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Continuous growth of human footprint risks compromising the benefits of protected areas on the Qinghai-Tibet Plateau

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ABSTRACT

Protected areas (PAs) are the critical societal tool to preserve biodiversity and ecosystem services (ESs), but human disturbances frequently threaten them. Here, we used multiple data sources to map the human footprint as a proxy for identifying the intensity of human activities on the Qinghai-Tibet Plateau and therein nature reserves (NRs, the primary category of PAs in China). We found that the human footprint on the Qinghai-Tibet Plateau has increased by 22% since 2000, and on average, human pressure inside NRs was 60% lower than outside. However, human pressure was identified in the majority of the NRs, with only 30% of protected land free from any measurable pressure. From a total of 53 NRs, 28 showed over 10% increase in human footprint, and 6 NRs had over 70% of their extent under intense human pressure (human footprint score≥4). Furthermore, a higher proportion of ESs in NRs is subjected to high levels of human pressure and are therefore at risk, particularly soil and water retention. The applied regression model revealed that large NRs are more resilient to human pressure than NRs with the longer establishment. The continuous human footprint increase may hinder the current and future ESs supply. Our analysis shows evidence-based results to promote the mitigation of human pressures in PAs.

1. Introduction

In their quest for resources, goods, and services, humans have dramatically and irreversibly transformed terrestrial ecosystems, with the extent and magnitude of transformations varying over time and space (Song et al., 2018; Watson and Venter, 2019). These transformations negatively affected the global biodiversity, the resilience and stability of ecosystems, and the goods and services provided (Steffen et al., 2015; Ouyang et al., 2016). To safeguard biodiversity and mitigate these transformations, PAs have been established worldwide in different environments (Dudley et al., 2008). However, increasing human activity, lack of financial support,

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and competition for resources jeopardise this vision, making PAs conservation challenging (Butchart et al., 2010). As a result, understanding the spatial pattern and change of human activities in PAs is necessary to promote evidence-based management and improve conservation effectiveness.

Several researchers attempted to map human pressure. For instance, Chi et al. (2020) and Gosselin and Callois (2021) used population density, land use, or economic indicators to proxy human activity intensity. Nighttime light observations have also been introduced to map human activities, including urbanisation (Zhou et al., 2014, 2015), demographic and economic dynamics (Zhuo et al., 2009). However, they do not adequately describe the human pressure's complexity and diversity that can be expressed in different forms (e.g., urbanisation, agriculture, and grazing) (Rounsevell et al., 2012; Kennedy et al., 2019) and can be a consequence of multiple activities from the anthropogenic origin (Kennedy et al., 2019). These multiple and co-occurring anthropogenic pressures can have a super-linear and profound influence on biodiversity and ecosystems, and an assessment based on a single/minority stressor risks leading to incomplete and limited results (Raiter et al., 2014). Sanderson et al. (2002) and Venter et al. (2016) proposed and developed a new approach known as human footprint, defined as the sum of a continuum of human influence across the land surface. Human footprint has been assessed and linked to biodiversity loss (Di Marco et al., 2018; Weinzettel et al., 2018), ESs (Li et al., 2018b), and PAs (Ebersole et al., 2020; Shrestha et al., 2021). These assessments serve as a valuable tool for facilitating and improving conservation planning. Furthermore, the increasingly powerful mapping techniques and the emergence of high-resolution and accuracy datasets, apart from the methodological evolution, allowed to map anthropogenic influence with better detail and resolution.

PAs are the cornerstones of biodiversity conservation efforts. However, a series of studies observed that PAs are not exempted by human pressure, potentially hampering their ability to maintain the integrity of ecosystems (Geldmann et al., 2014; Jones et al., 2018; Xia et al., 2021). Jones et al. (2018) revealed that one-third of global PAs are affected by intense human pressure. Nevertheless, the relationship between human footprint and some PAs indicators, such as geometric features and established time, is key to PAs effectiveness (Geldmann et al., 2014; Gonçalves-Souza et al., 2021; Yang et al., 2021), but it is not well quantified.

The Qinghai-Tibet Plateau has over 30% of China's PAs to conserve biodiversity and ecosystems in the region. Qinghai-Tibet Plateau is subjected to extreme climatic conditions, and it is highly vulnerable to climate change and human disturbances (Chen et al., 2013; Zhang et al., 2021b). Li et al. (2018b) and Yin et al. (2020) tried to measure the human footprint in some regions of the Qinghai-Tibet Plateau (e.g. Tibet Autonomous Region and Hengduan Mountain region), but spatially-explicit information of human footprint on the whole Qinghai-Tibet Plateau is still limited. Besides, current regional evaluation is still uncertain due to a lack of required validation and sensitivity tests.

This study aims to: (1) detect the spatial-temporal variation of the human footprint on the Qinghai-Tibet Plateau; (2) investigate the extent and intensity of human pressure within NRs; (3) measure the proportion of NRs' ESs subjected to intense human pressure and (4) unravel the relationship between human footprint and NRs' characteristics.

