

The global distribution of plants used by humans

Article

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29 Abstract:

- 30 Plants sustain human life. Understanding geographic patterns of the diversity of species used by
- 31 people is thus essential for the sustainable management of plant resources. Here, we investigate
- the global distribution of 35,687 utilised plant species spanning ten use categories (e.g., food,
- 33 medicine, material). Our findings indicate general concordance between utilised and total plant
- diversity, supporting the potential for simultaneously conserving species diversity and its
- 35 contributions to people. While Indigenous lands across Mesoamerica, the Horn of Africa, and

36 Southern Asia harbor a disproportionate diversity of utilised plants, the incidence of protected

areas is negatively correlated with utilised species richness. Finding mechanisms to preserve

areas containing concentrations of utilised plants and traditional knowledge must become a

39 priority for the implementation of the Kunming-Montreal Global Biodiversity Framework.

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- 41

42 **One Sentence Summary:**

Plants and their contributions to people are insufficiently protected globally, pointing to the needto preserve biocultural hotspots.

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47 Main Text:

Biodiversity provides essential goods and services sustaining human life and well-being 48 (e.g., food, medicines, materials, fuel) (1, 2). The balance between humanity's needs and the 49 protection of the natural environment is nevertheless fragile, as increased consumption of 50 resources, global trade, land and sea use change, and socio-economic inequalities are having a 51 dramatic influence on biodiversity (3, 4). To minimise biodiversity loss, conservation biologists 52 have focused on identifying and prioritising regions of high species richness, endemism, and threat 53 (5). The "biodiversity hotspot" concept (6) assumes that species diversity is spatially congruent 54 with the contributions that it provides to people and therefore, protecting areas with the largest 55 concentrations of threatened species will also protect humanity indirectly (5). Moreover, as 56 biodiversity is most concentrated where human cultural diversity is highest, it is assumed that high 57 biocultural diversity is associated with high concentrations of species used by humans (7). Yet, 58 59 these assumptions lack empirical support, leading to growing calls for better integration of humannature interactions into conservation planning and implementation (3, 8-10), as highlighted by the 60 recently adopted Kunming-Montreal Global Biodiversity Framework (GBF) and the 2022 61 assessment report on the sustainable use of wild species of the Intergovernmental Science-Policy 62 Platform on Biodiversity and Ecosystem Services (IPBES) (2). 63

Plants are essential structuring components of ecosystems and human livelihoods (9, 11). 64 Although the geography of terrestrial plant diversity has been extensively investigated globally (6, 65 12, 13), our understanding of the distribution of ecosystem services and societal benefits provided 66 by plants is incipient, despite the importance of this information for decision-makers and local 67 stakeholders in supporting the sustainable development agenda (14, 15). Recent modelling efforts 68 have been dedicated to the global distribution of nature's contributions to people, including water 69 quality, crop pollination and carbon stocks (16, 17). However, the extent to which these 70 contributions relate to species diversity remains largely unknown, hampering progress towards a 71 more sustainable management of biodiversity. Assessing the global diversity and distribution of 72 plant species used by people is thus critical to better understand, manage and preserve both the 73 intrinsic and instrumental values of biodiversity (18). 74

75 The global distribution of utilised plant species richness and endemism

Most plant species can potentially be useful to people, but only a fraction of plant diversity is currently known to be used. Here we consider utilised plants as vascular terrestrial species for

which material and non-material benefits to humans have been reported and made publicly 78 accessible (19, 20). By extracting information from twelve databases containing plant uses (Table 79 S1; (21)), we identified 35,687 utilised species and assembled >11 million georeferenced 80 81 occurrence records to map their global distribution (i.e., native and introduced ranges) (Figs. S1-2; (19)). We built species distribution models for each utilised species and stacked the resulting 82 maps to assess the global distribution of their potential richness (Figs. S3-6; (19)). We find the 83 highest concentrations of utilised plant species in the tropics (Fig. 1), but several temperate areas 84 also contain high native (e.g., China, the Himalayas; Fig. S7) and introduced richness (e.g., 85 Western Europe, Eastern USA; Fig. 1). Despite large discrepancies in the sampling of species 86 geographic records (Fig. S1; (22)), these results match our estimates using coarser but more 87 complete independent distribution data from the World Checklist of Vascular Plants (WCVP (23); 88 Fig. S8), which provides additional support for our predictions. 89

90 Distribution patterns in species richness do not systematically match those of other biodiversity indices considered important for conservation such as rarity or threat (5, 6). Therefore, 91 we also estimated the distribution of utilised plant species richness weighted by each species' range 92 size (i.e., weighted endemism) to identify areas with high concentrations of rare and potentially 93 irreplaceable species. We find that many areas with high richness of utilised plant species also 94 exhibit high endemism (e.g., Mesoamerica, Gulf of Guinea, Southern Africa, the Himalayas, 95 South-East Asia; Fig. 1, Fig. S8). Other areas also to emerge as exceptional centers of endemic 96 utilised plant species include California, Macaronesia, Madagascar, the Eastern Mediterranean, 97 the Western Ghats, Sri Lanka, Eastern Australia, and the Pacific islands. Conversely, 98 concentrations of endemic utilised species are relatively low across temperate areas. This confirms 99 that the high species richness observed in some temperate regions is due to a high concentration 100 of well-surveyed, widely distributed, and often introduced plant species of economic importance 101 (22, 24). Overall, the distribution of utilised plant endemicity mirrors patterns observed across all 102 vascular plants, with higher endemism in areas with insularity and high topographic and 103 environmental heterogeneity (25, 26). 104

105 The latitudinal distribution of utilised plant species and their different uses

106 To refine our understanding of the geographic patterns underpinning the diversity of utilised plant species, we disaggregated plant use reports into ten use categories, adapted from the 107 Economic Botany Data Collection Standards: human food (including beverages and additives), 108 vertebrate food (forage and fodder), invertebrate food (e.g., plants feeding honey bees or 109 silkworms), materials (e.g., wood, fiber), fuels (e.g., charcoal, alcohol), social uses (e.g., narcotics, 110 ritual, religious uses), poisons (for both vertebrates and invertebrates), medicines (for both human 111 and veterinary use), environmental uses (e.g., intercrops, windbreaks, ornamentals), and gene 112 sources (e.g., crop wild relatives) (19, 21). We find that latitudinal variation of utilised plant 113 species richness is broadly consistent for all ten use categories, with higher values in the tropics 114 gradually declining towards high latitudes (Fig. 2, Figs. S9-10). Therefore, areas with high 115 concentrations of utilised plant species also contain large numbers of species for each use type. 116 Despite the overall similarity in latitudinal patterns among use categories, there are striking 117 differences amongst temperate regions that are proportionally richer in plant species associated 118 with vertebrate food, social uses and poisons, compared to species-rich tropical environments that 119 contain proportionally more species associated with the most essential uses for human subsistence 120 (i.e., human food, material, and medicine). Concentrations of species used as gene sources are 121 exceptionally high around the equator and thus diverge from domestication centers originally 122

proposed by Vavilov (27). This is due to our consideration of a larger set of both domesticated
species and wild relatives of potential interest for contemporary breeding programmes (15).
Utilised plant weighted endemism also follows a latitudinal gradient with larger relative
concentrations of species at higher latitudes and consistent latitudinal variation among uses (Figs.
S11-13).

