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Pro-poor child nutrition gains from decentralised forest governance

Thomas Pienkowski

t.pienkowski@kent.ac.uk

Durrell Institute of Conservation and Ecology, University of Kent https://orcid.org/0000-0002-3803-7533

Mahesh Poudyal

Durrell Institute of Conservation and Ecology, University of Kent

Matt Clark

University of Sydney https://orcid.org/0000-0002-3217-1192

Bishnu Dulal

HERD International

Ghanshyam Gautam

HERD International

Birendra Karna

ForestAction Nepal https://orcid.org/0000-0002-0556-728X

Zoe Davies

University of Kent https://orcid.org/0000-0003-0767-1467

Jeffrey Andrews

Max Planck Institute for Evolutionary Anthropology

Johan Oldekop

University of Manchester https://orcid.org/0000-0003-0565-812X

Hollie Booth

University of Oxford https://orcid.org/0000-0003-4339-820X

Bruce Donald

Durrell Institute of Conservation and Ecology, University of Kent

Kris Murray

Centre on Climate Change and Planetary Health & MRC Unit The Gambia, London School of Hygiene and Tropical Medicine

Sanjeev Poudel

School of Geosciences, University of Sydney

Sushil Baral

HERD International

Article

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Pro-poor child nutrition gains from decentralised forest governance

Authors

Thomas Pienkowski (1, a): ORCID: 0000-0002-3803-7533
Mahesh Poudyal (1, b): ORCID: 0000-0002-0351-7764
Matt Clark (2, c): ORCID: 0000-0002-3217-1192
Bishnu Dulal (3, d): ORCID: 0000-0003-3588-5112
Ghanshyam Gautam (3, e): ORCID: 0000-0001-8718-3759
Birendra Karna (4, f): ORCID: 0000-0002-0556-728X
Zoe Davies (1, g): ORCID: 0000-0003-0767-1467
Jeffrey Andrews (5, h): ORCID: 0000-0003-1130-0423
Johan A. Oldekop (6, i): ORCID: 0000-0003-0565-812X
Hollie Booth (7, j): ORCID: 0000-0003-4339-820X
Bruce Donald (1, k): ORCID: 0009-0006-0238-0600
Kris Murray (8, l): ORCID: 0000-0002-8382-0674
Sanjeev Poudel (2, m): ORCID: 0000-0002-2413-6223
Sushil Baral (3, n): ORCID: 0000-0002-1850-9820

Affiliations

1: Durrell Institute of Conservation and Ecology, School of Natural Sciences, University of Kent, Canterbury, CT2 7NR, United Kingdom
2: School of Geosciences, University of Sydney, Sydney, Australia
3: HERD International, Kathmandu, Nepal
4: ForestAction Nepal, Kathmandu, Nepal
5: Department of Human Behavior, Ecology and Culture, Max Planck Institute for Evolutionary Anthropology, Leipzig, Germany
6: Global Development Institute, University of Manchester, Manchester, United Kingdom
7: Department of Biology, University of Oxford, Oxford, United Kingdom
8: Centre on Climate Change and Planetary Health & MRC Unit The Gambia, London School of Hygiene and Tropical Medicine, London, United Kingdom

Email

a: t.pienkowski@kent.ac.uk
b: m.poudyal@kent.ac.uk
c: matthew.clark@sydney.edu.au
d: bishnu.dulal@herdint.com
e: ghanshyam.gautam@herdint.com
f: birendrakarna@gmail.com
g: z.g.davies@kent.ac.uk
h: jeffrey_andrews@eva.mpg.de
i: johan.oldekop@manchester.ac.uk
j: hollie.booth@biology.ox.ac.uk
k: bd338@kent.ac.uk
l: kris.murray@lshtm.ac.uk
m: sanjeev.poudel@sydney.edu.au

n: sushil@herdint.com

Correspondence

Thomas Pienkowski. Durrell Institute of Conservation and Ecology, University of Kent, Canterbury CT2 7NR. Email: t.pienkowski@kent.ac.uk.

Abstract

Robust, population-level causal evidence on how natural resource governance paradigms affect human health remains scarce, and few studies trace mediating pathways. We evaluate eight health outcomes under Nepal's decentralised Community Forestry programme from 2006 to 2022. Using causal mediation approaches we link georeferenced health data from 24,586 households with 18,184 Community Forests. Effects were clearest for child nutrition: Community Forestry reduced socioeconomic deprivation, particularly in poorer regions, with downstream reductions in stunting and underweight. Scaled nationally, Community Forestry coverage was associated with reductions of 11.3 cases of stunting (89% CI: 3.9 to 18.3) and 8.5 cases of underweight (89% CI: 1.3 to 14.9) per 1,000 children under five annually, equivalent to 33,965 and 25,490 fewer cases nationally each year, relative to a zero-Community-Forestry counterfactual. Our findings indicate that decentralised environmental governance can deliver the long-term co-benefits for the health of people and nature that remain elusive in other paradigms.

Keywords

Community Forestry; Community-based conservation; Decentralised forest governance; Equity; Global Health; Planetary Health; Public health; Pro-poor.

Introduction

Human health and well-being are closely coupled to the state of Earth's ecosystems, with accelerating anthropogenic destabilisation causing widespread health impacts[1]. Wildfire smoke[2], changing disease ecologies[3], reduced animal pollination[4], and other threats are deepening global health burdens. The scale of these threats is recognised in the Global Action Plan on Biodiversity and Health, negotiated by 196 governments in 2024[5], and the wider Kunming-Montreal Global Biodiversity Framework with its overarching ambition for "a world of living in harmony with nature"[6]. Simultaneously, within the Framework, countries globally have committed to expanding area-based conservation to 30% of the world's surface by 2030[6], potentially altering land and resource access among 2.2 billion people[7]. To achieve this goal, the Framework emphasises the "full, effective, and inclusive participation" of Indigenous peoples and local communities (IP & LCs), and recognition of their rights and territories, as foundational to biodiversity conservation outcomes[8]. Indigenous territories span 28% of land worldwide (despite representing <5% of the global population)[9], contain over one-third of intact forests[10], and support crucial habitats for ~60 % of

terrestrial mammals[11]. Pressure is mounting across countries to decentralise governance to IP & LCs at scale, thereby enabling effective stewardship of their territories[12–14].

Yet, there remains limited understanding of how decentralised natural resource governance affects human health and well-being outcomes when applied at scale and through which causal pathways. Emerging evidence, largely from local case studies, indicates that decentralised stewardship may influence social and ecological outcomes[12,15] with potential downstream health impacts[16,17]. For example, legally recognised Indigenous territories in the Amazon may interact with forest cover and fragmentation to shape fire-related and zoonotic disease incidence[16]. While climate-health research has increasingly incorporated social determinants – the non-medical factors that affect health outcomes over the life course[18] – to map causal pathways (e.g.,[19,20]), there is a paucity of such approaches in nature-health research. Illustratively, much of the research linking nature and mental health overlooks how ecosystems underpin the economic and material conditions of people's lives (i.e., the social determinants of health)[21]. This gap is particularly salient for tropical countries, where 1.2 billion people are highly dependent on nature to meet their basic needs[22], which are well-established social determinants of numerous health outcomes[23,24].

Furthermore, the benefits and burdens of decentralised natural resource governance are rarely equitably distributed within and between communities[25]. Elite capture – where individuals with privileged political, social, or economic status amass disproportionate benefits – can be widespread[26]. For example, Cook et al.[27] found that Nepal's Community Forestry programme reduced poverty among dominant ethnic and caste groups but delivered smaller gains to marginalised minorities, increasing rural inequality. Recent research suggests that the largest within-country health inequalities are found in sub-Saharan Africa and Asia[28], often in countries with high levels of direct natural resource dependence[22] and emerging decentralised natural resource governance regimes[29,30]. Therefore, research is critically needed to assess the health outcomes of decentralized natural resource governance and delineate their causal pathways across socioeconomic segments of the population.

