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Adam Hastie^{1,2,*} , J Ethan Householder³, Eurídice N Honorio Coronado^{4,5}, C Gabriel Hidalgo Pizango⁶ , Rafael Herrera⁷, Outi Lähteenoja⁸, Johan de Jong⁹ , R Scott Winton^{10,11}, Gerardo A Aymard Corredor^{12,13}, José Reyna⁶, Encarni Montoya¹⁴ , Stella Paukku¹⁵, Edward T A Mitchard², Christine M Åkesson⁴, Timothy R Baker¹⁶, Lydia E S Cole⁴, César J Córdova Oroche⁶ , Nállarett Dávila⁶, Jhon Del Águila^{6,17}, Frederick C Draper¹⁸, Etienne Fluet-Chouinard¹⁹ , Julio Grández⁵, John P Janovec²⁰, David Reyna⁶, Mathias W Tobler²¹, Dennis Del Castillo Torres⁶, Katherine H Roucoux⁴, Charlotte E Wheeler²², Maria Teresa Fernandez Piedade²³, Jochen Schöngart²³, Florian Wittmann³, Marieke van der Zon⁹ and Ian T Lawson⁴

- ¹ Department of Botany, Physical Geography and Geoecology, Charles University, Faculty of Science, Prague, Czech Republic
- ² School of GeoSciences, University of Edinburgh, Edinburgh, United Kingdom
- ³ Wetland Ecology, Institute for Geography and Geoecology, Karlsruhe Institute for Technology, Karlsruhe, Germany
- ⁴ School of Geography and Sustainable Development, University of St Andrews, St Andrews, United Kingdom
- ⁵ Royal Botanic Gardens, Kew—Richmond, Surrey, TW9 3AE, United Kingdom
- ⁶ Instituto de investigaciones de la Amazonía Peruana, Iquitos, Peru
- ⁷ Instituto Venezolano de Investigaciones Científicas (IVIC), Caracas, Venezuela
- ⁸ Helsinki, Finland
- ⁹ Forest Ecology and Forest Management, Wageningen University & Research, Droevendaalsesteeg 3, 6708 PB Wageningen, The Netherlands
- ¹⁰ Department of Environmental Studies, University of California Santa Cruz, Santa Cruz, CA, United States of America
- ¹¹ Department of Earth System Science, Stanford Doerr School of Sustainability, Stanford University, Stanford, CA, United States of America
- ¹² UNELLEZ-Guanare, Programa de Ciencias del Agro y el Mar, Herbario Universitario (PORT), Mesa de Cavacas, estado Portuguesa 3350, Venezuela
- ¹³ Jardín Botánico de Bogotá José Celestino Mutis, Calle 63 #68–95, Bogotá, D.C, Colombia
- ¹⁴ Geosciences Barcelona, CSIC, c/Lluís Solé i Sabaris s/n, 08028 Barcelona, Spain
- ¹⁵ ETH Zurich, Zurich, Switzerland
- ¹⁶ School of Geography, University of Leeds, Leeds, United Kingdom
- ¹⁷ Universidad Nacional de la Amazonia Peruana (UNAP), Iquitos, Peru
- ¹⁸ School of Environmental Sciences, University of Liverpool, Liverpool, United Kingdom
- ¹⁹ Earth System Science Division, Pacific Northwest National Laboratory, Richland, WA, United States of America
- ²⁰ Herbario Forestal UNALM, Facultad de Ciencias Forestales, Universidad Nacional Agraria La Molina, Lima, Peru
- ²¹ San Diego Zoo Wildlife Alliance, Conservation Science and Wildlife Health, Escondido, CA, United States of America
- ²² Department of Plant Sciences, University of Cambridge, The David Attenborough Building, Pembroke Street, Cambridge CB2 3QZ, United States of America
- ²³ Research Group in Ecology, Monitoring and Sustainable Use of Wetlands (MAUA), National Institute for Amazonian Research (INPA), Manaus, Brazil

* Author to whom any correspondence should be addressed.

E-mail: hastiea@natur.cuni.cz

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Abstract

Tropical peatlands are among the most carbon-dense terrestrial ecosystems yet recorded. Collectively, they comprise a large but highly uncertain reservoir of the global carbon cycle, with wide-ranging estimates of their global area (441 025–1700 000 km²) and below-ground carbon storage (105–288 Pg C). Substantial gaps remain in our understanding of peatland distribution in some key regions, including most of tropical South America. Here we compile 2413 ground reference points in and around Amazonian peatlands and use them alongside a stack of remote sensing products in a random forest model to generate the first field-data-driven model of peatland distribution across the Amazon basin. Our model predicts a total Amazonian peatland extent of

251 015 km² (95th percentile confidence interval: 128 671–373 359), greater than that of the Congo basin, but around 30% smaller than a recent model-derived estimate of peatland area across Amazonia. The model performs relatively well against point observations but spatial gaps in the ground reference dataset mean that model uncertainty remains high, particularly in parts of Brazil and Bolivia. For example, we predict significant peatland areas in northern Peru with relatively high confidence, while peatland areas in the Rio Negro basin and adjacent south-western Orinoco basin which have previously been predicted to hold *Campinarana* or white sand forests, are predicted with greater uncertainty. Similarly, we predict large areas of peatlands in Bolivia, surprisingly given the strong climatic seasonality found over most of the country. Very little field data exists with which to quantitatively assess the accuracy of our map in these regions. Data gaps such as these should be a high priority for new field sampling. This new map can facilitate future research into the vulnerability of peatlands to climate change and anthropogenic impacts, which is likely to vary spatially across the Amazon basin.

1. Introduction

Tropical peatlands, which include some of the most carbon dense terrestrial ecosystems known to science (Dommain *et al* 2011, Draper *et al* 2014), are a substantial but highly uncertain component of the global carbon cycle. Estimates of their total area range from 441 025 (Page *et al* 2011) to 1700 000 km² (Gumbricht *et al* 2017), and of their total below-ground carbon from 105 (70–130) to 215 (152–288) Pg C (Dargie *et al* 2017, Ribeiro *et al* 2021). Tropical peatlands host invaluable biodiversity (Posa *et al* 2011, Draper *et al* 2018) and support the livelihoods of local populations throughout the tropics (Page and Baird 2016; Roucoux *et al* 2017, Girkin *et al* 2022). However, various pressures including climate and land use change threaten the integrity of tropical peatlands (Roucoux *et al* 2017, Baker *et al* 2019, Dargie *et al* 2019, Mishra *et al* 2021, Lawson *et al* 2022), with South-East Asia being a cautionary example. Approximately 80% of South-East Asian peatlands have been deforested and drained to make way for plantations and agriculture (Mishra *et al* 2021) and peat fires in Indonesia have caused huge pulses of CO₂ emissions to the atmosphere (Page *et al* 2002, Huijnen *et al* 2016). These events have also been linked to tens of thousands of premature human deaths (Johnston *et al* 2012), the loss of invaluable flora and fauna (Posa *et al* 2011), as well as huge economic costs (Kiely *et al* 2021). It is thus urgent that we develop reliable estimates of tropical peatland distribution and carbon stocks to inform and prioritise conservation and climate change mitigation actions.

Decades of research have resulted in relatively high confidence in peatland mapping in Southeast Asia (Jaenicke *et al* 2008, Warren *et al* 2017), yet substantial gaps remain in our understanding of the distribution of peatlands and their carbon stores in other key tropical regions (Xu *et al* 2018, Ribeiro *et al* 2021, Melton *et al* 2022). There have been recent intensive field efforts in regions such as the Congo basin (Crezee *et al* 2022) and Peruvian Amazonia

(Hastie *et al* 2022), which have driven the development of more accurate regional peatland and below-ground carbon maps. Despite research on peatlands in the Tepuis region of Venezuela (Zinck and Huber 2011), recent progress in Peru (Honorio Coronado *et al* 2021, Hastie *et al* 2022), and ongoing efforts in Colombia (Santofimio-Tamayo and Benavides 2019, Winton *et al* 2021), the Amazon basin arguably remains the greatest remaining knowledge gap in tropical peatland research. Central, eastern, and southern Amazonia are particularly understudied. A 2013 study (Lähteenoja *et al* 2013) confirmed the presence of peat at a handful of sites within the Rio Negro River basin, but otherwise the distribution of peat across Brazil remains poorly understood. Pan-tropical peat distribution modelling by Gumbricht *et al* (2017) estimated that Brazil could hold the single greatest peatland area in the tropics, more than twice that of Indonesia.

Maps of peatlands across the Amazon basin have primarily relied on modelling approaches due to the limited availability of field data. Gumbricht *et al*'s study was driven by a distributed hydrological model, as well as remote-sensing products, and required a positive interannual water balance for peatland presence. This approach is justified in regions with sparse field data, but the results remain extremely uncertain: Gumbricht *et al* (2017) used a total of only 275 field data points for ground-truthing (validation) of their maps across the entire tropics (and no data for model training). Melton *et al* (2022) developed a global peat distribution model, driven by various remote-sensing predictors and trained and tested using previously derived (i.e. secondary) peatland mapping products. The Melton map therefore inherits the limitations of its input maps and like the Gumbricht product is only indirectly guided by field data. Peatland mapping, particularly in the tropics, requires closer integration with expanded in situ databases to reach higher levels of accuracy and reliability for regional/national-scale applications.