128 Spatial concordance between utilised plant species, total plant species and human cultures

Although quantitative evidence is scarce, areas of high plant diversity are expected to 129 contain more beneficial species to human populations (5). Our global analyses at (sub-)country 130 resolution indicate that utilised plant species richness is strongly positively associated with total 131 plant species richness (t-value=20.703, P<0.001; Fig. S14-15; Table S2), and that this relationship 132 holds for all categories of uses and for endemism (Fig. S15; Table S3). It also highlights that large 133 proportions of the flora of relatively low diversity regions have documented uses (e.g., 134 Scandinavia, Canada, Sahel), while smaller proportions of utilised species are reported across 135 megadiverse regions (e.g., Madagascar, Brazil, tropical Andes; Fig. S14). Future investigation will 136 be required to identify whether this pattern is due to sampling gaps in our database or in the wider 137 literature for these regions, or because the areas have reached a maximum capacity of utilised plant 138 species richness. Overall, our findings substantiates the combined importance of preserving 139 hotspots of plant diversity, which not only contain many unique species but also a considerable 140 diversity of potential services for humanity (1). Nevertheless, while the spatial concordance 141 between total plant diversity and utilised plant diversity is evident at a global scale, it is now crucial 142 to assess whether this pattern holds at smaller scale, where political decisions are taken and 143 management strategies implemented (28, 29). 144

145 Biodiversity and cultural diversity have been shown to be highly intertwined spatially, giving rise to the notion of biocultural diversity (7, 30). Our data suggest that cultural diversity not 146 only correlates with total plant richness, but also covaries with utilised plant species richness (t-147 value=5.743, P<0.001; Fig. S14-15; Table S2) and inconsistently with endemism indices (Fig. 148 S15; Table S3). This finding supports previous hypotheses that geographic similarities between 149 biodiversity and cultural diversity could be due to increased competition or reduced necessity for 150 151 collaboration among human populations when biological resources (including plants) are widely available, ultimately causing social separation and generating greater linguistic diversity (7, 30, 152 31). However, other historical, evolutionary, and environmental factors may also be involved, and 153 the identity and directionality of causal links for these correlations remain elusive and deserve 154 future investigation (7, 30). 155

Indigenous Peoples and protected areas: preserving plant diversity and its contributions to people

158 Indigenous Peoples are particularly dependent on wild species for subsistence and wellbeing, in addition to being critical custodians of both plant diversity and traditional knowledge 159 (32). Surprisingly, at a large spatial scale, we find that the lands over which the estimated >370160 million Indigenous Peoples of the world exert traditional rights do not contain higher 161 concentrations of plant species with globally documented uses compared to neighbouring non-162 Indigenous regions (Fig. 3, Fig. S17). This finding may reflect the fact that many Indigenous 163 164 Peoples have been dispossessed of their lands throughout history (33), including biologically diverse areas, and that the largest remaining Indigenous territories are located in remote areas of 165 low primary productivity (e.g., Greenland, Siberia, the Tibetan plateau, the Sahara, Sahel, Central 166

Australia) (34). Exceptions include Indigenous lands located in multiple biocultural hotspots that 167 harbor higher utilised plant species richness/endemism than surrounding non-Indigenous regions: 168 Central America, the Horn of Africa, South and South-East Asia. While Indigenous areas 169 containing exceptionally high utilised plant diversity should be considered priorities for the joint 170 conservation of nature and traditional knowledge (34, 35), Indigenous lands containing fewer 171 species should not be overlooked given local populations may be particularly vulnerable to 172 changing environmental conditions and species losses (36). Fostering the engagement of 173 Indigenous, local and scientific knowledge systems will be essential for enhancing ethics and 174 actions towards protection at multiple scales (37). 175

Protected areas are at the forefront of global actions to preserve biodiversity and drive 176 sustainable development (38). However, despite currently covering ca. 17% of the Earth's 177 terrestrial surface, the protected area network contributes to the conservation of a small fraction of 178 plant diversity and ecosystem services (16). Spatial correlations between the proportion of land 179 that is protected, and utilised plant species richness and endemism indicate that regions with large 180 protected area networks do not contain higher numbers or more unique utilised plant species than 181 their non-protected counterparts (Fig. 3, Fig. S17). Indeed, although protected areas in Europe, the 182 Mediterranean, West Africa and the Horn of Africa contain more and more unique utilised plant 183 species than non-protected neighbouring regions, several regions exhibit higher relative richness 184 and endemism of utilised plant species outside of protected areas (e.g., Americas, Southern Africa, 185 Southeast Asia, Australia). Our results point to the urgent need of considering plant diversity and 186 its contributions to people in future area-based conservation planning (10, 29, 39), especially under 187 the ambitious Target 4 of the GBF, which aims to conserve biodiversity across 30% of global land 188 areas by 2030 (40). The latter also acknowledges the importance of "recognizing and respecting 189 the rights of Indigenous Peoples and local communities" and "ensuring that any sustainable use 190 [...] is fully consistent with conservation outcomes". In this context, it is essential to strike an 191 appropriate balance between strictly protected areas that limit access to humans, and protected 192 areas that accommodate the sustainable use of natural resources by local populations while 193 194 preserving of their well-being and cultural heritage (41, 42).

Halting the overexploitation of species and ensuring their sustainable use has also been 195 highlighted as a key priority by the GBF, notably in Target 5. The sustainable management of a 196 197 few animal and plant species has proved to be an efficient tool for conservation (43, 44). However, the sustainability of species use remains unknown across most plant diversity. Out of 2,800 utilised 198 plant species previously assessed by the International Union for Conservation of Nature (IUCN), 199 over one in three is considered to be at risk of global extinction (43). More than one in ten plant 200 species with a documented human food use in our study is also considered globally threatened 201 (45). While our findings show that utilised plant diversity remains largely under-protected in the 202 wild, most species (and their genetic diversity) additionally lack representation in ex-situ 203 collections such as seed banks and botanical gardens (46). Documenting and understanding the 204 diversity and distribution of plant species used by humans is thus crucial to implement 205 conservation strategies and develop plant-based solutions to address global societal challenges 206 such as hunger, diseases, and climate change (47–49). Our study aims to pave the way for efforts 207 towards reconciling human needs and biodiversity protection for a more sustainable future. 208

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211 References and Notes:

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- 596 Original conception: SP, IO, MD, TU, KJW
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- Authors declare that they have no competing interests.
- 610

611 Data and materials availability:

Occurrence records, environmental layers, lists of names and uses of the 35,687 modelled utilised

613 plant species, and outputs from species distribution models are available on Zenodo and Github

- 614 (50, 51) alongside the R package UsefulPlants, which gathers codes, functions, tutorials, and
- documentation allowing to reproduce analyses of the paper.
- 616

617 Supplementary Materials:

- 618 Materials and Methods
- 619 Figs. S1 to S17
- 620 Table S1 to S3
- 621 References (50-119)
- 622
- 623 Figure legends:

Figure 1. Global species richness and endemism of plants with known uses by humans. (A) Utilised plant species richness corresponds to the sum of species occurrence probabilities predicted in each ten arc-minutes (~20 km) pixel found across their native and introduced ranges. (B) Utilised plant species endemism corresponds to the sum of species occurrence probabilities predicted in each pixel weighted by the inverse of their range size, calculated as the sum of the predicted probabilities within their study region (i.e., weighted endemism). High values are thus associated with areas containing high concentrations of species with small geographic ranges.