Here, we present a national-scale causal evaluation of the socially differentiated impacts of Nepal's Community Forestry programme across multiple public health domains between 2006 and 2022. This flagship programme has involved over 3 million households across more than 22,000 communities since the 1980s, with Community Forests covering 2.3 million hectares (15.7% of Nepal's land area)[31]. We first ask how Community Forestry coverage affected rural household socioeconomic deprivation, and how this effect varied with an indicator of baseline (pre-study period) multidimensional poverty (Figure 1). We then ask how household socioeconomic deprivation affected mental health, child nutritional status (including stunting and underweight), anaemia, infant mortality, and child diarrhoeal disease outcomes.

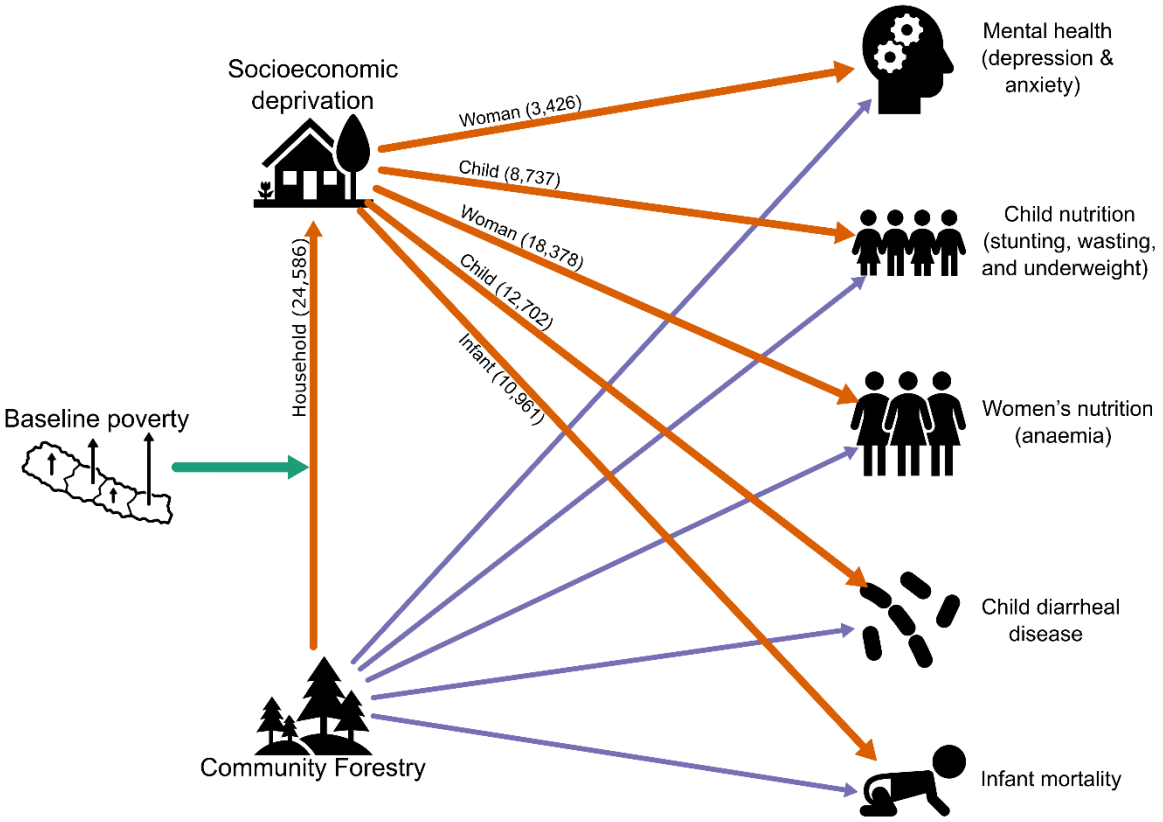


Figure 1. Schematic of the analytical approach used to examine causal pathways connecting Community Forestry, socioeconomic deprivation, and health outcomes. Eight outcomes grouped into five health domains. Orange thick arrows indicate mediated effects via socioeconomic deprivation (labelled with the corresponding unit of analysis and sample sizes), thin purple arrows indicate direct effects, and the thick green arrows indicate moderation (interaction term between Community Forestry and baseline poverty). Variables confounding associations are controlled for in the analysis but not shown here.

Our analysis combines USAID Demographic and Health Survey (DHS) data from 24,586 households in 653 Village Development Committees (rural administrative units prior to 2017) with spatial data on coverage of 18,184 Community Forests, census data, and other socio-economic and biophysical variables from 2001 to 2022. This provides a uniquely large, spatially explicit, and fine-scale dataset that links decentralised governance to individual- and household-level characteristics over two decades. To estimate the deprivation-mediated effects of Community Forestry on health outcomes, we applied a causal mediation approach, combining Bayesian models and g-computation (a method for estimating causal effects from observational data[32,33]). This approach allows us to translate regression model results into population-average contrasts between policy-relevant exposure scenarios, while disentangling the direct, indirect, and total effects.

Results

Community Forestry was associated with larger reductions in socioeconomic deprivation in areas with higher baseline poverty (Figure 2a & 2b). Increasing Community Forestry from 0% to 100% of

Village Development Committee area was associated with a 0.35 standard deviation (SD) reduction in household socioeconomic deprivation at the 75th percentile of baseline poverty (89% credibility interval [CI]: -0.61 to -0.11; probability of direction [pd] = 98.4%), compared with a 0.23 SD reduction at the 25th percentile (89% CI: -0.46 to 0.04; pd = 92.8%). The estimated reduction was, therefore, approximately 1.5 times larger at the 75th percentile. In a supplementary analysis that omitted the interaction with baseline poverty, increasing Community Forestry from 0% to 100% of Village Development Committee area was associated with a 0.30 SD reduction in socioeconomic deprivation (89% CI: -0.51 to -0.09 SD; pd = 98.6%; see Supplementary Discussion 1).

