

Long-term thermal sensitivity of Earth's tropical forests

Martin J. P. Sullivan^{1,2}, Simon L. Lewis^{1,3}, Kofi Affum-Baffoe⁴, Carolina Castilho⁵, Flávia Costa⁶, Aida Cuni Sanchez^{7,8}, Corneille E. N. Ewango^{9,10,11}, Wannes Hubau^{1,12,13}, Beatriz Marimon¹⁴, Abel Monteagudo-Mendoza¹⁵, Lan Qie¹⁶, Bonaventure Sonké¹⁷, Rodolfo Vasquez Martinez¹⁵, Timothy R Baker¹, Roel J. W. Brienen¹, Ted R. Feldpausch¹⁸, David Galbraith¹, Manuel Gloor¹, Yaduvinder Malhi¹⁹, Shin-Ichiro Aiba²⁰, Miguel N. Alexiades²¹, Everton C. Almeida²², Edmar Almeida de Oliveira²³, Esteban Álvarez Dávila²⁴, Patricia Alvarez Loayza²⁵, Ana Andrade²⁶, Simone Aparecida Vieira²⁷, Luiz Aragão²⁸, Alejandro Araujo-Murakami²⁹, Eric J.M.M. Arets³⁰, Luzmila Arroyo³¹, Peter Ashton³², Gerardo Aymard C.³³, Fabrício B. Baccaro³⁴, Lindsay F. Banin³⁵, Christopher Baraloto³⁶, Plínio Barbosa Camargo³⁷, Jos Barlow³⁸, Jorcely Barroso³⁹, Jean-François Bastin⁴⁰, Sarah A. Batterman^{1,41,42,43}, Hans Beeckman¹², Serge K. Begne^{17,44}, Amy C. Bennett⁴⁴, Erika Berenguer^{19,38}, Nicholas Berry⁴⁵, Lilian Blanc⁴⁶, Pascal Boeckx⁴⁷, Jan Bogaert⁴⁸, Damien Bonal⁴⁹, Frans Bongers⁵⁰, Matt Bradford⁵¹, Francis Q. Brearley², Terry Brncic⁵², Foster Brown⁵³, Benoit Burban⁵⁴, José Luís Camargo²⁶, Wendeson Castro⁵⁵, Carlos Céron⁵⁶, Sabina Cerruto Ribeiro⁵⁷, Victor Chama Moscoso¹⁵, Jérôme Chave⁵⁸, Eric Chezeaux⁵⁹, Connie J. Clark²⁵, Fernanda Coelho¹, Murray Collins⁶¹, James A. Comiskey^{62,63}, Fernando Cornejo Valverde⁶⁴, Massiel Corrales Medina⁶⁵, Lola da Costa⁶⁶, Martin Dančák⁶⁷, Greta C. Dargie¹, Stuart Davies⁶⁸, Nallaret Davila Cardozo⁶⁹, Thales de Haulleville^{12,48}, Marcelo Brilhante de Medeiros⁷⁰, Jhon del Aguila Pasquel⁷¹, Géraldine Derroire⁷², Anthony Di Fiore⁷³, Jean-Louis Doucet⁷⁴, Aurélie Dourdain⁷², Vincent Droissant⁷⁵, Luisa Fernanda Duque⁷⁶, Romeo Ekoungoulou⁷⁷, Fernando Elias⁷⁸, Terry Erwin⁷⁹, Adriane Esquivel-Muelbert⁸⁰, Sophie Fauset⁸¹, Joice Ferreira⁸², Gerardo Flores Llampazo⁸³, Ernest Foli⁸⁴, Andrew Ford⁵¹, Martin Gilpin¹, Jefferson S. Hall⁸⁵, Keith C. Hamer⁸⁶, Alan C. Hamilton⁸⁷, David J. Harris⁸⁸, Terese B. Hart^{89,90}, Radim Hédli^{91,92}, Bruno Herault⁷², Rafael Herrera⁹³, Niro Higuchi⁶, Annette Hladik⁹⁴, Eurídice Honorio Coronado⁷¹, Isau Huamantupa-Chuquimaco⁹⁵, Walter Huaraca Huasco⁹⁵, Kathryn J. Jeffery⁹⁶, Eliana Jimenez-Rojas⁹⁷, Michelle Kalamandeen¹, Marie-Noel Kamdem^{11,13,17,98}, Elizabeth Kearsley⁹⁹, Ricardo Keichi Umetsu¹⁰⁰, Lip Khoon Kho¹⁰¹, Timothy Killeen¹⁰², Kanehiro Kitayama¹⁰³, Bente Klitgaard¹⁰⁴, Alexander Koch¹⁰⁵, Nicolas Labrière⁵⁸, William Laurance¹⁰⁶, Susan Laurance¹⁰⁶, Miguel E. Leal¹⁰⁷, Aurora Levesley¹, Adriano J. N. Lima⁶, Janvier Lisingo¹¹, Aline P. Lopes^{108,109}, Gabriela Lopez-Gonzalez¹, Tom Lovejoy¹¹⁰, Jon Lovett¹, Richard Lowe¹¹¹, William E. Magnusson¹¹², Jagoba Malumbres-Olarte^{113,114}, Ângelo Gilberto Manzatto¹¹⁵, Ben Hur Marimon Junior¹¹⁶, Andrew R. Marshall^{8,117,118}, Toby Marthews¹¹⁹, Simone Matias de Almeida Reis^{14,19}, Colin Maycock¹²⁰, Karina Melgaço¹, Casimiro Mendoza¹²¹, Faizah Metali¹²², Vianet Mihindou^{123,124}, William Milliken¹⁰⁴, Edward Mitchard¹²⁵, Paulo S. Morandi¹⁴, Hannah L. Mossman², Laszlo Nagy¹²⁶, Henrique Nascimento⁶, David Neill¹²⁷, Reuben Nilus¹²⁸, Percy Núñez Vargas⁹⁵, Walter Palacios¹²⁹, Nadir Pallqui Camacho^{1,95}, Julie Peacock¹, Colin Pendry¹³⁰, Maria Cristina Peñuela Mora¹³¹, Georgia C. Pickavance¹, John Pipoly¹³², Nigel Pitman¹³³, Maureen Playfair¹³⁴, Lourens Poorter¹³⁵, John R. Poulsen²⁵, Axel D. Poulsen¹³⁶, Richard Preziosi², Adriana Prieto¹³⁷, Richard Primack¹³⁸, Hirma Ramírez-Angulo¹³⁹, Jan Reitsma¹⁴⁰, Maxime Réjou-Méchain⁷⁵, Zorayda Restrepo Correa¹⁴¹, Thaianie Rodrigues de Sousa⁶, Lily Rodriguez Bayona¹⁴², Anand Roopsind¹⁴³, Agustín Rudas¹³⁷, Ervan Rutishauser^{42,144}, Kamariah Abu Salim¹²², Rafael P. Salomão^{145,146}, Juliana Schiatti⁶, Douglas Sheil¹⁴⁷, Richarlly C. Silva^{57,148}, Javier Silva Espejo¹⁴⁹, Camila Silva Valeria³⁸, Marcos Silveira⁵⁷, Murielle Simo-Droissart¹⁷, Marcelo Fragomeni Simon⁷⁰, James Singh¹⁵⁰, Yahn Carlos Soto Shareva¹⁵, Clement Stahl⁵⁴, Juliana Stropp¹⁵¹, Rahayu Sukri¹²², Terry Sunderland^{152,153}, Martin Svátek¹⁵⁴, Michael D. Swaine¹⁵⁵, Varun Swamy¹⁵⁶, Hermann Taedoum¹⁷, Joey Talbot¹, James Taplin¹⁵⁷, David Taylor¹⁵⁸, Hans ter Steege^{159,160}, John Terborgh²⁵, Raquel Thomas¹⁴³, Sean C. Thomas¹⁶¹, Armando Torres-Lezama¹⁶², Peter Umunay^{163,164}, Luis Valenzuela Gamarra¹⁵, Geertje van der Heijden¹⁶⁵, Peter van der Hout¹⁶⁶, Peter van der Meer¹⁶⁷, Mark van Nieuwstadt¹⁶⁸, Hans Verbeeck⁹⁹, Ronald Vernimmen¹⁶⁹, Alberto Vicentini⁶, Ima Célia Guimarães Vieira¹⁴⁶, Emilio Vilanova Torre¹⁷⁰, Jason Vleminckx³⁶, Vincent Vos¹⁷², Ophelia Wang¹⁷³, Lee J. T. White^{124,174,175}, Simon Willcock¹⁷⁶, John T. Woods¹⁷⁷, Verginia Wortel¹⁷⁸, Kenneth Young¹⁷⁹, Roderick Zagt¹⁸⁰, Lise Zemagho¹⁷, Pieter A. Zuidema⁵⁰, Joeri A. Zwarts^{178,181}, Oliver L. Phillips¹

Affiliations:

- 1 School of Geography, University of Leeds, Leeds, UK
- 2 Department of Natural Sciences, Manchester Metropolitan University, Manchester, UK
- 3 Department of Geography, University College London, London, UK
- 4 Mensuration Unit, Forestry Commission of Ghana, Kumasi, Ghana
- 5 Embrapa Roraima, Brazilian Agricultural Research Corporation (EMBRAPA), Brasília, Brazil
- 6 Instituto Nacional de Pesquisas da Amazônia (INPA), Manaus, Brazil
- 7 Department of Ecosystem Science and Sustainability, Colorado State University, USA
- 8 Department of Environment and Geography, University of York, York, UK
- 9 DR Congo Programme, Wildlife Conservation Society, Kisangani, Democratic Republic of Congo
- 10 Centre de Formation et de Recherche en Conservation Forestiere (CEFRECOF), Epulu, Democratic Republic of Congo
- 11 Faculté de Gestion de Ressources Naturelles Renouvelables, Université de Kisangani, Kisangani, Democratic Republic of Congo
- 12 Service of Wood Biology, Royal Museum for Central Africa, Tervuren, Belgium
- 13 Department of Environment, Laboratory of Wood Technology (Woodlab), Ghent University, Ghent, Belgium
- 14 Faculdade de Ciências Agrárias, Biológicas e Sociais Aplicadas, Universidade do Estado de Mato Grosso, Nova Xavantina-MT, Brazil
- 15 Jardín Botánico de Missouri, Oxapampa, Peru
- 16 School of Life Sciences, University of Lincoln, Lincoln, UK
- 17 Plant Systematics and Ecology Laboratory, Higher Teachers' Training College, University of Yaoundé I, Yaoundé, Cameroon
- 18 Geography, College of Life and Environmental Sciences, University of Exeter, Exeter, UK
- 19 Environmental Change Institute, School of Geography and the Environment, University of Oxford, Oxford, UK
- 20 Graduate School of Science and Engineering, Kagoshima University, Japan
- 21 School of Anthropology and Conservation, University of Kent, Canterbury, UK
- 22 Instituto de Biodiversidade e Florestas, Universidade Federal do Oeste do Pará, Santarém - PA, Brazil
- 23 Universidade do Estado de Mato Grosso, Cáceres - MT, Brazil
- 24 Escuela de Ciencias Agrícolas, Pecuarias y del Medio Ambiente, National Open University and Distance, Colombia
- 25 Center for Tropical Conservation, Nicholas School of the Environment, Duke University, Durham, NC, USA
- 26 Projeto Dinâmica Biológica de Fragmentos Florestais, Instituto Nacional de Pesquisas da Amazônia, Manaus, Brazil
- 27 Universidade Estadual de Campinas, Campinas - SP, Brazil
- 28 National Institute for Space Research (INPE), São José dos Campos-SP, Brazil
- 29 Museo de Historia Natural Noel Kempff Mercado, Universidad Autónoma Gabriel René Moreno, Santa Cruz, Bolivia
- 30 Wageningen Environmental Research, Wageningen, The Netherlands
- 31 Dirección de la Carrera de Biología, Universidad Autónoma Gabriel René Moreno, Santa Cruz, Bolivia
- 32 Department of Organismic and Evolutionary Biology, Harvard University, Cambridge, MA, USA
- 33 Programa de Ciencias del Agro y el Mar, Herbario Universitario, Barinas, Venezuela
- 34 Departamento de Biologia, Universidade Federal do Amazonas, Manaus, Brazil

- 35 Centre of Ecology and Hydrology, Penicuik, UK
- 36 International Center for Tropical Botany, Department of Biological Sciences, Florida International University, Florida, FL, USA
- 37 Centro de Energia Nuclear na Agricultura, Universidade de São Paulo, São Paulo, SP, Brazil
- 38 Lancaster Environment Centre, Lancaster University, Lancaster, UK
- 39 Centro Multidisciplinar, Universidade Federal do Acre, Cruzeiro do Sul - AC, Brazil
- 40 Institute of Integrative Biology, ETH Zurich, Zurich, Switzerland
- 41 Priestley International Centre for Climate, University of Leeds, Leeds, UK
- 42 Smithsonian Tropical Research Institute, Panama, Panama
- 43 Cary Institute of Ecosystem Studies, Millbrook, NY, USA
- 44 School of Geography, School of Geography, Leeds, UK
- 45 The Landscapes and Livelihoods Group, Edinburgh, UK
- 46 UR Forest & Societies, CIRAD, Montpellier, France
- 47 Isotope Bioscience Laboratory-ISOFYS, Ghent University, Ghent, Belgium
- 48 Gembloux Agro-Bio Tech, University of Liège, Liège, Belgium
- 49 UMR Silva, INRA, Nancy, France
- 50 Department of Forest Ecology and Forest Management Group, Wageningen University, Wageningen, The Netherlands
- 51 CSIRO, Canberra, Australia
- 52 Congo Programme, Wildlife Conservation Society, Brazzaville, Republic of Congo
- 53 Woods Hole Research Center, Falmouth, MA, USA
- 54 Ecologie des Forêts de Guyane (ECOFOG), INRA, Kourou, French Guiana
- 55 Programa de Pós-Graduação Ecologia e Manejo de Recursos Naturais, Universidade Federal do Acre, Rio Branco - AC, Brazil
- 56 Herbario Alfredo Paredes, Universidad Central del Ecuador, Quito, Ecuador
- 57 Centro de Ciências Biológicas e da Natureza, Universidade Federal do Acre, Rio Branco - AC, Brazil
- 58 Laboratoire Évolution et Diversité Biologique - UMR 5174 (CNRS/IRD/UPS), CNRS, Toulouse, France
- 59 Rougier-Gabon, Libreville, Gabon
- 60 Nicholas School of the Environment, Duke University, Durham, NC, USA
- 61 Grantham Research Institute on Climate Change and the Environment, London, UK
- 62 Inventory & Monitoring Program, National Park Service, Fredericksburg, VA, USA
- 63 Smithsonian Institution, Washington, DC, USA
- 64 Proyecto Castaña, Madre de Dios, Peru
- 65 Universidad Nacional de San Agustín de Arequipa, Arequipa, Peru
- 66 Instituto de Geociências, Faculdade de Meteorologia, Universidade Federal do Pará, Belém - PA, Brazil
- 67 Faculty of Science, Department of Ecology and Environmental Sciences, Palacký University Olomouc, Olomouc, Czech Republic
- 68 Center for Tropical Forest Science, Smithsonian Tropical Research Institute, Panama, Panama
- 69 Facultad de Ciencias Biológicas, Universidad Nacional de la Amazonía Peruana, Iquitos, Peru
- 70 Embrapa Genetic Resources & Biotechnology, Brazilian Agricultural Research Corporation (EMBRAPA), Brasília, Brazil
- 71 Instituto de Investigaciones de la Amazonía Peruana, Iquitos, Peru
- 72 Ecologie des Forêts de Guyane (ECOFOG), CIRAD, Kourou, French Guiana

- 73 Department of Anthropology, The University of Texas at Austin, Austin, TX, USA
- 74 Forest Resources Management, Gembloux Agro-Bio Tech, University of Liège, Liège, Belgium
- 75 AMAP Lab, IRD, CIRAD, CNRS, INRA, Univ Montpellier, Montpellier, France
- 76 Socioecosistemas y Cambio Climatico, Fundacion con Vida, Medellín, Colombia
- 77 School of Forestry, Beijing Forestry University, Beijing, China
- 78 Institute of Biological Sciences, Universidade Federal do Pará, Belém - PA, Brazil
- 79 National Museum of Natural History, Smithsonian Institute, Washington, DC, USA
- 80 School of Geography, Earth and Environmental Sciences, University of Birmingham, Birmingham, UK
- 81 School of Geography, Earth and Environmental Sciences, University of Plymouth, Plymouth, UK
- 82 Embrapa Amazônia Oriental, Brazilian Agricultural Research Corporation (EMBRAPA), Brasília, Brazil
- 83 Universidad Nacional Jorge Basadre de Grohmann (UNJBG), Tacna, Peru
- 84 Forestry Research Institute of Ghana (FORIG), Kumasi, Ghana
- 85 Smithsonian Institution Forest Global Earth Observatory (ForestGEO), Smithsonian Tropical Research Institute, Washington, DC, USA
- 86 School of Biology, University of Leeds, Leeds, UK
- 87 128 Busbridge Lane, Godalming, Surrey, UK
- 88 Royal Botanic Garden Edinburgh, Edinburgh, UK
- 89 Lukuru Wildlife Research Foundation, Kinshasa, Democratic Republic of Congo
- 90 Division of Vertebrate Zoology, Yale Peabody Museum of Natural History, New Haven, CT, USA
- 91 Institute of Botany, Czech Academy of Sciences, Brno, Czech Republic
- 92 Department of Botany, Palacký University in Olomouc, Olomouc, Czech Republic
- 93 Instituto Venezolano de Investigaciones Científicas (IVIC), Caracas, Venezuela
- 94 Département Hommes, natures, sociétés, Muséum National d'Histoire Naturel, Paris, France
- 95 Universidad Nacional de San Antonio Abad del Cusco, Cusco, Peru
- 96 Biological and Environmental Sciences, University of Stirling, Stirling, UK
- 97 Instituto IMANI, Universidad Nacional de Colombia, Leticia, Colombia
- 98 Faculty of Science, Department of Botany and Plant Physiology, University of Buea, Buea, Cameroon
- 99 Department of Environment, Computational & Applied Vegetation Ecology (Cavelab), Ghent University, Ghent, Belgium
- 100 PELD, Universidade do Estado de Mato Grosso, Nova Xavantina-MT, Brazil
- 101 Tropical Peat Research Institute, Malaysian Palm Oil Board, Kuala Lumpur, Malaysia
- 102 Agteca, Santa Cruz, Bolivia
- 103 Graduate School of Agriculture, Kyoto University, Japan
- 104 Royal Botanic Gardens Kew, Richmond, London, UK
- 105 Department of Earth Sciences, University of Hong Kong, HKSAR
- 106 Centre for Tropical Environmental and Sustainability Science (TESS) and College of Marine and Environmental Sciences, James Cook University, Australia
- 107 Uganda Programme, Wildlife Conservation Society, Kampala, Uganda
- 108 Remote Sensing Division, National Institute for Space Research (INPE), São José dos Campos-SP, Brazil
- 109 Department of Ecology, University of Brasília, Brasília, Brazil
- 110 Environmental Science and Policy, George Mason University, Fairfax, VA, USA

