Improving rural health care reduces illegal logging and conserves carbon in a tropical forest

Isabel J. Jones1,2, Andrew J. MacDonald3,4,5, Skylar R. Hopkins3,4,6, Andrea J. Lund7, Zac Yung-Chun Liu8, Nurul Ihsan Fawzi9,10, Mahardika Putra Purba10,11, Katie Fankhauser12, Andrew J. Chamberlin13,4, Monica Nirmala10, Arthur G. Blundell12, Ashley Emerson12, Jonathan Jennings8, Lynne Gaffikin11,13, Michele Barry14, David Lopez-Carr10,11, Kinari Webb15, Giulio A. De Leo16,17, and Susanne H. Sokolow18,19,20

1Hopkins Marine Station, Department of Biology, Stanford University, Pacific Grove, CA 93950; 2Department of Biology, Stanford University, Stanford, CA 94305; 3Earth Research Institute, University of California, Santa Barbara, CA 93106; 4Stern School of Environmental Science and Management, University of California, Santa Barbara, CA 93106; 5National Center for Ecological Analysis and Synthesis, Santa Barbara, CA 93101; 6Department of Applied Ecology, North Carolina State University, Raleigh, NC 27607; 7Emmett Interdisciplinary Program in Environment and Resources, Stanford University, Stanford, CA 94305; 8Alam Sehat Lestari, Sukadana, West Kalimantan 78852, Indonesia; 9Oregon Health and Science University, School of Public Health, Portland, OR 97239; 10Natural Capital Advisors, New Orleans, LA 70115; 11Health In Harmony, Portland, OR 97214; 12Department of Obstetrics and Gynecology, Stanford University, Stanford, CA 94305; 13Center for Innovation in Global Health, Stanford University, Stanford, CA 94305; 14Department of Geography, University of California, Santa Barbara, CA 93117; 15Woods Institute for the Environment, Stanford University, Stanford, CA 94305; and 16Marine Science Institute, University of California, Santa Barbara, CA 93106

Edited by Thomas E. Lovejoy, George Mason University, Fairfax, VA, and accepted by Editorial Board Member Carl Folke September 16, 2020 (received for review May 8, 2020)

Tropical forest loss currently exceeds forest gain, leading to a net greenhouse gas emission that exacerbates global climate change. This has sparked scientific debate on how to achieve natural climate solutions. Central to this debate is whether sustainably managing forests and protected areas will deliver global climate mitigation benefits, while ensuring local peoples’ health and well-being. Here, we evaluate the 10-y impact of a human-centered solution to achieve natural climate mitigation through reductions in illegal logging in rural Borneo: an intervention aimed at expanding health care access and use for communities living near a national park, with clinic discounts offsetting costs historically met through illegal logging. Conservation, education, and alternative livelihood programs were also offered. We hypothesized that this would lead to improved health and well-being, while also alleviating illegal logging activity within the protected forest. We estimated that 27.4 km² of deforestation was averted in the national park over a decade (~70% reduction in deforestation compared to a synthetic control, permuted P = 0.038). Concurrently, the intervention provided health care access to more than 28,400 unique patients, with clinic usage and patient visitation frequency highest in communities participating in the intervention. Finally, we observed a dose-response in forest change rate to intervention engagement (person-contacts with intervention activities) across communities bordering the park: The greatest logging reductions were adjacent to the most highly engaged villages. Results suggest that this community-derived solution simultaneously improved health care access for local and indigenous communities and sustainably conserved carbon stocks in a protected tropical forest.

Significance

Here, we show how a conservation–health care exchange in rural Borneo preserved globally important forest carbon and simultaneously improved human health and well-being, in a region of historically intense environmental destruction, widespread poverty, and unmet health needs. To evaluate this long-term conservation and health intervention, we analyzed earth observation data, clinic health records, and socioeconomic surveys to quantify conservation, health, and sustainable development outcomes simultaneously. Results demonstrate an actionable framework for aligning cross-sectoral goals and objectively quantifying intervention outcomes across both conservation and human health targets.

Author contributions: I.J.J., A.J.M., S.R.H., A.J.L., Z.Y.-C.L., A.E., I.J.J., L.G., M.B., D.L.-C., K.W., G.A.D.L., and S.H.S. designed research; M.N., A.G.B., A.E., J.J., L.G., M.B., D.L.-C., K.W., G.A.D.L., and S.H.S. performed research; N.I.F., M.P.P., K.F., K.W., and S.H.S. analyzed data; and I.J.J. and S.H.S. wrote the paper.

Competing interest statement: N.I.F., M.P.P., M.N., A.G.B., A.E., J.J., and K.W. are currently or recently employed with the nonprofit organization that contributed to intervention design, implementation, and data collection.

This article is a PNAS Direct Submission. T.E.L. is a guest editor invited by the Editorial Board.

This open access article is distributed under Creative Commons Attribution-NonCommercial-NoDerivatives License 4.0 (CC BY-NC-ND).

To whom correspondence may be addressed. Email: isajones@stanford.edu or ssokolow@stanford.edu.

This article contains supporting information online at https://www.pnas.org/lookup/suppl/doi:10.1073/pnas.2009240117/-/DCSupplemental.

First published October 26, 2020.

www.pnas.org/cgi/doi/10.1073/pnas.2009240117

PNAS November 10, 2020 | vol. 117 | no. 45 | 28515–28524

planetary health | natural climate solutions | human health | tropical forests | conservation

