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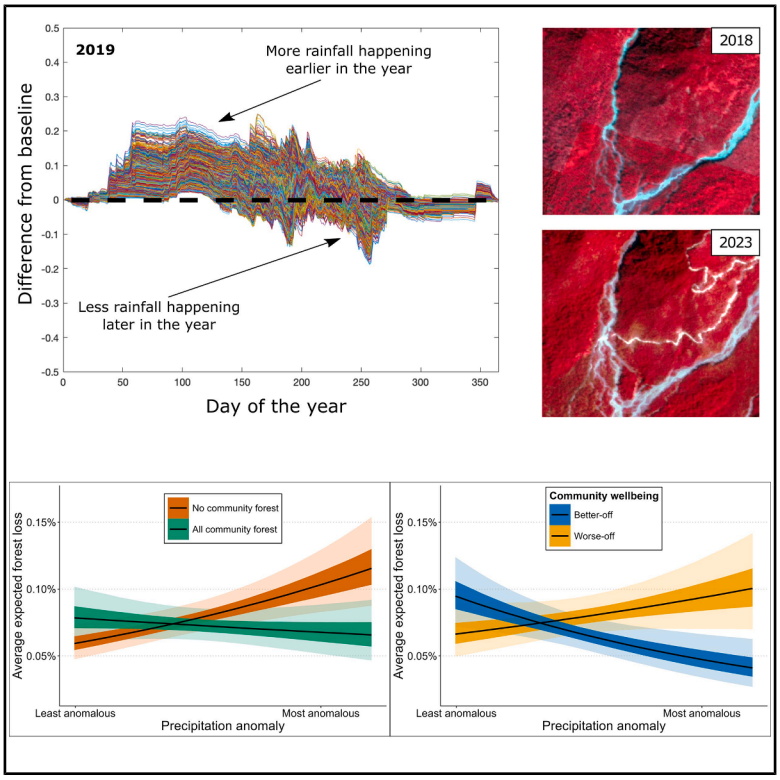
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Community management and material wellbeing limit forest loss following precipitation anomalies

Graphical abstract



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In brief

Clark et al. combine daily observations of precipitation, 3-m resolution observations of forest cover, and location information for nearly 20,000 community forests in Nepal. They show that, overall, forest cover loss remained low from 2018 to 2023. However, anomalous precipitation patterns were associated with a doubling of tree loss in both economically disadvantaged communities and those not affiliated with the country's community-based forest management program.

Highlights

- Forest loss in Nepal is overall very low
- 3-m resolution mapping allows nation-scale observations of individual tree loss
- Anomalous precipitation was linked to doubling of tree clearing
- Community forestry and community material wellbeing limited tree loss

Clark et al., 2027, Cell Reports Sustainability *4*, 100903
January 22, 2027 © 2026 The Author(s). Published by Elsevier Inc.
https://doi.org/10.1016/j.crsus.2026.100903

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Community management and material wellbeing limit forest loss following precipitation anomalies

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https://doi.org/10.1016/j.crsus.2026.100903

SCIENCE FOR SOCIETY Climate change is destabilizing local weather patterns, putting forests and the communities that depend on them under growing pressure. Community-based conservation is widely seen as an important way to protect forests and support local livelihoods. Yet little is known about whether community forestry programs can protect forests from changing weather patterns, especially when communities rely on forests to buffer lost livelihoods. In this study, we use high-resolution satellite data to track tree cover changes from 2018 to 2023 and link them to unusual rainfall. We find that while the country experienced overall very little forest loss, anomalous precipitation was associated with a doubling of the rate of tree clearing in communities not participating in the community forestry program. By contrast, communities that participated in the program showed no increase in tree cutting, and wealthier communities also showed no increase. These findings suggest that community management and material wellbeing can help forests withstand climate shocks.

SUMMARY

Community-based conservation is essential for mitigating climate change and biodiversity loss. Yet little is known about whether community forestry programs can protect forests from changing weather patterns, especially when communities rely on forests to buffer lost livelihoods. We examine this dynamic across nearly 20,000 community-managed forests in Nepal using high-resolution mapping of forest change from 2018 to 2023. We find that although overall forest loss remained low (0.13%), anomalous precipitation regimes were associated with a two-fold increase in tree clearing in communities not participating in community forestry. By contrast, participating communities showed no change in forest loss under the same conditions. Higher material wellbeing also reduced sensitivity of forest loss to anomalous precipitation. Moreover, spatial distributions of tree clearing in community forests resembled non-conserved areas, suggesting communities retain access to resources when needed. Sustaining conservation gains under climate change may therefore increasingly depend on supporting local communities' autonomy and wellbeing.

INTRODUCTION

Hundreds of millions—if not billions—of people directly harvest local natural resources to meet their daily needs, with the most economically vulnerable disproportionately utilizing areas critical for biodiversity conservation and carbon sequestration.[1–4] Accordingly, governments around the world are increasingly recognizing the contributions of indigenous peoples and local communities in the race to meet global climate and biodiversity goals.[5–7] This focus on local management is reflected in the

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prioritization of "community-based natural resource management" for funding in the Kunming-Montreal Global Biodiversity Framework.[8] Reviews of hundreds of such initiatives show they can meaningfully advance local-to-global scale environmental goals while supporting rural livelihoods and traditional practices, particularly through the devolution of tenure rights and increased local management capacity.[9–13]

Although community-based conservation is widely considered to be a bulwark against the worst impacts of climate change, we know surprisingly little about whether these institutions limit nature loss under increasingly uncertain and extreme weather patterns.[14–18] Successful community-based natural resource management regimes have generally emerged and been studied in stable and predictable environments.[19–21] Yet, the destabilization of Earth's climate is intensifying cascading weather, ecological, and economic shocks across community-managed conservation areas.[22,23] Shocks can drive increased local harvesting and potentially destabilize sustainable management institutions as households attempt to compensate for economic losses, a phenomenon especially pronounced in low-income areas.[24–30] Hence, it is critical to identify whether community-based management regimes buffer natural resources from anomalous climatic conditions (e.g., Kerr et al.[31]) to effectively plan toward large-scale environmental goals under climate change.[32]

This is the gap we aim to address in this study. Specifically, we link anomalous precipitation conditions with observed rates of tree clearing inside and outside areas with community-based conservation, interpreting rates of clearing as direct observations of community behavior. We use the community-based forest management program in Nepal as a case study. To achieve this, we combine information on approximately 20,000 community forests with a measure of precipitation anomaly and high-resolution mapping of forest cover change at the country scale, along with several key contextual covariates.

Our forest cover change maps use 3-m resolution satellite imagery to identify losses in forest cover from 2018–2023 and gaps in contiguous forest areas pre-dating these loss observations, presumed to be indicative of longer-term trends. These high-resolution data are much more likely than standard 10- to 30-m observations to capture the dynamics of selective cutting (and other mortality) of single or small groups of trees within closed canopies—the form of harvesting expected in acute response to climate variability.[33,34] While less overtly destructive than clear-cutting, selective harvesting of single trees can increase the prevalence of invasive species and decrease the carbon storage of tropical forests for decades.[35] Moreover, even low levels of unsanctioned harvesting can collapse the cooperative rules and norms required for community-based forest management.[34,36,37] These near-comprehensive observations represent an advance from using reported participation in community-based conservation,[38,39] which systematically overestimates adherence to management rules.[40,41]

Three factors justify our focus on Nepal in studying this general dynamic. First, the community-based forest management program is one of the largest and longest living community-based conservation initiatives in the world, with a large proportion of the rural population involved. Second, Nepal is among the countries most vulnerable to climate change,[42] with extreme rainfall, worsening droughts, floods, and landslides and overwhelming households' coping capacity.[43] Third, the prominence of the community-based forest management program supports the availability of high-quality data on community management. We observe the proportion of forest cover under community management across each of 3,983 village development committee (VDC) boundaries, the country's lowest administrative unit from 1990–2015, nested within several larger jurisdictional levels. Although VDCs in Nepal have since been replaced by an alternative governance structure, we use the VDC boundaries as a standard unit of analysis. We do this because community forests have continued to be georeferenced by VDCs and because they are the lowest geographical unit of analysis at which we can aggregate our data and retain statistical power. Moreover, our study relies on precipitation data from 1981–2023, spanning the period in which VDCs were active. Although VDCs are no longer in place legislatively, we refer to their previous boundaries (our unit of analysis) simply as "VDCs" throughout this manuscript.