- 111 Botany Department, University of Ibadan, Ibadan, Nigeria
- 112 Coordenação da Biodiversidade, Instituto Nacional de Pesquisas da Amazônia (INPA), Manaus, Brazil
- 113 cE3c – Centre for Ecology, Evolution and Environmental Changes / Azorean Biodiversity Group, Universidade dos Açores, Angra do Heroísmo, Azores, Portugal
- 114 LIBRe – Laboratory for Integrative Biodiversity Research, Finnish Museum of Natural History, University of Helsinki, Helsinki, Finland
- 115 Laboratório de Biogeoquímica Ambiental Wolfgang C. Pfeiffer, Universidade Federal de Rondônia, Porto Velho - RO, Brazil
- 116 Faculdade de Ciências Agrárias, Biológicas e Sociais Aplicadas, Universidad do Estado de Mato Grosso, Nova Xavantina-MT, Brazil
- 117 Tropical Forests and People Research Centre, University of the Sunshine Coast, Australia
- 118 Flamingo Land Ltd., North Yorkshire, UK
- 119 Centre for Ecology and Hydrology, Wallingford, UK
- 120 School of International Tropical Forestry, Universiti Malaysia Sabah, Kota Kinabalu, Malaysia
- 121 Escuela de Ciencias Forestales, Unidad Académica del Trópico, Universidad Mayor de San Simón, Sacta, Bolivia
- 122 Faculty of Science, Universiti Brunei Darussalam, Brunei
- 123 Agence Nationale des Parcs Nationaux, Libreville, Gabon
- 124 Ministère de la Forêt, de la Mer, de l'Environnement, Chargé du Plan Climat, Libreville, Gabon
- 125 University of Edinburgh, Edinburgh, UK
- 126 Biologia Vegetal, Universidade Estadual de Campinas, Campinas - SP, Brazil
- 127 Facultad de Ingeniería Ambiental, Universidad Estatal Amazónica, Puyo, Pastaza, Ecuador
- 128 Forest Research Centre, Sabah Forestry Department, Sepilok, Malaysia
- 129 Carrera de Ingeniería Forestal, Universidad Técnica del Norte, Ibarra, Ecuador
- 130 Royal Botanical Garden Edinburgh, Edinburgh, UK
- 131 Universidad Regional Amazónica IKIAM, Tena, Ecuador
- 132 Public Communications and Outreach Group, Parks and Recreation Division, Oakland Park, FL, USA
- 133 Keller Science Action Center, Field Museum, Chicago, IL, USA
- 134 Centre for Agricultural Research in Suriname (CELOS), Paramaribo, Suriname
- 135 Department of Forest Ecology and Forest Management Group, Wageningen University and Research, Wageningen, The Netherlands
- 136 University of Oslo, Oslo, Norway
- 137 Instituto de Ciencias Naturales, Universidad Nacional de Colombia, Leticia, Colombia
- 138 Department of Biology, Boston University, Boston, USA
- 139 Institute of Research for Forestry Development (INDEFOR), Universidad de los Andes, Mérida, Venezuela
- 140 Bureau Waardenburg, Culemborg, The Netherlands
- 141 Socioecosistemas y Cambio Climático, Fundación Con Vida, Medellín, Colombia
- 142 Centro de Conservación, Investigación y Manejo de Áreas Naturales, CIMA Cordillera Azul, Lima, Peru
- 143 Iwokrama International Centre for Rainforest Conservation and Development, Georgetown, Guyana
- 144 Carboforexpert, Geneva, Switzerland
- 145 Universidade Federal Rural da Amazônia/CAPES, Belém - PA, Brazil
- 146 Museu Paraense Emílio Goeldi, Belém - PA, Brazil
- 147 Faculty of Environmental Sciences and Natural Resource Management, Norwegian University of Life Sciences, Ås, Norway

- 148 Instituto Federal do Acre, Rio Branco - AC, Brazil
- 149 Universidad de San Antonio Abad del Cusco, Cusco, Peru
- 150 Guyana Forestry Commission, Georgetown, Guyana
- 151 Federal University of Alagoas, Maceió, Brazil
- 152 Sustainable Landscapes and Food Systems, Center for International Forestry Research, Bogor, Indonesia
- 153 Faculty of Forestry, University of British Columbia, Vancouver, Canada
- 154 Department of Forest Botany, Dendrology and Geobiocoenology, Mendel University in Brno, Brno, Czech Republic
- 155 Department of Plant & Soil Science, School of Biological Sciences, University of Aberdeen, Aberdeen, UK
- 156 Institute for Conservation Research, San Diego Zoo, San Diego, USA
- 157 UK Research & Innovation, Innovate UK, London
- 158 Department of Geography, National University of Singapore, Singapore, Singapore
- 159 Naturalis Biodiversity Center, Leiden, The Netherlands
- 160 Systems Ecology, VU University, Amsterdam, The Netherlands
- 161 Faculty of Forestry, University of Toronto, Toronto, Canada
- 162 Universidad de los Andes, Merida, Colombia
- 163 Wildlife Conservation Society, New York, NY, USA
- 164 Yale School of Forestry & Environmental Studies, Yale University, New Haven, CT, USA
- 165 School of Geography, University of Nottingham, Nottingham, UK
- 166 Van der Hout Forestry Consulting, Rotterdam, The Netherlands
- 167 Van Hall Larenstein University of Applied Sciences, Velp, The Netherlands
- 168 Utrecht University, Utrecht, The Netherlands
- 169 Deltares, Delft, The Netherlands
- 170 School of Environmental and Forest Sciences, University of Washington, Seattle, OR, USA
- 171 Department of Biological Sciences, Florida International University, Florida, FL, USA
- 172 Centro de Investigación y Promoción del Campesinado, La Paz, Bolivia
- 173 School of Earth Sciences and Environmental Sustainability, Northern Arizona University, Flagstaff, AZ, USA
- 174 Institut de Recherche en Ecologie Tropicale, Libreville, Gabon
- 175 School of Natural Sciences, University of Stirling, Stirling, UK
- 176 School of Natural Sciences, University of Bangor, Bangor, UK
- 177 University of Liberia, Monrovia, Liberia
- 178 Forest Management, Centre for Agricultural Research in Suriname (CELOS), Paramaribo, Suriname
- 179 Department of Geography and The Environment, University of Texas at Austin, Austin, TX, USA
- 180 Tropenbos International, Wageningen, The Netherlands
- 181 Biology, Utrecht University, Utrecht, The Netherlands

Abstract

The sensitivity of tropical forest carbon to climate is a key uncertainty in predicting global climate change. While short-term drying and warming are known to impact forests it is unknown if such effects translate into long-term responses. Here we analyse 590 permanent plots measured across the tropics to derive the equilibrium climate controls on forest carbon. Maximum temperature is the most important predictor of aboveground biomass ($-9.1 \text{ Mg C ha}^{-1} \text{ }^{\circ}\text{C}^{-1}$), primarily by reducing woody productivity, and with a greater rate of decline in the hottest forests ($>32.2 \text{ }^{\circ}\text{C}$). Our results nevertheless reveal greater thermal resilience than observations of short-term variation imply. To realise the long-term climate adaptation potential of tropical forests requires both protecting them and stabilising the Earth's climate.

One sentence summary. Biome-wide variation in tropical forest carbon stocks and dynamics shows long-term thermal resilience.

Main text

The response of tropical terrestrial carbon to environmental change is a critical component of global climate models (1). Land-atmosphere feedbacks depend on the balance of positive biomass growth stimulation by CO₂ fertilisation (i.e. β) and negative responses to warmer temperatures and any change in precipitation (i.e. γ). Yet the climate response is so poorly constrained that it remains one of the largest uncertainties in Earth system models (2, 3), with the temperature sensitivity of tropical land carbon stocks alone differing by $> 100 \text{ Pg C } ^\circ\text{C}^{-1}$ among models (2). Such uncertainty impedes our understanding of the global carbon cycle, limiting our ability to simulate the future of the Earth system under different long-term climate mitigation strategies. A critical long-term control on tropical land-atmosphere feedbacks is the sensitivity to climate (γ) of tropical forests, where c. 40 % of the world's vegetation carbon resides (4).

The sensitivity to environmental change of tropical biomass carbon stocks, their rate of production and their persistence, can all be estimated by relating their short-term and inter-annual responses to variation in climate (5-7). These sensitivities are then used to constrain longer-term projections of climate responses (2). Such approaches typically find that higher minimum temperatures are strongly associated with slower tree growth and reduced forest carbon stocks, likely due to increased respiration at higher temperatures (7-9). Tropical forest carbon is also sensitive to precipitation (10), with, for example, elevated tree mortality occurring during drought events (11).

Yet the sensitivity of ecosystems to inter-annual fluctuations may be an unreliable guide to their longer-term responses to climate change. Such responses will also be influenced by physiological acclimation (12), changes in demographic rates (13), and shifts in species composition (14). For example, both respiration and photosynthesis can acclimate under sustained temperature increases (15-17), and tropical trees exhibit physiological plasticity (18) and shifts in species composition (14) under sustained drought. These processes could mean that tropical forests are less sensitive to climate than estimates derived from inter-annual variability imply. An alternative, complimentary approach to assessing sensitivity to climate is to measure and analyse spatial variation in tropical ecosystems across climate gradients as a space-for-time substitution. Such biome-wide spatial variation in forest

carbon stocks, fluxes and persistence offers a unique and largely unexplored window into the potential equilibrium sensitivity of tropical forest vegetation to warming, as it captures real-world vegetation responses that allow for physiological and ecological adaptation (12).

To assess the long-term climate controls on tropical forest growth and carbon stocks, here we have assembled, measured, and analysed a pan-tropical network of 590 permanent, long-term inventory plots (Fig. 1, see Figs. S1-2 for ability to capture biome climate space). Our analysis combines standardised measurements from across South American, African, Asian and Australian tropical lowland forests (273, 239, 61 and 17 plots respectively). For every plot we calculated aboveground carbon stocks (19). Then, to better assess the dynamic controls on aboveground carbon stocks, we also computed the rate of carbon gained by the system (aboveground woody carbon production, calculated as tree growth plus newly recruited trees, in $\text{Mg C ha}^{-1} \text{ yr}^{-1}$), and the carbon residence time in living biomass (calculated as the ratio of living C stocks to C gains, in years).

We find considerable variation in biomass carbon among continents, with lower stocks per unit area in South America compared with the Paleotropics even after accounting for environmental variables (Fig. 1). Continents with high carbon stocks had either large carbon gains (Asia), or long carbon residence times (Africa, Fig. 1). Because of these differences among continents, which are potentially due to differences in evolutionary history (20), we analyse the environmental drivers of spatial variation in carbon stocks while accounting for biogeographical differences. We fitted linear models with explanatory variables representing hypothesised mechanistic controls of climate on tropical forest carbon (Table S1). We also included soil covariates, continent intercepts and eigenvectors describing spatial relationships amongst plots to account for other sources of variation (21).

Forest carbon stocks were most strongly related to maximum temperature (-5.9% per 1°C increase in maximum temperature, 95 % CI = -8.6 to -3.1% , Fig. 2, equivalent to $-9.1 \text{ Mg C ha}^{-1} \text{ }^\circ\text{C}^{-1}$ for a stand with the mean carbon stocks in our dataset, $154.6 \text{ Mg C ha}^{-1}$), followed by rainfall ($+2.4\%$ per 100 mm increase in precipitation in the driest quarter, 95 % CI = 0.6 – 4.3% , Fig. 2, equivalent to $0.04 \text{ Mg C ha}^{-1} \text{ mm}^{-1}$ for a stand with the mean carbon stocks in our dataset), with no statistically significant relationship with minimum temperature, wind speed or cloud cover (Fig 2). The effects of

maximum temperature and precipitation are also evident in an analysis considering a wider suite of climate variables than those tied to hypothesised mechanisms (Fig. S3), and in an additional independent pantropical dataset of 223 single-census plots (for which carbon gains and residence time cannot be assessed, Fig. S4).

The negative effect of maximum temperature on aboveground carbon stocks mainly reflects reduced carbon gains with increasing temperature (-4.0 % per 1°C, 95% CI = -6.2 to -1.8 %, Fig. 2) while the positive effect of precipitation emerges through longer carbon residence times with increasing precipitation in the driest quarter (3.3 % per 100 mm, 95 % CI = 0.9 – 5.7 %, Fig. 2). Carbon residence time also increased with the proportion of clay in the soil (Fig. 2). The additive effects of precipitation and temperature on carbon stocks were modified by an interaction between them (Δ AIC = 15.4 comparing full linear model with or without interaction), with temperature effects more negative when precipitation is low (Fig. S6). The interaction was through shortening carbon residence time (Δ AIC = 11.9) rather than reducing carbon gains (model without interaction better, Δ AIC = 1.4).

An alternative analysis using decision tree algorithms (22) also showed maximum temperature and precipitation to be important (Fig. S7). This decision tree approach, which can capture complex non-linear relationships (22), indicated potential non-linearity in the relationships between carbon stocks and both temperature and precipitation, with the positive effect of increasing dry season precipitation on residence times strengthening when precipitation was low, and the negative effect of maximum temperature intensifying at high temperatures (Fig. S7).

We further investigated non-linearity in the temperature relationship using breakpoint regression (supported over linear regression based on lower AIC, Δ AIC = 15.0), which revealed that above 32.2 °C (95 % CI = 31.7 – 32.6 °C) the relationship between carbon stocks and maximum temperature became more negative (cooler than breakpoint: -3.8 % °C⁻¹, warmer than breakpoint: -14.7 % °C⁻¹, Fig. 3). By partitioning carbon stocks into their production and persistence we find that this non-linearity reflects changes to carbon residence time (Δ AIC = 10.6) rather than gains (Δ AIC = 1.7). Overall, our results thus indicate two separate climate controls on carbon stocks: a negative linear

effect of maximum temperature through reduced carbon gains, and a non-linear negative effect of maximum temperature, ameliorated by high dry-season precipitation, through reduced carbon residence time.

The effect of temperature on carbon residence time only emerges when dry season precipitation is low so is consistent with theoretical expectations that negative effects of temperature on tree longevity are exacerbated by moisture limitation, rather than being independent of it and due to increased respiration costs alone (23). This could occur through high vapour pressure deficits in hot and dry forests increasing mortality risk by causing hydraulic stress (23, 24), or carbon starvation due to limited photosynthesis as a result of stomatal closure (23). Notably, the temperature-precipitation interaction we find for aboveground stocks is in the opposite direction to temperature-precipitation interactions reported for soil carbon. In soils, moisture limitation suppresses the temperature response of heterotrophic respiration (25), while in trees moisture limitation enhances the mortality risks of high temperatures.

The temperature effects on biomass carbon stocks and gains are primarily due to maximum rather than minimum temperature. This is consistent with high daytime temperatures reducing CO₂ assimilation rates, for example due to increased photorespiration or longer duration of stomatal closure (26, 27), whereas if negative temperature effects were to have increased respiration rates there should be a stronger relationship with minimum (i.e. night-time) temperature. Critically, minimum temperature is unrelated to aboveground carbon stocks both pan-tropically and in the one continent, South America, where maximum and minimum temperature are largely decoupled ($r = 0.33$; Fig. S8). While carbon gains are negatively related to minimum temperature (Fig S9) this bivariate relationship is weaker than with maximum temperature, and disappears once the effects of other variables are accounted for (Fig. 2). Finally, in Asia, the tropical region which experiences the warmest minimum temperatures of all, both carbon stocks and carbon gains are highest (Fig. 1, Fig. S11).

Overall our results suggest that tropical forests have considerable potential to acclimate and adapt to the effects of night-time minimum temperatures, but are clearly sensitive to the effects of daytime maximum temperature. This is consistent with ecophysiological observations suggesting that the

acclimation potential of respiration (15) is greater than that of photosynthesis (17). The temperature sensitivity revealed by our analysis is also considerably weaker than short-term sensitivities associated with inter-annual climate variation (8). For example, by relating short-term annual climate anomalies to responses in plots, the effect of a 1°C increase in temperature on carbon gains has been estimated as more than three-fold our long-term, pantropical result (28). This stronger long-term thermal resilience is likely due to a combination of individual acclimation and plasticity (15-17), differences in species' climate responses (29) leading to shifts in community composition due to changing demographic rates (12) and the immigration of species with higher performance at high temperatures (12).

Our pantropical analysis of the sensitivity to climate of aboveground forest carbon stocks, gains and persistence shows that warming reduces carbon stocks and gains from woody productivity. Using a reference carbon stock map (30) and applying our estimated temperature sensitivity (including non-linearity) while holding other variables constant leads to an eventual biome-wide reduction of 14.1 Pg C in live biomass (including scaling to estimate carbon in roots) for a 1°C increase in maximum temperature (95 % CI = 6.9 – 20.7 Pg). This compares with a large range of projected sensitivities in the subset of coupled climate carbon cycle models that report vegetation carbon (1 – 58 Pg C °C⁻¹), although we note that these models have not been run to equilibrium (see SI Methods).

Our results suggest that stabilising global surface temperatures at 2°C above pre-industrial levels will cause a potential long-term biome-wide loss of 35.3 Pg C (95 % CI = 20.9 – 49.0 Pg, estimates with alternative baseline biomass maps 24.0 – 28.4 Pg, Fig. S12). The greatest long-term reductions in carbon stocks are projected in South America, where baseline temperatures and future warming are both highest (Fig. 4, Fig. S13). This warming would push 71 % of the biome beyond the thermal threshold – maximum temperature of 32.2°C – where larger long-term reductions in biomass are expected (Fig. S14). Of course, growth stimulation by carbon dioxide (31) will partially or wholly offset the effect of this temperature increase, depending on both the level of atmospheric carbon dioxide that limits warming to 2°C above pre-industrial levels and the fertilization effect of this carbon dioxide on tropical trees. Although CO₂ fertilisation is expected to reduce temperature induced

carbon losses from biomass across the tropics (Table S3), our analysis indicates that CO₂ fertilisation is not enough to offset long-term temperature induced carbon losses within Amazonia (Fig. S15).

The long-term climate sensitivities derived from our pan-tropical field measurements incorporate ecophysiological and ecological adaptation, and so provide an estimate of the long-term, quasi-equilibrium, response of tropical vegetation to climate. We note that this thermal adaptation potential may not be fully realised in future responses because (i) the speed of temperature rises may exceed species' adaptive capabilities, (ii) habitat fragmentation may limit species' ability to track changes in the environment, and (iii) other human impacts such as logging and fire can increase the vulnerability of forest carbon stocks to high temperatures. While many tropical forests are under severe threat of conversion, our results show that, in the long-run, tropical forests that remain intact can continue to store high levels of carbon under high temperatures. Achieving the biome-wide climate resilience potential we document depends on limiting heating and on large-scale conservation and restoration to protect biodiversity and allow species to move.

