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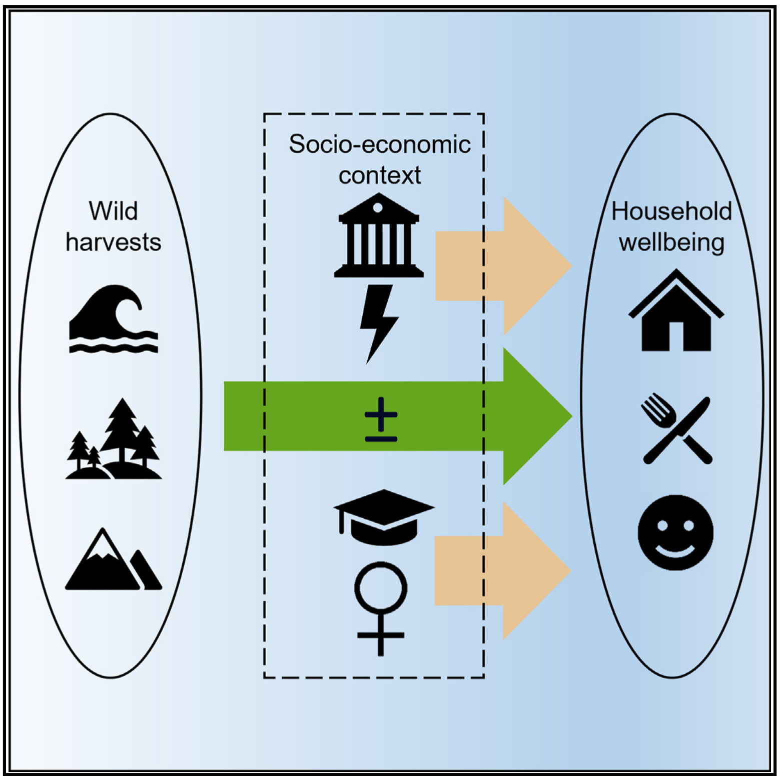
Hundreds of millions of people in the tropics need both wild harvests and other forms of economic development for their well-being

Graphical abstract



Highlights

- Hundreds of millions of people in the tropics harvest “wild” common-pool resources
- Wild harvests are correlated with high relative well-being in remote and poor areas
- Access to infrastructure, cities, assets, and skills also increase well-being overall
- The well-being of many people relies on both wild resources and economic development

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In brief

The contribution of wild resources to human well-being in different contexts remains debated. We analyze associations between wild harvesting, food security, and life satisfaction across ∼10,800 households across the tropics. We find that, while harvests are very common and strongly correlate with well-being in remote and poor areas, access to infrastructure, markets, and skills are also highly important. Policies should aim to maintain wild resource access while investing in equitable access to infrastructure, markets, and skills.

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Hundreds of millions of people in the tropics need both wild harvests and other forms of economic development for their well-being

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SCIENCE FOR SOCIETY Hundreds of millions of local people in the tropics harvest food, firewood, and other products from unmanaged (or "wild") forests, grasslands, rivers, lakes, and seas. Yet global demand for resources, and proposals for large protected areas, are set to reduce the local availability of these wild products.

Many people argue that local wild harvesters can be sufficiently compensated by investing in better infrastructure, improving skills, and creating alternative sources of income. However, new evidence calls for caution in assuming that wild harvests can be so easily substituted, especially in the short term. While improved access to infrastructure, markets and skills is beneficial, it needs to be balanced with continued access to wild harvests if the well-being of all groups is to be protected—especially among more remote, marginalized, and poorer communities.

SUMMARY

Local access to "wild," common-pool terrestrial and aquatic resources is being diminished by global resource demand and large-scale conservation interventions. Many theories suggest the well-being of wild harvesters can be supported through transitions to other livelihoods, improved infrastructure, and market access. However, new theories argue that such benefits may not always occur because they are context dependent and vary across dimensions of well-being. We test these theories by comparing how wild harvesting and other livelihoods have been associated with food security and life satisfaction in different contexts across ~10,800 households in the tropics. Wild harvests coincided with high well-being in remote, asset-poor, and less-transformed landscapes. Yet, overall, well-being increased with electrical infrastructure, proximity to cities, and household capitals. This provides large-scale confirmation of the context dependence of nature's contributions to people, and suggests a need to maintain local wild resource access while investing in equitable access to infrastructure, markets, and skills.

INTRODUCTION

Many people in low- and middle-income countries harvest food, fiber, fodder, and fuel from wild or uncultivated ecosystems, including forests, savannas, grasslands, inland water bodies, and coastal seas.[1–3] However, these resources are often over-exploited due to demand from local and global markets,[4] while large-scale conservation interventions sometimes restrict access.[5] Thus, while economic development and environmental protection are both integral to global sustainable development objectives,[6] many interventions risk disrupting the livelihoods and well-being of local communities that rely on wild harvesting—often poorer people in marginal areas, or Indigenous Peoples for whom wild resources are an integral part of their economic and cultural heritage.[7] Debates persist on the magnitude of such disruption to local communities, and whether the impacts of reduced access to wild ecosystems can be offset by transitions to other sources of livelihood, and improved access to services, infrastructure, and markets.[8–10]

Historically, development theory and policy has commonly assumed that transitions away from wild harvesting (e.g., to industrialized production or service sectors) generally improve well-being.[11] Within this paradigm, well-being is often assumed to be synonymous with monetary income,[12] and wild resources on their own are rarely seen as important contributors.[13] More recent advances challenge this view in two ways. First, a newer literature argues that human well-being is in fact a *multidimensional* construct that goes beyond simple measures like income to include more fundamental dimensions such as food security and life satisfaction[14,15]—dimensions that are not solely determined by income.[16,17] Wild ecosystems and other aspects of development are in turn argued to contribute to these different dimensions in different ways that are potentially missed when only income (or similar) is considered.[18–20]

Second, an accompanying body of theory argues that the determinants of well-being (including contributions from wild resources) are highly *context dependent*, and vary greatly between different people and geographies.[1,21–23] Acontextual theories of development can therefore mislead in contexts where wild resources do indeed make important contributions to well-being. Combined, these new theories suggest that analyses of the potential contributions of wild resources (and other factors) to well-being need to consider *multiple dimensions of well-being* and the *context dependence* of its determinants.

These recent advances are founded on a rich case study literature documenting site-specific examples of multidimensionality and context dependence in human-nature relationships (see experimental procedures: theoretical background; see the IPBES Wild Species Assessment[7] for a comprehensive overview of gray and peer-reviewed literature). However, large multi-country, peer-reviewed quantitative studies testing the generalizability of these theories remain scarce. Existing multi-country studies of wild resources are mainly at relatively coarse spatial scales (e.g., national or sub-national regions). Together they indicate that wild harvests are very common globally,[24–27] but they are unable to determine the influence of different contexts at finer scales. They also focus on the level of wild resource use, rather than subsequent impacts on well-being.

Finer-resolution (e.g., household-level) analyses that do assess contextual variation across different social-ecological systems and social groups are rarer, and are also focused primarily on the use of wild resources and income. For example, Angelsen et al.[1] find that, across 24 low- and middle-income countries, wild harvests make up a greater share of income among poorer households, but are higher in absolute terms among wealthier households. In a study using the same dataset, Wunder et al.[28] find that poorer households more commonly rely on forests to cope with shocks.

Together these existing multi-country quantitative studies support theories that wild harvesting is common among a wide range of households in low- and middle-income areas. However, a research frontier remains in large-scale assessments of how wild harvesting is actually associated with different dimensions of well-being in different contexts, and how this compares with well-being outcomes under other types of (non-wild) livelihoods and economic development.

In this study we begin to address this gap using Bayesian modeling and a spatially explicit dataset of ∼10,800 households representative of diverse peri-urban and rural areas across the tropics. The dataset was generated by combining suitable data from the Nature4SDGs[29] and Poverty Environment Network[30] databases (for details see experimental procedures: data). We conduct a cross-sectional analysis comparing the food security and life satisfaction of wild harvesting households with other (non-wild harvesting) households across a diversity of peri-urban and rural contexts.

We focus on food security and life satisfaction as two ultimate "ends" of well-being, which were consistently measured across our dataset, and which are commonly analyzed to capture material and subjective dimensions of well-being (see experimental procedures: theoretical background).[31,32] We relate food security to the reported absence of food shortages in a household during the survey period (i.e., sufficient within-household food provision within the survey period),[31] while life satisfaction captures if the survey respondent gave a high (above median) response to a Likert scale question on the level of satisfaction with their life.[32]

We define wild harvesting as the direct harvesting of food, fiber, fodder, or fuel from non-cultivated ecosystems by a household (see experimental procedures: theoretical background).[1] We categorize each household by the presence/absence of wild harvesting in their self-reported harvests during the survey period (i.e., wild harvesting vs. non-wild harvesting households; see experimental procedures: data).[33–35] We then assess variation in well-being outcomes of these groups across 10 "contextual factors" drawn from theory, and which we could robustly measure across our datasets (Table 1; Figure S3; see experimental procedures: theoretical background): access to electrical infrastructure; proximity to cities; spatial extent of natural terrestrial and aquatic resources; the *de facto* (as distinct from *de jure*) presence of rules regulating the access and withdrawal of common pool resources (CPRs); and household attributes on wealth, gender of head, education, presence of cultivation, other income, and productive assets.

Our primary findings are that wild harvesting is widespread (even close to cities), and is correlated with relatively high well-being in remote, asset-poor and less-transformed landscapes.

Table 1. Results on generalizability of theories on how contextual factors moderate contributions of wild harvesting to well-being

Contextual factor	Theorized moderation of wild harvesting's effect on well-being	Generalizability supported?
Stable night light intensity	↓ by offering infrastructure for more profitable non-wild occupations	yes
	↑ by enabling more efficient access to, and harvesting of, wild products	yes
Distance to nearest city	↓ by increasing access to more profitable non-wild occupations	no
	↑ by increasing demand for, and substitutability of, wild products	yes
Extent of wild terrestrial and aquatic resources	↑ by offering greater stocks of wild resources	yes
	↓ where degraded landscapes improve physical accessibility	no
De facto presence of CPR rules	↑ by securing tenure and management arrangements, curbing overextraction and degradation	yes
Household capitals (wealth rank, education, gender, productive assets, cultivation, other income)	↓ by providing the skills, assets and opportunities for more profitable (non-wild)	yes
	↑ by enabling more efficient access to, and harvesting of, wild products	yes
	↑ by enabling privileged access to wild products	yes

However, the presence of electrical infrastructure, proximity to cities, and household capitals remained overarching predictors of high well-being whether a household was wild harvesting or not. In addition, the two well-being dimensions of food security and life satisfaction sometimes varied differently with context: for example, food security increased with access to physical assets, but the opposite was true for life satisfaction. Our findings thus provide large-scale quantitative evidence of the context dependence and multidimensionality of nature's contributions to people. We argue that, together, these results indicate that analysts need to take a multidimensional and context-sensitive approach to understanding nature's impacts on well-being. For policy, our results indicate a need for balance in environment and development policy-making that maintains local-level wild resource access while investing in improved and equitable access to infrastructure, markets and skills.

Table 2. Estimated influence of contextual variables on the presence of wild harvesting

Contextual variable	Median estimate	Low 95% CI	High 95% CI
Stable night light intensity*	−9.45	−14.83	−3.85
Distance to city	−0.19	−0.79	0.44
Natural cover (%)*	1.35	0.39	2.43
CPR rules presence*	1.31	0.88	1.79
Wealth rank*	0.23	0.14	0.34
Other income presence*	−0.59	−0.74	−0.42
Education*	−0.35	−0.46	−0.24
Male household head*	0.28	0.10	0.48
Productive asset presence*	−0.26	−0.41	−0.11
Cultivation presence	−0.08	−0.23	0.07

Median posterior parameter estimates. Log odds with 95% credibility intervals (HPD). * indicates difference from zero at 95% certainty.

RESULTS

How does the prevalence of wild harvesting vary with context?

We first assessed contextual variation in the prevalence of wild harvesting across the region. We implemented a Bayesian logistic generalized linear mixed effects model (GLMM) to estimate the association between contextual variables and the probability that a household engages in wild harvesting (Table 2; see experimental procedures: regression models). Wild harvesting was more strongly associated with lower night lights, higher natural land cover, and the presence of CPR rules. Distance to city had no clear effect. Household capitals played a secondary role, with wild harvesting being marginally more prevalent among less-capitalized households (with lower education, fewer productive assets, and fewer non-harvest livelihood alternatives), yet also associated with indicators of higher wealth and male-headed households.

