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Assessing forest conservation outcomes of a nature reserve in a subtropical forest ecosystem: effectiveness, spillover effects, and insights for spatial conservation prioritization

Hao Xia [a,*], Han Li [b,c], Alexander V. Prishchepov [a]

[a] Department of Geosciences and Natural Resource Management (IGN), University of Copenhagen, København 1350, Denmark
[b] College of Economics and Management, Northwest A&F University, Yangling 712100, China
[c] Department of Food and Resource Economics, University of Copenhagen, København 1958, Denmark

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ABSTRACT

Protected areas (PAs) are pivotal in the conservation of global forest ecosystems, and understanding their effectiveness and spillover effects is crucial to evaluate their overall performance. While PAs are well-documented for their role in reducing deforestation, research examining their influence on mitigating non-stand replacement forest degradation or forest carbon emissions remains insufficient. Additionally, the nuanced heterogeneity in the effectiveness and spillover effects of PAs are not yet fully understood, impeding our ability to leverage outcome-based evidence for crafting spatial conservation strategies to expand PAs. In this study, integrating a rigorous counterfactual analysis and remote sensing observations, we probed the effectiveness and spillover effects of the Gutianshan National Nature Reserve (GNNR), located in Kaihua County of China, in curbing forest degradation, forest loss, and forest carbon emissions. We also explored the heterogeneity of these effects and identified spatial conservation priorities based on nonuniform impacts of effectiveness. Our findings showed that the GNNR designation remarkably curtailed forest degradation, forest loss, and forest carbon emissions by 78.56 %, 95.54 %, and 97.01 %, respectively, while also extending these mitigating effects to adjacent areas. However, we also detected leakage effects, causing a displacement of forest carbon emissions in areas 5–15 km around the reserve. The effectiveness and spillover effects exhibited heterogeneous patterns across geographical conditions. Informed by this heterogeneity, we pinpointed areas showing high conservation suitability as spatial conservation priorities, covering 35.64 % of Kaihua County, thereby boosting future forest and carbon management efforts. Our results advance the understanding of PA effectiveness and spillover effects within low-altitude subtropical forest ecosystems and offer insights into integrating outcome-based and area-based conservation approaches to achieve the 30 × 30 conservation target at a regional scale.

1. Introduction

Forest ecosystems, covering approximately 31 % of the global land area (Keenan et al., 2015), play a crucial role in mitigating climate change, maintaining hydrological services, conserving biodiversity, preserving indigenous cultures, and sustaining human well-being (Watson et al., 2018). They support the majority of global terrestrial biodiversity (Pimm et al., 2014) and constitute 72 % of the global vegetation carbon stock (Xu et al., 2021). However, anthropogenic threats to forests have been intensifying (Díaz et al., 2019), including deforestation, land conversion for agriculture, and urbanization, all of which have detrimental impacts on biodiversity and ecosystem functions and services (Maxwell et al., 2016; Ghazoul and Chazdon, 2017). To mitigate the threats, posed by human encroachment on forest ecosystems, protected areas (PAs) are considered essential tools for maintaining natural habitats and species (Schleicher et al., 2019; Geldmann, 2023). The recently adopted Kunming-Montreal Biodiversity Framework proposes to expand PAs to cover 30 % of the global land and water areas by 2030 (i.e. the 30 × 30 conservation target) (CBD, 2022). This ambitious goal is part of an approach known as area-based conservation (Maxwell et al., 2020), which aims to improve the coverage of conservation, thereby preserving biodiversity and ecosystems.

In addition to area-based conservation, there is a need for increased emphasis on outcome-based conservation to provide us with a stronger

* Corresponding author.
E-mail address: hao@ign.ku.dk (H. Xia).

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evidence-based foundation for conservation (Rodrigues and Cazalis, 2020). Therefore, assessing the effectiveness of PAs is essential to determine if they fulfill their intended conservation objectives. Despite the high expectations placed on PAs, they are not always successful or effective due to issues such as misplacement, poor management, lack of funding and personnel, and insufficient legislation (Watson et al., 2014; Coad et al., 2019; Appleton et al., 2022). These factors may lead to unintended outcomes for PAs. Firstly, PAs may be ineffective in achieving their conservation goals, and this outcome is not coincidental. A recent evaluation in Great Britain demonstrated that species declined equally rapidly both in PAs and non-PAs (Cooke et al., 2023), revealing their limited impact. Similarly, a global study of PAs indicated that while many PAs have positive effects in reducing human threats, they do not decrease overall human pressure, implying they either fail to mitigate the expected pressure or even increase it in some regions (Geldmann et al., 2019). Secondly, the positive results achieved by PAs may be offset by negative spillover effects on surrounding areas, known as "leakage" (Fuller et al., 2019), which occurs when harmful land-use activities are displaced to adjacent areas. An assessment of 120 pantropical and subtropical PAs revealed that approximately 46 % of them experience leakage effects, with 78.2 % of leakage instances resulting in an insufficient reduction of deforestation within PAs to compensate for the deforestation in buffer zones (Ford et al., 2020). Conversely, "blockage" refers to the unexpected beneficial spillover effects of PAs on neighboring areas (Fuller et al., 2019). Studies have identified blockage effects in locations like Sumatra, where PAs promoted forest conservation in surrounding unprotected lands (Gaveau et al., 2009). On the other hand, some studies have found no significant spillover effects, as seen in Costa Rica's PAs and Brazilian PAs established between 2004 and 2017 (Andam et al., 2008; de Assis Barros et al., 2022). These varied findings underscore the complexity of spillover effects in different regions and contexts, highlighting the importance of examining leakage, blockage, and no spillover effects on a case-by-case basis. Overall, evaluating the effectiveness of PAs and assessing their spillover effects are both crucial for designing plausible conservation strategies and gaining a comprehensive understanding of their overall impact.

Current research on the effectiveness and spillover effects of PAs in conserving forest ecosystems primarily focuses on changes in forest cover (e.g., Zhao et al., 2019; Ford et al., 2020; Rahman and Islam, 2021; Shen et al., 2022; de Assis Barros et al., 2022; Li et al., 2022). Most of these studies utilized the Global Forest Change Dataset (GFCD) produced by Hansen et al. (2013) to investigate forest loss and gain. The GFCD provides high-resolution (30 m) global forest change data covering forest loss from 2001 to 2021 and forest gain from 2000 to 2020, which is well-suited for revealing forest dynamics in PAs and their surrounding regions. However, the GFCD defines forest loss as "a stand-replacement disturbance or the complete removal of tree cover canopy at the Landsat pixel scale," thus neglecting more subtle non-stand replacement disturbances. Thereafter we refer to this subtle disturbance as forest degradation in the current study, i.e., degrading forests without stand replacement. Forest degradation can alter species composition and stand structure, depending on the disturbance factors, severity, and intensity (Cohen et al., 2016). While forest loss represents a severe disturbance, it does not capture subtle degradation signals and intensities, such as climatic events, fire, pests, and diseases (FAO, 2022). Dense time series data and more sophisticated change detection methods can help detect subtle degradation signals and provide a range of forest degradation detection from mild to severe (Cohen et al., 2018). This information can be used to assess the impact of PAs on forest degradation. Forest loss and degradation have profound effects on the fluxes of water, carbon, nutrients, and biodiversity (Edwards et al., 2014). In terms of forest carbon emissions, according to the Global Carbon Budget 2022 (Friedlingstein et al., 2022), deforestation carbon emissions, as a primary driver of the global total carbon sources, generated 1.8 ± 0.4 GtC yr^{-1} of emissions during 2012–2021. However, compared to the effectiveness and spillover effects of PAs in reducing forest loss, our understanding of their impact on forest degradation and carbon emissions is more limited, and there is still a need for a more nuanced understanding of these impacts.

To attain the 30 × 30 conservation target, it is imperative to acquire more outcome-based evidence regarding the effectiveness of PAs. This evidence will catalyze augmenting the extent of protected area coverage, thereby optimizing the quality of conservation endeavors (Barnes et al., 2018). We believe that exploiting outcome-based evidence to identify conservation priorities is essential, as many PAs tend to be located in areas that may not necessarily require protection (referred to as the "residual nature" of PAs) (Joppa and Pfaff, 2009; Vieira et al., 2019). These PAs are often located in areas that are under marginal land conversion pressure even in the absence of conservation efforts, thereby reducing costs and minimizing potential conflicts with activities such as mining or agriculture (Vieira et al., 2019; Venter et al., 2018). Currently, there is limited research focused on leveraging spatially heterogeneous responses to conservation for generating suitability maps that inform spatially explicit conservation prioritization (Ferraro et al., 2011). Therefore, we aim to identify areas within the general landscape outside of the current PAs, where establishing new PAs could be more efficient, effective, and better aligned with conservation goals. This will be achieved by analyzing the heterogeneity of protected area effectiveness and exploiting this information to establish new conservation priorities.

In a nutshell, the current research gap exists in understanding the nuanced impacts of PAs on forest degradation and forest carbon emissions, and their spillover effects, while the lack of studies harnessing spatially heterogeneous responses hinders the provision of outcome-based evidence for spatially explicit conservation prioritization. To address the gap, this study examines the Gutianshan National Nature Reserve (GNNR) in Zhejiang Province, China, which hosts the world's most pristine and intact low-altitude subtropical evergreen broad-leaved forests. Combining rigorous counterfactual analysis and remote sensing observations, we analyzed the reserve's effectiveness and spillover effects in mitigating forest degradation, loss, and forest carbon emissions and explored the heterogeneity of impacts. By leveraging spatial heterogeneity of effectiveness, we identified potential conservation priorities. Specifically, we aimed to answer the following questions:

(1) Does the designation of GNNR mitigate forest degradation, loss, and carbon emissions?
(2) Does the designation of GNNR lead to leakage or blockage effects of conservation?
(3) What heterogeneous impacts do the effectiveness and spillover effects of the nature reserve have?
(4) Where additional unprotected forests can be identified as conservation priorities based on the heterogeneity of impacts to meet the 30 × 30 conservation target?

