Millions of people in the tropics harvest wild resources, but other socio-economic factors are also important for their wellbeing

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This document contains the following sections:

- Abstract
- Main Manuscript
- Methods
- Acknowledgements
- References
- Figures and Tables

Abstract

Global resource demand and large-scale conservation interventions are diminishing peoples' access to 'wild', common-pool terrestrial and aquatic resources. Theory disagrees on whether the wellbeing of these people can be protected by a transition to non-wild livelihoods and other economic development. We present a pantropical cross-sectional analysis assessing in which contexts households with non-wild livelihoods experience superior food security and life satisfaction relative to wild harvesters. Using Bayesian modelling and a ~10,800 household dataset representative of diverse tropical contexts, we estimate that ~650 million people were directly wild harvesting in 2015. The wellbeing of all households increased with electrical infrastructure, proximity to cities and household capitals. Within this, non-wild harvesters achieved superior outcomes in most contexts—but wild harvesters maintained relatively high outcomes in remote and less converted areas, and amongst asset-poor households. Our results support policies that balance access to wild resources with longer-term improvements to services, infrastructure and markets.

Main manuscript

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 wellbeing of some of the world's poorest people. Debates persist on the magnitude of such disruption, and whether the wellbeing impacts of reduced access to wild ecosystems can be offset by transitions to non-wild livelihoods, and improved access to services, infrastructure and markets (7–9).

Historically, development theory and policy has commonly assumed that transitions to non-wild livelihoods (e.g. in industrialized production or service sectors) generally improve wellbeing (10). Within this paradigm, wellbeing is often assumed to be synonymous with monetary income (11), and wild resources on their own are rarely seen as important contributors (12). More recent advances challenge this view in two ways. First, a newer literature argues that human wellbeing is in fact a *multidimensional* construct which goes beyond simple measures such as income to include more fundamental dimensions, such as food security and life satisfaction (13, 14)—dimensions which are not solely determined by income (15, 16). 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 (17, 18).

Second, an accompanying body of theory argues that the determinants of wellbeing (including contributions from wild resources) are highly *context-dependent*, and vary greatly between different people and geographies (1, 19–21). Acontextual theories of development can therefore miss important contexts where wild resources do indeed make important contributions to wellbeing. Combined, these new theories suggest that analyses of the potential contributions of wild resources (and other factors) to wellbeing need to consider *multiple dimensions of wellbeing* 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 Methods: theoretical background). However, large multi-country quantitative studies testing the generalizability of these theories remain scarce. Existing multi-country studies of wild resources in low- and middle-income areas of the tropics are mainly at relatively coarse spatial scales (e.g. national or sub-national regions) that are unable to determine the influence of different contexts. They also focus on the level of wild resource use, rather than subsequent impacts on wellbeing. Together they indicate that such use is widespread in the region (22–24).

Finer-resolution (e.g. household-level) analyses that do assess contextual variation across different social-ecological systems are rarer, and are also focused primarily on the use of wild resources. 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 related study using the same dataset, Wunder et al. (25) find that poorer households more commonly rely on forests to cope with shocks.

Together these existing multi-country quantitative studies support theories that wild livelihoods are 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 wellbeing, and how this compares to wellbeing outcomes under other types of (non-wild) livelihoods.

In this study we begin to address this gap using Bayesian modelling 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 (26) and Poverty Environment Network (27) databases (for details see Methods: 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 wellbeing which were consistently measured across our dataset, and which are commonly analyzed to capture material and subjective dimensions of wellbeing (see Methods: Theoretical background)(31, 38). 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 (38).

We define wild harvesting as the direct harvesting of food, fiber, fodder or fuel from non-cultivated ecosystems by a household (see Methods: Theoretical background)(1). Following established methods in environmental and development economics, we categorize each household by the presence/absence of wild harvesting in their livelihood portfolio (i.e. a wild- vs non-wild livelihoods) (41–43). We then assess variation in wellbeing outcomes of these groups across ten contextual factors drawn from theory (see Methods: Theoretical background): access to electrical infrastructure; proximity to cities; spatial extent of natural terrestrial and aquatic resources; the presence of rules on common pool resources (CPR); and household attributes on wealth, gender of head, education, and presence of cultivation, other income and productive assets.

Results

<u>How does the prevalence of wild livelihoods vary with context?</u>

We first assessed contextual variation in the prevalence of wild livelihoods 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 Methods: Regression models). Wild livelihoods were more strongly associated with lower night lights, higher natural land cover and the presence of regulated access to CPR. Distance to city had no clear effect. Household capitals played a secondary role, with wild livelihoods being marginally more prevalent amongst 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 livelihoods 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, 1B; see Methods). We conservatively estimate that 648 million people in the study region (median estimate; 95% CI [191M, 886M]); Supplementary Information [SI] Table S7), lived in households directly harvesting wild resources (excluding populations in dense urban areas, arid biomes and small island states; see Methods). 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 et al. (22) estimate that 2.7 billion people use products from forests or fisheries, while other global studies propose that 2.4 billion people use fuelwood (23), 120 million people use fisheries (23), and 1.7 to 3 billion use non-timber forest products (24).