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Acknowledgements: This paper is a product of the RAINFOR, AfriTRON and T-FORCES networks, and is facilitated by ForestPlots.net technology for data management which promotes science synergies across countries and continents. While these initiatives have been supported by numerous people and grants since their inception we are particularly indebted to hundreds of institutions, field assistants and local communities for help in establishing and maintaining the plots. For additional assistance with access to datasets we thank Jon Lloyd, Carlos Quesada, Michel Baisie, Olaf Banki, Wemo Betian, Vincent Bezar, Rene Boot, Mireille Breuer-Ndoundou Hockemba, Ezequiel Chavez, Douglas Daly, Armandu Daniels, Darcy Galiano Cabrera, Toby Gardner, Paolo Graca, Andrew Graham, Olivier Hardy, Eduardo Hase, David Hilvert, Muhammad Idhamsyah, Phillipe Jeanmart, Cisquet Keibou Opepa, Jeanette Kemp, Wilmar Lopez Oviedo, Jean-Remy Makana, Faustin Mbaya Mpanya Lukasu, Irina Mendoza Polo, Edi Mirmanto, Sam Moore, Jacques Mukinzi, Pétrus Naisso, Lucas Ojo, Raimunda Oliveira de Araújo, Sonia Cesarina Palacios Ramos, Alexander Parada Gutierrez, Guido Pardo, Marielos Peña-Claros, Freddy Ramirez Arevalo, Antonio Lima, Rodrigo Sierra, Natalino Silva, Marc Steininger, Marisol Toledo, John Tshibamba Mukendi, Darlington Tuagben, Hannsjoerg Woell and Ishak Yassir. We thank Jon Lloyd, Carlos Quesada for discussions and three anonymous reviewers for helpful comments and suggestions. **Funding:** The networks have been supported by multiple grants, most notably the European Research Council (ERC Advanced Grant 291585 – ‘T-FORCES’), the Gordon and Betty Moore Foundation (#1656 ‘RAINFOR’ and Monitoring Protected Areas in Peru to Increase Forest Resilience to Climate Change), the David and Lucile Packard Foundation, the European Union’s Seventh Framework Programme (283080 – ‘GEOCARBON’, 282664 – ‘AMAZALERT’), the Natural Environment Research Council (NERC grants NE/D005590/1 – ‘TROBIT’, NE/F005806/1 – ‘AMAZONICA’, ‘PPFOR’ E/M0022021/1, NERC Urgency Grants to O.L.P., and NERC New Investigators Grant to S.L.L. and T.F.), the NERC/State of São Paulo Research Foundation (FAPESP) consortium grants ‘BIO-RED’ (NE/N012542/1, 2012/51872-5) and ‘ECOFOR’ (NE/K016431/1, 2012/51509-8), the Royal Society, the Centre for International Forestry (CIFOR) and Gabon’s National Parks Agency (ANPN). Additional data were included from the Tropical Ecology Assessment and Monitoring (TEAM) Network, a collaboration between Conservation International, the Missouri Botanical Garden, the Smithsonian Institution and the Wildlife Conservation Society, and partly funded by these institutions, the Gordon and Betty Moore Foundation, and other donors. M.J.P.S. was supported by the ERC (T-FORCES), NERC (‘BIO-RED’) and the Royal Society (CH160091), S.L.L. by a Royal Society University Research Fellowship, ERC Advanced Grant and a Phillip Leverhulme Prize, and O.L.P. by an ERC Advanced Grant, a Royal Society Wolfson Research Merit Award, and a Royal Society Global Challenges Award (‘FORAMA’, ICA/R1/180100). We thank the National Council for Science and Technology Development of Brazil (CNPq) for support to the Cerrado/Amazonia Transition Long-Term Ecology Project (PELD/403725/2012-7), the PPBio Phytogeography of Amazonia/Cerrado Transition project (CNPq/PPBio/457602/2012-0) and a Productivity Grant to B.S.M. and B.H.M.-J.. Funding for plots in the Udzungwa Mountains (Tanzania) was obtained from the Leverhulme Trust under the Valuing the Arc project. This study is contribution number XXX to the Technical Series (TS) of the BDFFP (INPA – STRI). Data from RAINFOR, AfriTRON and T-FORCES are stored and curated by ForestPlots.net, a cyber-infrastructure initiative developed at the University of Leeds that unites permanent plot records and their contributing scientists from the world’s tropical forests. The development of ForestPlots.net and curation of most data analysed here was funded by several grants to O.L.P. (principally from NERC NE/B503384/1, NE/N012542/1 BIO-RED, ERC AdG 291585 T-FORCES’, and Gordon and Betty Moore Foundation #1656, ‘RAINFOR’), E.G. (‘GEOCARBON’, and NE/F005806/1 ‘AMAZONICA’), T.R.B. (Gordon and Betty Moore Foundation ‘Monitoring Protected Areas in Peru to Increase Forest Resilience to Climate Change’), S.L.L. (Royal Society University Research Fellowship; NERC New Investigators Award; Phillip Leverhulme Prize), and D.G. (NERC NE/N004655/1, ‘TREMOR’). **Author contributions:** O.L.P., S.L.L. and Y.M. conceived the RAINFOR, AfriTRON and T-FORCES forest census network programmes; M.J.P.S., O.L.P. and S.L.L. conceived and designed the study. L.A., A.A.-M., T.R.B., R.J.W.B., S.K.B., K.A-

B., F.C., C.C., E.A.D., A.C.S., C.E.N.E., T.R.F., W.H., S.L.L., A.M.M., B.S.M., O.L.P., L.Q., B.S., T.S., R.V. and L.J.T.W. coordinated data collection with the help of most co-authors. O.L.P., T.R.B., G.L.-G. and S.L.L. conceived and managed ForestPlots.net; O.L.P., T.R.B., D.G., E.G. and S.L.L. funded it, and R.B., T.F., G.L.-G., A.L., G.C.P. and M.J.P.S. helped develop it. M.J.P.S., T.R.B., W.H., S.L.L., A.E.-M., and L.Q. contributed tools to analyse data. All authors collected or supported the collection of field data, M.J.P.S. analysed the data, M.J.P.S., O.L.P. and S.L.L. wrote the manuscript with contributions from other authors. All co-authors commented on or approved the manuscript. **Competing interests:** The authors declare no competing financial interests. **Data and materials availability:** Plot-level input data and R scripts will be deposited as a data package on ForestPlots.net (doi-xxx).

Supplementary Materials:

Materials and Methods

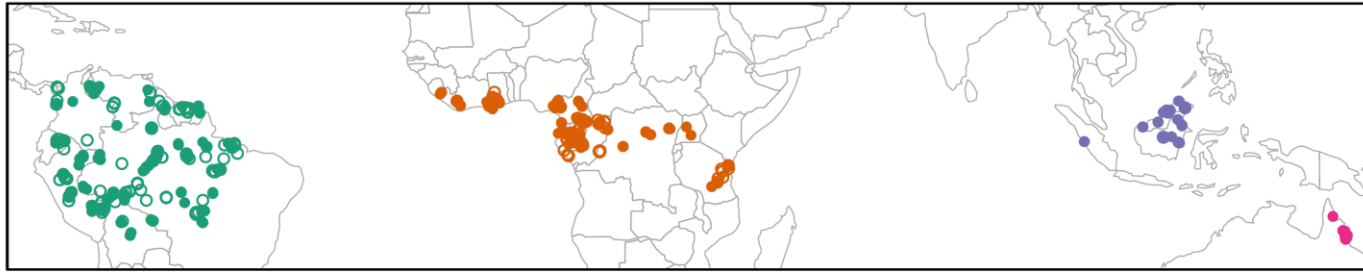
Figures S1-S15

Tables S1-S3

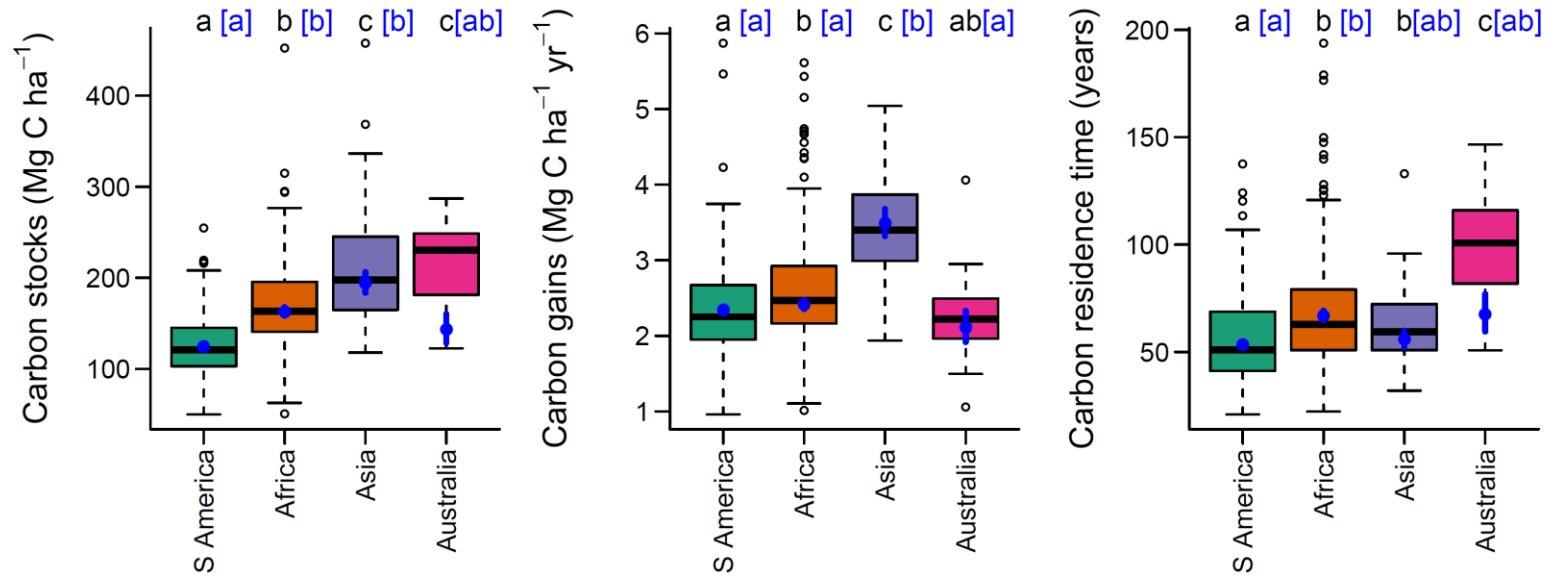
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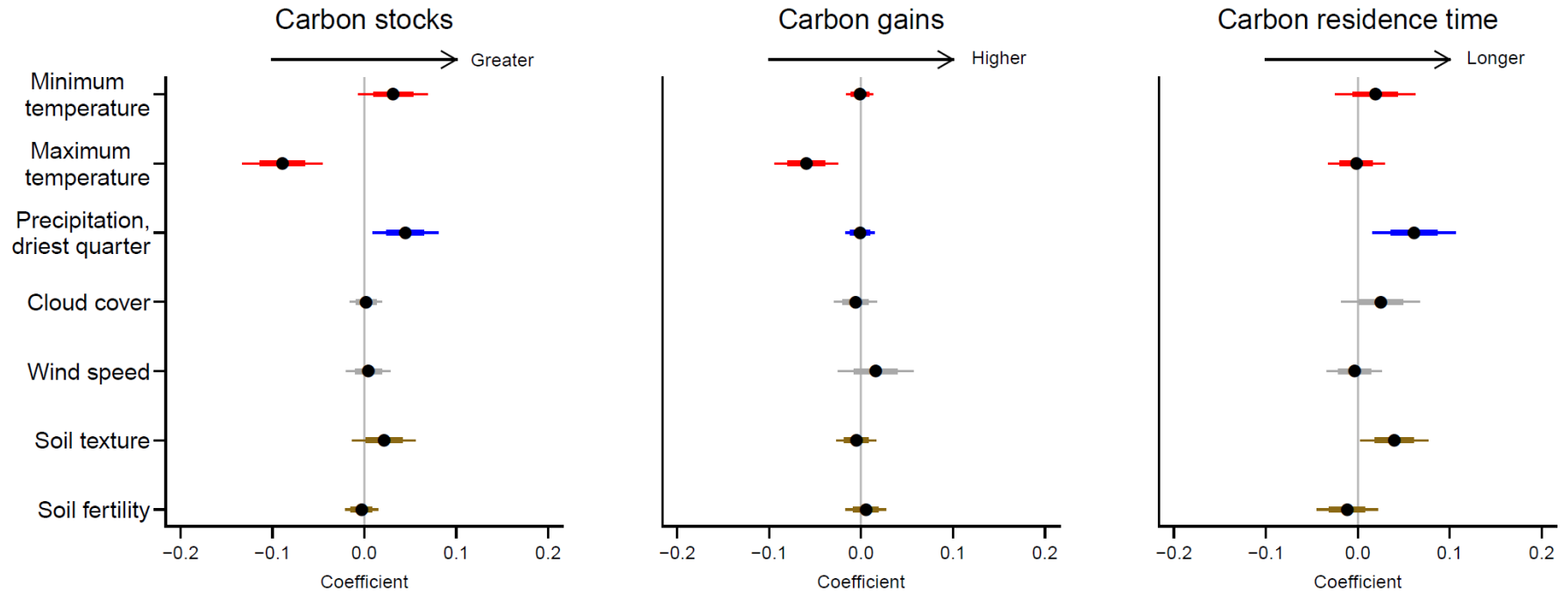
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3 **Figure 1.** Spatial variation in tropical forest carbon. (A) Our plot network. Filled symbols show multi-census plots used in the main analysis, open symbols
 4 show single-census plots used as an independent dataset. (B) Variation in carbon among continents. Boxplots show raw variation while blue points show
 5 estimated mean values (\pm SE) after accounting for environmental variation. Letters denote statistically significant differences between continents ($P < 0.05$)
 6 based on raw data (black) or accounting for environmental effects (blue, square brackets).

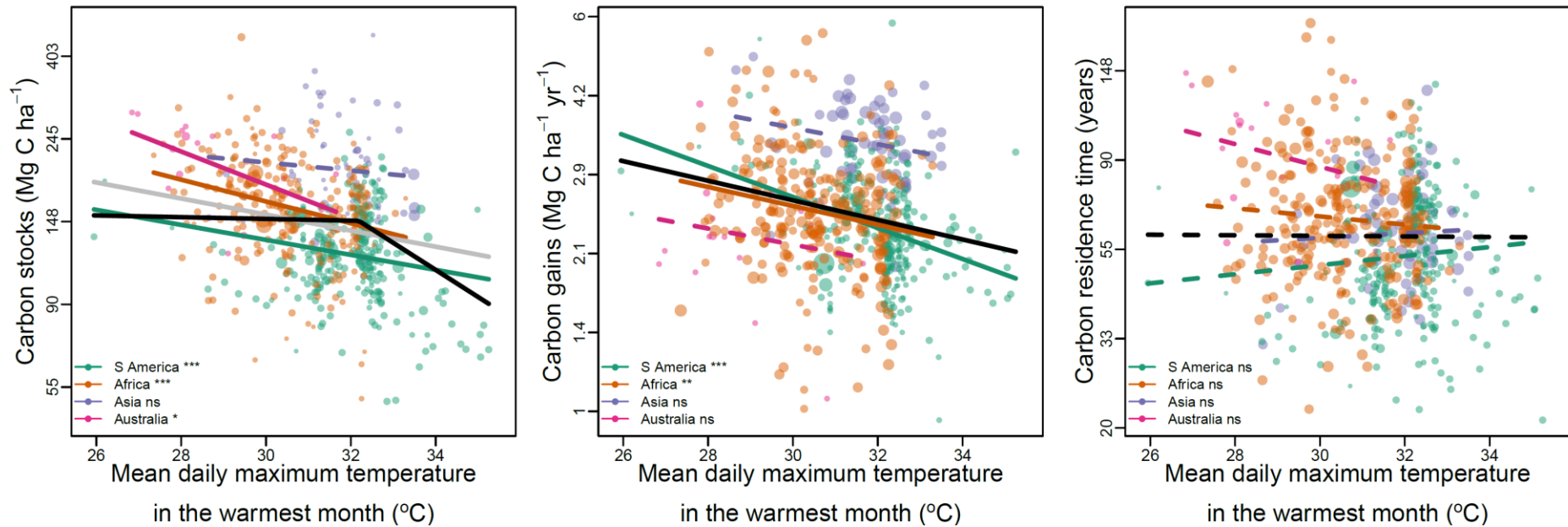
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12 **Figure 2.** Correlates of spatial variation in tropical forest carbon. Points show coefficients from model-averaged general linear models. Variables that did not
 13 occur in well-supported models are shrinkage adjusted towards zero. Coefficients are standardised so that they represent change in the response variable for
 14 one standard deviation change in the explanatory variable. Error bars show standard errors (thick lines) and 95% confidence intervals (thin lines). Soil texture
 15 is represented by the percentage clay, and soil fertility by cation exchange capacity. The full models explained 44.1 %, 31.4 % and 30.9 % of spatial variation
 16 in carbon stocks, gains and residence time respectively. Coefficients are shown in Table S2. Results are robust to using an alternative allometry to estimate
 17 tree biomass (Fig. S5).

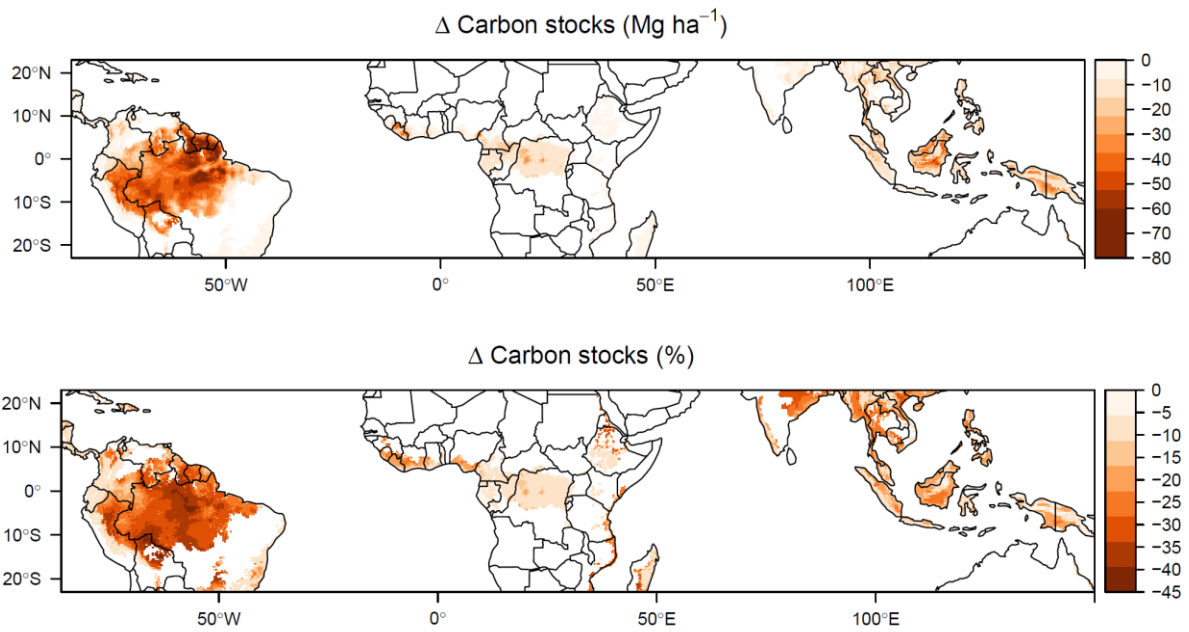
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21 **Figure 3.** Temperature effects on tropical forest carbon stocks, carbon gains from woody productivity and carbon residence time. Black lines show the best
 22 pan-tropical relationships accounting for environmental covariates. The grey line shows the additional linear pan-tropical relationship for carbon stocks.
 23 Coloured lines show bivariate relationships within each continent. Statistically significant relationships are shown with solid lines, non-significant with
 24 dashed lines. Note that the y-axis is on a log-scale. Symbol point size is proportional to weights used in model fitting based on plot size and monitoring
 25 length, see SI Materials and Methods. For stocks and gains linear and break-point pan-tropical relationships are all statistically significant ($P < 0.001$), as are
 26 better sampled continents. For carbon residence time, relationships with temperature are non-significant but there is a statistically significant interaction
 27 between maximum temperature and precipitation in the driest quarter (Figure S6). Relationships with other variables are shown in Fig. S8-S10. *** $P <$
 28 0.001, ** $P < 0.01$, * $P < 0.05$, ns $P \geq 0.05$

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30

31 **Figure 4.** Long-term change in carbon stocks due to global surface temperature warming of
 32 approximately 2°C . Maps show the predicted absolute and relative change in tropical forest carbon
 33 stocks. Note that parts of the biome become warmer than currently observed in our dataset (Fig. S14).
 34 See Fig. S12 for predictions using alternative carbon reference maps. Predictions are based on
 35 temperature alone and do not include precipitation changes (for which future patterns of change are
 36 uncertain) or potential moderation via elevated CO_2 (see Fig. S15 for analysis incorporating this).