2. Methods

2.1. Study area

The GNNR (118°03′56″-118°10′56″E, 29°10′32″-29°17′44″N) is situated in Zhejiang Province, China (Fig. 1). It spans 8107 ha with an elevation range of 164–1258 m. The GNNR, originally established in 1975 as the Gutianshan Nature Reserve, was upgraded to a national-level nature reserve in 2001. It is located in Kaihua County, which lies within the subtropical monsoon climate zone and is greatly influenced by the summer monsoon. The area experiences distinct seasonal variations and is home to typical low-altitude subtropical evergreen broad-leaved primary forests (Zhang et al., 2019). This region serves as a transitional zone connecting the flora of South and North China, characterized by vast tracts of natural secondary forests in their original state, complex forest structures, and rich biodiversity (PGKC, 2013). It hosts 2251 species of higher plants and 463 terrestrial wild vertebrates,

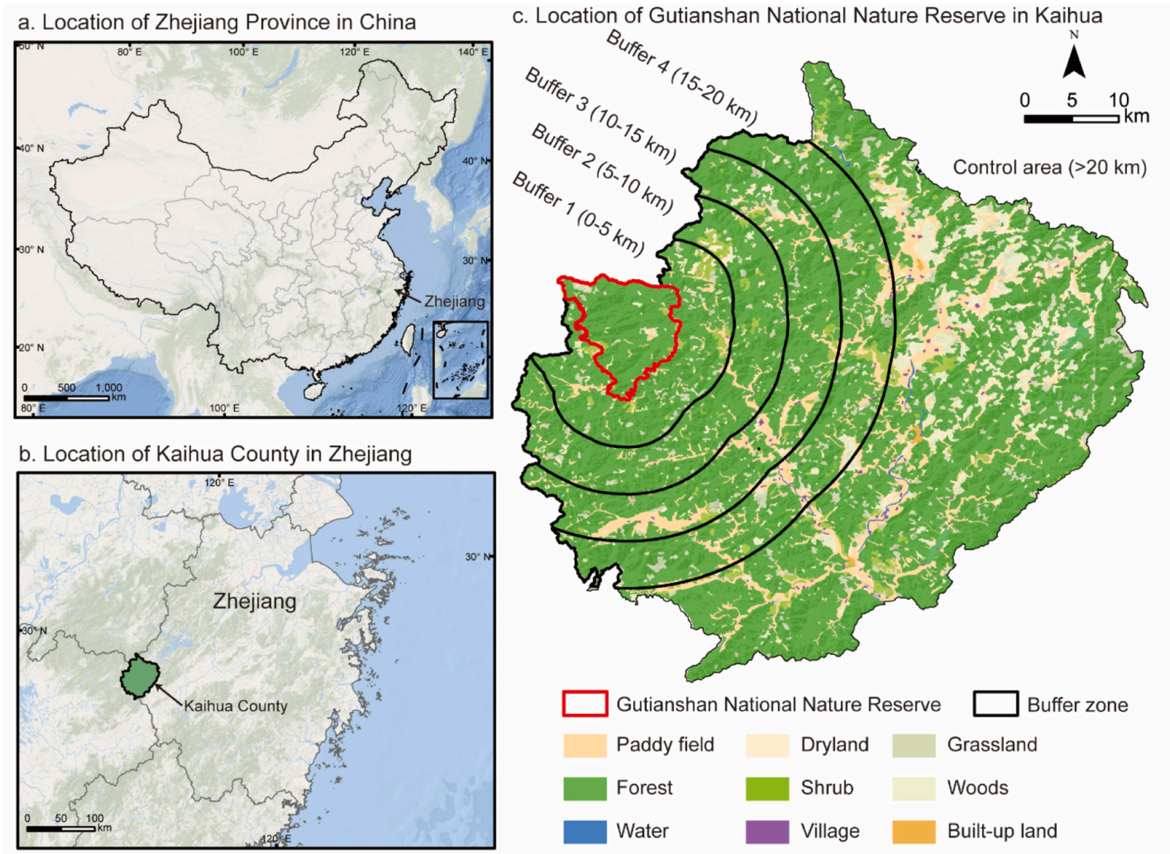

Fig. 1. Location of the study area, Gutianshan National Nature Reserve, Kaihua County, Zhejiang Province, in Southeast China, and land use/land cover in Kaihua County.

accounting for approximately 37 % and 59 % of the province's total, respectively. The GNNR primarily aims to protect the subtropical evergreen broad-leaved forest ecosystem and various rare and endangered species. These include 37 key national protected animals, such as *Syrmaticus ellioti*, *Muntiacus crinifrons*, *Neofelis nebulosa*, *Lophura nycthemera*, and *Ursus thibetanus*, as well as 32 endangered plants including *Emmenopterys henryi*, *Michelia skinneriana*, and *Parthenocissus suberosa*. The ancient, primitive subtropical forest system and abundant biodiversity make this region one of Southeast China's biodiversity hotspots and key conservation areas. Moreover, this region is also one of the fastest urbanizing areas in China, characterized by rapid economic development, increased energy consumption, and carbon emissions (Yang et al., 2018). Achieving sustainable development in the area necessitates the delineation and expansion of PAs and ecological functional zones to reconcile the conflicts between conservation and development (Xia et al., 2023).

2.2. Counterfactual analysis

The establishment of PAs faces a self-selection issue, as decisions are made by specific groups influenced by factors like natural conditions, conservation priorities, and stakeholder interests. This non-random site selection for protection may create bias when assessing the reserve's effectiveness in mitigating forest degradation, loss, and carbon emissions (Cuenca et al., 2016). Ideally, one of the valid ways to assess the effectiveness of PAs would be by comparing scenarios with and without their presence, i.e. counterfactual analysis. However, this approach is infeasible since we cannot observe forest dynamics in a scenario where the nature reserve is absent. To tackle this issue, we employed statistical matching, a quasi-experimental method that reduces bias by creating a counterfactual comparison group. This method allowed us to match treated samples within the GNNR with control samples within the control area with similarities, thereby eliminating potential selection bias, and then compare their differences to measure the effectiveness of the nature reserve.

We limited our study area to Kaihua County due to the GNNR's location at the junction of three provinces (Fig. 1b), enabling us to eliminate the unobservable bias caused by administrative divisions and policy differences. We divided Kaihua County into six sections, including the GNNR, four buffer zones at 5 km intervals within 20 km of the GNNR, and a control area beyond 20 km from the GNNR (Fig. 1c). We refer to Yang et al. (2021) to use 5 km as the variation interval of the buffer zone to better analyze the spatial variation of the spillover. Meantime, 20 km is often considered the farthest distance involved in the spillover effect (Yang et al., 2021; Shen et al., 2022), which is also confirmed by our subsequent results. We partitioned the study area into 200 m $\times$ 200 m grid cells, serving as the basic units for our research. This division enables us to coordinate data at different resolutions and ensures that the cell area remains sufficiently small, allowing us to determine conservation priorities with precision at a fine-grained level. To minimize potential selection bias, we matched units from the GNNR and buffer zones with those in the control area, further estimating the reserve's effectiveness and spillover effects.

2.2.1. Outcome variables

2.2.1.1. Forest degradation. We first extracted forests of Kaihua County from Hansen et al. (2013) as the baseline forest data to distinguish between forests and non-forests. We then employed the LandTrendr algorithm, a Landsat-based spectral-temporal segmentation method for change detection (Kennedy et al., 2010), to identify forest degradation in forests of Kaihua County between 2000 and 2020. This analysis utilized the Google Earth Engine (GEE) platform and normalized burn ratio (NBR) data. We acquired surface reflectance data for Kaihua County from all Landsat TM/ETM+/OLI images taken between 2000 and 2020 in the GEE platform. These data have undergone atmospheric correction and cloud, shadow, water, and snow masking based on CFSMask (De Marzo et al., 2021; Foga et al., 2017). To reduce the impact of phenological differences on spectral recognition, we selected images from the same season during periods of vigorous vegetation growth. Based on the vegetation productivity in the study area, we set the image acquisition timeframe between June 20th and September 1st annually.

Using the constructed time series dataset, we calculated spectral indices for monitoring forest degradation. Previous research has demonstrated that NBR is sensitive to vegetation disturbances (Kennedy et al., 2010). Therefore, we selected NBR as the monitoring index for forest degradation in this study, which is a ratio between the near-infrared (NIR) and shortwave infrared (SWIR) values, i.e. NBR = (NIR-SWIR)/(NIR + SWIR).

The core of the LandTrendr algorithm involves the segmentation of time-series trajectories by dividing spectral trajectories into a series of connected segments and fitting them based on a constructed time-series spectral dataset, thereby eliminating noise and highlighting spectral trajectory trends (Kennedy et al., 2010). Model parameters need to be set during the segmentation and fitting process. This study determined the model parameters (Table S1) by comparing the segmentation and fitting results of different parameter combinations.

The resulting 30-m spatial resolution forest degradation data reflects forest degradation in Kaihua County from 2000 to 2020 (Fig. 2a). To evaluate the accuracy of the forest degradation data, the degradation pixels were compared with actual ground validation data using visual interpretation. First, we selected 500 degradation pixels and 500 stable (non-degradation) pixels using stratified random sampling from the forest degradation map (Fig. S4). Next, to validate the NBR change trajectories of the degradation and stable pixels, we visually identified and recorded the validation categories based on the combined utility of Landsat images, including Landsat 5, 7, and 8, high-resolution very-high-resolution imagery available via Google Earth Pro, and a time-series vegetation change detection tool based on GEE developed by Zhang et al. (2023) (available via https://tingtinghe2011.users.earthengine.app/view/chinaabandonsample). Finally, we generated a confusion matrix using the recorded 1000 degradation-stable validation data and calculated the producer's accuracy, user's accuracy, overall accuracy, and Kappa coefficient. The accuracy evaluation results (Table S2) show a Kappa coefficient of 0.862 and an overall accuracy of 93 % for forest degradation, indicating that the forest degradation classification based on LandTrendr is highly accurate and suitable for subsequent analysis. To match our study's basic units, we summed the forest degradation values within the grid cells to represent the cumulative maximum forest degradation from 2000 to 2020 of grid cells.

2.2.1.2. Forest loss. Forest loss data for the period 2001–2021 were obtained from GFCD (version 1.9) (Hansen et al., 2013) with a spatial resolution of approximately 30 m (Fig. 2b). The data was downloaded from Global Forest Watch (https://www.globalforestwatch.org/). In this dataset, "forest loss" indicates the removal or mortality of tree cover and can be due to a variety of factors, including mechanical harvesting, fire, disease, or storm damage. As such, "loss" does not equate to deforestation. To match our study's basic units, we aggregated the number of forest loss pixels within the grid cells to represent the total forest loss area from 2001 to 2021 of grid cells.