The Forest Act of 1993 decentralized management of Nepal's forests to local user groups, leading to a near doubling of forest cover and reductions in poverty over the next two decades.[44–46] These changes further benefited biodiversity, ecosystem services, carbon storage, and local economic recovery from Nepal's massive 2015 earthquake.[47–51] Having since been reaffirmed and better integrated with Nepal's new political structure in the Forest Act of 2019, the success of this program is generally attributed to clear, legally recognized tenure rights of the local forest user groups.[52] The program also encourages the commercialization of non-timber forest products, with value chain support by governments and nonprofits.[53] By demonstrating the outcomes of this program in response to climate change, we offer a glimpse into the potential of community-based conservation to protect nature in the coming decades, as well as methodological advances for assessing these effects.

RESULTS

Spatial distribution of forest loss

To assess forest loss, we generated a time series of PlanetScope-based tree cover maps at 3-m resolution, with five layers for each year from 2018–2023. Approximately 2.4% (164,283 ha) of the forested area in Nepal was characterized by forest gaps, defined here as small non-forest patches surrounded by contiguous forests (Figure 1; Table 1). Those gaps likely result from forest removal in the medium- to long-term prior to 2018. Over 2018–2023, only 0.13% (8,554 ha) of the total forest area was directly observed to be lost (Figure 1; Table 1). Note that we observe gaps and losses only, rather than net forest change accounting for tree cover gain.

Although the numbers are small, we found clear differences in the spatial distributions of both forest losses and gaps in community-conservation areas compared with formal protected areas. Forest losses and gaps tended to occur deeper into the forest (i.e., further from the edge) inside protected areas, while outside protected areas—in VDCs both with and without

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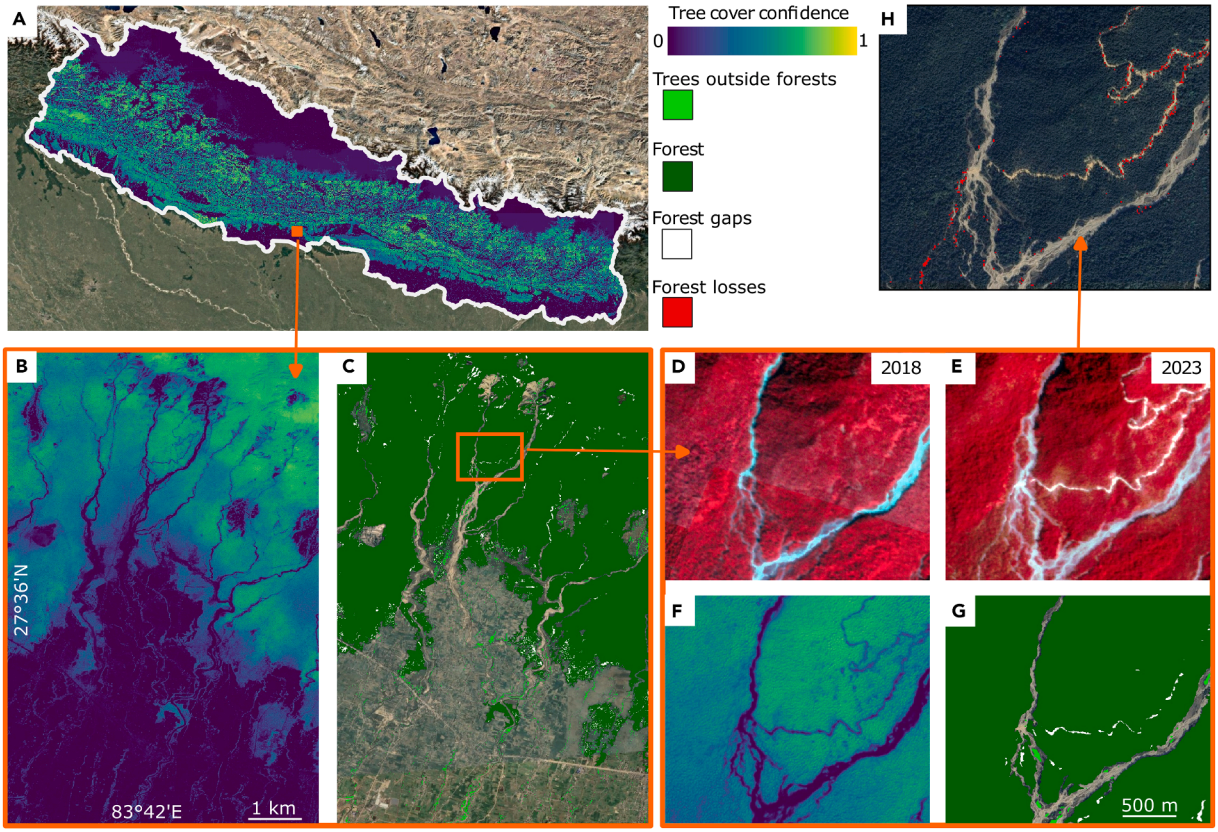


Figure 1. Tree cover in Nepal from 2018–2023

(A) National-scale tree detections aggregated for 2018–2023.

(B) Tree detections close-up.

(C) Same area as (B) but showing the corresponding forest classification: trees outside forests, forest, and forest gaps.

(D and E) Micro-scale PlanetScope imagery in 2018 and 2023, shown in false color composite.

(F and G) Tree cover confidence and forest classification maps for the same area.

(H) Tree losses 2018–2023.

community forestry—they occurred almost exclusively within one kilometer from the forest edge. Nearly all observations of forest loss occurred in distinct patches of less than 500 m^2, roughly equivalent to a 22-m pixel, and thus likely to be obscured by coarser-resolution (yet longer-timespan) products (Figure S1). Figure 2 shows the complete distributions of size and distance to forest edge of all distinct patches of forest loss (n = 240,153) and forest gaps (n = 2,999,334).

Correlates of forest loss

We used two distinct statistical models to examine the correlates of recent, observed forest loss (2018–2023) and pre-existing forest gaps (<2018; considered indicative of forest loss in the medium to long term). We quantified the association of observed forest loss with anomalous precipitation patterns over the same period (2018–2023), capturing the effects of early onset monsoons, extended dry periods, off-season storms, and similar events (see methods). We further quantified how community forest management and community material wellbeing moderate this association. In addition, we assessed the relationships that human population and migration, pre-existing forest gap cover, and road density had with recent patterns of forest loss. Finally, we estimated the associations of community management and wellbeing, human population and migration, and road density with pre-existing forest gaps. We did not attempt to link forest gaps to anomalous precipitation patterns as we did not directly observe gap and weather patterns as co-occurring in time.