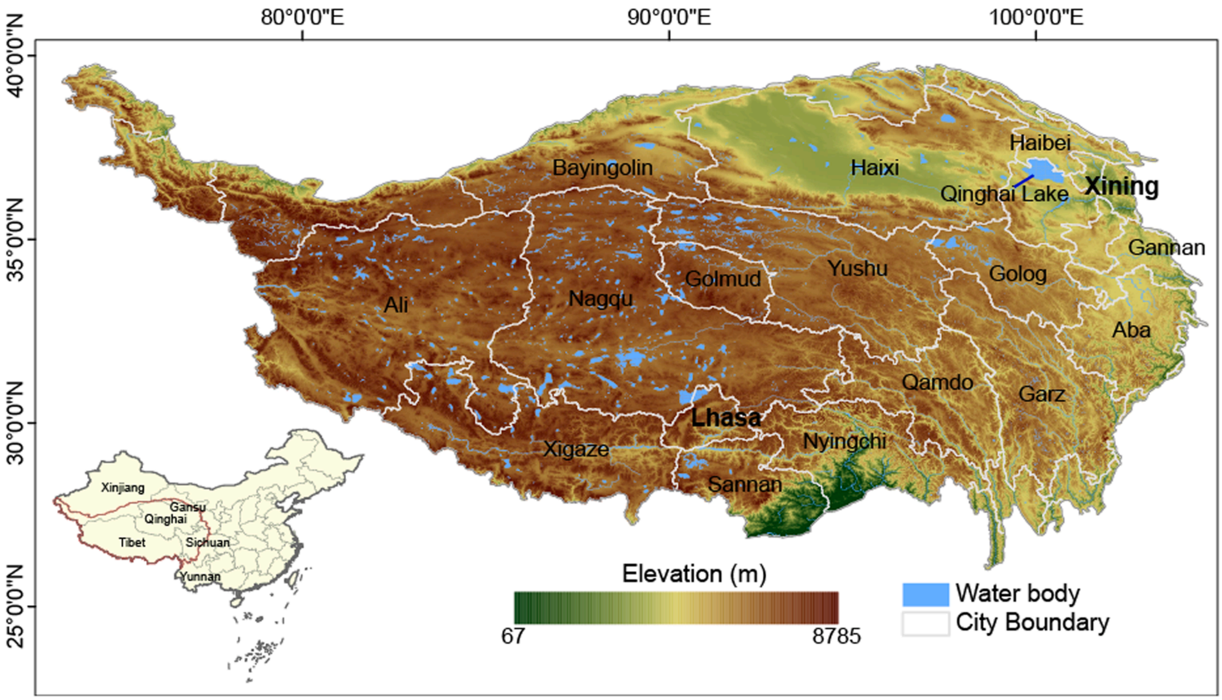

Fig. 1. Location of the study area. See Fig. S1, Tab. S1 for distribution and name of NRs.

2. Materials and method

2.1. Study area

The Qinghai-Tibet Plateau, known as "the third pole", is a giant geomorphic unit covering 2.5 million km^2 (Fig. 1). It provides a variety of ESs to hundreds of millions of downstream residents and serves as an important ecological security barrier (Ouyang et al., 2016; Hou et al., 2021; Hua et al., 2021). Annual precipitation ranges from 1000 mm in the southeast to 100 mm in the northwest, with annual temperatures ranging from 20 °C to − 5 °C (Sun et al., 2020). Alpine meadows and alpine steppes are the most common vegetation types. Furthermore, most PAs in China are located in the Qinghai-Tibet Plateau (Fig. S1). The principal PAs in Qinghai-Tibet Plateau are NRs, the most strictly protected PAs, primarily for biodiversity conservation, but their effectiveness is often questioned (Xu et al., 2017; Li et al., 2020a).

2.2. Data and preprocessing

Seven variables were chosen to map the human footprint with a 1 km resolution on the Qinghai-Tibet Plateau for two periods (2000–2010, 2011–2020) (Table 1). Globeland30 has higher overall accuracy (82.39%) and higher resolution (30 m) than other land cover products in China (Chen et al., 2015; Yang et al., 2017). Subsequently, we used the moving window method to generate 1 km-resolution land cover density to map human footprint based on Gloleand30 (details on the moving window methods are provided in the flowing sections). Furthermore, we used a temporal consistent nighttime light product developed by Li et al. (2020b). It was generated by harmonising the nighttime light data from the Defense Meteorological Satellite Program (DMSP)/Operational Linescan System (OLS) and Visible Infrared Imaging Radiometer Suite (VIIRS) on the Suomi National Polar-orbiting Partnership satellite. The nighttime light product strongly relates to socio-economic activities, such as gross domestic product (GDP) and electricity consumption (Li et al., 2020b). Also, we used grazing intensity from Sun et al. (2021) and population density data Gridded Population density of the World (GPW v4) from the Center for International Earth Science Information Network. Due to the unavailability of some data, not all data corresponds to the consistent time. For instance, we used nightlight (grazing intensity) data from 2018 (2015) for the second period of human footprint mapping, which is slightly inconsistent with the other data. However, this is expected to have a negligible impact on the final results.