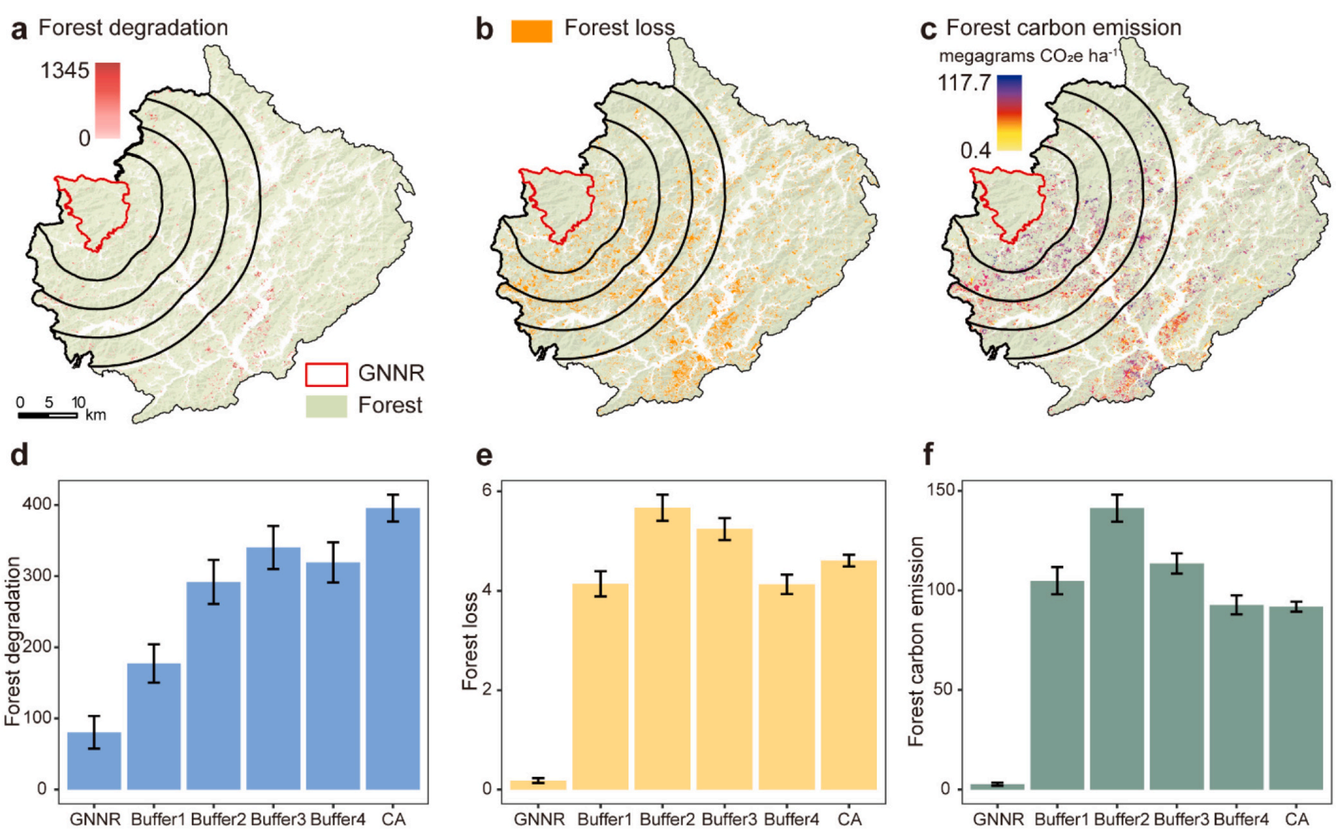

Fig. 2. Spatial distribution of forest degradation (a), forest loss (b), and forest carbon emissions (c) at 30-m resolution and average values with 95 % confidence intervals of forest degradation (d), forest loss (e), and forest carbon emissions (f) in the Gutianshan National Nature Reserve (GNNR), four buffers (Buffer 1–4), and the control area (CA) at the 200 m × 200 m grid-cell scale. Forest degradation (d) is unitless; the unit of forest loss (e) is the number of forest loss pixels per grid cell; the unit of forest carbon emission (f) is megagrams CO_2e ha^{-1}.

2.2.1.3. Forest carbon emissions. Forest carbon emissions data for 2001–2021 was generated by Harris et al. (2021) and obtained from Global Forest Watch (https://www.globalforestwatch.org/) at 30-m resolution (Fig. 2c). Forest carbon emissions represent greenhouse gas emissions resulting from forest disturbances that replace tree cover in each simulated year. These emissions encompass all related ecosystem carbon pools (aboveground biomass, belowground biomass, deadwood, litter, soil) and greenhouse gases (CO_2, CH_4, N_2O), and carbon emissions for each pixel are based on carbon density in 2000 and adjusted for cumulative carbon between 2000 and the disturbance year (Harris et al., 2021). We used data in units of megagrams of CO_2e emissions per pixel to facilitate summation within grid cells. To match our study's basic units, we summed the forest carbon emissions values within the grid cells to represent the total forest carbon emissions from 2001 to 2021 of grid cells.

2.2.2. Covariates

We used covariates to match treated samples with control samples to mitigate potential selection biases. The covariates used for matching should influence both the intervention selection, i.e., the establishment of PAs, and outcome variables, including forest degradation, loss, and carbon emissions in this study (Schleicher et al., 2020). We ultimately selected seven covariates: distance to settlements, distance to forest edges, annual precipitation, annual mean temperature, elevation, slope, and forest cover. These confounders have been widely used in previous studies to control for overt bias due to their strong association with both intervention and outcome variables (Andam et al., 2008; Gaveau et al., 2009; Ferraro et al., 2011; Geldmann et al., 2019; Ford et al., 2020; Rahman and Islam, 2021; Shen et al., 2022; de Assis Barros et al., 2022). Also, these variables are closely related to the motivation for the establishment of PAs. Detailed variable descriptions and data sources are presented in Table S3.

2.2.3. Statistical matching

In statistical matching, the treated samples correspond to grid cells in the GNNR and buffer zones, while control samples represent grid cells in the control area. We established five buffer zones around the GNNR, including Buffer 1 (0–5 km), Buffer 2 (5–10 km), Buffer 3 (10–15 km), and Buffer 4 (15–20 km). The area beyond 20 km from the GNNR but within Kaihua County was considered the control area. Our basic units for statistical matching are 200 m × 200 m grid cells. We calculated the outcome variable values and extracted the covariate values from these grid cells for statistical matching. Covariates with finer spatial resolution were aggregated by their mean value.

We followed the approach of Yang et al. (2019) to determine the number of grid cells in the GNNR and buffers that were included in the statistical matching process. Additionally, we adopted the method employed by Shen et al. (2022) to set a minimum distance between units to limit spatial autocorrelation. Specifically, we set the distance between the centroids of grid cells to be at least 1 km. We exploited Correlogram in Geoda 1.18.0 to assess autocorrelation as a function of distance (for detailed methods, see Supplementary Methods). The results indicated that the spatial autocorrelation of forest degradation, forest loss, and forest carbon emissions tended towards zero beyond 1 km (Fig. S5). Within the range of 1–1.5 km, the spatial autocorrelation for forest degradation, forest loss, and forest carbon emissions was measured at 0.050, 0.081, and 0.091, respectively (Fig. S5). These values suggest that spatial autocorrelation is very weak in this range. Consequently, we can confidently assert that the selected 1 km minimum distance is reasonable and effectively controls for spatial autocorrelation.

Statistical matching is a method that enables causal inference by aiming to achieve a covariate balance between treated and control groups, similar to the balance achieved through randomization. While randomization ensures balance across both observable and unobservable confounders, matching focuses on achieving balance across important observable confounders by re-weighting the data (Hanauer and Canavire-Bacarreza, 2015). To estimate the average treatment effect on the treated (*ATT*) in our analysis, we select the nearest neighbor from the pool of unprotected units for each protected unit based on multivariate covariate distance. Readers can refer to Ferraro et al. (2011) for a detailed description of calculating *ATT* using statistical matching.

We employed propensity score matching (PSM) in R using "MatchIt" package to match treated and control samples. We set the matching to be 1:1 with replacement, meaning that each treated sample is matched with only one most similar control sample, while the control sample can be matched with multiple treated samples. We also set the caliper for matching as 0.25, which represents the degree of difference between treated and control samples, ensuring that the difference between treated samples and their matched control samples does not exceed 0.25 standard deviation (SD), thereby maximizing the similarity between the two groups.

A successful matching must satisfy three conditions (Schleicher et al., 2020): first, the post-matching differences between treated and control samples should be small; second, the post-matching treated samples should resemble the pre-matching treated samples; and third, it is essential to ensure that treatment units are not discarded to retain a higher number of them as much as possible during the matching process.

The matching results of samples within the GNNR and the four buffers indicate that the treated samples and control samples demonstrate significant similarity after matching (Fig. S1 and Table S4), with marginal differences (< 0.25 SD) (Fig. S2). Notwithstanding, the annual precipitation in Buffer 2 after matching exhibits a discrepancy >0.25 SD. However, since the difference remains <0.5 SD, it is deemed acceptable. Concurrently, the treated samples maintained similarity before and after matching (Fig. S1). Only 0.13 % to 2.63 % of the treatment samples were discarded during the matching process due to the absence of appropriate control samples, indicating that the vast majority of the treatment samples were retained. Therefore, the matching results can effectively mitigate the differences between the treated and control samples based on confounders that we have taken into account.

2.3. Assessment of conservation effectiveness and spillover effects

We can derive matched treated and control samples using PSM, thereby facilitating the estimation of reserve and buffers' effectiveness via the computation of the mean difference in outcome variables between treated and control samples after matching. It should be noted that, despite statistical matching mitigating differences between treated and control samples through covariates, complete homogeneity in covariates is not ensured. Thus, to reduce any residual biases amidst the matched groups, it is advisable to employ a post-matching regression strategy (Sonter et al., 2017). In the post-matching regression, we estimated the *ATT* by considering the outcome variable as the dependent variable, and the treatment status (treated = 1, control = 0) and covariates as independent variables.

The absolute effect we derive, measured by *ATT*, signifies the average impact per grid cell unit brought about by the designation of the reserve. To draw more general conclusions, we calculated the relative effect, represented as the ratio of *ATT* to the average value of the outcome variable in the control group (C) (von Staden et al., 2022), i.e. $ATT/C \times 100$ %. This demonstrates the extent to which the nature reserve has an effect relative to its counterfactual.

Similarly, we employed the same method to match units within different buffers with those in the control area and estimate their relative effects. For the three outcome variables we observed, a significant positive effect within a buffer indicates a leakage effect. This suggests an increase in forest degradation, loss, or carbon emissions in the surrounding areas due to the designation of the GNNR. Conversely, a significant negative effect signifies a blockage effect.

2.4. Heterogeneity analysis

To explore the heterogeneity of the effectiveness and spillover effects of the GNNR, we assessed the impact of six baseline factors: distance to nature reserve boundary, distance to settlements, distance to the forest edge, forest cover, elevation, and slope. We aimed to reveal how the effectiveness and spillover effects of the nature reserve vary with changes in these baseline factors. A comprehensive understanding of these heterogeneous impacts also provides evidence-based principles for subsequent spatial conservation prioritization (see Section 2.5).

We employed a two-stage semiparametric partial linear differencing model (PLM) for the heterogeneity analysis (Ferraro et al., 2011; Rasolofoson et al., 2017). This two-stage estimator controls for other baseline factors in the first stage and then estimates the results as a non-parametric function of the baseline factors of interest using a locally weighted scatter plot smoothing (LOESS) technique in the second stage. This two-stage estimation approach allows for the assessment of the impact of one of the baseline factors while holding other factors constant (Rasolofoson et al., 2017), thereby exploring the non-parametric continuous relationship between the factor of interest and outcomes. Detailed methodological descriptions of the PLM and LOESS can be found in Supplementary Methods. We utilized the code provided by Hanauer and Canavire-Bacarreza (2015) to implement the two-stage estimation methods in R.

2.5. Spatial conservation prioritization based on heterogeneity analysis

Heterogeneity analysis aids our understanding of the relationship between the effectiveness of the nature reserve designation and baseline factors (except for distance to nature reserve boundary), elucidating conditions under which the nature reserve effectively mitigates forest degradation, loss, and carbon emissions. These evidence-based conditions can be used to inform the suitability of conservation, speculating which unprotected forests would benefit from conservation interventions, thereby identifying potential spatial conservation priorities. We extend the heterogeneity-based suitability mapping approach proposed by Ferraro et al. (2011) to determine potential spatial conservation priorities in Kaihua County, as follows:

(i) Normalize the continuous non-parametric relationship between baseline factors and effectiveness derived from PLM heterogeneity analysis to a scale of [0,10].
(ii) Acquire corresponding normalized effectiveness values for all 200 m × 200 m grid cells' baseline factors using nearest neighbor matching.
(iii) Average the normalized effectiveness values of all baseline factors on each grid cell, which serves as the conservation suitability of that cell.
(iv) Repeat the above steps to ascertain the conservation suitability for forest degradation, loss, and carbon emissions, respectively, and apply local Moran's *I* analysis (Anselin et al., 2009; Yuan et al., 2021) to identify conservation hotspots.
(v) Conduct spatial overlay analysis on the conservation hotspots for forest degradation, loss, and carbon emissions to determine spatial conservation priorities and their area sizes.