The relative insensitivity of the presence of wild harvesting to proximity to cities, and its prevalence in converted landscapes, implies that such harvests are widespread. We used our model and global geospatial datasets of village-level variables to generate pan-tropical estimates of the number of households directly engaged in wild harvesting in 2015 (Figures 1A and 1B; see experimental procedures). We conservatively estimate that 648 million people in the study region (median estimate; 95% CI [191M, 886M]); Table S7), lived in households directly harvesting wild resources (excluding populations in dense urban areas, arid biomes, and small island states; see experimental procedures). This represents ∼67% of the non-urban population within the areas covered by our dataset, and ∼9% of the global population. While we are unaware of other regional estimates for the direct harvesting of wild resources, our estimates agree with existing, coarser estimates of their wider consumption, use, and trade, which cover a wider number of people in the value chain and so would be expected to be higher. In an analysis of higher-level administrative areas across a similar region Fedele

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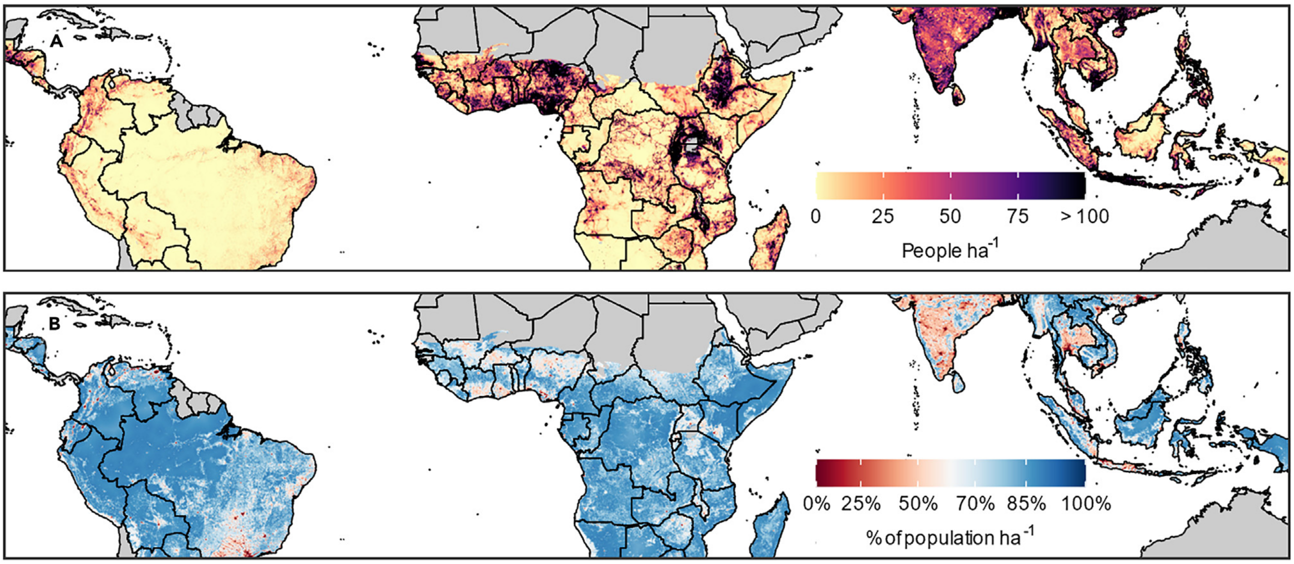

Figure 1. Prevalence of wild harvesting in non-urban areas

(A) Spatial estimates of the number of people in wild harvesting households and (B) the median estimated percentage (or probability) of the local population in wild harvesting households in 2015. Spatial estimates exclude gray areas: high income countries, dense urban areas, arid biomes, and small island states.

et al.[24] estimate that 2.7 billion people use products from forests or fisheries, while other global studies propose that 2.4 billion people use fuelwood,[25] 120 million people use fisheries,[25] and 1.7 to 3 billion use non-timber forest products.[26]

The absolute number of people directly engaged in wild harvesting (Figure 1A) was estimated to be higher in regional population centers (South Asia; the African Great Lakes region; Niger River in West Africa). As a proportion of the local population, however, direct wild harvesting was more prevalent outside of such economic centers (Figure 1B), broadly matching the spatial patterns of broader wild resource use found by Fedele et al.[24] Notably, many such areas occur in regions such as the Western Amazon, the Congo Basin, and the Malay Archipelago, which have a higher prevalence of lands controlled or managed by Indigenous Peoples.[36]

How does context moderate the associations between wild harvesting and well-being?

Next, we used Bayesian logistic GLMMs to compare how food security and life satisfaction outcomes varied for wild harvesting and other households across the different contextual factors (see experimental procedures). Regardless of wild harvesting status, food security was more prevalent closer to cities, and in the presence of higher wealth, male-headed households, productive assets, schooling, and CPR rules (Figure 2; Table S5). Within these general trends, households not engaged in wild harvesting had higher food security than wild harvesters in most, but not all, contexts. Outcomes for wild harvesters began to converge with, and in some cases exceed, those of non-harvesters in more natural and remote areas, among households in the presence of higher night lights, enforced CPR rules, and/or with higher household capitals.

Higher life satisfaction was associated with higher night lights, household wealth, and being a male-headed household, while lower life satisfaction was associated with the presence of cultivation and CPR rules (Figure 3; Table S6). As for food security, households not engaged in wild harvesting had higher life satisfaction than wild harvesters in most, but not all, contexts. Wild harvesters experienced equivalent (and sometimes higher) outcomes in more natural and remote areas, in the presence of enforced CPR rules and with higher wealth.

DISCUSSION

Together, our results offer strong, large-scale evidence in support of theories of the context dependence of nature-well-being relationships, and the importance of considering multiple dimensions of well-being in nature-well-being analyses. However, our results also support theories that overall improvements to well-being have been associated with other non-nature factors, such as access to infrastructure, markets, and other household capitals.

Context dependence of nature-well-being relationships

On context dependence, our results offer support for the generalizability of most of the theoretical propositions summarized in Table 1 within the contexts covered by our dataset (i.e., excluding dense urban and arid areas, and small island states). Most contextual factors strongly moderated either the overall prevalence of wild harvesting (Table 2) and/or the relative well-being outcomes of households engaged in it (Figures 2 and 3). Generally, these findings support understandings that, while wild harvesting is more common among less-capitalized households in areas with more natural land cover and lower infrastructure, well-being contributions from wild resources are generally enhanced with access to infrastructure, markets, and other household capitals.

Within this we point to three noteworthy distinctions. First, our findings support existing coarser-level studies showing that wild

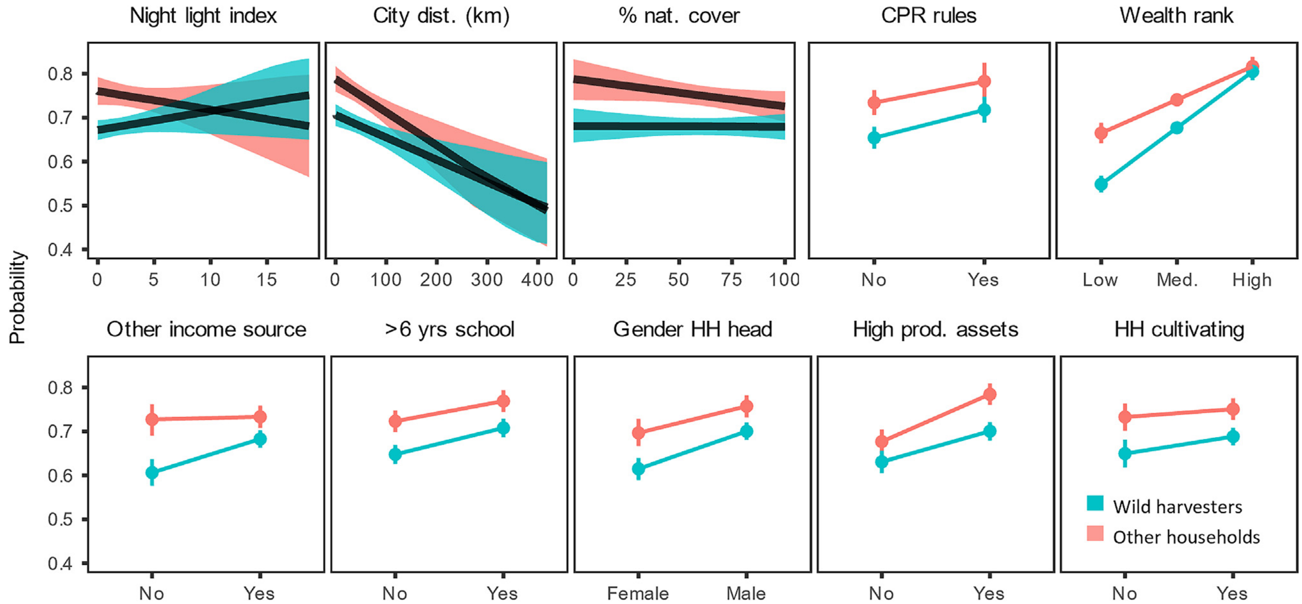

Figure 2. Trends in food security under wild- and non-wild livelihoods across contexts

Linear trends of Bayesian marginal probabilities of a household being food secure in a given context, with 95% Bayesian uncertainty intervals.

harvesting (and its contribution to well-being) is not only a rural phenomenon[1,2,26]—we find high-resolution evidence that such harvests remain common even in converted landscapes with close proximity to cities. Illustrative cases from our dataset include several agricultural and peri-urban settings where harvesting of wild resources is common (e.g., urban coastal fisheries in East Africa[18]; agriculture-mangrove mosaics in Bangladesh[37]; peri-urban forests in West Africa[38]).

Second, while site-specific studies have documented cases where degradation of landscapes can increase wild harvesting (e.g., by making resources easier to physically access),[39,40] our findings suggest that, on average, wild harvesting remains more prevalent in more natural (and notionally less-degraded) landscapes. This implies that wild resource stocks (and their quality) remain key moderators of the flow of ecosystem service benefits to humans.[23]

Finally, and relatedly, our findings support theories arguing that, within local communities, access to wild resources (and associated well-being benefits) is moderated by local rules and power structures. In our analysis, regulation of CPRs, wealth, and male-headed households were all positively associated with wild harvesting. This suggests that, even in more remote and less-capitalized areas where wild harvesting is more common, other modes of (intersectional) marginalization and existing rules continued to direct access toward particular (e.g., locally elite) groups. A common example from our dataset is where more valuable wild resources are more likely to be subject to rules and claims by several groups, including local elites (e.g., grazing lands in eastern India[41]; charcoal tree species in Mozambique[31]; wild mushrooms in southwestern China[42]).

Multidimensional well-being

Our results also support theories that nature contributes to different dimensions of well-being in different ways. In our results, while food security and life satisfaction shared many similar trends, there were some key differences. While food security generally trended upward with the presence of CPR rules, cultivation, other income, and assets (Figure 2), life satisfaction displayed the opposite (Figure 3). The different dimensions also displayed different crossover interactions. For life satisfaction (Figure 3), wild harvester outcomes improved further from cities, while the opposite occurred for non-wild harvesters. For food security (Figure 2), this divergence occurred with night light radiance, where outcomes of wild harvesters increased with more night lights, while outcomes for non-wild harvesters (somewhat counterintuitively) declined.

Theory offers some explanations on the potential causality behind these different interactions (e.g., harder-to-fulfill aspirations among households with higher market integration[43]; widespread and sometimes higher food insecurity in more "modernized" food supply chains[44]). These results provide evidence of empirical differences between well-being dimensions and their contextual-determinants, including contributions from wild nature.

The importance of both wild harvests and economic development for well-being

Together, our results suggest that while wild harvesting was associated with relatively high well-being outcomes in particular contexts, other aspects of development (e.g., opportunities for non-wild harvesting livelihoods; access to non-natural capital and markets) have generally coincided with overarching improvements to well-being for all households. Even in more remote and natural areas where wild harvesters did achieve outcomes equivalent to non-harvesters, these outcomes usually co-occurred alongside higher access to infrastructure, markets, and household assets. For example, case studies of sites from within our dataset document improved food security among remote

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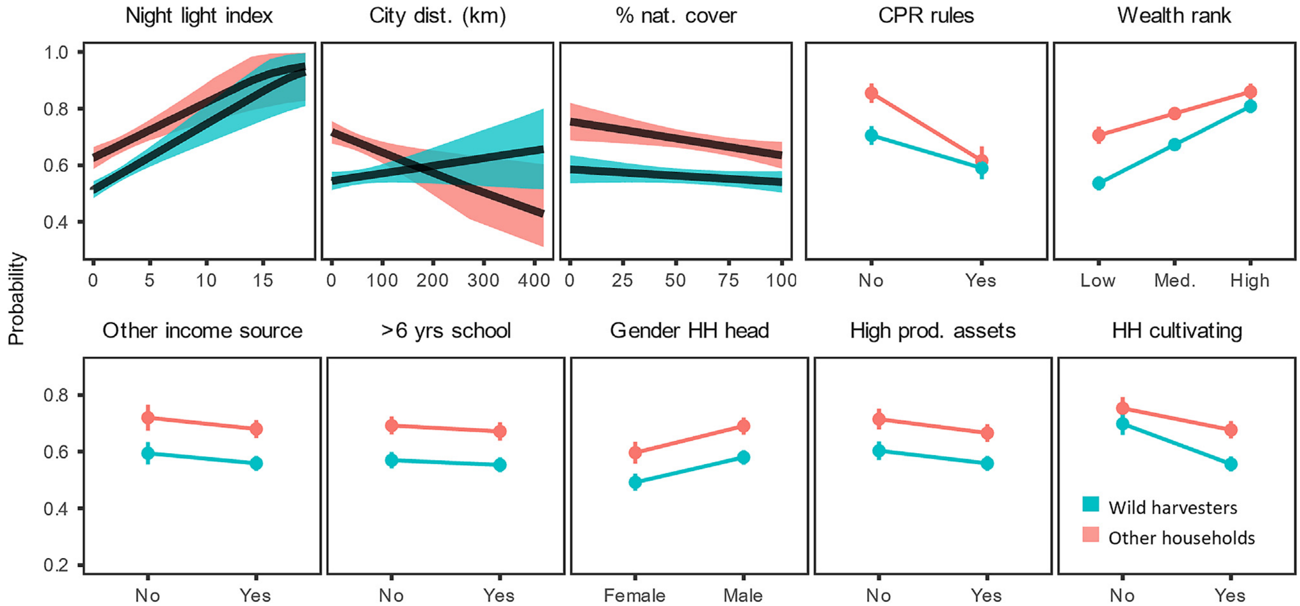

Figure 3. Trends in household head life satisfaction under wild- and non-wild livelihoods across contexts
Linear trends of Bayesian marginal probabilities of a household head being satisfied with their life in a given context, with 95% Bayesian uncertainty intervals.

households with agricultural land in Mozambique,[31] and in households with higher income in montane forests in Ethiopia.[45] Similarly, higher life satisfaction was observed among wealthier, wild harvesting households in coastal Bangladesh.[37] A combination of both economic development and wild harvests thus appears integral to the well-being of many in the tropics.