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632 Figure 2. Latitudinal distribution of utilised plant species richness across t

en categories of plant uses. The black curve on the left represents the latitudinal distribution of 633 all utilised plant species richness. The dendrogram on the top orders the ten use categories 634 according to the (dis-)similarity of their species richness latitudinal profiles. Black curves 635 636 underneath the dendrogram correspond to the species richness latitudinal profile for each use category. The heatmap describes the latitudinal variation in the deviation of utilised plant species 637 richness for the ten plant use categories from total utilised plant species richness. Colors indicate 638 higher (green) or lower (purple) proportions in utilised plant species richness of a given use relative 639 to the total utilised plant species richness pattern. The bar chart underneath the heatmap shows the 640 number of species considered in each use category. 641

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Figure 3. Spatial correlations between utilised plant species richness and proportions of both 643 Indigenous lands and terrestrial protected areas. Pearson's correlation coefficients were 644 computed across all values contained in 71 cells (~3,550km)-wide windows built around each 645 pixel. Pixel color indicates regions where utilised plant species richness is positively (green) or 646 negatively (pink) correlated with the proportion of Indigenous lands and terrestrial protected areas. 647 Regions crossed in beige indicate pixels containing more than 50% of Indigenous lands and 648 protected areas. All Indigenous lands and protected areas are thus not represented on the maps, 649 although they are all accounted for in the analyses. Frequencies of Pearson's correlation 650 coefficients found across the world are given in histograms. The median correlation across the 651 world is indicated by the black vertical line, while zero correlation is indicated by the red dashed 652 line. One-sample Wilcoxon signed rank tests were performed to assess whether median 653 correlations are significantly different from zero. 654

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6	The global distribution of plants used by humans
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15	The PDF file includes:
17	Materials and Methods
18	Figs S1 to S17
19	Tables S1 to S3
20	References (50-119)
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26 Materials and Methods

27 List of plant species used by humans

Analyses in this paper are based upon the "World Checklist of Useful Plant Species" (21). We use the term "utilised 28 29 plant" to refer to vascular terrestrial plant species for which material and non-material benefits to humans have been documented and made publicly accessible. Uses may represent direct (e.g., food, medicine, material) or indirect 30 benefits (e.g., contributions to environmental services such as water, soil or air quality protection). Utilised plants may 31 be wild, introduced, cultivated or weeds. Their uses may have been reported at different time periods (from prehistory 32 to contemporary times), scales (from local to global, by individuals or societies), and economic levels (from local 33 personal use to commercial enterprise). Although commonly referred to as "useful" plants in the literature, we used 34 the term "utilised" here to avoid relying on the subjective concept of "usefulness" and rather focus on the simple fact 35 36 of a plant being known to be used. In fact, it is likely that all plants have an effective or potential use, but utilised 37 plants are those for which the use by humans is documented in the scientific literature. This definition, derived from 38 (52, 53), was employed in the 2020 State of the World's Plants and Fungi report (11, 21).

39 The checklist was compiled using 12 available datasets, of which five have a global coverage: Crop Wild 40 Relatives ((54), https://www.cwrdiversity.org), Royal Botanic Gardens (RBG), Kew's Economic Botany Collection (http://apps.kew.org/ecbot/search), Germplasm Resources Information Network (GRIN) from the United States 41 Department of Agriculture (USDA: https://www.ars-grin.gov), Medicinal Plant Names Services version 8.2 42 43 (http://www.kew.org/mpns (55, 56)), and Palms of the World Online (http://www.palmweb.org); two cover primarily South-East Asia: Plant Resources of South-East Asia (PROSEA (57)) and the indigenous knowledge of New Guinea's 44 useful plants (58, 59); three span primarily Africa: Plant Resources for Tropical Africa (PROTA; 45 https://www.prota4u.org/database), Useful Plants of West Tropical Africa (UPWTA; (60)) and Survey of Economic 46 Plants for Arid and Semi-Arid Lands (http://apps.kew.org/sepasalweb/sepaweb); one has an American coverage: 47 Plants for Malaria, Plants for Fever: medicinal species in Latin America (61); and one project (Project MGU – the 48 49 Useful Plants Project (UPP; (62)) covers plants from both the Americas and Africa. A more comprehensive description 50 of the data sources is provided in Table S1 and (21). We acknowledge that these 12 datasets do not constitute a 51 complete list of all plant species used by humans across the world and knowledge gaps remain; nevertheless, this 52 selection of such a range of large-scale databases covering different continents, disciplines, and taxonomic groups 53 constitutes the most comprehensive source of utilised plant data. Because potential gaps, biases and uncertainties 54 inevitably remain in plant use data, and those have not been assessed previously at global scale contrary to plant distribution data (e.g., (22)), we then adopted a cautious approach by mainly focusing our analyses on regional to 55 continental differences and latitudinal gradients, and by avoiding over-interpretation. Our study thus emphasises the 56 need for additional collection and collaboration efforts to document and understand the sampling distribution of plant 57 use data at multiple spatial and temporal scales. 58

59 Describing plant uses requires a standardisation of use categories and terminologies. Our study used an adapted 60 version of level 1 of the Economic Botany data standards (*20*) with the ten following plant use categories:

- 1. FOOD: Food for humans only, including beverages and food additives (45).
- 2. ANIMAL FOOD: Forage and fodder for vertebrate animals only.
- INVERTEBRATE FOOD: Plants consumed by invertebrates used by humans, such as bees, silkworms, lac
 insects and edible grubs.
 - 4. MEDICINES: Both human and veterinary.

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- 5. POISONS: Plants which are poisonous to both vertebrates and invertebrates, both accidentally and intentionally, e.g., for hunting and fishing, molluscicides, herbicides, and insecticides.
- 68 6. MATERIALS: Woods, fibers, cork, cane, tannins, latex, resins, gums, waxes, oils, lipids, etc. and their derived products.
- FUELS: charcoal, petroleum substitutes, fuel alcohols, etc. Given the importance of energy plants for people
 (61), those were distinguished from MATERIALS.
- 8. ENVIRONMENTAL USES: Examples include intercrops and nurse crops, ornamentals, barrier hedges,
 shade plants, windbreaks, soil improvers, plants for revegetation and erosion control, wastewater purifiers,
 indicators of the presence of metals, pollution, or underground water.
- 9. SOCIAL USES: Plants used for social purposes, which cannot be defined as food or medicine, for instance,
 masticatories, smoking materials, narcotics, hallucinogens and psychoactive drugs, and plants with ritual or
 religious significance.
- 10. GENE SOURCES: Wild relatives of major crops which may possess traits associated with biotic or abiotic resistance and may be valuable for breeding programs.

80 While original sources of data provide information about the identity of species uses, they do not consistently inform

81 us about the parts of the plants that are used, the intensity of use, the identity and origin of the users, or the time at 82 which the use has been observed; therefore, questions associated with this information have not been addressed in this 83 study and will require further data collection at a smaller scale.

We standardised plant nomenclature and taxonomic following the World Checklist of Vascular Plants (WCVP) (23), which contains data for >1,400,000 scientific names found in the literature and >360,000 accepted names from >450 vascular plant families. To verify and correct species names, RBG Kew's semi-automated taxonomic namesreconciliation procedure was used (http://data1.kew.org/reconciliation/) to match names of each species of each source dataset against RBG Kew's taxonomic backbone on 26/11/2019. The backbone is built on the taxonomy from the WCVP employing names drawn from the International Plant Names Index (http://www.ipni.org). Once synonyms and

- non-accepted names were removed from the concatenated species lists, a total of 39,957 unique utilised plant species
- 91 was retrieved (21).

92 Species distribution modelling

93 Our modelling framework follows standards and best practices recently highlighted in the literature (*64*, *65*), by 94 pursuing the five following steps: 1. gathering and processing occurrence and environmental data, 2. selecting the 95 modelling technique 3 fitting models 4 evaluating models and 5 projecting species distribution

modelling technique, 3. fitting models, 4. evaluating models, and 5. projecting species distribution.