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. (22).

<u>How does context moderate the associations between wild livelihoods and wellbeing?</u>

Next, we used Bayesian logistic GLMMs to estimate contextual variation in the relative contribution of wild- and non-wild livelihoods to food security and life satisfaction (see Methods). Regardless of livelihood type, 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; SI Table S5). Within these general trends, households with non-wild livelihoods had higher food security than wild harvesters in most, but not all, contexts. Wild livelihood outcomes began to converge with, and in some cases exceed, those of non-harvesters in more natural and remote areas, among households with higher night lights, in the presence of 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; SI Table S6). As for food security, non-wild livelihoods again 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-wellbeing relationships, and the importance of considering multiple dimensions of wellbeing in nature-wellbeing analyses. However, our results also support theories that overall improvements to wellbeing have been associated with other non-nature factors, such access to infrastructure, markets and other household capitals.

Context-dependence of nature-wellbeing relationships

On context-dependence, our results offer support for most of the theoretical propositions summarized in Table 1. Most contextual factors strongly moderated either the overall prevalence of wild livelihoods (Table 2) and/or the relative wellbeing outcomes of households with wild livelihoods (Figures 2 and 3). Generally, these findings support understandings that while wild livelihoods are more common amongst less capitalized households areas with more natural land cover and lower infrastructure, wellbeing 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 livelihoods (and hence their contribution to wellbeing) are not only a rural phenomenon (1, 2, 24)—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 (17); agriculture-mangrove mosaics in Bangladesh (30); peri-urban forests in West Africa(99)).

Second, while site-specific studies have documented cases where degraded landscapes can make wild livelihoods more common (e.g. by making resources easier to physically access) (69, 70), our findings suggest that, on average, wild livelihoods (and associated wellbeing benefits) remain more prevalent in more natural (and probably less degraded) landscapes.

Finally, our findings emphasize theories that, while wild livelihoods are more common among less capitalized households, access to wild resources (and associated wellbeing benefits) remain moderated by local rules and power structures. In our analysis, regulation of CPR, wealth and male-headed households were all positively associated with wild livelihoods. This suggests that, even in less capitalized areas where wild harvesting is more common, other modes of (intersectional) marginalization and existing rules continued to direct access towards particular (e.g. elite) groups. A common example from our dataset is where more valuable wild resources are more likely to be subject rules and claims by several groups, including local elites (e.g. grazing lands in eastern India (71); charcoal tree species in Mozambique (31); wild mushrooms in southwestern China (72)).

Multi-dimensional wellbeing

Our results also support theories that nature contributes to different dimensions of wellbeing in different ways. In our results, while food security and life satisfaction shared many similar trends, there were some key differences. While food security of both livelihood types generally trended upwards 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 cross-over 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-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 (100); widespread and sometimes higher food insecurity in more ‘modernized’ food supply chains (101)). These results provide evidence of empirical differences between wellbeing dimensions and their contextual-determinants, including contributions from wild nature.

The importance of both wild livelihoods and economic development for wellbeing

Together, our results suggest that while wild livelihoods were associated with relatively high wellbeing outcomes in particular contexts, other aspects of development (e.g. transitioning to non-wild livelihoods; access to non-natural capital and markets) have generally coincided with overarching improvements to wellbeing 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 improved infrastructure and household capitals (e.g. among rural elites). For example, case studies of sites from within our dataset document improved food security among remote households with agricultural land in Mozambique (31), and in households with higher income in montane forests in Ethiopia (95)). Similarly, improved life satisfaction was observed amongst wealthier households in resource-dependent households in coastal Bangladesh (30). A combination of both economic development and wild harvests thus appears integral to the wellbeing 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 wellbeing. First, our results provide high resolution confirmatory evidence that wild resources contribute to the livelihoods of a large number of people in the region (1, 22–24). 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 (24).

Second, our results provide new large scale quantitative evidence in support of theories that associations between wild nature and wellbeing are multidimensional and greatly moderated by local environmental and socio-economic context. Sustainability science is challenged by the apparent empirical disconnect between wellbeing and nature at the global-level, where widespread environmental degradation has not coincided with reductions in human wellbeing (known as 'the environmentalist's paradox') (8). 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 ignore fine-scale (e.g. village- and household-level) variation in nature-wellbeing relationships, and which focus on unidimensional measures of wellbeing (e.g. only income) (17, 19, 44). 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 wellbeing.

For policy, our findings bolster calls for caution in introducing widespread restrictions or bans on wild resource extraction (102), and in assuming that wellbeing can be easily decoupled from wild resources (e.g. the complete substitution of natural for human-made capital, 7). Even if such interventions are feasible or sustainable in the long term (which is in dispute, 103, 4), in the short to medium term wild resources will remain integral to the livelihoods and wellbeing of a large proportion of the world's population—and particularly to remote and asset-poor people. 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 (104). For the wellbeing of many, wild nature and other aspects of economic development remain deeply entwined.