Tropical forest loss currently exceeds forest gain, leading to a net greenhouse gas emission that exacerbates global climate change. This has sparked scientific debate on how to achieve natural climate solutions. Central to this debate is whether sustainably managing forests and protected areas will deliver global climate mitigation benefits, while ensuring local peoples’ health and well-being. Here, we evaluate the 10-y impact of a human-centered solution to achieve natural climate mitigation through reductions in illegal logging in rural Borneo: an intervention aimed at expanding health care access and use for communities living near a national park, with clinic discounts offsetting costs historically met through illegal logging. Conservation, education, and alternative livelihood programs were also offered. We hypothesized that this would lead to improved health and well-being, while also alleviating illegal logging activity within the protected forest. We estimated that 27.4 km² of deforestation was averted in the national park over a decade (~70% reduction in deforestation compared to a synthetic control, permuted P = 0.038). Concurrently, the intervention provided health care access to more than 28,400 unique patients, with clinic usage and patient visitation frequency highest in communities participating in the intervention. Finally, we observed a dose-response in forest change rate to intervention engagement (person-contacts with intervention activities) across communities bordering the park: The greatest logging reductions were adjacent to the most highly engaged villages. Results suggest that this community-derived solution simultaneously improved health care access for local and indigenous communities and sustainably conserved carbon stocks in a protected tropical forest.
natural forest cover (12). A 2011 moratorium on new logging concessions was implemented to reduce total emissions from deforestation in Indonesia (12), but, at the same time, illegal logging was estimated to represent as much as 61% of all logging activity (13). Protected areas, which cover 12% of Indonesia, were lost to illegal logging was estimated to represent as much as 61% of all logging activity (12), but, at the same time, illegal logging was estimated to represent as much as 61% of all logging activity (12), but, at the same time, illegal logging was estimated to represent as much as 61% of all logging activity (12). At the request of community members in intervention areas, conservation programs, educational programs, and alternative livelihood trainings were also facilitated periodically in partnership with government entities. In 2007, 2012, and 2017, household surveys were conducted in random households across

To better understand local attitudes toward forests, conservation, and drivers of illegal logging in West Kalimantan, Indonesia, a nonprofit organization conducted more than 400 h of focus groups between 2005 and 2007 with nearly 500 community representatives (community leaders, farm group leaders, religious leaders, teachers, women’s group leaders, and interested community members). The open-ended conversations identified access to affordable, high-quality health care as a major basic need, and lack of access to health care a potential driver of illegal logging in 23 districts near Gunung Palung National Park (GPNP) (Fig. 1C) (18). This corresponds to a broader concern in Indonesia, which ranks in the lowest one-third of countries in terms of coverage of essential health services (Fig. 1A) (9), and where many populations contend with unmet water, sanitation, and hygiene needs, high maternal and infant mortality, and high burdens of infectious and noninfectious diseases (19). In response to local health care needs and conservation implications, the nonprofit established a local health clinic in 2007, in close partnership with the district government and the national park management. Clinic services and alternative payment options (e.g., barter options including seedlings and manure used in conservation activities) were available to anyone seeking care, complementing the limited health care available provided by the government. With the support of the National Park management, memorandum of understanding (MOU) agreements were signed by the nonprofit and 21 of 23 districts (“desa” administrative units), representing 73 villages (“dusun” administrative units), near GNP to participate in the health care—conservation exchange intervention. Through the intervention, clinic discounts were given to villages based on community-wide reductions in illegal logging activity, as reported by community liaisons and through monitoring of logging tail activity. At the request of community members in intervention areas, conservation programs, educational programs, and alternative livelihood trainings were also facilitated periodically in partnership with government entities. In 2007, 2012, and 2017, household surveys were conducted in random households across...
villages that engaged with the intervention to assess self-reported changes in well-being, knowledge, attitudes, behaviors, and livelihoods, in order to adapt intervention activities accordingly to meet community needs.

Here, we use more than 10 y of de-identified patient records from the health clinic coupled with remotely sensed earth observation data to test the hypothesis that a multisector health care–conservation intervention can simultaneously improve human health care access and use, and incentivize illegal deforestation in a carbon-rich tropical forest. First, we use a synthetic controls approach to compare park-level forest loss rates in GPNP before vs. after the intervention began in 2007, compared to all terrestrial Indonesian International Union for Conservation of Nature (IUCN) Category II National Parks as potential controls. MOU-signing villages bordered the national park and were thus nonrandomly assigned, precluding analysis as a randomized controlled trial. However, we were able to use clinic patient records collected between 2008 and 2018 to compare health care access, usage, and diagnosis trends between MOU-signing and non–MOU-signing patient groups in a quasi-experimental study design. We tested whether, near GPNP, 1) the clinic increased health care usage for patients from villages with signed MOUs compared to villages without signed MOUs, and 2) trends in disease diagnoses changed over the same time period for patients from villages with vs. without signed MOUs. To establish the plausibility of a causal relationship between the intervention and conservation outcomes, forest change data, clinic usage data, and records on village-level engagement with the intervention programs (i.e., health clinic use and periodic education and livelihood programs) were then used to test for a dose–response of village-level forest loss within the national park to village-level intensity of engagement with the intervention and its associated programs. Last, select responses from self-reported household survey data collected by the intervention team in 2007, 2012, and 2017 were used to assess changes in household livelihoods and income over the intervention period, and to gain further insight into potential mechanisms driving conservation–health linkages.

Results

Intervention Impact on Forest Change. Remotely sensed forest loss rates (1) in a synthetic controls analysis (20, 21) were significantly lower within districts intersecting the focal national park, GPNP, compared to a synthetic control assembled from districts in 32 control parks across Indonesia during the postintervention period from 2008 to 2018, compared to a preintervention period from 2001 to 2007 (estimate, 69.8% reduction of forest loss; 90% CI, 50.8–81.4; P = 0.003; Table 1 and Fig. 2A). This translates to an estimated 27.4 km² of forest loss averted postintervention to CI, 50.8 GPNP, compared to a synthetic control assembled from districts significantly lower within districts intersecting the focal national park, GPNP, compared to a synthetic control assembled from districts during 2007 (baseline), 2012, and 2017 demonstrated a strong and significant reduction in self-reported illegal logging activity: The number of adult males who reported logging inside GPNP during the intervention period compared to baseline declined (generalized linear regression with logit link; estimate, 68.8% reduction; 95% CI, 60.8–75.5; P < 0.001; Fig. 2A), as did the number of households reported to rely on logging as a primary income source (generalized linear regression with logit link; estimate, 90.6% reduction; 95% CI, 83.4–95.2; P < 0.001; Fig. 3C).

