal axes are different for each panel. Shaded grey shows 95% confidence intervals around each regression.
Extended Data Fig. 5 | Comparison of observed and predicted values in two peat thickness models. **a**, Multiple linear regression model with interaction effects (adj-$R^2$ = 73.6%, RMSE = 0.80 m). **b**, Random Forest regression model ($R^2$ = 93.4%, RMSE = 0.42 m). Both models are trained and validated against 463 field measurements and include the same four predictor variables: distance from the peatland margin, precipitation seasonality, climatic water balance, and distance from the nearest drainage point. Both panels show 277 aggregated means only to account for duplicates in observed values. The black lines indicate the 1:1 relationship.
Extended Data Fig. 6 | Spatial variability of the four predictor variables retained in the final Random Forest regression model of peat thickness. 

a, Distance from the peatland margin (km). b, Precipitation seasonality (coefficient of variation). c, Climatic water balance (precipitation minus potential evapotranspiration; mm). d, Distance from the nearest drainage point (km). All maps have been masked to the smoothed median Maximum Likelihood peatland extent (> 50% peat probability). Black lines represent national boundaries; grey lines represent sub-national administrative boundaries.
Extended Data Fig. 7 | Relationship between peat thickness and carbon density per unit area. Dots are coloured by transect region. Best-fitting line: carbon density (in Mg ha$^{-1}$) = $-942.4 + 2088.4 \times \sqrt{\text{peat thickness}}$, in m; $n=80$, $R^2=0.86$, $P<0.001$. Shaded grey shows the 95% confidence interval. 20 bootstrapped regressions, normally distributed around the best-fitting line, were used to include this uncertainty when scaling peat thickness to carbon density estimates.
Extended Data Fig. 8 | Distribution and sensitivity of peat carbon stock estimates in the central Congo Basin peatland complex. a, Distribution of 2,000 peat carbon stock estimates, obtained by combining 100 random peat probability thresholds in the peatland extent model and computing the associated RF peat thickness map, with 20 normally-distributed equations from the bootstrapped peat thickness-carbon density regression. Median, 29.0 Pg C; mean, 29.1 Pg C; 95% CI, 26.3–32.2 Pg C. b, Sensitivity analysis by in turn bootstrapping peat area estimates (n = 100), peat thickness measurements (n = 100), or carbon density regressions (n = 20), whilst keeping the other components constant. Central lines show the medians, box limits show the upper and lower quartiles, and the vertical lines show maximum and minimum values. Dots represent potential outlying values.
Extended Data Fig. 9 | Distribution of national protected areas and industrial concessions across the central Congo Basin peatland complex. The base map shows belowground peat carbon density (shaded grey; Fig. 4a), overlaid with protected areas at national-level (national parks and nature/biosphere/community reserves; adapted with permission from ref. 51), or industrial logging (adapted with permission from refs. 52,53), mining (adapted with permission from refs. 54,55), and palm oil (adapted with permission from refs. 56–58) concessions. Black lines represent national boundaries; grey lines represent sub-national administrative boundaries. Images from refs. 52–58 and 57 adapted under a CC BY licence.
Extended Data Fig. 10 | Estimated peatland area, peat thickness, carbon density and carbon stocks in industrial concessions and protected areas. Estimates are calculated for protected areas at national-level (national parks and nature/biosphere/community reserves)\(^5\) or for industrial logging\(^5\)\(^2\)\(^5\)\(^3\), mining\(^5\)\(^4\)\(^5\)\(^5\), and palm oil\(^5\)\(^6\)\(^7\)\(^8\)\(^9\) concessions combined (see Extended Data Fig. 9). All values are means (± s.d.) of the median peat thickness and carbon density maps, or median estimates for total peatland area and peat carbon stock. Percentages show the proportion of total peatland area or peat carbon stock in ROC, DRC and combined (Extended Data Fig. 2) that is found in either protected areas or industrial logging/mining/palm oil concessions.

| Country                          | Concessions / Protected areas | Peatland area (km\(^2\)) | Peat thickness (m) | Peat carbon density (Mg C ha\(^{-1}\)) | Peat carbon stock (Pg C) |
|----------------------------------|-------------------------------|--------------------------|-------------------|----------------------------------------|--------------------------|
| Republic of the Congo (ROC)      | Industrial logging / mining / palm oil concessions | 13,539 (25%) | 1.2 ± 0.6 | 1,299 ± 451 | 2.0 (22%) |
|                                  | National-level protected areas | 6,402 (12%) | 1.4 ± 0.6 | 1,463 ± 478 | 1.0 (11%) |
| Democratic Republic of the Congo (DRC) | Industrial logging / mining / palm oil concessions | 29,712 (26%) | 1.6 ± 0.7 | 1,671 ± 567 | 5.4 (28%) |
|                                  | National-level protected areas | 8,105 (7%) | 1.5 ± 0.8 | 1,552 ± 592 | 1.4 (7%) |
| ROC and DRC combined             | Industrial logging / mining / palm oil concessions | 43,250 (26%) | 1.5 ± 0.7 | 1,551 ± 560 | 7.4 (25%) |
|                                  | National-level protected areas | 14,511 (9%) | 1.5 ± 0.7 | 1,513 ± 547 | 2.4 (8%) |