Implications for science and policy

Overall, our study provides new quantitative evidence relevant to two areas of theory about the use of wild nature in low- and middle-income countries, and its contributions to human well-being. First, our results provide household-level confirmatory evidence that wild resources contribute to the livelihoods of a large number of people in the region.[1,24–26] Moreover, while our contextual analysis supports existing findings that wild harvests are relatively more important in less-capitalized and remote areas, our results provide additional fine-scale evidence that wild harvesting nonetheless remains relatively common even in heavily converted landscapes proximate to cities.[26]

Second, our results provide new large-scale quantitative evidence in support of theories that associations between wild nature and well-being are multidimensional and greatly moderated by local environmental and socio-economic context. Sustainability science is challenged by the apparent empirical disconnect between well-being and nature at the global level, where widespread environmental degradation has not coincided with reductions in human well-being (known as "the environmentalist's paradox").[9] Recent theory argues that one explanation for this is that the contribution of nature is in fact important for many people, but is often missed in generalized analyses that have not been able to explore fine-scale (e.g., village- and household-level) variation in nature-well-being relationships, and which focused on unidimensional measures of well-being (e.g., only income).[18,21,46] While our study does not directly assess environmental degradation, our results do suggest that, at least in the case of wild harvesting, we must take a multidimensional and context-sensitive approach to understanding its impacts on well-being.

For policy, in addition to illustrating the moderating effects of broader, structural economic (e.g., distance from markets), and biophysical factors (e.g., resource stocks), our results point to the importance and complexity of local (e.g., village-level) power dynamics in determining the distribution of benefits from local ecosystems. For example, female-headed wild harvesting households tended to experience worse well-being outcomes. Such social mechanisms of marginalization are already explored in much of the existing theoretical and case literature on gender, intersectionality, and ecosystem services,[47–49] and our results provide large-scale quantitative evidence of their generalizability. This implies that, even where access to wild harvests is maintained, science and policy must consider how local-level intersectionality influences the distribution of nature's benefits at the household and individual level.

More broadly, our findings bolster calls for caution in introducing widespread restrictions or bans on wild resource extraction,[50] and in assuming that well-being can be easily decoupled from wild resources, e.g., the complete substitution of natural for human-made capital.[8] Even if such interventions are feasible or sustainable in the long term, which is in dispute,[4,51] in the short- to medium-term wild resources will remain integral to the livelihoods and well-being of a large proportion of the world's population—particularly to remote and asset-poor people, and those who rely disproportionally on wild resources for their livelihoods and cultural identity, such as Indigenous Peoples.[7] Our evidence thus indicates the need for great caution in disrupting access to wild resources, and reinforces calls for an equal attention to environmentally sustainable and socially equitable investments in skills, services, and infrastructure.[52] For the well-being of many, wild nature and other aspects of economic development remain deeply entwined.

EXPERIMENTAL PROCEDURES

Resource availability

Lead contact

Requests for further information and resources and code can be directed to and will be fulfilled by the lead contact, Geoff Wells (geoff.wells@su.se).

Materials availability

This study did not generate new unique materials.

Data and code availability

The raw datasets used for this study are publicly available from Wells et al.[29] and CIFOR.[30] Village and household identifying information and spatial locations cannot be publicly shared due to confidentiality restrictions. The combined processed data and R code needed to reproduce the conclusions of the Bayesian GLMM regressions are publicly available at bitbucket.org/wildharvestsandwellbeing/wildharvestsandwellbeing.

Theoretical background

Well-being

Our approach to well-being is motivated by two areas of theory. First, we take a multidimensional approach. Until recently, large-scale empirical studies of human development and poverty have typically used income,[1] or singular aggregate indicators,[53] as proxies of human well-being. There is, however, a long history of broader conceptions of well-being, which in its broadest sense can be understood as "doing well–feeling good" across multiple material (e.g., health, food security, standards of living), subjective (e.g., life satisfaction), and relational (e.g., quality of personal relationships) dimensions.[14] Such disaggregated approaches are integral to understanding the diverse pathways by which nature affects humans,[22,23] and have already proved effective in site-specific quantitative analyses of such phenomena.[31,37,54]

Second, we focus on the ultimate *ends* of well-being that relate directly to the human condition (e.g., food security, life satisfaction), and we treat other more intermediate aspects (e.g., education, assets, income) as *means* by which ultimate well-being may be achieved. The diverse foundational literature on multidimensional well-being consistently makes such a distinction.[55–59] Yet recent commentaries point out that many widely used multidimensional measures of well-being[53,60] continue to conflate ultimate ends with context-specific means.[12] For studies of nature's contributions to well-being this is problematic in two ways. First, such indicators often class the direct use of nature itself as an indicator of low well-being (e.g., the use of natural materials for housing). Second, they assume that particular "means" (e.g., ownership of valuable assets) are the only pathways to (and therefore synonymous with) well-being. Both of these limitations reduce the utility of intermediate means (such assets and income) as outcome variables for understanding contributions of nature to well-being. We thus focus on indicators of ultimate ends as outcomes our analysis.

We focus on two ultimate ends which were consistently measured across our dataset, and which are commonly analyzed in studies of well-being to capture aspects of material and subjective dimensions: food security and life satisfaction.[31,32] We relate food security to the reported absence of food shortages in a household during the survey period,[31] while life satisfaction captures if the survey respondent gave a high (above midpoint) response to a Likert scale question on the level of satisfaction with their life.[32] To enhance data comparability across our sites, we examine whether a household is above or below a binary "well-being threshold" for each dimension (a common approach in multi-site assessments of human well-being).[18,61]

Nature's contributions to people, and wild harvesting

We define wild harvesting as the direct harvesting of food, fiber, fodder, or fuel from non-cultivated ecosystems by a household.[1] This distinguishes such harvests from other production systems that have been significantly altered from their more natural state (e.g., agriculture, aquaculture, plantations). Across our sites such wild ecosystems include forests, savannah woodlands, grasslands, mangroves, and freshwater and coastal water bodies.

Existing evidence suggests that wild harvests are highly prevalent globally, and even more so in low- and middle-income areas of the tropics.[24–26] A wide array of case studies and regional analyses further argue that such harvests make integral contributions to the well-being of harvesters and people involved in wider wild product value chains—by directly fulfilling people's basic material, subjective and relational needs, and by supporting local economies more widely.[1,3,15,54] Indeed, some scholars argue that access to the natural environment is indeed a constituent element of well-being itself.[50] Here, we assess the context dependence of these well-being contributions.[21] Our focus on wild harvests implies a focus on the direct consumptive use of wild nature,[62] which sits within a set of instrumental (as opposed to intrinsic or relational) values for nature.[19]

The context dependence of nature's contributions to well-being

The last decade has seen the emergence of a wide body of theory arguing that nature's contributions to people are greatly moderated by social-ecological context.[21,46] Here, we evaluate these theories by assessing if the associations between wild harvesting, food security, and life satisfaction change across selected contextual variables reflective of current theory, and for which we could generate robust variables (Table 1; Figure S3; for detailed descriptions of these variables see experimental procedures: data).

Stable night light intensity and distance to the nearest city are, respectively, proxies for access to (electrical) infrastructure and level of market access.[63,64] One body of theory argues that such factors will reduce the importance of wild harvesting to well-being by enhancing access to more profitable livelihood sources.[65–76] Conversely, other theories point to cases where they can enhance the contribution of wild resources by enabling more efficient production and increased trade in wild products.[65,70,77–83]

The spatial extent of wild terrestrial and aquatic resources and the *de facto* presence of CPR rules reflect, respectively, biophysical and social dimensions of access to wild resources. On the biophysical side, some argue that more abundant stocks of wild resources will increase the availability of wild harvests, and hence their overall contribution to well-being.[54,78,84–86] Conversely, already-degraded landscapes, with notionally more scarce resource stocks, have been shown to make it easier to access and benefit from wild resources in some cases (e.g., non-timber forest products).[39,40] On the social side, access to these wild CPRs is moderated by *de facto* rules (i.e., the prevailing practices, regardless of formal, *de jure* arrangements) that determine who can harvest and by how much.[41,42,87,88] The presence of *de facto* CPR rules are broadly theorized to increase and sustain over time the well-being benefits from wild harvests by allowing more secure and managed access to wild resources.[65,77,89–97]

We include five indicators of household capital[98] relating to financial (relative wealth rank, other income sources), human (education), social (gender of household head), and physical (presence of cultivation and productive assets) dimensions. There is a wide literature suggesting that increases in such household capitals will generally reduce the prevalence of wild harvests, and hence the prevalence of consumptive nature-well-being pathways, by allowing access to alternative livelihood sources and skills.[1,77,91,99–102] Among households that do continue to wild harvest, it is generally argued that more elite (or less-marginalized) wild harvesting households will continue to benefit more (e.g., by investing in more capital-intensive but higher return wild value chains; through privileged access to high-value resources).[1,84,91,103–105] Such marginalization can occur across several axes of social difference (e.g., gender, ethnicity) and is cumulative: any one person or household may be subject to several types of marginalization at once ("intersectionality"; e.g., due to gender + ethnicity + etc.).[47,49,106] For wild harvests, theory thus emphasizes gradations of social exclusion, where less (although still)-marginalized groups may be able to better access and benefit from wild harvests relative to the most marginalized.[45,48,84,102,107,108]

Study region

We generated our dataset from existing household surveys and global geospatial data. In selecting household surveys to include in the study our objective was to maximize coverage of household-level and spatially explicit data across different regions and ecosystems of low- and middle-income countries in the tropics. Within this region we selected surveys based on four criteria: (1) whether the original survey had household-level data on the variables of interest that were equivalent to the other surveys, (2) whether the dataset contained precise village-level spatial coordinates for each household, (3) whether the within-village sampling strategy could be treated as random, and so representative of each village, and (4) if there was sufficient documentation to assess the robustness of the survey questions and sampling strategy.

We sourced household surveys in two phases. First, we generated a new combined dataset from all suitable surveys from the former Ecosystem Services for Poverty Alleviation program (ESPA),[109] Robinson et al.,[110] and Devagiri et al.[111] This produced a dataset[29] with good coverage of different ecosystems (e.g., forest-agriculture frontiers, grasslands, inland fisheries, coastal areas), but excluded regions in West Africa and Southeast Asia. We thus added suitable surveys from CIFOR's publicly available Poverty and Environment Network (PEN) global dataset.[30] Other potential large household-level datasets were excluded due to a lack of (precise) geospatial coordinates, e.g., DHS, LSMS.[112] The resulting combined dataset provided more balanced coverage across the study region (see Figures S1 and S2). All surveys contained data for at least one year between 2005 and 2015.

The dataset contains 10,793 households representative of 438 villages in 24 low- and middle-income countries, spanning Latin America, sub-Saharan Africa, South Asia, and South East Asia (Figure S1). In the original survey instruments, households were selected randomly within each village. Together the villages represent close to the full range of variation in the extent of natural land cover and remoteness within the tropics, excluding high-income countries, dense urban areas, arid biomes, and small island states (Figures S1 and S2). We thus limited predictions from our models (see regression models: estimates of wild harvesting population) to low- and middle-income areas within the latitudes of our dataset (24° N, 24° S), excluding high-income countries, dense urban areas, arid biomes, and small island states.

Data

Well-being

We generated binary indicators that capture whether a household is above or below a deprivation threshold (Table S1). Across all original surveys, food security questions were posed to respondents through similar questions on the degree of food availability (e.g., did the household have sufficient food for all family members during the survey period?). For life satisfaction, all original surveys posed Likert scale questions on life satisfaction to the household head (e.g., all things considered, how satisfied are you with your life as a whole these days?). Responses to these life satisfaction questions ranged from "very dissatisfied" to "very satisfied" on a 3- to 5-point scale across different surveys. In the binary indicators, we related food security to the self-reported absence of food shortages in a household in the preceding year, while life satisfaction captures whether the survey respondent (household head) gave a high (above survey median) response to the Likert scale question.

While binary measures are highly reductionist measures of complex social and economic phenomena, simple ordinal (including binary) measures of food security and life satisfaction have been demonstrated to be useful for comparing across diverse cultural and geographical contexts.[113,114] In addition, while such approaches are more commonly used to study deprivation and poverty as special cases of low well-being, here we use the simplifying assumption proposed by Agarwala et al.,[22] where "[w]ell-being is … conceptualized as the flip side of multidimensional … poverty. As multidimensional poverty declines, well-being increases." We thus assume that having a basic need met is synonymous with higher well-being.

Wild harvesting

Given methodological weaknesses in generating robust and comparable continuous measures of often-untraded and informal wild harvests,[115] and the varying availability of robust and equivalent continuous measures of wild harvesting in our source data, we focus on the binary presence of wild resources in a household's self-reported harvests during the survey period. We use this variable as a simple and pragmatic proxy for the direct use of nature by a household. Such binary presence variables are widely used in development economics to distinguish between different classes of livelihood strategies and practices.[33–35] Our analysis is thus focused on the effects of the presence of wild harvesting in a household's livelihood strategy, and does not comment on effects from the level of wild harvesting, indirect benefits higher in the value chain, nor other non-consumptive values (e.g., recreation, regulating services).

For each household we generated a binary "wild harvesting presence" variable indicating if the household had reported any direct harvesting of food, fodder, fiber, or fuel from uncultivated resource systems during the survey period (Table S1). Differences in the underlying survey questions necessitated different data processing for households from the ESPA and PEN datasets. For ESPA households we undertook an extended coding exercise where we generated a list of all harvests and other livelihood sources reported in each household (in total, 54,479 unique livelihood observations) then used site descriptions and classification exercises with site experts (all co-authors) to categorize the source of the livelihood. For PEN households, we used existing binary questions on the presence of harvests from forests and wild fisheries, and of any other wild products.

Contextual variables

Contextual variables were split into those at household and village level (Table S1). From the household surveys, we generated six household-level social variables (Table S1) related to household physical, financial, social, and human capital: binary presence of cultivation; binary presence of other income; binary presence of productive assets; binary presence of adult with more than 6 years of education; binary gender of household head; and a 3-point wealth rank on a household's relative wealth within each settlement.

For cultivation and income, we generated standardized binary presence variables from various binary (e.g., did the household harvest any crops in the survey period?) or continuous measures (e.g., quantities or monetary values of harvests) in the original surveys. Binary variables on productive assets and education were generated by applying globally applicable thresholds from Alkire et al.[53] to ordinal variables generated from the asset and household member rosters in each original survey. We generated the within-settlement wealth rank by grouping households by the 33rd, 66th, and 100th percentiles of valuable asset counts (as defined in Alkire et al.[53]) within a village.