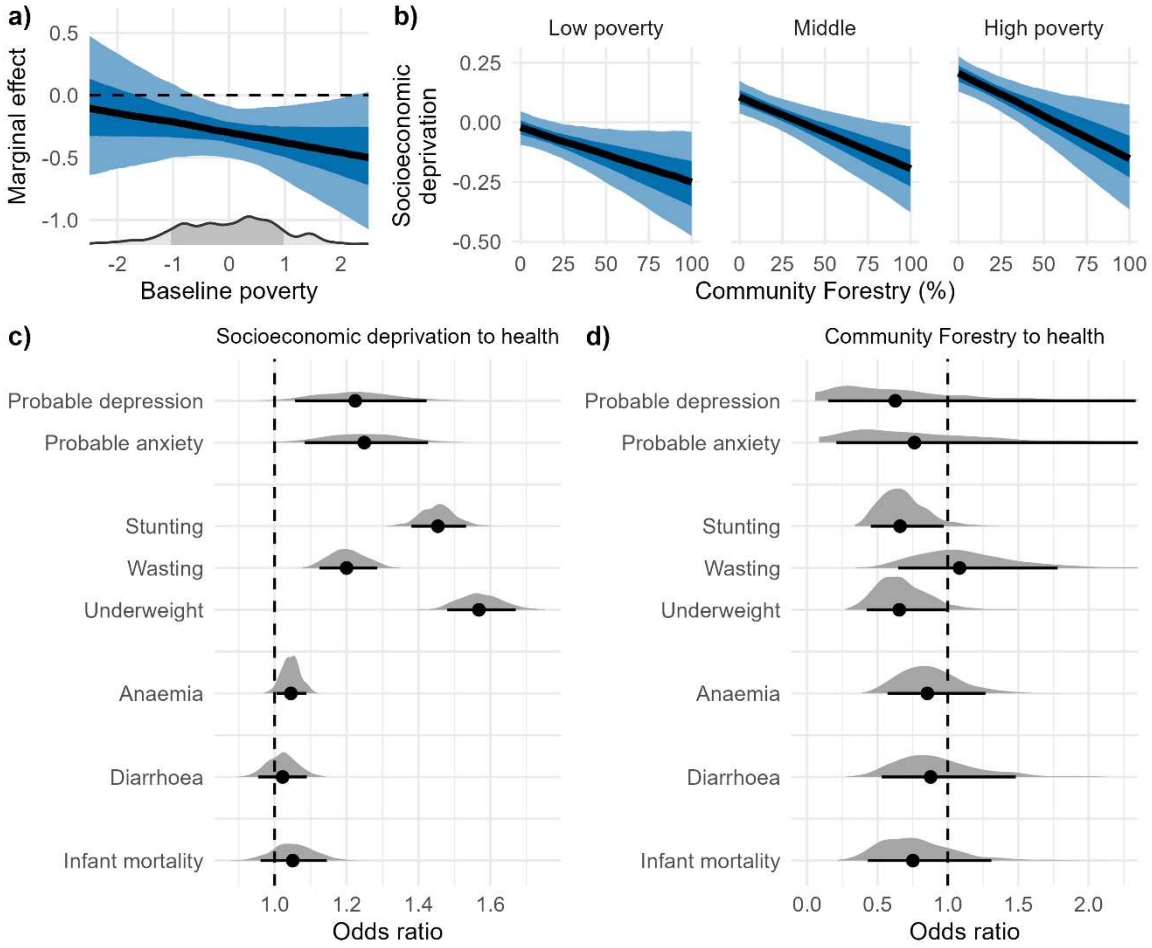


Figure 2. Posterior estimates from the Bayesian mediation analysis. Panel (a) shows the marginal effect of Community Forestry (percentage of Village Development Committee area under Community Forestry) on household socioeconomic deprivation across baseline poverty. The solid line is the posterior median; dark and light blue bands show 50% and 89% credible intervals. The grey density at the base shows the observed distribution of baseline poverty, with shaded regions indicating the central 1 and 2 standard deviations. Panel (b) shows predicted socioeconomic deprivation across the Community Forestry gradients for low- (25th percentile), middle- (50th percentile), and high-poverty (75th percentile) Village Development Committees. Panels (c) and (d) show posterior distributions for the estimated associations of socioeconomic deprivation and Community Forestry on binary health outcomes. Grey densities show posterior distributions, points show

posterior medians, and black bars show 89% credible intervals on the odds-ratio scale. Values above 1 indicate higher predicted odds of the outcome, while values below 1 indicate lower odds.

Higher socioeconomic deprivation was associated with higher predicted probabilities of several adverse health outcomes (Figure 2c). A 1 SD increase in socioeconomic deprivation was associated with higher predicted probabilities of probable depression, probable anxiety, stunting, wasting, underweight, and anaemia (ranging from 0.8 percentage point [pp] to 9.2 pp changes). Associations were largest for child nutritional outcomes, especially stunting (8.3 pp, 89% CI: 7.3 pp to 9.3 pp) and underweight (9.2 pp, 89% CI: 8.0 pp to 10.3 pp).

Community Forestry also showed direct associations with some health outcomes after adjusting for household socioeconomic deprivation and confounders (Figure 2d). Increasing Community Forestry from 0% to 100% of Village Development Committee area was associated with lower predicted probabilities of stunting (-9.0 pp, 89% CI: -16.0 pp to -1.6 pp) and underweight (-7.6 pp, 89% CI: -14.5 pp to -0.1 pp). Direct associations with probable depression, probable anxiety, wasting, anaemia, diarrhoea, and infant mortality were weaker or less consistent.

In the g-computation analysis, observed Community Forestry coverage was associated with lower annual stunting and underweight prevalence (compared to the zero-Community-Forestry counterfactual) across all levels of baseline poverty (Figure 3a). Moreover, observed Community Forestry coverage shifted predicted household deprivation toward lower-deprivation categories relative to the counterfactual across survey years (Figure 3b; see Supplementary Tables 1-7). The clearest shifts were a reduced share of extremely deprived households in 2006 (-3.5 pp, 89% CI: -7.2 pp to -0.6 pp) and increased shares of non-deprived households in 2011 (7.2 pp, 89% CI: 1.6 pp to 13.0 pp), 2016 (3.8 pp, 89% CI: 0.0 pp to 6.7 pp), and 2022 (1.8 pp, 89% CI: 0.0 pp to 4.1 pp).

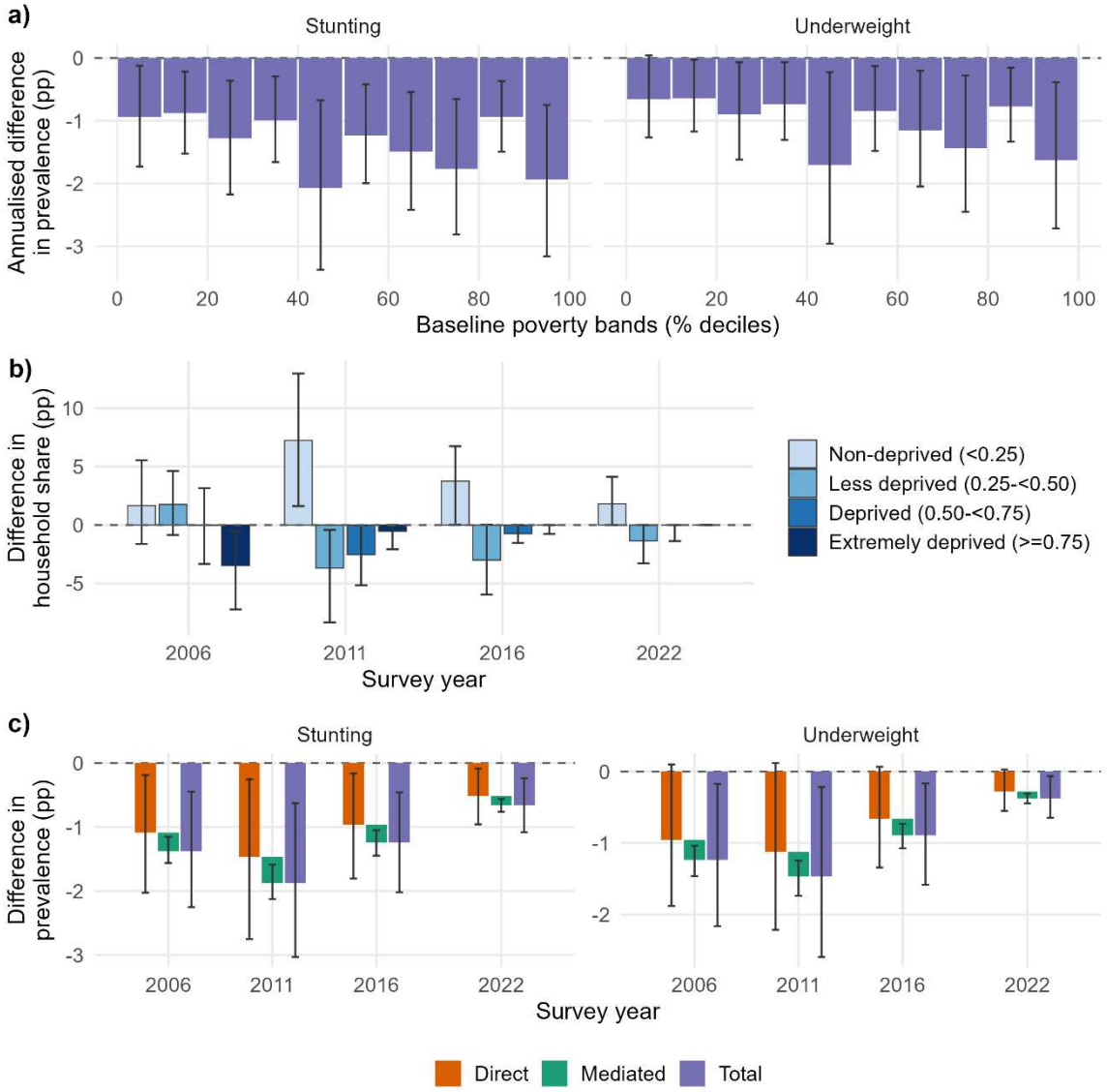


Figure 3. G-computation estimates of percentage point (pp) differences in child under five stunting and underweight prevalence and household socioeconomic deprivation, comparing observed Community Forestry coverage with a zero-Community-Forestry counterfactual. Panel (a) shows annualised differences in stunting and underweight prevalence within deciles of baseline poverty. Panel (b) shows differences in the share of households across four socioeconomic deprivation categories by survey year. Panel (c) shows total differences (purple) in predicted stunting and underweight prevalence and their direct (orange) and socioeconomic-deprivation-mediated (green) components by survey year. Bars show posterior medians, and error bars show 89% credible intervals. Values below zero indicate lower prevalence and values above zero indicate higher prevalence under observed Community Forestry.

