

1 **Peat thickness and carbon maps of the central Congo Basin from extensive *in*
2 *situ* sampling**

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1 In 2017 the first field-based map of the central Congo Basin peatlands revealed
2 them to be the world's largest tropical peatland complex. However, peat was
3 only sampled in largely rain-fed interfluvial basins in northern Republic of the
4 Congo. Here we present the first extensive field surveys of peat in the
5 Democratic Republic of the Congo, which contains two-thirds of the estimated
6 peatland area, including from previously undocumented river-influenced
7 settings. We use data from both countries to compute the first spatial models of
8 peat thickness (mean 1.7 ± 0.9 m) and peat carbon density (mean $1,712 \pm 634$ Mg
9 C ha⁻¹) for the central Congo Basin peatlands. We show that the peatland
10 complex covers $167,600$ km², 15% more than previously estimated; and that 29.0
11 Pg C is stored belowground in peat across the region (95% confidence interval,
12 26.3-32.2 Pg C). This is similar to the 2017 estimate, but with the lower
13 confidence interval having increased from just 6 Pg C, our analysis gives high
14 confidence of globally significant carbon stocks – approximately one-third of
15 the world's tropical peat carbon – in the central Congo Basin. Only 8% of this
16 peat carbon lies within nationally protected areas, suggesting vulnerability to
17 future land-use change.

18

19 Peatlands cover just 3% of Earth's land surface¹, yet store an estimated 600 Pg of
20 carbon (C)^{2,3}, approximately one-third of Earth's soil carbon⁴. While most peatlands
21 are located in the temperate and boreal zones¹, recent research is revealing the
22 existence of tropical peatlands with high carbon densities^{1,2,5,6}. Tropical peatlands are
23 vulnerable to drainage and drying, with subsequent fires resulting in large carbon
24 emissions from degraded peatlands, particularly in Southeast Asia^{3,6-8}.

1 In the central depression of the Congo basin (the ‘Cuvette Centrale’) the only field-
2 verified peatland map to date reported that peat underlies 145,500 km² of swamp
3 forests, making this the world’s largest tropical peatland complex⁹. The field data used
4 in this estimate are from northern Republic of the Congo (ROC), yet two-thirds of the
5 central Congo Basin peatlands are predicted to be found in neighbouring Democratic
6 Republic of the Congo (DRC)⁹, sometimes hundreds of kilometres from existing field
7 data (Fig. 1a). Similarly, peat carbon stocks are estimated to be 30.6 Pg C, but the
8 lower confidence interval is just 6 Pg C (ref. ⁹). Thus, it is unclear if the central Congo
9 peatlands are truly as extensive or deep as suggested, and it is unclear whether they
10 store globally significant quantities of carbon.

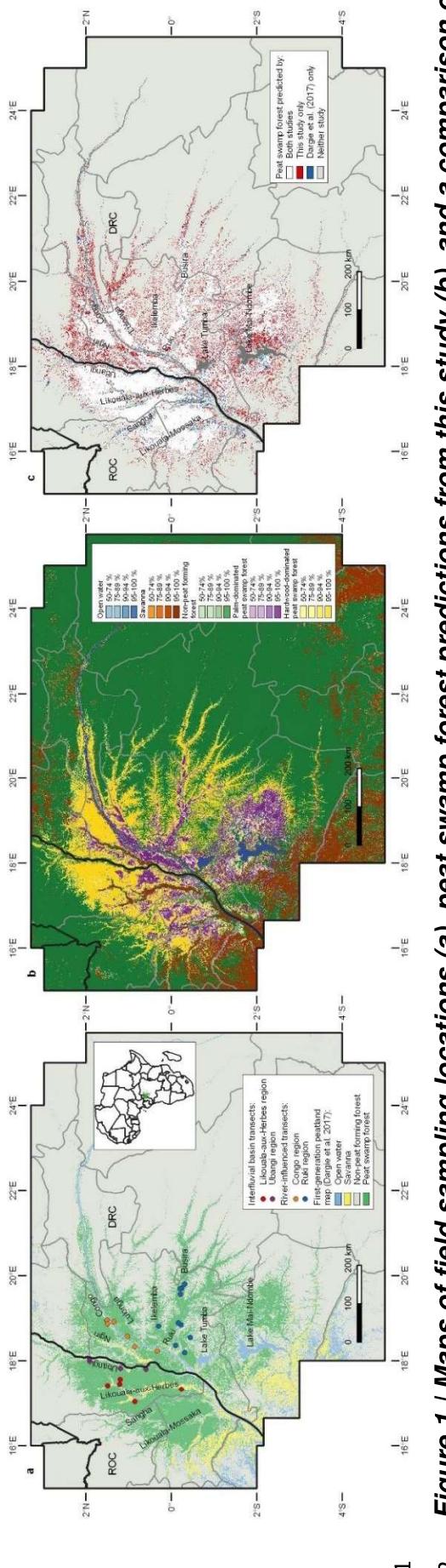
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12 Uncertainties are further compounded by a limited understanding of the processes
13 that determine peat formation in central Congo, particularly hydrology^{9,10}. Peat has
14 only been systematically documented in interfluvial basins in ROC^{9,11}, where an
15 absence of annual flood waves⁹, modest domes¹², and remotely-sensed water-table
16 depths¹³ all suggest peatlands are largely rain-fed and receive little river water input.
17 However, peat is also predicted in other hydro-geomorphological settings⁹, including
18 what appear to be river-influenced regions close to the Congo River mainstem and
19 dendritic-patterned valley-floors along some of its left-bank tributaries⁹ (Fig. 1a). These
20 areas of swamp forest are likely seasonally inundated¹⁴ to depths up to 1.5 m during
21 the main wet season¹⁵, suggesting seasonal river flooding and/or upland runoff as key
22 sources of water. Whether peat accumulates under these river-influenced conditions
23 is currently unknown.

1 Here, we present the first *in situ* data on peat presence, thickness, and carbon density
2 (mass per unit area) from the central Congo Basin in DRC. We specifically investigated
3 the river-influenced swamp forests along the Congo River and its Ruki, Busira and
4 Ikelemba tributaries that contrast with previous data collection from interfluvial basins⁹
5 (Fig. 1a). Every 250 m along 18 transects, we recorded vegetation characteristics,
6 peat presence and thickness. We targeted a first group of ten transects in locations
7 highly likely to contain peat, to help test hypotheses (detailed in Supplementary Table
8 1) about the role of vegetation, surface wetness, nutrient status, and topography in
9 peat accumulation. To improve mapping capabilities, we sampled a second group of
10 eight transects specifically to test preliminary maps that gave conflicting results or
11 suspected false predictions of peat presence (detailed in Supplementary Table 1). We
12 combine these new field measurements from DRC with previous transect records in
13 ROC using the same protocols⁹ and other ground-truth data (Supplementary Table 2)
14 to produce (i) a second-generation map of peatland extent, (ii) a first-generation map
15 of peat thickness, and (iii) a first-generation map of belowground peat carbon density
16 for the central Congo Basin. These maps enable us to compute the first well-
17 constrained estimate of total belowground peat carbon stocks in the world's largest
18 tropical peatland complex.

19

20 ***Mapping peatland extent***

21 We found peat along all ten hypothesis–testing transects in DRC that were predicted
22 to be peatlands⁹. Our new field data shows that extensive carbon-rich peatlands are
23 present in the forested wetlands of the DRC's Cuvette Centrale, including in
24 geomorphologically distinct river-influenced regions predicted as peatlands by Dargie
25 et al.⁹.



2 Figure 1 | Maps of field sampling locations (a), peat swamp forest predictions from this study (b), and a comparison of our predictions with a previous map⁹ (c). **a.** Points indicate transects, coloured by region. The Congo and Ruki River regional groups

- 4 appear to be in largely rain-influenced peatlands, predominating in ROC, from Ref. ⁹. The base map, in green,
- 5 Ubangi River regional groups are in largely rain-fed interfluvial basins, predominating in DRC, sampled for this study. The Likouala-aux-Herbes and
- 6 shows the first-generation peat swamp forest map⁹. **Inset:** Location of central Congo Basin peatlands. **b.** Predicted landcover classes
- 7 across the central Congo Basin as the most likely class per pixel (>50%), using a legend identical to Ref. ⁹ to facilitate comparison.
- 8 **c.** Peat swamp forest predictions from this study and Ref. ⁹ using the most likely class per pixel. White indicates peat in both studies;
- 9 red indicates peat in this study only; blue indicates peat only in Ref. ⁹. Open water is dark grey. In all panels, national boundaries are
- 10 black lines; sub-national boundaries are grey lines; non-peat forming forest includes both terra firme and non-peat forming seasonally
- 11 inundated forests.

1 The best-performing algorithm (Maximum Likelihood classifier, based on its ability to
2 most accurately predict in regions with no training data; see Methods) was run 1,000
3 times on nine remotely-sensed datasets, using a random two-thirds of 1,736 ground-
4 truth datapoints each time (ED Fig. 1), giving a median total peatland area for the
5 central Congo Basin of 167,600 km² (95% CI, 159,400-175,100 km²). This is 15%
6 higher than the previous estimate⁹. We found that 90% of all pixels that are predicted
7 as peat in the median map result were predicted as peat in at least 950 out of 1,000
8 runs (i.e., with $\geq 95\%$ probability, either as hardwood- or palm-dominated peat swamp
9 forest; Fig. 1b), showing that peat predictions are consistent across model runs and
10 thus are robust. Overall model performance, using the Matthews correlation coefficient
11 is 78.0% (95% CI, 74.2-81.6%).

12

13 Comparing our field results with the original first-generation map⁹ shows that of the
14 382 locations assessed across DRC, 77.7% were correctly classified as either being
15 peat swamp or not by the first-generation map⁹. Comparing our new map with the first-
16 generation map⁹ shows large areas of agreement (white in Fig. 1c). However, we
17 predict areas of peat which were previously not mapped⁹, particularly around Lake
18 Mai-Ndombe and the Ngiri and upper Congo/Lulanga Rivers in DRC (red in Fig. 1c).
19 In addition, small areas of previously predicted peat deposits⁹ are no longer predicted
20 by our new model, particularly along the Sangha and Likouala-Mossaka Rivers in ROC
21 (blue in Fig. 1c). These areas of difference are likely areas of high uncertainty and
22 should therefore be priorities for future fieldwork.