For village-level contextual variables, for the relevant year of the survey in each village, we generated variables on distance to city, percentage of natural land cover in a 3 km buffer around the village centroid, nighttime light intensity, and presence of *de facto* regulated CPRs in the village (Table S1). We calculated distance from city as the Euclidean distance from the nearest area with an estimated population density >1,500 per square kilometer according to WorldPop.[64,116] While modeled "travel time" is likely a more precise measure of remoteness,[117] such data were not available for relevant years for all surveys. To indicate the proportion of natural land cover we first reclassified existing satellite ESA-CCI land cover classifications at 300-m resolution[118] into a binary gridded dataset of natural (forest, shrub, herbaceous, wetland, water bodies, ocean) and all other (non-natural) land classes. We then calculated the proportion of natural land cover in a 3 km radius around each village. For nighttime light intensity we used average annual nighttime radiance in a 3 km buffer around the village centroid from Li et al.[63]

To indicate the presence of a regulated CPRs in the village, we first used survey data and site descriptions to list and categorize all types of resources utilized within a settlement boundary (e.g., forests, rivers, farm land, reefs, etc.). A resource was categorized as a CPR where (1) it would be costly to exclude access by individuals and (2) harvests by one individual would diminish those available to others.[119] We then used this same information and existing frameworks on tenure and property rights[120,121] to identify resource types where "access" and "withdrawal" rights were *de facto* regulated (as opposed to unregulated; i.e., open access). We focus on the *de facto* (as opposed to *de jure*) status of the resource to reflect the actual, prevailing status of the rules (e.g., as opposed to CPRs that are regulated on paper, but not in practice; e.g., "paper parks" in conservation).

Regression models

Modeling approach

For each outcome of interest (presence of wild harvesting, food security, and life satisfaction), we implemented a GLMM within a Bayesian framework. A Bayesian approach was selected due to advantages fitting complex models to large datasets with a hierarchical structure (i.e., households within settlement within region) and in reducing bias from imbalanced data (e.g., uneven observations across outcome, explanatory, and grouping variables).[122–124] We selected a linear approach to reduce the risk of overfitting in our subsequent predictions and spatial estimates.[125]

Likelihood function and hierarchical structure

All outcome variables were binary and we fit all models with a logit link function. We included random intercepts in our main models to control for unobserved variation between villages and OECD region (Sub-Saharan Africa, South Asia, Latin America, Southeast Asia).

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Priors

For all models we used a weakly informative prior suitable for logistic regression where there is a prior expectation of most parameter estimates being close to zero with occasionally large values (i.e., a narrow distribution with long tails): a Student's t distribution with 7 degrees of freedom, location 0, and scale 2.5.[126] This corresponds to our initial expectation that the determinants of wild harvesting and well-being are diverse, and any one factor will likely only have a small to moderate linear association with the outcomes of interest. To check that our prior generates simulated data consistent with our expectation, for each outcome we ran 50 prior-only simulations of the data and compared this with the observed outcomes using density plots using bayesplot in R[127] (Figure S4).

Model structures

We first estimated the probability of a household having a wild harvesting in a given context by implementing a GLMM with binary presence of wild harvesting as the outcome and all other contextual variables as predictors (Equation 1).

$$Y_{ij} \sim \mathrm{Bin}(1, p_{ij})$$

$$\mathrm{logit}(p_{ij}) = \propto + \beta_1 \times C_1 + \beta_2 \times C_2 + \ldots + \alpha_i$$

$$\alpha = \mathrm{N}(0, \sigma_{a^2}) \qquad \text{(Equation 1)}$$

where, within the binomial distribution of our outcome, Y_{ij} is 1 if household j in region i is wild harvesting; logit is the logistic link function; p_{ij} is the probability that a is wild harvesting; C_1, C_2, etc., are the values of the contextual variables for the household; and α is the normally distributed random intercept (with mean 0 and variance σ_α^2).

Next, to test associations between wild harvesting and our two well-being dimensions of food security and life satisfaction, and how these vary with social-ecological context, we implemented a GLMM for each well-being dimension, with the binary well-being indicator as the outcome and other covariates as predictors, including presence of wild harvesting (Equation 2). To test if the association between wild harvesting and well-being varied with context, we included interaction terms between the presence of wild harvesting and each contextual variable.

$$Y_{ij} \sim \mathrm{Bin}(1, p_{ij})$$

$$\mathrm{logit}(p_{ij}) = \propto + \beta_1 + \beta_2 + \beta_1(\mathrm{WH}_{ij} \times C_1) + \beta_2(\mathrm{WH}_{ij} \times C_2) + \ldots + \alpha_i$$

$$\alpha = \mathrm{N}(0, \sigma_{a^2}) \qquad \text{(Equation 2)}$$

where, within the binomial distribution of our outcome, Y_{ij} is 1 if the well-being of household j in region i is above the minimum threshold; logit is the link function, p_{ij} is the probability that the household is above the given well-being threshold; WH_{ij} is the presence of wild harvesting in the household; C_1, C_2, etc., are the values of the contextual factor in the household; and α is the normally distributed random intercept (with mean 0 and variance σ_α^2). Presence of wild harvesting has an interaction term with each contextual variable, which provides coefficient estimates for both main and interaction effects for all explanatory variables.

Multicollinearity checks

Prior to fitting the models we checked for missingness among all available predictors, and used bivariate correlations and variance inflation factor (VIF) estimates to check for (multi)collinearity between proposed explanatory variables. High missingness led to the exclusion of three initially proposed explanatory variables related to household-level social and human capital (socio-cultural dominance; time household head had lived in village; and household dependency ratio), and to village-level market access (percentage of households trading in the village). Multicollinearity led to the further exclusion of one village-level variable (population density). The final outcome and explanatory variables, their inclusion in the three models, and their VIFs are in Table S1.

Model selection

We evaluated three candidate models for each regression: a null model consisting of only a village random intercept (i.e., an intercept only model); the full model with only village as a random intercept; the full model with both village and region as random intercepts. We evaluated the models using the leave-one-out information criterion (using the loo package in R) (Table S2).[128] In all cases we selected the full model with both village and region as the random intercept (Table S2).

Computation and convergence

We fit all candidate models using Hamiltonian Markov chain Monte Carlo (MCMC) estimation via the rstanarm package in R.[129] Four MCMC chains were run in parallel for 4,000 samples each, with the first 1,000 samples in each chain discarded as warm-up. We checked convergence of each MCMC fit by examining the percentage of divergent iterations and the Gelman-Rubin convergence statistic, $r < 1.02$.[130]

Assessing model fit

For each model we ran posterior predictive checks by running repeated ($n = 10$) simulations of the data from our fitted model, and using binned residual plots to observe how often the model makes predictions are outside 2 standard errors of the observed data (using bayesplot in R)[131] (Figure S5). Where >95% of predictions lie within ±2 standard errors, this is evidence of model validity. We also used Moran's I statistic to test for spatial-autocorrelation of outcomes (Table S3), with all models displaying a Moran's I of close to zero (i.e., no evidence of strong spatial autocorrelation).

Reporting results

We report the full median posterior parameter estimates with their 95% credibility intervals (highest posterior densities [HPD]) in Tables 2, S5, and S6. To more clearly communicate the results of the two well-being models in the main manuscript, we used the existing models and the tidybayes package in R[132] to predict and plot the trend of the village-level marginal effects (effect averaged over all levels of other predictors) of each covariate.[130] We report Bayesian uncertainty intervals of the linear trend.

Estimates of wild harvesting population

Gridded estimates

After fitting and assessing the model on the prevalence of wild harvesting, we used the model to generate pan-tropical ∼1 km resolution gridded estimates of the probability of a household having a wild harvesting in a particular location. We used global geospatial datasets of all spatial village-level covariates (Table S1) to predict prevalence across all areas. To help extrapolate between regions, we included in the prediction the random-intercept at the regional level. Household-level contextual variables and village-level CPR rules had no corresponding global data sources, so we used the conservative input value for each of these predictions (i.e., the value that would minimize the prevalence of wild harvesting). Predictions are thus conservative probabilities based on village-level geospatial factors.

Next, to generate estimates of the number of people wild harvesting in each pixel, we multiplied our gridded estimates of wild harvesting probability by existing ∼1 km resolution global gridded population count estimates for the year 2015 (unconstrained top-down global mosaics suitable for areas with many small rural settlements).[133] We excluded from these estimates areas not represented in our sample: excluding high-income countries, dense urban areas, arid biomes, and small island states. Estimates are reported in tabular form in Table S7.

Validation and uncertainty assessment

To propagate uncertainty of all explanatory variables in our population estimates, we ran three predictions of gridded wild harvesting probability using, respectively, the median parameter values, then their lower and upper credibility intervals (95% HPD). We assessed spatial predictive accuracy of the wild harvesting model using leave-one-out cross-validation across a systematic random sample of 50 points across our dataset (100 repetitions on each point). User's, producer's, and overall accuracy are reported at Table S4.

In addition to testing for spatial autocorrelation through Moran's I across all models (see above), we further assessed the impact on our wild harvesting predictions through a spatial leave-one-out cross-validation on the same points (100 repetitions), where we tested how overall accuracy of the model changed while excluding observations within spatial buffers of different sizes (Figure S6). This indicated only weak spatial autocorrelation of results with overall accuracy declining from ∼85% with no buffer to plateau at ∼65% at the 100 km exclusion buffer, with no further declines in accuracy at larger buffers. This is within the accuracy range of many commonly used mapping and land cover products,[134] and we believe that such accuracy is sufficient for the broad illustrative purposes of our mapping and estimates.

Visualization

For ease of interpretation we present maps with the gridded estimates of population count of wild harvesters, and the proportion of the local population in wild harvesting households (which is synonymous with probability of wild harvesting).

Software

All statistical analyses were conducted in the R statistical software environment (R Core Team 2021), version 4.0.3. The annotated R-code for our models can be found at bitbucket.org/wildharvestsandwellbeing/wildharvestsandwellbeing. Gridded estimates of the prevalence of wild harvesting were implemented in Google Earth Engine.[135]

Limitations of the study

Overall, the data and methods used in the analysis confer some limitations. One key limitation relates to the domain of inference of our results: due to the geographical coverage of datasets assessed as suitable for the study, our results do not apply to dense urban areas, arid biomes, and small island states. Thus, while other studies do indicate relatively high utilization of wild resources in such contexts,[3,15,26] our findings on the context dependence of well-being contributions cannot be extended to these areas.

Another set of limitations relates to our quantitative approach, which inevitably leads to some degree of social-ecological reductionism.[136] Our objective in this study was to produce a large-scale, household-level analysis examining variation in wild harvesting-well-being relationships across diverse contexts. Thus, a central consideration in the methodological design was to be able to concisely and robustly compare data across as many sites as possible. To efficiently summarize and compare data across diverse sites we thus opted for a quantitative (statistical) method. This introduced two further key limitations.

First, the data standardization and averaging approaches inherent in regression methods lead respectively to a loss of detail in describing rich, multifaceted phenomena, and to the veiling of non-dominant cases—both of which can often be more effectively explored through qualitative approaches.[137,138] We sought to minimize this in our quantitative design by disaggregating analyses at the household level, examining multiple dimensions of well-being (i.e., food security and life satisfaction), modeling the context dependence of relationships, and supporting quantitative results with (brief) qualitative examples from sites in our datasets. However, our study does not reflect the full richness and diversity of pathways by which wild resources affect well-being—many of which cannot be captured in standardized quantitative terms (e.g., many non-material and relational values of nature).[137] Nor does our study examine all dimensions of context dependence. Our results should thus only be considered as a quantitative illustration of selected dimensions of context dependence, on average, across two (quantifiable) dimensions of well-being: food security and life satisfaction. Qualitative approaches may reveal different or more nuanced stories at finer scales, while other dimensions of well-being and context may behave in different ways entirely.

Second, to maximize data comparability between surveys that vary in their design, we simplified various continuous measures of wild harvesting (e.g., harvest quantity, monetary values of harvests), life satisfaction (e.g., multipoint Likert scale responses), and household capitals (e.g., counts of household assets) into binary variables. Such transformations are widely used to achieve data comparability across surveys with different source survey questions (e.g., the Global Multidimensional Poverty Indicator; "Basic Needs" approaches to environmental benefits; categorization of livelihood portfolios),[18,34,61] and for phenomena that are prone to measurement error when measured continuously (e.g., untraded and informal wild harvests).[115] Yet such measures inevitably remain only *partial* (as opposed to *complete*) measures of a phenomenon.[139] In addition, by nominating and applying a binary threshold, such indicators can become more value laden, by emphasizing one (e.g., top-down) perspective on what is a meaningful threshold or outcome (e.g., the distinction between high or low assets).[18] Therefore, our results do not comment on interactions between multiple levels of wild harvesting, well-being, and household capitals, nor any resulting non-linearities (e.g., saturating effects at higher levels of harvest or capitals). Our findings also only illustrate relationships between relevant thresholds of harvesting, well-being, and capitals as defined in the wider development economics literature. Our results may thus differ if alternative (e.g., household or settlement specific) thresholds were used.

Apart from these general methodological issues, the nature of the source data also introduced two other key limitations in relation to particular variables and constructs. First, most datasets were at the household as opposed to intrahousehold level. Our results cannot therefore comment on within-household differences in well-being benefits (e.g., who in the household is food insecure?). Second, while wild harvests have often been shown to be most important to well-being during times of hardship (e.g., during droughts, economic shocks, seasonal hunger gaps),[28,39] most of our source datasets did not capture robust and comparable information on the timing or seasonality of wild harvests, nor on the presence of shocks during or near to the survey period. Thus, while the wide coverage and hierarchal nature of our analysis minimizes (as much as possible) the effect of this on our results, our findings do not comment on the relative importance of wild harvests relative to a household's vulnerability context.

Overall, our results can be considered as a partial, quantitative illustration of the context dependence of wild harvesting's contributions to people, at the household level across most non-urban areas in the Global South (excluding arid and small island ecoregions).

SUPPLEMENTAL INFORMATION

Supplemental information can be found online at https://doi.org/10.1016/j.oneear.2023.12.001.