Intervention Impact on Forest Carbon. Using published carbon equations parameterized specifically for Borneo (22) along with LiDAR (light detection and ranging)–estimated canopy heights in the focal national park, GPNP, in 2014 (Fig. 2C and SI Appendix, Fig. S2), the effect size of 69.8% reduction in annual forest loss was estimated to equate to a cumulative 0.59 Tg of aboveground carbon loss averted (90% CI, 0.27–1.13 Tg). Based on the maximum trade value of $30 per ton of CO₂ realized on the European Emissions Trading System (23), the gross value of the total carbon loss averted in GPNP on the European carbon market would have been approximately $65.3 million USD in 2019. The estimate of aboveground carbon loss averted is conservative, because 1) the LiDAR flight data in GPNP covered mixed and some previously burned forest types, and the derived average vegetation height (27 m) is much lower than the tallest canopy height recorded in GPNP (71 m) (Fig. 2B), and 2) the relationship between canopy height and aboveground carbon is convex and nonlinear, suggesting that averaging across 30 × 30-m pixels consistently underestimates the true carbon density (22). The carbon value of the intervention impact demonstrates a theoretical monetary return that would more than offset intervention costs if a carbon market were accessible to interventions aiming to couple rural health programs with forest conservation in a similar way.

Intervention Impact on Health Clinic Usage and Diagnoses. Overall, 28,462 unique patients visited the clinic at least once over the study period from 2008 to 2018. Most patients came from districts located on the periphery of GPNP that signed MOUs to participate in the intervention, but a substantial fraction of patients (42%) came from districts without MOUs, who sometimes traveled many hours or days to use clinic services (SI Appendix, Fig. S3). Clinic affordability (MOU status and associated discounts) and accessibility (estimated travel time to the clinic) jointly influenced two metrics of clinic usage: probability of clinic use, measured as the proportion of a district’s population that used the clinic at least once, and individual patient visitation frequency. Patients with shorter travel times to the clinic were more likely to use the clinic (Poisson generalized linear mixed model [GLMM] with population size offset and district random effect; estimate = −1.14; SE = 0.17; P < 0.0001) and visited the clinic more frequently (negative binomial GLMM with district random effect; estimate = −0.180; SE = 0.035; P < 0.0001) (SI Appendix, Fig. S4). At the same time, controlling for distance, signing of an MOU (and receiving clinic discounts) increased clinic use: A larger proportion of MOU-signing district populations used the clinic (on average 27.8% vs. 2.76%; estimate = 1.93; SE = 0.36; P < 0.0001; Fig. 3A and SI Appendix, Fig. S4A), and individual patients from MOU-signing districts visited the clinic 33% more often, on average (2.4 visits over 10 y vs. 1.8 visits; negative binomial GLMM with district random effect; estimate = 0.284; SE = 0.073; P < 0.0001; Fig. 3A and SI Appendix, Fig. S4B). Patients that visited more than two to three times were usually returning repeatedly for health care related to a chronic health condition, such as epilepsy, emphysema, or hypertension. Overall, the clinic usage statistics confirm that, controlling for distance effects on clinic usage, signing an MOU to participate in the intervention incentivized increased use of health care services at the clinic. Even so, patients without MOUs represented more than 40% of all patient visits (SI Appendix, Fig. S5A), likely because noncash payment options like exchange of tree seedlings, manure, handicrafts, or labor made service affordable.

Time Trends in Disease Outcomes Based on Diagnoses at the Clinic. De-identified diagnosis records from more than 61,000 unique doctor visits recorded during 2008 to 2018 showed improvements in many health outcomes for MOU and non-MOU patient populations.
We found significant declines over time in diagnosed cases of malaria, tuberculosis, childhood-cluster diseases, neglected tropical diseases (NTDs), chronic obstructive pulmonary disease (COPD), and diabetes (Fig. 3B). The only preventable and treatable diseases considered here that increased over time were lower and upper respiratory infections (Fig. 3B and SI Appendix, Fig. S5B). The increase in diagnosed cases of respiratory diseases regionally may have been related to region-wide fire activity that spiked in 2015 (24). Increases in upper respiratory infections might also be due to increased care-seeking for more minor illnesses as trust was built

Table 1. Results from the synthetic controls analyses on park-level forest loss in GPNP compared to a counterfactual derived from three subsets of Indonesian IUCN Category II National Park controls: All nonmarine parks established prior to 2001, all nonmarine parks, and all parks

| Model                        | Forest loss, treated, km² | Forest loss, control, km² | % Change | Permutated P value [90% CI] | No. obs. | No. district | No. parks |
|------------------------------|----------------------------|----------------------------|----------|-----------------------------|----------|--------------|-----------|
| Nonmarine parks, est. before 2001 | 11.891                     | 39.30                      | −69.75   | 0.003 [−83.7, −26.3]        | 27,702   | 1,539        | 32        |
| Nonmarine parks              | 11.891                     | 28.36                      | −58.1    | 0.013 [−78.3, −1.6]         | 36,738   | 2,041        | 44        |
| All parks                    | 11.891                     | 28.36                      | −58.1    | 0.013 [−74.0, −32.4]        | 40,320   | 2,240        | 52        |

The first two columns provide estimates of forest loss (in square kilometers) in the treated region following the intervention and loss in the synthetic control region. P values and confidence intervals are calculated from a standard normal sampling distribution and Taylor series linearization. A permuted P value and CI were calculated using 500 permuted “placebo” treatment groups to satisfy a more robust set of assumptions and generate a more conservative estimate of the sampling distribution [Robbins et al. (21)]. In both cases, the Cs do not contain 0, and based on a lower-tailed, one-sided hypothesis test, the null hypothesis that there is no intervention effect is rejected [Robbins et al. (21)].
Fig. 3. Health impacts. (A) Individual visitation frequency (Left, average visits/patient to the health clinic during the study period) and health care use (Right, the percentage of the district population that were recorded at least once during the study period as patients at the clinic), among patients from districts that signed an MOU and thus received discounts on care, and those that did not; partial responses to MOU status are shown after controlling for distance effects (travel time to the clinic). (B) Change in odds of disease diagnoses from clinic patient records (presented as odds ratios for MOU and non-MOU patient populations [controlling for distance effects], comparing odds of diagnosis in 2008 to 2009 vs. 2017 to 2018 with 95% CIs; Materials and Methods). (C) Change in primary livelihoods including self-reported logging (proportion of households, 95% CIs) from 2007 to 2017. (D) Change in reported perceptions of neighborhood wealth (Left, where most responses are “average” in medium pink, versus “poor” in light pink, and “wealthy” in dark pink) and mean purchasing power parity (PPP)-adjusted household monthly incomes (Right), as reported from household surveys at 5- and 10-y follow-up periods (2012 vs. 2017). N.S., not significant; ***P < 0.001.

between communities and the program. Time trends in diagnosed cases of disease were consistent whether or not district-level distance to the clinic was included as a covariate.