For more detailed descriptions, refer to Supplementary Methods and Fig. S3.

3. Results

3.1. Nature reserve effectiveness and spillover effects

The counterfactual analysis based on statistical matching indicated that forest degradation, loss, and carbon emissions of treated units within the GNNR were significantly less than their matched control units (Fig. 3a-c). Post-matching regression results demonstrated that the designation of the GNNR markedly reduced forest degradation, loss, and carbon emissions, averaging by 78.56 % [95 % confidence interval (CI) = 60.29 to 96.83; $p < 0.001$], 95.54 % (95 % CI = 85.71 to 100; $p < 0.001$), and 97.01 % (95 % CI = 87.16 to 100; $p < 0.001$), respectively (Fig. 3d-f and Table S5–7).

However, the spillover effects produced by the designation of the GNNR on different outcome variables were inconsistent, thereby generating mixed effects. Forest degradation in four buffers was less than their counterfactuals in the control area (Fig. 3a), suggesting that the designation of the GNNR generated statistically significant blockage effects, thereby reducing forest degradation within the 0–20 km buffer zones surrounding the nature reserve. These blockage effects weaken with increasing distance from the nature reserve, resulting in an average reduction of forest degradation ranging from 13.46 % - 58.95 % in buffers (Fig. 3d).

In terms of forest loss, only Buffer 1 showed less forest loss than counterfactuals, with no significant differences in forest loss between Buffer 2–4 and their counterfactuals (Fig. 3b). This implied that the designation of the GNNR generated a statistically significant blockage effect reducing forest loss within the 0–5 km buffers, leading to an average reduction of 23.83 % in forest loss within this range (Fig. 3e).

Regarding forest carbon emissions, the forest carbon emissions in Buffer 1 were lower than their counterfactuals, while those in Buffer 2 and Buffer 3 exceeded their counterfactuals (Fig. 3c). The carbon emissions in Buffer 4, however, were nearly identical to their corresponding counterfactuals (Fig. 3c). These results indicated that the blockage effects caused by the designation of GNNR reduced forest carbon emissions by 8.85 % within the 0-5 km buffer surrounding the GNNR. However, the leakage effects increased forest carbon emissions by 16.06 % and 11.54 % within the 5–10 km and 10–15 km buffers, respectively (Fig. 3f).

3.2. Heterogeneous impacts

3.2.1. Heterogeneity of effectiveness in mitigating forest degradation, loss, and carbon emissions within the GNNR

The effectiveness of the GNNR designation in mitigating forest degradation, loss, and carbon emissions was heterogeneous, meaning these effects varied in accordance with baseline factors (Fig. 4).

Regarding the distance to the nature reserve boundary, the GNNR designation consistently reduces forest loss and forest carbon emissions across different distances, with the average effect showing minor variance (Fig. 4b and Fig. 4c). However, in locations further from the reserve boundary (> 3200 m), although the estimated impact indicated a reduction in forest degradation, this impact was not statistically significant (Fig. 4a).

Concerning the distance to settlements, the average effect on reducing forest degradation did not show a significant variation across different distances, with the strongest mitigating effect observed approximately 3600 m from the settlements. However, the estimated effect was not statistically significant beyond 5700 m (Fig. 4d). The trends of the impact of the distance to settlements on forest loss and carbon emissions were consistent, with the effects initially decreasing and then increasing. The most potent effects occurred approximately 4000 m from the settlements, but beyond 6000 m, the effects were no longer statistically significant (Fig. 4e and Fig. 4f).

In terms of the distance to the forest edge, although the effectiveness of the nature reserve fluctuated within 500 m, overall, the places closer to the forest edge yield greater mitigating effects. As the distance increased, the effectiveness of the nature reserve gradually weakened. The effectiveness of the reserve on the three outcome variables was not statistically significant in places further than approximately 1300 m from the forest edge (Fig. 4 g-i).

For forest cover, the nature reserve did not significantly reduce forest degradation, loss, or carbon emissions in places with either low or high

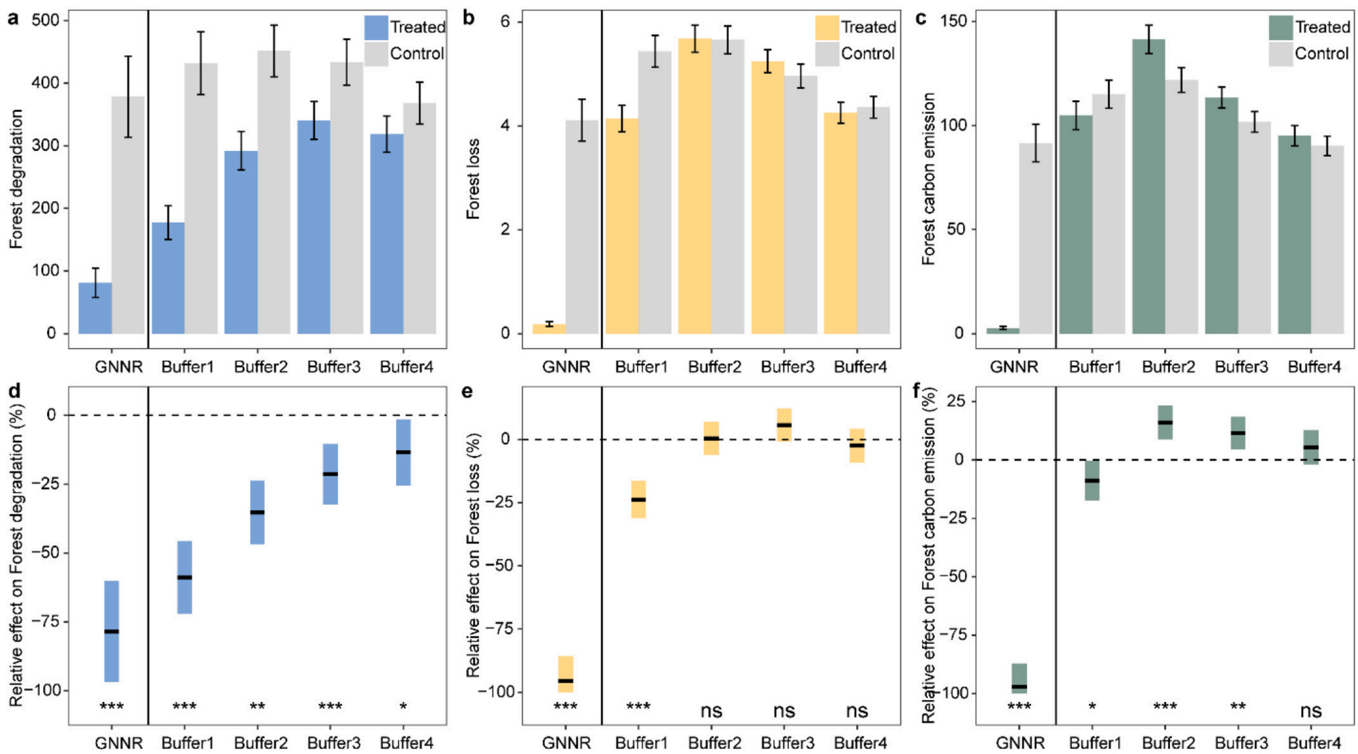

Fig. 3. Mean values (95 % CI) of forest degradation (a), forest loss (b), and forest carbon emissions (c) of treated units and matched control units and mean relative effects (95 % CI) on forest degradation (d), forest loss (e), and forest carbon emissions (f) in the Gutianshan National Nature Reserve (GNNR) and four buffers (Buffer 1–4). *** p < 0.001, ** $p < 0.01$, * $p < 0.05$, ns indicates no significance ($p > 0.05$). Forest degradation (a) is unitless; the unit of forest loss (b) is the number of forest loss pixels per grid cell; the unit of forest carbon emission (c) is megagrams CO_2e ha^{-1}.

forest cover (Fig. 4 j-l).

In terms of elevation, the effectiveness of the nature reserve was higher in lower altitude areas (< 400 m). However, the estimated effects became less precise and statistically significant in places above 1200 m.

Regarding slope, the trends of the effects on forest degradation, loss, and carbon emissions were consistent. The nature reserve did not produce statistically significant results in places with low and high slopes. The slope range within which the reserve effectively reduces forest degradation, loss, and carbon emissions was approximately between 15 and 50° (Fig. 4p-r).

3.2.2. *Heterogeneity of blockage and leakage effects*

The blockage and leakage effects attributed to the GNNR designation exhibit heterogeneous responses to baseline factors (Fig. 5 and Fig. 6). For a detailed analysis of this heterogeneity, we focused on the blockage effects of forest degradation observed within Buffer zones 1–4 (Fig. 3d), and the leakage effects of forest carbon emissions within Buffer 2–3 (Fig. 3f) as continuous blockage or leakage effects with varying degrees across conservation gradients can be observed in these areas.

In Fig. 5, the negative effects denoted the blockage effects of forest degradation caused by the GNNR designation, which reduced the forest degradation in Buffer 1–4. We observed that the blockage effects were more pronounced closer to the reserve boundary (Fig. 5a), in areas with lower forest coverage (Fig. 5d), and on less steep slopes (Fig. 5f). As the distance to the reserve boundary, forest coverage, and slope increase, the blockage effects gradually approached zero and became less significant. Simultaneously, the impact of the distance to settlements (Fig. 5b), distance to forest edges (Fig. 5c), and elevation (Fig. 5e) on the blockage effects exhibited a U-shaped non-linear influence. This indicated that, while other variables were constant, the strongest blockage effects occurred approximately 2200 m from settlements, 140 m from forest edges, and at an elevation of 600 m. Distances too far from settlements and forests or elevations too high or low failed to mitigate forest degradation and ceased the blockage effects.

In Fig. 6, the positive effects represented the leakage effects of forest carbon emissions caused by the GNNR designation, which increased forest carbon emissions in Buffers 2 and 3. We found that the leakage effects were present at varying distances from the reserve boundary within Buffer zones 2 and 3 (Fig. 6a). The distance to settlements, distance to forest edges, and slope affected the leakage effects in an inverse U-shaped pattern, resulting in the main leakage effects occurring between 450 and 3000 m from settlements (Fig. 6b), 100–600 m from forest edges (Fig. 6c), and slopes between 12 and 30° (Fig. 6f). The effects of forest cover and elevation on leakage effects were monotonically increasing with threshold values. Thus, the occurrence of leakage effects was mainly in areas with a forest cover higher than 60 % (Fig. 6d) and elevations above 500 m (Fig. 6e).