Here we combine new and published field data to establish a database of 2413 ground reference points (GRPs) in and around the peatlands of the Amazon basin, including 548 new GRPs in Brazil. We use these GRPs along with radar and optical remote sensing imagery and topographical data, in a random forest model to produce the first high-resolution (90 m resolution) field-data-driven map of peatland extent across the entire basin. We then use this map and an assessment of its uncertainties to identify and discuss the remaining gaps in our understanding of peatland distribution in the Amazon basin.

2. Methods

2.1. GRPs

The dataset used here represents more than a decade of fieldwork in and around the peatlands of the Amazon basin by several teams (table S1). The data include 1702 published (including grey literature-i.e. theses and governmental reports) GRPs from Peru (Lähteenoja *et al* 2009, 2012, Householder *et al* 2012, Draper *et al* 2014, de Jong 2019, Diaz Cardenas 2019, Honorio Coronado *et al* 2021, Hastie *et al* 2022, IIAP-PROFONANPE 2023, Lawson *et al* 2023); 548 unpublished GRPs from Brazil, plus nine published by Lähteenoja *et al* (2013); 147 GRPs from Colombia (comprising 87 GRPs digitized by Pauku (2021) from Duivenvoorden and Lips (1991a, 1991b), 56 unpublished GRPs by Winton *et al* (2021), and four GRPs from Santofimio-Tamayo 2019); five GRPs from Ecuador (Montoya, E., unpublished); and two from Bolivia (Escobar-Torrez *et al* 2020, Smith *et al* 2021) (table S1). At each GRP, substrate type was recorded, along with an assessment of overlying vegetation cover (in this study simply forest or non-forest). Peat thickness (where present) was measured using a gouge auger or a Russian-type corer, typically along transects at 100–500 m intervals.

Of the total 2413 GRPs, 1590 were defined as peat, meaning an organic layer of at least 30 cm, with the remaining 823 defined as non-peat (figure 1). At the majority of GRPs, no corresponding soil carbon concentration or organic matter measurements were taken. Thus, we could not impose a minimum carbon concentration or organic matter threshold for our definition of peat. However, we visually identified peat based on composition (e.g. roots, wood) and physical properties (e.g. structure, colour, texture) (Troels-Smith 1955, Kershaw 1997). Previous studies have shown that Amazonian peatlands typically show a clear transition from an organic layer to underlying mineral sediment. For example, Hastie *et al* (2022) found that material visually defined as peat had a mean loss on ignition (LOI) of 70%, whilst material defined as mineral had a mean LOI of only 13% (table S2). We are thus confident that our peat GRPs represent an LOI of at least 50%, a common definition

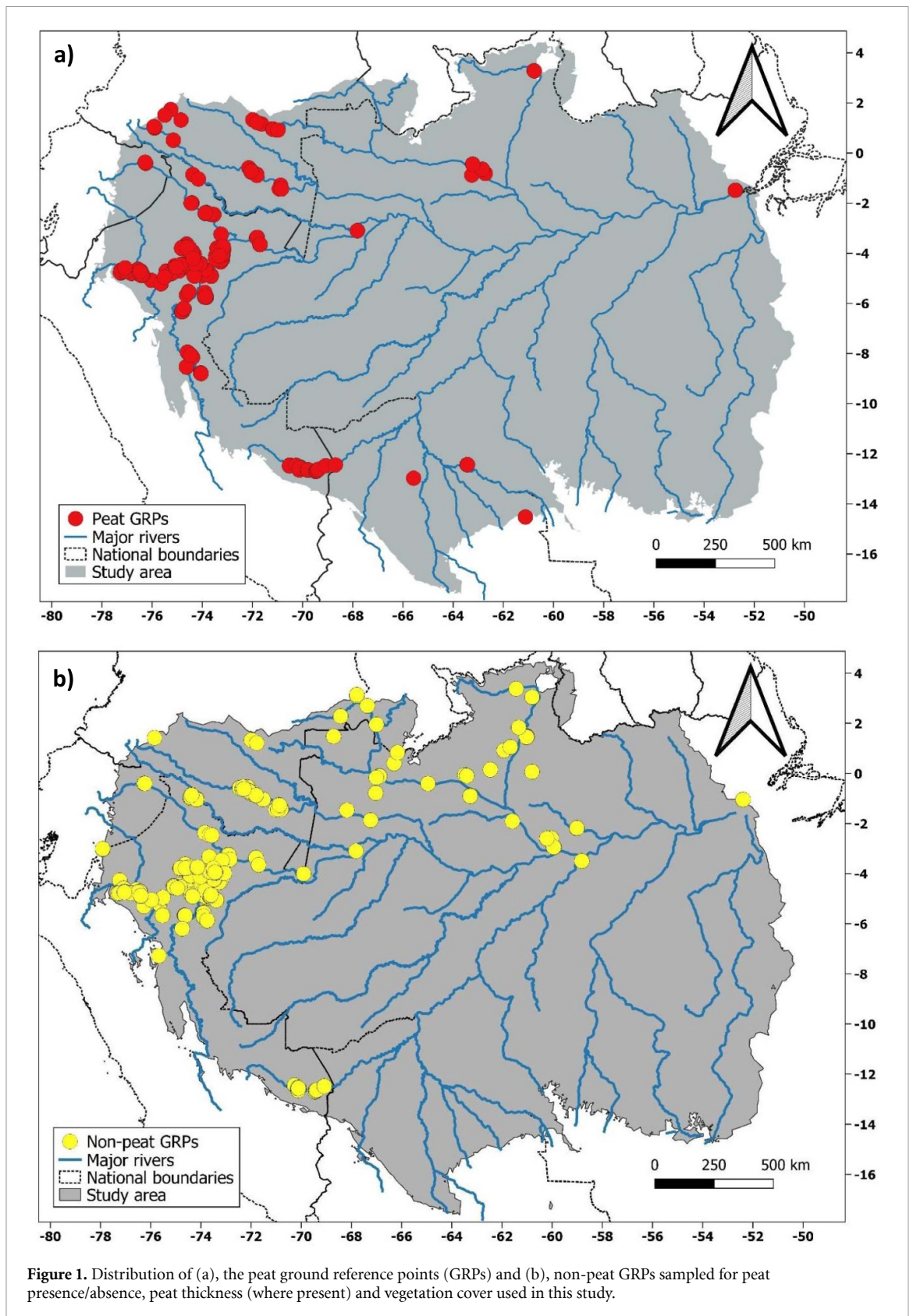
of peat (Burton & Hodgson, 1987, Gumbrecht *et al* 2017). Dargie *et al* (2017) also demonstrated that a similar visual method was effective at identifying peat in the Congo basin.

2.2. Model of peatland extent

We used our 2413 GRPs to train a supervised random forest algorithm (250 trees, three variables per split, at 90 m resolution) in Google Earth Engine. We used a minimum 20 m diameter buffer to create polygons around our sample points to sample gridded predictors. We merged adjacent polygons of the same class wherever possible; for example, in situations where they were sufficiently close together (i.e. within a 90 m grid cell) or where we were confident (based on field/local knowledge) that the soil did not substantially change between sites. We supplemented our GRPs with additional data points within or close to predicted peatlands, from the RADAMBRASIL soil profile database (figure S1, Negreiros *et al* 2009 e.g. in locations where preliminary maps predicted isolated peat patches), as well as with points which could be assumed to lack peat such as urban settlements and rivers (based on visual examination of satellite images).

The model was driven using a remote sensing stack (table 1, 11 bands in total) containing selected Landsat 7 bands and indices (Hansen *et al* 2013) including normalized difference water index (NDWI) and normalized difference vegetation index (NDVI), ALOS PALSAR HH polarisation & HH/HV (Shimada *et al* 2014), height above nearest drainage (HAND Donchyts *et al* 2016), upstream drainage area (UPA, Yamazaki *et al* 2019), slope (derived from SRTM 30 m DEM, Farr *et al* 2007), and topographic landforms (Theobald *et al* 2015). The Landsat bands and indices are important for inferring overlying ecosystem type and vegetation density. HAND, UPA, slope and topographic landforms provide information on the relative topographical and hydrological position of each grid cell, and in turn an approximation of wetness. Variation in PALSAR L-band backscatter is indicative of variation in soil/vegetation moisture as well as forest structure. We started the model with more variables but removed several bands to avoid overfitting. Namely, we removed Landsat 7 Band 3 (red), Band 7 and ALOS PALSAR-HV polarisation as they exhibited particularly high collinearity (Pearson correlation of >0.85 , $p < 0.001$) with other driver variables (table S3). Their removal only marginally reduced model performance.