Regional diagnosis records from government clinics were not available to use as controls against which to compare temporal trends at the intervention clinic, but trends in diagnosis of several diseases departed from population-based prevalence estimates published by independent Global Burden of Disease studies for West Kalimantan during the same time period. For example, tuberculosis and COPD showed an upward trend regionally (25), whereas tuberculosis declined strongly in the clinic population in our study from 2008 to 2018, when the intervention’s health clinic oversaw TB-DOTS treatment (i.e., directly observed treatment short course for tuberculosis) for all regionally diagnosed patients (including in local government facilities).

Comparing Disease Outcomes in Patients from MOU-Signing vs. Non-MOU Districts. We were unable to assess whether time trends in patient diagnoses were attributable to the increased health care access and use available through the clinic (beyond care available to all individuals through government-supported clinics in the region), because it would have been unethical to withhold access to any patient and comparable records for patients at other health facilities were not available to us for comparison over the same time period. As a result, we lacked a matched control (or “no clinic access”) group, but were able to statistically compare time trends in diagnoses among patients from MOU-signing districts vs. patients from districts without MOUs, to test whether community health outcomes benefited from clinic discounts associated with the intervention. Controlling for the distance between the clinic and patients’ home districts, we found few differences, indicating largely equitable health outcomes in terms of change in the proportion of patient diagnoses across all diseases (SI Appendix, Tables S1–S3). The few exceptions included cases of lower respiratory infections (LRIs) and upper respiratory infections (URIs), which increased across all patient populations over the 10 y study period, but increased significantly less in MOU-signing patient populations (URI estimate = −0.499; SE = 0.222; P = 0.0025; URI estimate = −0.650; SE = 0.222; P = 0.0036), as did cases of dental diseases (estimate = −0.877; SE = 0.167; P < 0.0001). In contrast, NTD diagnoses increased more in the MOU group than the non-MOU group in the 10-y intervention period (estimate = 0.675; SE = 0.253; P = 0.0076), a trend largely driven by an increase in leprosy diagnoses in the MOU group over time (estimate = 0.864; SE = 0.354; P = 0.015). This may signify true increases in leprosy rates in MOU-signing districts, or may signify increased health seeking behavior for rare and difficult-to-treat diseases, like leprosy, in MOU-signing populations compared to non-MOU populations.

Self-Reported Well-Being and Livelihood Impacts. Household surveys were conducted by the intervention team in 2007, 2012, and 2017 (see SI Appendix, Table S4 for survey demographic information). Between 2007 and 2017, annual birth rates and infant death rates declined significantly, and although the measurement method used in this survey is not directly comparable to standardized US Agency for International Development (USAID) Demographic and Health Survey (DHS) methods, these declines...
are consistent with substantial regional declines apparent in DHS data for the same region (SI Appendix, Table S5) (26, 27). As illegal logging declined as a livelihood in the 10-y intervention period, the decline did not correspond with significant changes in unemployment, as employment increased in other sectors (Fig. 3C). Monthly household income across all surveyed households in all districts was unchanged from 2012 to 2017 (t test, P = 0.28), but after adjusting income for change in purchasing power parity (PPP) (28), median household PPP-adjusted income decreased by 2.6% (t test, P = 0.001 Fig. 3D). However, in rural and low-income settings, national-level PPP adjustment of income may not accurately represent wealth, which might be better estimated by asset-ownership (29). Additionally, household perceptions of neighborhood wealth were not significantly changed over time (Fig. 3D).

**Dose–Response of the Intervention’s Effect on Deforestation.** We found evidence of a dose–response across 36 villages (dusun administrative units) with an access area >0.30 km² inside GPNP, whereby forest loss declined with increasing intervention engagement (engagement was defined as the sum of recorded person-contacts across all intervention activities, including clinic patient visits, forest liaisons meetings, conservation education activities, livelihoods training, and a number of other smaller programs; SI Appendix, Fig. S6). Comparing average forest loss rates over time (in three time periods: the preintervention period in 2002 to 2006, the first 5 y of the intervention in 2008 to 2012, and the most recent 5 y of the intervention in 2013 to 2017), forest loss rates near highly engaged villages decreased significantly (–0.15 ± 0.048%/y; P = 0.007), while forest loss rates near medium engaged villages did not change (0.06 ± 0.042%/y; P = 0.147), and forest loss rates near the least engaged villages showed an increasing trend (0.16 ± 0.085%/y; P = 0.067; Fig. 2D). There was also a dose–response in the probability that any 30-m² forested pixel was lost across the entire intervention period: controlling for slope; elevation; distance to nearest river, road, and park edge; and logging pressure (forest loss) outside the park, we found that highly engaged villages’ access areas inside GPNP lost significantly fewer forest pixels compared to that lost in low-engaged villages’ access areas (estimate = −0.85; SE = 0.013; P < 0.0001; Table 2), whereas medium-engaged villages’ access areas lost equivalent forest pixels to low-engaged villages’ access areas (estimate = −0.0087; SE = 0.012; P = 0.46). GPNP forest loss also decreased with average elevation of forest in GPNP access areas (estimate = −1.83; SE = 0.75; P = 0.015; Table 2) and increased with logging pressure outside of the park (estimate = 0.11; SE = 0.0073; P < 0.0001; Table 2). The dose–response of the intervention effect is consistent with a causal association between the intervention—consisting of expanded health care access and use, plus livelihood, education, and conservation programs—and ultimate reduced deforestation outcomes.