Community management and wellbeing mitigate forest loss during precipitation anomalies

We find strong evidence that both community forestry and community wellbeing mitigated the responsiveness of tree harvesting to anomalous precipitation across Nepal forests from 2018–2023. Under the most typical (least anomalous) precipitation patterns, VDCs with no community forests had an expected forest loss of 0.06% (90% credibility interval [CI], 0.05–0.07) of their total forest area, conditional on an average value of all other covariates. This is statistically indistinguishable from VDCs with all their forests under community management under the same conditions, where the expected loss was 0.08% (90% CI 0.06–0.10). This means that during years with typical precipitation conditions, rates of tree clearing are very low everywhere, so there is no observed difference between forests with and without

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Table 1. Descriptive statistics for the outcomes of interest in this study, including total observed forest area, forest gap area, and forest loss area for VDC boundaries in Nepal with and without community forestry

	Forest area (ha)	Gap area (ha)	Loss area (ha)	Forest gaps (percent of forest area)	Forest loss (percent of forest area)
All Nepal	6,801,816	164,283	8,554	2.42%	0.13%
VDCs with CF	5,644,276	142,389	7,579	2.52%	0.13%
VDCs without CF	1,157,540	2,1894	975	1.89%	0.084%

The area shown includes all loss and gap observations, including those at steep slopes unlikely to be caused by humans (i.e., more likely to be caused by landslides), which were removed for the statistical analyses presented in this manuscript. Although no longer in place in Nepal, VDCs were used as a standard unit of aggregation and analysis to ensure consistency across our dataset.

community management. Under the most highly anomalous precipitation conditions, however, VDCs without community forestry doubled their expected forest loss to 0.12% (90% CI 0.9–0.15) of forest cover (Figure 3A). In absolute terms, this represents an increase from 6 to 12 hectares of cover loss per 10,000 hectares of forest. By contrast, VDCs with forests entirely under community management appeared stable, showing no expected change under these same anomalous precipitation conditions (0.07%; 90% CI 0.05–0.09).

We observe a similar moderation pattern of community wellbeing on VDC responsiveness to anomalous precipitation (Figure 3B). Under typical precipitation patterns, VDCs with high (+1 standard deviation) and low (−1 standard deviation) wellbeing exhibited statistically indistinguishable rates of forest loss, with expected rates of 0.09% (90% CI 0.07–0.12) and 0.07% (90% CI 0.05–0.09), respectively. Under more anomalous precipitation patterns, however, VDCs with higher wellbeing tended to decrease forest loss to an expected rate of 0.04% (90% CI 0.03–0.06). Conversely, VDCs with lower wellbeing tended to increase tree loss under these same conditions, resulting in an expected loss of 0.10% (90% CI 0.07–0.14), more than double the rate of high-wellbeing VDCs (Figure 3B).

Our analysis also shows credible associations of community wellbeing and anomalous precipitation with forest losses, independent of their interactions with other variables. Specifically, our data show a 95% probability that increased community wellbeing is negatively associated with forest loss and a 97% probability that anomalous precipitation is positively associated with forest loss (Figure S2). We also observe credible associations of human population and road density with forest losses, which our data show had 97% and 100% probabilities of positive relationships with forest losses, respectively.

Finally, we note that neither net migration from 2015–2019 nor the proportion of forests under community management showed credible associations with forest loss, conditional on average values of all other covariates in our data. We speculate that net migration is manifested largely in the overall observations of human population (2022), resulting in a statistically indistinguishable association of migration itself. As shown in Figure 3A, the association between community forestry and forest losses is negligible overall and under typical precipitation as forest loss in all VDCs was near zero under these conditions during the time frame of this study. The prevalence of pre-existing forest gaps prior to 2018 was also not credibly associated with forest losses from 2018–2023. This finding indicates that small and distributed patches of cleared forest (for agriculture, livestock, etc.) are not necessarily being expanded over time in this system. Parameter plots displaying the parameter values and CIs can be found in Figure S2.

Community management, wellbeing, and road density show longer-term patterns in forest gaps (pre-2018)

Both the proportion of forest area under community management and the community wellbeing of VDCs showed a 100% probability of a negative association with the proportion of gaps in VDC forest area prior to 2018, given our data (Figure S2). VDCs with all their forested area under community management showed an average expected gap cover of 2.4% (90% CI 1.9–2.9), compared with VDCs without community management, which showed an average expected gap cover of 2.7% (90% CI 2.2–3.3), conditional on a mean value of all other covariates (Figure 4A). This represents a small yet statistically meaningful association between community forestry and forest integrity in the medium to long term. Similarly, under the lowest observed community wellbeing (2.1 standard deviations below the mean), the expected gap cover of forest area was 3.1% (90% CI 2.5–3.9). This value halved to 1.4% (90% CI 1.1–2.0) under the highest observed levels of community wellbeing (6.8 standard deviations above the mean), representing a strong association between community wellbeing and forest integrity in the medium to long term across the observed range of our data (Figure 4B).

Similar to the associations seen on forest losses, road density showed a 100% probability of a positive correlation with the proportion of forest gap cover prior to 2018. Across the observed range of road density values, the expected proportion of forest gap cover increased from 1.9% (90% CI 1.6–2.4) to 13.0% (90% CI 9.9–16.9), conditional on an average value of all other covariates. This represents a strong negative association between roads and forest integrity in Nepal in the medium to long term, based on our data (Figure 4C).

Somewhat counterintuitively, our data show 99% probabilities of negative associations for both 2015–2019 net migration and 2015 human population and expected forest gap cover prior to 2018 (Figure S2). This likely reflects the fact that the presence of forest gaps in the medium to long term can result from distributed forest clearing for small agricultural plots and livestock corrals, more commonly observed in rural and less populous VDCs. These results indicate that in VDCs with lower human populations, the integrity of existing forest areas is negatively associated with human use relative to

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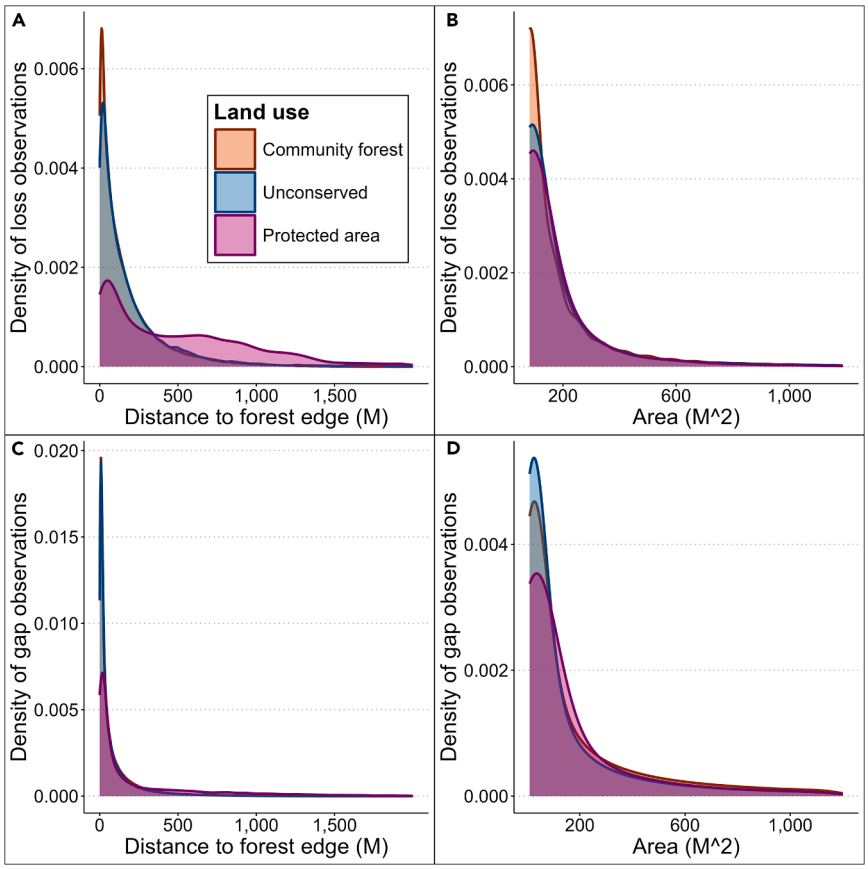


Figure 2. Density plots characterizing the spatial distributions of forest losses and forest gaps across Nepal

Across panels, orange shading shows the distribution of observations inside VDCs with any amount of community forestry, blue shading shows the distribution of observations inside VDCs without any recorded community forestry, and purple shading shows observations within formal protected areas (e.g., national parks).