In addition to the data required to map human footprint, MCD12Q1 land cover data from the United States Geological Survey (USGS) and population density data WorldPop from Open Spatial Demographic Data and Research were collected for a sensitivity test. Annual mean temperature and annual precipitation data were derived from Resource and Environment Science and Data Center, and the digital elevation model (DEM) was from Shuttle Radar Topography Mission DEM. We also gathered some ESs results of 2010, including carbon sequestration, soil retention, sandstorm prevention, water retention from Ouyang et al. (2016), and habitat quality from Hou et al. (2021).

2.3. Mapping human footprint

We applied the framework created by Venter et al. (2016) in this work. We used data with a better resolution and more recent, and we considered land cover percentage density, rather than land cover class, to circumvent the shortcomings of the fuzzy agricultural class of coarse resolution products. And the outputs will be more accurate, reliable and actual. We considered seven aspects of human pressure and attribute them different scores: (1) built environment (0−10); (2) Cropland (0−7); (3) Pasture lands (0−4); (4) Nighttime lights (0−10); (5) Population density (0−10); (6) Major roads (0−8); and (7) Railways (0−4). The scores refer to the degree of human modification and impervious cover and Venter et al. (2016). The higher the score, the more intense the pressure. We did not consider navigable waterways pressure as Qinghai-Tibet Plateau rivers are not developed for shipping. The human footprint pixel values can range from 0 to 50.

Table 1
Geographical datasets used to map human footprint.

Pressure	Datasets	Year	Resolution	Sources
Built environments	Artificial surfaces from GlobeLand30	2000, 2020	30 m	National Geomatics Center of China (http://www.globallandcover.com/)
Cropland	Cultivated land from GlobeLand30			
Pasture lands	Grassland from GlobeLand30			
	Grazing intensity	2000, 2015	1 km	Sun et al. (2021)
Nighttime lights	Harmonisation of DMSP and VIIRS nighttime light data	2000, 2018	30 s	Li et al. (2020b)
Population density	GPW, v4	2000, 2020	1 km	Center for International Earth Science Information Network (https://sedac.ciesin.columbia.edu/data/collection/gpw-v4)
Roads and railways	National main road dataset	2000, 2020	–	Peking University Geographic data platform (https://geodata.pku.edu.cn/)

2.3.1. Built environments

Built environments refer to buildings, rural settlements, and paved land (Foley et al., 2005; Song et al., 2018). Because it has a finite ESs supply and is unsuitable for species conservation, built environments were listed as one of the leading human pressure stressors (Li et al., 2018b; Shen et al., 2020; Venter et al., 2016).

Globeland30 urban class with 30 m resolution in 2000 and 2020 were used to map the human pressure from built environments. We used a moving window with 33 pixels (approximately 1 km) to count the percentage density of the built environment within the window. After this step, we multiply the built environments density map (units: %) by 10 to obtain the built environments pressure score, which we upscaled to match the resolution of the other datasets.

2.3.2. Cropland

Human beings transformed the land for agricultural expansion to meet the growing demand for food and feed. Therefore, cropland area assessment is key to mapping. We attribute it a lower score (7) than built environments for less impervious cover and adequate ES supply. We used the cropland class of Globeland30 data to identify the variable spatial distribution. The application of high-resolution land-use datasets also circumvents the shortcomings of the fuzzy agricultural class of coarse resolution products, such as agriculture mosaics with natural vegetation (Herold et al., 2008). Similar to the urban environment, we used moving windows to generate the cropland percentage density, and then we multiplied that by the score coefficient (7).

2.3.3. Pasture lands

Qinghai-Tibet Plateau, a major pastoral area of China, has one of the world's largest high-mountain grassland ecosystems. Therefore, pasture lands were identified as a significant human footprint factor (Fan et al., 2015). We used a grazing intensity dataset from Sun et al. (2021), combined with Globeland30, to map the pressure from pasture lands. Grazing intensity was derived from grazing census data at the county scale based on net primary productivity data (Sun et al., 2021). We assigned to pasture lands a pressure score from 0 to 4, according to grazing intensity data in 2000. Next, the same threshold of linear standardisation method for 2000 data was applied to 2015 data. The maximum value of 2000 data was used as the normalisation criterion because the maximum grazing intensity in 2000 was higher than the observed in 2015. Finally, we used Globeland30 grassland data to extract the pressure boundary of pasture lands, to match the land cover data used in the other pressure mappings.