Methods

Theoretical background

Wellbeing: our approach to wellbeing 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 (28), as proxies of human wellbeing. There is, however, a long history of broader conceptions of wellbeing, 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 (13). Such disaggregated approaches are integral to understanding the diverse pathways by which nature affects humans (20, 21), and have already proved effective in site-specific quantitative analyses of such phenomena (29–31).

Second, we focus on the ultimate *ends* of wellbeing that relate directly to the human condition (e.g. nutrition, life satisfaction), and we treat other more intermediate aspects (e.g. education, assets, income) as *means* by which ultimate wellbeing may be achieved. The diverse foundational literature on multidimensional wellbeing consistently makes such a distinction (32–36). Yet recent commentaries point out that many widely used multidimensional measures of wellbeing (28, 37) continue to conflate ultimate ends with context-specific means (11). For studies of nature's contributions to wellbeing this is problematic in two ways. First, such indicators often class the direct use of nature itself as an indicator of low wellbeing (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) wellbeing. Both of these limitations reduce the utility of intermediate means (such assets and income) as outcome variables for understanding contributions of nature to wellbeing. 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 wellbeing to capture aspects of material and subjective dimensions: food security and life satisfaction (31, 38). 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 (38). To enhance data comparability across our sites, we examine whether a household is above or below a binary 'wellbeing threshold' for each dimensions (a common approach in multi-site assessments of human wellbeing; see Methods)(17, 39).

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 (22–24). A wide array of case studies and regional analyses further argue that such harvests make integral contributions to the wellbeing 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, 14, 29). Here we assess the context dependence of these wellbeing contributions (19). Our focus on wild harvests implies a focus on the direct consumptive use of wild nature (40), which sits within a set of instrumental (as opposed to intrinsic or relational) values for nature (18).

The context-dependence of nature's contributions to wellbeing: 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 (19, 44). Here we evaluate these theories by assessing if the associations between wild (and non-wild) livelihoods, food security and life satisfaction change across selected contextual variables reflective of current theory (Table 1; for detailed descriptions of these variables see Methods: Data)

Stable night light intensity and distance to the nearest city are respectively proxies for access to (electrical) infrastructure and level of market access (45, 46). One body of theory argues that such factors will reduce contributions of wild livelihoods to wellbeing by enhancing access to more profitable non-wild livelihoods (47–58). 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 (47, 52, 59–65).

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 livelihoods, and hence their overall contribution to wellbeing (29, 60, 66–68). 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) (69, 70). On the social side, access to these wild common-pool resources 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 (71–74). The presence of *de facto* CPR rules are broadly theorized to increase the wellbeing benefits from wild harvests by allowing more secure and managed access to wild resources (47, 59, 75–83).

We include five indicators of household capital (84), 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 livelihoods, and hence the prevalence of direct nature-wellbeing pathways, by allowing access to alternative livelihoods and skills (1, 59, 77, 85–88). 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, 66, 77, 89–91). 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.) (92–94). For wild livelihoods, theory thus emphasizes gradations of social exclusion, where less (though still) marginalized groups may be able to better access and benefit from wild harvests relative to the most marginalized (66, 88, 95–98).

<u>Study region</u>

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 programme (ESPA) (105), Robinson et al. (106) and Devagiri et al. (107). This produced a dataset (26) 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 (108). Other potential large household-level datasets were excluded due to a lack of (precise) geospatial coordinates (e.g. DHS, LSMS; , 109). The resulting combined dataset provided more balanced coverage across the study region (see SI, 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 (SI, Figure S1). Together the villages represent close to the full range of variation in the extent of natural land cover and remoteness within the tropics (SI Figure S2). We focused our analysis on 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, which were not represented in our data.

<u>Data</u>

Wellbeing**.** We generated binary indicators that capture whether a household is above or below a deprivation threshold (SI, Table S1). 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 scale midpoint) response to a Likert scale question on the level of satisfaction with their life. 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 (110, 111). Additionally, while such approaches are more commonly used to study deprivation and poverty as special cases of low wellbeing, here we use the simplifying assumption proposed by Agarwala et al.(20), where “[w]ell-being is ... conceptualized as the flip side of multidimensional ... poverty. As multidimensional poverty declines, wellbeing increases”. We thus assume that having a basic need met is synonymous with higher wellbeing.

Wild- and non-wild livelihoods. Given methodological weaknesses in generating robust and comparable continuous measures of often-untraded and informal wild harvests (112), 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 harvesting in a household's livelihood. 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 (41–43). 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 livelihood 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 (SI, 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 livelihoods 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. Household with no reported harvesting of wild resources were classed as having non-wild livelihoods.