We used the algorithm to map the following five categories: peat below forest (PF), peat below non-forest (PN), non-peat below forest (NF), non-peat below non-forest (NN), and open water (WA). The forested versus non-forested categories were chosen largely for remote sensing reasons, i.e. they are easy for satellite derived data to delineate and because we



believe that the distribution of forested versus open peatlands could be of interest to the research community (figure S2).

We evaluated model accuracy using a spatial leave one out cross validation (e.g. Meyer *et al* 2019, Garcia 2021) tailored to our dataset. Our data was

collected in four main areas which were used to inform the selection of four clusters for the spatial cross validation: (1) Northern Peru (centred around the Pastaza-Marañón foreland basin, PMFB), (2) Colombian Amazonia, (3) Southern Amazonia, (4) Brazilian Amazonia (figure S3). These clusters of

Table 1. Data used as predictors in the peatland classification random forest model.

Dataset	Resolution (m)	Acquisition date	Polarisation/Bands/Indices	Source
PALSAR-2/PALSAR annual mosaics	25	2014–2023 (period median)	HH, HH/HV	Shimada <i>et al</i> (2014)
Landsat 7 mosaic	30	2021 (growing season median)	Band 4(NIR), Band 5 (SWIR), NDVI, NDWI	Hansen <i>et al</i> (2013)
Slope (SRTM)	30	2000	NA	Farr <i>et al</i> (2007)
Upstream drainage area (flow accumulation grids, MERIT)	50	1987–2017	NA	Yamazaki <i>et al</i> (2019)
Height above nearest drainage (HAND)	90	2016	NA	Donchyts <i>et al</i> (2016)
Landforms (SRTM)	90	2006–2011	NA	Theobald <i>et al</i> (2015)
Landforms (ALOS)	90	2006–2011	NA	Theobald <i>et al</i> (2015)

data were collected independently on separate field campaigns with different team members (albeit with some crossover between Southern Peru and Brazilian Amazonia). Moreover, none of these regions share a substantial contiguous peatland area. Thus, we consider these clusters as sufficiently independent and therefore suitable for cross validation purposes. In turn, we estimated the 95% confidence intervals of peatland area using the mean confusion matrix (mean of the four cross validations, tables S4 to S7, Goldblatt *et al* 2016), applying the method described in Olofsson *et al* (2013) (equations (9)–(13)). See supplementary materials for further discussion.

Note that for the final classification (figure 2), we used all polygons to train the model to produce the best map possible, following Honorio-Coronado *et al* (2021). For comparison, results of predicted peatland area per country are also given for the model trained using only 50% (random) of the data (table S8). While the accuracy assessment (based on the spatial leave one out cross validation, table 2) helped to inform our final model choice, we also undertook rigorous local-scale assessment of the map iterations. In line with the recommendations of Meyer and Pebesma (2022) we compared predicted peatland distributions to local data-driven products such as Householder *et al* (2012) and Hastie *et al* (2022), as well as examining areas where the authors have expert knowledge, e.g. the main stem of the Amazon.

To avoid extrapolating into regions which are climatologically unlikely to support the formation of peat, we masked out areas of the Amazon basin where annual precipitation is estimated at <1390 mm on average over the last decade in the CHIRPS database (Funk *et al* 2015). The cutoff of 1390 mm is based on the lowest mean annual precipitation at which peat has been observed in our GRPs (1393 mm in eastern Bolivia: Smith *et al* 2021), the next lowest peatland precipitation mean being 1455 mm at a GRP in northern Brazil. We further masked out areas above 500 m elevation, as our model was trained using only low-land data.

3. Results

Across the study region (Amazon basin below 500 m and mean annual precipitation >1390 mm) we estimate a total peatland area of 251 015 km² (128 671–373 359; 95th percentile confidence interval) (figure 2) at 90 m resolution, with the majority (66%) being overlain by forest (figure S2). The map broadly represents conditions over the period 2000–2021 when GRPs and remote sensing imagery were collected. Brazil contains the greatest estimated peatland area of 132 759 km² (68 024–197 493) followed by Peru with 55 890 km² (28 748–83 032) (table 2). Overlaying our peatland estimate with the 30 m-resolution deforestation map of Hansen *et al* (2013), we estimate that approximately 8743 km² or 3.5% of our predicted peatland area has been deforested from 2000 to 2023, with the greatest deforested areas found in Brazil and Bolivia.

Our peatland land cover classification algorithm has an overall accuracy of 89% based on the spatial leave one out cross validation (table 3). While accuracy per class is highly variable the model still performs relatively well with the lowest producer's and user's accuracy being 67% and 75% respectively (for the PN category). There is little confusion between the forested and non-forested categories, but greater confusion between the peat and non-peat forming classes. This is not surprising given that only the synthetic aperture radar bands (i.e. the L-band PALSAR) are capable of penetrating the canopy to any substantial degree. NDVI is the most important model variable, corresponding to the greatest mean decrease in the Gini coefficient, followed closely by NDWI and then PALSAR HH (figure 3). Please see supplementary materials for further information on model parameterization and accuracy assessment.

4. Discussion

Our map of peat distribution across Amazonia, the first high-resolution field-data-driven estimate

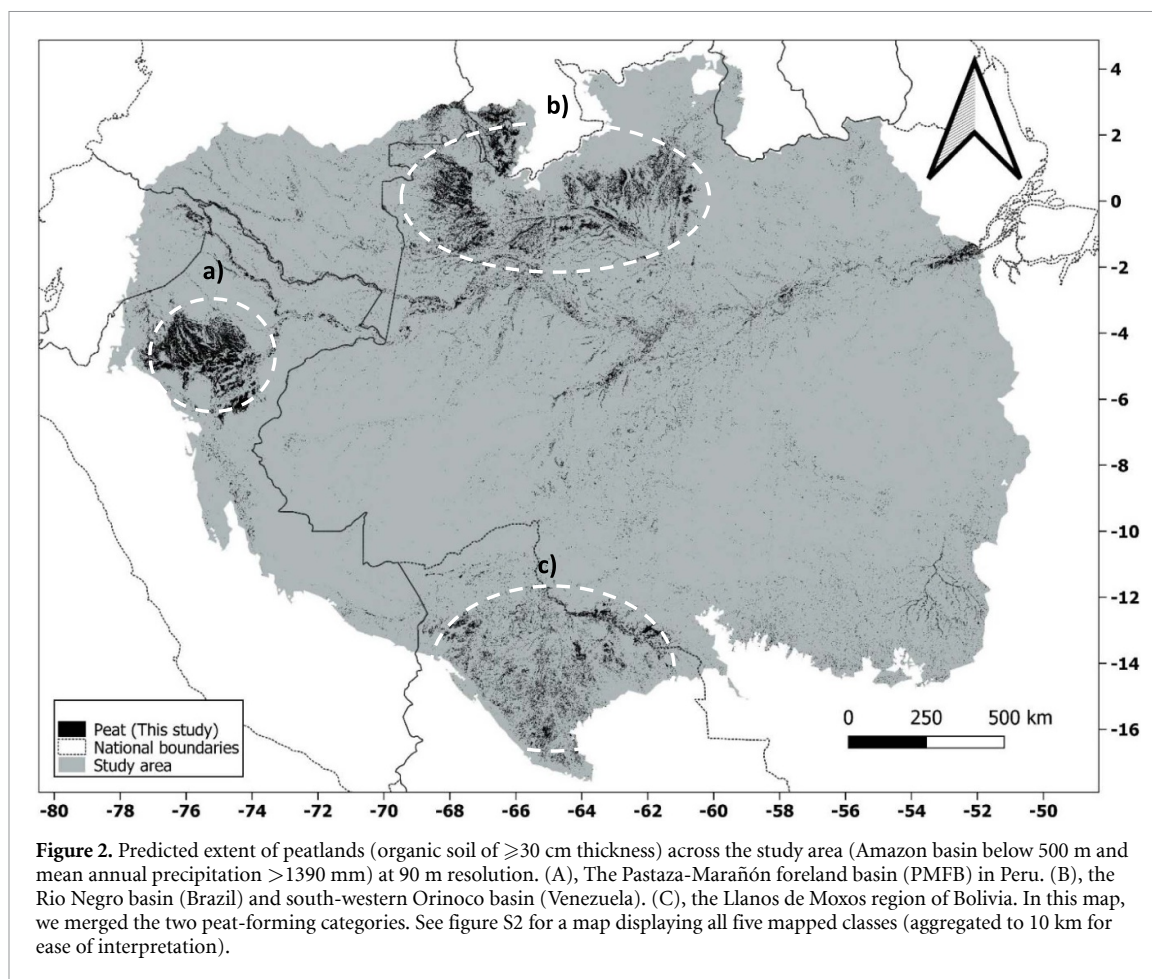


Table 2. Predicted area of peat below forest (PF), peat below non-forest (PN) and total peatland area by country within the study region.