(A and B) The distribution of patches of forest loss observed from 2018–2023 distributed by patch distance to forest edge and patch size, respectively.

(C and D) The distribution of patches of forest gaps distributed by patch distance to forest edge and patch size, respectively.

All distributions are filtered to not include observation at steep slopes (greater than 45°), as these are unlikely to be caused by humans. The word "unconserved" refers to areas outside of VDCs with community forestry and outside of protected areas. While not observed in our data, these areas may still be under private or leasehold managed for conservation.

remnant forest patches in highly populous VDCs, although forest cover in less populous VDCs tends to be much greater than in highly populous VDCs (Figure S3).

DISCUSSION

The observations in this study reaffirm that, overall, rates of forest clearing in Nepal are very low and the country continues to be a model for large-scale forest conservation. However, our study also reveals that increasing climatic instability in Nepal is reliably associated with an increase in selective harvesting of trees, which can meaningfully affect local ecologies, livelihoods, and social institutions. Furthermore, our results demonstrate that community forest management and community wellbeing can each play crucial roles in moderating this association, effectively buffering forests and the communities that depend on them against extreme climatic conditions. This dynamic shows a graded response, where the buffering effect scales with the severity of the precipitation anomaly (Figure 3). These findings contribute to a growing body of evidence indicating that forest conservation and restoration are more successful in regions with higher income and when paired with poverty alleviation initiatives and strengthened local land tenure.[54–57] They also align with broader research showing that material wellbeing is a key determinant of how sustainably communities can adapt to climate change.[58,59]

These results are particularly relevant as societies worldwide grapple with the triple challenge of reversing nature loss and mitigating climate change while supporting human wellbeing.[60] Despite the mixed success of community-based conservation initiatives,[61–63] governance systems characterized by greater equity and decentralization tend to be linked to better social and ecological outcomes.[11,64] Our results suggest local resource management may become progressively more important for people and nature as Earth's climate becomes increasingly unstable, driving cascading socio-ecological shocks. Future research might examine whether extreme climate shocks, beyond a given threshold, can overwhelm the adaptive capacity of local institutions, leading to their collapse (e.g., White and Wulfing[65]). This line of inquiry would substantially advance a growing body of work studying the persistence of community-based natural resource management institutions across time and space.[66]

Nepal's community forest management program has repeatedly been shown to have played an important role in reversing deforestation trends across the country from the mid-1990s to the 2010s.[45,46] Our 3-m resolution land cover analysis corroborates these findings, showing that VDCs with community forests had reliably more intact forest areas (less gap area) prior to 2018, controlling for socioeconomic and environmental covariates. Moreover, we build deeper understanding of landcover dynamics across the country, showing that while forest gaps may be indicative of distributed clearing for small-scale livestock and agriculture operations in the medium- to long-term, they were not associated with subsequent forest loss from 2018–2023. This finding aligns with broader literature suggesting that smallholder subsistence-driven land conversion often stabilizes

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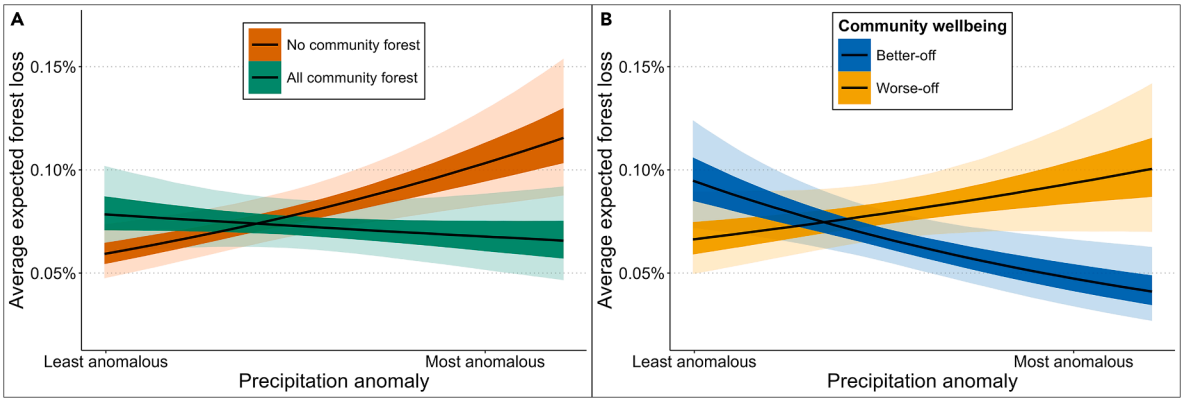


Figure 3. Estimated ststistical trends in anomalous precipitation and forest loss

Moderation trends of community forestry (A) and community wellbeing (B) on forest losses under anomalous precipitation across VDCs in Nepal from 2018–2023. Trends are conditional on an average value of all other covariates. Black lines show the median expected proportion of forest loss in each VDC. Dark shading shows the 50% CI. Light shading shows the 90% CI.

(A) Orange and green colors show expectations when 0% and 100% of the VDC forest area is under community management, respectively.

(B) Blue and yellow colors show expectations when VDC community wellbeing is one standard deviation above and below the mean observed value across all VDCs, respectively.

once household needs are met.[67] The COVID-19 pandemic, and associated economic losses, provided a natural experiment indicating that much of Nepal's forest clearing is indeed subsistence driven.[68–70]

Community forestry as a flexible management system

We show that tree harvesting in VDCs with and without community forestry have similar spatial patterns; trees are harvested overwhelmingly in small patches (possibly even single trees or branches) near the forest edge (Figure 2). By contrast, trees harvested from formal protected areas, while still harvested in small patches, are observed deeper into the forest on average. We speculate that this trend is indicative of people cutting trees illegally in formal protected areas—and thus hiding by going deeper into the forest—whereas community forests do not entirely restrict harvesting. The tenure rights conferred by community forest management presumably also enable communities to regulate extraction more adaptively in response to changing climatic and economic conditions. Furthermore, because the community-based forest management program encourages the cultivation of non-timber forest products, it is possible that associated communities consider forests to be long-term assets rather than immediate sources of fuelwood or timber.[53]

Road infrastructure and forest loss

While human population was only weakly associated with forest loss and negatively associated with forest gaps in our study, road density emerged as a strong predictor of both recent forest loss and pre-existing forest gaps. This finding is consistent with prior research indicating that road development is likely the most significant driver of deforestation across tropical forests in the Asia-Pacific region.[71] Roads not only provide physical access to forests but also serve as conduits for broader socioeconomic changes, facilitating human migration and market integration. Nepal is a global outlier in its limited road density and access,[72] with new roads directly increasing community economic growth.[73] Future development planning and research on forest conservation might carefully consider the tradeoffs between the economic benefits of road development and the direct damage done by increasing access.