Contextual variables. Contextual variables were split into those at household- and village-level (SI, Table S1). From the household surveys we generated six household-level social variables (SI, 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 six years of education; binary gender of household head; and a three-point wealth rank on a household's relative wealth within each 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 common pool resources in the village (SI, Table S1). We calculated distance from city as the Euclidean distance from the nearest area with an estimated population density >1500 per square kilometer according to WorldPop (46, 113). While modelled 'travel time' is likely a more precise measure of remoteness (114), 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 (115) 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. (45). To indicate the presence of a regulated common-pool resource in the village, we used survey data and site descriptions to construct a binary indicator on the *de facto* enforcement of customary or government rules on resource extraction from common pool resources around each village.

<u>Regression models</u>

Modelling approach. For each outcome of interest (presence of wild livelihoods, food security and life satisfaction), we implemented a generalized linear mixed effects model (GLMMs) 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) (116–118). We selected a linear approach to reduce the risk of overfitting in our subsequent predictions and spatial estimates (119). Below we describe the likelihood function and hierarchical structure, priors, model structure

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).

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 t distribution with 7 degrees of freedom, location 0 and scale 2.5 (120). This corresponds to our initial expectation that the determinants of wild harvesting and wellbeing 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 to the observed outcomes using density plots (using bayesplot in R, 121) (SI, Figure S3).

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

Equation 1.

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

$$logit\left(p_{ij}\right) = \propto + \beta_1 \times C_1 + \beta_2 \times C_2 + \cdots + \mathrm{\alpha}_i$$

$$\mathrm{\alpha} = \mathrm{N}(0, \sigma_{\alpha^2})$$

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 household has a wild livelihood; C_1, C_2 etc. are the values of the contextual variables for the household; and ɑ is the normally distributed random intercept (with mean 0 and variance σ_α^2).

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

Equation 2.

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

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

$$\alpha = \mathrm{N}(0, \sigma_{\alpha^2})$$

Where: within the binomial distribution of our outcome, Y_{ij} is 1 if household j in region i has their basic need met; logit is the link function, p_{ij} is the probability that the household is above the given wellbeing 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 ɑ is the normally distributed random intercept (with mean 0 and variance σ_α^2). Presence of wild livelihoods 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 (% 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 SI 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 (LOO-IC) (using the loo package in R) (SI, Table 2) (122). In all cases we selected the full model with both village and region as the random intercept (SI, Table S2).

Computation and convergence. We fit all candidate models using Hamiltonian Markov Chain Monte Carlo (MCMC) estimation via the rstanarm package in R (123). Four MCMC chains were run in parallel for 4000 samples each, with the first 1000 samples in each chain discarded as warm-up. We checked convergence of each MCMC fit by examining % of divergent iterations and the Gelman-Rubin convergence statistic, r < 1.02 (124).

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) (125) (SI, Figure S4). 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 (SI, Table S3), with all models displaying a Moran's I of close to zero (i.e. no evidence of strong spatial autocorrelation).

Assessing model fit. 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 wellbeing models in the main manuscript, we used the existing models and the tidybayes package in R (126) to predict and plot the trend of the village-level marginal effects (effect averaged over all levels of other predictors) of each covariate (124). We report Bayesian uncertainty intervals of the linear trend.

Estimates of wild livelihood population

Gridded estimates. After fitting and assessing the model on the prevalence of wild livelihoods, we used the model to generate pan-tropical ~1 km resolution gridded estimates of the probability of a household having a wild livelihood in a particular location. We used global geospatial datasets of all spatial village-level covariates (SI 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 livelihoods). 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) (127). 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 SI 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% highest posterior densities; HPD). We assessed spatial predictive accuracy of the wild livelihoods 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 SI 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 livelihood 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 S5).

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 (128).

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Data and materials availability
The raw datasets used for this study are publicly available at Wells et al. (26) and CIFOR (108). 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.