37

38

39 **Supporting information for Long-term thermal Sensitivity of the Earth's Tropical**40 **Forests**

41 Martin J. P. Sullivan^{1,2}, Simon L. Lewis^{1,3}, Kofi Affum-Baffoe⁴, Carolina Castilho⁵, Flávia Costa⁶, Aida
42 Cuni Sanchez^{7,8}, Corneille E. N. Ewango^{9,10,11}, Wannes Hubau^{1,12,13}, Beatriz Marimon¹⁴, Abel Monteagudo-
43 Mendoza¹⁵, Lan Qie¹⁶, Bonaventure Sonké¹⁷, Rodolfo Vasquez Martinez¹⁵, Timothy R Baker¹, Roel J. W.
44 Brienien¹, Ted R. Feldpausch¹⁸, David Galbraith¹, Manuel Gloor¹, Yadvinder Malhi¹⁹, Shin-Ichiro Aiba²⁰,
45 Miguel N. Alexiades²¹, Everton C. Almeida²², Edmar Almeida de Oliveira²³, Esteban Álvarez Dávila²⁴,
46 Patricia Alvarez Loayza²⁵, Ana Andrade²⁶, Simone Aparecida Vieira²⁷, Luiz Aragão²⁸, Alejandro Araujo-
47 Murakami²⁹, Eric J.M.M. Arets³⁰, Luzmila Arroyo³¹, Peter Ashton³², Gerardo Aymard C.³³, Fabrício B.
48 Baccaro³⁴, Lindsay F. Banin³⁵, Christopher Baraloto³⁶, Plínio Barbosa Camargo³⁷, Jos Barlow³⁸, Jorcely
49 Barroso³⁹, Jean-François Bastin⁴⁰, Sarah A. Batterman^{1,41,42,43}, Hans Beeckman¹², Serge K. Begne^{17,44}, Amy
50 C. Bennett⁴⁴, Erika Berenguer^{19,38}, Nicholas Berry⁴⁵, Lilian Blanc⁴⁶, Pascal Boeckx⁴⁷, Jan Bogaert⁴⁸, Damien
51 Bonal⁴⁹, Frans Bongers⁵⁰, Matt Bradford⁵¹, Francis Q. Brearley², Terry Brncic⁵², Foster Brown⁵³, Benoit
52 Burban⁵⁴, José Luís Camargo²⁶, Wendeson Castro⁵⁵, Carlos Céron⁵⁶, Sabina Cerruto Ribeiro⁵⁷, Victor
53 Chama Moscoso¹⁵, Jérôme Chave⁵⁸, Eric Chezeaux⁵⁹, Connie J. Clark²⁵, Fernanda Coelho¹, Murray
54 Collins⁶¹, James A. Comiskey^{62,63}, Fernando Cornejo Valverde⁶⁴, Massiel Corrales Medina⁶⁵, Lola da
55 Costa⁶⁶, Martin Dančák⁶⁷, Greta C. Dargie¹, Stuart Davies⁶⁸, Nallaret Davila Cardozo⁶⁹, Thales de
56 Haulleville^{12,48}, Marcelo Brilhante de Medeiros⁷⁰, Jhon del Aguila Pasquel⁷¹, Géraldine Derroire⁷², Anthony
57 Di Fiore⁷³, Jean-Louis Doucet⁷⁴, Aurélie Dourdain⁷², Vincent Droissant⁷⁵, Luisa Fernanda Duque⁷⁶, Romeo
58 Ekoungoulou⁷⁷, Fernando Elias⁷⁸, Terry Erwin⁷⁹, Adriane Esquivel-Muelbert⁸⁰, Sophie Fauset⁸¹, Joice
59 Ferreira⁸², Gerardo Flores Llampazo⁸³, Ernest Foli⁸⁴, Andrew Ford⁵¹, Martin Gilpin¹, Jefferson S. Hall⁸⁵,
60 Keith C. Hamer⁸⁶, Alan C. Hamilton⁸⁷, David J. Harris⁸⁸, Terese B. Hart^{89,90}, Radim Hédli^{91,92}, Bruno
61 Herault⁷², Rafael Herrera⁹³, Niro Higuchi⁶, Annette Hladik⁹⁴, Eurídice Honorio Coronado⁷¹, Isau
62 Huamantupa-Chuquimaco⁹⁵, Walter Huaraca Huasco⁹⁵, Kathryn J. Jeffery⁹⁶, Eliana Jimenez-Rojas⁹⁷,
63 Michelle Kalamandeen¹, Marie-Noel Kamdem^{11,13,17,98}, Elizabeth Kearsley⁹⁹, Ricardo Keichi Umetsu¹⁰⁰, Lip
64 Khoon Kho Khoon¹⁰¹, Timothy Killeen¹⁰², Kanehiro Kitayama¹⁰³, Bente Klitgaard¹⁰⁴, Alexander Koch¹⁰⁵,
65 Nicolas Labrière⁵⁸, William Laurance¹⁰⁶, Susan Laurance¹⁰⁶, Miguel E. Leal¹⁰⁷, Aurora Levesley¹, Adriano
66 J. N. Lima⁶, Janvier Lisingo¹¹, Aline P. Lopes^{108,109}, Gabriela Lopez-Gonzalez¹, Tom Lovejoy¹¹⁰, Jon
67 Lovett¹, Richard Lowe¹¹¹, William E. Magnusson¹¹², Jagoba Malumbres-Olarte^{113,114}, Ângelo Gilberto
68 Manzatto¹¹⁵, Ben Hur Marimon Junior¹¹⁶, Andrew R. Marshall^{8,117,118}, Toby Marthews¹¹⁹, Simone Matias de
69 Almeida Reis^{14,19}, Colin Maycock¹²⁰, Karina Melgaço¹, Casimiro Mendoza¹²¹, Faizah Metali¹²², Vianet
70 Mihindou^{123,124}, William Milliken¹⁰⁴, Edward Mitchard¹²⁵, Paulo S. Morandi¹⁴, Hannah L. Mossman², Laszlo
71 Nagy¹²⁶, Henrique Nascimento⁶, David Neill¹²⁷, Reuben Nilus¹²⁸, Percy Núñez Vargas⁹⁵, Walter Palacios¹²⁹,
72 Nadir Pallqui Camacho^{1,95}, Julie Peacock¹, Colin Pendry¹³⁰, Maria Cristina Peñuela Mora¹³¹, Georgia C.
73 Pickavance¹, John Pipoly¹³², Nigel Pitman¹³³, Maureen Playfair¹³⁴, Lourens Poorter¹³⁵, John R. Poulsen²⁵,
74 Axel D. Poulsen¹³⁶, Richard Preziosi², Adriana Prieto¹³⁷, Richard Primack¹³⁸, Hirma Ramírez-Angulo¹³⁹, Jan
75 Reitsma¹⁴⁰, Maxime Réjou-Méchain⁷⁵, Zorayda Restrepo Correa¹⁴¹, Thaianie Rodrigues de Sousa⁶, Lily
76 Rodriguez Bayona¹⁴², Anand Roopsind¹⁴³, Agustín Rudas¹³⁷, Ervan Rutishauser^{42,144}, Kamariah Abu
77 Salim¹²², Rafael P. Salomão^{145,146}, Juliana Schiatti⁶, Douglas Sheil¹⁴⁷, Richarlly C. Silva^{57,148}, Javier Silva
78 Espejo¹⁴⁹, Camila Silva Valeria³⁸, Marcos Silveira⁵⁷, Murielle Simo-Droissart¹⁷, Marcelo Fragomeni
79 Simon⁷⁰, James Singh¹⁵⁰, Yahn Carlos Soto Shareva¹⁵, Clement Stahl⁵⁴, Juliana Stropp¹⁵¹, Rahayu Sukri¹²²,
80 Terry Sunderland^{152,153}, Martin Svátek¹⁵⁴, Michael D. Swaine¹⁵⁵, Varun Swamy¹⁵⁶, Hermann Taedoum¹⁷,
81 Joey Talbot¹, James Taplin¹⁵⁷, David Taylor¹⁵⁸, Hans ter Steege^{159,160}, John Terborgh²⁵, Raquel Thomas¹⁴³,
82 Sean C. Thomas¹⁶¹, Armando Torres-Lezama¹⁶², Peter Umunay^{163,164}, Luis Valenzuela Gamarra¹⁵, Geertje
83 van der Heijden¹⁶⁵, Peter van der Hout¹⁶⁶, Peter van der Meer¹⁶⁷, Mark van Nieuwstadt¹⁶⁸, Hans Verbeeck⁹⁹,
84 Ronald Vernimmen¹⁶⁹, Alberto Vicentini⁶, Ima Célia Guimarães Vieira¹⁴⁶, Emilio Vilanova Torre¹⁷⁰, Jason
85 Vleminckx³⁶, Vincent Vos¹⁷², Ophelia Wang¹⁷³, Lee J. T. White^{124,174,175}, Simon Willcock¹⁷⁶, John T.
86 Woods¹⁷⁷, Verginia Wortel¹⁷⁸, Kenneth Young¹⁷⁹, Roderick Zagt¹⁸⁰, Lise Zemagho¹⁷, Pieter A. Zuidema⁵⁰,
87 Joeri A. Zwarts^{178,181}, Oliver L. Phillips¹

88

- 89 **This file includes:**
- 90 Materials and Methods
- 91 Figures S1 – S15
- 92 Tables S1 – S2
- 93

94 **Materials and Methods**

95 Forest census data

96 Our plots come from the RAINFOR, AfriTRON, and T-FORCES networks. Forest inventory plots
97 were located in lowland (<1200 m), old-growth, closed-canopy forests that were not known to have
98 been subject to anthropogenic disturbance through fire or selective logging. Plots characterised
99 floristically as dry forest were not included, as were plots that received less than 1200 mm
100 precipitation each year. We also did not include plots in white sand, swamp and seasonally flooded
101 forests, as we expect these to experience marked edaphic constraints (extreme nutrient limitation for
102 white sand forests (32), stress caused by hypoxic conditions for swamp and seasonally flooded forests
103 (33)). All plots were ≥ 0.2 ha (median size = 1 ha) and were monitored for at least two years (median
104 monitoring period = 9.7 years). All censuses were prior to the 2015-16 very strong El Niño event, as
105 we expected that event to suppress carbon gains relative to the long-term mean.

106 Forest inventory plots were sampled using standardised protocols (34), where all live stems with
107 diameter ≥ 100 mm were measured at 1.3 m or 50 cm above buttresses and deformities. Trees were
108 tagged so that the same tree could be identified in subsequent censuses. In some cases the point of
109 diameter measurement (POM) had to be moved due to upward growth of buttresses and deformities.
110 For these trees we use the D_{mean} approach from Talbot et al. (35).

111 In a few cases (6 plots) the minimum diameter measured changed over time, or palms and
112 *Phenakospermum* were excluded in some censuses. For these, we estimated aboveground biomass
113 (AGB, subsequently converted to carbon stocks) and aboveground woody production (AGWP,
114 subsequently converted to carbon gains) using a minimum diameter or taxonomic protocol that could
115 be consistently applied across censuses, and scaled these values by the aboveground biomass ratio
116 between that protocol and all stems ≥ 100 mm protocol for censuses when all stems were measured.
117 Some plots had nested designs where the plot was split into subplots with different minimum diameter
118 protocols (69 plots). For these, we only analysed the area conforming to our minimum diameter
119 protocol. For analysis, we grouped small (≤ 0.5 ha) plots within 1 km of each other, and also grouped
120 contiguous larger plots (18 plots), as these will experience equivalent climate and larger plots are less
121 sensitive to stochastic tree fall events (36).

122 Data were curated in ForestPlots.net (37, 38), or were subject to equivalent offline handling, and
123 experienced the same quality control procedures. Details of quality control procedures are described
124 in Brienen et al. (39). Our final dataset consists of 590 sampling units (hereafter plots) covering 637.2
125 ha, with 2.2 million measurements of 670,499 unique stems. For validating models of carbon stocks
126 an additional dataset of 223 single-census plots using the same measurement protocols was assembled
127 from the same networks (see section “Validation with independent single-census plot dataset” below).

128

129 Estimating above-ground biomass

130 Diameter measurements were converted to estimates of aboveground biomass (AGB). For dicot trees
131 we used the allometric equation

$$132 \text{ AGB} = 0.673 \times (\rho D^2 H)^{0.976}, \quad [1]$$

133 from Chave et al. (40), where ρ is wood density (from (41, 42)) and H is tree height estimated using
134 allometric equations described below. For monocots and tree ferns, we used a palm-specific
135 allometric equation

$$136 \ln(\text{AGB}) = -3.3488 + 2.7483 \ln(D), \quad [2]$$

137 from Goodman et al. (43), where D is the measured diameter.

138 The heights of a subset of trees in our dataset were measured in the field, either with a laser
139 rangefinder, hypsometer, or clinometer, or directly by climbing the tree. We filtered this dataset to
140 stems with measured diameters, height ≤ 90 m, diameters ≥ 90 mm DBH, as height-diameter
141 allometries of saplings differ from those of more mature trees, and to stems that were not broken,
142 leaning or fallen. This gave a total of 78,899 height measurements. We used this dataset to fit local
143 height-diameter allometric models, as these refine AGB estimates by capturing spatial variation in
144 height-diameter allometries missed by large-scale allometric models (44). Height data were not
145 available from every plot, so to ensure consistent treatment of plots height-diameter models were
146 constructed for each biogeographic region. We fitted three parameter asymptotic models (45) of the
147 form

$$148 H = a(1 - \exp(-bD^c)), \quad [3]$$

149 where a , b and c are estimated parameters ('Weibull' models, 46). We fitted these models either
150 treating each observation equally or with case weights proportional to each trees' basal area. These
151 weights give more importance to large trees during model fitting. We selected the best fitting of these
152 models, determining this as the model that minimised prediction error of stand biomass when
153 calculated with estimated heights or observed heights (44). Weibull models were implemented using
154 the nls function in R with default settings. Starting values of $a = 25$, $b = 0.05$ and $c = 0.7$ were chosen
155 following trial and error as they led to regular model convergence. Where models did not converge
156 this was usually because the height-diameter relationship did not reach an asymptote, so in these cases
157 we used the log-log model $\ln(H) = a + b(\ln(D))$ to estimate height, where b gives the scaling exponent
158 of a power law relationship between height and diameter. We checked if models gave unrealistic
159 predictions by applying models to predict the height of all trees in the biogeographic region, and

160 excluded models that predicted any tree height 10 % higher than the tallest tree we recorded in that
161 continent.

162

163 Estimating above-ground woody production

164 We estimated AGWP following Talbot et al. (35). AGWP is comprised of four components, (1) the
165 sum of growth of surviving trees, (2) the sum of AGB of new recruits, (3) the sum of unobserved
166 growth of trees that died during a census interval and (4) the sum of growth of unobserved recruits
167 that entered then died during a census interval. Accounting for the latter two components is necessary
168 to avoid census-interval length effects, as more AGWP in these components will be missed due to the
169 greater mortality of trees that accumulates over longer census intervals.

170 Components 3 and 4 can be estimated using two quantities that can be calculated from observed stem-
171 dynamics in each plot; per-area annual recruitment (R_a) and per-capita annual mortality (m_a). Per-
172 capita mortality is calculated from the ratio of surviving stems to initial stems, using equation 5 in
173 Kohyama et al. (47). Per-area annual recruitment is calculated using estimated mortality rates and the
174 observed change in the number of stems over a census interval, using equation 11 of Kohyama et al.
175 (47).

176 To estimate the unobserved growth of stems that died during a census interval, we first use plot-level
177 per-capita mortality rates (m_a) to estimate how many trees are expected to have died in each year of
178 the census interval, and from that calculate the mean number of years that trees that died during the
179 census interval would have lived before death. The diameter of tree at death (D_{death}) can then be
180 estimated as

$$181 \quad D_{\text{death}} = D_{\text{start}} \times G \times Y_{\text{mean}} \quad [4]$$

182 where D_{start} is the diameter at the start of the census interval, G is the plot-level median growth rate of
183 the size class the tree was in at the start of the census interval (size classes are defined as $D < 200$ mm,
184 $400 \text{ mm} > D \geq 200$ mm, and $D \geq 400$ mm) and Y_{mean} is the mean number of years trees survived in
185 the census interval before dying. The diameter at death is then converted to AGB at death using
186 allometric equations (equation 1, except for ferns and monocots where equation 2 is used), and the
187 unobserved growth is calculated as the difference between AGB at death and AGB at the start of the
188 census.

189 To estimate the growth of recruits that were not observed because they died during the census
190 interval, we first need to estimate the number of unobserved recruits. This can be estimated from per-
191 area annual recruitment (R_a) and per-capita annual mortality (m_a): R_a gives the number of stems per ha
192 that recruit in a given year, and the probability of each recruit surviving until the next census (P_{surv}) is

193 $P_{surv} = (1 - m_a)^T$, where T is the number of years remaining in the census interval. The number of
194 recruits in a given year that survive to the next census is $R_a - P_{surv}R_a$. Summing this for each year in a
195 census interval gives the total number of unobserved recruits in that census interval. We then need to
196 estimate how long each recruit was alive for. From m_a we can calculate the number of recruits in a
197 given year that died in each subsequent year, and from this calculate the mean life-span of recruits in a
198 given year that died before the next census. The average life-span of unobserved recruits ($Y_{mean-rec}$) is
199 the weighted mean of each cohort's lifespan, weighted by the number of unobserved recruits in each
200 year. Diameter at death is given in mm by

$$201 \quad D_{death} = 100 + (G \times Y_{mean-rec}) \quad [5]$$

202 where G is the plot-level median growth rate of the smallest size class (i.e. $D < 200$ mm).
203 Aboveground biomass of recruits at the time of death is estimated using equation 1. These corrections
204 for unobserved growth have a marginal impact on AGWP calculations, collectively accounting on
205 average for just 2.3 % of estimated plot-level AGWP.

206 AGB was calculated for each census, and AGWP was calculated for each census interval, and the
207 time-weighted mean of each was taken to give one value per plot. We used a time-weighted mean to
208 give greater importance to AGB estimates separated by longer census-intervals, as these will be more
209 independent. Estimates of AGB and AGWP were converted to carbon stocks and carbon gains by
210 multiplying by 0.456 (48). Carbon residence time was then estimated as carbon stocks /carbon gains,
211 and represents the length of time carbon resides in living biomass before being passed to the litter and
212 necromass pools (49). Calculations to estimate AGB and AGWP were performed using the R package
213 BiomasaFP (50).