3.3. *Spatial conservation prioritization*

We assessed the conservation suitability of forest degradation, forest loss, and forest carbon emissions based on heterogeneous responses of effectiveness to baseline factors (Fig. 7a-c). We then applied local spatial autocorrelation analysis to identify conservation hotspots of forest degradation, loss, and carbon emissions, which respectively constitute 15.96 %, 21.38 %, and 21.80 % of the total county area (Fig. 7d-f). The areas within the GNNR designated as conservation hotspots for forest degradation, forest loss, and forest carbon emissions were respectively 2128 ha, 2788 ha, and 2976 ha, making up 26.25 %, 34.39 %, and 36.71 % of the GNNR's total area.

We identified spatial conservation priorities by overlaying the three conservation hotspots (Fig. 7g). The more overlapping hotspots in an area, the higher its priority and importance for spatial conservation. The total area of the spatial conservation priorities we identified was 74,992 ha, comprising 35.64 % of the total county area. Areas with overlaps of three, two, and one hotspots account for 8.48 %, 12.61 %, and 14.55 %

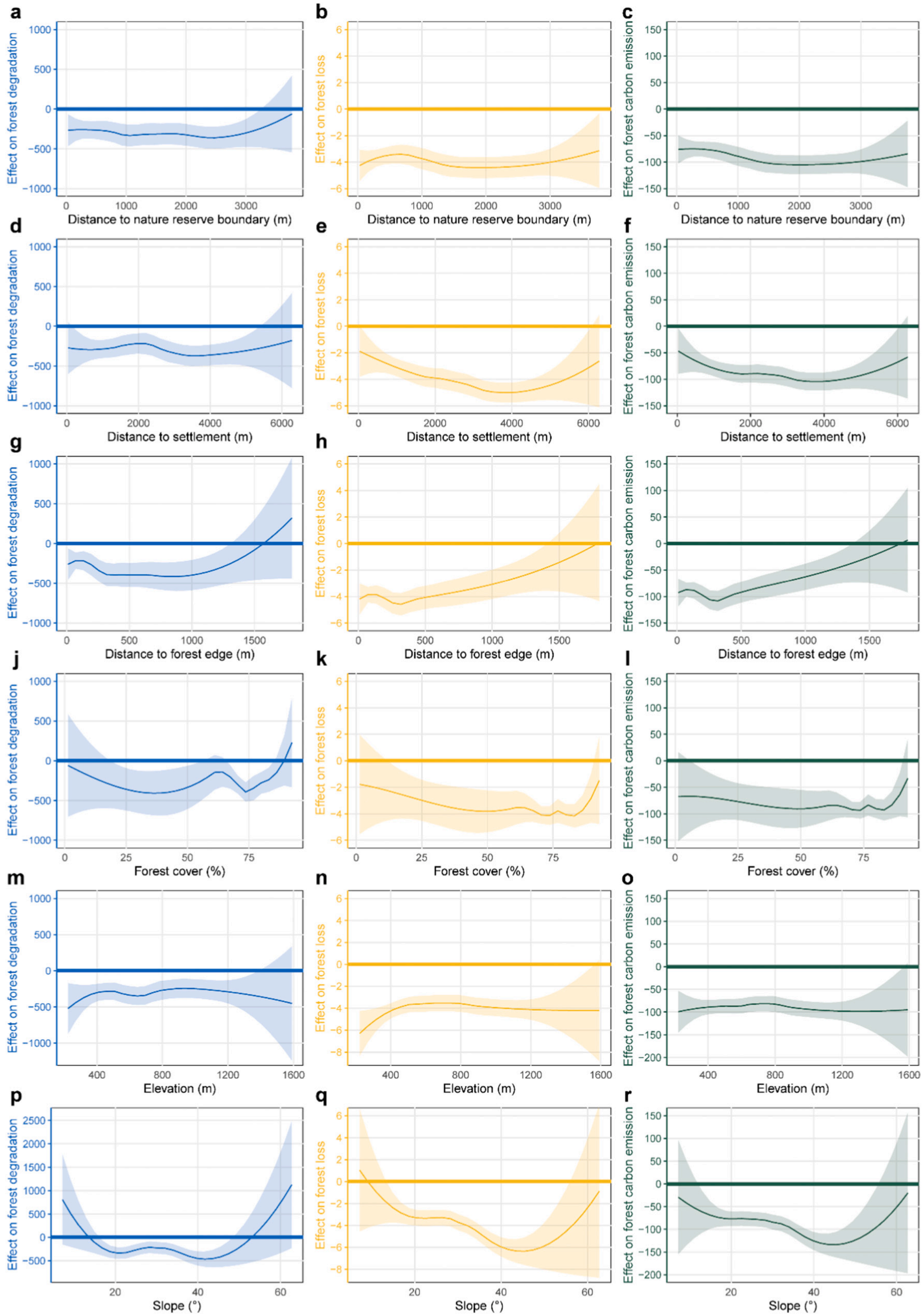

Fig. 4. Heterogeneous responses of effectiveness to six baseline factors in the Gutianshan National Nature Reserve. The shading areas refer to the confidence band at the 95 % confidence level.

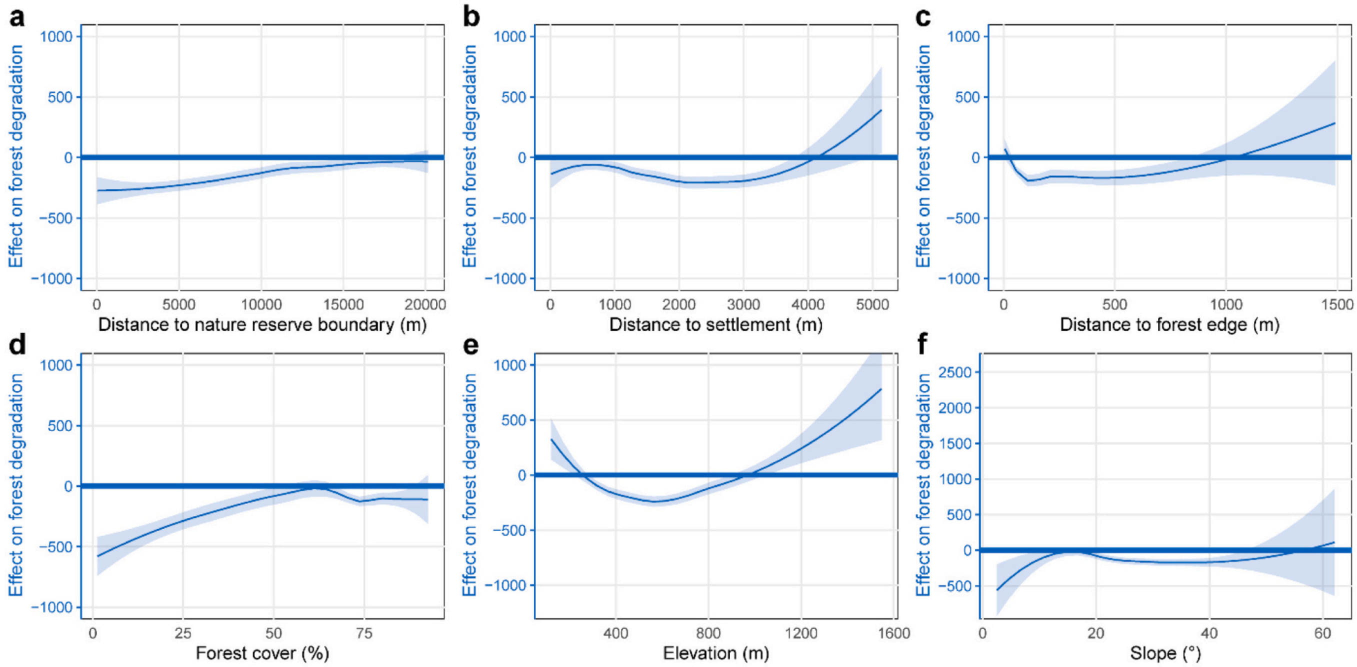

Fig. 5. Heterogeneous responses of blockage effects of forest degradation to six baseline factors in Buffer 1–4. The shading areas refer to the confidence band at the 95 % confidence level.

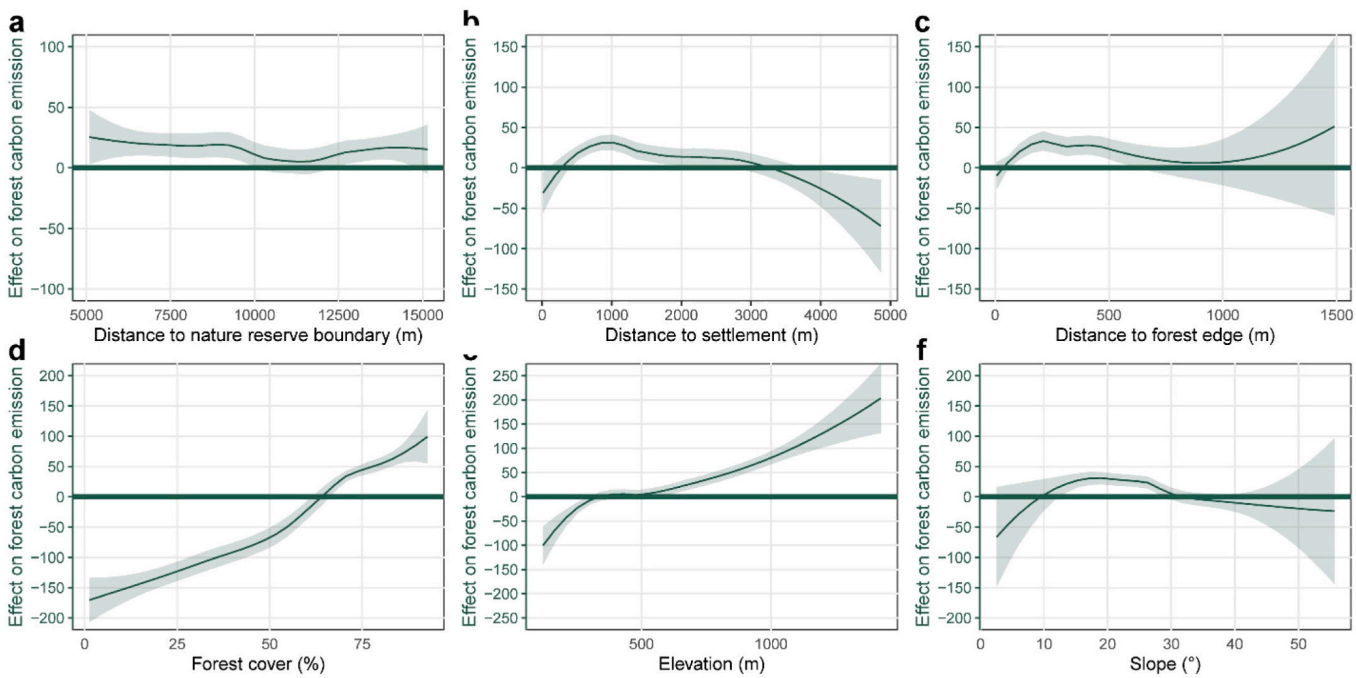

Fig. 6. Heterogeneous responses of leakage effects of forest carbon emissions to six baseline factors in Buffer 2 and Buffer 3. The shading areas refer to the confidence band at the 95 % confidence level.

of the total county area, respectively. From the perspective of different proportions of spatial conservation priorities (percentage chart in Fig. 7g), areas with overlaps of three and two hotspots constituted 57.58 % of all conservation priorities, suggesting a high spatial consistency among the hotspots for forest degradation, forest loss, and forest carbon emissions. The most critical spatial conservation priorities were primarily located in the southwestern, southeastern, and northern parts of Kaihua County. These areas should accordingly be given paramount consideration in the development of future conservation strategies.