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AUTHOR CONTRIBUTIONS

We use the CRediT model to recognize author contributions, with first and last author emphasis in paper's authorship order. Conceptualization, all authors; methodology, G.J.W., T.M.D., A.D., S.A., M.P., S.L., C.M.R., K.S., B.E.R., and A.K.; software, G.J.W., A.D., S.A., and M.P.; validation, all authors; formal analysis, G.J.W.; data curation, all authors; writing, all authors; visualization, G.J.W. and C.M.R.; supervision, T.M.D., M.P., S.L., and K.S.; project administration, T.M.D., M.P., S.L., and K.S.; funding acquisition, T.M.D., M.P., S.L., C.M.R., K.S., K.M.H., J.P.G.J., J.A.F., M.M., T.P.D., H.A., and R.S.S.

DECLARATION OF INTERESTS

The authors declare no competing interests.

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REFERENCES

1. Angelsen, A., Jagger, P., Babigumira, R., Belcher, B., Hogarth, N.J., Bauch, S., Börner, J., Smith-Hall, C., and Wunder, S. (2014). Environmental Income and Rural Livelihoods: A Global-Comparative Analysis. World Dev. *64*, S12–S28.
2. Belton, B., and Thilsted, S.H. (2014). Fisheries in transition: Food and nutrition security implications for the global South. Global Food Secur. *3*, 59–66.
3. Ryan, C.M., Pritchard, R., McNicol, I., Owen, M., Fisher, J.A., and Lehmann, C. (2016). Ecosystem services from southern African woodlands and their future under global change. Philos. Trans. R. Soc. Lond. B Biol. Sci. *371*, 20150312.
4. Nyström, M., Jouffray, J.-B., Norström, A.V., Crona, B., Søgaard Jørgensen, P., Carpenter, S.R., Bodin, Ö., Galaz, V., and Folke, C. (2019). Anatomy and resilience of the global production ecosystem. Nature *575*, 98–108.
5. IPBES (2019). Global Assessment Report on Biodiversity and Ecosystem Services of the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES).
6. Hopkins, S.R., Sokolow, S.H., Buck, J.C., De Leo, G.A., Jones, I.J., Kwong, L.H., LeBoa, C., Lund, A.J., MacDonald, A.J., Nova, N., et al. (2020). How to identify win–win interventions that benefit human health and conservation. Nat. Sustain. *4*, 298–304.
7. IPBES (2022). Thematic Assessment Report on the Sustainable Use of Wild Species of the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES Secretariat).
8. Davies, G.R. (2013). Appraising weak and strong sustainability: Searching for a middle ground. Consilience, 111–124.
9. Raudsepp-Hearne, C., Peterson, G.D., Tengö, M., Bennett, E.M., Holland, T., Benessaiah, K., MacDonald, G.K., and Pfeifer, L. (2010). Untangling the Environmentalist's Paradox: Why Is Human Well-being Increasing as Ecosystem Services Degrade? Bioscience *60*, 576–589.
10. BurnSilver, S., Magdanz, J., Stotts, R., Berman, M., and Kofinas, G. (2016). Are mixed economies persistent or transitional? Evidence using social networks from Arctic Alaska. Am. Anthropol. *118*, 121–129.
11. Weber, H., and Weber, M. (2020). When means of implementation meet Ecological Modernization Theory: A critical frame for thinking about the Sustainable Development Goals initiative. World Dev. *136*, 105129.
12. Lele, S. (2020). Environment and well-being. N. Left Rev. 41–63.
13. Bergius, M., and Buseth, J.T. (2019). Towards a Green Modernization Development Discourse? the New, Green Revolution in Africa.
14. White, S.C. (2010). Analysing wellbeing: a framework for development practice. Dev. Pract. *20*, 158–172.
15. Coulthard, S., Evans, L., Turner, R., Mills, D., Foale, S., Abernethy, K., Hicks, C., and Monnereau, I. (2017). Exploring 'islandness' and the impacts of nature conservation through the lens of wellbeing. Envir. Conserv. *44*, 298–309.
16. Silvestri, S., Sabine, D., Patti, K., Wiebke, F., Maren, R., Ianetta, M., Carlos, Q.F., Mario, H., Anthony, N., Nicolas, N., et al. (2015). Households and food security: lessons from food secure households in East Africa. Agric. Food Secur. *4*. 23–15.
17. Eckersley, R.M. (2016). Is the West really the best? Modernisation and the psychosocial dynamics of human progress and development. Oxf. Dev. Stud. *44*, 349–365.
18. Chaigneau, T., Coulthard, S., Brown, K., Daw, T.M., and Schulte-Herbrüggen, B. (2019). Incorporating basic needs to reconcile poverty and ecosystem services. Conserv. Biol. *33*, 655–664.
19. Pascual, U., Balvanera, P., Díaz, S., Pataki, G., Roth, E., Stenseke, M., Watson, R.T., Başak Dessane, E., Islar, M., Kelemen, E., et al. (2017). Valuing nature's contributions to people: the IPBES approach. Curr. Opin. Environ. Sustain. *26–27*, 7–16.
20. Betley, E.C., Sigouin, A., Pascua, P., Cheng, S.H., MacDonald, K.I., Arengo, F., Aumeeruddy-Thomas, Y., Caillon, S., Isaac, M.E., Jupiter, S.D., et al. (2021). Assessing human well-being constructs with environmental and equity aspects: A review of the landscape. People and Nature.
21. Daw, T., Hicks, C.C., Brown, K., Chaigneau, T., Januchowski-hartley, F.A., and Cheung, W.W.L. (2016). Elasticity in Ecosystem Services: Exploring the Variable Relationship between Ecosystems and Human Well-Being, *21*.
22. Agarwala, M., Atkinson, G., Fry, B., Homewood, K., Mourato, S., Rowcliffe, J., Wallace, G., and Milner-Gulland, E.J. (2014). Assessing the relationship between human well-being and ecosystem services: a review of frameworks. Conserv. Soc. *12*, 437–449.
23. Daw, T., Brown, K., Rosendo, S., and Pomeroy, R. (2011). Applying the ecosystem services concept to poverty alleviation: the need to disaggregate human well-being. Environ. Conserv. *38*, 370–379.
24. Fedele, G., Donatti, C.I., Bornacelly, I., and Hole, D.G. (2021). Nature-dependent people: Mapping human direct use of nature for basic needs across the tropics. Global Environ. Change *71*, 102368.
25. IPBES (2022). Summary for Policymakers of the Thematic Assessment of the Sustainable Use of Wild Species of the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES Secretariat).
26. Shackleton, C.M., and de Vos, A. (2022). How many people globally actually use non-timber forest products? For. Pol. Econ. *135*, 102659.
27. Arnold, J.M., Köhlin, G., and Persson, R. (2006). Woodfuels, livelihoods, and policy interventions: changing perspectives. World Dev. *34*, 596–611.
28. Wunder, S., Börner, J., Shively, G., and Wyman, M. (2014). Safety nets, gap filling and forests: a global-comparative perspective. World Dev. *64*, S29–S42.
29. Wells, G., Das, A., Attiwilli, S., Poudyal, M., Kraft, F., Lele, S., Daw, T., and Schreckenberg, K. (2022). Nature's Contribution to Poverty Alleviation, Human Wellbeing and Sustainable Development Goals, 2019–2022 (UK Data Service).
30. CIFOR (2016). CIFOR's Poverty and Environment Network (PEN) Global Dataset, V2 (Center for International Forestry Research (CIFOR)).
31. Smith, H.E., Ryan, C.M., Vollmer, F., Woollen, E., Keane, A., Fisher, J.A., Baumert, S., Grundy, I.M., Carvalho, M., Lisboa, S.N., et al. (2019). Impacts of land use intensification on human wellbeing: Evidence from rural Mozambique. Global Environ. Change *59*, 101976.
32. Camfield, L., Guillen-Royo, M., and Velazco, J. (2010). Does needs satisfaction matter for psychological and subjective wellbeing in developing countries: A mixed-methods illustration from Bangladesh and Thailand. J. Happiness Stud. *11*, 497–516.
33. Omotilewa, O.J., Jayne, T.S., Muyanga, M., Aromolaran, A.B., Liverpool-Tasie, L.S.O., and Awokuse, T. (2021). A revisit of farm size and productivity: Empirical evidence from a wide range of farm sizes in Nigeria. World Dev. *146*, 105592.
34. Martin, S.M., and Lorenzen, K.A.I. (2016). Livelihood diversification in rural Laos. World Dev. *83*, 231–243.
35. Morgan, S.N., Mason, N.M., Levine, N.K., and Zulu-Mbata, O. (2019). Dis-incentivizing sustainable intensification? The case of Zambia's maize-fertilizer subsidy program. World Dev. *122*, 54–69.
36. Garnett, S.T., Burgess, N.D., Fa, J.E., Fernández-Llamazares, Á., Molnár, Z., Robinson, C.J., Watson, J.E.M., Zander, K.K., Austin, B., Brondizio, E.S., et al. (2018). A spatial overview of the global importance of Indigenous lands for conservation. Nat. Sustain. *1*, 369–374.
37. Adams, H., Adger, W.N., Ahmad, S., Ahmed, A., Begum, D., Matthews, Z., Rahman, M.M., Nilsen, K., Gurney, G.G., and Streatfield, P.K. (2020). Multi-dimensional well-being associated with economic dependence on ecosystem services in deltaic social-ecological systems of Bangladesh. Reg. Environ. Change *20*, 42.
38. Pouliot, M., and Treue, T. (2013). Rural people's reliance on forests and the non-forest environment in West Africa: evidence from Ghana and Burkina Faso. World Dev. *43*, 180–193.

39. Pritchard, R., Grundy, I.M., van der Horst, D., Dzobo, N., and Ryan, C.M. (2020). Environmental resources as 'last resort'coping strategies following harvest failures in Zimbabwe. World Dev. *127*, 104741.
40. Ambrose-Oji, B. (2003). The contribution of NTFPs to the livelihoods of the'forest poor': evidence from the tropical forest zone of south-west Cameroon. int. forest. rev. *5*, 106–117.
41. Lakerveld, R.P., Lele, S., Crane, T.A., Fortuin, K.P.J., and Springate-Baginski, O. (2015). The social distribution of provisioning forest ecosystem services: Evidence and insights from Odisha, India. Ecosyst. Serv. *14*, 56–66.
42. Robinson, B.E., Provencher, B., and Lewis, D.J. (2013). Managing wild resources: institutional choice and the recovery of resource rent in Southwest China. World Dev. *48*, 120–132.
43. Davis, L., and Wu, S. (2020). The taste for status in international comparison. J. Happiness Stud. *21*, 2237–2256.
44. Davis, J., Magadzire, N., Hemerijckx, L.-M., Maes, T., Durno, D., Kenyana, N., Lwasa, S., Van Rompaey, A., Verburg, P.H., and May, J. (2022). Precision approaches to food insecurity: A spatial analysis of urban hunger and its contextual correlates in an African city. World Dev. *149*, 105694.
45. Tesfaye, Y., Roos, A., Campbell, B.M., and Bohlin, F. (2011). Livelihood strategies and the role of forest income in participatory-managed forests of Dodola area in the bale highlands, southern Ethiopia. For. Pol. Econ. *13*, 258–265.
46. Fisher, J.A., Patenaude, G., Giri, K., Lewis, K., Meir, P., Pinho, P., Rounsevell, M.D., and Williams, M. (2014). Understanding the relationships between ecosystem services and poverty alleviation: A conceptual framework. Ecosyst. Serv. *7*, 34–45.
47. Cruz-Torres, M.L., and McElwee, P. (2017). Gender, livelihoods, and sustainability: Anthropological research. In Routledge Handbook of Gender and Environment (Routledge)), pp. 133–145.
48. Wosu, A. (2019). Access and institutions in a small-scale octopus fishery: A gendered perspective. Mar. Pol. *108*, 103649.
49. Nightingale, A.J. (2011). Bounding difference: Intersectionality and the material production of gender, caste, class and environment in Nepal. Geoforum *42*, 153–162.
50. Schleicher, J., Zaehringer, J.G., Fastré, C., Vira, B., Visconti, P., and Sandbrook, C. (2019). Protecting half of the planet could directly affect over one billion people. Nat. Sustain. *2*, 1094–1096.
51. Fischer, J., Abson, D.J., Butsic, V., Chappell, M.J., Ekroos, J., Hanspach, J., Kuemmerle, T., Smith, H.G., and von Wehrden, H. (2014). Land sparing versus land sharing: moving forward. Conservation Letters *7*, 149–157.
52. Jagger, P., Cheek, J.Z., Miller, D., Ryan, C., Shyamsundar, P., and Sills, E. (2022). The Role of Forests and Trees in Poverty Dynamics. For. Pol. Econ. *140*, 102750.
53. Alkire, S., and Jahan, S. (2018). The New Global MPI 2018: Aligning with the Sustainable Development Goals.
54. Chaigneau, T., Brown, K., Coulthard, S., Daw, T.M., and Szaboova, L. (2019). Money, use and experience: Identifying the mechanisms through which ecosystem services contribute to wellbeing in coastal Kenya and Mozambique. Ecosyst. Serv. *38*, 100957.
55. Max-Neef, M., Elizalde, A., and Hopenhayn, M. (1992). Development and human needs. Real-life economics: Understanding wealth creation *197*, 213.
56. Sen, A. (1999). Development as Freedom (Oxford University Press).
57. Doyal, L., and Gough, I. (1991). A Theory of Human Need (Macmillan International Higher Education).
58. Dasgupta, P. (2003). Human Well-Being and the Natural Environment (Oxford University Press).
59. McGregor, J.A., McKay, A., and Velazco, J. (2007). Needs and resources in the investigation of well-being in developing countries: illustrative evidence from Bangladesh and Peru. J. Econ. Methodol. *14*, 107–131.
60. Sagar, A.D., and Najam, A. (1998). The human development index: a critical review. Ecol. Econ. *25*, 249–264.
61. Alkire, S., and Santos, M.E. (2014). Measuring acute poverty in the developing world: Robustness and scope of the multidimensional poverty index. World Dev. *59*, 251–274.
62. TEEB (2010). The Economics of Ecosystems and Biodiversity: Ecological and Economic Foundations (Earthscan).
63. Li, X., Zhou, Y., Zhao, M., and Zhao, X. (2020). A harmonized global nighttime light dataset 1992–2018. Sci. Data *7*, 168–169.
64. Melchiorri, M., Florczyk, A., Freire, S., Schiavina, M., Pesaresi, M., and Kemper, T. (2018). Unveiling 25 years of planetary urbanization with remote sensing: Perspectives from the global human settlement layer. Rem. Sens. *10*, 768.
65. Van Vliet, N., Quiceno-Mesa, M.P., Cruz-Antia, D., Tellez, L., Martins, C., Haiden, E., Oliveira, M.R., Adams, C., Morsello, C., Valencia, L., et al. (2015). From fish and bushmeat to chicken nuggets: the nutrition transition in a continuum from rural to urban settings in the Tri frontier Amazon region. Ethnobio. Conserv. *4*.
66. Chaves, W.A., Monroe, M.C., and Sieving, K.E. (2019). Wild Meat Trade and Consumption in the Central Amazon, Brazil. Hum. Ecol. *47*, 733–746.
67. Peralta, P.A., and Kainer, K.A. (2008). Market integration and livelihood systems: a comparative case of three Asháninka villages in the Peruvian Amazon. J. Sustain. For. *27*, 145–171.
68. Lu, F. (2007). Integration into the market among indigenous peoples: A cross-cultural perspective from the Ecuadorian Amazon. Curr. Anthropol. *48*, 593–602.
69. Popkin, B.M. (2001). The nutrition transition and obesity in the developing world. J. Nutr. *131*, 871S–873S.
70. Piperata, B.A., Ivanova, S.A., Da-gloria, P., Veiga, G., Polsky, A., Spence, J.E., and Murrieta, R.S.S. (2011). Nutrition in transition: dietary patterns of rural Amazonian women during a period of economic change. Am. J. Hum. Biol. *23*, 458–469.
71. Godoy, R., Reyes-García, V., Vadez, V., Leonard, W.R., Tanner, S., Huanca, T., Wilkie, D., and Team, T.B.S. (2009). The relation between forest clearance and household income among native Amazonians: Results from the Tsimane'Amazonian panel study, Bolivia. Ecol. Econ. *68*, 1864–1871.
72. Howell, C.J., Schwabe, K.A., and Samah, A.H.A. (2010). Non-timber forest product dependence among the Jah Hut subgroup of Peninsular. Environ. Dev. Sustain. *12*, 1–18.
73. Kramer, D.B., Urquhart, G., and Schmitt, K. (2009). Globalization and the connection of remote communities: a review of household effects and their biodiversity implications. Ecol. Econ. *68*, 2897–2909.
74. Nygren, A., Lacuna-Richman, C., Keinänen, K., and Alsa, L. (2006). Ecological, socio-cultural, economic and political factors influencing the contribution of non-timber forest products to local livelihoods: case studies from Honduras and the Philippines. Small-scale Forest Economics, Management and Policy *5*, 249–269.
75. De la Montaña, E., del Pilar Moreno-Sánchez, R., Maldonado, J.H., and Griffith, D.M. (2015). Predicting hunter behavior of indigenous communities in the Ecuadorian Amazon: insights from a household production model. Ecol. Soc. *20*.
76. Sirén, A.H., Cardenas, J.C., and Machoa, J.D. (2006). The relation between income and hunting in tropical forests: an economic experiment in the field. Ecol. Soc. *11*, art44.
77. Masferrer-Dodas, E., Rico-Garcia, L., Huanca, T., Reyes-García, V., and Team, T.B.S. (2012). Consumption of market goods and wellbeing in small-scale societies: An empirical test among the Tsimane'in the Bolivian Amazon. Ecol. Econ. *84*, 213–220.
78. Ghate, R., Mehra, D., and Nagendra, H. (2009). Local institutions as mediators of the impact of markets on non-timber forest product extraction in central India. Environ. Conserv. *36*, 51–61.