**Discussion**

Our results offer objective evidence that increasing access to affordable, high-quality health care as part of a comprehensive conservation intervention—in this case, to rural communities with limited resources and income options living near a densely forested national park in Indonesia—benefits both conservation and human health. In addition, community members self-reported that the intervention was working: By 2012, more than 97% of surveyed households indicated that they believed the intervention was reducing illegal logging. Further insight into mechanisms by which the intervention was reducing illegal logging was gained in 2017 via a household survey question asking, “which programs are most helpful” to stop logging in GPNP. Among the subset of households that interacted with intervention programs, roughly half identified health care discounts alone or in combination with other intervention activities (representing a plurality of responses) as the most important incentive to reduce illegal logging in the park, roughly one-quarter identified livelihood programs alone or in combination with other activities (including health care) as most important, while only a few (6%) indicated that the intervention is not effective at reducing illegal logging. Further investigation is required to establish whether this approach may be effective in other tropical forest parks where high tree cover, high poverty, and lack of access to affordable, high-quality health care fuel illegal logging and forest loss, even within protected areas (30).

Early and continued collaboration with local communities, who identified mechanisms driving linked health–environment problems and potential regional solutions, was essential to the intervention’s multisector success. Globally, about 35% of protected areas are traditionally owned, managed, used, or occupied by indigenous and local communities, yet the perspective and guidance of indigenous peoples and local communities is rarely considered in the design of conservation and climate mitigation programs (31). As a result, many interventions have had negative consequences for local communities that rely on natural resources for subsistence (31). Incentive-based conservation approaches, developed to integrate community development and conservation, have had mixed success, as benefits are not always distributed equitably or do not reflect community needs (32). In contrast, we found that community leadership in the design and implementation of a conservation intervention focusing on pressing health and well-being needs resulted in strong positive benefits to local communities as well as to global conservation goals.

This work demonstrates an actionable framework for aligning cross-sectoral goals. Frameworks such as this are urgently needed to advance effective policy efforts aimed at achieving the

### Table 2. Dose–response of forest change to the intervention: Results of a generalized linear mixed-effects regression of forest loss within GPNP over time and the effect of engagement level of each village with the intervention’s programs and activities (see SI Appendix, Fig. S6, for details on engagement activities and quantification of engagement levels)

| Log-odds   | CI          | P       |
|-----------|-------------|---------|
| Intercept | −0.12       | −8.40–8.16 | 0.977 |
| Population| −0.47       | −1.15–0.20 | 0.171 |
| Forest lost outside | 0.11 | 0.09–0.12 | <0.001 |
| Average elevation | −1.83 | −3.31–−0.36 | 0.015 |
| Average slope | 1.7  | −0.68–4.08 | 0.162 |
| Distance to nearest river | 0.47 | −0.48–1.42 | 0.335 |
| Distance to nearest road | −0.12 | −1.00–0.76 | 0.792 |
| Distance to park edge | 0.03 | −0.60–0.65 | 0.936 |
| Medium engagement | −0.02 | −0.88–0.83 | 0.955 |
| High engagement | 0.80 | −0.14–1.74 | 0.096 |
| Year | 0.34 | 0.32–0.35 | <0.001 |

Interaction terms estimating engagement effect

| Log-odds   | CI          | P       |
|-----------|-------------|---------|
| Medium engagement*year | −0.01 | −0.03–0.01 | 0.456 |
| High engagement*year | −0.85 | −0.88–−0.83 | <0.001 |

**Random effects**

| σ² | τ² Village | Marginal R² | Conditional R² |
|----|----------|-------------|----------------|
| 3.29 | 0.83 | 0.134 | 0.308 |

No. obs. 108 obs. 36 villages
We evaluated outcomes related to conservation (Life on land, SDG 15) and health (Good health and well-being, SDG 3) resulting from an intervention that actually addressed several additional goals, including Climate action (SDG 13), Decent work and economic growth (SDG 8), and Partnerships for the goals (SDG 17). Because the SDGs are deeply interconnected, there is both opportunity and urgency to address multiple targets at once. This intervention offers a case study of how programs can be designed, implemented, and evaluated to address health and conservation goals simultaneously.

The forest carbon results reported here do not include measures of belowground carbon conservation in mineral soils or peatland, the latter of which stores more carbon than aboveground forest biomass in Borneo (35) and is particularly vulnerable to carbon loss and subsidence following deforestation events (36). We also do not include measures of forest regrowth in preserved areas or previously degraded areas being restored through intervention activities (37), which undoubtedly amplified carbon storage and sequestration benefits of the intervention. Furthermore, over the long term, preserving and restoring forest-related ecosystem services might also benefit human health by reducing the risk of waterborne diarrheal disease (38), lowering heat stress (39), or reducing vectors of malaria and arboviruses (40). Measuring these longer-term effects of ecosystem integrity on human health remains an important goal for future linked conservation and public health interventions.

A more nuanced assessment of how health-care-conservation exchange programs influence disease occurrence is another important future direction for research. In the context of this study, clinic health records offered a rich dataset on more than 1,250 unique ICD-10 (10th revision of the International Statistical Classification of Diseases and Related Health Problems) codes detected in the patient population (SI Appendix, Table S6). However, ethical and logistical constraints prevented the establishment of a control group for evaluating health care outcomes: Denying health care access to certain individuals was antithetical to the intervention’s goal to improve health and well-being, and measuring disease occurrence for hundreds of ICD-10 codes in a group of nonpatient individuals was unrealistic. Therefore, we cannot fully account for the contribution of 10 y of regional improvements in government health systems and infrastructure development. However, by comparing clinic usage and diagnosis trends in MOU-signing patients receiving clinic discounts vs. non-MOU signing patients, we established that the intervention incentivized increased health-seeking behavior (with higher non-MOU signing patients, we established that the intervention trends in MOU-signing patients receiving clinic discounts vs. those in untreated patients). All models required from the World Database on Protected Areas (10).

We ran synthetic controls models using three different data subsets defining the donor pool of possible control units. These subsets included 1) all districts in terrestrial (nonmarine) parks established before 2001 (i.e., dropping any parks that are designated as marine only parks and those that were established after the start of the deforestation dataset in 2001; 2) all districts in all terrestrial parks (i.e., dropping only entirely marine parks, but ignoring year of establishment; and 3) all districts in all National Parks in Indonesia (i.e., the most inclusive group of possible control districts in National Parks). Models were run using annual data using 2001 to 2007 as the preintervention period (since the intervention was not expected to lead to immediate changes in deforestation rates in mid-2007, when the intervention started), and 2008 to 2018 as the postintervention period.