Assumptions and limitations

We isolate the associations between our predictors and outcomes of interest by conditioning on confounding variables as identified through structural causal modeling shown visually in Figure S4, using directed acyclic graphs.[74,75] This approach is one of several techniques for controlling for confounding processes with observational data, each requiring different assumptions.[76,77] Conditioning on hypothesized confounding variables, as done here, implies strong assumptions relative to other methods. These include assuming accurate knowledge of all relevant causal relationships, the absence of unmeasured confounders, a stable functional relationship between predictors and outcomes across their observed ranges, and the absence of reverse causality. For example, forest gaps can result from non-human factors such as underlying geology, lightning, wind, or disease. Our statistical approach assumes that these processes do not confound our results (i.e., they affect forest gaps but do not affect the predictors of interest). We suggest that readers interpret the associations presented here considering these assumptions and the limitations described below.

A core limitation of our study is our observation of the proportion forest area under community management, rather than the exact community forest boundaries for each VDC. Therefore, we do not observe the fragmentation of community forests or whether they share boundaries with formal protected areas, features that could both feasibly confound our analyses. In cases where neither all nor none of the forest area were under community management, it is also possible that

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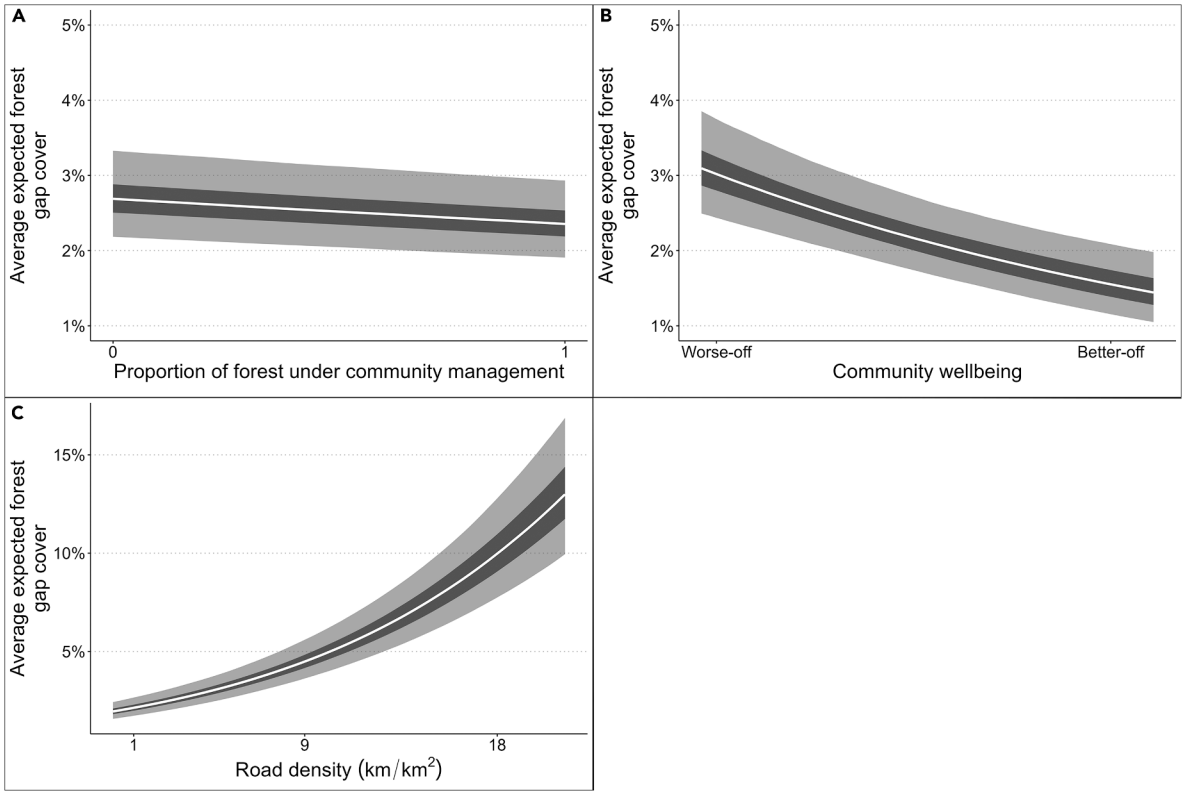


Figure 4. Estimated statistical trends in forest gaps

Associations of community forestry (A), Community wellbeing (B), and road density (C) with expected forest gap proportion across VDCs in Nepal, prior to 2018. Gap proportion was calculated by removing overlapping forest losses observed in 2018–2023 from the total observed gap cover over this period. Trends are conditional on an average value of all other covariates. White lines show the median expected proportion of gap cover in each VDC. Dark shading shows the 50% CI. Light shading shows the 90% CI. All *x* axes show the observed range of each predictor in the dataset used in this study.

there were disproportionate changes in forest cover inside versus outside the community forest areas that are obscured, resulting in potential misclassification. However, while not an explicit consideration in this study, assessing the outcomes of community forestry in this way may inadvertently help to account for the effect of "leakage," where resource conservation simply displaces extraction to nearby unconserved areas.[78,79] More specifically, if tree harvesting inside community forests were simply displaced to non-community forest areas within the same VDC, our analysis would still account for these changes.

Similarly, we do not account for the occurrence of other forest management regimes outside of protected areas and community forests. These include private forests, leasehold forests, collaborative forests, and other government-managed forests. While this study is focused exclusively on community forestry, similar work might compare the outcomes of these other forest types to each other or against the results shown here. Moreover, the specific management objectives and respective practices of community forestry vary across the country; future work might attempt to isolate the impacts of specific practices on institutional resilience to climate change.

While the large-scale remote sensing data used in this study (Table 2), are valuable for global monitoring, they are often imprecise at finer scales, introducing another source of measurement error.[80,81] Measurement error in predictor variables, in particular, has the potential to bias statistical associations.[77] Emerging methods for uncertainty propagation may help overcome this issue and present an avenue of future productive research.[82] Yet, even with increasingly powerful statistical and remote sensing tools, we are unlikely to observe selective cutting of branches, roots, or undergrowth at scale, representing a major blind spot in current studies of forest sustainability in response to climate change.[34] Similarly, our measure of community material wellbeing is not currently available through time, potentially directionally biasing our results in places where wellbeing materially changed from 2018–2023.[83]

High-resolution spatial data in the study of social-ecological systems

High-resolution earth observation data—often also with large extents and rapid return intervals—are revolutionizing our ability to monitor natural resources such as grasslands,[88] coral reefs,[89] and terrestrial vegetation.[90] These data are also simultaneously being integrated with advances in machine learning to observe human behavior at unprecedented scales (e.g., Sirko et al.[91]). Some have argued that increasingly high-resolution mapping is

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Table 2. All data used in statistical analyses assessing the correlates of near-term forest loss (2018–2023) and longer-term gaps (<2018) in forest cover across Nepal