96 1.a. Utilised plant occurrence data

97 We compiled occurrence records for each utilised plant species from the following seven databases: (i) Global 98 Biodiversity Information Facility (GBIF, https://www.gbif.org; accessed on January-March 2020) using the function 99 get_gbifid from the R package taxize for species name matching and then the function occ_download from the R 100 package rgbif for downloading records; (ii) Botanical information and Ecology Network (BIEN version 4.1, https://bien.nceas.ucsb.edu/bien; accessed on January 2020) using the function BIEN occurrence species from the R 101 package BIEN; (iii) RAINBIO, which provides direct access to wild and native species occurrence records from Sub-102 103 Saharan Africa, but from which we also obtained introduced and cultivated records directly from the authors (66); (iv) 104 speciesLink, which provides occurrences for species found in Brazil (spLink, http://www.splink.org.br/); (v) BioTIME that provides local species assemblage data globally (67); (vi) Genesys from the global portal to information about 105 Plant Genetic Resources for Food and Agriculture (PGRFA), discarding records from markets and stores 106 107 (https://www.genesys-pgr.org); and (vii) the Crop Wild Relatives global occurrence database accessed via GBIF (http://www.cwrdiversity.org). 108

109 Because georeferencing errors, imprecisions and biases are common in occurrence databases and can 110 significantly impact species distribution modelling (68), we first discarded possibly erroneous points found outside of each species' known geographic range according to the WCVP. Known ranges correspond to both species' native and 111 112 introduced areas at the level-2 (regional or sub-continental scale) of the World Geographical Scheme for Recording 113 Plant Distribution (WGSRPD) developed by the International Working Group on Taxonomic Databases for Plant Sciences (69). Here we used level-2 because level-1 (continental scale) was too coarse, and levels-3 and 4 114 (national/sub-national scales) were less reliable given a few countries have not been assessed by the WCVP and 115 probabilities of assigning false presences and absences are significantly higher at local scale. We then used metadata 116 117 information kept from primary data sources to only retain (i) records collected from 1945 onwards (70), and remove 118 those with (ii) latitude or longitude coordinates out of their ranges ([-90, 90] and [-180, 180] respectively); (iii) coordinates uncertainty above 20 km; (iv) no decimal (i.e. rounded coordinates); (v) a count of individuals set to zero; 119 120 (vi) both coordinates set to zero; (vii) coordinates equal to each other (i.e. latitude equals longitude); (viii) coordinates 121 located within a buffer distance of ten kilometers around the centroids of countries, provinces, capitals, and botanical 122 institutions, and (ix) within a buffer distance of 1km around the GBIF headquarters. We used the cc * functions from 123 the R package *CoordinateCleaner* (71) to clean the data according to the nine points given above. To limit spatial 124 autocorrelation and avoid redundant information (72), we finally kept only one record per ten arc-minutes (~20 km) 125 grid cell for each species.

After cleaning, we did not retrieve any occurrence point for 4,270 utilised plant species. We thus performed analyses for 35,687 species (89% of the original list), of which 6,461 (18%) have reported uses for human food, 4,087 (11%) for animal food, 971 (3%) for invertebrate food, 23,842 (67%) for medicines, 2,816 (8%) for poisons, 12,418 (35%) for materials, 2,348 (7%) for fuels, 8,314 (23%) for environmental uses, 2,385 (7%) for social uses, and 4,713 130 (13%) for gene sources (considering that species can have more than one use). The final occurrence dataset contained

131 >11 million records (Fig. S2).

132 1.b. Environmental data

133 We assembled an original set of 28 environmental variables. We used the 19 bioclimatic variables (temperature and precipitation averages over the 1979-2013 period) provided by the Climatologies at High resolution for the Earth's 134 135 land Surface Areas (CHELSA v.1.2). CHELSA has recently shown to outperform other climate data products for predicting species distribution (73). We collected four terrain variables calculated from a Digital Elevation Model 136 137 (DEM) provided by the Global Multi-resolution Terrain Elevation Database (GMTED) (74): terrain roughness (R) 138 and Topographic Ruggedness Index (TRI), two measures of local terrain heterogeneity as the maximum difference 139 and the square root of averaged differences in elevation found within 3-by-3 cell size windows around each grid cell, calculated using the *focal* function from the R package raster; Topographic Wetness Index (TWI), calculated with the 140 141 GRASS GIS (version 7.6.0) (75) r.topidx module, that combines local land slope and the upslope area converging to 142 a grid cell to describe hydrological processes contributing to soil wetness spatial patterns; and the land slope, calculated with the function Slope from the Spatial Analyst toolbox of ARC/INFO GIS ESRI (version 10.5). We used 143 144 three soil related variables (averages across a range of 0-1m depth) obtained from the International Soil Reference and 145 Information Centre (ISRIC; http://www.data.isric.org): soil organic carbon stock (SOC), soil pH, and soil water capacity (76). We also considered the Enhanced Vegetation Index (EVI) derived from MODIS time-series data 146 147 spanning the 2000–2013 period, extracted from the LEFT tool (77), and the Human Footprint Index representing the anthropogenic impacts on the environment for the 1995-2004 period based on human population pressure, land use 148 149 and infrastructure, and access, and produced by the Wildlife Conservation Society (WCS) and the Columbia 150 University Center for International Earth Science Information Network (CIESIN) (78). The 28 variables were available for time slices that do not always match with each other's and occurrence data; however, we believe that 151 considering a wide set of climatic, vegetation, edaphic, topographic, and human-related variables would better help 152 unravel the distribution of utilised plants for the broad period going from mid-20th to early 21st century. For 153 homogeneity and to match our occurrence records, all layers were resampled at a ten arc-min resolution and masked 154 155 non-terrestrial lands based on the revised map of Terrestrial Ecoregions of the World (79), using the Resample and 156 ExtractbyMask modules from the geoprocessing toolboxes Data management and Spatial Analyst of ArcGIS.

From this pool of 28 variables, we then made a sub-selection intending to: (i) capture most of the variation 157 158 in environmental conditions across the world; (ii) limit multi-collinearity, and (iii) make the most sense ecologically 159 (80-82). We performed a Principal Component Analysis (PCA) using the function dudi.pca from the R package ade4 to assess how much of the variance is explained by the variables and correlations among them. Then, we carried out 160 161 a stepwise selection and a pairwise correlation analysis to exclude (multi-)collinear variables. The former consists in iteratively computing the Variance Inflation Factor (VIF) (83) of each variable and excluding one variable at a time if 162 its VIF value exceeds a threshold of ten, until all remaining variables have VIF values below ten. The latter consists 163 in excluding variables with the highest VIF values out of pairs of highly correlated variables (i.e., Pearson's correlation 164 coefficient r > 0.7). VIF analyses were conducted using functions vifstep and vifcor from the R package usdm. Based 165 on the combination of these analyses and criteria, we finally selected nine predictors: precipitation seasonality, mean 166 temperature of the coldest quarter, precipitation of the driest quarter, terrain roughness (R), Topographic Wetness 167 168 Index (TWI), Enhanced Vegetation Index (EVI), Soil Organic Carbon stock (SOC), mean soil pH and the human 169 footprint index. This diverse set of variables is well known to influence plant species distribution (84-86).

170 2. Algorithm selection

171 Occurrence records alone are unreliable to retrieve species richness patterns and macroecological transitions due to the numerous geographic and taxonomic biases that they contain (22, 87). However, they have been shown to perform 172 173 better when modelled along environmental gradients (87). To retrieve species composition and richness across space, 174 we therefore decided to use a "stacked-species distribution" approach, which consists in stacking modelled species 175 distribution maps (88). Species Distribution Models (SDMs) are probabilistic models relating species occurrence to 176 environmental variables to project their distribution across space and/or time through an estimate of environmental 177 similarity (89). Many species distribution modelling techniques are available, but we decided to use MaxEnt version 178 3.4.1. as it is a commonly used model that (i) relies on presence-only data and (ii) has shown to be one of the methods 179 performing best in many different ecological contexts (81, 90). Because SDMs are sensitive to sample size (91), 180 simpler models are usually recommended when very few occurrence points are available for each species (92).