2.3.4. Population density

The number of people per unit area was identified as a primary underlying cause of human pressure (Burney and Flannery, 2005). The human population density was mapped using GPW V4. The population density pressure effect usually has a logarithmic shape with a threshold constraint. For the pixels with $\geq$ 1000 people/km^2, we set a pressure score of 10, while for other sparsely populated areas ($<$ 1000 people/km^2), we assigned a logarithmically-state pressure score following the formula (1).

$$Socre_{pd} = 3.333 \times \log(PD + 1) \tag{1}$$

$Score_{pd}$ is the pressure score of population density, and PD is population density (units: people/km^2). The conversion formula of population density was widely used in measuring human pressure (Venter et al., 2016; Karimi and Jones, 2020).

2.3.5. Nighttime lights

Nighttime lights capture flowing and unobtrusive infrastructures in rural and suburban areas, such as electrical installations, small-scale residential areas, and working landscapes (Elvidge et al., 1997). Due to the limitation of time coverage, the two common types of nighttime light data (DMSP:1992–2013; VIIRS: 2012–2018) are challenging to meet our cartographic needs. Therefore, we used an integrated nighttime light dataset based on DMSP and VIIRS datasets, performing well in temporal consistency compared to other approaches (Li et al., 2020b). The nighttime lights digital numbers (DN) were used, and pixels with DN $\leq$ 6 were excluded from consideration for severe distortion of very low DN values (Li et al., 2020b; Venter et al., 2016). The DN values from 2000 nighttime light data were rescaled and standardised to a maximum value of 10, using the equal quantile method. The same equal quantile threshold method considered in 2000 data was also applied in 2018 nighttime data.

2.3.6. Roads and railways

The roads and railways construction shortens the distance between humans and nature, putting a strain on habitat quality (Trombulak and Frissell, 2000). We assigned a pressure score of 8 for 0.5 km out for both sides of the road. Also, we applied a pressure score of 4 at 0.5 km, which decayed exponentially out to 15 km on either side of the road, following Venter et al. (2016).

The pressure mode differs from road networks for railways since the passengers rarely get off the train outside the station. Human pressure in railroads has a short distance impact than the roads due to the limitation of passenger movement. Therefore, we only set the direct pressure score of 8 within 0.5 km on both sides of the railways.

2.4. Validation and sensitivity test

Five hundred random sample points with a size of 1 km^2 were employed to interpret the human footprint visually. For this, we used high-resolution images and geographic labels on Google earth pro. The images' colour, shape, size, and texture were used as important references to judge human pressure's visual score. In addition, linear regression and the root mean square error (RMSE) was considered for judging the evaluation. We discarded 30 samples in the comparison process due to image quality (cloud cover or unrecognisable scenes).

We conducted the sensitivity test for the indicators' weight and dataset selection. We randomly increase the indicator's weight by 50%, decrease it by 50%, or keep it the same. Increasing the weight by 50% means multiplying the original scores of this indicator by 1.5, while decreasing the weight by 50% means multiplying that by 0.5. We calculated the seven indicators' total score based on the adjusted weights. After this, we calculated the new county-scale average human footprint score for each county based on Zonal statistics tools of ArcGIS. We compared the county-scale human footprint new total score and the original score to get proportional change. We divided the proportion change for each county by the overall change of study area to get the relative proportional change under different indicators' weight combinations. According to the relative proportional change and a Spearman correlation coefficient at the county scale, we judged the robustness of the evaluation. Statistical significance was considered at a $p < 0.05$. We experimented with all the weight combinations and got a total of 2187 (3^7) new layers of human footprint score.

We also tried other datasets to conduct a sensitivity test for dataset selection, including coarse resolution land-cover datasets (MCD12Q1) and population density (WorldPop). We recalculated the human footprint using these datasets and judged the robustness following the abovementioned method.

2.5. Relationship between human footprint and NRs

In order to analyse the NRs current human footprint state on the Qinghai-Tibet Plateau, we calculated the NRs proportion under intense human pressure. A human footprint score of ≥ 4 was used to define an intense human pressure according to Venter et al. (2016) and Jones et al. (2018). This threshold selection was equal to pasture lands, representing the land subject to anthropogenic modification. Besides, we also repeated this analysis using two alternative thresholds (human footprint score ≥ 1 & human footprint score ≥ 7) to characterise intense human pressure for the sensitivity test.