Country	PF area (km ²)	PN area (km ²)	Total peatland area (95% confidence intervals) (km ²)
Brazil	83 450	49 309	132 759 (68 024–197 493)
Peru	49 649	6241	55 890 (28 748–83 032)
Bolivia	13 403	25 010	38 413 (19 600–57 226)
Colombia	7275	2538	9813 (5037–14 589)
Venezuela	8493	2919	11 412 (5857–16 967)
Ecuador	2237	154	2391 (1231–3551)
Guyana	91	171	262 (134–390)

across the basin, predicts substantial peatland areas that are currently unconfirmed by field research. To place these results, their associated uncertainties, and remaining knowledge gaps into context, we compared our map to previous model-based estimates and discuss the field evidence for peat formation across the region.

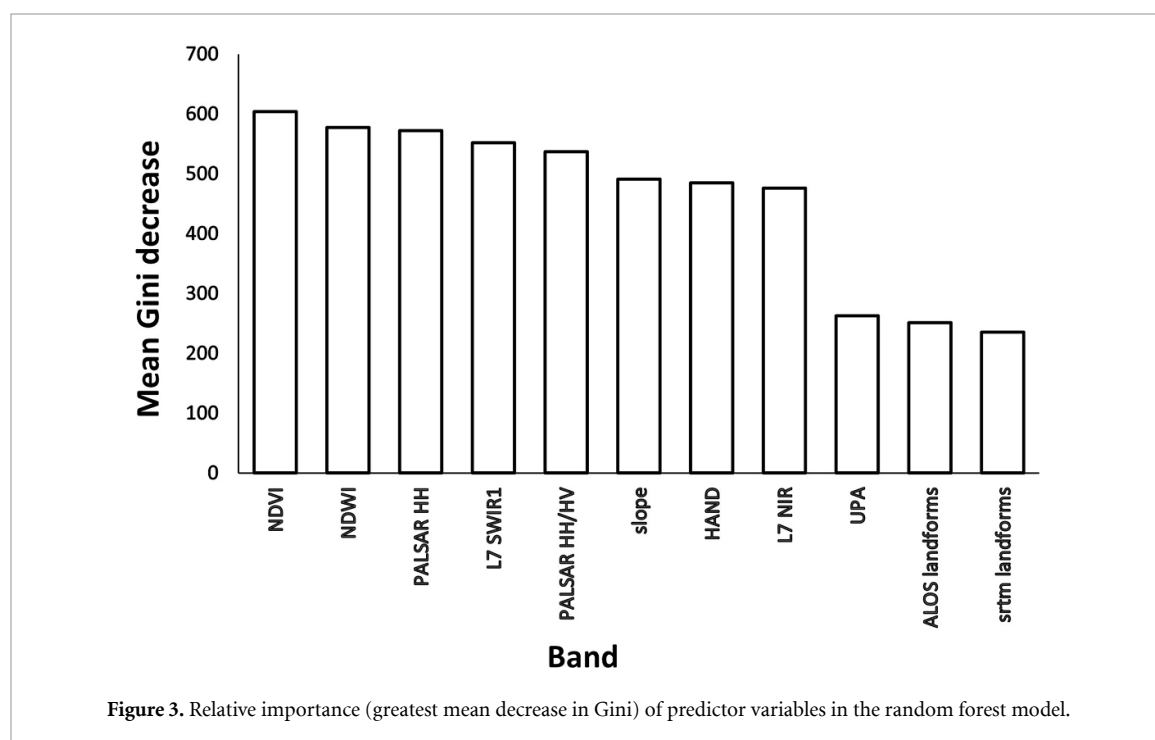
Our total estimated peatland area of 251 015 km² is substantially less than the 359 711 km² estimated by Gumbrecht *et al* (2017) over the same study area, who mapped peatlands at a resolution of 232 m. This

is at least in part because the Gumbrecht map predicts greater peatland areas along rivers, including the Amazon main stem (figure 4). We are doubtful that peatlands along the Amazon main stem could be so extensive given the highly seasonal nature of the flooding in várzea forests (Junk 1983), and the associated influx of nutrients and mineral material (Wittman *et al* 2004). Indeed, our map has a relatively high degree of uncertainty in this region (figure S4) and may therefore also be overpredicting peatland extent along the main stem.

Table 3. Random Forest (250 trees) classification accuracy matrix for the peatland map, based on a spatial leave one out cross validation (mean of four iterations). Units are pixels. Includes producer's (PA) and user's accuracy (UA) for five classes: non-peat below forest (NF), peat below forest (PF), peat below non-forest (i.e. herbaceous vegetation and shrubland, PN), non-peat below non-forest (NN) and open water (WA).

Class	NF	PF	PN	NN	WA	Total	PA (%)
NF	522	39	10	2	0	573	0.91
PF	66	234	23	0	0	323	0.72
PN	7	30	136	29	0	202	0.67
NN	4	2	13	714	5	738	0.97
WA	2	2	0	8	1669	1681	0.99
Total	601	307	182	753	1674	3507	
UA (%)	0.87	0.76	0.75	0.95	1.00		

Overall accuracy (%): 89.



The Melton *et al* (2022) global map of percentage peat cover (figure 4, multiplying each 10 km grid cell by surface area per cell) yields an estimated total peatland area of 183 263 km². Our distribution of peat across Peru, Venezuela, Ecuador, and some areas of Colombia broadly resembles the estimated distribution in both previous studies (figure 4), while greater divergence is apparent across some regions of Brazil and Bolivia, particularly compared to the Melton map. These different regions are discussed later in more detail.

4.1. Country level comparisons

Our predicted distribution of peat in Peru closely aligns with the data-driven distribution predicted by Hastie *et al* (2022) (figure 5). The largest area of peatland is forested and located in the PMFB (figure 2(a)), a major geological depression with very

flat topography situated in one of the climatically wettest parts of Amazonia. Smaller areas of peatland are concentrated on the floodplains of the Napo, Putumayo, and upper Amazon rivers in northern Peru, Ucayali River in central Peru and Madre de Dios River in southern Peru. However, our total area of 55 890 (28 748–83 032) km² is somewhat less than the 62 714 km² predicted by Hastie *et al* (2022) despite sharing some GRPs over Peru, for two reasons: firstly, the present model was run at a lower resolution (90 m) than Hastie *et al* (50 m), and thus may exclude some smaller peatlands; secondly, the Hastie *et al* (2022) model had the benefit of additional high-resolution driver variables which only cover Peru (e.g. MINAM *et al* 2019).

Our distribution along the Madre de Dios River is very similar to that mapped by Householder *et al* (2012) (figure 5), and our predicted peatland area of