214

215 Obtaining environmental data

216 Most climate data were obtained from climate data from Worldclim2 (51) as it provides the highest
217 resolution (~ 1 km) pantropical climate data, although we note that some regions, such as central
218 Africa, have limited station data. We extracted monthly data for the following variables: mean daily
219 minimum temperature, mean daily maximum temperature, precipitation, solar radiation and wind
220 speed, In addition to calculating the standard series of 19 bioclimatic variables, using the dismo R
221 package (52), we calculated 1) mean daily maximum temperature, $BIO1 + BIO2/2$, 2) mean daily
222 minimum temperature, $BIO1 - BIO2/2$, 3) maximum cumulative water deficit as the minimum across
223 the year of monthly cumulative water deficit W ,

$$224 \quad W_i = W_{i-1} - \min(0, P_i - 100) , \quad [6]$$

225 where P is monthly precipitation in mm, and 100 represents measured evapotranspiration. This
226 calculation was run for a year from the wettest month in the year, starting at a water deficit of zero, 4)
227 the number of months where monthly cumulative water deficit was negative, 5) the number of months
228 where monthly precipitation was below 100 mm (i.e. less than evapotranspiration), 6) mean annual
229 solar radiation, 7) mean annual wind speed, and 8) vapour pressure deficit ($VPD = SVP - \text{vapour}$
230 pressure , where saturated vapour pressure, $SVP, = 0.611 \times e^{(17.502 \text{ temperature}) / (\text{temperature} + 240.97)}$). We also
231 obtained data on cloud frequency at ~1 km resolution from Wilson & Jetz (53), who processed twice-
232 daily MODIS satellite images. Temperature values were adjusted for differences in altitude between
233 the plot and the 1 km grid cell used for Worldclim interpolation, as these can differ in topographically
234 diverse regions, using lapse rates, so that $T_{plot} = T_{worldclim} + 0.005 \times (A_{worldclim} - A_{plot})$, where T is
235 temperature ($^{\circ}\text{C}$) and A is altitude (m). Temperature values were also corrected for systematic
236 warming trends. To do this, the mean annual temperature in each grid-cell in each year was extracted
237 from the CRU TS 3.24 dataset (54), and robust linear regression used to estimate grid-cell specific
238 warming rates. These were used to adjust Worldclim2 temperature values for the difference between
239 the midpoint of plot monitoring and the midpoint of the Worldclim2 climatology.

240 Data on soil texture and chemistry was obtained at 1 km resolution from the SoilGrids dataset (55),
241 with this resolution selected to match the resolution of the climate data. From this we extracted CEC,
242 representing soil fertility, and percentage clay, representing soil texture. For each soil variable we
243 calculated the depth-weighted average for 0 – 30 cm.

244 Statistical analysis

245 We used linear models to relate carbon, carbon gains and carbon residence time to environmental
246 explanatory variables. The role of different explanatory variables was assessed using multi-model
247 inference.

248 Response variables were positively skewed and had positive mean-variance relationships, so were
249 log-transformed to meet the assumption of normality and reduce heterogeneity in variances. The log-
250 normal nature of forest carbon stocks and dynamics means that there is greater potential for variation
251 when forests are large, which could be due to the non-linear scaling of tree biomass and tree basal
252 area.

253 We selected explanatory variables to represent hypothesised ways in which climate could affect
254 carbon stocks (Table S1). We assessed collinearity within this set of explanatory variables using
255 variance inflation factors (VIF) and pairwise correlations. Because of collinearity, we had to exclude
256 VPD, total precipitation, use only one of MCWD and precipitation in the driest quarter, and could
257 include both minimum and maximum temperature but not mean annual temperature. We used
258 precipitation in the driest quarter rather than MCWD as the latter is zero truncated and so is less
259 amenable to regression analysis. After removing these variables all pairwise correlations (including

260 with soil explanatory variables) were weak enough not to cause problems through collinearity ($r < 0.6$
261 and $VIF < 3$).

262 To account for variation other than in climate we also included soil variables relating to texture (%
263 clay) and fertility (CEC), and included continent specific intercepts to account for biogeographic
264 variation in carbon. To account for unmeasured environmental gradients (e.g. soil variation not
265 captured by the SoilGrids variables), we used Moran's eigenvector maps as explanatory variables,
266 selecting eigenvectors that corresponded to positive spatial autocorrelation in the distance matrix (56).
267 These variables act as a proxy for unmeasured spatial gradients by capturing positive spatial
268 associations between plots.

269 Plots differed in their area and the length of time they were monitored for. This is likely to affect the
270 variance of carbon stocks, carbon gains and carbon residence time, as smaller plots or plots only
271 monitored for short periods are more likely to be sensitive to the mortality of a few large trees. To
272 account for this, we used case weights relating to plot area and monitoring period. Following Lewis et
273 al. (57), we selected weights by relating residuals from our linear models to plot area and to plot
274 monitoring period, and subsequently assessing which root transformation of plot area/ monitoring
275 period removed the pattern in the residuals when used as a weight. Selected weights were: carbon
276 stocks, $\text{Area}^{1/3}$; carbon gains, $\text{Monitoring length}^{1/7}$; carbon residence time, $\text{Area}^{1/9} + \text{Monitoring}$
277 $\text{length}^{1/12} - 1$.

278 We fitted all subsets of the general linear model with explanatory variables described above, forcing
279 spatial eigenvectors into all models. We then averaged the subset of models where $\Delta \text{AIC} < 4$, using
280 full averaging so variables that do not appear in the model get the value of zero for their coefficients.
281 This means that model averaged coefficients of terms with limited support exhibit shrinkage towards
282 zero. Multi-model inference was performed using the MuMIn R package (58).

283 We assessed whether the two climate variables found to have important additive effects on carbon
284 stocks in this analysis (mean daily maximum temperature in the warmest month and precipitation in
285 the driest quarter) interacted with each other by adding an interaction term between these variables to
286 the full generalised linear model of carbon stocks as a function of other climate and soil variables,
287 continent and spatial eigenvectors. We compared these two models using AIC. We repeated this with
288 carbon gains and carbon residence time as response variables.

289 To assess whether the temperature carbon relationship was non-linear we used breakpoint regression
290 implemented in the segmented R package (59). This estimates a breakpoint in the explanatory variable
291 at which the slope of the relationship with the response variable changes. We estimated the breakpoint
292 for the mean daily maximum temperature in the warmest month variable in the full model with a
293 temperature-precipitation interaction described above. We assessed the support for the breakpoint by

294 comparing the AIC of the model with a breakpoint with the AIC of a model with a linear relationship.
295 We repeated this with carbon gains and carbon residence time as response variables.

296 We also analysed spatial variation in carbon stocks as a function of the above climate and soil
297 variables and spatial eigenvectors using Random Forest decision tree algorithms (22) implemented
298 using the randomForest R package (60). We assessed variable importance by calculating the average
299 increase in node purity across all decision trees (measured by residual sum of squares) when using the
300 variable to split the data. We assessed modelled relationships between response and explanatory
301 variables using partial plots, which show predicted change in the response variable, averaged across
302 trees, when changing the explanatory variable and holding all other variables constant.

303 To compliment this analysis based on relationships expected *a priori*, we also performed an
304 exploratory analysis to assess whether other climate variables excluded from the full general linear
305 models had an effect on carbon. To do this, we fitted linear models to assess the bivariate relationship
306 of carbon with each climate variable, with continent also included as an explanatory variable to
307 account for biogeographic variation in forest characteristics.

308

309 Validation with independent single-census plot dataset

310 We assessed whether the relationships with environmental variables identified in the analyses of
311 multi-census plot data described above held when applied to an additional dataset of 223 single-
312 census plots. As the single-census data were not used in any of the analyses above they did not
313 influence modelling decisions, so provide an independent test of the relationships identified with the
314 multi-census plot analysis.

315 Single-census plots were extracted from the ForestPlots.net database (37, 38) using the same plot-
316 selection criteria as for the multi-census plots, except that censuses during or following the 2015-16
317 strong El Niño were included in the single-census plot dataset as we expected that carbon stocks,
318 unlike gains, would still remain close to their long-term mean.

319 We fitted a general linear model with the five climate explanatory variables, soil fertility and texture,
320 continent and spatial eigenvector, and model averaging of all subsets of this model as described for
321 the multi-census plots. We performed this analysis using just the single-census plots and a combined
322 dataset of single and multi-census plots.

323

324

325

326 Scaling results to the biome

327 We applied the non-linear relationship between carbon stocks and mean daily maximum temperature
328 in the warmest month identified by the breakpoint regression to estimate the total change in carbon
329 stock due to temperature effects alone for different scenarios of temperature increase. We delimited
330 the biome extent using the WWF tropical and subtropical moist broadleaved forest biome (61),
331 restricted to tropical latitudes, and further refined it by excluding grid-cells with $< 50 \text{ Mg C ha}^{-1}$ using
332 data from (30), as these are unlikely to be forest. Calculations were conducted at 10-minute
333 resolution. The non-linear relationship between temperature and carbon means that the change in
334 biomass for a given increase in temperature will depend on the baseline temperature. For each grid-
335 cell we predicted the percentage change in carbon for a given temperature increase from the baseline
336 temperature in that grid-cell based on the non-linear relationship identified in our statistical model,
337 holding all other variables constant. We then used a reference carbon stock map (30) to convert
338 percentage change to change in carbon stocks per hectare (in Mg ha^{-1}). To calculate change in carbon
339 stocks for the whole grid-cell, we multiplied change per hectare by the area of the grid-cell in
340 hectares, and then adjusted this by the proportion of the grid-cell that was forested by multiplying by
341 2014 forest cover (62). Total change for the biome (in Pg) was calculated by summing these grid-cell
342 level values. Uncertainty due to our statistical model was assessed by generating multiple predictions
343 by resampling model parameters (breakpoint threshold, slope below breakpoint, slope above
344 breakpoint), and extracting quantiles from the resultant distribution of predicted change values.
345 Aboveground biomass carbon values were scaled to include root biomass based on a root to shoot
346 ratio of 0.19 in tropical evergreen forests (63).

347 The Avitabile et al (30) aboveground biomass map was chosen to provide reference carbon stocks.
348 While other maps have previously been produced by Saatchi et al. (64) and Baccini et al. (65) we
349 selected the Avitabile map because it synthesises the earlier maps (see Mitchard et al. (66) for
350 discussion of substantial differences between these maps) and is anchored by more field data.
351 Importantly, the Avitabile map reproduces spatial patterns in aboveground biomass that have been
352 described from field data but are absent in the Saatchi or Baccini maps, including the much higher
353 biomass density of north-east Amazonian forests due to tall trees and very high wood density (67).
354 Nevertheless, we also investigated the consequences of using the Saatchi or Baccini maps for our
355 estimates of biomewide thermal sensitivity and spatial patterns of change in carbon stocks (Fig S15).

356 We investigated three temperature change scenarios. Firstly, we applied a 1°C increase to all
357 locations. Secondly, we assessed the consequence of global temperatures stabilizing 1.5°C above pre-
358 industrial levels for the equilibrium temperature response of tropical forest carbon. Finally, we
359 assessed the consequence of global temperatures stabilizing 2°C above pre-industrial levels. For the
360 latter two we obtained data from CMIP5 climate models, using downscaled future climate projections

361 based on the Worldclim climatology (68). As downscaling was performed using Worldclim version
 362 1.4 (69) and our statistical models use Worldclim version 2, we calculated the warming anomaly in
 363 each grid-cell from the current Worldclim version 1.4 conditions, and applied this to the Worldclim 2
 364 data to obtain future temperature. RCP scenarios and time-points were chosen to give global
 365 temperature increases that best match 1.5°C and 2°C above pre-industrial. Importantly, these future
 366 climate projections were used to capture the spatially varying nature of warming, and our predictions
 367 relate to the long-term response of vegetation if the climate stabilised at these new warming levels,
 368 rather than being predictions of transient responses at these specific time-points. For 1.5°C we used
 369 RCP 2.6 averaged for 2040-2060 (median temperature increase across models = 1.5°C, (70)). For
 370 2°C, we used RCP 2.6 averaged for 2040-2060 (median temperature increase models = 1.9°C (70)).
 371 Note that predicted increases in maximum temperatures were often considerably greater than the
 372 global increase, especially in South America. For both scenarios we used the median predicted
 373 temperature change for each grid-cell from an ensemble of 15 models (BCC-CSM1-1, CCSM4,
 374 CNRM-CM5, GFDL-CM3, GFDL-ESM2G, GISS-E2-R, HadGEM2-AO, HadGEM-ES, IPSL-
 375 CM5A-LR, MIROC-ESM-CHEM, MIROC-ESM, MIROC5, MPI-ESM-LR, MRI-CGCM3,
 376 NorESM1-M).

377 We assessed the potential for long-term carbon dioxide growth stimulation to offset these long-term
 378 temperature effects. We used CO₂ concentrations from the RCP scenarios and time-points described
 379 above, which approximate the long-term concentrations if the climate stabilised at the new
 380 temperatures (71). Thus the 1.5°C and 2°C scenarios were associated with CO₂ concentrations of 443
 381 ppm and 487 ppm respectively (72). We cannot assess the effect of CO₂ on biomass from our spatial
 382 dataset, so instead used independent estimates of CO₂ effects from other sources. Firstly, we obtained
 383 CO₂ only effects on net primary production (NPP) extracted from an ensemble of CMIP5 earth system
 384 models by (73). This gives the proportional change in NPP for evergreen forests (note that this also
 385 includes boreal forests) over 1980-2010, standardised to a 100 ppm increase in CO₂ concentration. To
 386 propagate this through to changes in AGB under future CO₂ conditions we first estimated the
 387 logarithmic dependency of NPP on CO₂ (74) by substituting values of NPP and CO₂ at time zero and t
 388 (from (73)) into the equation,

$$389 \quad NPP_t = NPP_0 \left[1 + \beta \ln \left(\frac{[CO_2]_t}{[CO_2]_0} \right) \right] \quad \text{Equation 7}$$

390 This equation can be used to compute NPP annually given an initial NPP estimate and a time series of
 391 atmospheric CO₂ concentrations (from a combination of the observed record from pre-industrial and
 392 the RCP 4.5 scenario, modified so that it stabilises at 487 or 443 ppm depending on warming
 393 scenario). Initial pre-industrial NPP was back-calculated from present-day values using Equation 7,
 394 with 13.3 Mg C ha⁻¹ yr⁻¹ (mean of nine Amazon plots where NPP has been measured, from (75)) used

395 for present-day NPP. To propagate NPP into change in woody biomass (following (49)) we used the
 396 equation

$$397 \quad \frac{dM_{\text{wood}}}{dt} = \alpha_{\text{wood}} N_{\text{P}} - \frac{M_{\text{wood}}}{\tau_{\text{wood}}} \quad \text{Equation 8}$$

398 where M_{wood} is woody biomass, N_{p} is NPP, α_{wood} is the allocation of NPP to wood (taken as 0.33, the
 399 mean value across nine plots from (75)) and τ_{wood} is the residence time of woody biomass, taken as
 400 59.1 years (the median value across plots used in this study). This model (equations 7 and 8) was run
 401 from pre-industrial to 2500, enabling us to see the equilibrium effect of increased CO₂ concentrations
 402 on biomass, assuming temporally invariant allocation and residence time. We calculated the
 403 proportional change in biomass from 2000 to 2500, and applied this to the reference carbon stock map
 404 to obtain predicted equilibrium change in aboveground biomass due to CO₂ effects.

405 The effects of CO₂ in earth system models have been reported to be larger than those deduced from
 406 satellite data or CO₂ enrichment experiments (73), so we also ran the above model using changes in
 407 NPP reported from a synthesis of free-air CO₂ enrichment experiments conducted in forests (73).
 408 Finally, we looked at the impact of using CO₂ effects derived from a recent large meta-analysis of
 409 CO₂ enrichment experiments (76), which reported a 12.5 % increase in biomass of tropical trees for a
 410 250 ppm increase in CO₂ concentration. As this relationship was reported to be linear (76) we used
 411 linear interpolation to estimate the change in biomass under CO₂ concentrations associated with each
 412 warming scenario (i.e. 443 and 487 ppm). To estimate long-term changes in biomass accounting for
 413 both temperature and carbon dioxide, we first applied the CO₂ relationship to estimate the change in
 414 biomass due to carbon dioxide growth stimulation, and then assessed the effects of warmer
 415 temperatures from this revised baseline. Our approach allows a simple assessment of CO₂ effects
 416 exploring a range of different effect strengths. Real-world responses will likely be more complex,
 417 with, for example, nutrient limitation potentially affecting the extent to which growth is stimulated by
 418 CO₂ (76).

419 Temperature sensitivity of CMIP5 models

420 The temperature sensitivity (γ_{LT}) of coupled climate carbon cycle models can be identified by
 421 comparing responses of carbon stocks in coupled and uncoupled simulations forced with a 1%
 422 increase in CO₂ concentrations per year (respectively, these are the 1pctCO2 and esmFixClim
 423 simulations), following Wenzel et al. (77). Both coupled and uncoupled simulations are exposed to
 424 the same increase in CO₂ concentration, but in the uncoupled simulation temperature is not directly
 425 affected by this increase in CO₂.

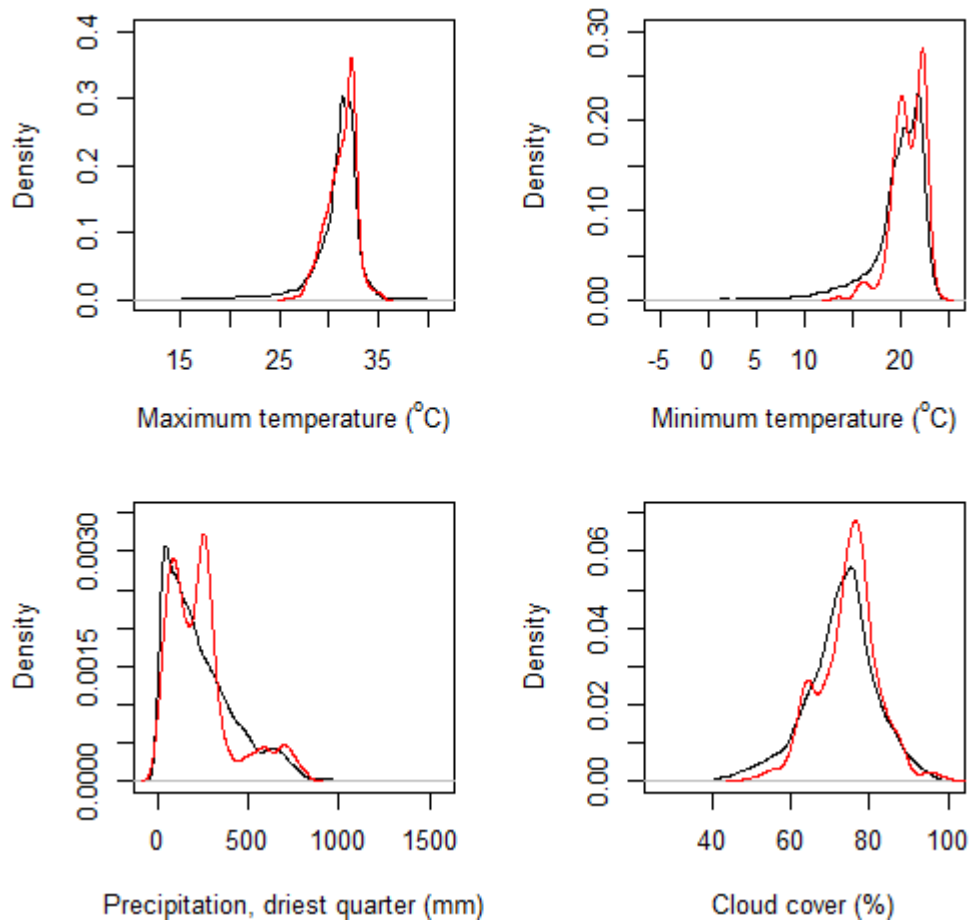
426 Vegetation carbon outputs are reported from six CMIP5 models, each with coupled and uncoupled
 427 simulations (78, 79). For all simulations, we calculated the change in vegetation carbon (the *cVeg*

428 variable) in the tropics between year 110 and year 30 of the experiment, and also calculated the
429 difference in land temperature (the *tas* variable). The change in vegetation carbon due to temperature
430 alone was calculated by taking the difference in change in vegetation carbon in the coupled (ΔC_{vegC})
431 and uncoupled (ΔC_{vegU}) simulation, and this was then divided by the change in tropical land
432 temperature (ΔT) to obtain the temperature sensitivity of the model,

$$433 \quad \gamma_{LT} = (\Delta C_{vegC} - \Delta C_{vegU}) / \Delta T \quad \text{Equation 9.}$$

434 We calculated the temperature sensitivity of the six CMIP5 models that report vegetation carbon:
435 CESM-1-BGC ($\gamma_{LT} = -0.7 \text{ Pg C } ^\circ\text{C}^{-1}$), GFDL-ESM2M ($\gamma_{LT} = -58.4 \text{ Pg C } ^\circ\text{C}^{-1}$), HadGEM2-ES ($\gamma_{LT} = -$
436 $9.2 \text{ Pg C } ^\circ\text{C}^{-1}$), IPSL-CM5A-LR ($\gamma_{LT} = -11.3 \text{ Pg C } ^\circ\text{C}^{-1}$), MPI-ESM-LR ($\gamma_{LT} = -22.8 \text{ Pg C } ^\circ\text{C}^{-1}$) and
437 NorESM1-ME ($\gamma_{LT} = -1.0 \text{ Pg C } ^\circ\text{C}^{-1}$). Note that the simulations do not run to equilibrium (77), so
438 changes in carbon stocks due to increased temperature may not be fully realised.