In addition, we selected some factors, including geometric features of NRs (area and perimeter), established/upgrade time (when the NRs was established or upgraded to national level), climatic factors (mean annual temperature and annual precipitation) and topography conditions (elevation). The reasons for choosing these factors are as follows. NRs' size (area and perimeter) have been linked to the effectiveness of NRs in previous studies (Geldmann et al., 2014; Gonçalves-Souza et al., 2021). Large NRs tend to be in areas with low agricultural potential and thus may face less human pressure (Struhsaker et al., 2005). New NRs are often established in remote areas with little predisposition for human impacts (Butchart et al., 2012; Jones et al., 2018; Gonçalves-Souza et al., 2021). China's NRs are often divided into national, provincial, and other levels. National level NRs mean more stringent levels of protection and adequate funding. Therefore we considered the established time and time upgraded to the national level as influencing factors. Besides, human settlements have preferences for a specific temperature, precipitation, and elevation, driven by resources availability and suitable climatic conditions, which are also key factors influencing human footprint (Shen et al., 2020). We used different types of regression models ("line2P", "line3P", "log", "exp" and "power", see formula (2–6)") to construct the relationship between human footprint scores and these influencing factors.

$$line2P : y = a \times x + b \tag{2}$$

$$line3P : y = a \times x^2 + b^* x + c \tag{3}$$

$$\log : y = a \times \ln(x) + b \tag{4}$$

$$\exp : y = a \times \exp(b \times x) + c \tag{5}$$

$$power : y = a \times x^b + c \tag{6}$$

where *x* is the value of a certain influencing factor, *y* is human footprint scores, and a, b, and c are the regression coefficients. Based on the largest coefficient of determination (R-square), the optimal regression equation was established. We used the p-scores to evaluate the significance of each factor. Statistically significant regressions were considered at a $p < 0.05$. For climatic and topography factors, the regression model was constructed based on 500 random points in NRs. For other factors, we collected parameters from each PA to conduct a regression model.

Based on ESs evaluation collected from Ouyang et al. (2016) and Hou et al. (2021), we quantified the ratio of ESs amount under intense human pressure to the total amount within the NRs. We considered five types of ESs: carbon sequestration, soil retention, sandstorm prevention, water retention, and habitat quality. This analysis aimed to figure out the proportion of ESs within NRs at risk of potential loss due to intense human pressure.

3. Results

3.1. Model validation and sensitivity test

Our validation showed acceptable agreement between visual interpretation and human footprint evaluation ($R^2 = 0.91$, $p < 0.01$, RMSE = 1.28, n = 475; Fig. S2). The sensitivity test showed that adjusting the weight of indicators by half resulted in an 8.4% relative change at county-scale human footprint scores. The correlation coefficients between the original assessment and the additional assessment produced by the sensitivity test at the county level were all above 0.93 ($p < 0.01$) under various weight combinations. The introduction of the coarse land cover dataset (MCD12Q1) and another population density dataset (WorldPoP) resulted in a 9.1% relative change in the county-scale evaluation on average. The correlation coefficients of human footprint at the county level were all above 0.97 ($p < 0.01$) under different datasets used (MCD12Q1 & WorldPoP). These results demonstrated that our model is reliable.

3.2. Spatial-temporal variation of the human footprint on the Qinghai-Tibet Plateau

The Qinghai-Tibet Plateau's had an average human footprint score of 1.942 in 2020, increasing 22.3% from 2000 levels (Fig. 2). The high human footprint score regions were located in provincial capital cities (Xining and Lhasa) and surrounding areas. By contrast, areas with no measurable human footprint were about 20%, mainly concentrated in bare land and tundra in the northwest. Further, there was a clear distinction between northwest and southeast, with the boundary line, roughly extending from 86°E, 28°N to 102°E, 38°N.

Human pressure has increased in 28.3% of the overall coverage of the research region and all county administrative districts. However, the upward trend was uneven (Fig. 2e, f). Regarding the changes in each category of human pressure, the mean scores of the built environment and nighttime light grow rapidly. Population density had the largest proportional contribution to this increase (59.6%), followed by nighttime lights (22.0%). The red line in Fig. 2e shows that the road and railways construction modified the local human footprint, indicating that rapid population growth and infrastructure construction were the main driving force.