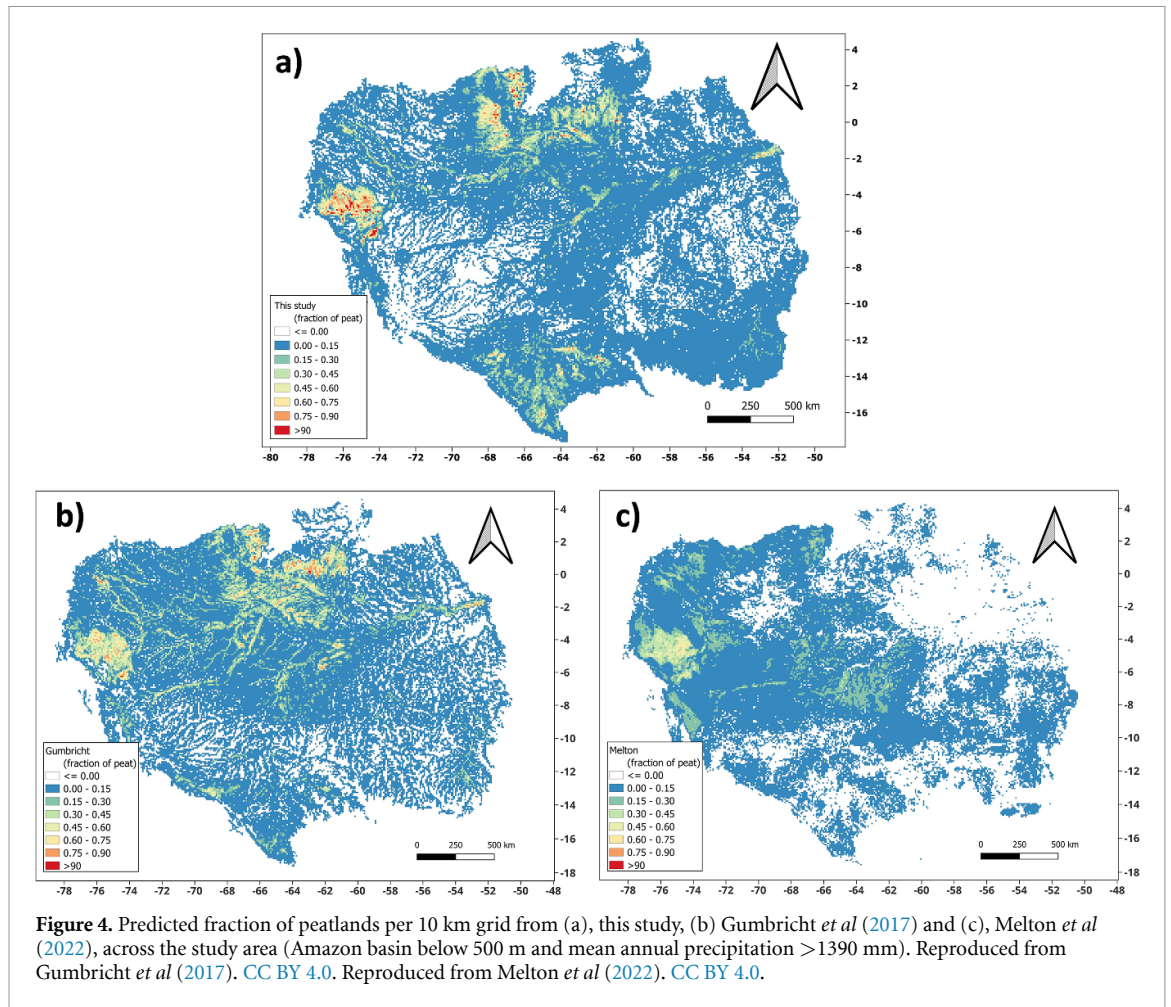


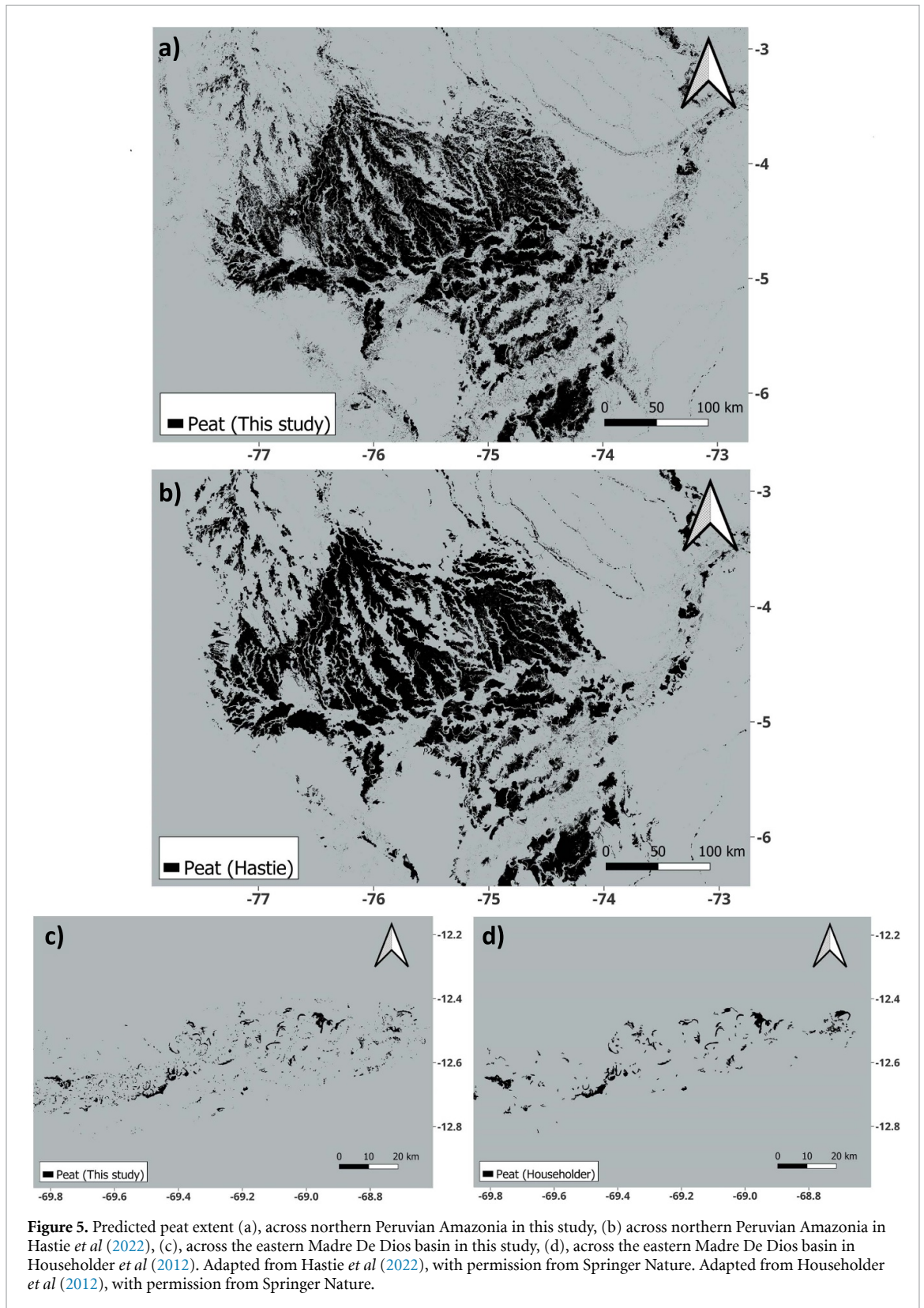
Figure 4. Predicted fraction of peatlands per 10 km grid from (a), this study, (b) Gumbricht *et al* (2017) and (c), Melton *et al* (2022), across the study area (Amazon basin below 500 m and mean annual precipitation >1390 mm). Reproduced from Gumbricht *et al* (2017). CC BY 4.0. Reproduced from Melton *et al* (2022). CC BY 4.0.

408 km² across this region is also relatively close to their value of 294 km². As a comparison, Gumbricht *et al* (2017) mapped 908 km² of peatlands along the same section of the Madre de Dios, more than three times the estimate of Householder *et al* (2012). Peruvian peatlands are dominated by palm swamps and to a lesser extent by pole forest and open peatlands (Honorio Coronado *et al* 2021, Hastie *et al* 2022).

In common with Gumbricht *et al* (2017), we predict that Brazil holds the greatest peatland area in the Amazon, covered mostly by forest (63%, figure S2), albeit distributed across several different regions, unlike the dense concentration of peatlands in the PMFB in Peru (Hastie *et al* 2022, figure 2(a)). One of the most substantial peatland areas in Brazil is predicted to occur in the Rio Negro basin; adjacent to another large peatland predicted in the south-western Orinoco basin in Venezuela (figure 2(b)).

There has been very little fieldwork undertaken in the wetlands of the Rio Negro, but a few previous studies have confirmed the presence of peat. Fieldwork has documented several wetland sites forming peat ~1 m thick in the lower Rio

Negro (Lähteenoja *et al* 2013 and unpublished data, included in our analysis), and the presence of peat at two sites in the upper Rio Negro (Dubroeuq and Volkoff 1998), albeit without high-precision coordinates. The predicted peatlands in this region are distinctive, apparently overlapping with what have previously been mapped as ‘white sand’ forests (Adeney *et al* 2016), which typically have a thin-stemmed and/or dwarfed forest structure known as Campinarana or Campinarana florestada in Brazil (IBGE 2004, 2009) and as Caatinga Amazonica in Venezuela (Coomes and Grubb 1996). Previous field studies have certainly indicated that white sand forests occur on ‘white sands’—heavily leached podzols or hydromorphic podzols—not only in Brazil, but also in Peru, Colombia, Venezuela, Guyana and Suriname (Coomes and Grubb 1996, Quesada *et al* 2011, Adeney *et al* 2016). These forests are structurally similar to ombrotrophic ‘peatland pole forest’ (varillal hidromorfico) which are nutrient-poor habitats occurring on generally thick peats in Peru (Draper *et al* 2014, 2018, Honorio Coronado *et al* 2021). However, Dubroeuq and Volkoff (1998) also described ‘histosols [i.e. soils with high organic material] scattered among giant spodosols [i.e.



podzols]’ at one of their sites in the upper Rio Negro. Similar intermingling of peats and white sands has been observed by the authors (S.W., I.L., K.R.) in white-sand forests in Colombia and Peru (García-Villacorta *et al* 2003). While we were unable to access any high-resolution peat GRPs located in the

upper Rio Negro, we were able to use four published GRPs for non-peat-forming podzol sites (Doupoux *et al* 2017) in our training/testing data. Furthermore, comparison of our results with less precisely geolocated reports of white sand forests (Herrera 1977, 1979, Montes *et al* 2011, Lucas *et al* 2012) suggests

that our model correctly identifies these sites as non-peat-forming (i.e. while they do not provide precise enough coordinates to test quantitatively, they lie outside of our larger peatland areas).