181 Geographic models (GMs) can provide a suitable alternative to SDMs since they do not rely on an environmental 182 niche approach but rather consider the spatial structure of occurrence locations. They can recover endogenous spatial 183 determinants such as dispersal limitation, which are particularly important factors shaping the distribution of small 184 range species (93). Therefore, we decided to fit a GM for species having less than ten occurrence records. The 185 minimum number of ten points to fit SDMs may prevent from overfitting, which often occurs when the number of explanatory variables (nine in our case) exceeds the number of predictors (low degree of freedom). Because GMs 186 187 cannot be used for extremely low sample size (e.g., for very rare species), we simply rasterised occurrences for species 188 having less than three points using the function *fasterize* from the R package *fasterize*.

189 3. Model fitting

190 MaxEnt contrasts environmental conditions where species have been observed with conditions available or accessible 191 in their surroundings (i.e., background region). Background selection is such a critical step of the modelling process 192 (64) that we decided to individualise it for each species, as recommended in (94). We built an alpha-hull around 193 occurrence points, which is a generalization of the convex-hull particularly useful for estimating species ranges whose habitat is irregularly shaped (95). Alpha-hulls were buffered using the " $1/10^{th}$ maximum" method to better account for 194 195 spatially structured populations (96). We then selected the biomes (79) that intersect with the alpha-hull. To avoid 196 extreme cases where a small alpha-hull intersects with biomes spreading over vast territories and provides an oversized 197 background, we implemented two conditions: (i) the number of occurrence points lying inside each intersected biome 198 must be higher or equal to ten, and (ii) the proportion of the biomes' area covered by the alpha-hull must be higher or 199 equal to ten percent. If the conditions are not met for a particular biome, we then selected the ecoregion (79). Since 200 the alpha-hull algorithm was set up to exclude up to 5% of the records (i.e., geographic outliers), we also searched for 201 the ecoregion polygons occupied by these points and merged them back to the background. Thus, the background 202 region extends to the boundaries of the biomes or ecoregions where species were found and where other populations 203 could potentially occur.

204 Occurrence records are highly unevenly distributed in space and biased towards developed countries and 205 sampling priorities of major botanical institutions (22, 97). As this uneven geographic coverage may significantly 206 impact species distribution modelling, we accounted for this bias by (i) generating a biased prior map giving a non-207 uniform weighting to background points (90, 98, 99), and (ii) integrating this map into the model building through the MaxEnt argument biasfile. This bias map representing the effort in sampling utilised plants was generated in two 208 209 steps: (i) we used the *rasterize* function of the *raster* package in R to count the total number of utilised plant occurrence 210 records found in each ten arc-min grid cell (based on the original dataset, before removing points occurring in the 211 same cells), and (ii) we used the kde2d function from the R package MASS to interpolate these counts using a two-212 dimensional kernel density estimator with a two degrees bandwidth value (Fig. S1).

We ran MaxEnt models for 28,235 (79%) utilised plant species using the *biasfile*, a maximum number of 500 iterations and 50,000 samples from the background area. We specified an automatic selection of response shapes (hereafter called feature classes) and allowed MaxEnt to fit linear, quadratic, product (interaction) and hinge (threshold-like response) feature classes to the data. We used the complementary log-log output (cloglog), which is a more appropriate estimate of species probability of presence that avoids assumptions about species prevalence (*100*).

218 We fitted GMs for 5,464 (15%) utilised plant species using the Inverse Weighting Distance (IDW) method 219 (101). IDW is a spatial interpolation model that computes the probability of occurrence as a weighted average of 220 neighboring occurrences, with weights inversely proportional to the distance between locations. Distance-based GMs 221 thus assume that species are more likely to occur close to known locations than further away (93). Since IDW requires 222 absence data, we generated pseudo-absences to achieve a minimum prevalence of ten percent (i.e., 1:10 ratio between 223 the number of cells occupied by species records and the number of non-occupied cells in the study ecoregion). IDW 224 also requires a local neighborhood that we defined as the seven nearest locations using the function geoIDW from the 225 R package dismo. Occurrence records were directly rasterised for the remaining 1,988 species (6%) that had less than 226 three cleaned occurrence points.

4. Model evaluation

We used a species-specific tuning of the MaxEnt β regularization coefficient (hereafter called β multiplier) to assess the performance of our SDMs, as recommended in the literature (98, 102). MaxEnt uses the β multiplier to prevent

the model from overfitting, notably by penalizing the use of overly complex feature classes. We use the masked

231 geographically structured approach (102) to explore a range of β multipliers based on (103, 104): 1(default), 2, 6, 10.

232 This method is a variant of the k-fold cross-validation that provides a better ability to detect overfitting and more 233 realistic estimates of model performance than other cross-validation approaches (102). We spatially segregated the 234 occurrence records into k=3 geographical bins with approximately the same number of points in each bin using a 235 customised algorithm using the *kmeans* function from the R package stats. Models were then trained iteratively using k-1 (= 2) bins and tested on the third. At each iteration, we calculated for each β multipliers: (i) the corrected Akaike 236 237 Information criterion (AIC_c) (103, 105) using the function *ic* from the R package *rmaxent*, (ii) the tenth percentile of 238 the training omission rate (OR10) and (iii) the Area Under the Curve of the receiver operating characteristic on the 239 testing dataset (AUC) as exported automatically from MaxEnt (106), and (iv) the maximum of the True Skill Statistics 240 (TSS) (107) using the functions prediction and performance of the R package ROCR. We averaged these values over 241 the iterations and ranked as *best model* the one with the regularization multiplier giving the lowest AIC_c. When the 242 difference between the AIC_c values of the top models was not substantial (i.e., $\Delta AIC_c < 2$), we ranked them 243 successively by the lowest OR10_{test}, highest TSS_{test} and highest AUC_{test} (where the subscript test indicates that the metric is calculated on the testing dataset). We therefore ranked the models according to their capacity to minimise 244 245 overfitting before accounting for their discriminatory ability, as recommended in the literature (102, 108).

GMs' predictions were assessed using the *leave-one-out* (LOO) method, a form of *k-fold* cross-validation suitable when sample size is small (*109*). LOO consists in iteratively training the model using *n-1* data points (where *n* is the total number of points) and testing on the withheld point. The AUC was computed and averaged across the iterations.

250 5. Projection of species distribution, richness, and endemism

Individual SDMs performed well according to AUC (mean AUC: 0.809 ± 0.121 ; Fig. S3), OR10 (mean OR10: 0.239 ± 0.137 ; Fig. S4), and TSS (mean TSS: 0.618 ± 0.160 ; Fig. S5) values, which indicate good discriminatory ability of the models and minimised overfitting. GMs indicate fair overall performance (mean AUC: 0.741 ± 0.177 ; Fig. S6). We therefore projected the probability of occurrence of each species from our SDMs and GMs onto the geographical area used for model training (background region) based on species biomes and/or ecoregions and known total range (i.e., native and introduced) or native range only according to the WCVP. Probabilities of one were assigned to the pixels occupied by the 1,988 (6%) utilised plant species represented by less than three records.

258 To retrieve species richness across space, we used a "Stacked-Species Distribution Models" (S-SDMs) approach, 259 which consists in stacking individual species distribution maps obtained from SDMs (88). We summed species 260 occurrence probabilities instead of using thresholded (binary) maps, as this has been shown to provide better estimates of species richness (110). We repeated this process considering species native and introduced ranges, and native ranges 261 only to retrieve two global maps of species richness. Areas containing a large proportion of species with restricted 262 263 ranges are potentially highly irreplaceable and do not match areas with high species richness, so they represent major targets for conservation (5, 6, 111). For this reason, we also estimated endemism as the sum of each species' 264 occurrence probabilities weighted by the inverse of their range size calculated as the sum of the predicted probabilities 265 within their study region (112, 113). Finally, given that the location of the different uses of the 35,687 species remains 266 largely unknown, we stress that our study does not intend to map the uses of plants but rather the distribution of species 267 268 documented to be used somewhere in the world. Therefore, our results rather refer to a potential usage of the species 269 occurring in different regions of the world rather than their actual use in those regions. Similarly, temporal variation 270 in plant uses has not been quantified at such large taxonomic and spatial scales. Our results thus report a rather static 271 view of the global distribution of plants used by humans.