23

24 More formally, we compare our new second-generation map with the original map⁹
25 using balanced accuracy (BA), which is similar to Matthews correlation coefficient but

1 better suited for comparison across different datasets¹⁶. For our new map, median BA
2 is 91.9% (95% CI, 90.2-93.6%), compared with 89.8% (86.0-93.4%) for the first-
3 generation map⁹. The substantially smaller BA interval indicates improved confidence
4 in our new peatland map, despite only a small increase in median BA. This is likely
5 due to the effect of our larger sample size being partly offset by an increase in its
6 spatial extent and ecological diversity, particularly data from the Congo River region,
7 where all algorithms that we tested are underperforming (Supplementary Table 3).
8 Overall, our *in situ* data from DRC, including from river-influenced settings that are
9 being reported for the first time, confirm the central Congo Basin peatlands as the
10 world's largest tropical peatland complex, and that DRC and ROC are the second and
11 third most important countries in the tropics for peatland area after Indonesia⁵,
12 respectively (ED Table 1).

13

14 ***Mapping peat thickness and carbon density***

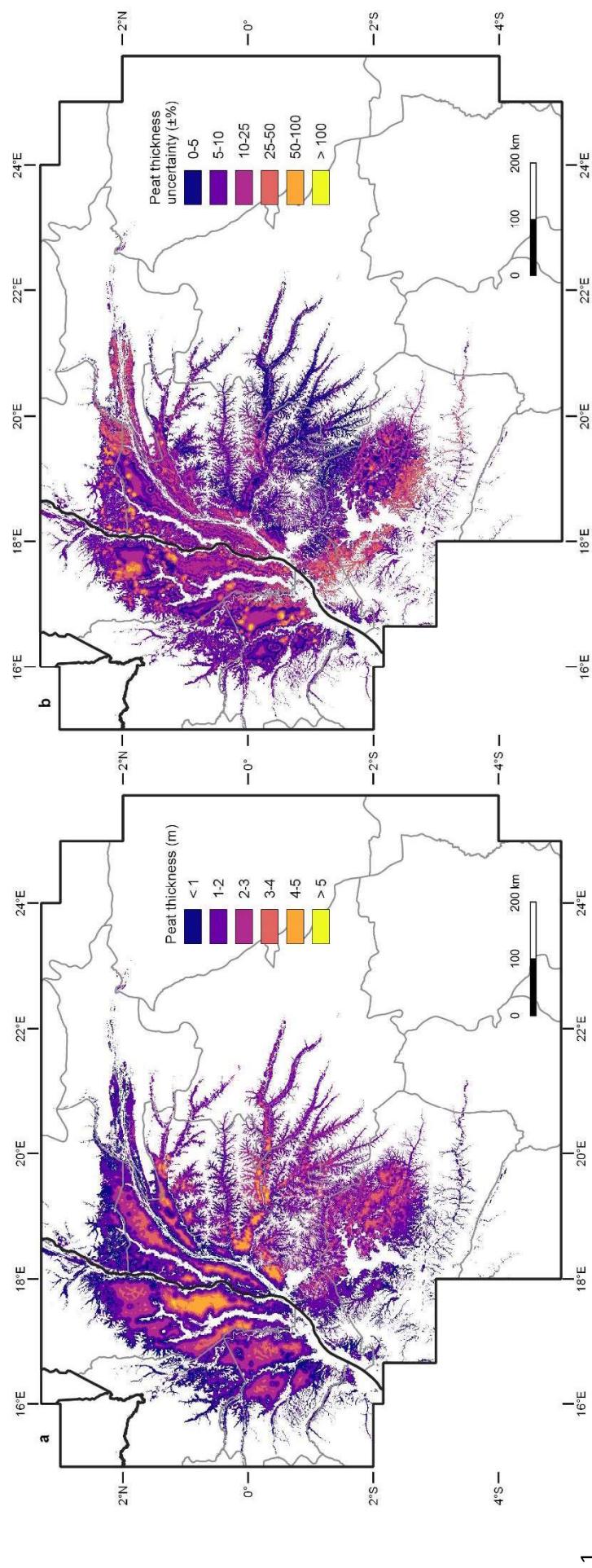
15 We measured peat thickness at 238 locations in DRC, finding a mean (\pm s.d.)
16 thickness of 2.4 (\pm 1.6) m and a maximum of 6.4 m, showing that river-influenced
17 peatlands can attain similar peat thickness as rain-fed interfluvial basins reported in
18 ROC⁹ (Table 1). There is no uniform increase in peat thickness with distance from the
19 peatland margin (ED Fig. 3), with linear regression being only a modest fit (R^2 = 41.0%;
20 RMSE = 1.21 m). Thus, we developed a Random Forest (RF) regression to estimate
21 peat thickness, using 463 thickness measurements across both countries. Our final
22 RF model includes four predictors after variable selection (see Methods): distance
23 from the peatland margin, precipitation seasonality, climatic water balance
24 (precipitation minus potential evapotranspiration), and distance from the nearest
25 drainage point (R^2 = 93.4%; RMSE = 0.42 m). The RF model outperforms multiple

1 linear regression with interactions using the same four variables (adj- R^2 = 73.6%,
2 RMSE = 0.80 m; ED Fig. 4).

3

4 Spatially, we predict thick peat deposits in the centres of the largest interfluvial basins
5 (far from peatland margins), and in smaller, river-influenced valley-floor peatlands
6 along the Ruki/Busira Rivers (Fig. 2a). The river valley's thick deposits are most likely
7 driven by greater climatic water balance and lower precipitation seasonality in the
8 eastern part of the Cuvette Centrale region (ED Fig. 5), plus potentially greater water
9 inputs from nearby higher ground, which offsets the shorter distances from peatland
10 margins. Our modelled results are consistent with our field data, as the two deepest
11 peat cores are from the interfluvial Centre transect in ROC (5.9 m), and the river-
12 influenced Bondamba transect on the Busira River in DRC (6.4 m). Overall, mean (\pm
13 s.d.) modelled peat thickness (1.7 ± 0.9 m) is lower than our field measurements (2.4
14 ± 1.5 m; Table 1), as expected given our linear transects, which oversample deeper
15 peat at the centre relative to the periphery in approximately ovoid peatlands. Areas of
16 high uncertainty in peat thickness occur where distance from the margin is uncertain
17 (Fig. 2b). Our results contrast strongly with an “expert system approach” that assigned
18 peat thickness values based on hydrological terrain relief alone and estimated a
19 thickness of 6.5 ± 3.5 m for the central Congo Basin peatlands¹⁷, compared to our
20 field-derived estimate of 1.7 ± 0.9 m (Fig. 2a).

21
22



2 **Figure 2 / Maps of peat thickness and uncertainty across the central Congo Basin. a. Median prediction of peat thickness (m)**
 3 from 100 Random Forest regression models with four predictors: distance from the peatland margin, precipitation seasonality, climatic
 4 water balance, and distance from the nearest drainage point. b. Relative uncertainty (%) of the peat thickness estimate, expressed
 5 as \pm half the width of the 95% confidence interval as percentage of the median. Black lines represent national boundaries; grey lines
 6 represent sub-national administrative boundaries.

1 After distance from the margin, precipitation seasonality and climatic water balance
2 are the most important predictors of peat thickness in the RF model, reflecting the
3 relative importance of rainfall inputs in peat accumulation in central Congo. This
4 appears to differ from smaller-scale assessments in temperate¹⁸ or other tropical
5 peatlands¹⁹, where surface topography (elevation and slope) are primary predictors of
6 peat thickness. However, this is potentially merely an artefact of the spatial scale of
7 the studies, as climate only varies over large scales. Alternatively, the relatively low
8 rainfall in the central Congo Basin (~1700 mm yr⁻¹), compared to other tropical
9 peatland regions (e.g., ~2,500-3,000 mm yr⁻¹ in Northwest Amazonia and Southeast
10 Asia)^{9,20}, may mean that peat thickness is more strongly related to climate in central
11 Congo, as it implies greater exposure to (seasonal) drought conditions that may cross
12 thresholds that negatively impact peat accumulation rates.

13

14 Peat bulk density measured across the central Congo Basin is $0.17 \pm 0.06 \text{ g cm}^{-3}$
15 (mean \pm s.d.; n = 80 cores), and mean carbon concentration is $55.7 \pm 3.2 \%$ (n = 80;
16 56.6 [\pm 4.5] % for the 22 well-sampled cores). While peat bulk density is significantly
17 lower in largely river-influenced sites than in rain-fed interfluvial basins ($P < 0.01$), no
18 significant difference between these peatland types is found for either peat carbon
19 concentration or carbon density (mass per unit area; Table 1).

20

21 We used the peat thickness, bulk density, and carbon concentration measurements to
22 construct a linear peat thickness-carbon density regression (ED Fig. 6). We applied
23 this regression model to our peat thickness map to spatially model carbon stocks per
24 unit area (Fig. 3a). Modelled belowground peat carbon density for the central Congo
25 Basin is $1,712 \pm 634 \text{ Mg C ha}^{-1}$, similar to the field-measured mean of $1,741 \pm 1,186$

1 Mg C ha⁻¹ (mean ± s.d., n = 80; Table 1). This carbon density is approximately nine
2 times the mean carbon stored in aboveground live tree biomass of African tropical
3 moist forests (~198 Mg C ha⁻¹)²¹. Spatial patterns of peat carbon density (Fig. 3a) and
4 uncertainty (Fig. 3b) follow similar patterns as peat thickness (Figs. 2a and 2b).

5

6 ***Estimating basin-wide peat carbon stocks***

7 Median estimated total peat carbon stock in the central Congo Basin is 29.0 Pg (95%
8 CI, 26.3-32.2; ED Fig. 7a), based on bootstrapping the area estimate and peat
9 thickness-carbon density regression. This is similar to the median 30.6 Pg C reported
10 by Dargie et al.⁹, but their lower 95% confidence interval was 6.3 Pg, which our study
11 increases to 26.3 Pg, because our larger dataset allows a spatial modelling approach
12 so that we can sum carbon density across all peat pixels. Therefore, the possibility of
13 low values of carbon storage in the central Congo peatlands can now confidently be
14 discarded.

15

16 Our new results show that the central Congo Basin peatlands are a globally important
17 carbon stock, harbouring approximately one-third of all the carbon stored in the world's
18 tropical peatlands^{5,9}. About two-thirds of this peat carbon is in DRC (19.6 Pg C; 95%
19 CI, 17.9-21.9), and one-third in ROC (9.3 Pg C; 95% CI, 8.4-10.2; ED Table 1), which
20 is equivalent to approximately 82% and 238% of each country's aboveground forest
21 carbon stock, respectively²². The high peat carbon stocks are found across several
22 administrative regions in both countries, with the largest stocks in DRC's Équateur
23 province (ED Table 1). Sensitivity analysis shows that uncertainty in total peat carbon
24 stock is now mostly driven by uncertainty in peatland area (ED Fig. 7b).