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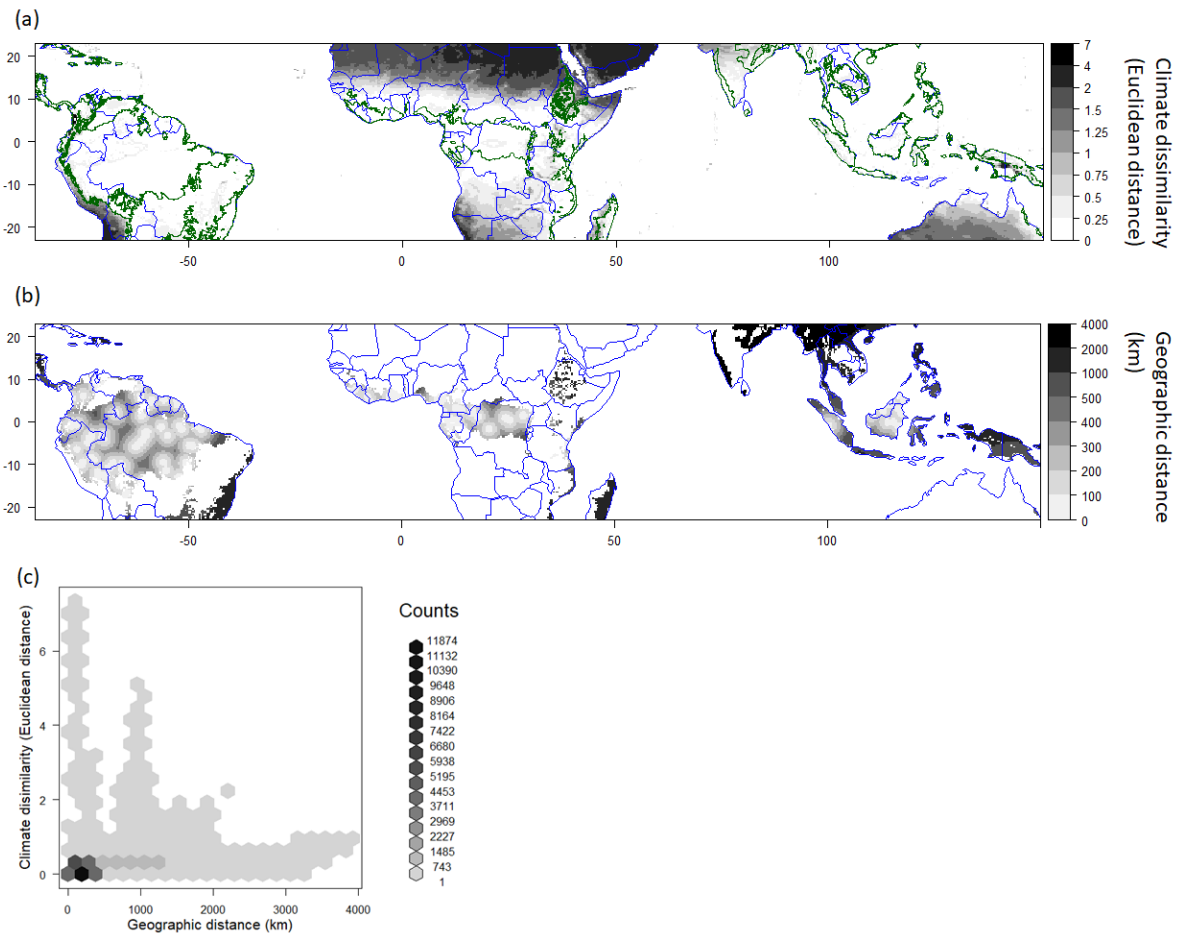
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Figure S1. Climate space represented by our plot network. Red lines show the probability density function of each variable in our multi-census plot network. Black lines show the probability density across 10 minute grid-cells in the biome, restricted to areas with forest cover in GLC 2000 (80).

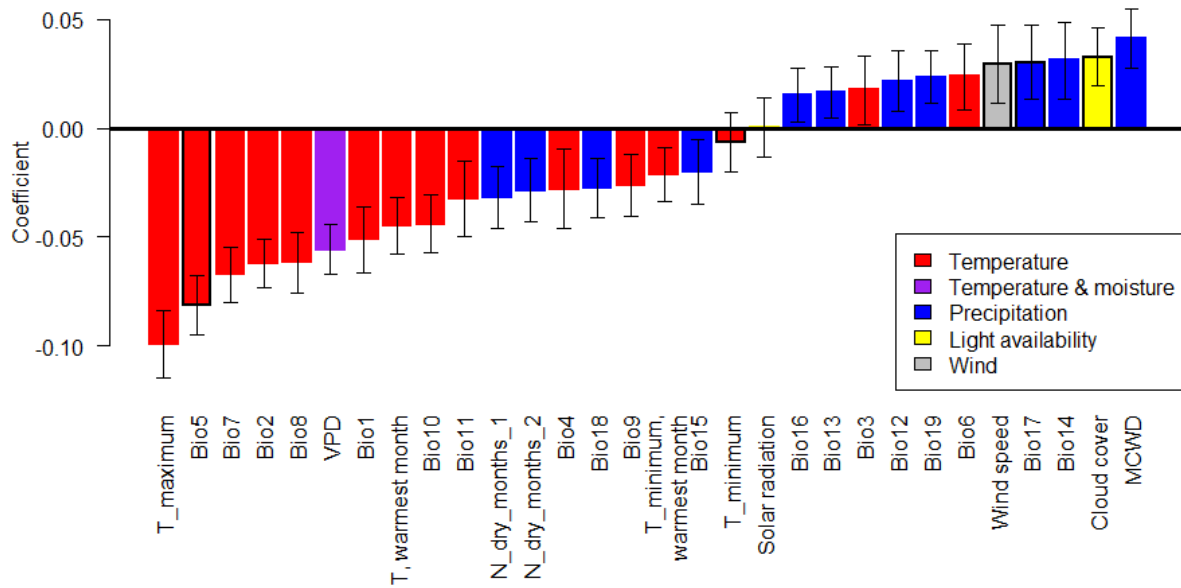
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447 **Figure S2.** Ability of our plot network to represent the climate conditions found in the moist tropical
 448 forest biome. (a) Minimum climate dissimilarity (measured as Euclidean distance on variables scaled
 449 by their standard deviation). Climate variables used are the same as in Fig. 2) between 10 minute grid
 450 cells and the multi-census plot network. Green lines indicate the extent of the biome. (b) Geographic
 451 distance (km) between grid cells and the multi-census plot network. (c) Relationship between climatic
 452 and geographic distance of 10 minute grid cells across the tropical forest biome to our plot network.
 453 The lack of relationship between climate dissimilarity and geographical distance, alongside the mostly
 454 low climatic dissimilarities, shows that our sampling is sufficient to capture the environmental space
 455 of the biome and that we can reasonably extrapolate to geographically distant areas from our plots,
 456 which are in any case largely deforested already and hence contribute very little to our projected
 457 biome-wide carbon response to climate change. (These tropical moist forest areas that are poorly
 458 sampled and largely lost include the Atlantic Forests in Brazil, Andean Forests in western South
 459 America, eastern Caribbean, Madagascar, and much of tropical South Asia, south China, continental
 460 Southeast Asia, Philippines, Sumatra and Java).

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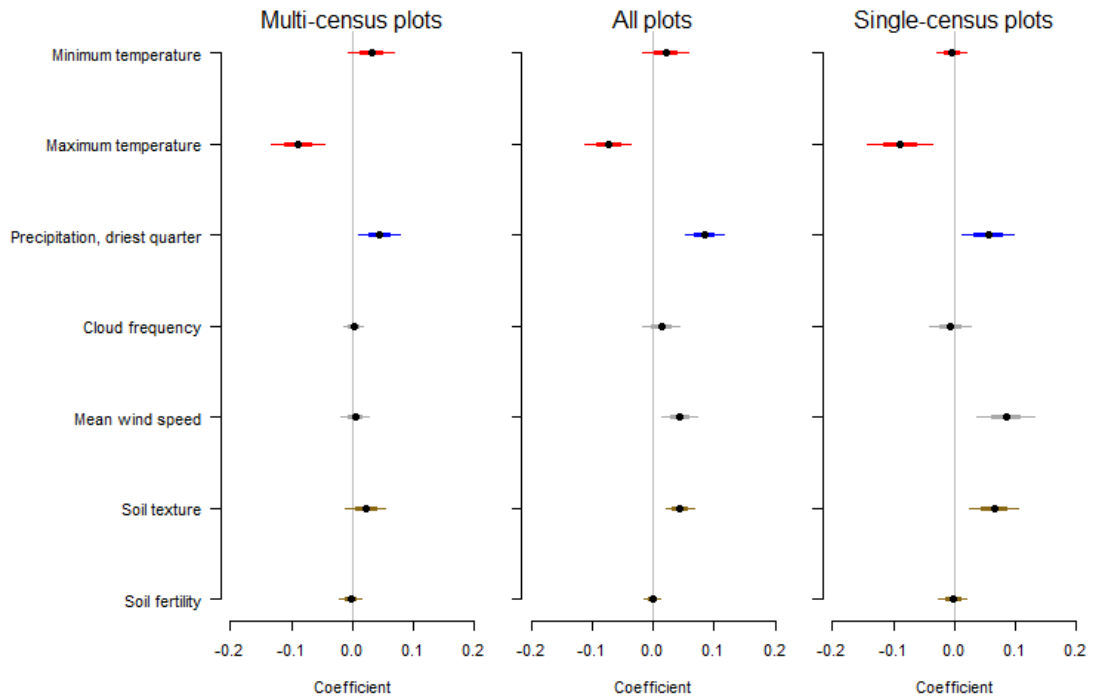
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Figure S3. Relationships between individual climate variables and tropical forest aboveground carbon stocks. Standardised coefficients are from models with the climate variable and continent as explanatory variables and show change in $\ln(\text{carbon})$ for a standard deviation change in the explanatory variable. Error bars show standard errors. Variables used in the main analysis have black outlines. Full variable names are: T_maximum – mean daily maximum temperature, Bio5 – mean daily maximum temperature in the warmest month, Bio7 – annual temperature range, Bio2 – mean diurnal temperature range, Bio8 – mean temperature in the wettest quarter, VPD – vapour pressure deficit, Bio1 – mean annual temperature, Bio10 – mean temperature in the warmest quarter, Bio11 – mean temperature in the coldest quarter, N_dry_months_1 – number of months with negative cumulative water deficit, N_dry_months_2 – number of months where precipitation is less than evapotranspiration, Bio4 – temperature seasonality, Bio18 – precipitation in the warmest quarter, Bio9 – mean temperature in the driest quarter, T_minimum warmest month – mean daily minimum temperature in the warmest month, Bio15 – precipitation seasonality, T_minimum – mean daily minimum temperature, Bio16 – precipitation in the wettest quarter, Bio13 – precipitation in the wettest month, Bio3 – isothermality, Bio12 – annual precipitation, Bio19 – precipitation in the coldest quarter, Bio6 – mean daily minimum temperature in the coldest month, Wind speed – mean daily wind speed, Bio17 – precipitation in the driest quarter, Bio14 – precipitation in the driest month, Cloud cover – proportion of MODIS passes with cloud present, MCWD – maximum cumulative water deficit (note this is negative when water deficit is high, so a positive relationship with MCWD indicates higher carbon when water deficits are less).

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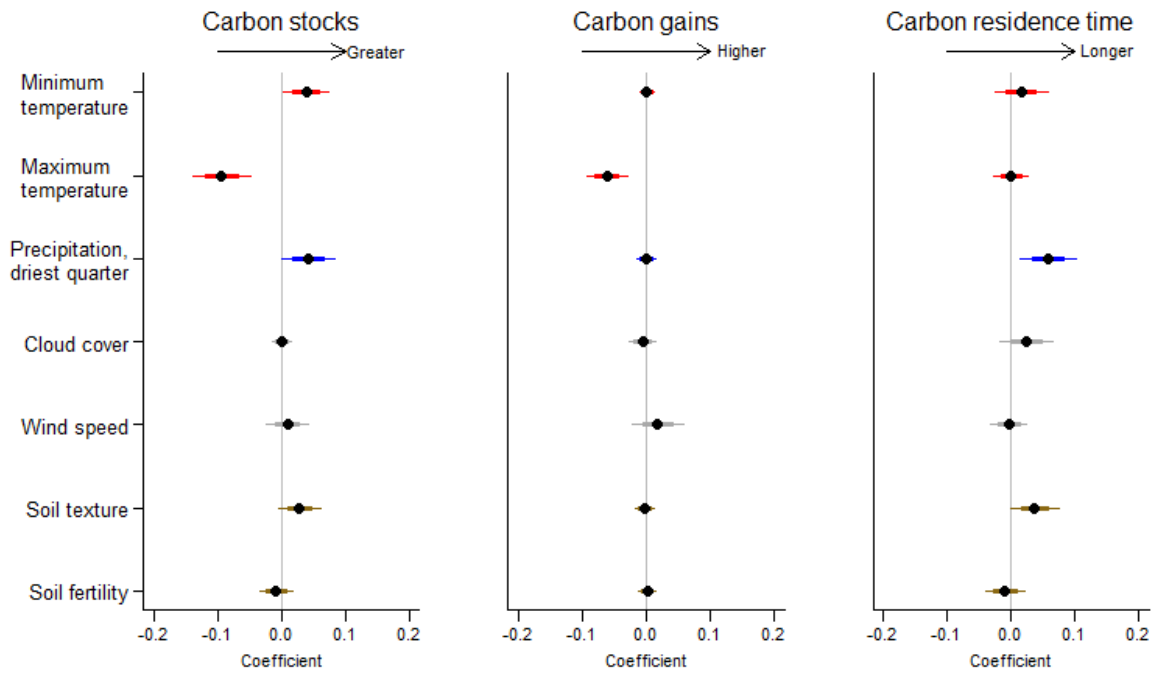
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487 **Figure S4.** Validation of tropical forest carbon stock sensitivity model against an independent dataset
 488 of 223 single-census plots from our networks measured with the same protocols. Model-averaged
 489 shrinkage adjusted coefficients from multiple regression models of biomass carbon stocks as a
 490 function of climate, soil, biogeography and spatial eigenvectors. Models were either fitted to the
 491 multi-census plot dataset (as in Fig. 2), to the single-census plot dataset, or to the combined dataset.
 492 This analysis shows that the relationships identified to be most important in the main multi-census
 493 plot analysis (i.e. the negative relationship between carbon stocks and maximum temperature and
 494 positive relationship with precipitation in the driest quarter) are also found in an independent dataset,
 495 which was not used for preliminary analysis so did not influence the choice of explanatory variables.

496



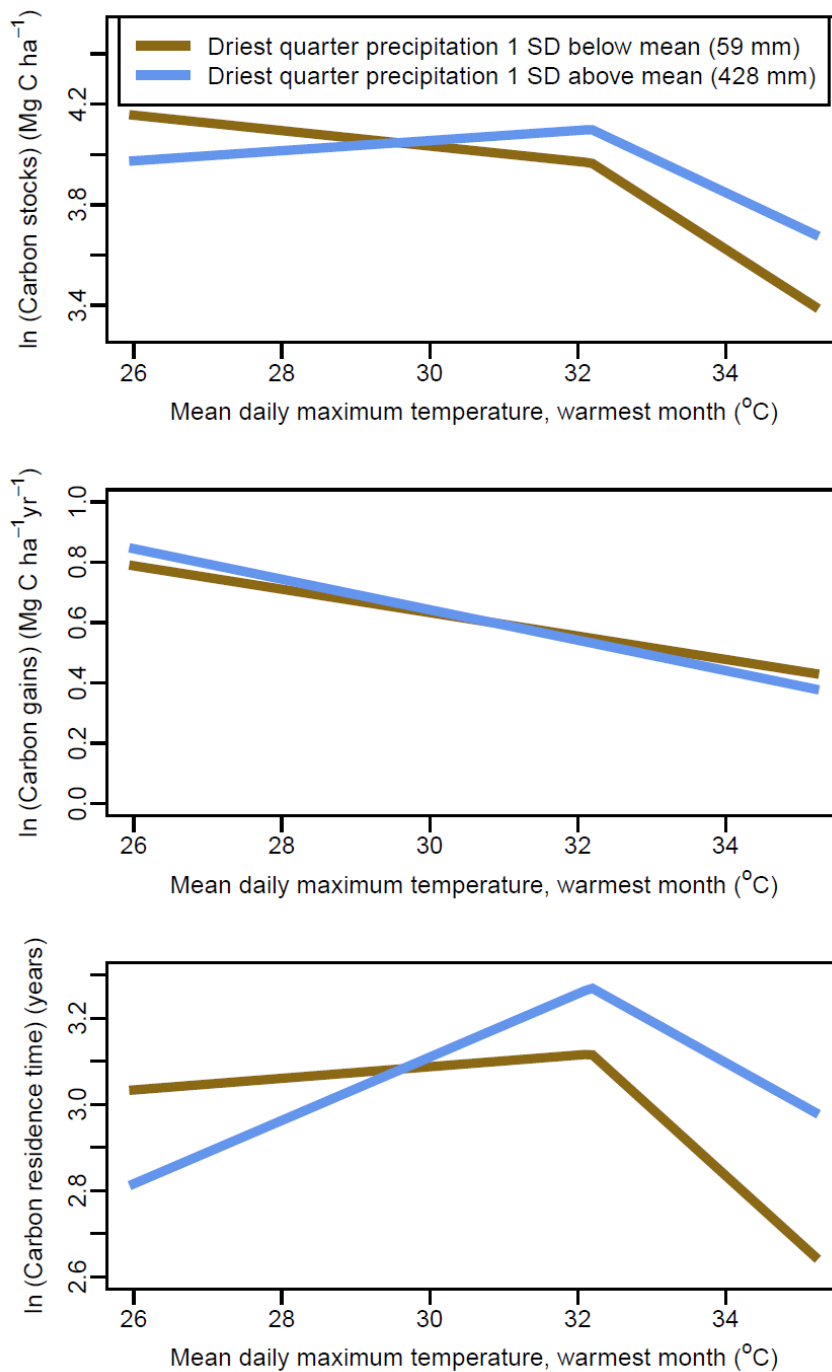
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498 **Figure S5.** As Figure 2, but with aboveground biomass estimated using the Chave et al. 2005 (81)
499 moist forest allometric equation, which does not include a height term and is instead based on a third-
500 order polynomial relationship between diameter and aboveground biomass. This indicates that our
501 results are robust to using an alternative allometry to estimate aboveground biomass.