Under observed Community Forestry (compared to the counterfactual), estimated effects were consistently negative for stunting and underweight across survey years (Figure 3c). For stunting, the largest total prevalence difference occurred in 2011 (-1.9 pp, 89% CI: -3.0 pp to -0.6 pp). For underweight, the largest total prevalence difference occurred in 2011 (-1.5 pp, 89% CI: -2.6 pp to -

0.2 pp). The corresponding socioeconomic-deprivation-mediated changes accounted for 21% to 26% of the total changes.

Annualised over the 2006-2022 period and scaled nationally, observed Community Forestry coverage was associated with prevalence reductions in stunting of 11.3 cases per 1,000 children under five (89% CI: 3.9 to 18.3) and in underweight of 8.5 cases per 1,000 children under five (89% CI: 1.3 to 14.9), relative to the zero-Community-Forestry counterfactual. These prevalence differences corresponded to 33,965 fewer expected cases nationally per year (89% CI: 11,639 to 54,899) for stunting and 25,490 fewer expected cases nationally per year (89% CI: 3,887 to 44,789) for underweight.

Discussion

Robust causal evidence of the health and well-being impacts of natural resource governance is limited and rarely delineates socially determined and differentiated pathways. Combining two decades of health and governance data, we find that decentralised Community Forestry in Nepal was associated with lower socioeconomic deprivation, particularly in areas with greater baseline poverty, with downstream benefits for child stunting and underweight. This echoes previous evidence. In a national-scale statistical matching and regression study, Oldekopet al.[15] find that Community Forestry led to a 4.3% relative reduction in multidimensional poverty in Nepal between 2000 and 2012. Likewise, material poverty – the inability to meet basic material needs – is often associated with a range of worse health outcomes across countries and contexts[23,24,34]. Moreover, although modest at the individual level, our observed effect sizes were similar in magnitude to some common social protection programmes. A meta-analysis of 129 studies, for example, found that cash transfers reduced child stunting by 1.35 pp (95% confidence interval: -2.35 pp to -0.35 pp)[35]. When scaled across Nepal, our estimates of population-level effects of Community Forestry were substantial. However, these findings do not reflect the programme's public health effects over its full lifetime, since up to 80% of Community Forests were established before 2000[36]. Additionally, our Community Forestry data only describes coverage across Village Development Committee areas, and so our results are not differentiated by individual household engagement. Nevertheless, our results show that the health effects of environmental conservation depend not only on ecological change, but also on the institutions that determine who can access, manage, and benefit from natural resources.

The apparent pro-poor pattern observed in our study may, at face value, appear inconsistent with prior evidence that socially advantaged groups often benefit disproportionately from Community Forestry[27,37–39]. For example, Cook et al.[27] found stronger poverty-alleviating effects among dominant ethnic and caste groups than among marginalised groups in Nepal. Our findings are not necessarily contradictory. Much of this prior evidence examines how benefits are distributed

between social groups within communities or administrative units. In contrast, our analysis examines how treatment effects vary across areas with different baseline poverty. Community Forestry may reduce deprivation most in poorer regions while still distributing direct benefits unequally within those regions (see Supplementary Discussion 2). This suggests that conservation programmes can be both distributively inequitable locally and geographically progressive nationally.

Community Forestry had its clearest total effects on child stunting and underweight. This is important because nutritional deficiencies remain a major source of disability among children under five, with 96.6 million children being underweight globally in 2020[40]. In our study, the deprivation-mediated pathway accounted for around a quarter of the estimated total effects on stunting and underweight. This is plausible, as poverty can cause long-term malnutrition by limiting access to sufficient, diverse, nutrient-rich foods and by worsening sanitation, health-care access, maternal nutrition, and infection risk[41]. The weaker effect on wasting is also consistent with expectations, given its closer link to acute food shortage and illness[42]. Yet, most of the estimated total effect operated through pathways not captured by household deprivation. One plausible pathway is via food security: Community Forests may support nutrition through direct food sources, income, employment, agricultural inputs, and cooking fuel[43,44]. We explored this pathway by modelling associations between Community Forestry, dietary diversity, and child nutritional outcomes, following Rasolofoson et al.[45], but these results were inconclusive, likely due to a small sample size (see Supplementary Discussion 3). More broadly, Community Forestry may improve community-level infrastructure in ways not captured in our analysis[46,47], which may be determinants of anaemia, diarrhoea, and infant mortality[48–51] (see Supplementary Discussion 4). Furthermore, unmeasured baseline local governance capacity may confound our estimates: communities able to cooperate to establish Community Forestry[52–56] may also work together in ways that reduce deprivation and improve health ([e.g., 57,58]). This could mean that our estimates partly reflect pre-existing governance capacity rather than Community Forestry alone (see Supplementary Discussion 5). However, this would not invalidate the broader policy implication of our study: conservation policies that strengthen collective action, local institutions, and resource governance are still likely to benefit public health. Finally, there are plausible pathways connecting Community Forestry to worse health outcomes that were not explored in our study, such as if growing wildlife population lead to greater human-wildlife conflict[59]. Further research, especially using qualitative causal attribution methods such as process tracing[60], could untangle precisely which features of decentralised governance generate health benefits (and possible costs) and how.

Community Forestry's role in rural Nepal may be at an inflexion point. The annual formation of new Community Forest User Groups declined from a peak of over 1,500 in 1995 to around 150 in 2020[31]. Moreover, participation appears to be declining as livelihood diversification and profitable out-migration reduce the relative benefits of engagement, especially among younger people[61] (see

Supplementary Discussion 6). This may heighten the risk of conservation abandonment[62], including non-implementation of management plans or non-renewal of agreements. If accelerating, such abandonment may matter since many rural regions still face pressures from agricultural expansion, infrastructure development, extractive industries, and climate change[63,64]. If these pressures drive deforestation, new and widespread health risks may emerge, such as via declining water quality and diarrhoeal disease[65,66], altered infectious-disease ecology[3,67], heat exposure[68], and fire-related respiratory illness[2]. Consequently, there is an urgent need to ensure that the Community Forestry model – or a suitable replacement that respects local rights and interests – remains relevant to rural communities, for example, by promoting forest-based social enterprises.

Nepal's Community Forestry programme is widely regarded as a flagship model of decentralised natural resource governance and has influenced analogous programmes globally. Evidence from 643 community forest cases across 51 countries shows that these programmes often generate income and environmental gains but can also restrict forest access and resource rights[69]. Our findings suggest decentralised governance may also improve public health. These findings indicate two clear policy implications. First, indicators of the health impacts of decentralised governance programmes should be monitored alongside biodiversity, livelihood, and tenure outcomes. Climate-smart public health frameworks show how environmental, socioeconomic, and health data can be integrated to support surveillance, risk assessment, and policy response[70]. Applied to decentralised governance programmes, such systems could track effects on outcomes such as child nutrition and health inequalities. This aligns with the Global Action Plan on Biodiversity and Health[5], which calls for integrated indicators, impact assessments, and monitoring systems that evaluate the effects of conservation and restoration on the health of both people and nature. Second, decentralised governance should be considered a potential public health intervention, requiring clarification and enhancement of the mechanisms benefitting child nutrition, as well as a conservation and livelihood strategy. Countries have committed to expanding area-based conservation to 30% of the world by 2030[6], which will affect billions of people[7]; doing so in ways that restrict resource access could be severely detrimental to public health and well-being[21,71,72]. In contrast, well-designed decentralised governance could help deliver biodiversity gains while strengthening the upstream social-ecological conditions that support public health at scale.