We also note that our study is not the first to predict high soil carbon stocks in the Rio Negro/Orinoco region (Bernoux *et al* 2002, Gomes *et al* 2019). Interestingly, Melton *et al* (2022) also predicted peat in the Rio Negro Campinarana ecoregion but removed it during post-processing on the conservative grounds that the ecoregion was associated with white sands, not peat. In conclusion, while previous mapping studies have largely classified these Rio Negro ecosystems as white sand forests underlain by podzols, there are multiple lines of evidence, including firm field observations, which suggest that peatlands are present in the Rio Negro basin (and similar habitats in adjacent countries; IITL & SRW, pers. comm). Nevertheless, our prediction in this area is associated with a high degree of uncertainty (figure S4). The true extent of peat (including in what are presently mapped as ‘white sand’ forests), and crucially the variation in peat thickness (existing evidence suggests that mean thickness may be lower in Brazil than in Peru), remains to be determined through targeted fieldwork. Although the largest areas of predicted peat in our map are remote, further fieldwork in the Rio Negro and Orinoco basins (figure 2(b)) is important to test for the presence of large soil carbon stocks, and to help to refine our understanding of the relationship between white sand forests and peat.

Peatlands have also been directly sampled in Venezuela (Rull 1992, Vegas-Vilarrúbia *et al* 2010, Montoya and Rull 2011), and French Guiana (Cubizolle *et al* 2013), and observed in Guyana (Guyana Lands & Surveys Commission 2013) and Suriname (Sevenhuijsen 1977), but the points lie outside of our study area. While we were only able to include two unpublished peat GRPs (of five total GRPs) in Ecuador in our study, all three pan-Amazon maps (this study, Gumbrecht *et al* 2017 and Melton *et al* 2022) predict a substantial concentration of peat in the same region where our GRPs are located (within the Yasuni and Cuyabeno National Parks).

Over Bolivia, our map estimates 38 413 (19 600–57 226) km² of peatland, a substantial area given the strong climatic seasonality found in the majority of Bolivian Amazonia. Much of this large peat-forming area is predicted to occur along rivers and lakes and between the large grasslands of the Llanos de Moxos (figure 2(c)), where the topography may promote water retention even during the dry season. Only two peatland GRPs were available for inclusion in our study (Escobar-Torrez *et al* 2020, Smith *et al* 2021), but Brugger *et al* (2016) also described peatlands north and south of Lake Rogaguado in the Llanos de Moxos, in agreement with our map

(figure 2(c)). Consistent across the descriptions of the ecosystems described in the Bolivian studies is the presence of *Mauritia flexuosa* and/or *Mauritiella* sp. palm communities, which is potentially significant as they are common in peat-forming swamps elsewhere in Amazonia (Householder *et al* 2012, Honorio Coronado *et al* 2021).

Winton *et al* (2021) and Montoya and Rull (2011) describe the presence of peat in the climatically similar Llanos of Colombia and Venezuela, despite strong seasonal and El Niño–Southern Oscillation-driven drought cycles. Melton *et al* (2022) also predicted peat deposits in the Llanos de Moxos, but removed these peatlands from their final model on the assumption that peats were unlikely to occur under strongly seasonal climates. The combination of consistent model predictions and field evidence of peat presence in areas of strongly seasonal climate suggests that this assumption should be tested. Our map has relatively low confidence in Bolivian Amazonia (figure S4). Further fieldwork would help to refine our understanding of soil carbon storage in seasonally dry parts of the Amazon basin.

5. Conclusion

As the first high-resolution field-data-driven map of peatland extent across the Amazon basin, our map represents a significant step forward in our understanding of the distribution of tropical peatlands and can inform future research priorities. Our analysis confirms the presence of peat underlying a diverse set of Amazonian ecosystems including the typical palm swamps in extensive depressions and along rivers and streams, as well as the less-known peat-forming ‘white sand’ forests. Nonetheless, comparisons of our map to a regional field-data-driven study (Hastie *et al* 2022), along with a relatively conservative precipitation mask, indicate that our map may be underestimating total peatland area in some regions.

Most sites which have so far been sampled in these regions are restricted to peatland edges, the sampling of more remote areas being limited by cost, time and logistical considerations. Substantial uncertainties thus remain. Most notably, the central Amazon basin urgently requires further investigation, particularly the Upper Rio Negro, the adjacent south-western Orinoco basin, and Bolivian Amazonia (figure S4). Data needs include not only sampling of peat depth and carbon density, but data on substrate, nutrient status, hydrological regime, and floristic diversity/composition, all of which would help us to better understand the mechanistic drivers explaining peat distribution and help to inform the choice of data products for future mapping studies. The extent and carbon storage of peat soils associated with ‘white sand’ forests, a relatively understudied topic, could be a key focus. Even in relatively densely sampled

regions such as northern Peru, research is still in an exploratory phase and is regularly uncovering new insights into Amazonian peatlands. Recent fieldwork (IIAP-PROFONANPE 2023) discovered peats up to 8 m thick (included in this study) in the Datem del Marañón region, some of the deepest Amazonian peats ever recorded. Much more fieldwork will be needed before we can claim to have a solid understanding of the distribution of peat carbon in Amazonia.

We also know little about the palaeoecological history of Amazonian peatlands and their vulnerability to land-use and climate change (Cole *et al* 2022, Girkin *et al* 2022). Their past response to climate and land-use change, particularly in terms of carbon accumulation, requires investigation given that the central and eastern Amazon is projected to undergo more significant climatic change than the western basin (Duffy *et al* 2015). Even in the NW of the basin where climate change is likely to be less pronounced, there has been an intensification of the hydrological cycle (Barichivich *et al* 2018, Gloor *et al* 2013) which could have a significant impact on the floristic composition and formation of fluvial peatlands (Flores Llampazo *et al* 2022). Moreover, recent research in the middle Rio Negro suggests that repeated fires can induce ecosystem shifts from floodplain forest to white sand savannah over relatively short timescales, namely within 40 years (Flores and Holmgren 2021). With these points in mind, it is crucial to understand the climatological, ecological, and hydrological tipping points at which peat carbon storage will cease and even reverse, and whether these tipping points vary across the basin. The Hansen forest-change maps (2013) suggest that deforestation on the forested peatlands has been modest thus far but threats to peatlands, as well as carbon losses associated with degradation, may be increasing (Hastie *et al* 2022, Lawson *et al* 2022, Hergoualc'h *et al* 2023).

Many of these predicted peatlands are found on indigenous land (Adeney *et al* 2016) and appear to be used sustainably (Hidalgo Pizango *et al* 2022), so it is vital that indigenous and local communities' perspectives are included in future research efforts. These research priorities must be urgently pursued before further land-use-change threatens the integrity of the peatlands of the Amazon basin.

Data availability statement

The data that support the findings of this study are available upon request from the authors. A subset of data from Peru is available to freely download at the following link- <https://catalogue.ceh.ac.uk/documents/ab13a06f-392f-4bc6-b1bf-06dd8b020307>.

The map of predicted peat distribution (90 m) can be downloaded here- <https://zenodo.org/records/13142590>.

The map of predicted landcover/ecosystem distribution (90 m) can be downloaded here- <https://zenodo.org/uploads/13142855>.

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Conflict of interest

The authors declare no competing interests.