4. Discussion

4.1. Effectiveness and spillover effects of forest dynamics derived from the GNNR designation

In line with most match-based studies focused on tropical forests (Andam et al., 2008; Gaveau et al., 2009; Nolte et al., 2013; Carranza et al., 2014; Bebber and Butt, 2017; Gonçalves-Souza et al., 2021), our research provided evidence from low-altitude subtropical forest

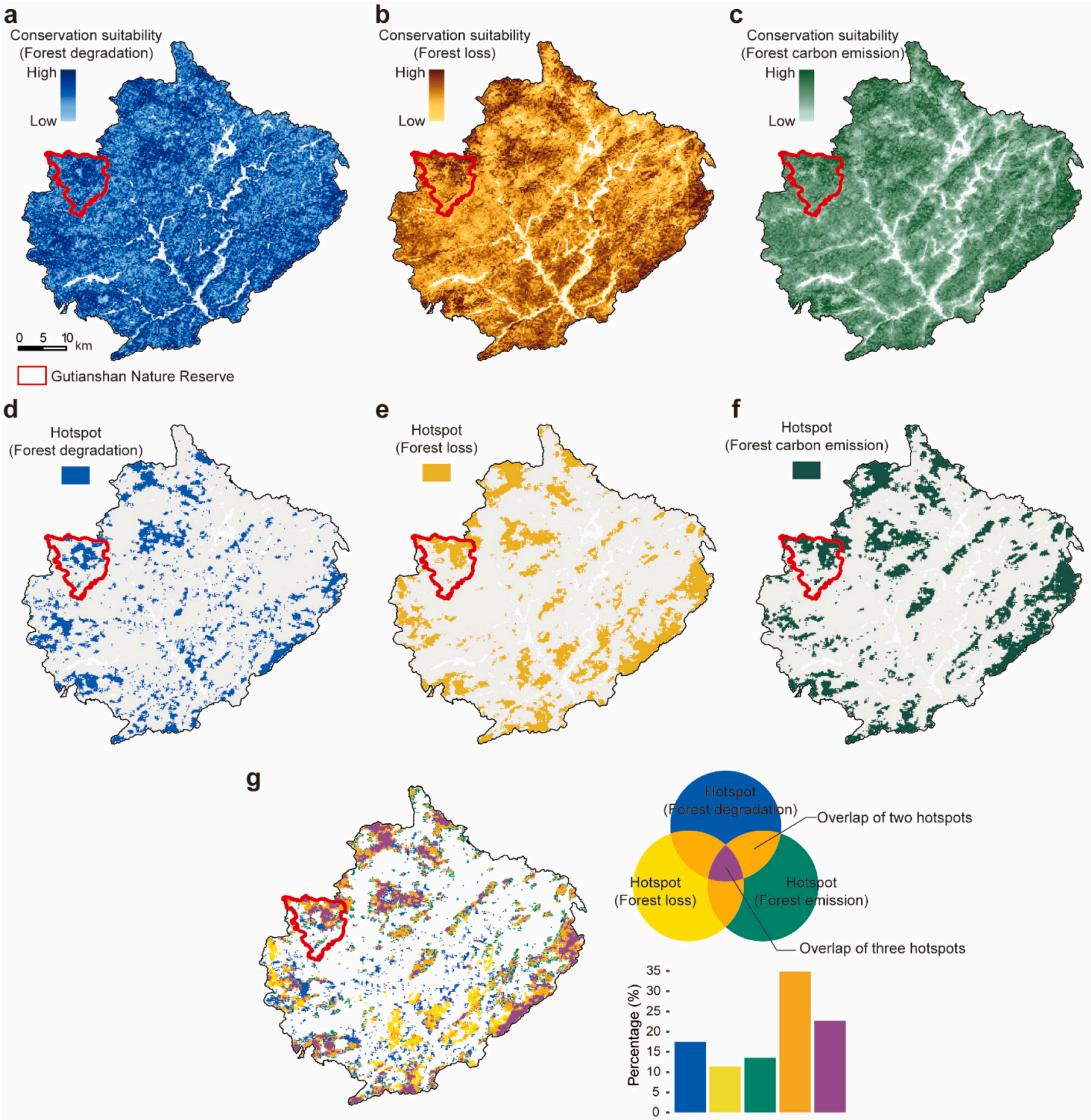

Fig. 7. Spatial conservation suitability of forest degradation (a), forest loss (b), and forest carbon emissions (c) derived from heterogeneity analysis; Spatial conservation hotspots of forest degradation (d), forest loss (e), and forest carbon emissions (f) based on conservation suitability; Spatial conservation priorities and their area percentage derived from the overlay of conservation hotspots (g). Note that a high value in (a-c) means that the conservation suitability of the area is higher, i.e., the more likely it is to curb forest degradation, forest loss, or forest carbon emissions.

ecosystem, confirming the positive impact of PA on forest conservation and the reduction of forest carbon emissions. More specifically, we found that the designation of the GNNR resulted in significantly lower forest degradation, loss, and carbon emissions within the reserve compared to external buffer zones and the control area.

Our estimations of GNNR's effectiveness are highly encouraging, with an average reduction of 78.56 %, 95.54 %, and 97.01 % observed for forest degradation, loss, and carbon emissions, respectively. These results indicate a significant success in forest protection achieved by the GNNR. We also compared these findings with assessments that did not employ counterfactual analysis and found that assessments without such analysis tend to misestimate effectiveness and spillover effects (for detailed comparisons, refer to Supplementary Text). This underscores the importance of conducting rigorous impact assessments for conservation interventions to prevent wastage of conservation resources and design cost-effective conservation programs (Ferraro and Pattanayak, 2006; Baylis et al., 2016; Cuenca et al., 2016; Schleicher et al., 2020).

Despite the universal leakage effects of forest deforestation due to the designation of PAs (Oliveira et al., 2007; Fuller et al., 2019; Ford et al., 2020; Shen et al., 2022), we did not observe leakage in forest degradation and loss in our study. Conversely, we found that the GNNR designation generated a blockage effect, leading to reductions in forest degradation and loss in areas adjacent to the GNNR (Fig. 3). However, we indeed observed leakage effects on forest carbon emissions within 5–15 km around the GNNR. Although our study observed the same phenomenon as previous research, i.e., that PAs reduced deforestation carbon emissions (Bebber and Butt, 2017), it also provided rare evidence of the leakage effects on forest carbon emissions caused by the designation of PAs (Gizachew et al., 2018). Our results revealed the inconsistent spillover effects on forest carbon emissions and forest degradation and loss. While PAs may not cause leakage effects on forest degradation and loss, they may still generate leakage effects on forest carbon emissions. One plausible explanation for the divergent carbon emission changes between the GNNR and the 5–15 km buffer zone lies in the disproportionate impact of land-use change on these regions. Although both areas have encountered forest degradation and loss, the buffer zone likely faced a more substantial degree of land-use change compared to the GNNR. Consequently, the conversion of high-carbon-density forests into agricultural or developed land likely resulted in a notable surge in carbon emissions in the buffer zone. This speculative interpretation needs to be verified in a follow-up study using more detailed in-situ data. Nevertheless, this result still highlights the necessity to address forest carbon emissions leakage, which arises due to the designation of PAs, within the framework of planning and management of PAs, and emphasizes the imperative for an integrated approach that balances environmental conservation and carbon management strategies.

4.2. Heterogeneity of effectiveness and spillover effects

Our study illuminated the heterogeneous impacts associated with variations in baseline factors within the GNNR, as demonstrated in Fig. 4. The overall heterogeneity of the impacts on forest degradation, loss, and carbon emissions appeared highly congruent, and these responses were predominantly non-linear, attesting to the complexity of successful conservation conditions.

Two baseline factors merit particular attention: the distance to forest edges and the slope. Previous studies suggested a strong association between deforestation and the proximity to forest edges (Andam et al., 2008). Consistent with this, we observed that protected lands located closer to forest edges tend to exhibit higher effectiveness, mitigating more forest degradation, loss, and carbon emissions, whereas protected lands far from forest edges did not demonstrate significant conservation effects. This can be attributed to the higher rates of forest degradation, loss, and carbon emissions in unprotected lands near the forest edges, resulting in greater conservation effectiveness.

Additionally, the slope normally affects the suitability for agricultural production. Steeper slopes imply less suitability for agriculture production, resulting in lower deforestation pressures and, consequently, lower opportunity costs of conservation and lesser conservation effectiveness (Ferraro et al., 2011; Joppa and Pfaff, 2011). The current establishment of PAs faces a dilemma known as the “residual nature of PAs,” where their distribution tends to favor marginal lands. These marginal lands are characterized by higher elevations, steeper slopes, and greater distances from cities, making them less suitable for agriculture (Joppa and Pfaff, 2009; Vieira et al., 2019; Venter et al., 2018). However, even without PAs, these lands may still retain natural land cover, which introduces a bias in the distribution of PAs (Joppa and Pfaff, 2009). Our research also confirms this pattern as we observed that lands with higher slopes exhibit lower and more uncertain conservation effectiveness (Fig. 4). These findings underline the importance of considering the heterogeneity of conservation effectiveness in relation to landscape characteristics, such as slope, when determining conservation priorities. This approach is both reasonable and necessary for our subsequent prioritization processes.

However, we also noted a discrepancy from previous research. Prior studies highlighted the association between protected lands with gentle slopes and deforestation avoidance due to higher deforestation rates in unprotected lands compared to protected lands (Ferraro et al., 2011; Hanauer and Canavire-Bacarreza, 2015). However, in our study, lands with gentle slopes ($< 15^\circ$) did not display significant effectiveness, indicating lower and uncertain conservation outcomes. This suggests that both protected and unprotected lands on gentle slopes witnessed similar levels of forest degradation, loss, and carbon emissions.

Furthermore, we elucidated the non-linear heterogeneous impacts of baseline factors on blockage and leakage effects within buffers (Fig. 5 and Fig. 6). These findings help identify the potential conditions that could trigger blockage and leakage effects, aiding in the amplification of beneficial blockage effects and minimization of adverse leakage effects.

4.3. Bridging outcome-based conservation and area-based conservation

In response to declining biodiversity and ecosystem degradation, area-based conservation and outcome-based conservation have been recognized as promising strategies for a nature-positive future (Barnes et al., 2018; Maxwell et al., 2020; Obura et al., 2023). Area-based conservation requires the identification of areas of importance for biodiversity, critical ecosystems, and nature’s contributions to people to expand the coverage of PAs (Xu et al., 2017; Maxwell et al., 2020; Jung et al., 2021). Concurrently, outcome-based conservation is oriented towards the outcomes produced by PAs and the factors influencing these outcomes, promoting PA management for maximal benefits of conservation interventions (Baylis et al., 2016; Barnes et al., 2018; Ghoddousi et al., 2022; Durán et al., 2022).