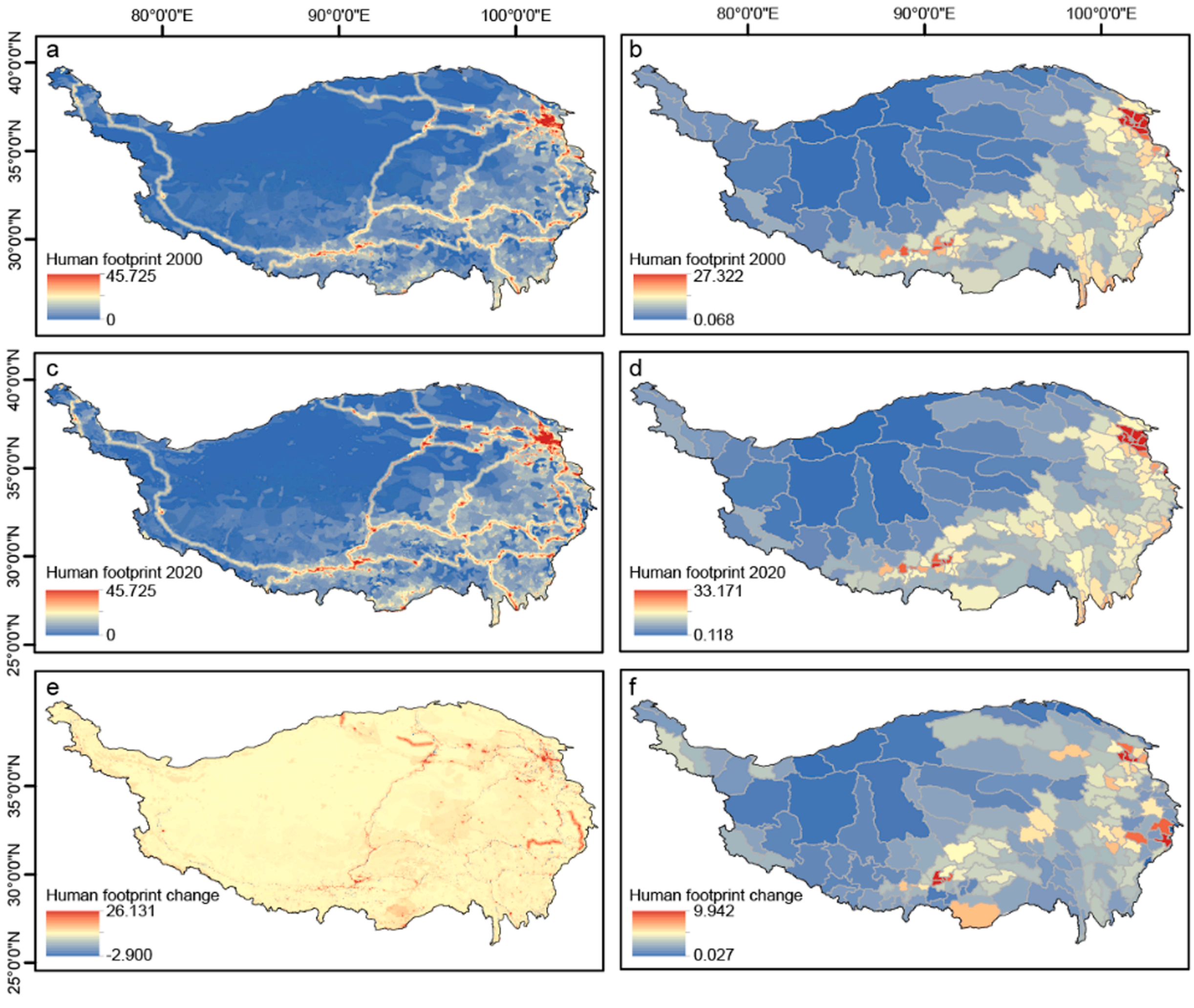

Fig. 2. The human footprint and recent change on the Qinghai-Tibet Plateau. (a, c) The human footprint map for 2000 and 2020 at pixel scale. (b, d) The human footprint map for 2000 and 2020 at the county scale. (e, f) shows the change of human footprint between 2000 and 2020 at pixel and county scale.

3.3. Human footprint within NRs

On average, human pressure was lower inside NRs (0.914) than in unprotected land (2.309). This was nearly half as low as the average of the study areas (1.942) (Fig. 3, Fig. S3). However, human activities were prevalent in many NRs. Out of 7.19×10^5 km^2 NRs, only 30.24% of protected land was not disturbed by human activities. The road/railways construction impact was mainly observed in part NRs' edge, such as Sanjiangyuan NR, Hoh Xil NR, and Selincuo NR. High-resolution satellite images confirmed that agricultural areas (Fig. 3c), urban development (Fig. 3d), and habitat fragmented by major roads (Fig. 3e) are occurring within the NRs.

We also explored the NRs proportion under intense human pressure. Approximately 11% of NRs had over 70% of their area affected by intense human pressure (human footprint score ≥ 4). These heavily impacted NRs were mainly located in the south and southeast of the Qinghai-Tibet Plateau. About 40% have less than 10% of their coverage affected by intense human pressure (Fig. 3b). Considerable differences were identified in the spatial pattern of intense human pressure when using different thresholds (Fig. S4). In general, smaller NRs located southeast of the study area were much more likely to have a higher coverage of areas affected by an intense human pressure than larger NRs under the different threshold.

We further analysed the human footprint for the individual NRs (Tab. S1). The change rate of human footprint varied greatly across NRs, ranging from − 16% to over 150% (Tab. S1). In 28 out of 53 NRs, we observed an over 10% increase in human footprint, and the proportion of intense human footprint increased by more than 10% in 22 NRs (Tab. S1). The human footprint was low in large-size NRs, such as Arjin Mountain (0.02), Hoh Xil (0.27), and Changtang (0.18), as shown in Fig. S3. Some major roads fragmented the central regions and edge of some NRs, including Qinghai Lakes, Gahai-Zecha, and Zoije Wetland.