Variable	Role	Used to model	Unit	Source
Forest loss (2018–2023)	outcome	forest loss (2018–2023)	9-m pixels	derived from PlanetScope (see forest classification and change)
Pre-existing forest gaps (<2018)	outcome/estimand	gap prevalence (<2018)/forest loss (2018–2023)	3-m pixels	derived from PlanetScope (see forest classification and change)
Precipitation anomaly (2018–2023)	estimand	forest loss (2018–2023)	functional half space depth	derived from CHIRPS (see precipitation anomaly; Funk et al.[84])
Community forest cover (2024)	estimand	forest loss (2018–2023) and gap prevalence (<2018)	proportion of forest area	ForestAction Nepal (see community forest management)
Deprivation (2010–2020)	estimand	forest loss (2018–2023)/gap prevalence (<2018)	relative index 1-km pixels	NASA Socioeconomic Data and Applications Center[83]
Population (2022)	estimand	forest loss (2018–2023)	total individuals	LandScan—Oak Ridge National Laboratory[85]
Population (2015)	estimand	gap prevalence (<2018)	total individuals	LandScan—Oak Ridge National Laboratory[85]
Net human migration (2015–2019)	estimand	forest loss (2018–2023) and gap prevalence (<2018)	5-year sum of individuals	Niva et al.[86]
Road density (2024)	estimand	forest loss (2018–2023) and gap prevalence (<2018)	road km/VDC area (km^2)	derived from Humanitarian OpenStreetMap (tasks.hotosm.org)
Topographic slope (2000)	control	forest loss (2018–2023) and gap prevalence (<2018)	degrees	NASA Shuttle Radar Topography Mission[87]
Development region (2022: largest administrative unit)	control	forest loss (2018–2023) and gap prevalence (<2018)	administrative boundary	Global Administrative Boundaries Database 4.1 (www.gadm.org)
Zone (2022: intermediate administrative unit)	control	forest loss (2018–2023) and gap prevalence (<2018)	administrative boundary	Global Administrative Boundaries Database 4.1 (www.gadm.org)
District (2022: smallest administrative unit)	control	forest loss (2018–2023) and gap prevalence (<2018)	administrative boundary	Global Administrative Boundaries Database 4.1 (www.gadm.org)

unnecessary or even counterproductive, especially for carbon monitoring.[92] Moreover, others have raised concerns about data injustices associated with satellite remote sensing, drones, camera traps, audio monitoring, and other sources.[93–95] Our remote sensing framework, in particular, has been shown to favor overstory trees and regions with high data quality, biases that may feasibly propagate existing inequities among individual forest users and communities as forest monitoring is linked to various community payment schemes.[96] Nevertheless, these data are generally recognized as enabling more precise estimates of conditions that were previously assessed with greater uncertainty and bias.[97–101]

In addition to straightforward accounting of resources, exciting advances are emerging in our ability to track changes in resources over time[102] and in their associations with covariates.[103] While nascent, these conceptual and technological means are expected to become readily available in the near future.[104] These data streams will undoubtedly both enrich and challenge the study of social-ecological systems. Namely, they may increase the prevalence of spurious associations if not rigorously integrated with ground-based observations and robust theoretical frameworks.[105]

METHODS

Data collection

Forest classification and change

Forest maps are based on PlanetScope images. PlanetScope is a constellation of more than 200 nanosatellites that sense the entire globe every day at 3-m resolution. Images have four bands: red, green, blue, and near infrared. We generated five layers covering all of Nepal for each year, 2018–2023, summing to a total of 30 layers. We filtered the available images according to the metadata, using only cloud-free, high-quality scenes but did not consider the acquisition time. It is not possible to build composites (for example, using the median over several images for each pixel) with high-resolution images without losing details, so each layer was treated as a separate image. We used the convolutional neural network-based tree detection model from Brandt et al.[102] but added more training data from Nepal to improve the performance in closed canopy forests. The tree detection model is based on points, which are converted to Gaussian kernels. During training, the Gaussian kernels scale with the tree crown area, so the peak of the Gaussian kernels reflects the tree crown center. When

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predicting Gaussian kernels, the model searches for tree crowns, and the heatmap, which is the confidence of the Gaussian kernels, marks areas covered by trees, reflecting the tree cover. Trees outside forests are mapped as individuals, and within forests a Gaussian kernel typically reflects a group of trees. In dense forests, the Gaussian kernels are so close to each other that a solid canopy layer is mapped. The 3-m pixel size restricts the mapping to larger trees, with a crown size that is typically larger than 20 m^2.

To study change in forest cover, we used a regression slope over heatmap predictions on all layers, building on Brandt et al.[102] To filter out real losses from spurious changes, we applied a ruleset: the *p* value of the regression slope should be less than 0.05; the normalized difference vegetation index (NDVI) of the final image should be less than 0.6 because the soil that becomes visible after a tree was removed has typically a low NDVI, and the regression slope should have a magnitude of at least 15. We also classified the detected trees into contiguous forests (heatmap values >30), forest gaps (small areas surrounded by contiguous forests), and trees outside forests (single trees or groups of trees with an area covering less than 100 contiguous 3-m pixels), building on the methodology validated in Gominski et al.[96] as similarly accurate to airborne LiDAR. Regression slope values showing forest losses were aggregated to the 9-m resolution to reduce the presence of forest loss observations driven by image quality, rather than actual tree removals.

Before characterizing the spatial positioning or statistical associations of forest losses and gaps, we removed observations likely to be caused by landslides. Specifically, we removed all observations occurring on slopes at 45 degrees or steeper estimated at a 30-m resolution.[87] Pandey et al.[106] report sites above 45 degrees to be inaccessible in Nepal's Gorkha district. Similarly, in a sample of 65 community forests across the country, Luintel et al.[49] find that very little forest management occurs on slopes greater than 40 degrees. While there are complex, bidirectional relationships between landslides and land use change in Nepal,[107] and excluding steep slopes does not entirely remove the possibility of landslides,[108] it does limit our observations to only those that could be conceivably caused by humans. Moreover, while there are several natural drivers of forest gaps, we would not expect these to mutually drive changes in anomalous precipitation, community forestry, or community material wellbeing, and thus confound our analysis.

After filtering out forest losses and gaps on steep slopes, we grouped loss and gap observations into distinct patches of touching pixels. We then calculated the size of each patch for the loss and gap data, respectively. Finally, we calculated the distance to the forest edge (non-forest area) for each loss and gap patch and identified whether each patch was observed inside a VDC with community forestry, inside a VDC without community forestry, or inside a formal protected area (e.g., national park). We accessed spatial boundaries of formal protected areas in Nepal using the World Protected Area Database.[109] Beyond these descriptive measures at the patch level, we aggregated the total loss and gap patch areas to the VDC level for all statistical analyses. Specifically, we calculated the proportion of observed forest area that experienced tree loss from 2018–2023 and, after filtering out gaps that overlapped with observed losses from 2018–2023, the proportion of forest area in each VDC that was identified as having gaps in tree cover prior to 2018 (Table 2). We refer to this gap cover as "pre-existing forest gaps" throughout the manuscript and consider these to be reflective of longer-term processes of forest cover loss. We omit VDCs without any forest cover from our analysis.