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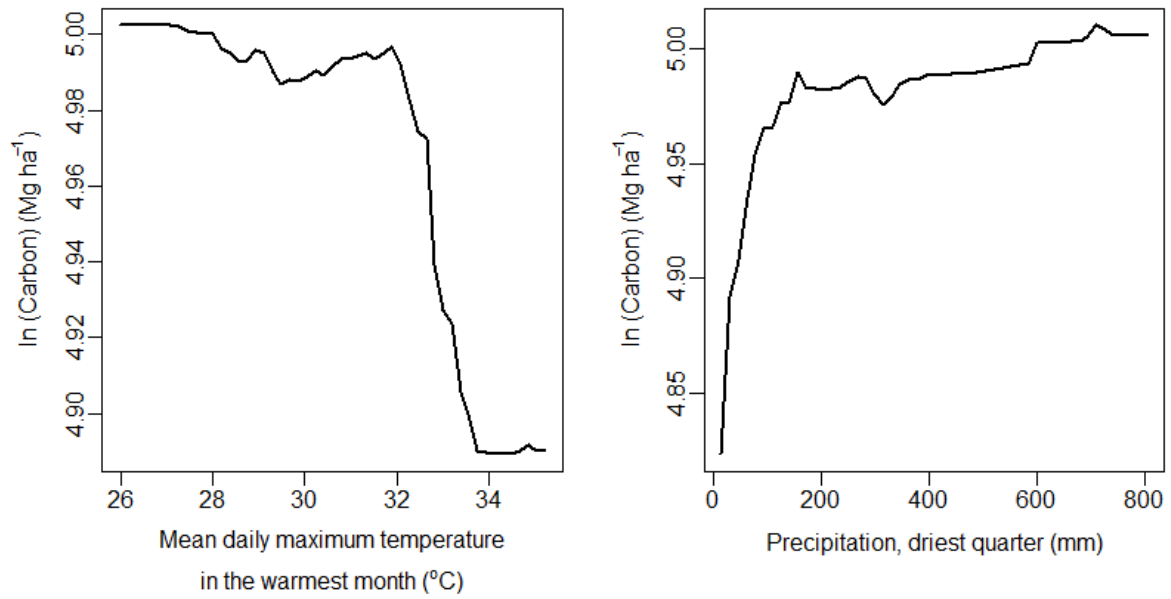
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506 **Figure S6.** Interaction between mean daily maximum temperature in the warmest month and
 507 precipitation in the driest quarter in determining aboveground tropical forest carbon stocks, gains and
 508 residence time. Modelled relationships with temperature are shown holding precipitation either one
 509 standard deviation above or below the mean. Models with breakpoints are shown for carbon stocks
 510 and residence time as they were found to be better supported based on lower AIC ($\Delta AIC > 2$). Note
 511 that the temperature-carbon relationship is steeper when precipitation is low for carbon stocks and
 512 (above the breakpoint threshold) carbon residence time, but does not change with precipitation for
 513 carbon gains. Response curves are predicted with continent set as Africa.

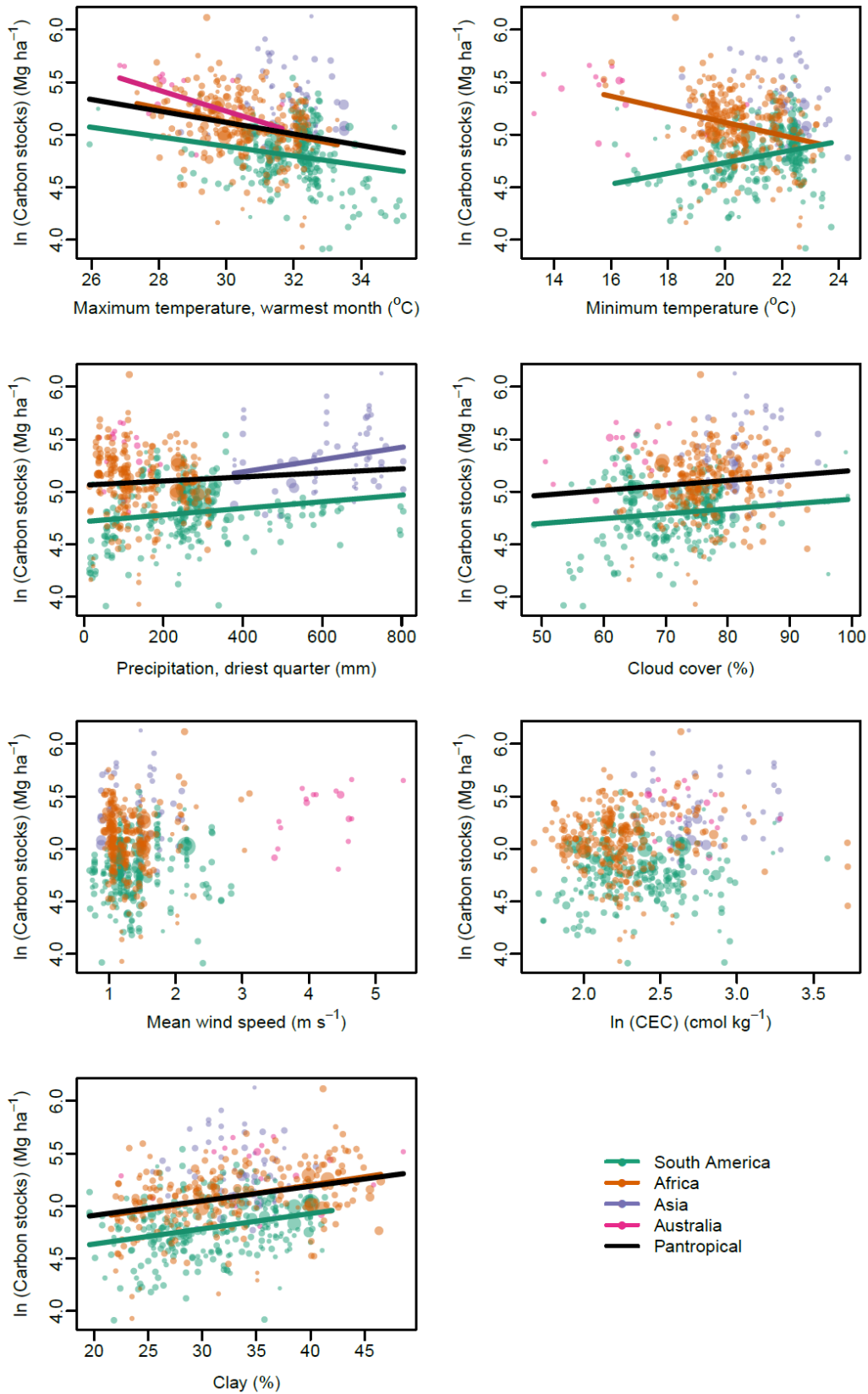
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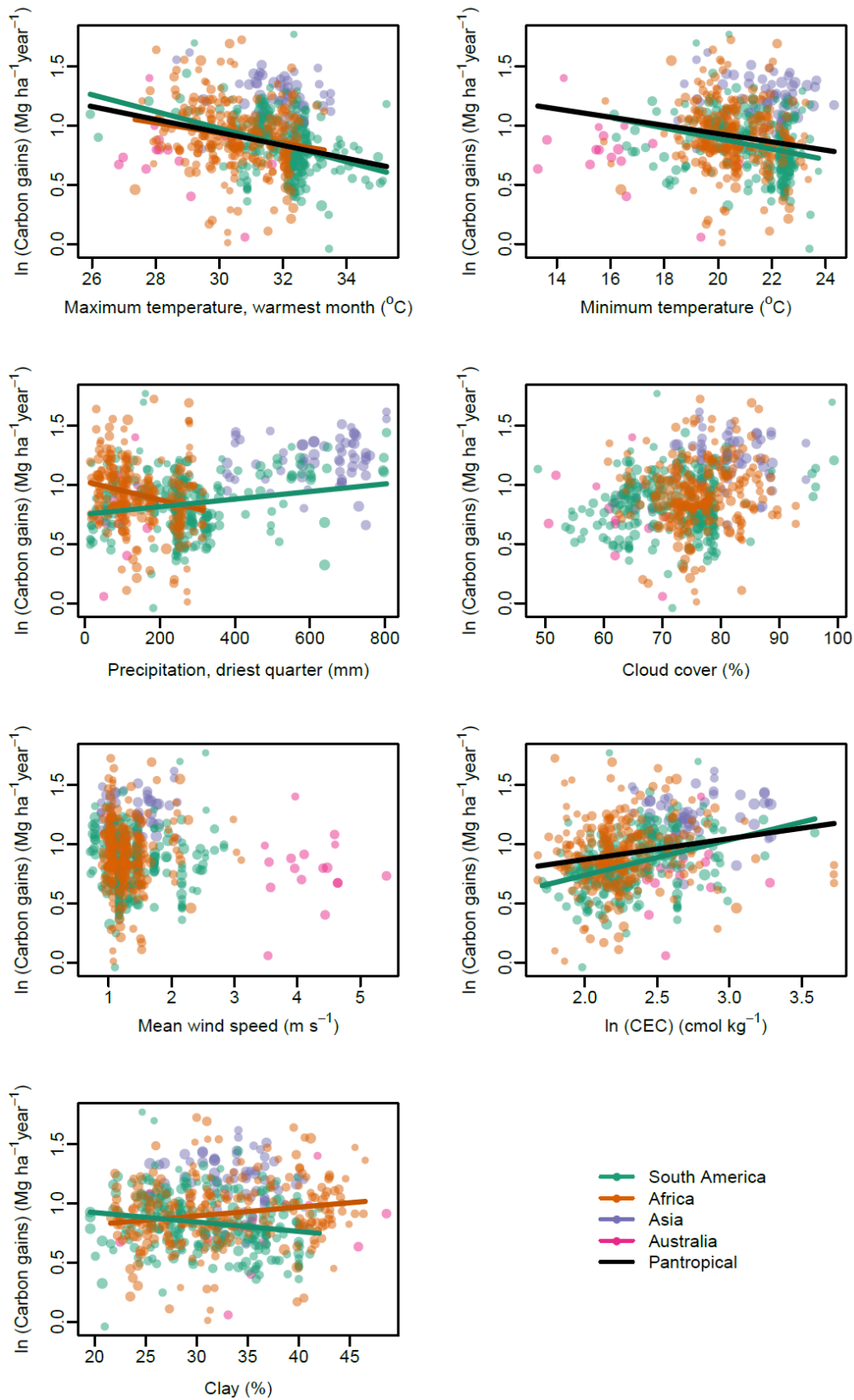
516 **Figure S7.** Partial relationships between tropical forest carbon stocks and the two climate variables
517 identified to be most important by the random forest decision tree algorithm. Partial plots show
518 predicted values of carbon stocks averaged across an ensemble of decision tree models when
519 changing the explanatory variable of interest and holding other variables constant. The importance of
520 variables in random forest analysis is assessed by calculating the average increase in node purity
521 across all decision trees (measured by residual sum of squares) when using the variable to split the
522 data. Higher values indicate greater importance. Maximum temperature increased node purity by 4.8
523 and precipitation by 4.7. For all other climate variables increases in node purity were < 3.5.

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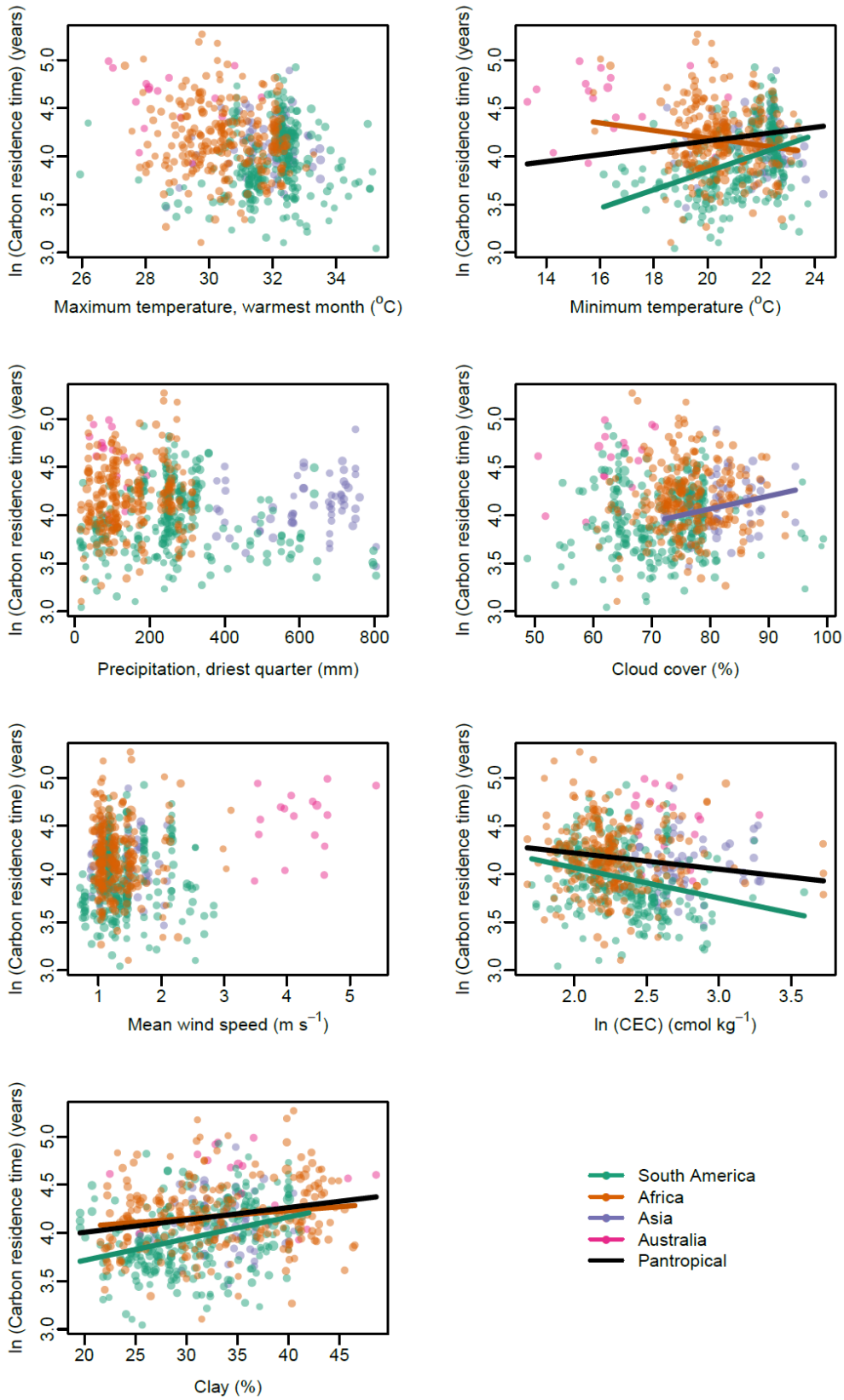
526 **Figure S8.** Relationships between aboveground tropical forest carbon stocks and environmental
 527 predictors. Symbols and colours as in Fig. 3. Coloured lines show bivariate relationships in each
 528 continent, and black lines show pan-tropical relationships also accounting for the effect of continent.
 529 Lines are only plotted where statistically significant.



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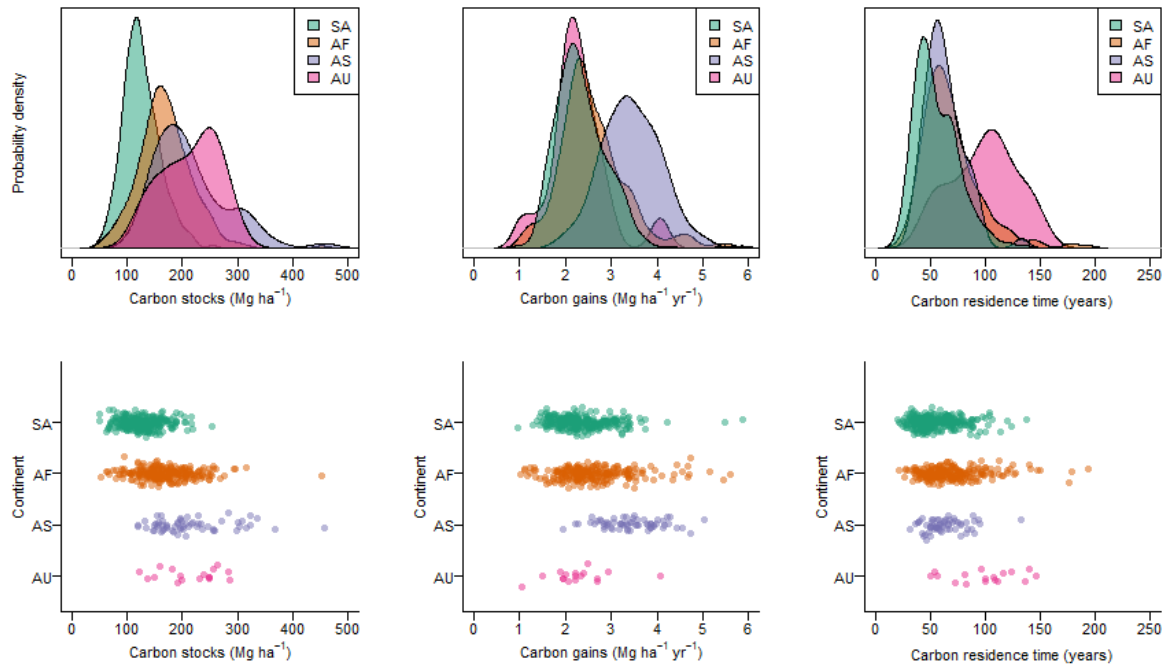
532 **Figure S9.** As Fig. S8, but showing relationships with carbon gains.



533

534 **Figure S10.** As Fig. S8, but showing relationships with carbon residence time.