In each model, P values and 90% confidence intervals (for a one-tailed lower test) were calculated using a standard normal sampling distribution and Taylor series linearization to estimate the variance and produce CIs (21). In addition, P values and CIs were also calculated using 500 permuted placebo treatment groups for comparison with the estimated effect for the actual treatment group to satisfy a more robust set of assumptions and to generate a more robust and conservative estimate of the sampling distribution (21). These “permutations” are placebo tests in that they randomly assign districts in the “control” group to the placebo treatment group, the synthetic controls model is rerun, and the magnitude of the placebo treatment result is compared to the actual treatment group result (21). All models were run using the “microsynth” package in R (43, 44) following established methods outlined in Robbins et al. (21).
Administration and Oak Ridge National Laboratory Distributed Active Ar-

malaria, malnutrition, NTDs, trauma, and tuberculosis. Other unspecified
text, for details) into the following groups to be tracked: childhood-cluster

used a binomial GLMM with a logit link (which yields coefficients that can be

each disease in each district, annually. Each patient only counts toward one

Even so, carbon densities were high, in part, because this region of South-

teragrams carbon per hectare) conserved in the period from 2008 to 2018.

This method is conservative, as using the mean pixel height of the LiDAR

of the population in each district that used the clinic at least

sional Ministry of Cultural Affairs, #AHU-08962.50.10.2014; clinic operations

identifier data, requiring no further review as human subjects research.
The clinic data were gathered within routine operations of the ASRI medical
clinic (Indonesian nonprofit Alam Sehat Lestari is registered by the Indone-

We were interested in understanding how increases in clinic affordability

The Alam Sehat Lestari (ASRI) medical center opened in July 2007 and remains open. Our analyses consider the period from 2008 to 2018, beginning with the first

To track changes in disease occurrence in the patient population, we estimated the proportion of unique patients that received a diagnosis for
each disease in each district, annually. Each patient only counts toward one

Dose–Response of the Intervention’s Effect on Deforestation within GPNP.

after demonstrating a significant correlation between the intervention and pre-intervention forest loss trajectories in GPNP compared to a synthetic control, we tested whether there was any evidence of a dose–response relationship within GPNP, among villages (dusun) with

quantify differences in the proportion of disease diagnoses over time (early,

We also tested whether MOU status impacted disease outcomes among

patients over time, while controlling for a patient’s average distance (in

minutes) from district to clinic (see SI Appendix for details on calculating

time travel). To do so, we used binomial GLMMs with a logit link, using

the full time series showing changes in the period prevalence of each disease

in the patient population are shown in SI Appendix, Fig. 55.

For reported livelihoods and perceptions of neighborhood wealth, we

we calculated the average monthly income at the household level and the

the proportion of households that felt neighborhood wealth had increased,
decreased, or remained the same at each time point. We also calculated the

5-y period preceding the survey, and average

among household women in the 3-y period preceding the survey, and av-

average annual births, defined as average annual births per women ages 19 to

In total, 1,348, 1,498, and 1,379 households were surveyed in 2007,

the rural communities in and around GPNP (SI Appendix, Table S5). From

we expect to be a more accurate representation of the rural communities in and around GPNP (SI Appendix, Table S5). From

we calculated the average monthly income at the household level and the

quantified change over time using generalized linear models with binomial

effects of forest distance to the clinic. That was followed by a 2017 survey

SMSA. The Alam Sehat Lestari (ASRI) medical center opened in July 2007 and remains open. Our analyses consider the period from 2008 to 2018, beginning with the first

To understand how patient-level visit frequency was affected by afford-

ability (MOU status) and access (travel time), we ran a negative binomial

Generalized and Health Survey data for Indonesia in 2007 and 2017 (26, 27).

That was followed by a 2017 survey question that specifically asked what intervention programs

lasting (and, correspondingly, ~10% of the total population of ~60,000 people) were randomly selected for participa-

tion. In total, 1,348, 1,498, and 1,379 households were surveyed in 2007,

percent of households (and, correspondingly, ~10% of the total population of ~60,000 people) were randomly selected for participa-

the 2018 population size in each district was included as an offset. For

health, wealth (income), perceptions of wealth (designation of the

SI Appendix, Fig. S3) districts are available in

the 2018 population size in each district was included as an offset. For

the proportion of the population in each district that used the clinic at least

rates (IMR) and general fertility rates (GFR) in a 5-y period from USAID De-

totate and without controlling for district distance to the clinic, with nearly identical outcomes.
The full time series showing changes in the period prevalence of each disease

We were interested in understanding how increases in clinic affordability

We also tested whether MOU status impacted disease outcomes among

we tested whether MOU status impacted disease outcomes among

the full time series showing changes in the period prevalence of each disease

the unique patients to which the untracked ICD-10 codes were assigned are

the intervention period, we classified 824 ICD-10 codes

unique patients that received a diagnosis (ICD-10 code) of a particular dis-

To track changes in disease occurrence in the patient population, we
estimated the proportion of unique patients that received a diagnosis for
each disease in each district, annually. Each patient only counts toward one
varying levels of engagement with the intervention programs (including use of the health clinic, and other periodic programs; SI Appendix, Fig. 56) and forest loss rates. To answer this question, we quantified engagement effort as cumulative person-contacts (i.e., number of contacts with persons reached by all program activities associated with the intervention from 2007 to 2017, allowing for repeated contacts with the same individuals over time) achieved through the following: the health care intervention (ASRI clinic visits, mosquito net distribution), conservation programs (Community Conservation Liaisons or "Forest Guardian" Program, Chainsaw Buyback Program), alternative livelihood trainings (Organic Agriculture Program, Goats for Widows Program, Green Kitchen Program), and education activities (ASRI Kids Program, Community Education Program) (SI Appendix, Fig. 56). Engagement effort was not distributed evenly across all villages and was predominated by frequent engagement with community liaisons for the intervention as well as doctor–patient contacts at the clinic (SI Appendix). Variation in engagement across the participating villages intersecting GPNP allowed us to test for evidence of a dose–response of intervention effort on deforestation within different access areas nearest each village around the park.