79. Gössling, S. (2003). Market integration and ecosystem degradation: Is sustainable tourism development in rural communities a contradiction in terms? Environ. Dev. Sustain. *5*, 383–400.

80. Minkin, D., and Reyes-García, V. (2017). Income and wellbeing in a society on the verge to market integration: the case of the Tsimane'in the Bolivian Amazon. J. Happiness Stud. *18*, 993–1011.

81. Valeggia, C.R., and Snodgrass, J.J. (2015). Health of indigenous peoples. Annu. Rev. Anthropol. *44*, 117–135.

82. Chaves, W.A., Wilkie, D.S., Monroe, M.C., and Sieving, K.E. (2017). Market access and wild meat consumption in the central Amazon, Brazil. Biol. Conserv. *212*, 240–248.

83. Gurven, M., and Kaplan, H. (2007). Longevity among hunter-gatherers: a cross-cultural examination. Popul. Dev. Rev. *33*, 321–365.

84. Smith, H.E., Jones, D., Vollmer, F., Baumert, S., Ryan, C.M., Woollen, E., Lisboa, S.N., Carvalho, M., Fisher, J.A., Luz, A.C., et al. (2019). Urban energy transitions and rural income generation: Sustainable opportunities for rural development through charcoal production. World Dev. *113*, 237–245.

85. Narayanan, S., Lentz, E., Fontana, M., and Kulkarni, B. (2022). Rural women's empowerment in nutrition: A framework linking food, health and institutions. J. Dev. Stud. *58*, 1–18.

86. Ickowitz, A., Powell, B., Salim, M.A., and Sunderland, T.C. (2014). Dietary quality and tree cover in Africa. Global Environ. Change *24*, 287–294.

87. Robinson, B.E. (2016). Conservation vs. livelihoods: spatial management of non-timber forest product harvests in a two-dimensional model. Ecol. Appl. *26*, 1170–1185.

88. López-Feldman, A., and Wilen, J.E. (2008). Poverty and spatial dimensions of non-timber forest extraction. Environ. Dev. Econ. *13*, 621–642.

89. Roche, M.L., Creed-Kanashiro, H.M., Tuesta, I., and Kuhnlein, H.V. (2007). Traditional food system provides dietary quality for the Awajún in the Peruvian Amazon. Ecol. Food Nutr. *46*, 377–399.

90. Reyes-García, V., McDade, T., Vadez, V., Huanca, T., Leonard, W.R., Tanner, S., and Godoy, R. (2008). Non-market returns to traditional human capital: nutritional status and traditional knowledge in a native Amazonian society. J. Dev. Stud. *44*, 217–232.

91. Shackleton, C.M., and Shackleton, S.E. (2006). Household wealth status and natural resource use in the Kat River valley, South Africa. Ecol. Econ. *57*, 306–317.

92. Ncube, K., Shackleton, C.M., Swallow, B.M., and Dassanayake, W. (2016). Impacts of HIV/AIDS on food consumption and wild food use in rural South Africa. Food Secur. *8*, 1135–1151.

93. Dietz, T., Ostrom, E., and Stern, P.C. (2003). The struggle to govern the commons. science *302*, 1907–1912.

94. Gurven, M., Jaeggi, A.V., Von Rueden, C., Hooper, P.L., and Kaplan, H. (2015). Does market integration buffer risk, erode traditional sharing practices and increase inequality? A test among Bolivian forager-farmers. Human ecology *43*, 515–530.

95. Gurven, M. (2004). Reciprocal altruism and food sharing decisions among Hiwi and Ache hunter–gatherers. Behav. Ecol. Sociobiol. *56*, 366–380.

96. Diener, E., and Biswas-Diener, R. (2002). Will money increase subjective well-being? A literature review and guide to needed research. Soc. Indic. Res. *57*, 119–169.

97. Galik, C.S., and Jagger, P. (2015). Bundles, duties, and rights: A revised framework for analysis of natural resource property rights regimes. Land Econ. *91*, 76–90.

98. Scoones, I. (1998). Sustainable rural livelihoods: a framework for analysis.

99. Fisher, M. (2004). Household welfare and forest dependence in Southern Malawi. Envir. Dev. Econ. *9*, 135–154.

100. Illukpitiya, P., and Yanagida, J.F. (2010). Farming vs forests: Trade-off between agriculture and the extraction of non-timber forest products. Ecol. Econ. *69*, 1952–1963.

101. Dash, M., Behera, B., and Rahut, D.B. (2016). Determinants of household collection of non-timber forest products (NTFPs) and alternative livelihood activities in Similipal Tiger Reserve, India. For. Pol. Econ. *73*, 215–228.

102. Sunderland, T., Achdiawan, R., Angelsen, A., Babigumira, R., Ickowitz, A., Paumgarten, F., Reyes-García, V., and Shively, G. (2014). Challenging Perceptions about Men, Women, and Forest Product Use: A Global Comparative Study. World Dev. *64*, S56–S66.

103. Adhikari, B., Di Falco, S., and Lovett, J.C. (2004). Household characteristics and forest dependency: evidence from common property forest management in Nepal. Ecol. Econ. *48*, 245–257.

104. Jain, P., and Sajjad, H. (2016). Household dependency on forest resources in the Sariska Tiger Reserve (STR), India: Implications for management. J. Sustain. For. *35*, 60–74.

105. Godoy, R., Brokaw, N., Wilkie, D., Colón, D., Palermo, A., Lye, S., and Wei, S. (1998). Of trade and cognition: markets and the loss of folk knowledge among the Tawahka Indians of the Honduran rain forest. J. Anthropol. Res. *54*, 219–234.

106. Kabeer, N. (2015). Gender, poverty, and inequality: a brief history of feminist contributions in the field of international development. Gend. Dev. *23*, 189–205.

107. Cornwall, A. (2003). Whose voices? Whose choices? Reflections on gender and participatory development. World Dev. *31*, 1325–1342.

108. Meinzen-Dick, R., DiGregorio, M., and McCarthy, N. (2004). Methods for studying collective action in rural development. Agric. Syst. *82*, 197–214.

109. K. Schreckenberg, G. Mace, and M. Poudyal, eds. (2018). Ecosystem Services and Poverty Alleviation: Trade-offs and Governance, (Routledge).

110. Robinson, B.E., Zheng, H., and Peng, W. (2019). Disaggregating livelihood dependence on ecosystem services to inform land management. Ecosyst. Serv. *36*, 100902.

111. Devagiri, G.M., Kushalappa, C.G., Ravikumar, D., Anilkumar, K., Siddappa, S., Javed, R., Pal, S., Tomar, S., Gurav, M., and Anand, M. (2015). Western Ghats Household Baseline (ATREE).

112. Grace, K., Nagle, N.N., Burgert-Brucker, C.R., Rutzick, S., Van Riper, D.C., Dontamsetti, T., and Croft, T. (2019). Integrating environmental context into DHS analysis while protecting participant confidentiality: A new remote sensing method. Popul. Dev. Rev. *45*, 197–218.

113. Dolan, P., and Metcalfe, R. (2012). Measuring Subjective Wellbeing: Recommendations on Measures for use by National Governments. J. Soc. Pol. *41*, 409–427.

114. Webb, P., Coates, J., Frongillo, E.A., Rogers, B.L., Swindale, A., and Bilinsky, P. (2006). Measuring household food insecurity: why it's so important and yet so difficult to do. J. Nutr. *136*, 1404S–1408S.

115. Menton, M.C., Lawrence, A., Merry, F., and Brown, N.D. (2010). Estimating natural resource harvests: Conjectures? Ecol. Econ. *69*, 1330–1335.

116. Tatem, A.J. (2017). WorldPop, open data for spatial demography. Sci. Data *4*. 170004–4.

117. Weiss, D.J., Nelson, A., Gibson, H.S., Temperley, W., Peedell, S., Lieber, A., Hancher, M., Poyart, E., Belchior, S., Fullman, N., et al. (2018). A global map of travel time to cities to assess inequalities in accessibility in 2015. Nature *553*, 333–336.

118. ESA (2017). Land Cover CCI Product User Guide Version 2 (Tech. Rep. (European Space Agency Climate Change Initiative)).

119. Ostrom, E., Gardner, R., and Walker, J. (1994). Rules, Games, and Common-Pool Resources (University of Michigan press).

120. Robinson, B.E., Masuda, Y.J., Kelly, A., Holland, M.B., Bedford, C., Childress, M., Fletschner, D., Game, E.T., Ginsburg, C., Hilhorst, T., et al. (2018). Incorporating land tenure security into conservation. Conservation Letters *11*.

121. Schlager, E., and Ostrom, E. (1992). Property-Rights Regimes and Natural Resources: A Conceptual Analysis. Land Econ. *68*, 249–262.

122. Thompson, M.E. (2019). Combining data from new and traditional sources in population surveys. Int. Statistical Rev. *87*, S79–S89.

123. Bolker, B.M., Brooks, M.E., Clark, C.J., Geange, S.W., Poulsen, J.R., Stevens, M.H.H., and White, J.-S.S. (2009). Generalized linear mixed models: a practical guide for ecology and evolution. Trends Ecol. Evol. *24*, 127–135.

124. Johndrow, J.E., Smith, A., Pillai, N., and Dunson, D.B. (2018). MCMC for imbalanced categorical data. J. Am. Stat. Assoc. *114*, 1394–1403.

125. Ploton, P., Mortier, F., Réjou-Méchain, M., Barbier, N., Picard, N., Rossi, V., Dormann, C., Cornu, G., Viennois, G., and Bayol, N. (2020). Spatial validation reveals poor predictive performance of large-scale ecological mapping models. Nat. Commun. *11*, 1–11.

126. Gelman, A., Jakulin, A., Pittau, M.G., and Su, Y.-S. (2008). A weakly informative default prior distribution for logistic and other regression models. Ann. Appl. Stat. *2*, 1360–1383.

127. Gabry, J., Simpson, D., Vehtari, A., Betancourt, M., and Gelman, A. (2019). Visualization in Bayesian workflow. J. Roy. Stat. Soc. *182*, 389–402.

128. Vehtari, A., Gelman, A., and Gabry, J. (2017). Practical Bayesian model evaluation using leave-one-out cross-validation and WAIC. Stat. Comput. *27*, 1413–1432.

129. Goodrich, B., Gabry, J., Ali, I., and Brilleman, S. (2020). rstanarm: Bayesian applied regression modeling via Stan. R package version 2.21.1.

130. Gelman, A., Carlin, J.B., Stern, H.S., Dunson, D.B., Vehtari, A., and Rubin, D.B. (2021). Bayesian Data Analysis (CRC press).