Data availability statement

Code is available at: https://github.com/Pienkowski/Health_CF_project_public. The underlying data cannot be shared because their redistribution are restricted by data providers.

Conflict of interest disclosure

BK is employed by ForestAction Nepal, where MP also worked from April to August 2011; the organisation promotes and supports Community Forestry in Nepal.

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Author contributions

Conceptualization: TP; MP; MC; BD; GG; BK; JA; JO; HB; SB, Methodology: TP; MP; MC; BD; GG; BK; JA; JO; SB, Software: TP, Validation: TP, Formal analysis: TP, Data Curation: TP; MC; BD, Writing - Original Draft: TP; MP; MC; JA, Writing - Review & Editing: TP; MP; MC; BD; GG; BK; ZD; JA; JO; HB; BD; RF; KM; SP; SB, Visualization: TP, Project administration: TP, Funding acquisition: ZD; SB.

Methods

Ethics approval

Our study used secondary datasets, so no ethical approval was sought.

Conceptual model

Community Forestry in Nepal

Decentralised natural resource governance has been promoted since the 1980s to support sustainable use, devolve management responsibilities and resource-use rights to local groups, and reduce rural poverty[69,73,74]. Nepal's Community Forestry programme builds upon traditional forest management practices, formalised in policy reforms in the late 1970s to mid-1990s[36,75,76]. Within the 1993 Nepal Forest Act, Community Forest User Groups were granted rights to manage nearby national forests, extract resources for subsistence, and earn income from forest products under sustainable use plans[39]. The programme is widely credited for helping nearly double Nepal's forest cover[77–79] and reducing poverty over recent decades[15], alongside other social[80] and ecological benefits[81–83], including in response to climate change[64,84]. However, these impacts are heterogeneous between places and social

groups, alongside evidence of intra-community elite capture[27,37–39]. Within this same period, Nepal has experienced significant public health gains. For instance, life expectancy at birth has increased from 48 to 70 years between 1980 and 2023, while infant mortality has declined from 150 to 25 per 1,000 live births[85].

Treatment assignment mechanism

The treatment assignment mechanism is simultaneously demand-driven, through communities actively seeking Community Forestry status, and supply-driven, via promotion and facilitation by governmental and non-governmental organisations. More broadly, treatment assignment is shaped by both biophysical and socioeconomic factors. Community Forestry applies only to national forests, making forest presence a necessary biophysical precondition[39]. Adoption further requires awareness of the programme and expectations of net benefits aligned with needs and current practices, which may vary among communities and community members with different decision-making power[86,87]. Awareness may be influenced by external outreach and diffusion through social networks[86,88,89], especially in cases where Community Forestry has been promoted around state-protected areas (known as "Buffer Zone Community Forestry")[90]. Expected benefits relative to costs are likely shaped by opportunity costs (e.g., agricultural suitability and market access) and alignment with existing livelihood practices (e.g., historically living in forested landscapes). Interested communities then form Community Forest User Groups – autonomous, self-governing institutions with an elected executive committee – that prepare an operational plan detailing sustainable forest use. These plans are reviewed and approved by the District or Division Forest Office, after which Community Forest User Groups are granted secure use and management rights over forest resources (though land ownership remains with the state), with ongoing technical support from government forestry staff[91]. This treatment assignment mechanism guided the choice of confounding variables (see *Confounding variables*).

Community Forestry and the social determinants of health

Community Forests may shape socioeconomic deprivation through multiple pathways. Community Forestry allows households to harvest forest foods, fuelwood, agricultural inputs, medicinal plants, timber (though this is often restricted) and other forest resources, and can support forest-based enterprises[15,92–95]. Evidence suggests these forest resources are often relatively small direct sources of income[47,96]. However, these resources may substitute for purchased goods, thereby reducing household expenditures and indirectly supporting wealth accumulation. For households with livestock and land, Community Forestry may act as a wealth multiplier by improving access to fodder and fertilising leaf litter, thereby increasing agricultural productivity[97,98]. Furthermore, Community Forestry may buffer households against shocks (e.g., the 2015 earthquake, the 2015-16 Indian fuel blockade, the COVID-19 pandemic) if forests provide material safety nets and Community Forest User Groups facilitate collective support and organisation[99–101]. Community Forests may also

influence other aspects of people's socioeconomic characteristics that shape their health. Some communities reinvest forest revenues in public goods like schools, irrigation, and community buildings by establishing internal levies on forest products (though such fees can burden poorer members[102])[46]. Devolving land and resource rights to communities can foster collective action and local rule-making[103]. This facilitates the enforcement of regulations that curb unsustainable practices such as illegal logging and agricultural expansion (which can entail restrictions on residents' access to forests), potentially maintaining ecosystem services with long-term cascading effects on residents' socioeconomic characteristics and health[104]. Consequently, in line with previous national-scale causal evidence[69], we expect Community Forestry to improve socioeconomic deprivation through multiple pathways.

Furthermore, we expect this treatment effect to be greatest in the poorest regions of Nepal, where forest dependence is highest and alternative livelihoods, such as agriculture, are more limited (controlling for regional differences in forest cover, elevation, and other factors). Consequently, our analysis includes baseline poverty as a moderator variable (see *Variable description*).

Household socioeconomic deprivation is expected to be an important social determinant of multiple health outcomes. Although social determinants vary between health outcomes, factors including income and wealth, education, neighbourhood conditions, and discrimination are consistently influential[105]. For example, material poverty increases exposure to risk factors while limiting the capacity to prevent, treat, and recover from illness across the life course[106]. Likewise, education shapes the health of individuals and their dependents through improved awareness of health risks, adoption of preventive practices, and more effective care-seeking and caregiving behaviours[48–51,107–114].

Taken together, these processes suggest multiple, context-dependent pathways linking Community Forestry to the social determinants of health. We focus explicitly on socioeconomic deprivation, a testable mediating pathway (see *Variable description*). This approach allows us to estimate the indirect effect operating through socioeconomic deprivation alongside a residual direct effect of Community Forestry on health that captures all other unobserved pathways.

Equally, there may be direct effects of Community Forestry on some health outcomes that are not mediated by socioeconomic deprivation. For example, as mentioned, Community Forestry can enhance access to forest foods and agricultural inputs, potentially improving dietary diversity and nutrient adequacy, and thus better child nutritional outcomes[43]. Consequently, our analysis also models the direct effects of Community Forestry on health outcomes. Additionally, there are potential co-morbidities between some of our health outcomes, such as between child diarrheal disease and nutritional outcomes. Our analysis does not model these dependencies, so such pathways are subsumed within the direct effect components rather than estimated as distinct mediated effects.

Data description

Study units and sampling

The unit of analysis includes households (n = 24,586) and infants under 12 months (n = 10,961), children under five years (n = 12,702), and women aged 15 to 49 years (n = 18,378) sampled by the DHS program in 2006, 2011, 2016, and 2022. The DHS program seeks nationally and sub-nationally representative estimates for key demographic and health indicators. To achieve this, the DHS program uses multistage probability samples (see Supplementary Discussion 7). Individuals are nested within households, which in turn are nested within survey clusters with georeferenced locations for community centres. These georeferenced locations are spatially dislocated to ensure anonymity (see Supplementary Discussion 8). Our analysis excludes all observations within urban strata (i.e., includes only residents in rural areas). Observations where the Community Forestry treatment variable could not be calculated were also discarded (see Supplementary Discussion 9).