Precipitation anomaly

For each of the 3,983 VDCs in Nepal, we collated estimates of daily total precipitation from January 1, 1981–December 31, 1990, resulting in over 14 million observations. Daily total precipitation was calculated by taking the mean value in each VDC from the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) database at the 0.25-degree resolution.[84] These data are derived from a mix of *in situ* rain gauges and infrared imagery across the country and across time; rain gauge data for Nepal are collected from Nepal's Department of Hydrology and Meteorology.[110] We used 1981–1990 data to fit baseline precipitation patterns in Nepal, as this was the latest 10-year period on record without a major drought event.[111]

We used these baseline data to develop a novel measure of "precipitation anomaly" using principles from functional data analysis. The goal of our measure is to detect deviations in the intra-annual patterns of precipitation with respect to the baseline yearly fluctuation, rather than simply detecting the predictable precipitation extremes (e.g., the monsoon or dry season) which would be a poor predictor of human behavioral change at the 5-year scale. While a collection of simpler measures such as yearly total, date of seasonal onset, or Gini index can collectively capture aspects of anomalous precipitation, these tend to be correlated in practice and increase the risk of spurious associations through the inclusion of many variables. Commonly used percentile-based moving window approaches have been shown to artificially mix seasonal cycles into measures of extremity and bias results.[112] Our method overcomes these issues by measuring functional half space depth[113] in cumulative daily precipitation patterns from January 1, 2018–December 31, 2023 (vs. baseline) to detect outlying curves of unusual precipitation (e.g., an early/late monsoon season or unexpected dry period/storm; Figure S5) using a single metric that can capture a wide range of anomalous precipitation patterns.

Specifically, for each VDC we compute cumulative daily intra-annual precipitation curves for each year from January 1, 2018 to December 31, 2023, as well as a baseline cumulative daily intra-annual precipitation curve by aggregating daily precipitation patterns across the baseline period (1981–1990). We then normalize all curves to grow from 0 to 1 (i.e., representing the proportion of yearly precipitation received), and subtract the baseline curve from each of the years from 2018–2023, as depicted in Figure S5 for the year 2019. Each value of the curve should therefore be interpreted as "the proportion of extra total annual precipitation in this VDC at this time of year relative to the baseline period," such that, for example, a value of (±) 0.2 means this VDC at this time of year has experienced 20% more/less of its total annual precipitation versus a typical year. These curves therefore represent deviations from expected precipitation patterns throughout the year. For each year (2018–2023) we then computed the functional halfspace depth of these curves for each VDC, which orders the curves from most outlying to most

typical, providing a measure of extremity or centrality within a sample of curves, with smaller values of the depths relating to more outlying precipitation patterns as depicted in Figure S5 for the year 2019. Finally, for each VDC we aggregate the functional half space depths for each of the years (2018–2023) to provide a single measure of extremity across the entire time period, per VDC, to be used in our analysis. Functional half space depth was computed using the "mfd" command in the "mrfDepth" package in R using default values.[114]

Community forest management

We obtained the latest records of all community forests established up to 2018 in Nepal from ForestAction Nepal. This ensures that all community forests considered in our analysis were implemented from the onset of forest loss observations (2018). These records contain estimates of the number of community forests and the size of each community forest in all VDCs across the country, representing 19,914 individual observations. The names of the VDCs wherein each community forest is recorded did not entirely match the VDC names available in the Global Administrative Boundaries Database v.4.1 (GADM; https://gadm.org), which we used to delineate the spatial bounds of each VDC. In these instances, we matched the text string containing the combined district and VDC name in the community forest database to the GADM database using Levenshtein distance string matching with a 0.75 match threshold. Community forest records without clear matches to the GADM database were discarded under the assumption that these would be randomly distributed and thus, not systematically bias our statistical results. For each VDC, we then calculated the proportion of observed forest cover under community management, as derived from the total estimated community forest size across all records in the community forest database (Table 2). This database showed that 1,847,366 ha of forest were under community management, representing 27% of the Nepal's forest area (Table 1). Furthermore, 68% of VDCs contained at least one community forest, with 29% of each VDC's forest area under community management on average (Figure S6).

Publicly available data

In addition to the novel datasets described above, we compiled several publicly available datasets spanning our study period and location. Community wellbeing was measured using the Global Gridded Relative Deprivation Index available from the United States National Aeronautics and Space Administration (NASA) Socioeconomic Data and Applications Center.[83] We refer to this measure as "community wellbeing" throughout this manuscript. These data are a relative index of community wellbeing calculated using the subnational Human Development Index, infant mortality, child dependency, and remotely sensed data products measuring built-up areas, and nighttime lights. These input data span 2010 through 2021. We calculated the median value of all 1-km pixels within each VDC, considering these relative values to be static from 2018–2023 (Table 2).

Similarly, we collected raster data on the estimated human population (2015 and 2022; 1-km resolution) and net human migration (2015–2019; 10-km resolution) across Nepal, taking the sum of both estimates across each VDC. These datasets are available from Oak Ridge National Laboratory's LandScan[85] and Niva et al.,[86] respectively (Table 2). Finally, we derived the road density of each VDC in km/km^2 by calculating the total road length of all roads in the Humanitarian OpenStreetMap database (tasks.hotosm.org) and dividing this length by the area of each VDC recorded in the GADM database. Maps showing the spatial distributions of net human migration (2015–2019), total human population (2022), community wellbeing (deprivation index), road density, and the topographic slope summarized at the VDC level is available in Figure S6.

Statistical analyses

Variable selection

As the goal of this research is inference,[115] we constructed directed acyclic graphs (Figure S4) showing the hypothesized potential causal pathways between our predictors and the outcomes of interest: forest loss and forest gaps (Table 2). The hypothesized causal paths were decided through an iterative process informed by relevant literature and the extensive ethnographic experience of our team. This approach allowed us to identify the necessary covariates required to generate unbiased associations between each of our predictors of interest (estimands) and each outcome.[116,117] This exercise demonstrated that for both outcomes, we should be able to reliably estimate the unbiased associations for all predictors of interest by controlling only for the topographic slope within each VDC. We calculated this as the spatial median slope value derived from 30-m pixels.[87] Finally, for both models, we include the development region, zone, and district of each VDC as a nested hierarchical intercept (Equations 1 and 2), allowing us to control for spatial autocorrelation and jurisdictional effects (e.g., policy).

Recent tree removals (2018–2023)

As shown in, for each VDC (i) with forest cover (N = 3,551), we statistically model 2018–2023 forest losses (Y_i) as resultant of community wellbeing (Deprvtn_i), precipitation anomaly (PrecipAnom_i), and community management (CommFrst_i). We estimate the independent associations of each of these predictors with linear coefficients ($\beta 1, \beta 2, and\ \beta 3$). Additionally, we estimate the independent associations of net human migration (Migration_i), pre-existing forest gaps (PreGapArea_i), human population in 2022 (Ppl2022_i), and road density (RoadDensity_i) with forest losses ($\beta 4, \beta 5, \beta 6, and\ \beta 7$). In inferring the mitigating patterns of both community management and community wellbeing on tree clearing associated with anomalous precipitation, we estimate the multiplicative interaction terms of both variables and precipitation anomaly ($\beta 8\ and\ \beta 9$). Our ability to reliably estimate both interaction terms is conditional on the lack of a correlative association between community forestry and community wellbeing shown in Figure S7. Finally, we condition on the median topographic slope of each VDC (Slope_i) by including the term $\beta 10$. As described above, we account for spatial autocorrelation by including a nested, variable intercept structure at three distinct jurisdictional levels ($\beta 0_j, \beta 0_{k(j)}, and\ \beta 0_{m(k,j)}$), as additive to the global intercept ($\alpha 0$). As these data are zero inflated, we model forest loss using a zero-inflated beta distribution (ZIB), estimating forest losses in each VDC as the deterministic outcome of all covariates (μ_i), dispersed as φ, and zero inflated as π. We implemented this statistical model in a Bayesian