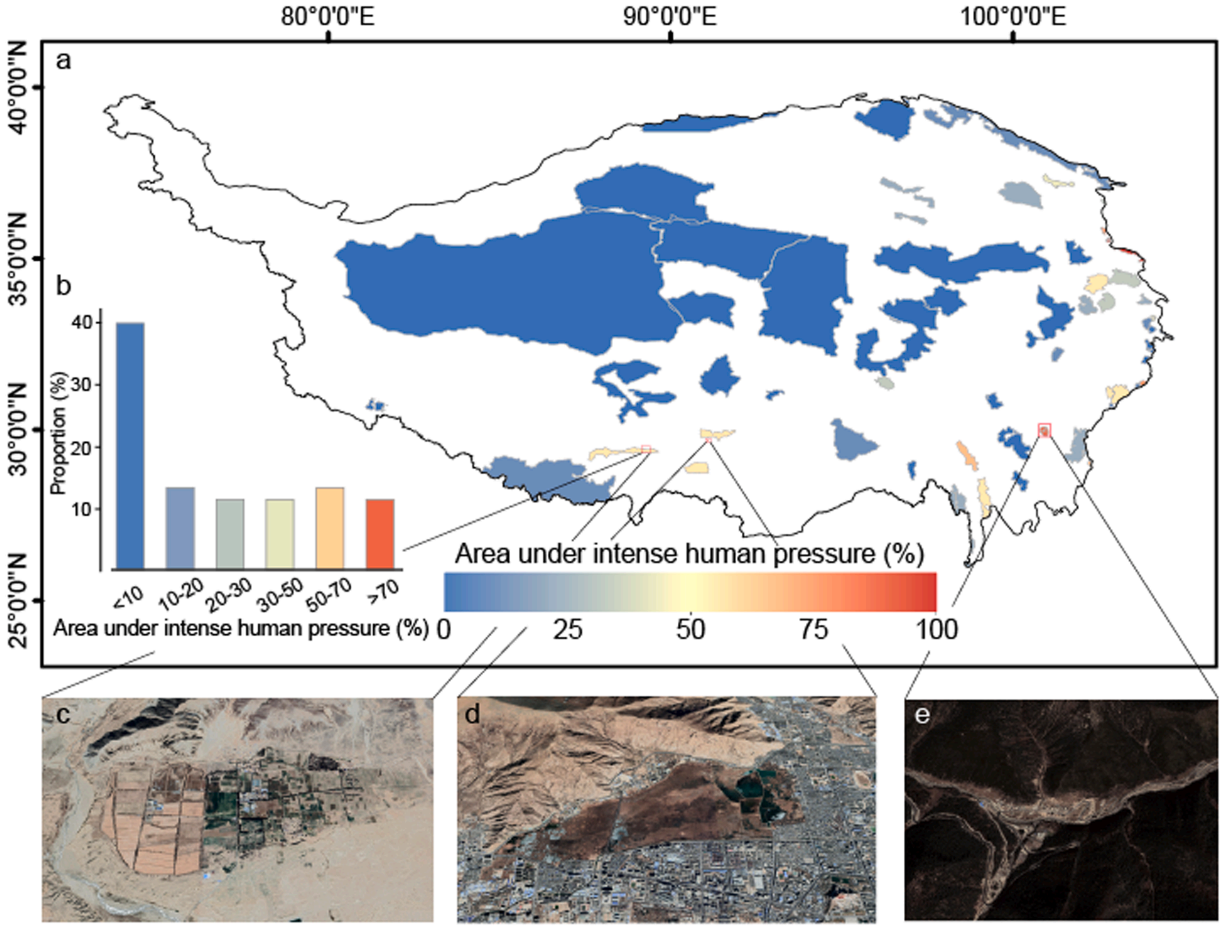

Fig. 3. Human footprint within NRs. (a) Area (%) of each NR under intense human pressure. (b) Distribution of area of each NR under intense human pressure (n = 53). The X-axis indicated different categories of intense human pressure (i.e. area under intense human pressure, %), and the y-axis indicated the proportion of different categories. (c-e) showed agricultural extension, urban expansion, and major roads construction within the NRs.