272 Although we used extensive information and accounted for sampling biases in our modelling framework, SDM 273 predictions can still suffer from data incompleteness and uncertainty (22). For this reason, we also mapped utilised 274 plant species richness and weighted endemism using independent data from the WCVP at the level-3 of the WGSRPD 275 (69). Level-3 provides plant species distribution data at a country scale for most of the world, except in a few large 276 countries for which information is available at a sub-country scale. While species richness is simply the count of species found in each level-3 region, weighted endemism weighs each species by the total area of level-3 regions that 277 278 it occupies. To account for differences in surface area between regions, we estimated a scaling exponent that describes 279 the species-area relationship (SAR) between the counts of species (weighted or not) and the level-3 region areas (zvalues range between 0.101 (social uses) and 0.141 (all uses)). Then, we used this exponent to rescale species counts 280 281 for a standard area of 10,000 square kilometers as in (114). We executed this procedure for all utilised plant species 282 together and for each individual use category.

283 <u>Analyses</u>

284 We investigated the variation of utilised plant species richness and weighted endemism across latitude, a well-known 285 biogeographical gradient (115). To achieve this, we fitted Generalised Additive Models (GAM) between latitude and 286 species richness/weighted endemism values across all pixels of our global maps following the approach from (116). 287 Model fitting was performed using the function *bam* from the R package *mgcv* with our predicted estimates of species richness and weighted endemism per grid cell as response variable and a penalised cubic regression spline on the 288 latitude of the grid cells as smooth term. Then, we predicted utilised plant species richness/endemism for each unique 289 290 latitude value and divided each prediction by the total sum of the predictions to obtain a relative measure of utilised 291 plant species richness/endemism along the latitudinal gradient. To better visualise differences among plant use 292 categories, we considered species richness and endemism across all utilised plants grouped together as a baseline and 293 then represented the deviation of the latitudinal patterns of each use category from this baseline. We used the function 294 hclust from the stats package to assess (dis-)similarities and clustering among latitudinal profiles of each use by 295 building dendrograms.

296 We assessed potential associations between distribution patterns in the diversity of all plant species, utilised 297 plant species, and human cultures. To our knowledge, no continuous map is available for both overall plant richness 298 and cultural diversity, thus we worked at a country scale. Estimates of human cultural diversity were compiled by 299 (117) for 256 countries. Estimates of total vascular plant species richness/endemism and utilised plant species 300 richness/endemism were compiled from the WCVP (23). Level-3 geographic data were aggregated at a country scale 301 for each individual species using a global map of countries provided by the Database of Global Administrative Areas 302 (GADM; http://www.gadm.org) version 3.6, before computing area-corrected richness and weighted endemism 303 indices as described previously (Figs. S15-16). Due to geographic mismatches between certain botanical regions and countries, and the absence of cultural diversity data for certain territories, we only kept 163 countries for analyses. 304 305 Cultural diversity is a composite index made of three estimates: total number of languages, religions, and ethnic groups 306 per country (117–119). The cultural diversity index uses SAR to account for variable country sizes and ranges from 0 to 1, with values close to 0 indicating the least diverse countries and values close to 1 the most diverse ones. We 307 308 assessed relationships between human cultural diversity, total plant, and utilised plant species richness/endemism 309 using Generalised Least Squares (GLS) models with the gls function of the R package nlme. Unlike Ordinary Least 310 Squares (OLS) models, GLSs allow to accommodate for potential spatial (auto-)correlation in the data. We used the 311 latitude and longitude coordinates of the centroids of each country as spatial covariates, and tested three different correlation functions: exponential, gaussian and spherical. We fitted our GLS models using the restricted maximum 312 313 likelihood method (REML) and selected the correlation structure with the lowest AIC. Analyses were repeated for all utilised plants together and for each individual use category separately. 314

315 We assessed spatial associations between utilised plant species richness, endemism, Indigenous lands, and 316 protected areas at a finer resolution given the availability of raster maps for all variables. Indigenous lands represent areas managed and/or controlled by Indigenous Peoples (as defined by the International Labour Organization (120)). 317 The global map was built based on 127 source documents and provides a percentage of each 50 km grid cell covered 318 by Indigenous lands across the world (34). The completeness of this data cannot be guaranteed; it represents known 319 Indigenous land areas based on publicly available geospatial data only. We used the World Database on Protected 320 Areas (WDPA) (121) to extract the percentage of all protected areas contained in each 50 km cell of the Indigenous 321 322 land grid. The WDPA is the most comprehensive global database of marine and terrestrial protected areas, comprising 323 both spatial data with associated attribute data. It includes protected areas that meet definitions set by the International 324 Union for Conservation of Nature (IUCN) and the Convention on Biological Diversity (CBD). Protected area coverage 325 was calculated using ArcGIS and ESRI's Modelbuilder. Utilised plant species richness and endemism maps obtained from SDMs were aggregated to the same 50 km resolution using the Resample tool from the Data Management 326 toolbox in ArcGIS. Spatial correlations between utilised plant species richness/endemism and both Indigenous lands 327 and protected areas were assessed by computing Pearson's correlation coefficients across all values contained in 71 328 329 cells (~3,550km)-wide windows built around each pixel. This resulted in global maps indicating the strength and 330 direction of regional correlations between the different variables. The size of the moving window was selected so that 331 all pixels of the world map have a correlation value (i.e., all windows contain at least one Indigenous land and one protected area) and our analysis provides a broad estimate of the geographical variation of the correlations at large 332 333 spatial scale. For this analysis we used the *focal* and *cor* functions from the *raster* and *stats* R packages, respectively. 334 All analyses and data processing were based on the R statistical software version 3.6.1, ArcGIS version 10.5 and 335 GRASS GIS version 7.6.0.





Figure S1. Sampling intensity in occurrence records for all utilised plant species. Red indicates high sampling

density, whereas green indicates low sampling density based on counting the number of occurrence records available for all utilised plant species in each 400 km² grid cell and a kernel density probability approach providing a unitless

for all utilised plant specirelative index of density.

Histogram of species occurence points



344 Figure S2. Number of occurrence records used for modelling the distribution of each utilised plant species.

345



Performance of Maxent model predictions

346

Figure S3. AUC evaluation scores of utilised plant species distribution models. Boxes represent upper and lower 347 348 extremes, upper and lower quartiles, medians and outliers of AUC indices for all utilised plant species distribution models. Evaluation scores are given for MaxEnt models calibrated with more than ten occurrence records. 349

Performance of Maxent model predictions Based on testing records from different geographic blocks 1.00 0.75 0.50 0.50 0.25 Expected : 10% Omission Rate_{10%}

351

Based on 28168 species

Figure S4. OR10 evaluation scores of utilised plant species distribution models. Boxes represent upper and lower extremes, upper and lower quartiles, medians and outliers of OR10 indices for all utilised plant species distribution

models. Evaluation scores are given for MaxEnt models calibrated with more than ten occurrence records.