Variable description

The treatment variable is the percentage of Village Development Committee administrative area under Community Forest governance (see Supplementary Discussion 10). Village Development Committees were subdistrict administrative units equivalent to municipalities in other countries. Between 2015 and 2017, Village Development Committees were replaced by a new local governance structure called Gaunpalikas (rural municipalities) as part of a national federalisation process. However, the majority of Community Forests were established prior to 2017 and formally constituted and managed within Village Development Committee boundaries. Using Village Development Committees as the treatment unit, therefore, aligns the governance unit of interest with the historical spatial patterns of the intervention and is appropriate for a retrospective impact evaluation. Moreover, because Gaunpalikas largely aggregate former Village Development Committees, treatment assignment at the Village Development Committee and Gaunpalika levels is statistically equivalent for causal inference and does not affect the interpretation of the results. Additionally, as many as 80% of all Community Forest User Groups were established prior to 2000[36]. Therefore, the treatment variable was relatively stable across the study period. However, we conceptualise Community Forestry as generating cumulative effects on the social determinants of health over time, rather than a discrete, one-off change following establishment.

We include Village Development Committee-level baseline multidimensional poverty (i.e., baseline poverty) as a moderator variable, which shapes the magnitude of the treatment effect[115]. As discussed above, substantial evidence suggests that the costs and benefits of Community Forestry are often unevenly distributed within communities[27,38,39]. However, comparatively less evidence explores inter-community and regional differences. Therefore, we construct a variable describing baseline poverty, following the Multidimensional Poverty Index approach developed by Alkire and Foster[116]

and used by Oldekop et al.[15] in prior research in Nepal. We calculate these scores from the 2001 Nepal census, first generating eight binary household deprivation indicators encompassing health (child mortality; premature mortality), education (school non-attendance; low schooling), and living standards dimensions (solid-fuel cooking; no electricity; unimproved drinking water; unimproved sanitation). Each dimension was weighted equally (1/3), with equal weights applied to indicators within each dimension (1/6 for health and education indicators; 1/12 for each living-standards indicator), while missing values were treated as non-deprived following Alkire and Santos[117] (which results in more conservative estimates of deprivation). For each household, we summed the weighted indicators to obtain a deprivation score, classifying households as multidimensionally poor if their score was ≥0.333, following Alkire and Foster[116]. We then computed the Village Development Committee-level poverty headcount ratio as the proportion of sampled households classified as poor in each Village Development Committee. This assessed whether the health impacts of Community Forestry varied systematically across Village Development Committees with higher versus lower baseline levels of multidimensional poverty. Additionally, this variable was included as a key confounder within the statistical analysis (see Supplementary Discussion 11).

We also included socioeconomic deprivation as a potential mediator, defined as a variable that may lie on the causal pathway between exposure and outcome[115]. We derived this variable following Dirksen et al.[118], which adapts the Alkire and Foster[116] framework to measure socioeconomic deprivation as a social determinant of health using DHS data. We generated eight binary household deprivation indicators spanning education (school non-attendance; low schooling) and living standards (solid-fuel cooking; unimproved sanitation; unimproved drinking water; no electricity; inadequate housing; low asset ownership). In contrast to the Alkire and Foster[116] method, this household-level measure excludes health indicators to avoid overlap with outcomes. Each dimension was weighted equally (1/2), with equal weights applied to indicators within each dimension (1/4 for each education indicator and 1/12 for each living-standards indicator). We summed these weighted indicators to obtain each household's socioeconomic deprivation score, with higher values indicating greater socioeconomic deprivation, and standardised the score for use in statistical models.

The socioeconomic deprivation and the baseline poverty variables intentionally overlap conceptually, but they differ in scale, timing, and their role in the analysis. Baseline poverty is a pre-study, Village Development Committee-level measure from 2001. Including this as a confounder adjusts for pre-study differences in area-level poverty, so the estimated Community Forestry effect reflects cumulative effects after 2001. Moreover, including baseline poverty as a moderator allows us to assess whether these effects vary across historical poverty levels. We use this fixed historical measure because contemporaneous (i.e., in each survey phase) poverty may itself be affected by Community Forestry, which could introduce post-treatment bias if used as a moderator. In contrast,

socioeconomic deprivation is a household-level measure observed among sampled households in each DHS survey phase and modelled as the mediator.

Community Forestry and socioeconomic deprivation plausibly influence multiple health outcomes, while the DHS contains numerous health indicators. We therefore selected a focused set of outcomes that illustrate the breadth of potential impacts across demographic groups and health domains while ensuring each could be robustly modelled with careful control of confounding. These illustrative domains were common mental disorders (probable depression and generalised anxiety), child nutrition (stunting, wasting, and underweight), women's nutrition (anaemia), infant mortality, and child communicable diseases (diarrhoea).

Mental disorders ranked as the leading cause of years lived with disability and the fifth leading cause of disability-adjusted life years globally in 2023, affecting around one in seven people[40]. Our analysis includes two indicators of common mental disorders: screening instrument scores for depression (the Patient Health Questionnaire) and generalised anxiety (the Generalised Anxiety Disorder scale). Both scales focus on symptoms experienced in the 2 weeks preceding the survey. Full details on translation and validation of the Patient Health Questionnaire and Generalised Anxiety Disorder scales are found in the Nepal 2022 DHS full report[119] (see Supplementary Discussion 12). We modelled Patient Health Questionnaire and Generalised Anxiety Disorder scores as binary outcomes using standard diagnostic cut-offs, with scores ≥10 indicating probable depressive disorder and probable generalised anxiety disorder, respectively.

Nutritional deficiencies were the top cause of years lived with disability and the seventh leading cause of disability adjusted life years among children under five years of age, with over 8% suffering from protein-energy malnutrition[40]. Stunting, wasting, and underweight are informative and widely used indicators of child nutritional status[120], which we use in our study. These were measured using DHS child anthropometry z-scores for height-for-age, weight-for-height, and weight-for-age, modelled as binary outcomes using standard World Health Organization cut-offs, where z-scores <-2 standard deviations indicated moderate or severe undernutrition among children under 5 years of age[121].

Although in decline, anaemia affects about 24% of the world population and is causing an estimated 52 million years lived with disability, with the highest burden among young children, women, and populations in South Asia and sub-Saharan Africa[122]. We measured anaemia using DHS-adjusted haemoglobin concentrations, modelled as a binary outcome using standard World Health Organization thresholds, with haemoglobin <12.0 g/dL for non-pregnant women and <11.0 g/dL for pregnant women indicating anaemia[121].

While also in decline since the 1990s, child mortality remains a major global health concern, with under-5 mortality at 38 deaths per 1,000 live births in 2021[123]. More than 50 countries are off track

to meet the Sustainable Development Goal under-5 mortality target by 2030[124]. We focus on infant mortality (children dying before their first birthday). To avoid right-censoring, observations were restricted to children born 12-59 months before the survey, ensuring that all included children were fully observed over the entire first 12-month risk period. Infant mortality was modelled as a binary outcome.

Enteric diseases were the fifth leading cause of disability-adjusted life years among children under five in 2023, over 80% of which are attributable to diarrheal diseases[40]. Our analysis included under-5 diarrheal disease, defined as reported diarrhoea among children under five at any time in the two weeks preceding the survey. Diarrheal disease was modelled as a binary outcome.

Statistical analysis

Estimand

Our primary estimand for each health outcome, k, was the total effect, $TE^{(k)}$, of observed Community Forestry coverage, compared with a hypothetical counterfactual where coverage was set to zero. We separate $TE^{(k)}$ into the indirect effect, $IE^{(k)}$ and direct effect, $DE^{(k)}$. We also estimated this difference across levels of historical baseline poverty and DHS survey phases.

We estimated these differences using g-computation[32,33]. G-computation is a method for estimating outcomes under exposure scenarios, often used for causal inference in epidemiology and other fields[125,126]. G-computation involves fitting a regression model to the observed data, then using that model to predict expected outcomes by setting the treatment variable to specific values for each observation (without modifying the covariates). The treatment effect is the difference between the average predicted outcomes of the scenarios. For example, in the case of a binary treatment, the average treatment effect is estimated by contrasting scenarios where all observations are set to treated and untreated. For a continuous exposure, the treatment effect is the expected difference under chosen exposure scenarios. We extended the mediation analysis into the g-computation framework by allowing socioeconomic deprivation to change under each Community Forestry scenario, thereby estimating the total, direct, and deprivation-mediated components of the effect[127] (see *Estimator*).