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Figures and Tables

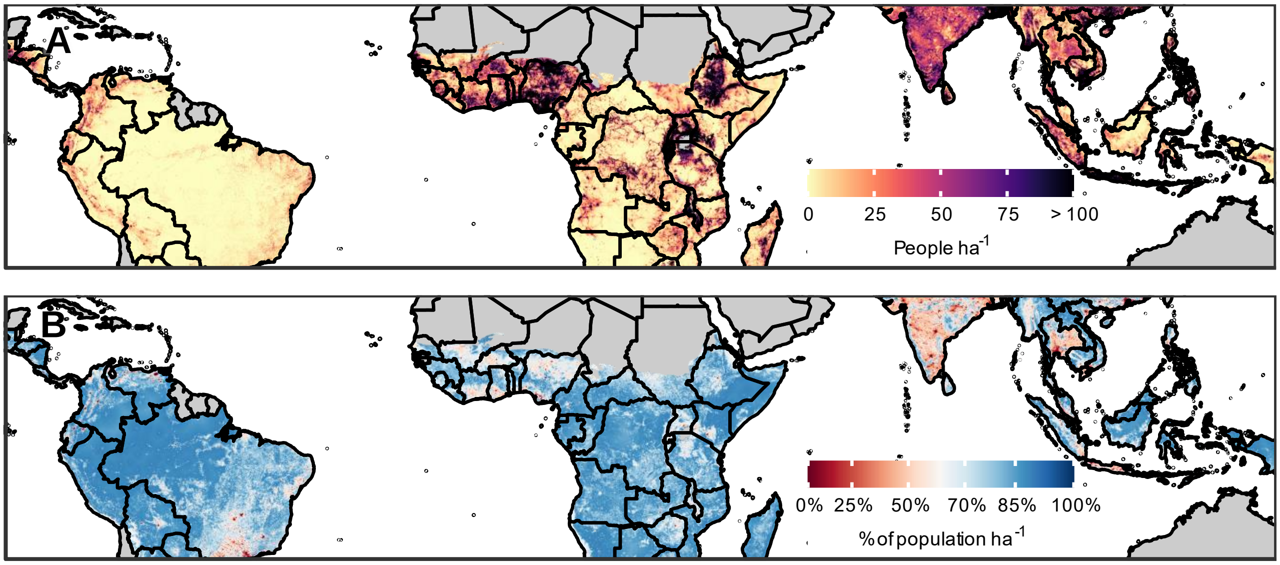

Figure 1. Prevalence of wild harvesting in non-urban areas. (A) Spatial estimates of the number of people in wild harvesting households; and **(B)** the percentage (or probability) of the local population in wild harvesting households in 2015. Spatial estimates exclude grey areas: high income countries, dense urban areas, arid biomes and small island states.

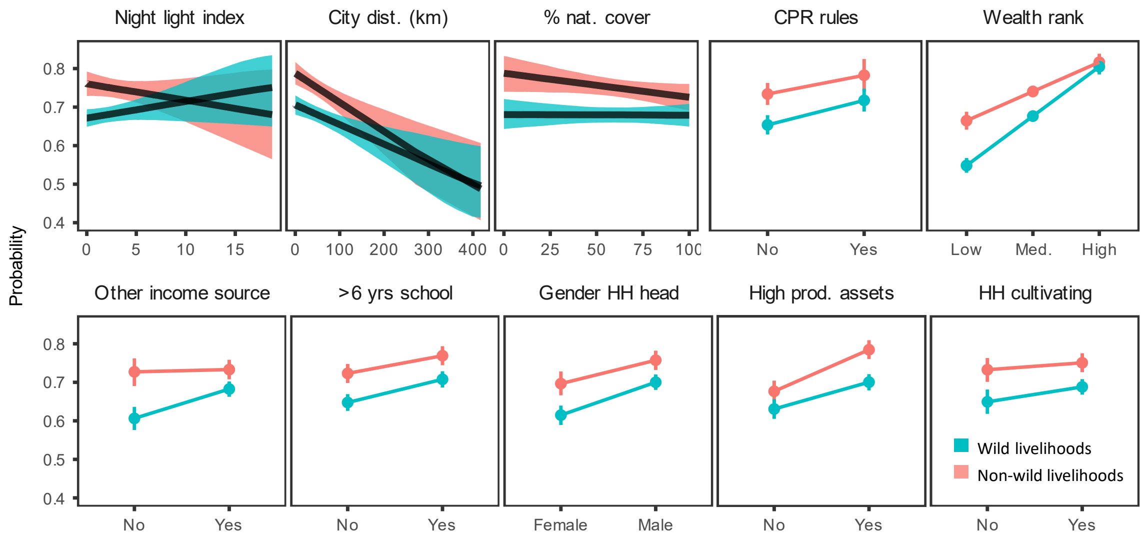

Figure 2. Trends in food security under wild- and non-wild livelihoods across contexts. Linear trends of Bayesian marginal probabilities of a household being food secure in a given context, with 95% Bayesian uncertainty intervals.