131. Gelman, A., and Hill, J. (2006). Data Analysis Using Regression and Multilevel/hierarchical Models (Cambridge university press).

132. Kay, M. (2020). tidybayes: Tidy data and geoms for Bayesian models. R package version *2*, 1.

133. Lloyd, C.T., Chamberlain, H., Kerr, D., Yetman, G., Pistolesi, L., Stevens, F.R., Gaughan, A.E., Nieves, J.J., Hornby, G., MacManus, K., et al. (2019). Global spatio-temporally harmonised datasets for producing high-resolution gridded population distribution datasets. Big Earth Data *3*, 108–139.

134. Liu, L., Zhang, X., Gao, Y., Chen, X., Shuai, X., and Mi, J. (2021). Finer-resolution mapping of global land cover: Recent developments, consistency analysis, and prospects. J. Remote Sens. *2021*.

135. Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., and Moore, R. (2017). Google Earth Engine: Planetary-scale geospatial analysis for everyone. Remote sensing of Environment *202*, 18–27.

136. Dawson, N., and Martin, A. (2015). Assessing the contribution of ecosystem services to human wellbeing: A disaggregated study in western Rwanda. Ecol. Econ. *117*, 62–72.

137. Ellis, E.C., Pascual, U., and Mertz, O. (2019). Ecosystem services and nature's contribution to people: negotiating diverse values and trade-offs in land systems. Curr. Opin. Environ. Sustain. *38*, 86–94.

138. Post, G., and Geldmann, J. (2018). Exceptional responders in conservation. Conserv. Biol. *32*, 576–583.

139. Sen, A. (1997). On Economic Inequality (Oxford university press).

One Earth, Volume *7*

Supplemental information

Hundreds of millions of people in the tropics need both wild harvests and other forms of economic development for their well-being

Geoff J. Wells, Casey M. Ryan, Anamika Das, Suman Attiwilli, Mahesh Poudyal, Sharachchandra Lele, Kate Schreckenberg, Brian E. Robinson, Aidan Keane, Katherine M. Homewood, Julia P.G. Jones, Carlos A. Torres-Vitolas, Janet A. Fisher, Sate Ahmad, Mark Mulligan, Terence P. Dawson, Helen Adams, R. Siddappa Setty, and Tim M. Daw

Supplementary File

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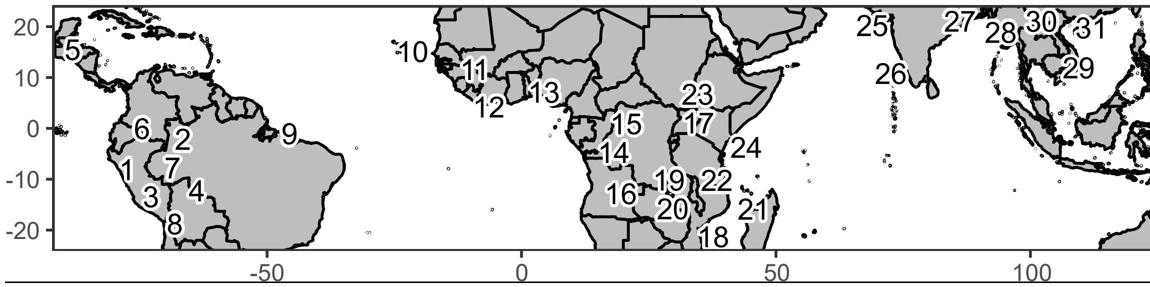
Figure. S1. Village locations and number of observations in each region.



ID	Global region and category	Local region	n villages	n hh.	citation[1–8]
1	Central Peruvian Amazon	Latin America	3	98	1
2	Colombian Amazon	Latin America	10	180	2
3	Southern Peruvian Amazon	Latin America	14	64	3
4	Western Brazilian Amazon (west)	Latin America	4	53	3
5	Western Guatemala	Latin America	10	113	3
6	Ecuadorian Amazon	Latin America	20	58	3
7	Bolivian Amazon	Latin America	8	110	3
8	Central Bolivia	Latin America	6	115	3
9	Eastern Brazilian Amazon	Latin America	4	138	3
10	Western Senegal	Sub-Saharan Africa	5	138	3
11	South eastern Burkina Faso	Sub-Saharan Africa	26	569	3
12	South western Ghana	Sub-Saharan Africa	15	284	3
13	Southern Nigeria	Sub-Saharan Africa	4	74	3
14	Central DR Congo	Sub-Saharan Africa	5	179	3
15	South eastern Cameroon	Sub-Saharan Africa	5	68	3
16	Central Zambia	Sub-Saharan Africa	4	188	3
17	Western Uganda	Sub-Saharan Africa	18	506	3
18	Southern Mozambique	Sub-Saharan Africa	7	248	4
19	Central Malawi	Sub-Saharan Africa	25	73	3
20	Southern Malawi	Sub-Saharan Africa	4	329	5
21	Central Mozambique	Sub-Saharan Africa	10	695	4
22	Northern Mozambique	Sub-Saharan Africa	10	623	4
23	Coastal Kenya	Sub-Saharan Africa	3	460	6
24	Central Ethiopia	Sub-Saharan Africa	19	75	3
25	Gujarat, India	South Asia	3	124	3
26	Western Ghats, India	South Asia	10	241	7
27	Coastal Bangladesh	South Asia	9	221	8
28	South eastern Bangladesh	South Asia	7	70	3
29	Cambodia	East Asia	15	539	3
30	Southern China	East Asia	6	218	3
31	Coastal Northern Vietnam	East Asia	6	155	3
32	Western Indonesia (Kalimantan)	East Asia	6	246	3
33	Eastern Indonesia (East Nusa Tenggara)	East Asia	2	116	3

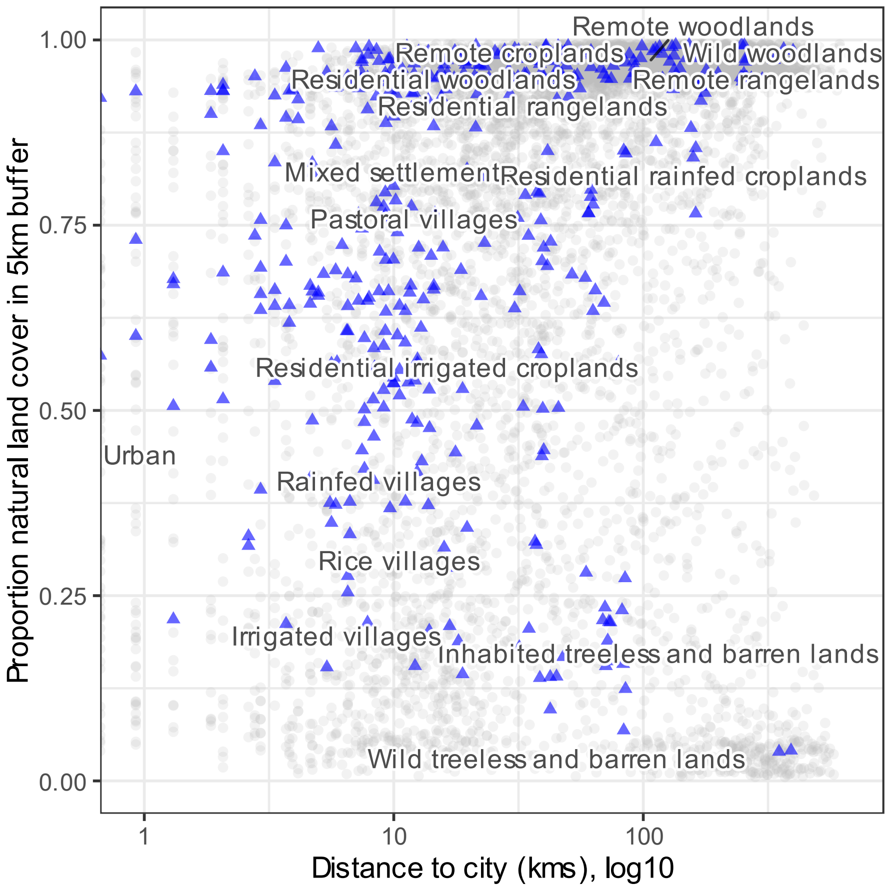


Figure. S2. Social-ecological contexts covered by observations. Villages selected for the study (blue triangles) and a systematic random (~50 km grid) sample of >14,000 points (grey points) across the study region (excluding urban and arid areas). Travel time [9] and natural land cover [10] in 2015. Labels are median location of anthromes in year 2000 [11].

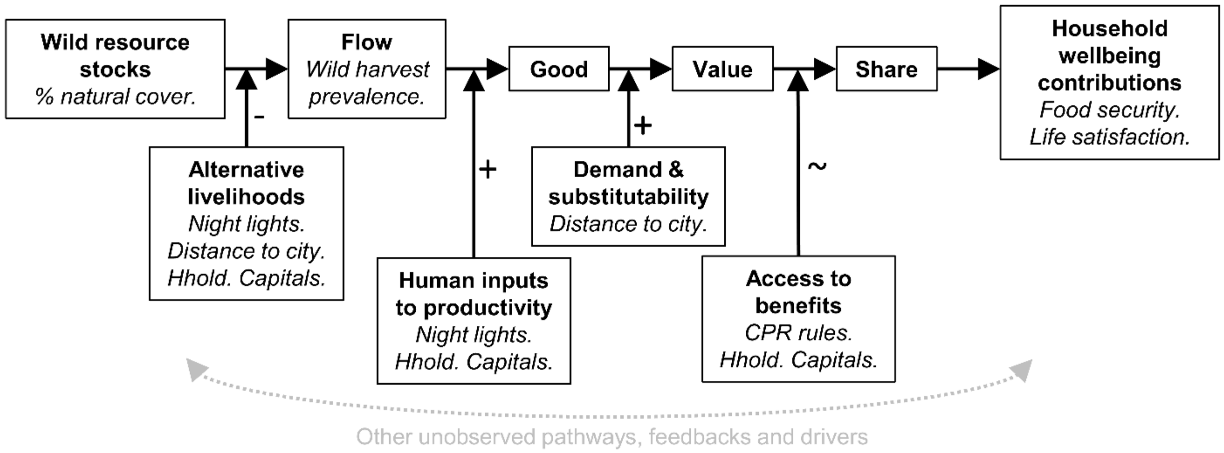


Figure S3. Path diagram of relationships tested in the study. A graphical representation of the theorized relationships summarized in Table 1. Adapted to a path diagram from the conceptual framework on the context-dependence of ecosystem-wellbeing relationships proposed by Daw et al. [12]. Latent (i.e. high level) constructs are in bold, while observed variables used in the regression models are in italics. Some observed variables are theoretically linked to several latent constructs. Arrows pointing into the lines of other arrows indicate positive (+), negative (-) or varied (~) effects. The effects of unobserved drivers are controlled for as much as possible through the hierarchical modelling approach, and the uncertainty terms of the estimates.

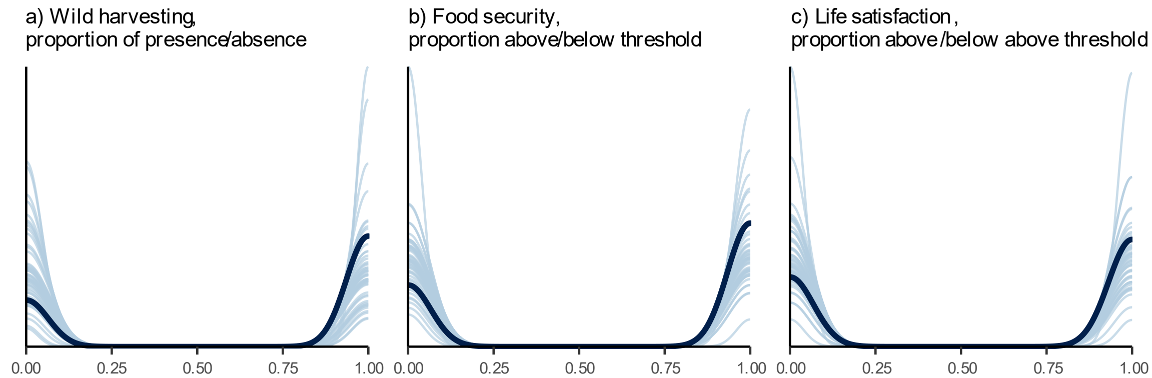


Figure. S4 Prior distribution checks for selected models. Density plots of 50 prior-only simulated datasets (light blue lines) relative to actual data (dark blue line). Plots show proportions of binary outcomes for each simulation.

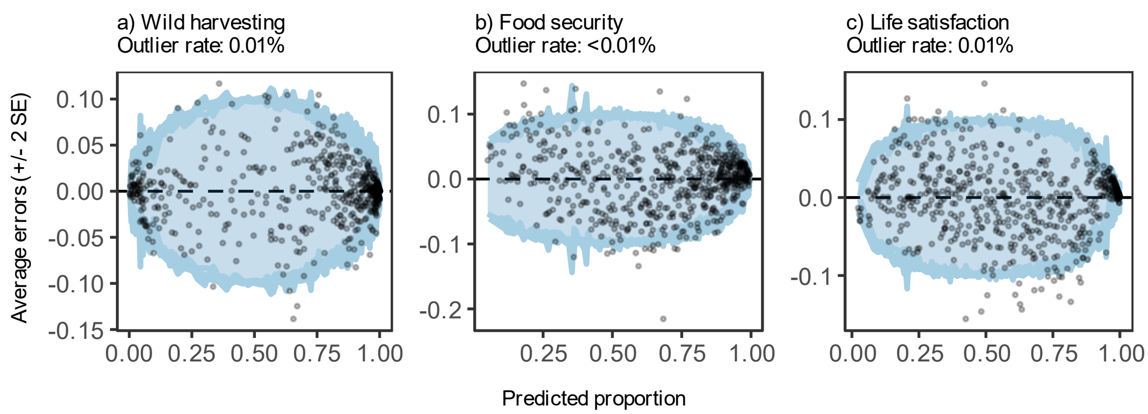


Figure. S5 Posterior distribution checks for selected models. Binned residual plots for each model showing binned residuals (black points) related to +/- 2 standard errors (blue) for 10 simulations with 100 bins.