We used a k-means clustering algorithm to bin engagement (cumulative person-contacts in each village across all of the intervention programs from 2007 to 2018 (SI Appendix, Fig. 56)) into low, medium, and high categories [r package “cluster” (29)]. We examined the effect of cumulative engagement effort on the proportion of forest lost in each village’s access area in the national park (number of remotely sensed 30-m pixels lost out of total forested pixels remaining). Village-level access areas within GPNP were determined by a local team that mapped the parts of each village bordering GPNP that extended into GPNP and represented that village area for illegal logging. Ultimately, 36 villages bordering GPNP with logging allowed us to test for evidence of a dose–response of intervention effort on deforestation within different access areas nearest each village around the park.

Data and Code Availability. Data and code have been deposited in Github (https://github.com/deleo-lab/Papers/tree/main/Jones_et_al_PNAS_2020).

ACKNOWLEDGMENTS. We express gratitude to the communities near and around GPNP who helped design and implement and continue to participate in the ongoing intervention. We thank the dedicated medical and conservation staff and volunteers at ASRI and Health In Harmony, as well as patients who visited the clinic. We thank the local and national Indonesian government for collaboration on all aspects of this work, including the GPNP staff, the Kayong Utara Regency government, and the Department of Health. We thank Campbell Webb for early contributions on methodology and data interpretation, Erin Mordecai and Steve Palumbi for feedback, and this manuscript’s editor, Thomas E. Lovejoy, and reviewers for helpful suggestions. We thank the Woods Institute for the Environment at Stanford University for general support for this research collaboration and for facilitating communications. Last, we thank Made By We for assisting in the design of figures. J.J. was supported by a National Science Foundation Graduate Research Fellowship (Grant 1656518). A.J.M. was supported by a National Science Foundation Postdoctoral Research Fellowship in Biology (Grant 1611767). A.J.L. was supported by a James and Nancy Kelso Fellowship through the Stanford Center for Innovation and Global Health of Stanford University. M.N. was supported by the Fulbright Foreign Student Program. I.J.J., A.J.M., S.R.H., A.J.L., Z.Y.-C.L., A.J.C., L.G., D.L.-C., K.F., A.E., and K.W. were partially supported by a seed grant from the Program for Disease Ecology, Health, and the Environment at Stanford University. G.A.D.L. and S.M.H. were partially supported by a Stanford University Freeman Spogli Institute for International Studies–Stanford Institute for Innovation in Developing Economies Global Poverty and Development Initiative Grant 1611767. G.A.D.L. was partially supported by a Stanford University Freeman Spogli Institute for International Studies–Stanford Institute for Innovation in Developing Economies Global Poverty and Development Initiative. Variation in engagement across the participating villages intersecting GPNP allowed us to test for evidence of a dose–response of intervention effort on deforestation within different access areas nearest each village around the park.

1. M. C. Hansen et al., High-resolution global maps of 21st-century forest cover change. Science 342, 850–853 (2013).
2. A. Baccini et al., Tropical forests are a net carbon source based on aboveground measurements of gain and loss. Science 358, 230–234 (2017).
3. M. W. Griscom et al., Natural climate solutions. Proc. Natl. Acad. Sci. U.S.A. 114, 11645–11650 (2017).
4. Intergovernmental Panel on Climate Change, Global warming of 1.5°C (2018). https://www.ipcc.ch/15; Accessed 25 July 2019.
5. T. O. McShane et al., Hard choices: Making trade-offs between biodiversity conservation and human well-being. Biol. Conserv. 144, 966–972 (2011).
6. W. M. Adams et al., Biodiversity conservation and the eradication of poverty. Science 306, 1146–1149 (2004).
7. C. B. Barrett, A. J. Travis, P. Dasgupta, On biodiversity conservation and poverty traps. Proc. Natl. Acad. Sci. U.S.A. 108, 13967–13972 (2011).
8. A. Garchitorena et al., Disease ecology, health and the environment: A framework to account for ecological and socio-economic drivers in the control of neglected tropical diseases. Philos. Trans. R. Soc. Lond. B Biol. Sci. 372, 20160127 (2017).
9. Global Burden of Disease Collaborative Network, Global Burden of Disease Study 2017 (GBD 2017) Health-Related Sustainable Development Goals (SDG) Indicators 1990–2030, (Institute for Health Metrics and Evaluation, Seattle, WA, 2018).
10. UNEP-WCMC, Protected Area Profile for Indonesia from the World Database of Protected Areas (2018). https://www.protectedplanet.net. Accessed 1 July 2018.
11. J. A. Lutz et al., Global importance of large-diameter trees. Glob. Ecol. Biogeogr. 27, 849–864 (2018).
12. J. Busch et al., Reductions in emissions from deforestation from Indonesia’s moratorium on new oil palm, timber, and logging concessions. Proc. Natl. Acad. Sci. U.S.A. 112, 1328–1333 (2015).
13. S. Lawson, L. MacFaul; Royal Institute of International Affairs, “Illegal logging and related trade: Indicators of the global response” (Chatham House, 2010).
14. N. S. Sudhi, L. P. Koh, B. W. Brook, P. K. L. Ng, Southeast Asian biodiversity: An indicator of forest structure and function. Sci. Total Environ. 555, 126–138 (2016).
15. D. L. A. Gaveau et al., Reconciling forest conservation and logging in Indonesian Borneo. PLoS One 8, e69887 (2013).
16. L. M. Curran et al., Lowland forest loss in protected areas of Indonesian Borneo. Science 303, 1000–1003 (2004).
17. B. A. Margono, P. V. Potapov, S. Turubanova, F. Stolle, M. C. Hansen, Primary forest cover loss in Indonesia 2000–2012. Nat. Clim. Change 4, 730–735 (2014).
18. K. J. G. Webb, J. Jennings, D. M. Fordo, A community-based approach to integrating conservation, livelihoods, and health care: Indonesia’s Baceo Lanac. Lancet Planet. Health 2, S26 (2018).
19. World Health Organization, State of Health Inequality, (World Health Organization, Indonesia, 2017).
20. A. Abadie, A. Diamond, J. Hainmueller, Synthetic control methods for comparative case studies: Estimating the effect of California’s tobacco control program. J. Am. Stat. Assoc. 105, 493–505 (2010).
21. M. W. Robbins, J. Saunders, B. Kliner, A framework for synthetic control methods with high-dimensional, micro-level data: Evaluating a neighborhood-specific crime intervention. J. Am. Stat. Assoc. 112, 109–126 (2017).
22. T. Jucker et al., Estimating aboveground carbon density and its uncertainty in Borneo’s structurally complex tropical forests using airborne laser scanning. BioScience 55, 831–838 (2015).
23. D. Burtraw, M. Themann, “Pricing Carbon Effectively: Lessons from the European Emissions Trading System” [Resources for the Future]. https://media.ifr.org/documents/PricingCarbonEffectively_Report_1.pdf. Accessed 25 July 2019.
24. P. Crippa et al., Population exposure to hazardous air quality due to the 2015 fires in Southeast Asia. Sci. Rep. 6, 37074 (2016).
25. Global Burden of Disease Collaborative Network, Global Burden of Disease Study 2017 (GBD 2017) Disability-Adjusted Life Years and Healthy Life Expectancy 1990–2017, (Institute for Health Metrics and Evaluation, Seattle, WA, 2018).
26. Statistics Indonesia, “Estimating aboveground carbon density and its uncertainty in Borneo’s structurally complex tropical forests using airborne laser scanning.” BioScience 55, 831–838 (2015).
27. National Population and Family Planning Board [BKKBN] Statistics Indonesia–BPS, Ministry of Health–Kemenkes and ICF, Indonesia Demographic and Health Survey 2007.” (IDIRS1FLDTA, IDIRS1FLDTA, ICF [distributor]: BPS and Macro International, Calverton, MD, 2008).
28. National Population and Family Planning Board-BKKBN, Statistics Indonesia–BPS, Ministry of Health–Kemenkes and ICF, Indonesia Demographic and Health Survey 2017” (IDIRS1FLDTA, IDIRS1FLDTA, BKKBN, BPS, Kemenkes, and ICF, Jakarta, Indonesia, 2018).
28. World Bank, International Comparison Program (ICP). https://www.worldbank.org/en/programs/icp. Accessed 20 August 2019.