Previous studies on the effectiveness of PAs and their influencing factors have provided beneficial outcome-based conservation strategies (e.g., Andam et al., 2008; Bebber and Butt, 2017; Bowker et al., 2017; Ford et al., 2020; Cooke et al., 2023). However, scant research has integrated this outcome evidence with spatially explicit conservation prioritization, which could provide insight into area-based conservation. In this study, we adopted and expanded the approach of Ferraro et al. (2011), who assessed conservation suitabilities based on the heterogeneity of PA effectiveness. We further incorporated spatial autocorrelation analysis as a novel approach to identify spatial suitability hotspots and determine conservation priorities through superposition. By accounting for spatial autocorrelation, we can identify ecologically significant areas that are spatially connected (Lin et al., 2017; Wang et al., 2022). This prioritization facilitates the movement of species and ecological processes across the landscape, enhancing the overall effectiveness of conservation planning. Finally, we have pinpointed 74,992 ha of conservation priorities of varying importance, covering 35.64 % of Kaihua County (Fig. 7). We designate these areas as conservation priorities based on two considerations. Firstly, our analysis of effectiveness heterogeneity provides outcome-based evidence indicating that the landscape characteristics of these areas have the potential to yield favorable conservation outcomes once protected. Secondly, our consideration of the heterogeneity of conservation effectiveness offers a spatially explicit, outcome-based approach for planners and decision-makers to develop cost-effective spatial conservation schemes, which is particularly useful when confronted with decision trade-offs or budgetary constraints. It enables prioritization of areas exhibiting the highest conservation effectiveness, thereby strengthening efforts towards forest conservation and forest carbon management.

Although the identified conservation priorities are distributed across three regions: the GNNR, buffers, and the general landscape outside the GNNR and buffers, their conservation strategies should differ. Firstly, conservation priorities in the general landscape merit the highest designation as they are currently unprotected and lack the positive conservation spillover effects observed in the GNNR. However, being situated in border regions and close to densely populated centers, these conservation priorities require cross-administrative border ecological protection and measures to mitigate human encroachment. Secondly, conservation priorities within the buffers benefit from positive conservation spillover effects from the GNNR. Nevertheless, some areas also experience negative spillover effects leading to increased forest carbon emissions. Therefore, conservation strategies in these priorities should focus on effective forest carbon management and the establishment of stricter land-use conversion approval processes. Lastly, conservation priorities within the GNNR can be managed as core areas within the nature reserve.

5. Conclusion

Leveraging remote sensing observations of forest dynamic changes and rigorous counterfactual analysis, our research has unveiled the effectiveness of the GNNR designation in reducing forest degradation, loss, and carbon emissions. We have also uncovered various degrees of blockage effects, which have lessened these environmental impacts in different surrounding regions of the GNNR. However, our study also highlighted the presence of leakage effects, causing a displacement of carbon emissions in forest areas situated 5–15 km around the reserve. We further discovered that these effectiveness and spillover effects show heterogeneity based on baseline factors, thereby serving as outcome-based evidence and offering valuable insights for spatial conservation prioritization. In the context of future forest management, spatial conservation priorities, informed by this understanding of heterogenous impacts, can drive more cost-effective strategies for forest and forest carbon management. These most important conservation priorities are located primarily in northern, eastern, and southwestern Kaihua County. Moreover, these insights bridge the understanding gap between outcome-based conservation and area-based conservation. Collectively, our findings enhance our comprehension of the effectiveness, spillover effects, and optimal management strategies of PAs within low-altitude subtropical forest ecosystems to meet the 30 $\times$ 30 conservation target.

CRediT authorship contribution statement

Hao Xia: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing, Visualization, Project administration, Funding acquisition. **Han Li:** Methodology, Software, Validation, Writing – review & editing. **Alexander V. Prishchepov:** Conceptualization, Writing – original draft, Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data and code can be accessed at https://github.com/XiaHaoKU

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.biocon.2023.110254.

References

Andam, K.S., Ferraro, P.J., Pfaff, A., Sanchez-Azofeifa, G.A., Robalino, J.A., 2008. Measuring the effectiveness of protected area networks in reducing deforestation. Proc. Natl. Acad. Sci. 105 (42), 16089–16094. https://doi.org/10.1073/pnas.0800437105.
Anselin, L., Syabri, I., Kho, Y., 2009. GeoDa: An introduction to spatial data analysis. In Handbook of Applied Spatial Analysis: Software Tools, Methods and Applications (pp. 73–89). Berlin, Heidelberg: Springer Berlin Heidelberg.
Appleton, M.R., Courtiol, A., Emerton, L., et al., 2022. Protected area personnel and ranger numbers are insufficient to deliver global expectations. Nature Sustainability 1-11. https://doi.org/10.1038/s41893-022-00970-0.
de Assis Barros, L., Venter, M., Delgado, J.P.R., Coelho-Junior, M.G., Venter, O., 2022. No evidence of local deforestation leakage from protected areas establishment in Brazil's Amazon and Atlantic Forest. Biol. Conserv. 273, 109695 https://doi.org/10.1016/j.biocon.2022.109695.
Barnes, M.D., Glew, L., Wyborn, C., Craigie, I.D., 2018. Prevent perverse outcomes from global protected area policy. Nature Ecology & Evolution 2 (5), 759–762. https://doi.org/10.1038/s41559-018-0501-y.
Baylis, K., Honey-Rosés, J., Börner, J., et al., 2016. Mainstreaming impact evaluation in nature conservation. Conserv. Lett. 9 (1), 58–64. https://doi.org/10.1111/conl.12180.
Bebber, D.P., Butt, N., 2017. Tropical protected areas reduced deforestation carbon emissions by one third from 2000–2012. Sci. Rep. 7 (1), 14005. https://doi.org/10.1038/s41598-017-14467-w.
Bowker, J.N., De Vos, A., Ament, J.M., Cumming, G.S., 2017. Effectiveness of Africa's tropical protected areas for maintaining forest cover. Conserv. Biol. 31 (3), 559–569. https://doi.org/10.1111/cobi.12851.
Carranza, T., Balmford, A., Kapos, V., Manica, A., 2014. Protected area effectiveness in reducing conversion in a rapidly vanishing ecosystem: the Brazilian Cerrado. Conserv. Lett. 7 (3), 216–223. https://doi.org/10.1111/conl.12049.
CBD, 2022. The Kunming-Montreal global biodiversity framework. Convention on Biological Diversity 19 December. Available from: https://www.cbd.int/meetings/COP-15.
Coad, L., Watson, J.E., Geldmann, J., et al., 2019. Widespread shortfalls in protected area resourcing undermine efforts to conserve biodiversity. Front. Ecol. Environ. 17 (5), 259–264. https://doi.org/10.1002/fee.2042.
Cohen, W.B., Yang, Z., Stehman, S.V., et al., 2016. Forest disturbance across the conterminous United States from 1985–2012: the emerging dominance of forest decline. For. Ecol. Manag. 360, 242–252. https://doi.org/10.1016/j.foreco.2015.10.042.
Cohen, W.B., Yang, Z., Healey, S.P., Kennedy, R.E., Gorelick, N., 2018. A LandTrendr multispectral ensemble for forest disturbance detection. Remote Sens. Environ. 205, 131–140. https://doi.org/10.1016/j.rse.2017.11.015.
Cooke, R., Mancini, F., Boyd, R.J., Evans, K.L., Shaw, A., Webb, T.J., Isaac, N.J., 2023. Protected areas support more species than unprotected areas in Great Britain, but lose them equally rapidly. Biol. Conserv. 278, 109884 https://doi.org/10.1016/j.biocon.2022.109884.
Cuenca, P., Arriagada, R., Echeverría, C., 2016. How much deforestation do protected areas avoid in tropical Andean landscapes? Environ. Sci. Pol. 56, 56–66. https://doi.org/10.1016/j.envsci.2015.10.014.
De Marzo, T., Pflugmacher, D., Baumann, M., Lambin, E.F., Gasparri, I., Kuemmerle, T., 2021. Characterizing forest disturbances across the argentine dry Chaco based on Landsat time series. Int. J. Appl. Earth Obs. Geoinf. 98, 102310 https://doi.org/10.1016/j.jag.2021.102310.
Díaz, S., Settele, J., Brondízio, E.S., et al., 2019. Pervasive human-driven decline of life on earth points to the need for transformative change. Science 366 (6471), eaax3100. https://doi.org/10.1126/science.aax3100.
Durán, A.P., Barbosa, O., Gaston, K.J., 2022. Understanding the interacting factors that determine ecological effectiveness of terrestrial protected areas. J. Nat. Conserv. 126264 https://doi.org/10.1016/j.jnc.2022.126264.
Edwards, D.P., Tobias, J.A., Sheil, D., Meijaard, E., Laurance, W.F., 2014. Maintaining ecosystem function and services in logged tropical forests. Trends Ecol. Evol. 29 (9), 511–520. https://doi.org/10.1016/j.tree.2014.07.003.
FAO, 2022. The State of the World's Forests 2022. In: Forest Pathways for Green Recovery and Building Inclusive, Resilient and Sustainable Economies. FAO, Rome. https://doi.org/10.4060/cb9360en.
Ferraro, P.J., Pattanayak, S.K., 2006. Money for nothing? A call for empirical evaluation of biodiversity conservation investments. PLoS Biol. 4 (4), e105 https://doi.org/10.1371/journal.pbio.0040105.
Ferraro, P.J., Hanauer, M.M., Sims, K.R., 2011. Conditions associated with protected area success in conservation and poverty reduction. Proc. Natl. Acad. Sci. 108 (34), 13913–13918. https://doi.org/10.1073/pnas.1011529108.
Foga, S., Scaramuzza, P.L., Guo, S., et al., 2017. Cloud detection algorithm comparison and validation for operational Landsat data products. Remote Sens. Environ. 194, 379–390. https://doi.org/10.1016/j.rse.2017.03.026.
Ford, S.A., Jepsen, M.R., Kingston, N., et al., 2020. Deforestation leakage undermines conservation value of tropical and subtropical forest protected areas. Glob. Ecol. Biogeogr. 29 (11), 2014–2024. https://doi.org/10.1111/geb.13172.
Friedlingstein, P., O'sullivan, M., Jones, M.W., et al., 2022. Global carbon budget 2022. Earth System Science Data 14 (11), 4811–4900. https://doi.org/10.5194/essd-14-4811-2022.
Fuller, C., Ondei, S., Brook, B.W., Buettel, J.C., 2019. First, do no harm: A systematic review of deforestation spillovers from protected areas. Global Ecology and Conservation 18, e00591. https://doi.org/10.1016/j.gecco.2019.e00591.
Gaveau, D.L., Epting, J., Lyne, O., Linkie, M., Kumara, I., Kanninen, M., Leader-Williams, N., 2009. Evaluating whether protected areas reduce tropical deforestation in Sumatra. J. Biogeogr. 36 (11), 2165–2175. https://doi.org/10.1111/j.1365-2699.2009.02147.x.