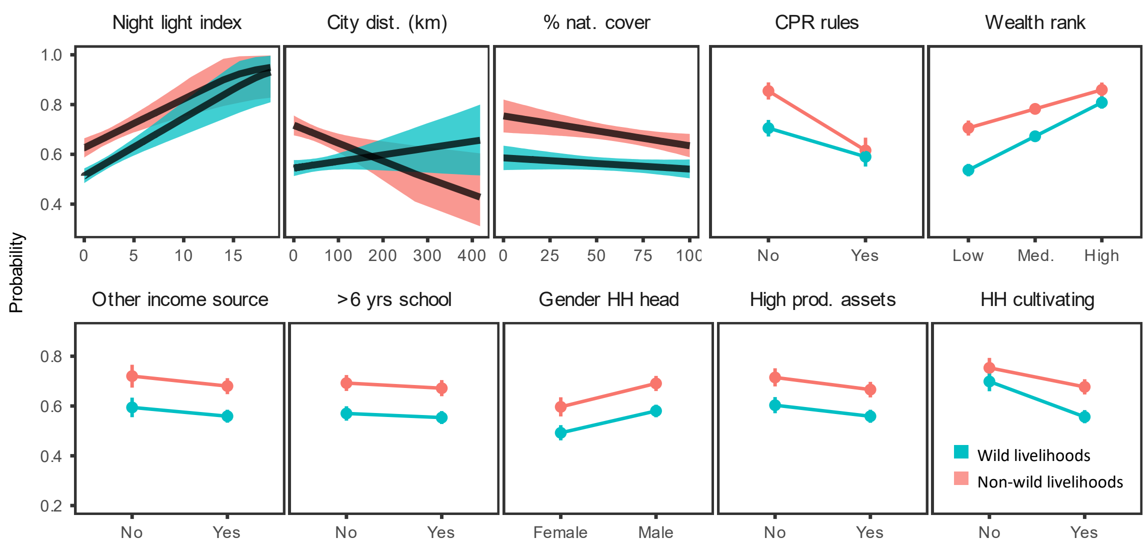

Figure 3. Trends in household head life satisfaction under wild- and non-wild livelihoods across contexts. Linear trends of Bayesian marginal probabilities of a household head being satisfied with their life in a given context, with 95% Bayesian uncertainty intervals.

Table 1. Theorized influences of contextual variables on the contribution of wild livelihoods to wellbeing

Contextual factor	Theorised influence on contribution of wild livelihoods to wellbeing
Stable night light intensity	↓ by offering infrastructure for more profitable non-wild occupations ↑ by enabling more efficient access to, and harvesting of, wild products
Distance to nearest city	↓ by increasing access to more profitable non-wild occupations ↑ by increasing demand for, and substitutability of, wild products
Extent of wild terrestrial and aquatic resources	↑ by offering greater stocks of wild resources ↓ where degraded landscapes improve physical accessibility
De facto presence of CPR rules	↑ by securing tenure and management arrangements, curbing overextraction and degradation
Household capitals (wealth rank, education, gender, productive assets, cultivation, other income)	↓ by providing the skills, assets and opportunities for more profitable non-wild livelihoods ↑ by enabling more efficient access to, and harvesting of, wild products ↑ by enabling privileged access to wild products

Table 2. Estimated influence of contextual variables on the presence of wild livelihoods. Median posterior parameter estimates. Log odds with 95% credibility intervals (HPD). * indicates difference from zero at 95% certainty.

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

Supporting Information for

Millions of people in the tropics harvest wild resources, but other socio-economic factors are also important for their wellbeing

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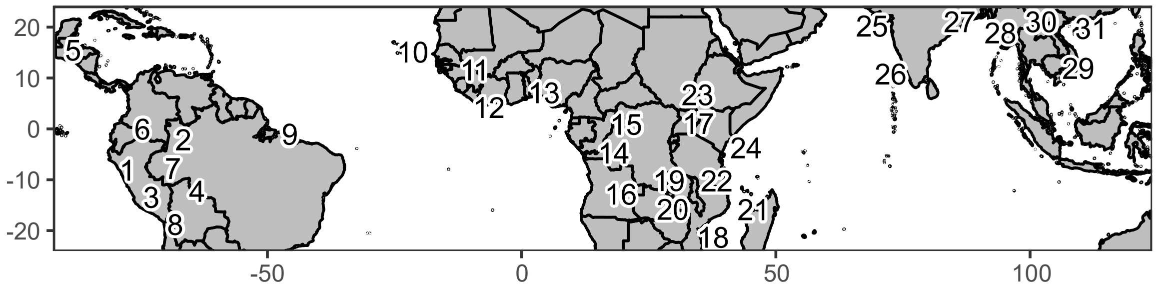
This document contains:

Figures. S1 to S5

Tables S1 to S7

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



ID	Global region and category	Local region	n villages	n hh.	citation
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

Sources

1 Francesconi, W., et al., 2018. Hunters and hunting across indigenous and colonist communities at the forest-agriculture interface: an ethnozoological study from the Peruvian Amazon. J. Ethnobiol. Ethnomedicine 14, 1–11.

2 Cruz-Garcia, G.S., et al., 2019. He says, she says: Ecosystem services and gender among indigenous communities in the Colombian Amazon. Ecosyst. Serv. 37, 100921.

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

4 Smith, H. E., et al. (2019). Impacts of land use intensification on human wellbeing: Evidence from rural Mozambique. Global Environmental Change, 59, 101976.

5 Maseko, H., et al. 2017. Children and Wild Foods in the Context of Deforestation in Rural Malawi. Hum. Ecol. 45, 795–807. https://doi.org/10.1007/s10745-017-9956-8

6 Chaigneau, T., et al. (2019). Incorporating basic needs to reconcile poverty and ecosystem services. Conservation Biology, 33(3), 655–664. https://doi.org/10.1111/cobi.13209

7 Devagiri, et al. (2015). Western Ghats Household Baseline. ATREE.

8 Adams, H., et al (2016). Data Descriptor: Spatial and temporal dynamics of multidimensional well-being, livelihoods and ecosystem services in coastal Bangladesh. Scientific Data, 3(November). https://doi.org/10.1038/sdata.2016.94