Identification

Our study draws causal inferences from observational data, so the validity of our findings rests on the plausibility of several assumptions, including conditional exchangeability, positivity, consistency, and non-interference (Table 1)[128].

529 Table 1. Assessment of causal identification assumptions and potential violations.

Assumption	Description	Assessment
Conditional exchangeability	After conditioning on covariates, exposed and unexposed units have the same average potential outcomes[128].	Community Forestry engagement is shaped by geophysical features, community demand, and external facilitation (see *Treatment assignment mechanism*). Some of these factors are also expected to affect socioeconomic deprivation and health outcomes. We identify and adjust for plausible confounders through a structured evidence review and workshop with expert co-authors (see Supplementary Discussion 10). Baseline local governance capacity remains a plausible unmeasured confounder; sensitivity analysis shows that our primary findings are robust to confounders as strong as the measured ones but could be invalidated by one that explains ≥3.7% of the residual variance in both treatment and outcome (see *Study limitations* and Supplementary Discussion 5).
Positivity	All units have a non-zero probability of receiving any level of the treatment[128].	A potential violation is that Community Forestry can only occur in areas with forest cover, meaning areas without forest have a zero probability of exposure. Community Forestry is also highly unlikely to occur in urban areas or other forest management designations such as national parks or leasehold forests. The g-computation estimand contrasts observed Community Forestry exposure with a counterfactual scenario in which Community Forestry is set to zero (it does not assign Community Forestry to areas where it could not occur). The analysis also excludes urban observations. Overlap diagnostics comparing Village Development Committees with near-zero and positive Community Forestry coverage showed substantial but incomplete common support, providing partial support for the positivity assumption while indicating that the results reflect extrapolation in less-supported regions of the covariate space (see Supplementary Discussion 5). However, because the g-computation counterfactual reduces coverage to zero rather than assigning Community Forestry to areas where it never occurred, this extrapolation is largely within-sample.
Consistency	A unit's observed outcome under a given treatment condition corresponds to the potential outcome for that unit under that treatment condition[129]. This assumption can be violated if there are multiple versions of a treatment with different causal effects[130].	Community Forestry is not a single standardised intervention, but a flexible set of governance and management practices. The treatment is also measured as Village Development Committee-level coverage, not household-level engagement. Therefore, the estimand is the average effect of Village Development Committee-level Community Forestry coverage as implemented nationally, encompassing variation in local governance, benefit-sharing, and management practices. This is appropriate for a national policy evaluation, but it cannot identify the specific practices or institutional features that drive effects.
Non-interference	A unit's potential outcome depends only on its own exposure, not on the exposure of other units[128]. This assumption can be violated by spillover effects.	Community Forestry may affect neighbouring Village Development Committees through ecological spillovers, displaced forest use, or changes in forest-product and labour markets. Temporal spillovers are also plausible, as Community Forestry may have cumulative effects on forest conditions, institutions, and livelihoods that continue after Community Forest agreements expire. However, clear Community Forest boundaries, access rules, and grievance mechanisms may reduce direct harvesting spillovers. The Village Development Committee-level exposure definition also precludes within-Village Development Committee spillovers, and DHS survey clusters are typically spatially separated (a mean of 12.5 km between nearest neighbours). Residual diagnostics showed no evidence of strong spatial dependence, although weak positive residual spatial autocorrelation was detected

		in 2011 and 2016. We could not assess temporal residual dependence due to the limited number of Village Development Committees observed across multiple survey phases (see Supplementary Discussion 5).

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To satisfy the conditional exchangeability assumption in our observational causal analysis[131], we conducted a structured, evidence-driven process to identify and justify confounders (Table 1). We first reviewed peer-reviewed literature on the determinants of Community Forestry engagement in Nepal, identifying regional-, community- and household-level factors that plausibly influence exposure to Community Forestry. For each candidate factor, we then assessed whether there was empirical evidence of a causal effect on socioeconomic deprivation or health outcomes. Likewise, we applied a similar process to examine the relationships between socioeconomic deprivation and each health outcome, reviewing outcome-specific literature to identify upstream determinants of health that plausibly influence socioeconomic deprivation, thus representing confounders. We did not adjust for downstream mediators, colliders, or post-treatment variables to minimise the risk of overadjustment and post-treatment bias. This information was consolidated into an evidence pack, which was iteratively and critically reviewed with co-authors who had expertise in Community Forestry, public health, and causal inference (see Supplementary Discussion 10). We use the term "baseline" to indicate confounder variables measured prior to the observed Community Forestry exposure period (i.e., in 2000 and 2001).

546 Table 2. The table lists measured variables used to adjust for confounding (additional fixed effects for the DHS survey phase and varying intercepts for clustered data were
547 included in the analysis but are not listed here).

Outcome domain(s)	Variable name	Description/calculation
Socioeconomic deprivation; mental health; child nutrition; anaemia; diarrhoea; infant mortality	Baseline poverty	See main text.
Socioeconomic deprivation; diarrhoea	Baseline forest cover	Proportion of the Village Development Committee area classified as forest in 2000, derived from Potapov et al.[132] tree-cover data using a 30% canopy-cover threshold.
Socioeconomic deprivation; child nutrition; anaemia; diarrhoea	Baseline elevation	Mean elevation within a 5 km buffer around each DHS sampling cluster, derived from the Copernicus Global Digital Elevation Model (90 m)[133*].
Socioeconomic deprivation; child nutrition; anaemia; diarrhoea	Baseline terrain ruggedness	Mean terrain ruggedness within a 5 km buffer around each DHS sampling cluster, derived from the Copernicus Global Digital Elevation Model (90 m)[133*], calculated from the elevation raster using the Terrain Ruggedness Index using the 'terra' package[134].
Socioeconomic deprivation; child nutrition; anaemia; diarrhoea	Baseline precipitation	Mean annual precipitation within a 5 km buffer around each DHS sampling cluster between 1970-2000, derived from monthly WorldClim precipitation data[135].
Socioeconomic deprivation; diarrhoea	Baseline population density	Mean population density within a 5 km buffer around each DHS sampling cluster in 2000, derived from Gridded Population of the World data[136].
Socioeconomic deprivation; child nutrition; anaemia; diarrhoea	Baseline agricultural effort	Village Development Committee-level agricultural effort derived from the 2001 Nepal census[137]. Each DHS sampling cluster was assigned the value of the Village Development Committee containing its centroid.
Socioeconomic deprivation	Out-migration	Village Development Committee-level proportion of households with members living abroad. Values were derived from census data for 2001[137], 2011[138], and 2021[139], with values for the years prior to each survey phase (2005, 2010, 2015, and 2021) estimated by linear interpolation between census years. Each DHS sampling cluster was assigned the interpolated Village Development Committee-level value corresponding to its survey phase. This is the only time-varying confounder used in the analysis (see Supplementary Discussion 13).
Socioeconomic deprivation; mental health; child nutrition;	Travel time to population centres	Travel time to the nearest population centre of at least 10,000 people in 2015. Values were extracted at DHS cluster centroids, derived from Nelson et al.[140], as a proxy for relative accessibility, as comprehensive pre-

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anaemia; diarrhoea; infant mortality		study-period travel-time data were not available. This assumes that Community Forestry did not substantially affect major transport infrastructure (which would lead to post-treatment adjustment bias).
Socioeconomic deprivation	Baseline community distance to protected areas	Distance from each DHS sampling cluster to the nearest protected area in 2001. Protected area data was derived from the World Database of Protected and Conserved Areas[141], retaining those established prior to 2001.
Mental health	Ethnoracial discrimination	Household caste/ethnicity group, used as a proxy for ethnoracial disadvantage (see Supplementary Discussion 2).
Mental health	Disaster and conflict	The 2015 Nepal earthquake represents a potentially traumatic event affecting a large portion of the Nepali population. Therefore, the mean Modified Mercalli Intensity within a 5 km buffer around each DHS sampling cluster was extracted from the USGS ShakeMap Atlas[142].
Mental health; anaemia; diarrhoea; infant mortality	Women's/mothers age	Age of the individual, derived from DHS data.
Mental health	Women's employment	Women's work and payment status, harmonised into not working, unpaid work, and paid work, derived from DHS data.
Child nutrition; diarrhoea	Household size	Number of household members, derived from DHS data.
Anaemia; infant mortality	Reproductive parity	Number of births reported by each woman, derived from DHS data.