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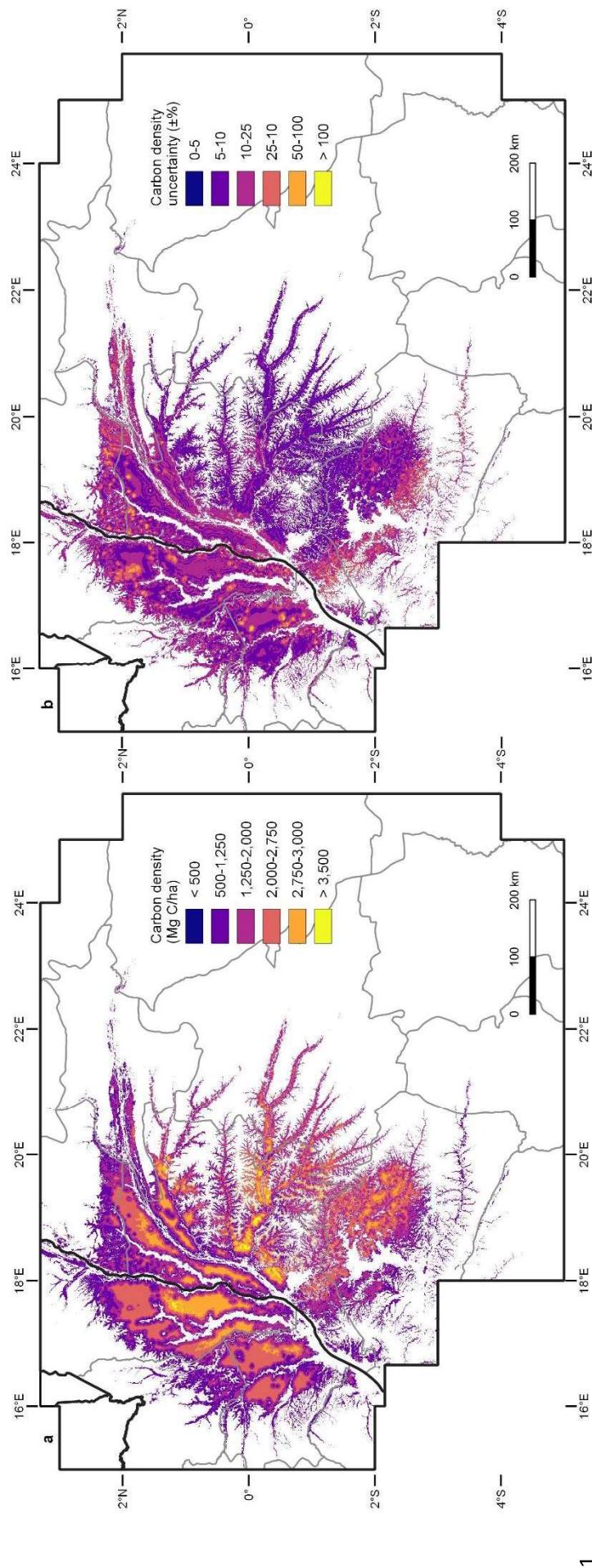


Figure 3 / Maps of belowground peat carbon density and uncertainty across the central Congo Basin. a. Median prediction of belowground peat carbon density ($Mg C ha^{-1}$), obtained from applying 20 normally distributed thickness-carbon density regressions (ED Fig. 6) to 100 peat thickness estimates (Fig. 2a), generating 2,000 carbon density estimates. b. Relative uncertainty (%) of the carbon density estimate, expressed as \pm half the width of the 95% confidence interval as percentage of the median. Black lines represent national boundaries; grey lines represent sub-national administrative boundaries.

1 Because the central Congo peatlands are relatively undisturbed^{23,24}, our new maps of
2 peatland extent, thickness and carbon density form a baseline description for the
3 decade 2000-2010, given the remotely-sensed data used. Today, the peatlands of the
4 central Congo Basin are threatened by hydrocarbon exploration, logging, palm oil
5 plantations, hydroelectric dams and climate change^{23,25}. While the peatlands are
6 largely within a UN Ramsar Convention transboundary wetland designation, we
7 estimate that only 2.4 Pg C in peat, just 8% of total stocks, currently lies within formal
8 national-level protected areas (ED Fig. 8; ED Table 2). Meanwhile, logging, mining, or
9 palm oil concessions together overlie 7.4 Pg C in peat, or 26% of total stocks (ED Fig.
10 8; ED Table 2), while hydrocarbon concessions cover almost the entire peatland
11 complex^{23,25}.

12

13 Keeping the central Congo Basin peatlands wet is vital to prevent peat carbon being
14 released to the atmosphere. The identification of extensive river-influenced peatlands
15 suggests that there is more than one geomorphological setting where peat is found in
16 the central Congo Basin. Further work is required to understand both the sources and
17 flows of water in these river-influenced peatlands, specifically the relative contributions
18 of water from precipitation, riverbank overflow, and run-off from higher ground to peat
19 formation and maintenance. Given the current areas of formal protection of peatlands
20 are largely centred around interfluvial basins, we suggest that additional protective
21 measures will be needed to safeguard the newly identified river-influenced peatlands
22 of the central Congo Basin. Keeping the central Congo peatlands free from
23 disturbance would also help protect the rich biodiversity, including forest elephants,
24 lowland gorillas, chimpanzees and bonobos^{23,26,27}, that form part of this globally
25 important, but threatened ecosystem.

1 **Table 1 / Field-measured and spatially modelled estimates of peat thickness, bulk density, carbon concentration, and**
 2 **carbon density in the central Congo Basin peatlands.**

	Field measurements*										Spatial model †								
	Peat thickness (m) #				Peat bulk density (g cm ⁻³) §				Peat carbon concentration (%) ‡				Peat thickness (m) ¶				Peat carbon density (Mg C ha ⁻¹) \$		
	Mean ± s.d.	Median	Max	Peat thickness (m) #	Mean ± s.d.	Median	Min	Max	Mean ± s.d.	Median	Min	Max	Mean ± s.d.	Median	Max	Mean ± s.d.	Median	Max	
Interfluvial basin peatlands (ROC)	2.4 (1.5)	2.1	5.9	0.19 (0.06)	0.10 (2.7)	0.31	56.2	56.5	49.6 (810)	61.8	1,619 (810)	1,640	3,183 (0.9)	1.7	1.3	5.4 (687)	1,653 (687)	1,402 (687)	3,852
River-influenced peatlands (DRC)	2.4 (1.6)	2.0	6.4	0.15 (0.07)	0.02 (3.6)	0.33	55.0	55.8	42.0 (1,511)	59.2	1,883 (1,511)	1,762	5,162 (0.8)	1.8	1.6	5.6 (604)	1,740 (604)	1,697 (604)	3,970
Central Congo Basin peatlands (ROC + DRC)	2.4 (1.5)	2.0	6.4	0.17 (0.06)	0.02 (3.2)	0.33	55.7	56.3	42.0 (1,186)	61.8	1,741 (1,186)	1,700	5,162 (0.9)	1.7	1.6	5.6 (634)	1,712 (634)	1,661 (634)	3,970

3 * Field measurement statistics include either the Likouala-aux-Herbes and Ubangi River groups of transects only ('Interfluvial basin peatlands'), or the Congo and Ruki River groups of transects only ('River-influenced peatlands'), or all groups ('Central Congo Basin peatlands').

4 † Spatial model statistics include all 50 m resolution pixels mapped in either Republic of the Congo only (ROC), Democratic Republic of the Congo only (DRC), or both countries (ROC + DRC).

5 # In situ measurements (laboratory and corrected pole-methods) from 213, 238 and 451 locations in ROC (ref. 9), DRC (this study) and combined, respectively. Peat is ≥ 0.3 m thickness and $\geq 65\%$ organic matter.

1 § $n = 43$, 37 , and 80 well-sampled cores in ROC (ref. 9), DRC (this study) and combined, respectively, based on $0.1\text{-}m$ thick
2 samples.
3 ‡ $n = 43$, 37 , and 80 well-sampled and interpolated cores in ROC (ref. 9), DRC (this study) and combined, respectively, based
4 on $0.1\text{-}m$ thick samples.
5 ¶ Median estimate from 100 thickness estimates per 50 m resolution pixel across the median extent map, with thickness
6 estimated from 100 RF regression models trained with four predictor variables, each with a randomly selected Maximum
7 Likelihood peat probability threshold to derive distance from the peatland margin.
8 \$ Median estimate from $2,000$ carbon density estimates per 50 m resolution pixel across the median peat area map, with
9 carbon density estimates derived from 20 normally distributed thickness-carbon regressions (ED Fig. 6) applied to 100 peat
10 thickness estimates.

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4

5

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1 **AUTHOR CONTRIBUTIONS**

2 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.,
3 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.,
4 S.L.L. C.E.N.E., O.E.B., P.B., J.K.T., N.T.G., and J-B.N.N. organised and conducted
5 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.
6 provided additional data; B.C., G.C.D., A.B. and H.B. performed laboratory analyses;
7 B.C. and E.T.A.M. analysed the remote sensing data and developed the models; B.C.,
8 S.L.L., E.T.A.M., G.C.D., A.J.B., T.R.B., P.J.M. and C.A.K. evaluated the results. B.C.
9 and S.L.L. wrote the paper, with input from all co-authors.

1 **METHODS**

2

3 ***Field data collection***

4 Fieldwork was conducted in DRC between January 2018 and March 2020. Ten
5 transects (4-11 km long) were installed, identical to Dargie et al.'s approach⁹, in
6 locations that were highly likely to be peatland. These were selected to help test
7 hypotheses about the role of vegetation, surface wetness, nutrient status, and
8 topography in peat accumulation (Fig. 1a; Supplementary Table 1). A further eight
9 transects (0.5-3 km long) were installed to assess our peat mapping capabilities (Fig.
10 1a; Supplementary Table 1).

11

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

19

20 Peat presence/absence was recorded every 250 m along all transects, and peat
21 thickness (if present) was measured by inserting metal poles into the ground until the
22 poles were prevented from going any further by the underlying mineral, identical to
23 Dargie et al.'s pole-method⁹. Additionally, a core of the full peat profile was extracted
24 every kilometre along the ten hypothesis-testing transects, if peat was present, with a

1 Russian-type corer (52-mm stainless steel Eijkelkamp model); these 64 cores were
2 sealed in plastic for laboratory analysis.

3

4 ***Peat thickness laboratory measurements***

5 Peat was defined as having an organic matter (OM) content of $\geq 65\%$ and a thickness
6 of ≥ 0.3 m (*sensu* Dargie et al.⁹). Therefore, down-core OM content of all 64 cores was
7 analysed to measure peat thickness. The organic matter content of each 0.1-m thick
8 peat sample was estimated via Loss-On-Ignition (LOI), whereby samples were heated
9 at 550°C for 4h. The mass fraction lost after heating was used as an estimate of total
10 OM content (% of mass). Peat thickness was defined as the deepest 0.1-m with OM
11 $\geq 65\%$, after which there is a transition to mineral soil. Samples below this depth were
12 excluded from further analysis. Rare mineral intrusions into the peat layer above this
13 depth, where OM $< 65\%$ for a sample within the peat column, were retained for further
14 analysis. In total, 60 out of 64 collected cores had LOI-verified peat thickness ≥ 0.3 m.