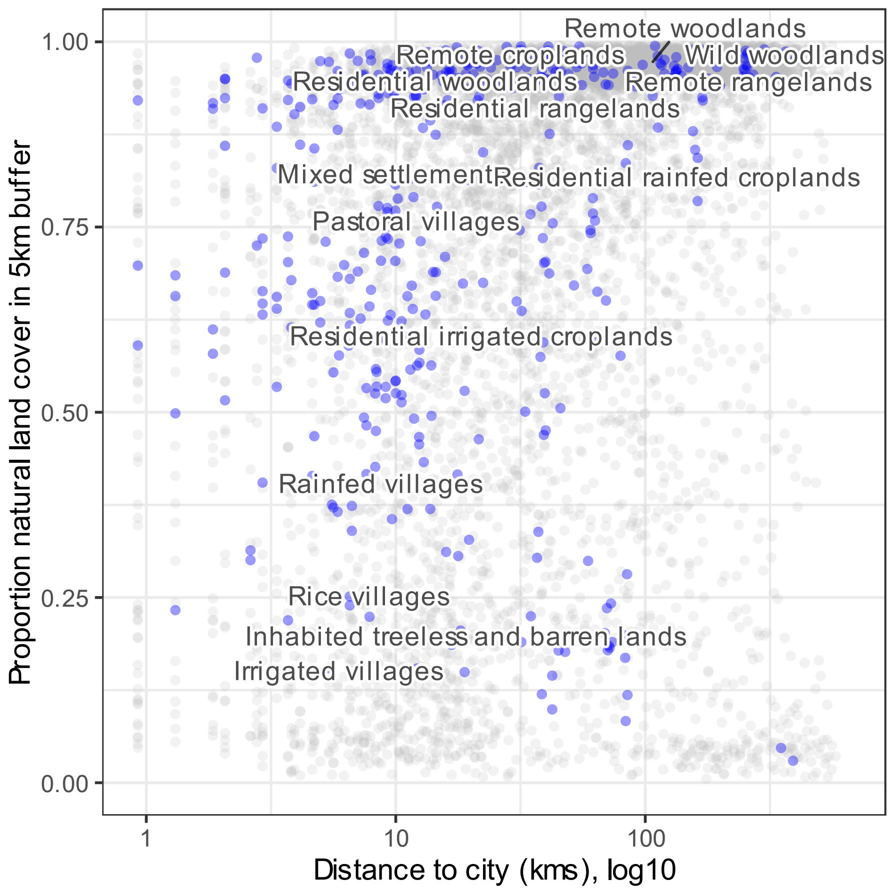


Fig. S2. Social-ecological contexts covered by observations. Villages selected for the study (blue points) and a systematic random (~50 km grid) sample of >14,000 points (grey points) across the study region (excluding urban and arid areas). Travel time (Weiss et al. 2018) and natural land cover (ESA 2017) in 2015. Labels are median location of anthromes in year 2000 (E. C. Ellis et al. 2010).

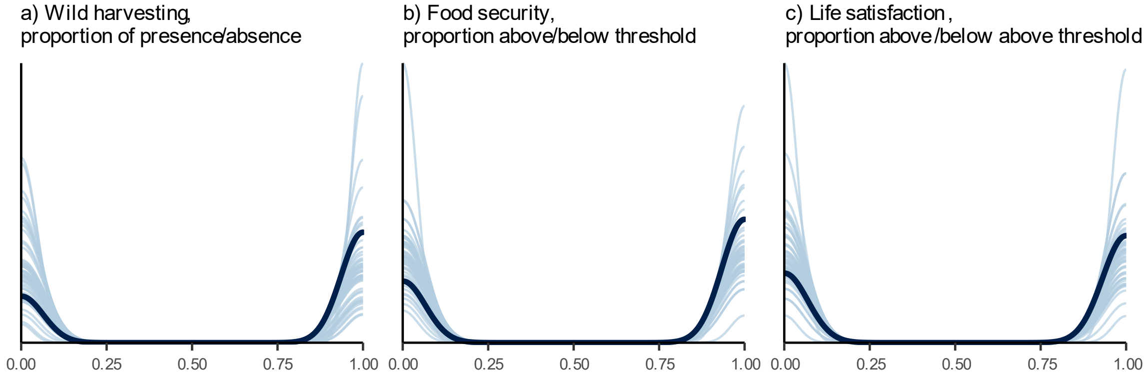


Fig. S3 Prior distribution checks for selected models. Density plots of 50 prior-only simulated datasets (light blue lines) relative to actual data (dark blue line). Plots show proportions of binary outcomes for each simulation.