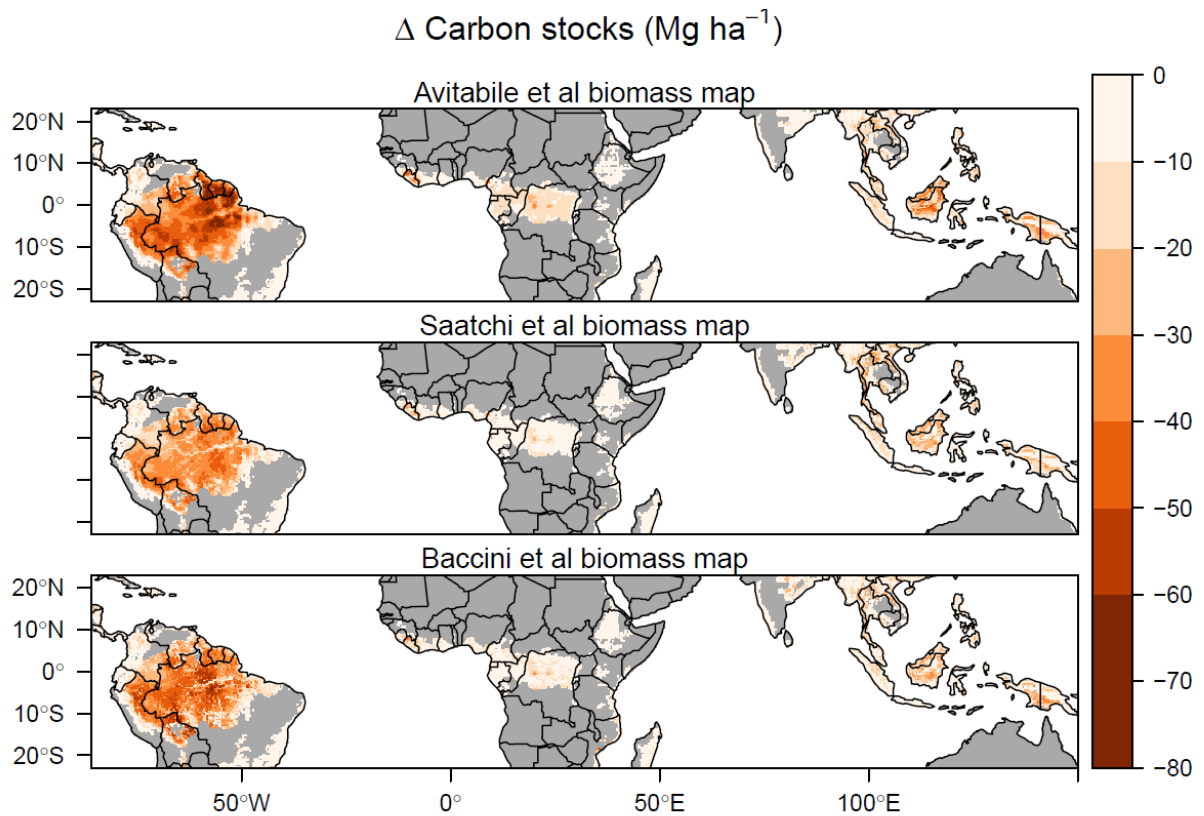
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536

537 **Figure S11.** Variation in tropical forest aboveground carbon stocks, gains and residence time within
538 and amongst continents. Data are presented as empirical probability density functions (top row) and
539 dot-plots showing raw data points for all our multi-census plots (bottom row). SA = South America,
540 AF = Africa, AS = Asia, AU = Australia.

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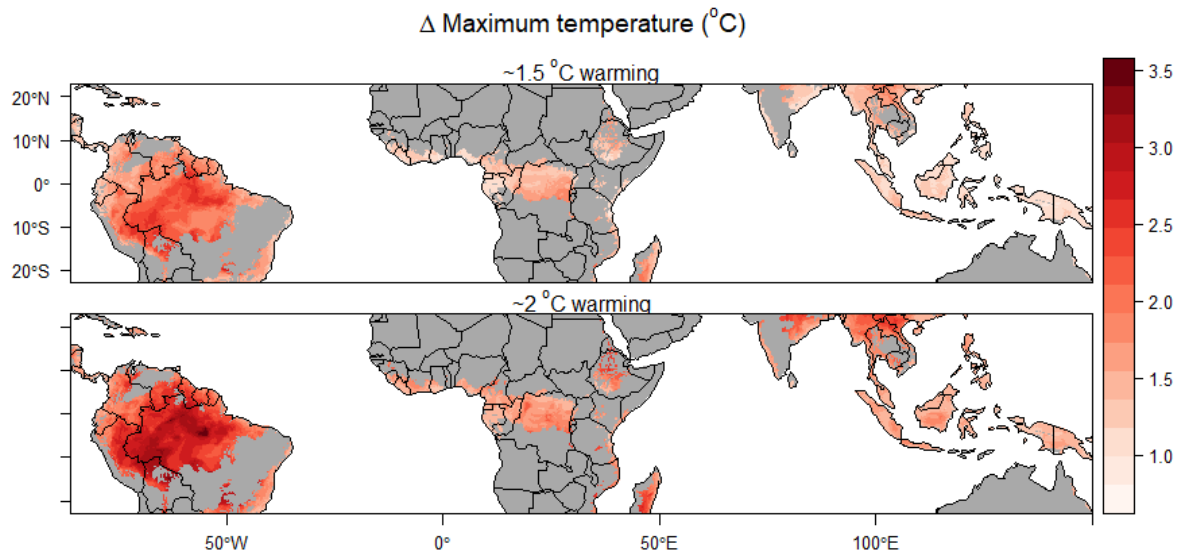
542

543 **Figure S12.** Effect of using earlier biomass reference maps for estimates of change in long-term
544 carbon stocks for global temperature increases of $\sim 2^\circ\text{C}$. Using aboveground biomass stock maps from
545 Saatchi et al. (64) and Baccini et al. (65) predicted biome-wide reductions in biomass carbon stocks
546 are 24.0 Pg (95 % CI = 5.8 – 39.6) and 28.4 Pg (95 % CI = 16.1 – 37.5) respectively. Under the \sim
547 1.5°C warming scenario these are 18.4 Pg (5.8 – 30.5) and 21.1 Pg (10.2 – 29.4) respectively. Results
548 in the main text use the 2016 Avitabile et al. baseline map (30) – see methods for justification.

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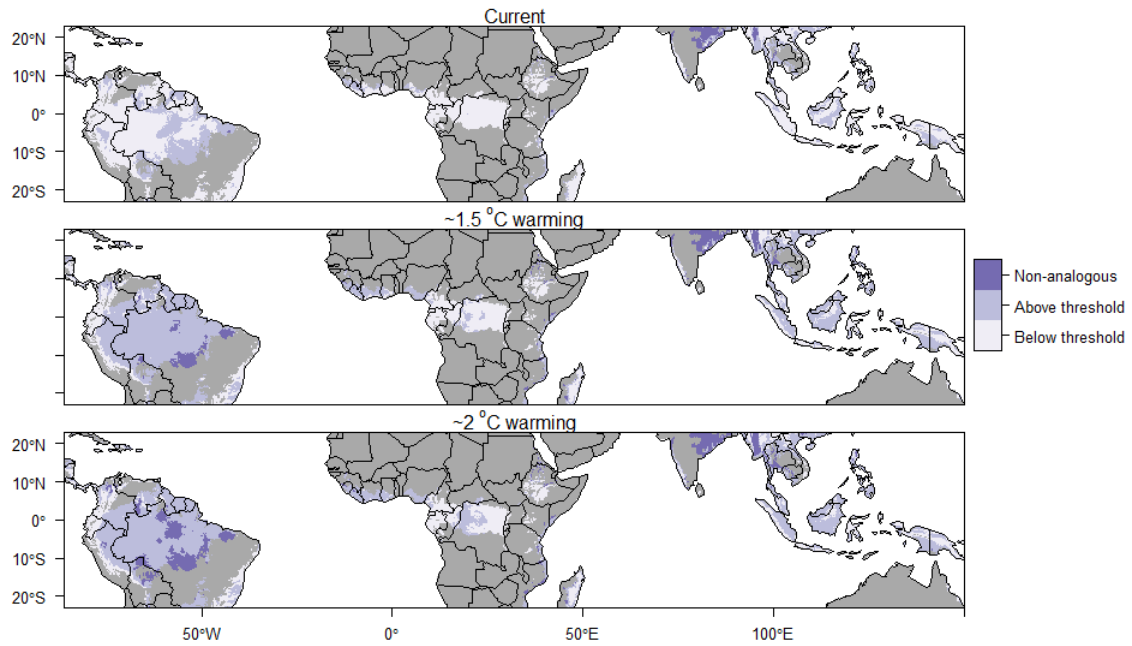
552

553 **Figure S13.** Biome-wide change in mean daily maximum temperature in the warmest month from
 554 present conditions (based on the Worldclim climatology, 1970-2000), given global increases in
 555 temperature of approximately 1.5 $^{\circ}$ C and 2 $^{\circ}$ C above pre-industrial levels. These levels of global
 556 temperature increase are obtained from, respectively, RCP 2.6, 2040-2060 and RCP 4.5, 2040-2060 to
 557 represent the potential spatial pattern of warming associated with global temperatures stabilising at
 558 these levels. Global temperature increases of 1.5 and 2 $^{\circ}$ C above pre-industrial levels (so ~0.8 $^{\circ}$ C and
 559 ~1.3 $^{\circ}$ C above our current baseline climate) would lead to mean increases in maximum temperature in
 560 the warmest month across the tropical forest biome of 1.9 $^{\circ}$ C and 2.4 $^{\circ}$ C the current baseline climate
 561 respectively.

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565

566 **Figure S14** Areas of the biome above or below the 32.2°C threshold, above which carbon stocks
 567 decline more rapidly with temperature, under current conditions and two warming scenarios (see Fig.
 568 4). Areas warmer than any currently observed in our dataset (35.2°C) are also shown (non-analogous
 569 conditions). Note that even the 1.5°C warming scenario pushes most South American forests above
 570 the 32.2°C threshold.

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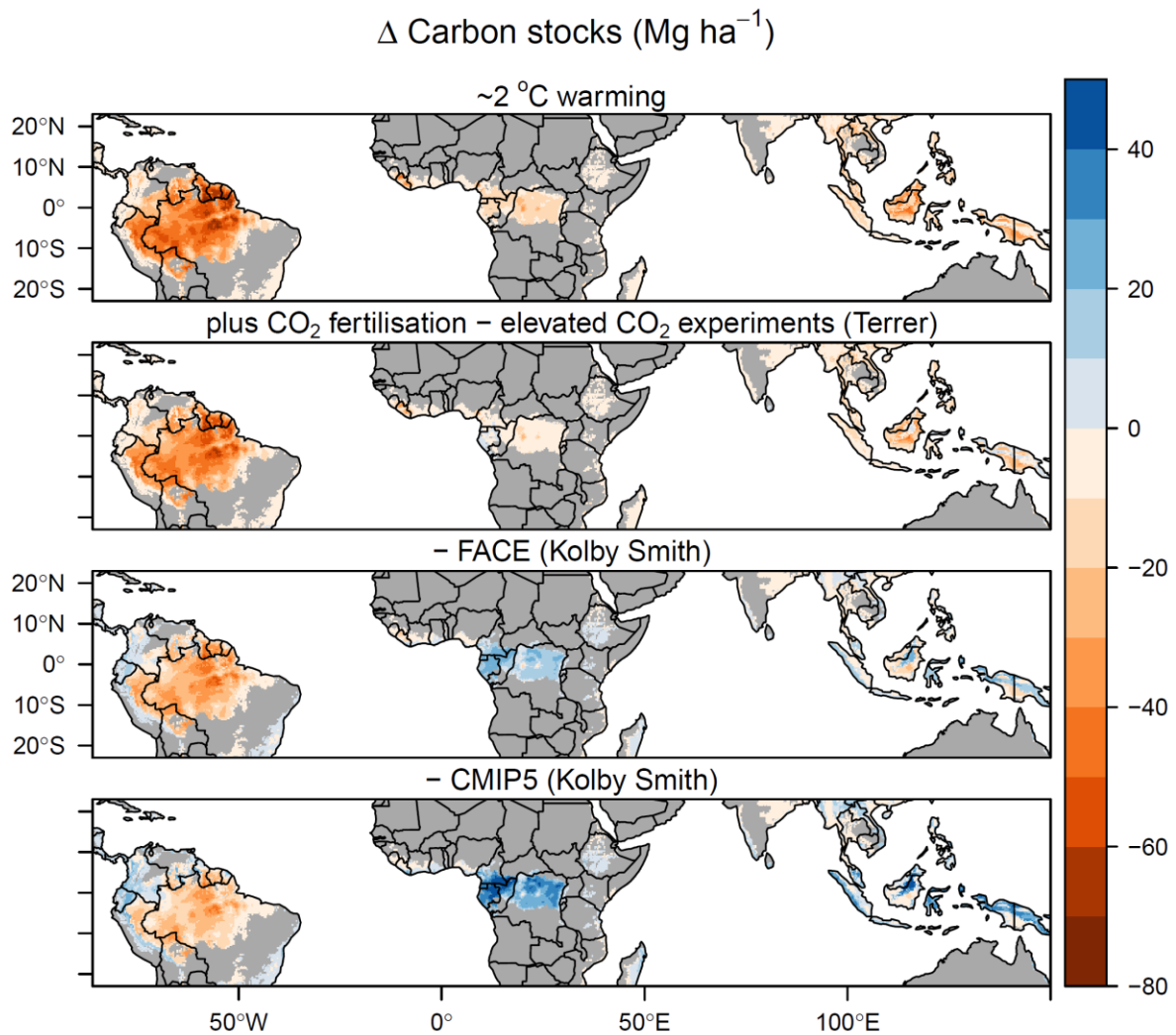
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578 **Figure S15.** Predicted long-term change in aboveground carbon stocks under $\sim 2^\circ\text{C}$ global warming,
 579 based on either temperature effects alone or when also accounting for carbon dioxide growth
 580 stimulation. CO₂ fertilisation effects on equilibrium biomass levels were obtained from a recent
 581 synthesis of results of elevated CO₂ experiments (Terrer et al. (76)), free-air CO₂ enrichment (FACE)
 582 experiments (Kolby Smith et al. (73)) and CMIP5 earth system models (Kolby Smith et al. (73)).
 583 Depending on their strength, CO₂ effects either partially or fully ameliorate the biome-wide negative
 584 effects of increasing temperatures on biomass carbon stocks (Table S3), but these carbon stocks are
 585 predicted to decline over much of Amazonia even under the strongest CO₂ effect considered.

586

587

588 **Table S1.** Climate variables selected for analysis and mechanisms by which they can affect carbon stocks.

Climate property	Variable selected for analysis	Mechanism to affect carbon stocks
Daytime temperature	Maximum temperature in the warmest month ¹	High daytime temperatures exceed photosynthesis optima (82), increase evaporative stress, causing stomatal closure and reducing time for photosynthesis (26) and increase risk of mortality through hydraulic failure and/or carbon starvation (23).
Night-time temperature	Mean daily minimum temperature	Respiration rate increases with temperature so proportion of carbon taken through photosynthesis that is allocated to wood should decline with temperature (83). Increased respiration cost could also reduce tree longevity (23). As respiration occurs day and night, and photosynthesis only in the day, nighttime temperature should better reflect respiration effects and daytime temperature better reflect photosynthesis effects.
Moisture availability	Precipitation in the driest quarter ²	Moisture availability could limit photosynthesis and hence carbon gains, with stomata closing when moisture availability is limiting. The risk of mortality through hydraulic failure or carbon starvation is higher when moisture is limiting (23), and this could also set a limit on potential tree size and hence tree longevity.
Light availability	Cloud frequency	Increased photosynthesis and hence AGWP when light availability is greatest (i.e. cloud cover is low) (84). Alternatively, light availability could have a negative effect due to high evapotranspiration stress when cloud cover is low.
Wind speed	Mean wind speed	Carbon stocks are expected to be lower where physical damage through wind throw or breakage is higher, as carbon is removed more quickly from the system through mortality (85). But there is potential for greater carbon gains if forests are more dynamic.

589 ¹ Mean daily temperature in the warmest month (bio5) was selected instead of mean daily maximum temperature as it was more strongly decoupled from
590 other climate variables. VPD could also represent some of these effects, but was too strongly correlation with maximum temperature to include as an
591 independent variable.

592 ² Moisture availability could also be represented by MCWD (maximum cumulative water deficit) or total precipitation, but only one of the three variables
593 could be included in the model due to collinearity. MCWD was excluded as it is zero truncated, so less amenable to regression fitting.

594

595 **Table S2.** Coefficients of model-averaged general linear models of carbon stocks, gains and residence time as a function of climate, soil, continent and spatial
 596 autocorrelation. Coefficients are AIC weighted averages across models with $\Delta AIC < 4$ from the best performing model; variables are given a score of zero if
 597 they did not appear in a model. NA indicates that a term did not occur in any model in this set. MEM1-8 are spatial eigenvectors.

Variable	Carbon stocks				Carbon gains				Carbon residence time			
	Estimate	SE	Z	P	Estimate	SE	Z	P	Estimate	SE	Z	P
Intercept - Africa	4.986	0.010	476.9	<0.001	0.571	0.525	1.09	0.278	3.909	0.688	5.67	<0.001
Minimum temperature	0.031	0.019	1.67	0.096	-0.001	0.007	0.18	0.861	0.019	0.022	0.88	0.381
Maximum temperature, warmest month	-0.089	0.022	4.11	<0.001	-0.060	0.017	3.47	<0.001	-0.001	0.015	0.10	0.924
Precipitation, driest quarter	0.045	0.018	2.54	0.011	-0.001	0.008	0.14	0.887	0.061	0.023	2.70	0.007
Cloud frequency	0.002	0.008	0.24	0.814	-0.006	0.011	0.54	0.592	0.025	0.021	1.17	0.241
Wind speed	0.004	0.012	0.38	0.705	0.016	0.020	0.78	0.437	-0.004	0.015	0.24	0.807
Soil texture (% clay)	0.021	0.017	1.26	0.208	-0.005	0.011	0.49	0.628	0.040	0.018	2.17	0.030
Soil fertility (CEC)	-0.003	0.009	0.34	0.732	0.005	0.011	0.51	0.613	-0.012	0.017	0.70	0.486
MEM1	0.115	0.014	7.96	<0.001	0.319	0.559	0.57	0.569	0.375	0.734	0.51	0.610
MEM2	0.098	0.017	5.67	<0.001	0.083	0.273	0.30	0.762	0.286	0.359	0.80	0.427
MEM3	-0.025	0.014	1.84	0.065	0.014	0.041	0.34	0.735	0.007	0.054	0.12	0.904
MEM4	-0.021	0.011	1.84	0.066	-0.038	0.020	1.84	0.066	-0.002	0.027	0.07	0.945
MEM5	0.027	0.011	2.46	0.014	0.020	0.015	1.33	0.182	0.020	0.020	0.98	0.327
MEM6	0.017	0.011	1.56	0.118	0.025	0.011	2.34	0.019	-0.014	0.014	1.05	0.293
MEM7	0.010	0.011	0.93	0.353	-0.017	0.010	1.61	0.107	0.036	0.014	2.57	0.010
MEM8	-0.072	0.013	5.64	<0.001	0.057	0.012	4.91	<0.001	-0.127	0.016	7.80	0.000
Asia	NA				0.380	0.542	0.70	0.485	-0.753	0.683	1.10	0.271
Australia	NA				-0.173	0.390	0.44	0.658	0.006	0.516	0.01	0.990
South America	NA				0.643	1.164	0.55	0.582	0.542	1.530	0.35	0.724

599 **Table S3.** Predicted biome-wide changes in long-term biomass carbon stocks (scaled to include root
600 biomass) under global temperature increases of ~ 1.5°C and ~ 2°C. Changes are based on temperature
601 effects alone, and when also accounting for the effect of increased CO₂ concentrations on tree growth.
602 CO₂ effects were obtained from a synthesis of results of elevated CO₂ experiments (Terrer et al. (76)),
603 free-air CO₂ enrichment (FACE) experiments (Kolby Smith et al. (73)) and CMIP5 earth system
604 models (Kolby Smith et al. (73)). 95% confidence intervals around changes (based on uncertainties in
605 temperature effects alone) are shown in parentheses.

CO ₂ effect	Change in biomass carbon stocks (Pg)	
	~ 1.5°C warming (443 ppm CO ₂)	~ 2°C warming (487 ppm CO ₂)
None	-26.9 (-38.4 - -15.8)	-35.3 (-49.0 - -20.9)
Terrer et al. elevated CO ₂ experiments	-22.0 (-33.0 - -9.9)	-26.3 (-37.6 - -11.5)
Kolby Smith et al. FACE experiments	-6.2 (-16.8 - 7.7)	-9.9 (-24.3 - 3.9)
Kolby Smith et al. CMIP5 models	3.9 (-8.3 - 12.6)	2.0 (-11.9 - 19.8)

606