Geldmann, J., 2023. Safeguarding biodiversity requires understanding how to manage protected areas cost effectively. One Earth 6 (2), 73–76. https://doi.org/10.1016/j.oneear.2023.01.008.
Geldmann, J., Manica, A., Burgess, N.D., Coad, L., Balmford, A., 2019. A global-level assessment of the effectiveness of protected areas at resisting anthropogenic pressures. Proc. Natl. Acad. Sci. 116 (46), 23209–23215. https://doi.org/10.1073/pnas.1908221116.
Ghazoul, J., Chazdon, R., 2017. Degradation and recovery in changing forest landscapes: a multiscale conceptual framework. Annu. Rev. Environ. Resour. 42, 161–188. https://doi.org/10.1146/annurev-environ-102016-060736.
Ghoddousi, A., Loos, J., Kuemmerle, T., 2022. An outcome-oriented, social–ecological framework for assessing protected area effectiveness. Bioscience 72 (2), 201–212. https://doi.org/10.1093/biosci/biab114.
Gizachew, B., Solberg, S., Puliti, S., 2018. Forest carbon gain and loss in protected areas of Uganda: implications to carbon benefits of conservation. Land 7 (4), 138. https://doi.org/10.3390/land7040138.
Gonçalves-Souza, D., Vilela, B., Phalan, B., Dobrovolski, R., 2021. The role of protected areas in maintaining natural vegetation in Brazil. Science Advances 7 (38), eabh2932. https://doi.org/10.1126/sciadv.abh2932.
Hanauer, M.M., Canavire-Bacarreza, G., 2015. Implications of heterogeneous impacts of protected areas on deforestation and poverty. Philosophical Transactions of the Royal Society B: Biological Sciences 370 (1681), 20140272. https://doi.org/10.1098/rstb.2014.0272.
Hansen, M.C., Potapov, P.V., Moore, R., et al., 2013. High-resolution global maps of 21st-century forest cover change. Science 342 (6160), 850–853. https://doi.org/10.1126/science.1244693.
Harris, N.L., Gibbs, D.A., Baccini, A., et al., 2021. Global maps of twenty-first century forest carbon fluxes. Nat. Clim. Chang. 11 (3), 234–240. https://doi.org/10.1038/s41558-020-00976-6.
Joppa, L.N., Pfaff, A., 2009. High and far: biases in the location of protected areas. PLoS One 4 (12), e8273. https://doi.org/10.1371/journal.pone.0008273.
Joppa, L.N., Pfaff, A., 2011. Global protected area impacts. Proc. R. Soc. B Biol. Sci. 278 (1712), 1633–1638. https://doi.org/10.1098/rspb.2010.1713.
Jung, M., Arnell, A., De Lamo, X., et al., 2021. Areas of global importance for conserving terrestrial biodiversity, carbon and water. Nature Ecology & Evolution 5 (11), 1499–1509. https://doi.org/10.1038/s41559-021-01528-7.
Keenan, R.J., Reams, G.A., Achard, F., de Freitas, J.V., Grainger, A., Lindquist, E., 2015. Dynamics of global forest area: results from the FAO global Forest resources assessment 2015. For. Ecol. Manag. 352, 9–20. https://doi.org/10.1016/j.foreco.2015.06.014.
Kennedy, R.E., Yang, Z., Cohen, W.B., 2010. Detecting trends in forest disturbance and recovery using yearly Landsat time series: 1. LandTrendr—temporal segmentation algorithms. Remote Sens. Environ. 114 (12), 2897–2910. https://doi.org/10.1016/j.rse.2010.07.008.
Li, J., Liu, S., Hong, T., You, W., Hu, X., 2022. Does leakage exist in China's typical protected areas? Evidence from 13 national nature reserves. Environ. Sci. Pollut. Res. 1-15 https://doi.org/10.1007/s11356-021-16068-7.
Lin, Y.P., Lin, W.C., et al., 2017. Systematically designating conservation areas for protecting habitat quality and multiple ecosystem services. Environ. Model Softw. 90, 126–146. https://doi.org/10.1016/j.envsoft.2017.01.003.
Maxwell, S.L., Fuller, R.A., Brooks, T.M., Watson, J.E., 2016. Biodiversity: the ravages of guns, nets and bulldozers. Nature 536 (7615), 143–145. https://doi.org/10.1038/536143a.
Maxwell, S.L., Cazalis, V., Dudley, N., et al., 2020. Area-based conservation in the twenty-first century. Nature 586 (7828), 217–227. https://doi.org/10.1038/s41586-020-2773-z.
Nolte, C., Agrawal, A., Silvius, K.M., Soares-Filho, B.S., 2013. Governance regime and location influence avoided deforestation success of protected areas in the Brazilian Amazon. Proc. Natl. Acad. Sci. 110 (13), 4956–4961. https://doi.org/10.1073/pnas.1214786110.
Obura, D.O., DeClerck, F., Verburg, P.H., et al., 2023. Achieving a nature-and people-positive future. One Earth 6 (2), 105–117. https://doi.org/10.1016/j.oneear.2022.11.013.
Oliveira, P.J., Asner, G.P., Knapp, D.E., et al., 2007. Land-use allocation protects the Peruvian Amazon. Science 317 (5842), 1233–1236. https://doi.org/10.1126/science.1146324.
People's Government of Kaihua County (PGKC), 2013. Gutianshan Nature Reserve. https://www.kaihua.gov.cn/art/2013/10/18/art_1229550459_59009850.html.
Pimm, S.L., Jenkins, C.N., Abell, R., et al., 2014. The biodiversity of species and their rates of extinction, distribution, and protection. Science 344 (6187), 1246752. https://doi.org/10.1126/science.1246752.
Rahman, M.F., Islam, K., 2021. Effectiveness of protected areas in reducing deforestation and forest fragmentation in Bangladesh. J. Environ. Manag. 280, 111711 https://doi.org/10.1016/j.jenvman.2020.111711.
Rasolofoson, R.A., Ferraro, P.J., Ruta, G., Rasamoelina, M.S., Randriankolona, P.L., Larsen, H.O., Jones, J.P., 2017. Impacts of community forest management on human economic well-being across Madagascar. Conserv. Lett. 10 (3), 346–353.
Rodrigues, A.S., Cazalis, V., 2020. The multifaceted challenge of evaluating protected area effectiveness. Nat. Commun. 11 (1), 5147. https://doi.org/10.1038/s41467-020-18989-2.
Schleicher, J., Peres, C.A., Leader-Williams, N., 2019. Conservation performance of tropical protected areas: how important is management? Conserv. Lett. 12 (5), e12650 https://doi.org/10.1111/conl.12650.
Schleicher, J., Eklund, J., Barnes, M.D., Geldmann, J., Oldekop, J.A., Jones, J.P., 2020. Statistical matching for conservation science. Conserv. Biol. 34 (3), 538–549. https://doi.org/10.1111/cobi.13448.
Shen, Y., Liu, G., Zhou, W., Liu, Y., Cheng, H., Su, X., 2022. Protected areas have remarkable spillover effects on forest conservation on the Qinghai-Tibet plateau. Divers. Distrib. 28 (12), 2944–2955. https://doi.org/10.1111/ddi.13466.
Sonter, L.J., Herrera, D., Barrett, D.J., Galford, G.L., Moran, C.J., Soares-Filho, B.S., 2017. Mining drives extensive deforestation in the Brazilian Amazon. Nat. Commun. 8 (1), 1013. https://doi.org/10.1038/s41467-017-00557-w.
von Staden, L., Lötter, M.C., Holness, S., Lombard, A.T., 2022. An evaluation of the effectiveness of critical biodiversity areas, identified through a systematic conservation planning process, to reduce biodiversity loss outside protected areas in South Africa. Land Use Policy 115, 106044. https://doi.org/10.1016/j.landusepol.2022.106044.
Venter, O., Magrach, A., Outram, N., Klein, C.J., Possingham, H.P., Di Marco, M., Watson, J.E., 2018. Bias in protected-area location and its effects on long-term aspirations of biodiversity conventions. Conserv. Biol. 32 (1), 127–134. https://doi.org/10.1111/cobi.12970.
Vieira, R.R., Pressey, R.L., Loyola, R., 2019. The residual nature of protected areas in Brazil. Biol. Conserv. 233, 152–161. https://doi.org/10.1016/j.biocon.2019.02.010.
Wang, Q., Liu, S., Liu, Y., Wang, F., Liu, H., Yu, L., 2022. Effects of urban agglomeration and expansion on landscape connectivity in the river valley region. Qinghai-Tibet Plateau. Global Ecology and Conservation 34, e02004. https://doi.org/10.1016/j.gecco.2022.e02004.
Watson, J.E., Dudley, N., Segan, D.B., Hockings, M., 2014. The performance and potential of protected areas. Nature 515 (7525), 67–73. https://doi.org/10.1038/nature13947.
Watson, J.E., Evans, T., Venter, O., et al., 2018. The exceptional value of intact forest ecosystems. Nature Ecology & Evolution 2 (4), 599–610. https://doi.org/10.1038/s41559-018-0490-x.
Xia, H., Yuan, S., Prishchepov, A.V., 2023. Spatial-temporal heterogeneity of ecosystem service interactions and their social-ecological drivers: implications for spatial planning and management. Resour. Conserv. Recycl. 189, 106767 https://doi.org/10.1016/j.resconrec.2022.106767.
Xu, L., Saatchi, S.S., Yang, Y., et al., 2021. Changes in global terrestrial live biomass over the 21st century. Science Advances 7 (27), eabe9829. https://doi.org/10.5281/zenodo.4161694.
Xu, W., Xiao, Y., Zhang, J., et al., 2017. Strengthening protected areas for biodiversity and ecosystem services in China. Proc. Natl. Acad. Sci. 114 (7), 1601–1606. https://doi.org/10.1073/pnas.1620503114.
Yang, H., Viña, A., Winkler, J.A., et al., 2019. Effectiveness of China's protected areas in reducing deforestation. Environ. Sci. Pollut. Res. 26, 18651–18661. https://doi.org/10.1007/s11356-019-05232-9.
Yang, H., Huang, Q., Zhang, J., Songer, M., Liu, J., 2021. Range-wide assessment of the impact of China's nature reserves on giant panda habitat quality. Sci. Total Environ. 769, 145081 https://doi.org/10.1016/j.scitotenv.2021.145081.
Yang, L., Xia, H., Zhang, X., Yuan, S., 2018. What matters for carbon emissions in regional sectors? A China study of extended STIRPAT model. J. Clean. Prod. 180, 595–602. https://doi.org/10.1016/j.jclepro.2018.01.116.
Yuan, S., Xia, H., Yang, L., 2021. How changing grain size affects the land surface temperature pattern in rapidly urbanizing area: a case study of the central urban districts of Hangzhou City, China. Environ. Sci. Pollut. Res. 28, 40060–40074. https://doi.org/10.1007/s11356-020-08672-w.
Zhang, M., Li, G., He, T., Zhai, G., Guo, A., Chen, H., Wu, C., 2023. Reveal the severe spatial and temporal patterns of abandoned cropland in China over the past 30 years. Sci. Total Environ. 857, 159591.
Zhang, T., Wang, X., Ren, H., et al., 2019. A comparative study on the community characteristics of secondary and old-growth evergreen broad-leaved forests in Gutianshan. Zhejiang Province. Biodiversity Science 27 (10), 1069. https://doi.org/10.17520/biods.2019059.
Zhao, H., Wu, R., Long, Y., et al., 2019. Individual-level performance of nature reserves in forest protection and the effects of management level and establishment age. Biol. Conserv. 233, 23–30. https://doi.org/10.1016/j.biocon.2019.02.024.