15

16 The pole-method used to estimate peat thickness in the field was calibrated against
17 LOI-verified measurements, by fitting a linear regression model between all LOI-
18 verified and pole-method peat thickness measurements sampled at the same location
19 (93 sites across ROC and DRC, including 37 from ref. ⁹). Three measurements from
20 DRC with a Cook's distance > 4 times the mean Cook's distance were excluded as
21 influential outliers. Mean pole-method offset was significantly higher along the DRC
22 transects (0.94 m) than along those in ROC (0.48 m; $P < 0.001$), due to the presence
23 of softer alluvium substrate in river-influenced sites in DRC. We therefore added this
24 grouping as a categorical variable to the regression. The resulting model ($\text{adj-}R^2 =$
25 0.95, $P < 0.001$; ED Fig. 2) was used to correct all pole-method measurements in each

1 group for which no LOI-verified thickness was available: corrected peat thickness = -
2 $0.1760 + 0.8626 \times (\text{pole-method thickness}) - 0.3284 \times (\text{country})$, with country dummy
3 coded as: ROC (0) and DRC (1).

4

5 ***Carbon density estimates***

6 To calculate carbon density (mass per unit area), estimates of carbon storage in each
7 0.1-m thick peat sample (thickness \times bulk density \times carbon concentration) were
8 summed to provide an estimate of total carbon density per core (in Mg C ha⁻¹),
9 identical to Dargie et al.⁹. We estimated carbon density for 80 peat cores (OM \geq 65%,
10 thickness \geq 0.3 m), located every other kilometre along 18 transects, including 37
11 cores from the ten transects used for hypothesis testing in DRC, and 43 cores from
12 transects in ROC⁹.

13

14 Peat thickness of the 80 cores was obtained by laboratory LOI. To estimate peat bulk
15 density, every other 0.1-m down-core, samples of a known peat volume were weighed
16 after being dried for 24h at 105°C (n = 906). Bulk density (in g cm⁻³) was then
17 calculated by dividing the dry sample mass (in g) by the volume of the sample taken
18 from the peat corer dimensions (in cm³). Within each core, linear interpolation was
19 used to estimate bulk density for the alternate 0.1m-thick samples of the core that were
20 not measured.

21

22 For total carbon concentration (%), only the deepest core per transect, plus additional
23 deep cores from the Lokolama transect (1) in DRC and Ekolongouma transect (3) in
24 ROC (22 in total, 11 from DRC and 11 from ROC⁹) were sampled down-core. Every
25 other 0.1-m thick sample was measured using an elemental analyser (Elementar Vario

1 MICRO Cube with thermal conductivity detection for all cores, except those from
2 Boboka, Lobaka and Ipombo transects, which were analysed using Sercon ANCA
3 GSL with isotope-ratio mass spectrometer detection, due to COVID-19 disruption). All
4 samples ($n = 422$) were pre-dried for 48h at 40°C and ground to $< 100 \mu\text{m}$ using a
5 MM301 mixer mill. Again, linear interpolation was used within each core for the
6 alternate samples that were not measured.

7

8 The remaining 58 cores had less-intensive carbon concentration sampling. We
9 therefore interpolated the carbon concentration for each 0.1-m thick sample, because
10 well-sampled cores show a consistent pattern with depth: an increase to a depth of
11 about 0.5 m, followed by a long, very weak decline, and finally a strong decline over
12 the deepest approximately 0.5 m of the core⁹. We used segmented regression on the
13 22 well-sampled cores (*segmented* package in R, version 1.3-1) to parameterize the
14 three sections of the core, using the means of these relationships to interpolate carbon
15 concentrations for the remaining 58 cores, following Dargie et al.⁹.

16

17 To estimate carbon density from modelled peat thickness across the basin, we
18 developed a regression model between peat thickness and per-unit-area carbon
19 density using the 80 sampled cores. We compared linear regressions for normal,
20 logarithmic-, and square root-transformed peat thickness, selecting the model with
21 lowest AICc and highest R^2 . A linear model with square root-transformed peat
22 thickness was found to provide the best fit ($R^2 = 0.86$; $P < 0.001$; ED Fig. 6).
23 Bootstrapping was applied (*boot* package in R, version 1.3-25) to assess uncertainty
24 around the regression.

25

1 **Modelling peatland extent**

2 Satellites cannot detect peat directly. We therefore mapped vegetation and used field-
3 based associations between peat and vegetation to infer peat presence^{9,28}. Five
4 landcover classes were used for the purpose of peatland mapping: water, savanna,
5 palm-dominated peat swamp forest, hardwood-dominated peat swamp forest, and
6 non-peat forming forest. In this classification, field recordings of non-peat forming
7 seasonally inundated forest (< 30 cm thickness of $\geq 65\%$ OM) were grouped together
8 with field recordings of *terra firme* forest, which also does not form peat, to form the
9 non-peat forming forest class. Our field recordings of hardwood- or palm-dominated
10 peat swamp forest, by definition, consist of all forest sites that form peat, including any
11 seasonally inundated forest that forms peat (≥ 30 cm of $\geq 65\%$ OM).

12

13 A total of 1,736 ground-truth datapoints was used: 172 in water, 476 in savanna, 632
14 in non-peat forming forest (97 non-peat forming seasonally inundated forest, and 535
15 *terra firme* forest), 188 in palm-dominated peat swamp forest, and 268 in hardwood-
16 dominated peat swamp forest (ED Fig. 1). This data comes from eight sources
17 (Supplementary Table 2). First, ground-truth locations collected for this study using a
18 GPS (Garmin GPSMAP 64s) at all transect sites in DRC for which a landcover class
19 was determined (382 points). Second, published ground-truth data from nine transects
20 in ROC (292 points)⁹. Third, 299 GPS locations of known savanna and *terra firme*
21 forest landcover classes from archaeological research databases across the
22 basin^{29,30}. Fourth, 191 GPS locations from permanent long-term forest inventory plots
23 of the African Tropical Rainforest Observation Network (AfriTRON), mostly from *terra*
24 *firme* forest³¹, retrieved from the ForestPlots database^{32,33}. Fifth, 229 GPS datapoints
25 from *terra firme* forest or savanna locations in and around Lomami National Park (pers.

1 *comm.*, R.B., G.I. and A. C-S.). Sixth, 24 published savanna datapoints in and around
2 Lomami NP³⁴. Seventh, 23 published locations of savanna, *terra firme* forest, palm- or
3 hardwood-dominated peat swamp forest in DRC¹¹. Eighth, 296 datapoints from
4 Google Earth for unambiguous savanna and water sites (middle of lakes or rivers),
5 distributed across the region.

6

7 We used nine remote sensing products to map peat-associated vegetation
8 (Supplementary Figure 1). Eight of these are identical to those used by Dargie et al.⁹:
9 three optical products (Landsat 7 ETM+ bands 5 [SWIR 1], 4 [NIR], and 3 [Red]); three
10 L-band Synthetic Aperture Radar products (ALOS PALSAR HV, HH, and HV/HH); and
11 two topographic products (SRTM DEM [Digital Elevation Model] void-filled with ASTER
12 GDEM v2 data, and slope; acquisition date 2000). To this, we added a HAND-index
13 (Height Above Nearest Drainage point), which significantly improved model
14 performances (median Matthews correlation coefficient [MCC]: 79.7%, compared with
15 77.8% or 75.6% for just DEM or HAND alone, respectively; $P < 0.001$).

16

17 HAND was derived from the SRTM DEM with Clubb et al.'s algorithm³⁵, using the
18 HydroSHEDS global river network at 15s resolution as reference product³⁶. Alternative
19 NASADEM- or MERIT DEM-derived³⁷⁻³⁹ combinations of DEM, HAND and slope were
20 tested with an initial subset of data in R, while keeping all other remote sensing
21 products the same (median MCC: 79.0% and 75.1%, respectively), but did not
22 significantly improve model performance compared with SRTM-derived products
23 (80.9% median MCC; $P < 0.001$).

24

1 The Landsat bands are pre-processed, seamless cloud-free mosaics for ROC
2 (composite of three years, 2000, 2005, 2010) and DRC (composite of six years, 2005-
3 2010)⁴⁰. These mosaics performed better than more recent basin-wide automated
4 cloud-free Sentinel-2 mosaics that we developed (bands 5, 8A, 11; composite of five
5 years, 2016-2020), likely because they contain less directional reflectance artefacts
6 (the median MCC of 80.9% for the pre-processed Landsat mosaics is significantly
7 higher than the 78.1% for our Sentinel-2 mosaics, $P < 0.005$).

8

9 The ALOS PALSAR radar bands are mosaics of mean values of annual JAXA
10 composites for the years 2007-2010 (ref. ⁹). More recent radar data (ALOS 2-PALSAR
11 2 HV, HH, HV/HH; 2015-2017) did not significantly improve model performances
12 (median MCC 80.9% and 80.6%, respectively; $P < 0.01$). All remote sensing products
13 were resized to a common 50 m grid, using a cubic convolution resampling method.

14

15 We then tested which classification algorithm to use, as more sophisticated algorithms
16 might improve overall accuracy against our training dataset, but might also reduce
17 regional accuracy of the map in areas far from test data, critical in this case given large
18 areas of the central Congo peatland region are unsampled.

19

20 Three supervised classification algorithms were tested in order of increasing
21 complexity: Maximum Likelihood (ML), Support Vector Machine (SVM) and Random
22 Forest (RF). We assessed each classifier using both a random and spatial cross-
23 validation (CV) approach⁴¹⁻⁴³. Random CV was implemented using stratified two-
24 thirds Monte Carlo selection, whereby we 1,000 times randomly selected two-thirds of

1 all datapoints per class as training data, to be evaluated against the remaining one-
2 third per class as testing data.

3

4 Spatial CV was implemented by grouping all transects datapoints in four distinct hydro-
5 geomorphological regions: (i) transects perpendicular to the blackwater Likouala-aux-
6 Herbes River (n = 179 datapoints); (ii) transects perpendicular to the white-water
7 Ubangi River (n = 113); (iii) transects perpendicular to the Congo River, intermediate
8 between black and white-water (n = 123); and (iv) transects perpendicular to the
9 blackwater Ruki, Busira and Ikelemba Rivers, plus other nearby transects (collectively
10 named the Ruki group; n = 258). To each group we added ground-truth datapoints
11 from other non-transect data sources (Supplementary Table 2) that belonged to the
12 same map regions (n = 82, 27, 20, 113, respectively). We then tested 1,000 times how
13 well each classifier performs in each of the four regions, when trained only on a
14 stratified two-thirds Monte Carlo selection of the remaining datapoints (i.e., datapoints
15 from the three other regional transect groups, plus ground-truth datapoints not
16 associated with or near any transect group (n = 821). For example, the savanna and
17 *terra firme* forest datapoints in Lomami National Park in DRC which are far (> 300 km)
18 from any transect group.