Performance of Maxent model predictions

Based on testing records from different geographic blocks



357 Figure S5. TSS evaluation scores of utilised plant species distribution models. Boxes represent upper and lower

- extremes, upper and lower quartiles, medians and outliers of TSS indices for all utilised plant species distribution models. Evaluation scores are given for MaxEnt models calibrated with more than ten occurrence records.
- 360



Performance of inverse distance weighting model predictions

361

Based on 5439 species

Figure S6. AUC evaluation scores of utilised plant species distribution models. Boxes represent upper and lower extremes, upper and lower quartiles, medians and outliers of AUC indices for all utilised plant species distribution models. Evaluation scores are given for geographic models (Inverse Distance Weighting) calibrated with less than ten occurrence records.



367

368 Figure S7. Global species richness of plants with known uses by humans. Utilised plant species richness

369 corresponds to the sum of species occurrence probabilities predicted in each ten arc-minutes (~20 km) pixel found

across their native ranges.



371

372 Figure S8. Global distribution of utilised plant species richness (A) and weighted endemism (B) at the level-3 373 (sub-national) of the World Geographical Scheme for Recording Plant Distribution (WGSRPD). Utilised plant species richness corresponds to the count of species found in each region. Utilised plant species endemism corresponds 374 375 to the number of species present in each region weighted by the inverse of their range size calculated as the total area 376 covered by the level-3 regions it occupies (i.e., weighted endemism). Geographic distribution for each species was 377 retrieved from the World Checklist of Vascular Plants at the level-3 of the WGSRPD. To account for differences in 378 surface area between regions, we estimated a scaling exponent that describes the species-area relationship (SAR) between the counts of species (weighted or not) and the level-3 region areas. We used this exponent to rescale species 379 380 counts for a standard area of 10,000 square kilometers.



- **Figure S9. Global distribution of utilised plant species richness across ten categories of uses.** Utilised plant species richness corresponds to the sum of each species occurrence probabilities predicted in each pixel by our "stacked-species distribution modelling" approach. 385



Figure S10. Global distribution of utilised plant species richness at the level-3 (sub-national) of the World Geographical Scheme for Recording Plant Distribution (WGSRPD) across ten categories of uses. Utilised plant species richness corresponds to the count of species found in each region. Geographic distribution for each species was retrieved from the World Checklist of Vascular Plants at the level-3 of the WGSRPD. To account for differences in surface area between regions, we estimated a scaling exponent that describes the species-area relationship (SAR) between the counts of species and the level-3 region areas. We used this exponent to rescale species counts for a standard area of 10,000 square kilometers.



395

Figure S11. Latitudinal distribution of utilised plant species endemism across ten categories of uses. The black 396 397 curve on the left represents the latitudinal distribution of all utilised plant species endemism. The dendrogram on the 398 top orders the ten use categories according to the (dis-)similarity of their species endemism latitudinal profiles. Black curves underneath the dendrogram correspond to the species endemism latitudinal profile for each use category. The 399 heatmap describes the latitudinal variation in the deviation of utilised plant species endemism for the ten plant use 400 categories from total utilised plant species endemism. Colors indicate higher (green) or lower (purple) proportions in 401 402 utilised plant species endemism of a given use relative to the total utilised plant species endemism pattern. The bar 403 chart underneath the heatmap shows the number of species considered in each use category. 404



Figure S12. Global distribution of utilised plant species endemism across ten categories of uses. Utilised plant species endemism corresponds to the sum of each species occurrence probabilities predicted in each pixel weighted by the inverse of their range size calculated as the sum of the predicted probabilities within their study region (i.e., weighted endemism).



- 412 Figure S13. Global distribution of utilised plant species endemism at the level-3 (sub-national) of the World
- 413 **Geographical Scheme for Recording Plant Distribution (WGSRPD) across ten categories of uses.** Utilised plant
- 414 species endemism corresponds to the number of species present in each region weighted by the inverse of their range
- 415 size calculated as the total area covered by the level-3 regions it occupies (i.e., weighted endemism). Geographic
- distribution for each species was retrieved from the World Checklist of Vascular Plants at the level-3 of the WGSRPD.
 To account for differences in surface area between regions, we estimated a scaling exponent that describes the species-
- 418 area relationship (SAR) between the counts of species and the level-3 region areas. We used this exponent to rescale
- 419 species counts for a standard area of 10,000 square kilometers.
- 420
- 421





Figure S14. Relationships between utilised plant species richness and total plant species richness (A), and human cultural diversity (B) across 163 countries/territories. Geographic distribution for each species was derived from the World Checklist of Vascular Plants at the level-3 of the WGSRPD. To account for differences in surface area between regions, we estimated a scaling exponent that describes the species-area relationship (SAR) between the counts of species and the region areas. We used this exponent to rescale species counts for a standard area of 10,000 square kilometers.



Figure S15. Global distribution of utilised plant species richness at a country/territory scale across ten categories of uses. Utilised plant species richness corresponds to the count of species found in each region. Geographic distribution for each species was derived from the World Checklist of Vascular Plants at the level-3 of the WGSRPD. To account for differences in surface area between regions, we estimated a scaling exponent that describes the species-area relationship (SAR) between the counts of species and the region areas. We used this exponent to rescale species counts for a standard area of 10,000 square kilometers.











Figure S16. Global distribution of utilised plant species endemism at a country/territory scale across ten categories of uses. Utilised plant species endemism corresponds to the number of species present in each region weighted by the inverse of their range size calculated as the total area covered by the regions it occupies (i.e., weighted endemism). Geographic distribution for each species was retrieved from the World Checklist of Vascular Plants at the level-3 of the WGSRPD. To account for differences in surface area between regions, we estimated a scaling exponent that describes the species-area relationship (SAR) between the counts of species and the region areas. We used this exponent to rescale species counts for a standard area of 10,000 square kilometers.





Figure S17. Spatial correlations between utilised plant species endemism and proportions of both Indigenous lands and terrestrial protected areas. Pearson's correlation coefficients were computed across all values contained in 71 cells (~3,550km)-wide windows built around each pixel. Pixel color indicates regions where utilised plant species endemism is positively (green) or negatively (pink) correlated with the proportion of Indigenous lands and terrestrial protected areas. Regions crossed in beige indicate pixels containing more than 50% of Indigenous lands and

453 protected areas. All Indigenous lands and protected areas are thus not represented on the maps, although they are all 454 accounted for in the analyses. Frequencies of Pearson's correlation coefficients found across the world are given in 455 histograms. The median correlation across the world is indicated by the black vertical line, while zero correlation is 456 indicated by the red dashed line. One-sample Wilcoxon signed rank tests were performed to assess whether median 457 correlations are significantly different from zero.

Project MGU-Useful Plants Project	Plants for Malaria, plants for fever	Survey of Economic Plants for Arid http://	Useful Plants of West Tropical Africa	Plant Resources of Tropical Africa ht	Indigenous knowledge of New Guinea's useful plants	Plant resources of South-East Asia	Palms of the world online	Medicinal Plant Names Services version 8.2	Gemplasm Resources Information Network, United States Department of Agriculture	Economic Botany Collection h	Crop wild relative inventory	Dataset
Ulian <i>et al.</i> 2017	Milliken 1997	/apps.kew.org/sepasalweb/sepaweb	Burkill 1994	tps://www.prota4u.org/database	Cámara-Leret et al. 2019	Jansen et al. 1991	http://www.palmweb.org	http://www.kew.org/mpns	https://www.ars-gnn.gov	ttp://apps.kew.org/ecbot/search	https://www.cwrdiversity.org Dempewolf et al. 2014	Source
UPP	MALARIA	SEPASAL	UPWTA	PROTA	NewGuinea	PROSEA	PalmWeb	MPNS	GRIN	EcBot	CWR	Acronym
905	748	3,479	3,349	4,534	3,071	4,182	152	26,690	10,988	8,162	2,459	Number of species
Sub-Saharan Africa and Mesoamerica	Latin America	Arid and semi-arid African lands	Western Africa	Sub-Saharan Africa	New Guinea	South-East Asia	Global	Global	Global	Global	Global	Geographic extent
Database compiling plant uses by local communities and partners of the UPP project from Botswana, South Africa, Mali, Kenya and Mexico	Literature review of plant species used to treat malaria and fever	Database of 16,407 uses records for species from the African Arid and Semi-Arid areas	Database of useful plants from West tropical Africa	Online resource of useful plant information from Sub-Saharan Africa	Quantitative review of 488 references reporting indigenous knowledge and plant uses in New Guinea	Book inventorying useful plants of a core area (Brunei, Indonesia, Malaysia, New Guinea, the Philippines and Singapore) occurring and used also in neighbouring areas (Burma, Cambodia, Laos, Thailand and Vietnam). Based on literature review.	An online palm encyclopaedia gleaned from taxonomic publications	Global resource for medicinal plant names with access to information about plants and plant products	Online database of taxonomic information on cultivated plants from the USDA-ARS germplasm resources information network (GRIN)	RBG Kew's Economic Botany Collection containing over 120,000 specimens/objects	A global priority Crop Wild Relatives inventory, based on both gene pool and taxon group concepts	Description