Figure. S6 Spatial buffer leave-one-out cross-validation assessment of spatial autocorrelation for wild harvesting model. See Figure 1 and Table 2. Testing 50 points at each buffer radius. The error plateaus at ~65% at buffers >= 100km, which is similar to many other widely used mapping products [13].

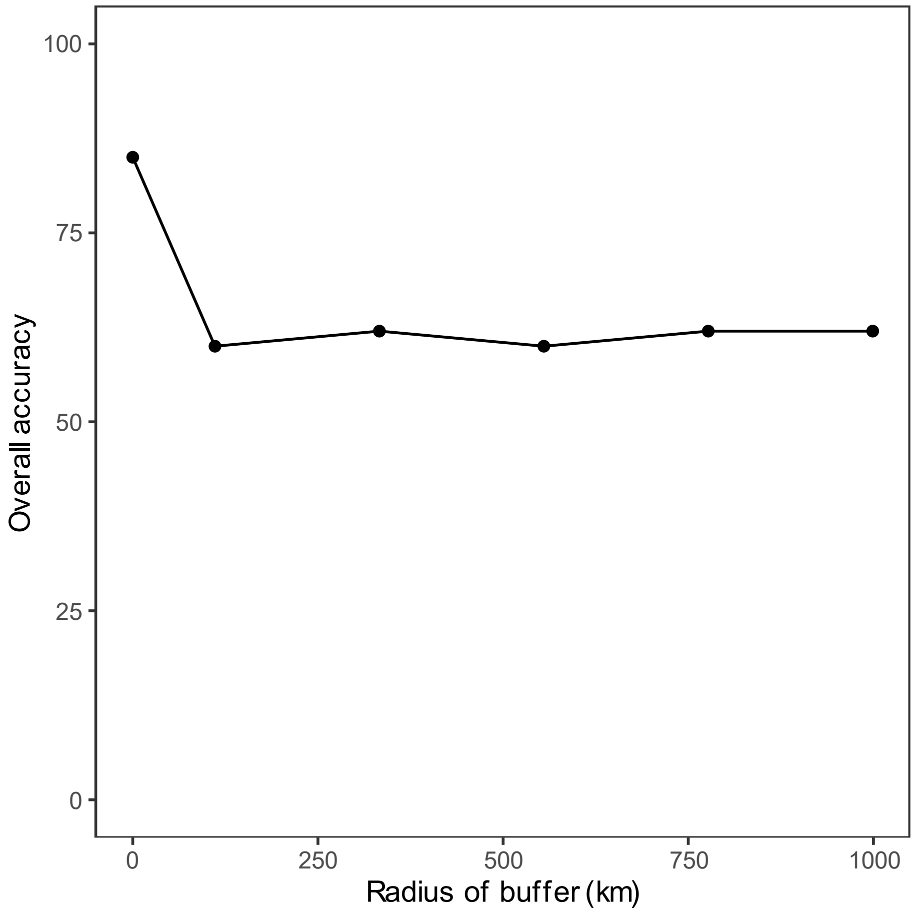


Table S1. Summary and variance inflation factors of observations.

Name	Description	Type	Summary stats Binary (0,1) as counts Numerical as median ± SD	VIF	Source
Wild harvesting					
Wild harvest presence	Household reported harvesting directly from an uncultivated resource system	Binary	0: 3200, 1: 7593	1.22	a
Wellbeing					
Food security	No missed meals in survey period	Binary	0: 3594, 1: 7199	1.15	a
Life satisfaction	Responded life satisfaction above mid-point on Likert-scale type question	Binary	0: 4253, 1: 6540	1.12	a
Household covars.					
Cultivation presence	Harvesting from, or an occupation in, a cultivated resource system	Binary	0: 1717, 1: 9076	1.44	a
Other income presence	Livelihood other than direct harvests/occupations in uncultivated or cultivated resource systems.	Binary	0: 2077, 1: 8716	1.25	a
Productive asset presence	Owns at least one of the following: agricultural land; fishing vessel; livestock	Binary	0: 2639, 1: 8154	1.29	a
Education	An adult has completed six years of schooling. Indicator of human capital.	Binary	0: 4734, 1: 6059	1.15	a
Male HH head	Household has a male head	Binary	0: 1334, 1: 9459	1.04	a
Wealth rank	Within-village wealth rank	Ordinal	1: 2450, 2: 5947, 3: 2396	1.10	a
Village covars.					
Regulated CPR presence	Presence of a *de facto* common-pool resource regulated by community.	Binary	0: 6596, 1: 4197	1.23	a
% natural LC within 5km	Prop. natural land cover within a 3km radius circular buffer from village centre.	Numeric	58 ± 36	1.10	b
Distance to nearest city	Euclidean distance to nearest high density population cluster (>1500 people per sq. kilometre). Mean value in 3km radius around village centre.	Numeric	22 ± 68	1.31	c
Stable night light intensity	Index of intensity of stable night time light emissions. Mean value in 3km radius around village centre. Max. possible is 63.	Numeric	1 ± 4	1.45	d

Sources

a. Household surveys

b. Derived from ESA, 2017[10]. Land Cover CCI Product Version 2.. European Space Agency Climate Change Initiative, Paris.

c. Derived from Lloyd et al. 2019[14]

d. Li et al., 2020 [15]

Table S2. Model selection. Leave-one-out information criterion for each candidate model. Selected model denoted by *.

Model	Model structure	LOOIC
Life satisfaction	Full model, village and regional intercepts*	10644
Life satisfaction	Full model, village intercept	10672
Life satisfaction	Null model, village intercept only	10986
Food security	Full model, village and regional intercepts*	10538
Food security	Full model, village intercept	10554
Food security	Null model, village intercept only	11068
Wild harvesting presence	Full model, village and regional intercepts*	6781
Wild harvesting presence	Full model, village intercept	6792
Wild harvesting presence	Null model, village intercept only	6907

Table S3. Spatial-autocorrelation of all models. Moran's **I** test statistic and the p-value of the difference from the null (no spatial autocorrelation) hypothesis.

Model	Moran's I	p
Wild harvesting	-0.002	0.864
Food security	-0.011	0.708
Life satisfaction	-0.007	0.826

Table S4. Cross-validation of wild harvesting model predictive accuracy. See Figure 1 and Table 1.

Outcome	User's accuracy	Producer's accuracy	Overall accuracy
Not wild harvesting	80	67	85
Wild harvesting	87	93	

Table S5. Food security model estimates. See Figure 2. Median posterior parameter estimates. Log odds with 95% credibility intervals (HPD). * indicates difference from zero at 95% certainty.

Parameter	Median estimate	Low 95% CI	High 95% CI
Wild harvest presence	-1.00*	-1.41	-0.56
Cultivation presence	0.11	-0.01	0.24
Other income presence	-0.17*	-0.32	-0.03
Wealth rank	0.64*	0.56	0.72
Education	0.24*	0.14	0.33
Productive asset presence	0.37*	0.27	0.49
Male household head	0.26*	0.09	0.42
Regulated CPR presence	0.25*	0.04	0.47
Distance to city	-0.06	-0.34	0.19
Stable night light intensity	-0.93	-3.13	1.31
% natural LC within 3km	-0.47*	-0.93	0.00
Wild harvest presence x Cultivation presence	0.10	-0.06	0.27
Wild harvest presence x Other income presence	0.23*	0.06	0.40
Wild harvest presence x Wealth rank	0.18*	0.07	0.30
Wild harvest presence x Education	0.04	-0.09	0.17
Wild harvest presence x Productive asset presence	-0.11*	-0.25	0.03
Wild harvest presence x Male household head	0.13	-0.09	0.37
Wild harvest presence x Regulated CPR presence	0.06	-0.12	0.24
Wild harvest presence x Distance to city	-0.08*	-0.27	0.11
Wild harvest presence x Stable night light intensity	1.34	-0.23	2.99
Wild harvest presence x % natural LC within 3km	0.23	-0.12	0.57

Table S6. Life satisfaction model estimates. See Figure 3. Median posterior parameter estimates. Log odds with 95% credibility intervals (HPD). * indicates difference from zero at 95% certainty.

Parameter	Median estimate	Low 95% CI	High 95% CI
Wild harvest presence	-0.49*	-0.95	-0.04
Cultivation presence	-0.05	-0.21	0.10
Other income presence	-0.04	-0.19	0.13
Wealth rank	0.64*	0.55	0.74
Education	-0.10	-0.20	0.01
Productive asset presence	-0.06	-0.19	0.08
Male household head	0.28*	0.11	0.45
Regulated CPR presence	-0.79*	-1.06	-0.52
Distance to city	0.22	-0.13	0.57
Stable night light intensity	4.53*	1.65	7.40
% natural LC within 3km	-2.08*	-2.71	-1.47
Wild harvest presence x Cultivation presence	0.00	-0.20	0.21
Wild harvest presence x Other income presence	-0.08	-0.26	0.11
Wild harvest presence x Wealth rank	0.13	0.01	0.26
Wild harvest presence x Education	0.01	-0.13	0.15
Wild harvest presence x Productive asset presence	0.11	-0.05	0.30
Wild harvest presence x Male household head	0.09	-0.15	0.33
Wild harvest presence x Regulated CPR presence	0.39*	0.20	0.57
Wild harvest presence x Distance to city	0.34*	0.12	0.56
Wild harvest presence x Stable night light intensity	-0.68	-2.39	1.00
Wild harvest presence x % natural LC within 3km	-0.02	-0.36	0.35

Table S7. Estimates of number of people in wild-harvesting households in 2015. Estimated population counts (millions) of people in households wild harvesting in by region.

Region	Total population (millions)	Total rural population (millions)	People in wild harvesting HH (millions)		
			Mean	Lower 95% CI	Upper 95% CI
All	3,481	963	648	190	886
East Asia & Pacific	858	165	103	8	161
Latin America	463	83	46	2	81
South Asia	853	206	63	2	189
Sub-Saharan Africa	1,307	509	436	178	455

References

1. Francesconi, W., Bax, V., Blundo-Canto, G., Willcock, S., Cuadros, S., Vanegas, M., Quintero, M., and Torres-Vitolas, C.A. (2018). Hunters and hunting across indigenous and colonist communities at the forest-agriculture interface: an ethnozoological study from the Peruvian Amazon. Journal of ethnobiology and ethnomedicine *14*, 1–11. 10.1186/s13002-018-0247-2.

2. Cruz-Garcia, G.S., Cubillos, M.V., Torres-Vitolas, C., Harvey, C.A., Shackleton, C.M., Schreckenberg, K., Willcock, S., Navarrete-Frías, C., and Sachet, E. (2019). He says, she says: Ecosystem services and gender among indigenous communities in the Colombian Amazon. Ecosystem Services *37*, 100921. 10.1016/j.ecoser.2019.100921.

3. CIFOR (2016). CIFOR's Poverty and Environment Network (PEN) global dataset, V2 (Center for International Forestry Research (CIFOR)).

4. Smith, H.E., Ryan, C.M., Vollmer, F., Woollen, E., Keane, A., Fisher, J.A., Baumert, S., Grundy, I.M., Carvalho, M., and Lisboa, S.N. (2019). Impacts of land use intensification on human wellbeing: Evidence from rural Mozambique. Global Environmental Change *59*, 101976. 10.1016/j.gloenvcha.2019.101976.

5. Maseko, H., Shackleton, C.M., Nagoli, J., and Pullanikkatil, D. (2017). Children and Wild Foods in the Context of Deforestation in Rural Malawi. Human Ecology *45*, 795–807. 10.1007/s10745-017-9956-8.

6. Chaigneau, T., Brown, K., Coulthard, S., Daw, T.M., and Szaboova, L. (2019). Money, use and experience: Identifying the mechanisms through which ecosystem services contribute to wellbeing in coastal Kenya and Mozambique. Ecosystem Services *38*, 100957. 10.1016/j.ecoser.2019.100957.

7. Devagiri, G.M., Kushalappa, C.G., Ravikumar, D., Anilkumar, K., Siddappa, S., Javed, R., Pal, S., Tomar, S., Gurav, M., and Anand, M. (2015). Western Ghats Household Baseline (ATREE).

8. Adams, H., Adger, W.N., Ahmad, S., Ahmed, A., Begum, D., Lázár, A.N., Matthews, Z., Rahman, M.M., and Streatfield, P.K. (2016). Spatial and temporal dynamics of multidimensional well-being, livelihoods and ecosystem services in coastal Bangladesh. Sci Data *3*, 160094. 10.1038/sdata.2016.94.

9. Weiss, D.J., Nelson, A., Gibson, H.S., Temperley, W., Peedell, S., Lieber, A., Hancher, M., Poyart, E., Belchior, S., Fullman, N., et al. (2018). A global map of travel time to cities to assess inequalities in accessibility in 2015. Nature *553*, 333–336. 10.1038/nature25181.

10. ESA (2017). Land Cover CCI Product User Guide Version 2. Tech. Rep. (European Space Agency Climate Change Initiative).

11. Ellis, E.C., Klein Goldewijk, K., Siebert, S., Lightman, D., and Ramankutty, N. (2010). Anthropogenic transformation of the biomes, 1700 to 2000. Global ecology and biogeography *19*, 589–606.

12. Daw, T., Hicks, C.C., Brown, K., Chaigneau, T., Januchowski-hartley, F.A., and Cheung, W.W.L. (2016). Elasticity in ecosystem services: exploring the variable relationship between ecosystems and human well-being. *21*. 10.5751/ES-08173-210211.

13. Liu, L., Zhang, X., Gao, Y., Chen, X., Shuai, X., and Mi, J. (2021). Finer-resolution mapping of global land cover: Recent developments, consistency analysis, and prospects. Journal of Remote Sensing.

14. Lloyd, C.T., Chamberlain, H., Kerr, D., Yetman, G., Pistolesi, L., Stevens, F.R., Gaughan, A.E., Nieves, J.J., Hornby, G., and MacManus, K. (2019). Global spatio-temporally harmonised datasets for producing high-resolution gridded population distribution datasets. Big Earth Data *3*, 108–139. 10.1080/20964471.2019.1625151.

15. Li, X., Zhou, Y., Zhao, M., and Zhao, X. (2020). A harmonized global nighttime light dataset 1992–2018. Scientific data *7*, 1–9.