19

20 Model performance was based on Matthews correlation coefficient (MCC) for binary
21 peat/non-peat predictions (hardwood- and palm-dominated peat swamp forest classes
22 combined into one peat class; water, savanna and non-peat forming forest combined
23 into one non-peat class). We compared MCC, rather than popular metrics such as
24 Cohen's kappa, F1-score or accuracy, because it is thought to be the most reliable
25 evaluation metric for binary classifications^{44,45}. We also computed balanced accuracy

1 (BA) from random cross-validation to compare with the first-generation map. While
2 less robust than MCC, BA is independent of imbalances in the prevalence of
3 positives/negatives in the data, thus allowing better comparison between classifiers
4 trained on different datasets¹⁶. The best estimate of each accuracy metric or area
5 estimate per model or region is the median value of 1,000 runs, alongside a 95%
6 confidence interval.

7

8 In the case of SVM and RF, random CV models were implemented in Google Earth
9 Engine (GEE)⁴⁶ using all nine remote sensing products. However, because ML is
10 currently not supported by GEE, random CV with this algorithm was implemented in
11 IDL-ENVI software (version 8.7-5.5), using a principal component analysis (PCA) to
12 reduce the nine remote sensing products to six uncorrelated principal components to
13 reduce computation time. All spatial CV models were implemented in R (*superClass*
14 function from the *RStoolbox* package, version 0.2.6), with PCA also applied in the case
15 of ML only. All RF models were trained using 500 trees, with three input products used
16 at each split in the forest (the default, the square root of the number of variables). All
17 SVM model were implemented with a radial basis function kernel, with all other
18 parameters set to default values.

19

20 Comparison of the ML, SVM and RF models with Dargie et al.'s model performance⁹,
21 using balanced accuracy from random cross-validation, shows improved results only
22 in the case of the ML classifier (Supplementary Table 3). Comparing MCC using the
23 spatial CV approach, we found that the ML algorithm is also most transferable to
24 regions for which we lack training data. While RF gives slightly better MCC with
25 random CV, when no regions are omitted, spatial CV shows particularly poor predictive

1 performance of this algorithm for the Congo and Ruki regions, when trained on data
2 from the other regions. SVM has lowest MCC of all three classifiers with random CV,
3 and also performs worst of all three in the Congo region with spatial CV.

4

5 Additionally, applying spatial CV to the largely interfluvial basin region (ROC transects;
6 $n = 401$), and the largely river-influenced region (DRC transects; $n = 540$), also shows
7 RF performs poorly (Supplementary Table 3). This further supports selecting the ML
8 algorithm to produce our second-generation peat extent map of the central Congo
9 peatlands. The final peatland extent estimate is then obtained as the median value
10 (alongside 95% confidence interval) out of the combined hardwood- and palm-
11 dominated peat swamp forest extent from 1,000 ML runs, each time trained with two-
12 thirds of the ground-truth data.

13

14 ***Modelling peat thickness***

15 A map of distance from the peatland margins was developed in GEE using the median
16 ML peat probability map, i.e. the ML map with a 50% peat probability threshold (> 500
17 hardwood- or palm-dominated peat swamp predictions out of 1,000 runs). For each
18 peat pixel in this binary classification, a cost function was used to calculate the
19 Euclidean distance to the nearest non-peat pixel, after speckle and noise were
20 removed using a 5x5 squared-kernel majority filter. Using this distance map, transects
21 were found to have markedly different relationships between peat thickness and
22 distance from the peatland margin, i.e. different slopes ($n = 18$, $P < 0.001$, ED Fig. 3).
23 The modest linear fit ($R^2 = 41.0\%$; $RMSE = 1.21$ m) cautions against a uniform
24 regression between peat thickness and distance from the margin across the basin.

25

1 Instead, we developed a spatially-explicit Random Forest regression model to predict
2 peat thickness, derived from 14 remotely-sensed potential covariates that may explain
3 variation in peat thickness. These 14 variables included the nine optical, radar and
4 topographic products used in the peatland extent analysis, as well as distance from
5 the peatland margin, distance from the nearest drainage point (same reference
6 network as for HAND)³⁶, precipitation seasonality⁴⁷, climatic water balance (mean
7 annual precipitation⁴⁷ minus mean annual potential evapotranspiration⁴⁸), and live
8 woody aboveground biomass⁴⁹. Ten of these variables were found to be significantly
9 correlated with peat thickness (Kendall's τ , $P < 0.01$): all three optical bands, all three
10 radar bands, distance from the peatland margin, distance from the nearest drainage
11 point, precipitation seasonality, and climatic water balance. Applying stepwise
12 backward selection, we tested combinations of these ten predictors by each time
13 dropping one predictor out of the model in order from low to high variable importance,
14 selecting as the best model the one with highest median R^2 and lowest median root
15 mean square error (RMSE) obtained from 100 random (two-thirds) cross-validations.
16 The importance of each variable was assessed by calculating Mean Decrease Impurity
17 (MDI), the total decrease in the residual sum of squares of the regression after splitting
18 on that variable, averaged over all decision trees in the random forest. Median MDI
19 was calculated for each variable based on 100 random (two-thirds) cross-validations
20 of the overall model containing all ten significant predictors.

21

22 The best model contained four predictors: distance from the peatland margin, distance
23 to the nearest drainage point, climatic water balance (all positively correlated with peat
24 thickness; Kendall's τ coefficient = 0.49, 0.15 and 0.13, respectively; $P < 0.001$ for all),

1 and precipitation seasonality (negatively correlated with thickness; Kendall's $\tau = -0.11$,
2 $P < 0.01$), see ED Figure 5 for their spatial variability.

3

4 The RF regression was implemented in GEE with 500 trees and all other parameters
5 set to default values. Predictor variables were resampled to 50 m resolution. As
6 training data, we included all LOI-verified and corrected pole-method thickness
7 measurements that fell within the masked map of > 50% peat probability ($n = 463$),
8 including thickness > 0 and < 0.3 m from non-peat sites that could improve predictions
9 of shallow peat deposits near the margins ($n = 12$).

10

11 Our final RF model ($R^2 = 93.4\%$, $RMSE = 0.42$ m) had consistently smaller residuals
12 compared to a multiple linear regression model containing the same four predictors
13 with interaction effects ($adj-R^2 = 73.6\%$, $RMSE = 0.80$ m; ED Fig. 4). It also performed
14 better when testing out-of-sample performance, using 100 random two-thirds cross-
15 validations of training data (median $R^2 = 82.2\%$, $RMSE = 0.68$ m; and median $adj-R^2$
16 = 73.6%, $RMSE = 0.85$ m; for RF model and multiple linear regression, respectively).

17

18 For uncertainty on our thickness predictions, we first estimated area uncertainty by
19 creating 100 different maps of distance from the peat margin, by randomly selecting
20 (with replacement) a minimum peat probability threshold $> 0\%$ and $< 100\%$, removing
21 speckle and noise, and re-calculating the closest distance to the nearest non-peat
22 pixel. We then combined the 100 distance maps each time with the three other
23 selected predictors (precipitation seasonality, climatic water balance, distance from
24 nearest drainage point) as input in a RF model to develop 100 different peat thickness
25 maps. For these model runs, we included all available thickness measurements (> 0

1 m) that fell within each specific distance map. Each output map was masked to an
2 area ≥ 0.3 m thickness, consistent with our peat definition. A map of median peat
3 thickness (Fig. 3a) and relative uncertainty (\pm half the width of the 95% CI as
4 percentage of the median; Fig. 3b) was then calculated for each pixel based on the
5 100 available thickness estimates.

6

7 ***Carbon stock estimates***

8 We mapped carbon density across the central Congo Basin in GEE, by applying 20
9 bootstrapped thickness-carbon regressions that were normally distributed around the
10 best fit (ED Fig. 6) to the 100 peat thickness maps from the RF regression model,
11 generating a map of median carbon density out of 2,000 estimates (Fig. 3a), together
12 with relative uncertainty (\pm half the width of the 95% CI as percentage of the median;
13 Fig. 3b).

14

15 Total peat carbon stocks were computed in GEE by summing carbon density (in Mg
16 ha^{-1}) over all 50 m grid squares defined as peat. To assess uncertainty around this
17 estimate, we again combined the 100 peat thickness maps (i.e., uncertainty from area
18 and thickness), with 20 bootstrapped thickness-carbon regressions (i.e., uncertainty
19 from carbon density, including bulk density and carbon concentration). We thus
20 obtained 2,000 peat carbon stock estimates for the total central Congo Basin peatland
21 complex, which were used to estimate the mean, median and 95% CI (ED Fig. 7a).

22

23 Regional carbon stock estimates were similarly obtained for each sub-national
24 administrative region (departments in ROC and provinces in DRC; ED Table 1), as
25 well as national-level protected areas (national parks and nature/biosphere/community

1 reserves)⁵⁰ and logging^{51,52}, mining^{53,54} and palm oil^{55–57} concessions (ED Fig. 8; ED
2 Table 2). As hydrocarbon concessions cover almost the whole peatlands area^{23,25},
3 they cover almost 100% of the central Congo peat carbon stocks.

4

5 Sensitivity analysis was performed by bootstrapping either the area, thickness, or
6 carbon density component, whilst keeping the others constant (ED Fig. 7b). For area,
7 we bootstrapped 100 randomly selected peatland area estimates; for thickness, 100
8 randomly selected two-thirds subsets of all thickness measurements; for carbon
9 density, 20 normally distributed regression equations from the bootstrapped thickness-
10 carbon relationship.

11

12

13 **DATA AVAILABILITY**

14 All map results from this study are available for download as raster files from
15 <https://congopeat.net/maps/>. The supporting ground-truth data, peat thickness
16 measurements, and carbon density measurements are available from
17 <https://figshare.com/s/ba6dc13288a901883812>. The remote sensing datasets used
18 are available for download from https://www.eorc.jaxa.jp/ALOS/en/dataset/fnf_e.htm
19 (ALOS PALSAR and ALOS-2 PALSAR-2 25 m HV and HH data), <http://osfac.net/>
20 (OSFAC ROC and DRC 60 m Landsat ETM+ bands 5, 4 and 3 mosaics), and
21 <http://earthexplorer.usgs.gov/> (SRTM DEM 1-arc second and ASTER GDEM v2 1-arc
22 second data).