ORCID iDs


Adam Hastie  <https://orcid.org/0000-0003-2098-3510>

C Gabriel Hidalgo Pizango  <https://orcid.org/0000-0003-3170-9939>

Johan de Jong  <https://orcid.org/0000-0002-1077-2210>

Encarni Montoya  <https://orcid.org/0000-0002-4690-190X>

César J Córdova Oroche  <https://orcid.org/0000-0002-0692-3186>

Etienne Fluet-Chouinard  <https://orcid.org/0000-0003-4380-2153>

References

- Adeny J M, Christensen N L, Vicentini A and Cohn-Haft M 2016 White-sand ecosystems in Amazonia *Biotropica* **48** 7–23
- Baker T R, Del Castillo Torres D, Honorio Coronado E, Lawson I, Brañas M M, Montoya M and Roucoux K 2019 The challenges for achieving conservation and sustainable development within the wetlands of the Pastaza Marañón basin, Peru 'Peru: Deforestation in times of climate change' ed A Chirif (International Work Group for Indigenous Affairs) pp 155–75
- Barichivich J, Gloor E, Peylin P, Brienen R J W, Schöngart J, Espinoza J C and Pattanayak K C 2018 Recent intensification of Amazon flooding extremes driven by strengthened Walker circulation *Sci. Adv.* **4** eaat8785
- Bernoux M, Carvalho M C S, Volkoff B and Cerri C C 2002 Brazil's soil carbon stocks *Soil Sci. Soc. Am. J.* **66** 888–96
- Brugger S O et al 2016 Long-term man–environment interactions in the Bolivian Amazon: 8000 years of vegetation dynamics *Quat. Sci. Rev.* **132** 114–28
- Burton R G O and Hodgson J M ed 1987 Lowland peat in England and Wales *Laws Agricultural Trust* (Soil Survey of England and Wales)
- Cole L E S, Åkesson C M, Hapsari K A, Hawthorne D, Roucoux K H, Girkin N T, Cooper H V, Ledger M J, O'Reilly P and Thornton S A 2022 Tropical peatlands in the anthropocene: lessons from the past *Anthropocene* **37** 100324
- Coomes D A and Grubb P J 1996 Amazonian caatinga and related communities at La Esmeralda, Venezuela: forest structure, physiognomy and floristics, and control by soil factors *Vegetatio* **122** 167–91
- Crezee B et al 2022 Mapping peat thickness and carbon stocks of the central Congo Basin using field data *Nat. Geosci.* **15** 639–44
- Cubizolle H, Mouandza M M and Muller F 2013 Mires and Histosols in French Guiana (South America): new data relating to location and area *Mires Peat.* **12** 3 (available at: www.mires-and-peat.net/pages/volumes/map12/map1203.php)
- Dargie G C, Lawson I T, Rayden T J, Miles L, Mitchard E T A, Page S E, Bocko Y E, Ifo S A and Lewis S L 2019 Congo Basin peatlands: threats and conservation priorities *Mitig. Adapt. Strateg. Glob. Change* **24** 669–86
- Dargie G C, Lewis S L, Lawson I T, Mitchard E T A, Page S E, Bocko Y E and Ifo S A 2017 Age, extent and carbon storage of the central Congo Basin peatland complex *Nature* **542** 86
- de Jong J 2019 The Impact of Indigenous and Local Communities in the Peruvian Amazon: Integrating Forest Inventory and Remote Sensing *MSc Thesis* Wageningen University and Research
- De Negreiros G H, Alencar A C, Schlesinger P, Nepstad D C and Lefebvre P A 2009 Pre-LBA RADAMBRASIL Project Data Data set. Available on-line [<http://daac.ornl.gov>] from Oak Ridge National Laboratory Distributed Active Archive Center (<https://doi.org/10.3334/ORNLDAAC/941>)
- Diaz Cardenas A A 2019 Determinación del contenido de carbono almacenado con relación a la profundidad de las turberas (ecosistemas de aguajales) de la provincia de coronel portillo—ucayali—peru *Tesis Para Optar el Título de Ingeniero Ambiental* Universidad Nacional de Ucayali
- Dommain R, Couwenberg J and Joosten H 2011 Development and carbon sequestration of tropical peat domes in south-east Asia: data to post-glacial sea-level changes and Holocene climate variability *Quat. Sci. Rev.* **30** 999–1010
- Donchyts G et al 2016 Global 30 m height above the nearest drainage (HAND) *Geophysical Research Abstracts* vol 18 EGU2016-17445-3, 2016, EGU General Assembly
- Doupoux C, Merdy P, Montes C R, Nunan N, Melfi A J, Pereira O J R and Lucas Y 2017 Modelling the genesis of equatorial podzols: age and implications for carbon fluxes *Biogeosciences* **14** 2429–40
- Draper F C et al 2014 The distribution and amount of carbon in the largest peatland complex in Amazonia *Environ. Res. Lett.* **9** 124017
- Draper F C et al 2018 Peatland forests are the least diverse tree communities documented in Amazonia, but contribute to high regional beta-diversity *Ecography* **41** 1256–69
- Dubroeuq D and Volkoff B 1998 Oxisols to Spodosols and Histosols: evolution of the soil mantles in the Rio Negro basin (Amazonia) *Catena* **32** 245–80
- Duffy P B, Brando P, Asner G P and Field C B 2015 Projections of future meteorological drought and wet periods in the Amazon *Proc. Natl Acad. Sci. USA* **112** 13172–7
- Duivenvoorden J F and Lips J M 1991a *Mapa de la Ecología del Paiaaje Del Medio Caqueta. [Landscape Ecological Map of the Middle Caqueta Basin]. Sheet Araracuara-Mariñame.—ESDAC—European Commission* (available at: <https://esdac.jrc.ec.europa.eu/content/mapa-de-la-ecologia-del-paiaaje-del-medio-caqueta-landscape-ecological-map-middle-caqueta-1>)
- Duivenvoorden J F and Lips J M 1991b *Mapa de la Ecología del Paiaaje del Medio Caqueta. [Landscape Ecological Map of the Middle Caqueta Basin]. Sheet Cahuinari.—ESDAC—European Commission.* (available at: <https://esdac.jrc.ec.europa.eu/content/mapa-de-la-ecologia-del-paiaaje-del-medio-caqueta-landscape-ecological-map-middle-caqueta>)
- Escobar-Torrez K, Ledru M, Ortuño T, Lombardo U and Renno J 2020 Landscape changes in the southern Amazonian foreland basin during the Holocene inferred from Lake Ginebra, Beni, Bolivia *Quat. Res.* **94** 46–60
- Farr T G et al 2007 The shuttle radar topography mission *Rev. Geophys.* **45**
- Flores B M and Holmgren M 2021 White sand savannas expand at the core of the Amazon After forest wildfires *Ecosystems* **24** 1624–37
- Flores Llampazo G et al 2022 The presence of peat and variation in tree species composition are under different hydrological controls in Amazonian wetland forests *Hydrol. Process.* **36** e14690
- Funk C et al 2015 The climate hazards infrared precipitation with stations—a new environmental record for monitoring extremes *Sci. Data* **2** 150066
- Garcia M 2021 *Investigating the Use of Spatially-Explicit Modelling and Cross-Validation Strategies in Spatial Interpolation Machine Learning Problems* (available at: <https://run.unl.pt/handle/10362/113881>)
- García-Villacorta R, Ahuite-Reátegui M and Olortegui-Zumaeta M 2003 Clasificación de bosques sobre arena blanca de la Zona Reservada Allpahuayo-Mishana *Folia Amazónica* **14** 17–33
- Girkin N T, Cooper H V, Ledger M J, O'Reilly P, Thornton S A, Åkesson C M, Cole L E S, Hapsari K A, Hawthorne D and Roucoux K H 2022 Tropical peatlands in the Anthropocene: the present and the future *Anthropocene* **40** 100354
- Gloor M, Brienen R J W, Galbraith D, Feldpausch T R, Schöngart J, Guyot J-L, Espinoza J C, Lloyd J and Phillips O L 2013 Intensification of the Amazon hydrological cycle over the last two decades *Geophys. Res. Lett.* **40** 1729–33
- Goldblatt R, You W, Hanson G and Khandelwal A K 2016 Detecting the boundaries of urban areas in india: a dataset for pixel-based image classification in google earth engine *Remote Sens.* **8** 634
- Gomes L C, Faria R M, de Souza E, Veloso G V, Schaefer C E G R and Filho E I F 2019 Modelling and mapping soil organic carbon stocks in Brazil *Geoderma* **340** 337–50
- Gumbricht T, Roman-Cuesta R M, Verchot L, Herold M, Wittmann F, Householder E, Herold N and Murdiyarto D