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framework by using the "brms" package[118] in R to access the Stan probabilistic programming language.[119,120] We use the default uninformative, weakly regularizing priors in brms for all model parameters.[118] This model was implemented as

$$\begin{aligned} Y_i &\sim \text{ZIB}(\mu_i, \varphi, \pi)(\text{Zero-Inflated Beta Distribution}) \\ \text{logit}(\mu_i) &= \alpha 0 + \beta 1\text{Deprvtn}_i + \beta 2\text{PrecipAnom}_i + \beta 3\text{CommFrst}_i \\ &+ \beta 4\text{Migration}_i + \beta 5\text{PreGapArea}_i + \beta 6\text{Ppl2022}_i + \beta 7\text{RoadDensity}_i \\ &+ \beta 8\text{PrecipAnom}_i \cdot \text{CommFrst}_i + \beta 9\text{PrecipAnom}_i \cdot \text{Deprvtn}_i \\ &+ \beta 10\text{Slope}_i + \beta 0_j + \beta 0_{k(j)} + \beta 0_{m(kj)} \end{aligned} \quad \text{(Equation 1)}$$

$$\begin{aligned} \beta 0_j &\sim \text{Norm}(\alpha 0, \sigma_j) \\ \beta 0_{k(j)} &\sim \text{Norm}(\beta 0_j, \sigma_k) \\ \beta 0_{m(kj)} &\sim \text{Norm}(\beta 0_{k(j)}, \sigma_m). \end{aligned}$$

we perform several sensitivity tests as recommended by Siegel and Dee,[77] to bolster the empirical support for meaningful associations between our predictors of interest and both forest losses and forest gaps. In Figure S8, we show that the within-sample predictive error (i.e., residuals) observed in both models is not associated with any of the predictors of interest in either model, limiting the likelihood of biases caused by reverse causality and omitted confounders. Furthermore, we assess the spatial clustering of this residual error for both forest losses and gaps by calculating Moran's *I* statistics for each model. We show that across the 3,551 included VDCs, there is only minor spatial clustering of residual error (Moran's *I* value of 0.11 and 0.28 for forest losses and gaps, respectively), further limiting the likelihood that unobserved variables are strongly biasing our estimated parameters. By comparison, Moran's *I* value for precipitation anomalies and economic wellbeing are 0.98 and 0.81, respectively. This indicates that our model appropriately controls for spatially varying confounders.

In presenting statistical coefficient estimates, we sample 10,000 draws from the posterior distribution and report the percentage of positive/negative samples for each parameter estimate as the probability that the given parameter has a positive/negative association with the outcome. We consider any estimand in which at least 95% of samples are either positive or negative to have a credible association. This corresponds to a lack of overlap between the 90% CI and the zero line in the parameter plots shown in Figure S2. In interpreting the relationship of each predictor of interest on the associated outcomes, we present the expected change in the outcome resulting from a change across the observed range of the predictor, conditional on the mean value of all other parameters. We show these conditional associations as the median expected value and the associated 50% and 90% credibility intervals (i.e., the inner quantile of posterior draws). This presentation allows for interpretations of both statistical credibility and the "biological significance/importance" of the association.

Pre-existing forest gaps (<2018)

In Equation 2, we show the statistical model used to estimate the longer-term associations of a subset of the predictors from Equation 1 and the human population in each VDC in 2015 on the pre-existing forest gaps observed prior to 2018. In this model, we assume that pre-existing forest gaps (Y_i) in each VDC (i) with forest cover (N = 3,551), are resultant of community wellbeing (Deprvtn_i), community management (CommFrst_i), net human migration (Migration_i), the human population in 2015 (Ppl2015_i), and road density (RoadDensity_i). We estimate the independent associations between each of these predictors with linear coefficients ($\beta 1, \beta 2, \beta 3, \beta 4, \textit{and}\ \beta 5$). As in Equation 1, we condition on the median topographic slope of each VDC (Slope_i) by including the term $\beta 6$. We again account for spatial autocorrelation by including a nested, variable intercept structure at three distinct jurisdictional levels ($\beta 0_j, \beta 0_{k(j)}, \textit{and}\ \beta 0_{m(kj)}$), as additive to the global intercept ($\alpha 0$). Finally, we also fit forest gaps as a zero-inflated beta process (ZIB), estimating pre-existing gap cover in each VDC as the deterministic outcome of all covariates (μ_i), dispersed as φ, and zero-inflated as π. We implement this model in the same computation framework as above. All data and code used in these analyses can be found in the resource availability section of this manuscript. This model was implemented as

$$\begin{aligned} Y_i &\sim \text{ZIB}(\mu_i, \varphi, \pi)(\text{zero-inflated beta distribution}) \\ \text{logit}(\mu_i) &= \alpha 0 + \beta 1\text{Deprvtn}_i + \beta 2\text{CommFrst}_i + \beta 3\text{Migration}_i \\ &+ \beta 4\text{Ppl2015}_i + \beta 5\text{RoadDensity}_i + \beta 6\text{Slope}_i \\ &+ \beta 0_j + \beta 0_{k(j)} + \beta 0_{m(kj)} \end{aligned}$$

$$\begin{aligned} \beta 0_j &\sim \text{Norm}(\alpha 0, \sigma_j) \\ \beta 0_{k(j)} &\sim \text{Norm}(\beta 0_j, \sigma_k) \\ \beta 0_{m(kj)} &\sim \text{Norm}(\beta 0_{k(j)}, \sigma_m). \end{aligned}$$

(Equation 2)

Model checking and interpretation

We deemed both statistical models to have found computationally stable solutions based on the adequate mixing of Markov chains and $\widehat{R}$ values equal to 1.0 for all parameters. In addition,

RESOURCE AVAILABILITY

Lead contact

Requests for further information and resources should be directed to, and will be fulfilled by, the lead contact, Matt Clark (matthew.clark@sydney.edu.au).

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Materials availability

This study did not generate any new materials.

Data and code availability

All data and code required to reproduce the results can be found here: https://zenodo.org/records/15178189.

ACKNOWLEDGMENTS

M.C., T.P., and M.M. were supported under the Leverhulme Trust funded project "The race to environmental sustainability" (RPG-2021-440). M.C., A.M.S., A.S., M.B., and S.L. were supported by the Turner-Kirk Trust grant "Forecasting conservation abandonment under climate stress." T.P. was supported by Research England's Expanding Excellence in England (E3) Fund, UK Research and Innovation. This is contribution #26 from the "Catalyzing Conservation at Scale" initiative. J.A.O. acknowledges support from UKRI through a Frontier Research grant (EP/X023222/1) selected by the European Research Council.

AUTHOR CONTRIBUTIONS

Conceptualization, M.C., A.M.S., and M.M.; methodology, M.C., A.M.S., S.L., A.S., T.P., J.A.O., S.S.S., and M.B.; investigation, M.C., A.M.S., S.L., A.S., B.K.K., S.S.S., and M.B.; writing—original draft, M.C., A.M.S., S.L., T.P., J.O.A., S.S.S., C.M.W., M.B., and M.M.; and writing—review and editing, M.C., A.M.S., T.P., S.S.S., C.M.W., and M.M.

DECLARATION OF INTERESTS

The authors declare no competing interests.

SUPPLEMENTAL INFORMATION

Supplemental information can be found online at https://doi.org/10.1016/j.crsus.2026.100903.

Received: December 10, 2025
Revised: September 22, 2026
Accepted: October 12, 2026

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Please cite this article in press as: Clark et al., Community management and material wellbeing limit forest loss following precipitation anomalies, Cell Reports Sustainability (2026), https://doi.org/10.1016/j.crsus.2026.100903

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