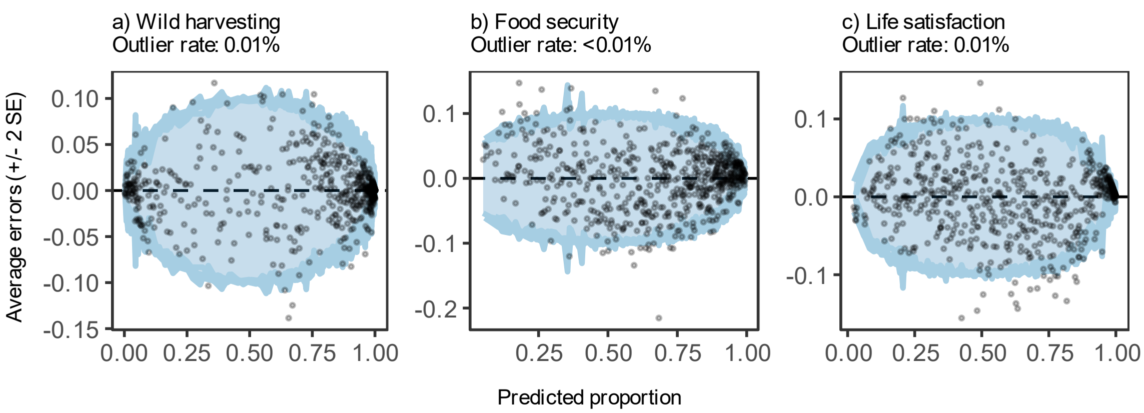
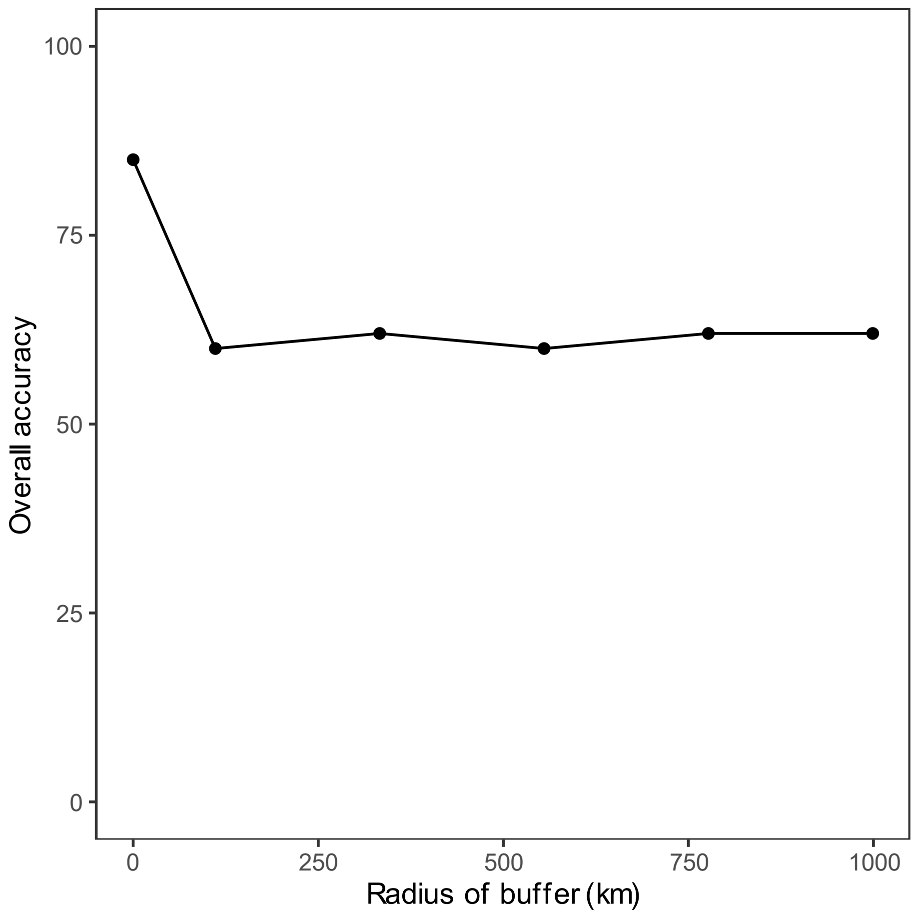


Fig. S4 Posterior distribution checks for selected models. Binned residual plots for each model showing binned residuals (black points) related to +/- 2 standard errors (blue) for 10 simulations with 100 bins.

Fig. S5 Spatial buffer leave-one-out cross-validation assessment of spatial autocorrelation for wild harvesting model. Testing 50 points at each buffer radius.



943 **Table S1.** Summary and variance inflation factors of observations.

Name	Description	Type	Summary stats Categorical: counts Numerical: 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 food shortage 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, an 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 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. kilometer). 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. Land Cover CCI Product Version 2.. European Space Agency Climate Change Initiative, Paris.

c. Derived from Lloyd, C.T., et al. 2019. Global spatio-temporally harmonised datasets for producing high-resolution gridded population distribution datasets. Big Earth Data 3, 108–139.

d. Li, X., Zhou, Y., Zhao, M., Zhao, X., 2020. A harmonized global nighttime light dataset 1992–2018. Sci. Data 7, 1–9.

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.

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. 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. 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.

		People in wild harvesting HH (millions)

Region	Total population (millions)	Total rural population (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