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Estimator

We used a mediation modelling approach within a Bayesian framework to estimate the effects of Community Forestry on health outcomes. Mediation analysis can help determine if and to what extent the effect of an exposure on an outcome is attributable to a mediating variable[143], and a Bayesian framework is well-suited to uncertainty propagation[144]. We fit the models in STAN[145] (version 2.32.10) via the R programming language[146] (version 4.4.2) using the brms package[147,148] (version 2.22) following Bürkner[149].

Each model was estimated separately (Figure 1). First, a household-level model estimated socioeconomic deprivation as a function of Community Forestry exposure moderated by baseline poverty, adjusting for confounders (see Table 2). Second, outcome-specific models regressed each health outcome on Community Forestry and socioeconomic deprivation, again adjusting for relevant confounders. Varying (i.e. "random") intercepts were specified at the district, Village Development Committee (excluded from the outcome-specific sub-models due to sparse data), sampling cluster, and household levels (only required in the outcome-specific models). These were included to reflect the nested structure of DHS data. By design, our analysis estimates the treatment effect of a between-Village Development Committee contrast; it does not estimate intra-Village Development Committee treatment effects.

Below, we index households by h and individuals by i. Bracketed subscripts map each observation to its district d,Village Development Committee v, sampling cluster c, household h, and survey phase t. Let M_h denote household socioeconomic deprivation, $A_{v[h]}$ denote Community Forestry coverage, and $P_{v[h]}$ denote standardised baseline poverty. Let $\mathbf{X}_h$ denote the confounder vector for the Community Forestry-socioeconomic deprivation model (Table 2). The socioeconomic deprivation model was

$$M_h \sim \text{Normal}(\mu_h, \sigma_M)$$

$$\mu_h = \beta_0 + \beta_A A_{v[h]} + \beta_P P_{v[h]} + \beta_{AP}\left(A_{v[h]} \cdot P_{v[h]}\right) + \boldsymbol{\beta}_X \mathbf{X}_h + \lambda_{t[h]} + u_{d[h]} + u_{v[h]} + u_{c[h]}$$

with varying intercepts

$$u_d \sim \text{Normal}(0, \sigma_d), \quad u_v \sim \text{Normal}(0, \sigma_v), \quad u_c \sim \text{Normal}(0, \sigma_c)$$

where $\lambda_{t[h]}$ denotes survey-phase fixed effects. The same model structure was fitted separately in the main and infant datasets.

Each binary health outcome $Y_i^{(k)}$, where k indexes the outcome-specific model, was modelled with a Bernoulli likelihood and logit link as

$$Y_i^{(k)} \sim \text{Bernoulli}\left(p_i^{(k)}\right)$$

$$\text{logit}\left(p_i^{(k)}\right) = \beta_0^{(k)} + \beta_A^{(k)} A_{v[i]} + \beta_M^{(k)} M_{h[i]} + \boldsymbol{\beta}_Z^{(k)} \mathbf{Z}_i^{(k)} + \lambda_{t[i]}^{(k)} + u_{d[i]}^{(k)} + u_{c[i]}^{(k)} + u_{h[i]}^{(k)}$$

with varying intercepts

$$u_d^{(k)} \sim \text{Normal}\left(0, \sigma_d^{(k)}\right), \quad u_c^{(k)} \sim \text{Normal}\left(0, \sigma_c^{(k)}\right), \quad u_h^{(k)} \sim \text{Normal}\left(0, \sigma_h^{(k)}\right)$$

Here, $A_{v[i]}$ is the Community Forestry coverage assigned to the individual's Village Development Committee, $M_{h[i]}$ is the socioeconomic deprivation score assigned to the individual's household, and $\mathbf{Z}_i^{(k)}$ is the outcome-specific confounder vector (Table 2). The survey-phase fixed effect $\lambda_{t[i]}^{(k)}$ was included for outcomes measured across multiple DHS phases and omitted from the probable depression and probable anxiety models because these outcomes were measured only in 2022. Each binary health outcome was fitted as a separate model. Models were fitted to outcome-specific subsets of observations, reflecting that different outcomes were linked to different household members and the DHS design.

Models were estimated using Markov chain Monte Carlo methods with four chains, 10,000 iterations per chain (3,000 warm-up), and weakly informative priors. Each model was evaluated following the *When to Worry and How to Avoid the Misuse of Bayesian Statistics* checklist[150] (see Supplementary Discussion 14, which includes details on priors). In the results, we present the probability of direction and coefficient estimates (median and 89% CIs, based on the Highest Density Interval)[151]. We did not apply frequentist multiple-comparison corrections because our results are based on posterior effect distributions rather than repeated null-hypothesis tests.

Rather than interpreting individual regression coefficients as treatment effects, we combined the fitted models to estimate average differences between Community Forestry scenarios across the study population. Specifically, we selected two policy-relevant exposure scenarios, contrasting the observed treatment versus a counterfactual with zero Community Forestry (i.e., the treatment for all observations is set to '0'). To decompose the indirect, direct, and total effects, we used the two exposure scenarios to construct three contrasts required for a mediated g-computation analysis, following Wang and Arah[127]. For each observation, we first predicted household socioeconomic deprivation under observed Community Forestry coverage, $M(A_{\text{obs}})$, and under zero Community Forestry coverage $M(A_{\text{zero}})$. We then predicted the health outcome under three combinations of

Community Forestry and socioeconomic deprivation: observed Community Forestry with deprivation predicted under observed coverage, $Y(A_{\text{obs}}, M(A_{\text{obs}}))$; zero Community Forestry with deprivation predicted under zero coverage, $Y(A_{\text{zero}}, M(A_{\text{zero}}))$; and observed Community Forestry with deprivation predicted under zero coverage, $Y(A_{\text{obs}}, M(A_{\text{zero}}))$. We averaged each set of predictions across observations, shown by $\bar{Y}^{(k)}$. Following VanderWeele[152], we calculated the estimated total, $\widehat{TE}^{(k)}$, indirect, $\widehat{IE}^{(k)}$ and direct, $\widehat{DE}^{(k)}$, effects as:

$$\widehat{TE}^{(k)} = \bar{Y}^{(k)}(A_{\text{obs}}, M(A_{\text{obs}})) - \bar{Y}^{(k)}(A_{\text{zero}}, M(A_{\text{zero}}))$$

$$\widehat{IE}^{(k)} = \bar{Y}^{(k)}(A_{\text{obs}}, M(A_{\text{obs}})) - \bar{Y}^{(k)}(A_{\text{obs}}, M(A_{\text{zero}}))$$

$$\widehat{DE}^{(k)} = \bar{Y}^{(k)}(A_{\text{obs}}, M(A_{\text{zero}})) - \bar{Y}^{(k)}(A_{\text{zero}}, M(A_{\text{zero}}))$$

Thus, the total effect is the sum of the deprivation-mediated indirect effect and the remaining direct effect. To propagate uncertainty between models, we repeated the g-computation procedure across 2000 posterior draws, each time predicting socioeconomic deprivation under the exposure scenarios, using those draw-specific predictions as mediator values, and estimating health outcomes using the corresponding posterior draw from the outcome model.

Inference

We extrapolated expected differences in stunting and underweight to all rural children under five across Nepal. We used gridded WorldPop data to estimate the under-five population in Village Development Committees in 2006, 2011, 2016, and 2022[153,154], then multiplied the DHS sample-level g-computation risk differences by the corresponding population totals (excluding urban populations). When doing this, we weighted households' contributions using their DHS sampling weights within each survey phase to obtain nationally representative national estimates. Finally, we calculated annualised differences in cases by taking the mean of the cases in each phase (weighted by the number of years between phases).

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