1 **CODE AVAILABILITY**

2 The IDL-ENVI script to run the Maximum Likelihood classification model is available
3 from <https://figshare.com/s/a1b26aa7f31bd8bb93f7>. The scripts to run the peat
4 thickness model and carbon stock calculations are available on Google Earth Engine:
5 https://code.earthengine.google.com/?accept_repo=users/gbjc/Central_Congo_Pea
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7

8

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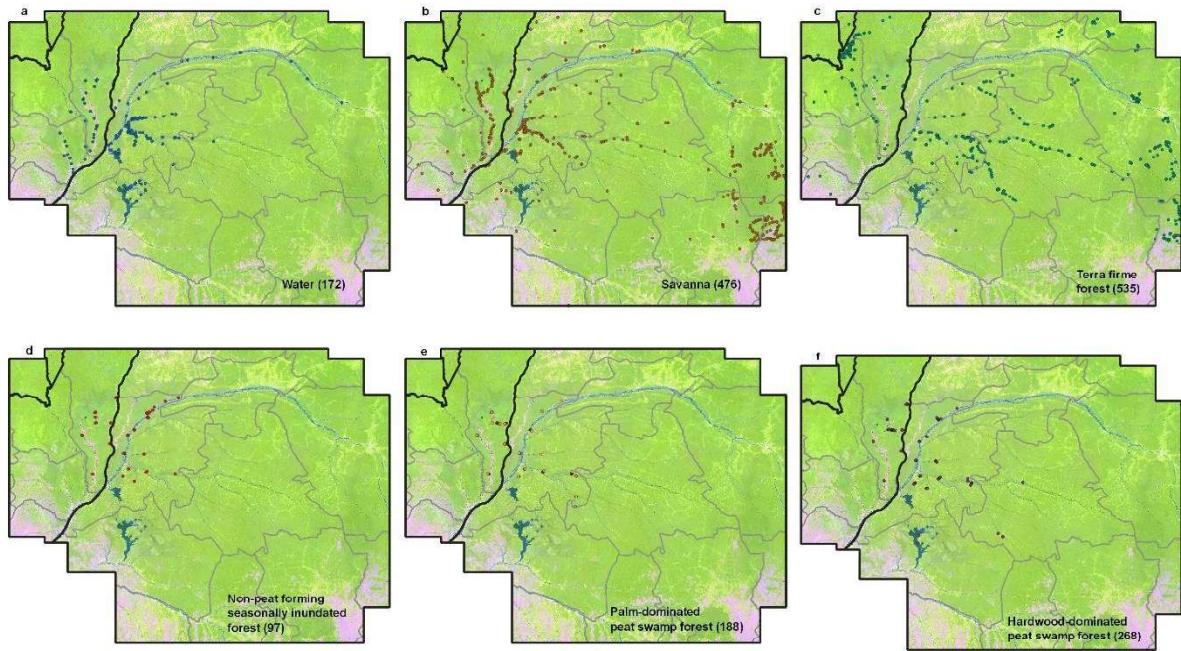
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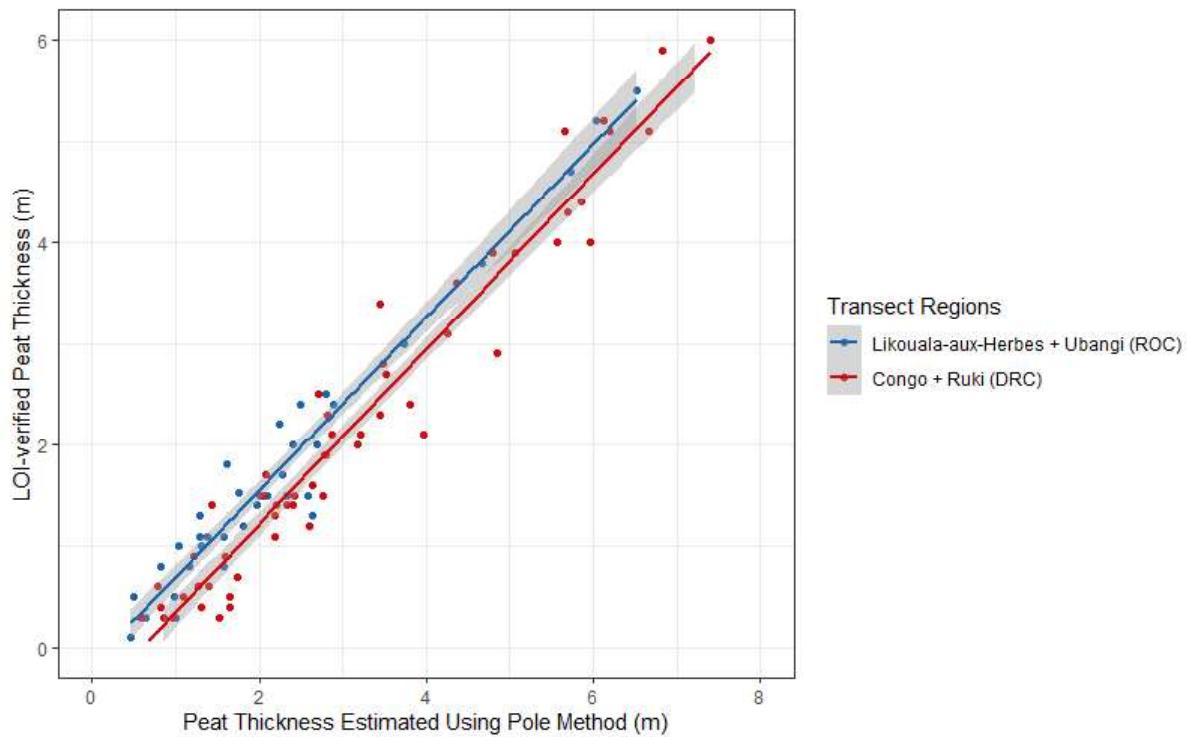
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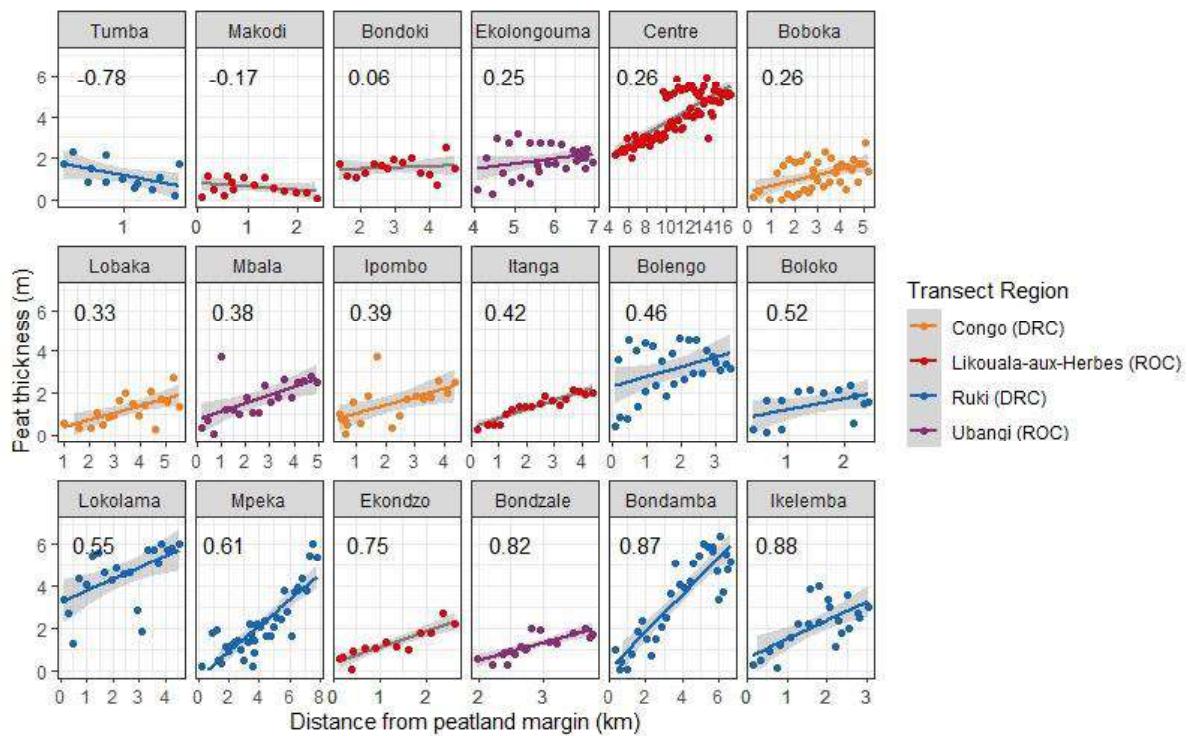
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1
 2 **Extended Data Figure 1 | Spatial overview of ground-truth datapoints (n = 1,736)**
 3 **across the central Congo basin study area, grouped by six landcover classes**
 4 **(a.-f.).** Only the palm-dominated and hardwood-dominated peat swamp forest classes
 5 **(e., f.)** are associated with the presence of peat. *Terra firme* forest **(c.)** and non-peat
 6 forming seasonally inundated forest **(d.)** are combined into a single non-peat forming
 7 forest class when running classification models. The RGB baselayer of Landsat ETM+
 8 (SWIR 1, NIR and Red bands) reflects different forest types (shades of green), open
 9 savanna (pink), agricultural land (yellow) and open water (blue).