- 2017 An expert system model for mapping tropical wetlands and peatlands reveals South America as the largest contributor *Glob. Change Biol.* **23** 3581–99
- Guyana Lands & Surveys Commission 2013 *Guyana National Land Use Plan* (Government of Guyana)
- Hansen M C *et al* 2013 High-resolution global maps of 21st-century forest cover change *Science* **342** 850–3
- Hastie A *et al* 2022 Risks to carbon storage from land-use change revealed by peat thickness maps of Peru *Nat. Geosci.* **15** 369–74
- Hergoualc'h K, van Lent J, Dezzo N, Verchot L V, van Groenigen J W, López Gonzales M and Grandez-Rios J 2023 Major carbon losses from degradation of *Mauritia flexuosa* peat swamp forests in western Amazonia *Biogeochemistry* **167** 327–45
- Herrera R 1979 Nutrient distribution and cycling in an Amazon Caatinga forest on Spodosols in Southern Venezuela *PhD thesis* University of Reading UK p 241
- Herrera R 1977 Soils and terrain conditions in the International Amazon Project site at San Carlos de Río negro, Venezuela. Correlation with vegetation types *Transactions MAB-IUFRO International Workshop on Rainforest Ecosystems Research* ed E Brüning pp 182–8
- Hidalgo Pizango C G, Honorio Coronado E N and Del Águila-pasquel J 2022 Sustainable palm fruit harvesting as a pathway to conserve Amazon peatland forests *Nat. Sustain.* **5** 479–87
- Honorio Coronado E N H *et al* 2021 Intensive field sampling increases the known extent of carbon-rich Amazonian peatland pole forests *Environ. Res. Lett.* **16** 74048
- Householder J E, Janovec J P, Tobler M W, Page S and Lähteenoja O 2012 Peatlands of the Madre de Dios River of Peru: distribution, geomorphology, and habitat diversity *Wetlands* **32** 359–68
- Huijnen V, Wooster M, Kaiser J, Gaveau D L A, Flemming J, Parrington M, Inness A, Murdiyarso D, Main B and van Weele M 2016 Fire carbon emissions over maritime southeast Asia in 2015 largest since 1997 *Sci. Rep.* **6** 26886
- IBGE 2009 Levantamento pedológico, folhas NA-19, NA-20, SA-19 e SA-20 (available at: www.ibge.gov.br/home/geociencias/download/arquivos/index9.shtml), (Accessed 27 September 2012) (CREN-IBGE)
- IIAP-PROFONANPE 2023 Medición y análisis de la dinámica y trayectoria de los niveles de stock de carbono a nivel de la provincia del datem del marañón con énfasis en el territorio en que se ejecuta el proyecto humedales del Datem *Resumen Ejecutivo* (available at: <https://profonanpe.org.pe/wp-content/uploads/2023/02/Medicion-y-Analisis-de-la-dinamica-y-trayectoria-de-stock-de-carbono.pdf>)
- Instituto Brasileiro de Geografia e Estatística (IBGE) 2004 *Mapa de Cobertura Vegetal Para O Brasil (Map of Vegetation Cover for Brasil)*
- Jaenicke J, Rieley J O, Mott C, Kimman P and Siegert F 2008 Determination of the amount of carbon stored in Indonesian peatlands *Geoderma* **147** 151–8
- Johnston F H, Henderson S B, Chen Y, Randerson J T, Marlier M, Defries R S, Kinney P, Bowman D M and Brauer M 2012 Estimated global mortality attributable to smoke from landscape fires *Environ. Health Perspect.* **120** 695–701
- Junk W J 1983 Ecology of swamps on the middle Amazon *Ecosystems of the World: Mires, Swamp, Bog, Fen and Moor. 3 Regional Studies A* J P Gore ed (Elsevier Amsterdam) pp 269–94
- Kershaw A 1997 A modification of the Troels-Smith system of sediment description and portrayal *Quat. Australas.* **15** 63–68 (available at: https://aqua.org.au/wp-content/uploads/2013/06/QA_Vol-15_No-2_1997.pdf#page=66)
- Kiely L, Spracklen D V, Arnold S R, Papargyropoulou E, Conibear L, Wiedinmyer C, Knot C and Adrianto H A 2021 Assessing costs of Indonesian fires and the benefits of restoring peatland *Nat. Commun.* **12** 7044
- Lähteenoja O, Flores B and Nelson B 2013 Tropical peat accumulation in central Amazonia *Wetlands* **33** 495–503
- Lähteenoja O, Reátegui Y R, Räsänen M, Torres D D C, Oinonen M and Page S 2012 The large Amazonian peatland carbon sink in the subsiding Pastaza-Marañón foreland basin, Peru *Glob. Change Biol.* **18** 164–78
- Lähteenoja O, Ruokolainen K, Schulman L and Oinonen M 2009 Amazonian peatlands: an ignored C sink and potential source *Glob. Change Biol.* **15** 2311–20
- Lawson I T *et al* 2023 Peat depths from the Pastaza-Marañón Basin, Amazonian Peru, 2019–2020 *NERC EDS Environmental Information Data Centre (Dataset)* (<https://doi.org/10.5285/ab13a06f-392f-4bc6-b1bf-06dd8b020307>)
- Lawson I T, Honorio Coronado E N, Andueza L, Cole L, Dargie G C, Davies A L, Laurie N, Okafor-Yarwood I, Roucoux K H and Simpson M 2022 The vulnerability of tropical peatlands to oil and gas exploration and extraction *Prog. Environ. Geogr.* **1** 84–114
- Lucas Y, Montes C R, Mounier S, Loustau Cazalet M, Ishida D, Achard R, Garnier C, Coulomb B and Melfi A J 2012 Biogeochemistry of an Amazonian podzol-ferralsol soil system with white kaolin *Biogeosciences* **9** 3705–20
- Melton J R, Chan E, Millard K, Fortier M, Winton R S, Martín-López J M, Cadillo-Quiroz H, Kidd D and Verchot L V 2022 A map of global peatland extent created using machine learning (Peat-ML) *Geosci. Modelling Dev.* **15** 4709–38
- Meyer H and Pebesma E 2022 Machine learning-based global maps of ecological variables and the challenge of assessing them *Nat. Commun.* **13** 2208
- MINAM (Ministerio del Ambiente) 2019 *Mapa de Ecosistemas del Peru. Direccion General de Ordenamiento Territorial Ambiental—Ministerio del Ambiente* (available at: www.gob.pe/institucion/minam/informes-publicaciones/277146-mapa-nacional-de-ecosistemas-del-peru) (Accessed 2 March 2020)
- Mishra S *et al* 2021 Degradation of Southeast Asian tropical peatlands and integrated strategies for their better management and restoration *J. Appl. Ecol.* **58** 1370–87
- Montes C R, Lucas Y, Pereira O J R, Achard R, Grimaldi M and Melfi A J 2011 Deep plant-derived carbon storage in Amazonian podzols *Biogeosciences* **8** 113–20
- Montoya E and Rull V 2011 Gran Sabana fires (SE Venezuela): a paleoecological perspective *Quat. Sci. Rev.* **30** 3430–44
- Olofsson P, Foody G M, Stehman S V and Woodcock C E 2013 Making better use of accuracy data in land change studies: estimating accuracy and area and quantifying uncertainty using stratified estimation *Remote Sens. Environ.* **129** 122–31
- Page S E and Baird A J 2016 Peatlands and global change: response and resilience *Annu. Rev. Environ. Resour.* **41** 35–57
- Page S E, Rieley J O and Banks C J 2011 Global and regional importance of the tropical peatland carbon pool *Glob. Change Biol.* **17** 798–818
- Page S E, Siegert F, Rieley J O, Boehm H-D V, Jaya A and Limin S 2002 The amount of carbon released from peat and forest fires in Indonesia during 1997 *Nature* **420** 61–65
- Paukku S 2021 Peatlands in Colombia *Bachelor's Thesis* ETH Zurich unpublished
- Posa M R C, Wijedasa L S and Corlett R T 2011 Biodiversity and conservation of tropical peat swamp forests *BioScience* **61** 49–57
- Quesada C A, Lloyd J, Anderson L O, Fyllas N M, Schwarz M and Czimczik C I 2011 Soils of Amazonia with particular reference to the RAINFOR sites *Biogeosciences* **8** 1415–40
- Ribeiro K *et al* 2021 Tropical peatlands and their contribution to the global carbon cycle and climate change *Glob. Change Biol.* **27** 489–505
- Roucoux K H *et al* 2017 Threats to intact tropical peatlands and opportunities for their conservation *Conserv. Biol.* **31** 1283–92

- Rull V 1992 Successional patterns of the gran sabana (Southeastern Venezuela) vegetation during the last 5000 years, and its responses to climatic fluctuations and fire *J. Biogeogr.* **19** 329–38
- Santofimio-Tamayo G A and Benavides J C 2019 Carbon accumulation patterns in soils of tropical peatlands from alluvial origin (Caquetá, Colombia) *Wetland Sci. Pract.* **36** 171
- Sevenhuijsen R J 1977 Irrigatie uit een moeras. Een hydrologische studie van de Nannizwamp in Suriname *Thesis Agricultural University, Wageningen* p 143
- Shimada M, Itoh T, Motooka T, Watanabe M, Shiraishi T, Thapa R and Lucas R 2014 New global forest/non-forest maps from ALOS PALSAR data (2007–2010) *Remote Sens. Environ.* **155** 13–31
- Smith R, Mayle F, Maezumi S and Power M 2021 Relating pollen representation to an evolving Amazonian landscape between the last glacial maximum and Late Holocene *Quat. Res.* **99** 63–79
- Theobald D M, Harrison-Atlas D, Monahan W B and Albano C M 2015 Ecologically-relevant maps of landforms and physiographic diversity for climate adaptation planning *PLoS One* **10** e0143619
- Troels-Smith J 1955 Characterisation of unconsolidated sediments *Danmarks Geol. Undersogelse IV* vol 73
- Vegas-Vilarrúbia T, Baritto F, López P, Meleán G, Ponce M E, Mora L and Gómez O 2010 Tropical Histosols of the lower Orinoco Delta, features and preliminary quantification of their carbon storage *Geoderma* **155** 280–8
- Warren M, Hergoualc'h K, Kauffman J B, Murdiyarso D and Kolka R 2017 An appraisal of Indonesia's immense peat carbon stock using national peatland maps: uncertainties and potential losses from conversion *Carbon Balance Manag.* **12** 1–12
- Winton S et al 2021 Diverse carbon-rich peatlands in the Amazonia and Orinoquia of Colombia *AGU Fall Meeting Abstracts, 2021* pp B51C–07
- Wittmann F, Junk W J and Piedade M T F 2004 The várzea forests in Amazonia: flooding and the highly dynamic geomorphology interact with natural forest succession *For. Ecol. Manage.* **196** 199–212
- Xu J, Morris P J, Liu J and Holden J 2018 PEATMAP: refining estimates of global peatland distribution based on a meta-analysis *Catena* **160** 134–40
- Yamazaki D, Ikeshima D, Sosa J, Bates P D, Allen G H and Pavelsky T M 2019 MERIT Hydro: a high-resolution global hydrography map based on latest topography datasets *Water Resour. Res.* **55** 5053–73
- Zinck J A and Huber O eds 2011 *Peatlands of the Western Guayana Highlands, Venezuela: Properties and Palaeographic Significance of Peats, Ecological Studies 217* (Springer)