460	Table S1. Data sources of the World (Checklist of Useful Plant Species
400	Table 51. Data sources of the world v	Checknet of Osciul I land Species

		Standardised regression coefficient + 95% Confidence Interval			Stud	ent's t-test	
Variable	Response	Estimate	Lower CI	Upper CI	t-value	<i>p</i> -value ⁽¹⁾	Correlation ⁽²⁾
Total plant species richness							
	All uses	0.865	0.782	0.947	20.703	1.86e-48***	exponential
	Animal Food	0.676	0.573	0.779	12.966	3.24e-27***	exponential
	Environmental Uses	0.874	0.765	0.982	15.890	1.66e-35***	exponential
	Fuels	0.494	0.392	0.597	9.518	1.89e-17***	exponential
	Gene Sources	0.747	0.631	0.863	12.705	2.38e-26***	exponential
	Human Food	0.692	0.589	0.796	13.184	1.04e-27***	exponential
	Invertebrate Food	0.684	0.567	0.801	11.554	3.95e-23***	exponential
	Materials	0.662	0.570	0.754	14.256	9.81e-31***	exponential
	Medicines	0.822	0.737	0.906	19.232	1.29e-44***	sperical
	Poisons	0.788	0.668	0.908	12.995	3.60e-27***	exponential
	Social Uses	0.522	0.431	0.613	11.305	1.99e-22***	exponential
Human cultural diversity							
	All uses	0.358	0.235	0.481	5.743	4.52e-08***	gaussian
	Animal Food	0.306	0.194	0.419	5.394	2.42e-07***	sperical
	Environmental Uses	0.349	0.217	0.481	5.217	5.53e-07***	sperical
	Fuels	0.377	0.275	0.479	7.322	1.10e-11***	sperical
	Gene Sources	0.314	0.183	0.445	4.737	4.74e-06***	exponential
	Human Food	0.355	0.239	0.471	6.043	1.01e-08***	exponential
	Invertebrate Food	0.392	0.268	0.517	6.219	4.14e-09***	exponential
	Materials	0.352	0.244	0.460	6.451	1.24e-09***	gaussian
	Medicines	0.328	0.204	0.451	5.242	4.93e-07***	gaussian
	Poisons	0.342	0.208	0.476	5.030	1.29e-06***	exponential
	Social Uses	0.323	0.223	0.424	6.359	2.01e-09***	exponential

⁽¹⁾Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

⁽²⁾Name of the correlation structure function selected for accommodating spatial autocorrelation

461 462 Table S2. Generalised Least Squares (GLS) summary statistics for the relationships between utilised plant 463 species richness and total plant species richness, and human cultural diversity across 163 countries/territories. GLS models account for potential spatial (auto-)correlation in the data. Latitudinal and longitudinal coordinates of the 464 centroids of each country were used as spatial covariates, and three different correlation functions were tested: 465 exponential, gaussian and spherical. GLS models were fitted using the restricted maximum likelihood method (REML) 466 and the correlation structure with the lowest AIC was selected. Analyses were repeated for all utilised plant species 467 together and for each individual use category separately. Human cultural diversity is a composite index made of three 468 estimates: total number of languages, religions, and ethnic groups per country. Total vascular plant species richness 469 and utilised plant species richness were compiled from the World Checklist of Vascular Plants. 470

		Standardise + 95%	ed regression Confidence Ir	coefficient nterval	Stude	ent's t-test		
Variable	Response	Estimate	Lower CI	Upper CI	t-value	<i>p</i> -value ⁽¹⁾	Correlation ⁽²⁾	
Total plant species endemism								
	All uses	0.297	0.213	0.381	7.001	5.54e-11***	gaussian	
	Animal Food	0.016	-0.118	0.149	0.231	8.18e-01	gaussian	
	Environmental Uses	0.065	0.007	0.123	2.209	2.85e-02*	gaussian	
	Fuels	-0.046	-0.174	0.082	-0.713	4.77e-01	gaussian	
	Gene Sources	0.435	0.371	0.498	13.456	1.79e-28***	gaussian	
	Human Food	0.146	0.030	0.263	2.477	1.42e-02*	sperical	
	Invertebrate Food	-0.066	-0.196	0.064	-1.003	3.17e-01	gaussian	
	Materials	0.184	0.111	0.256	5.009	1.38e-06***	gaussian	
	Medicines	0.353	0.218	0.488	5.153	7.00e-07***	sperical	
	Poisons	0.087	-0.048	0.222	1.279	2.03e-01	gaussian	
	Social Uses	-0.009	-0.134	0.116	-0.146	8.84e-01	gaussian	
Human cultural diversity								
	All uses	0.060	-0.037	0.157	1.218	2.25e-01	gaussian	
	Animal Food	0.312	0.181	0.443	4.696	5.65e-06***	gaussian	
	Environmental Uses	0.008	-0.050	0.066	0.269	7.88e-01	gaussian	
	Fuels	0.340	0.217	0.462	5.453	1.83e-07***	gaussian	
	Gene Sources	0.002	-0.104	0.108	0.038	9.70e-01	gaussian	
	Human Food	-0.028	-0.171	0.116	-0.381	7.04e-01	sperical	
	Invertebrate Food	0.336	0.209	0.463	5.223	5.37e-07***	gaussian	
	Materials	0.013	-0.065	0.090	0.328	7.43e-01	gaussian	
	Medicines	0.055	-0.108	0.218	0.670	5.04e-01	exponential	
	Poisons	0.245	0.109	0.380	3.568	4.74e-04***	gaussian	
	Social Uses	0.327	0.205	0.448	5.317	3.47e-07***	gaussian	

⁽¹⁾Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

⁽²⁾Name of the correlation structure function selected for accommodating spatial autocorrelation

474 Table S3. Generalised Least Squares (GLS) summary statistics for the relationships between utilised plant 475 species endemism and total plant species endemism, and human cultural diversity across 163 476 countries/territories. GLS models account for potential spatial (auto-)correlation in the data. Latitudinal and 477 longitudinal coordinates of the centroids of each country were used as spatial covariates, and three different correlation 478 functions were tested: exponential, gaussian and spherical. GLS models were fitted using the restricted maximum 479 likelihood method (REML) and the correlation structure with the lowest AIC was selected. Analyses were repeated 480 for all utilised plant species together and for each individual use category separately. Human cultural diversity is a composite index made of three estimates: total number of languages, religions, and ethnic groups per country. Total 481 vascular plant species endemism and utilised plant species endemism were compiled from the World Checklist of 482 483 Vascular Plants.

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Global distribution of utilised plant species richness



Global distribution of utilised plant species endemism







Terrestrial protected areas

В