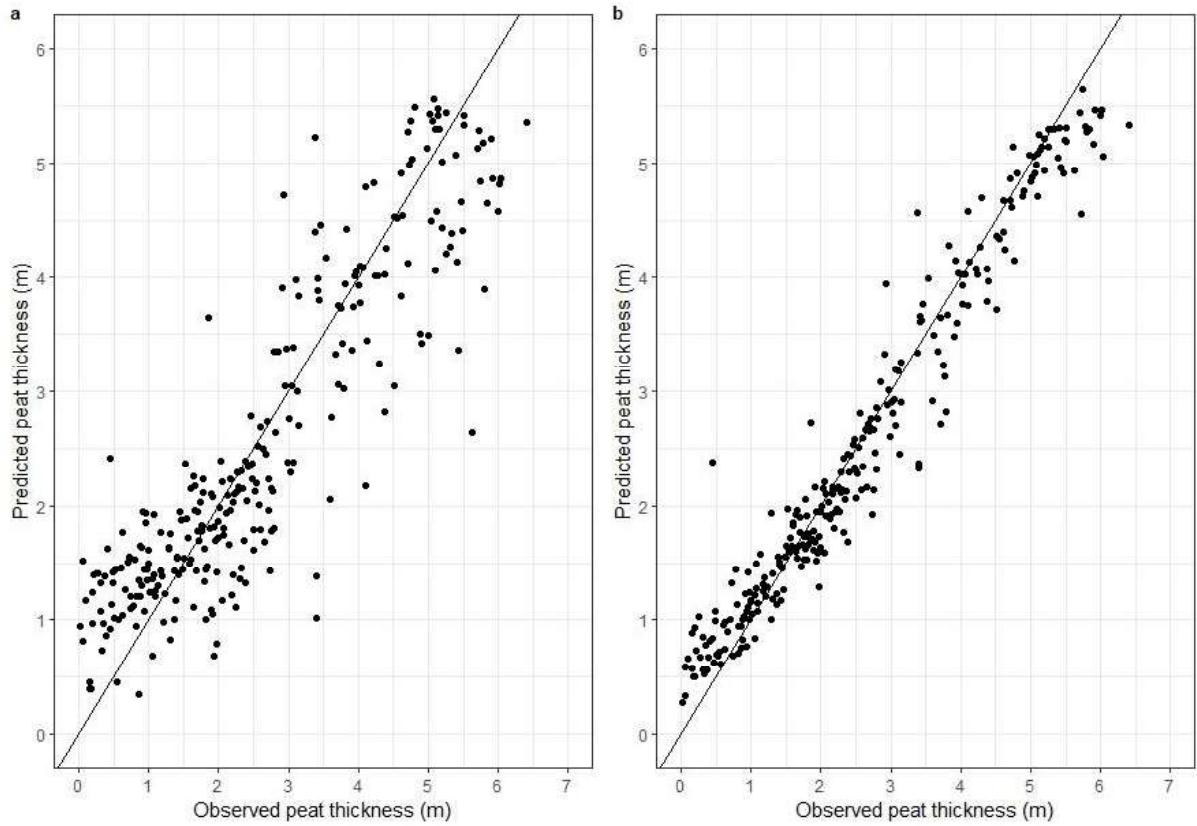


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 2 **Extended Data Figure 2 | Relationship between peat thickness estimated using**
 3 **the pole-method (in m) and laboratory-verified peat thickness using Loss-On-**
 4 **Ignition (LOI; in m) across four regional transect groups.** Mean pole-method offset
 5 is significantly higher in the largely river-influenced transects in DRC (0.94 m, blue
 6 line) than in mostly interfluvial basin transects in ROC (0.48 m, red line; $P < 0.001$).
 7 No significant differences were found between either the Likouala-aux-Herbes and
 8 Ubangi transects in ROC, or between the Congo and Ruki transects in DRC. Best-
 9 fitting line: Corrected peat thickness = $-0.1760 + 0.8626 \times (\text{pole-method thickness}) -$
 10 $0.3284 \times (\text{country})$; $n = 93$, $\text{adj-}R^2 = 0.95$; $P < 0.001$. Country is dummy coded as: ROC
 11 (0) and DRC (1). Shaded grey shows 95% confidence intervals. Outliers ($n = 3$) with
 12 $> 4 \times$ the mean Cook's distance are excluded from the analysis.

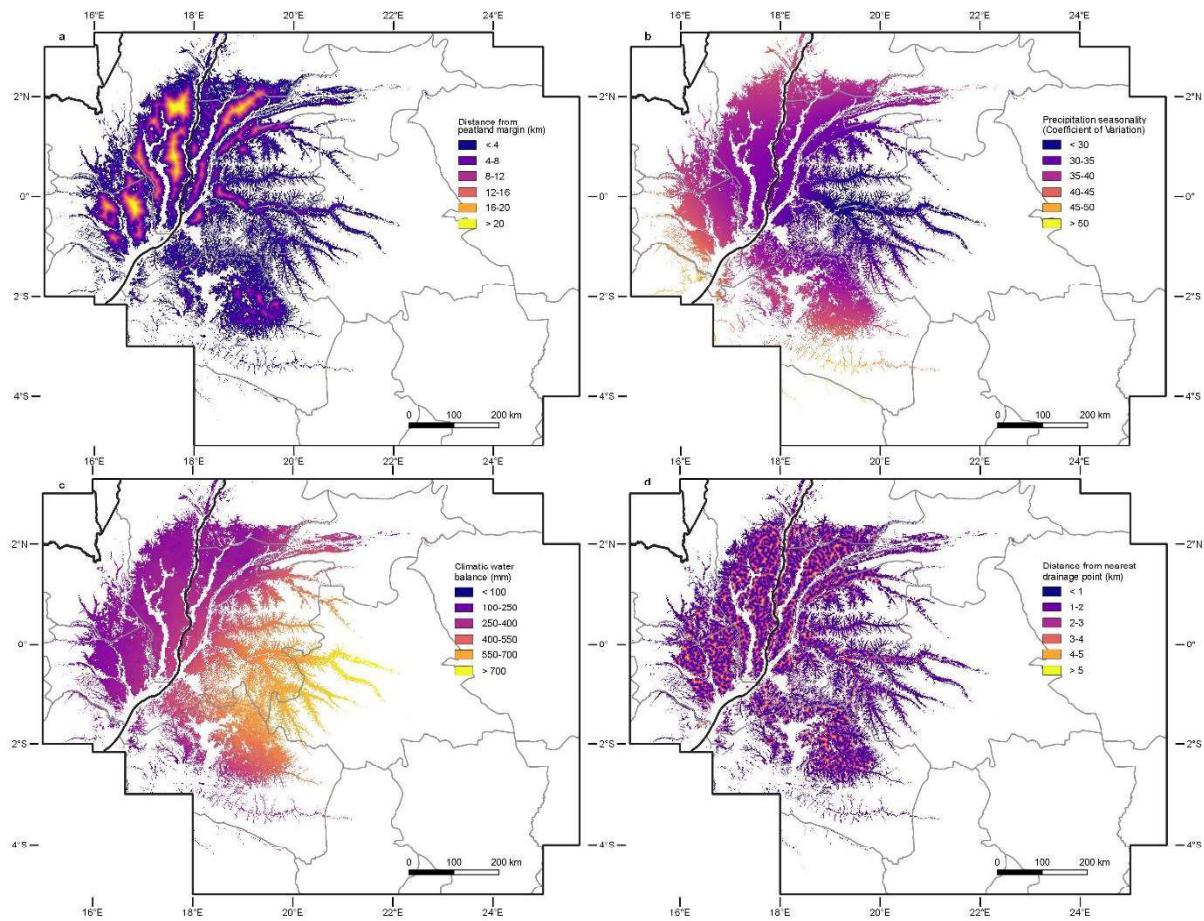


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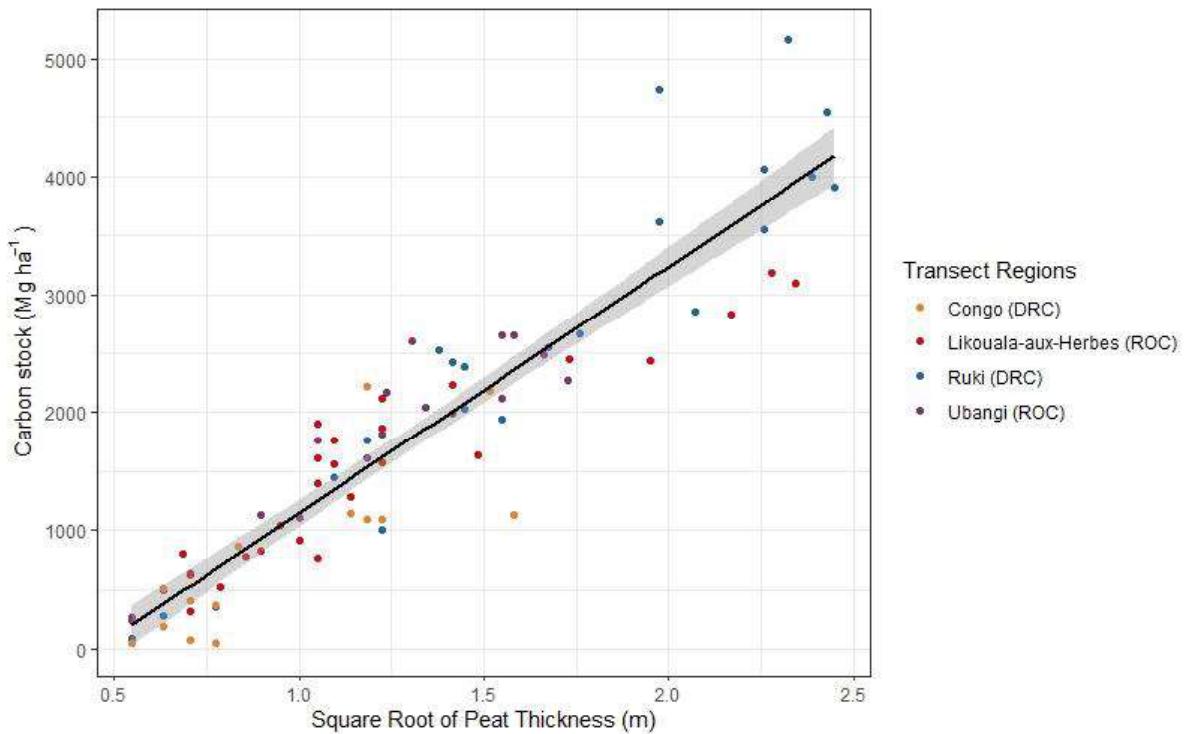
2 **Extended Data Figure 3 | Relationship between field-measured peat thickness**
 3 **(LOI + corrected pole-method measurements; in m) and distance from the**
 4 **peatland margin (km).** Distance from the peatland margin is calculated as the
 5 shortest distance to a non-peat pixel in any direction, based on the median Maximum
 6 Likelihood map of peatland extent ($> 50\%$ probability threshold). Transects are
 7 ordered by increasing regression slope (in m km^{-1} ; upper left corner of each panel),
 8 with colours indicating the four transect regions. Note that the horizontal axes are
 9 different for each panel. Shaded grey shows 95% confidence intervals for each
 10 regression.



1 **Extended Data Figure 4 | Relationship between observed and predicted peat**
 2 **thickness (in m).** **a.** Multiple linear regression model with interaction effects ($\text{adj-R}^2 =$
 3 73.6% , $\text{RMSE} = 0.80 \text{ m}$). **b.** Random Forest regression model ($R^2 = 93.4\%$, $\text{RMSE} =$
 4 0.42 m). Both models are trained and validated against 463 datapoints and include the
 5 same four predictor variables: distance from the peatland margin, precipitation
 6 seasonality, climatic water balance, and distance from the nearest drainage point.
 7 Both panels show 277 aggregated means only to account for duplicates in observed
 8 values. The black lines indicate the 1:1 relationship.