29. L. D. Howe, J. R. Hargreaves, S. R. Huttly, Issues in the construction of wealth indices for the measurement of socio-economic position in low-income countries. Emerg. Themes Epidemiol. 5, 3 (2008).

30. B. Fisher, T. Christopher, Poverty and biodiversity: Measuring the overlap of human poverty and the biodiversity hotspots. Ecol. Econ. 62, 93–101 (2007).

31. IPBES, Summary for policymakers of the global assessment report on biodiversity and ecosystem services of the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services, (IPBES Secretariat, Bonn, Germany, 2019).

32. A. Spiteri, S. K. Nepalz, Incentive-based conservation programs in developing countries: A review of some key issues and suggestions for improvements. Environ. Manage. 37, 1–14 (2006).

33. W. Rosa, Ed., “Transforming our world: The 2030 agenda for sustainable development” in A New Era in Global Health (Springer Publishing Company, 2017).

34. S. Whitmee et al., Safeguarding human health in the anthropocene epoch: Report of the Rockefeller foundation-lancet commission on planetary health. Lancet 386, 5137–2028 (2015).

35. M. Warren, K. Hergoualc'h, J. B. Kauffman, D. Murdiyarso, R. Kolka, An appraisal of Indonesia’s immense peat carbon stock using national peatland maps: Uncertainties and potential losses from conversion. Carbon Balance Manag. 12, 12 (2017).

36. A. M. Hoyt, E. Chaussard, S. S. Seppalainen, C. F. Harvey, Widespread subsidence and carbon emissions across Southeast Asian peatlands. Nat. Geosci. 13, 435–440 (2020).

37. N. I. Fawzi, V. N. Husna, J. A. Helms, Measuring deforestation using remote sensing and its implication for conservation in Gunung Palung national park, West Kalimantan, Indonesia. IOP Conf. Ser. Earth Environ. Sci. 149, 012038 (2018).

38. D. Herrera et al., Upstream watershed condition predicts rural children’s health across 35 developing countries. Nat. Commun. 8, 811 (2017).

39. Y. J. Masuda et al., How are healthy, working populations affected by increasing temperatures in the tropics? Implications for climate change adaptation policies. Glob. Environ. Change 56, 29–40 (2019).

40. N. D. Burkett-Cadena, A. Y. Vittor, Deforestation and vector-borne disease: Forest conversion favors important mosquito vectors of human pathogens. Basic Appl. Ecol. 26, 101–110 (2018).

41. K. Hemming, T. P. Haines, P. J. Chilton, A. J. Gibling, R. J. Lilford, The stepped wedge cluster randomised trial: Rationale, design, analysis, and reporting. BMJ 350, h391 (2015).

42. N. Gorelick et al., Google Earth engine: Planetary-scale geospatial analysis for everyone. Remote Sens. Environ. 202, 18–27 (2017).

43. M. Robbins, S. Davenport, microsynth: Synthetic Control Methods with Micro- and Meso-Level Data (2019). https://github.com/ssdavenport/microsynth. Accessed 1 November 2019.

44. R Core Team, R: The R Project for Statistical Computing (R Foundation for Statistical Computing, 2018). https://www.r-project.org/. Accessed 3 August 2019.

45. L. Melendy et al., Automated method for measuring the extent of selective logging damage with airborne LiDAR data. ISPRS J. Photogramm. Remote Sens. 139, 228–240 (2018).

46. World Health Organization, “International Statistical Classification of Diseases and Related Health Problems” (World Health Organization, ed. 5, 2016). https://apps.who.int/iris/handle/10665/246208. Accessed 1 July 2018.

47. R. Bivand, classInt: Choose Univariate Class Intervals (2018). https://CRAN.R-project.org/package=classInt. Accessed 1 February 2019.