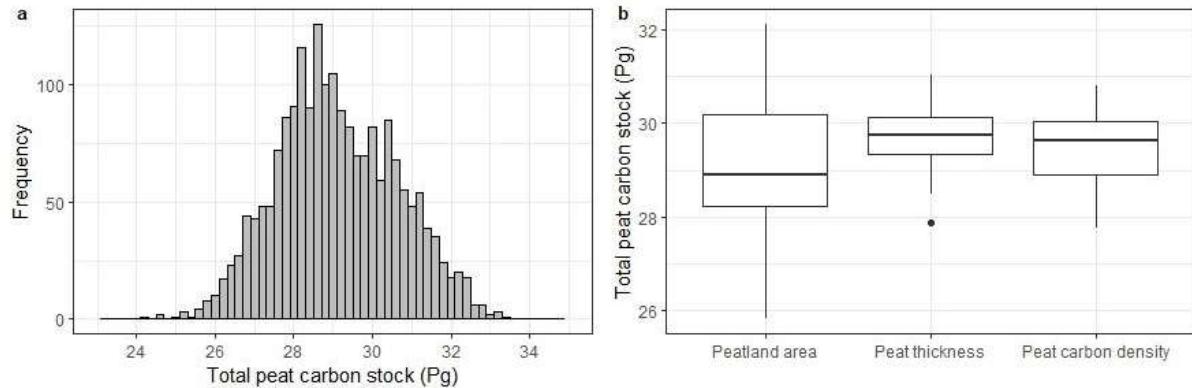


1 **Extended Data Figure 5 | Spatial variability of the four predictor variables**
 2 **retained in the final Random Forest regression model of peat thickness. a.**
 3 **Distance from the peatland margin (km). b. Precipitation seasonality (coefficient of**
 4 **variation). c. Climatic water balance (mm). d. Distance from the nearest drainage point**
 5 **(km). All maps have been masked to the smoothed median Maximum Likelihood**
 6 **peatland extent (> 50% peat probability). Black lines represent national boundaries;**
 7 **grey lines represent sub-national administrative boundaries.**



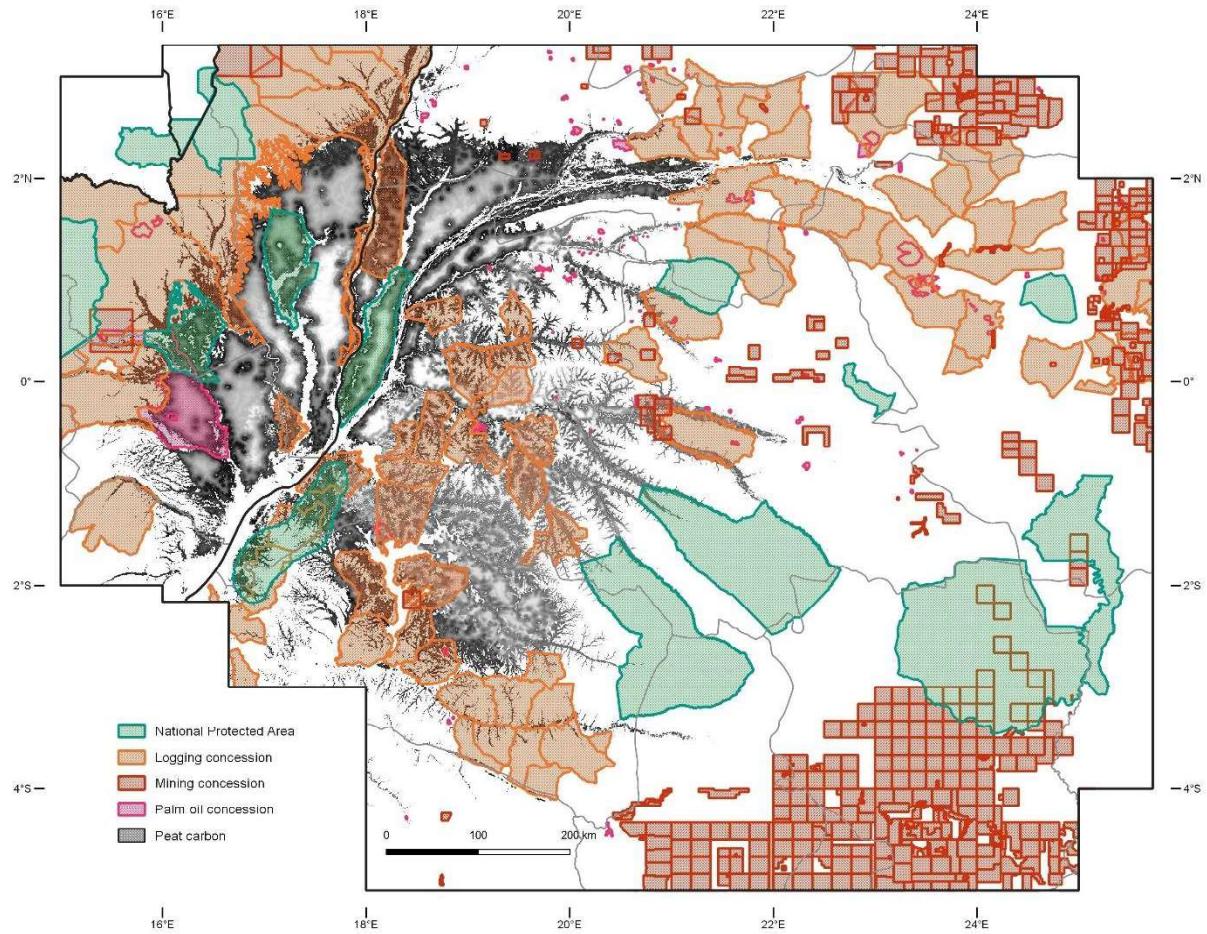
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2 **Extended Data Figure 6 | Relationship between peat thickness (in m) and carbon**
 3 **density (in Mg C ha⁻¹**). Dots are coloured by transect region. Best-fitting line: Carbon
 4 density = $-942.4 + 2088.4 \times \text{SqRt}$ (peat thickness); $n = 80$, $R^2 = 0.86$; $P < 0.001$.
 5 Shaded grey shows 95% confidence interval. 20 bootstrapped regressions, normally
 6 distributed around the best-fitting line, were used to include this uncertainty when
 7 scaling peat thickness to carbon estimates.



1

2 **Extended Data Figure 7 | Distribution and sensitivity of peat carbon stock**
 3 **estimates in the central Congo Basin peatland complex.** **a.** Distribution of 2,000
 4 peat carbon stock estimates, obtained by combining 100 random peat probability
 5 thresholds in the peatland extent model and computing the associated RF peat
 6 thickness map, with 20 normally-distributed equations from the bootstrapped peat
 7 thickness–carbon density regression. Median, 29.0 Pg C; mean, 29.1 Pg C; 95% CI,
 8 26.3–32.2 Pg C. **b.** Sensitivity analysis by in turn bootstrapping peat area estimates
 9 ($n = 100$), peat thickness measurements ($n = 100$), or carbon density regressions ($n =$
 10 20), whilst keeping the other components constant. Black lines show the median,
 11 boxes show the upper and lower quartiles, and the vertical lines show maximum and
 12 minimum values. Dots represent potential outlying values.



1
2 **Extended Data Figure 8 | Distribution of national protected areas and industrial**
3 **concessions across the central Congo Basin peatlands.** Base map shows
4 belowground peat carbon (shaded grey; Fig. 3a), overlaid with protected areas at
5 national-level (national parks and nature/biosphere/community reserves)⁵⁰, or logging
6 concessions^{51,52}, mining concessions^{53,54}, and palm oil^{55–57} concessions. Black lines
7 represent national boundaries; grey lines represent sub-national administrative
8 boundaries.

Region	Peatland area (km ²)	Peat thickness (m)	Peat carbon density (Mg C ha ⁻¹)	Peat carbon stock (Pg C)
Republic of the Congo (ROC)				
Likouala	28,636	1.9 ± 1.0	1,815 ± 740	5.4 (4.8 - 5.8)
Cuvette	17,757	1.6 ± 0.8	1,626 ± 624	2.9 (2.7 - 3.2)
Sangha	7,465	1.1 ± 0.4	1,218 ± 325	0.9 (0.8 - 1.0)
Plateaux	1,183	0.9 ± 0.1	1,059 ± 162	0.1 (0.1 - 0.1)
Total ROC	55,072	1.7 ± 0.9	1,653 ± 687	9.3 (8.4 - 10.2)
Democratic Republic of the Congo (DRC)				
Équateur	58,276	1.9 ± 0.9	1,822 ± 658	10.7 (9.9 - 11.7)
Mai-Ndombe	29,825	1.8 ± 0.7	1,752 ± 548	5.2 (4.8 - 5.7)
Tshuapa	11,628	1.9 ± 0.5	1,917 ± 343	2.1 (1.8 - 2.6)
Sud-Ubangi	7,557	1.1 ± 0.4	1,243 ± 370	1.0 (0.8 - 1.2)
Mongala	5,329	1.2 ± 0.4	1,259 ± 360	0.6 (0.5 - 0.8)
Total DRC	113,201	1.8 ± 0.8	1,740 ± 604	19.6 (17.9 - 21.9)
ROC and DRC combined				
Total central Congo Basin peatlands	167,648 (159,378 - 175,079)	1.7 ± 0.9	1,712 ± 634	29.0 (26.3 - 32.2)

1 **Extended Data Table 1 | Estimated peatland area, peat thickness, carbon density**
 2 **and carbon stocks per administrative region.** All values are regional means (± s.d.)
 3 of the median peat thickness and carbon density maps; or median estimates (with 95%
 4 confidence interval in parentheses) for total peatland area and peat carbon stock. For
 5 regional area estimates without confidence interval, the median peatland map (> 50%
 6 probability) was used. Sub-national administrative regions are provinces (DRC) or
 7 departments (ROC). Marginal peat predictions in other administrative regions (Kasaï,
 8 Tshopo, Kwilu, Nord-Ubangi in DRC; Cuvette-Ouest in ROC) are included in total
 9 country estimates, but not listed separately.

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

1 **Extended Data Table 2 | Estimated peatland area, peat thickness, carbon density**
 2 **and carbon stocks in industrial concessions and protected areas.** Estimates are
 3 calculated for protected areas at national-level (national parks and
 4 nature/biosphere/community reserves)⁵⁰; or for industrial logging^{51,52}, mining^{53,54}, and
 5 palm oil^{55–57} concessions combined (ED Fig. 8). All values are means (± s.d.) of the
 6 median peat thickness and carbon density maps, or median estimates for total
 7 peatland area and peat carbon stock. Percentages show the proportion of total
 8 peatland area or peat carbon stock in ROC, DRC and combined (ED Table 1), that is
 9 found in protected areas or industrial logging/mining/palm oil concessions.