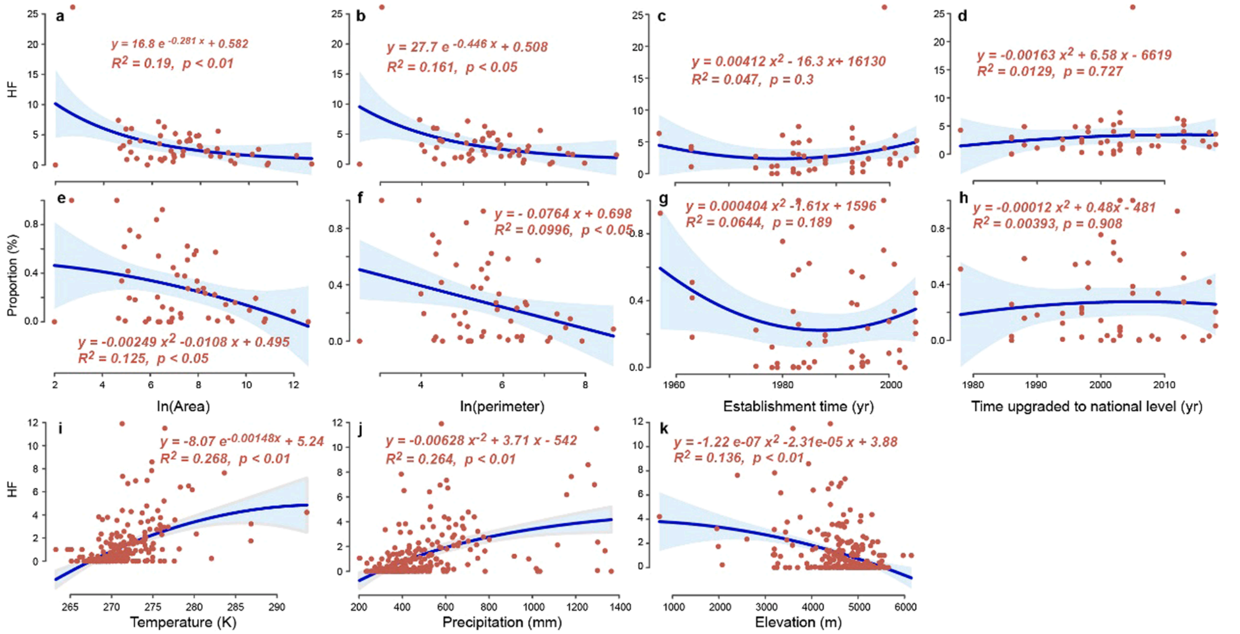

Fig. 4. The relationship between human footprint and PA's characteristics. Y-axis indicated the human footprint (HF) for the first and third row and proportion under intense human pressure (%) for the second row. x-axis represented different potential influencing factors, including NRs' geometric features (area and perimeter), established time (when the NRs was established and upgraded to national level), climatic factors (mean annual temperature and annual precipitation), and topography conditions (elevation).

3.4. Influence of NRs' characteristic on human footprint

The human pressure in NRs varied depending on their geometric features and climatic conditions (Fig. 4). There was a significant negative relationship ($p < 0.05$) between the human footprint score/proportion of intense human footprint and the size of NRs, including area and perimeter (Fig. 4a-b, e-f). Large-sized NRs were generally subjected to less human pressure. Also, no significant association was observed between human pressure and the establishment time or the time upgraded to nation-level (Fig. 4c-d, g-h). Besides, the regression model showed that high human footprint tended to be concentrated in regions with high temperature, precipitation, and low elevation with statistical significance, although the r-square was not high (Fig. 4i-k).

3.5. Intense human footprint versus ESs in NRs

Fig. 5 shows the distribution of five ESs in the NRs on the Qinghai-Tibet Plateau. Sandstorm prevention was mainly distributed in several large-size NRs in the northwest, such as Changtang, Sanjiangyuan, and Hoh Xil (Fig. 5a). Habitat quality was broadly distributed in several NRs throughout the region (Fig. 5b). The high soil retention, water retention, and carbon sequestration value was observed in some small NRs in the southeast (Fig. 5c-e). Furthermore, protected land with high ESs values was under high human pressure. 26.6% of the soil retention and 11.8% of the water retention in NRs are under intense human pressure, far exceeding the proportion of intense human footprint in NRs (6.28%), as shown in Fig. 5f. The habitat quality was also slightly above this proportion, while sandstorm prevention and carbon sequestration were substantially below this share.

4. Discussion

4.1. Overview of the human footprint on the Qinghai-Tibet Plateau

The human footprint is a simplified proxy for quantifying human pressure (Sanderson et al., 2002; Venter et al., 2016). Here, we considered seven categories of human pressure categories and adapted more accurate data to map the human footprint change on the Qinghai-Tibet Plateau for 2000 and 2020. According to our calculations, high human pressure was concentrated in the eastern regions of the Qinghai Province and central Tibet, particularly in the two provincial capitals (Xining and Lhasa) and their surrounding areas. This observation is consistent with previous research (e.g. Zhao et al., 2015a, 2015b; Li et al., 2018b; Sun et al., 2020). Compared to the developed areas of China (e.g. Jiangsu Province), the human footprint of the Qinghai-Tibet Plateau is obviously smaller because of the gaps in the levels of urbanisation and infrastructure (Shen et al., 2020). Previous works highlighted that Jiangsu Province is under an intense urbanisation process and destruction of fertile soils (Wang et al., 2019) and a high loss of ESs value (Wu et al., 2020). This increases the human footprint drastically.

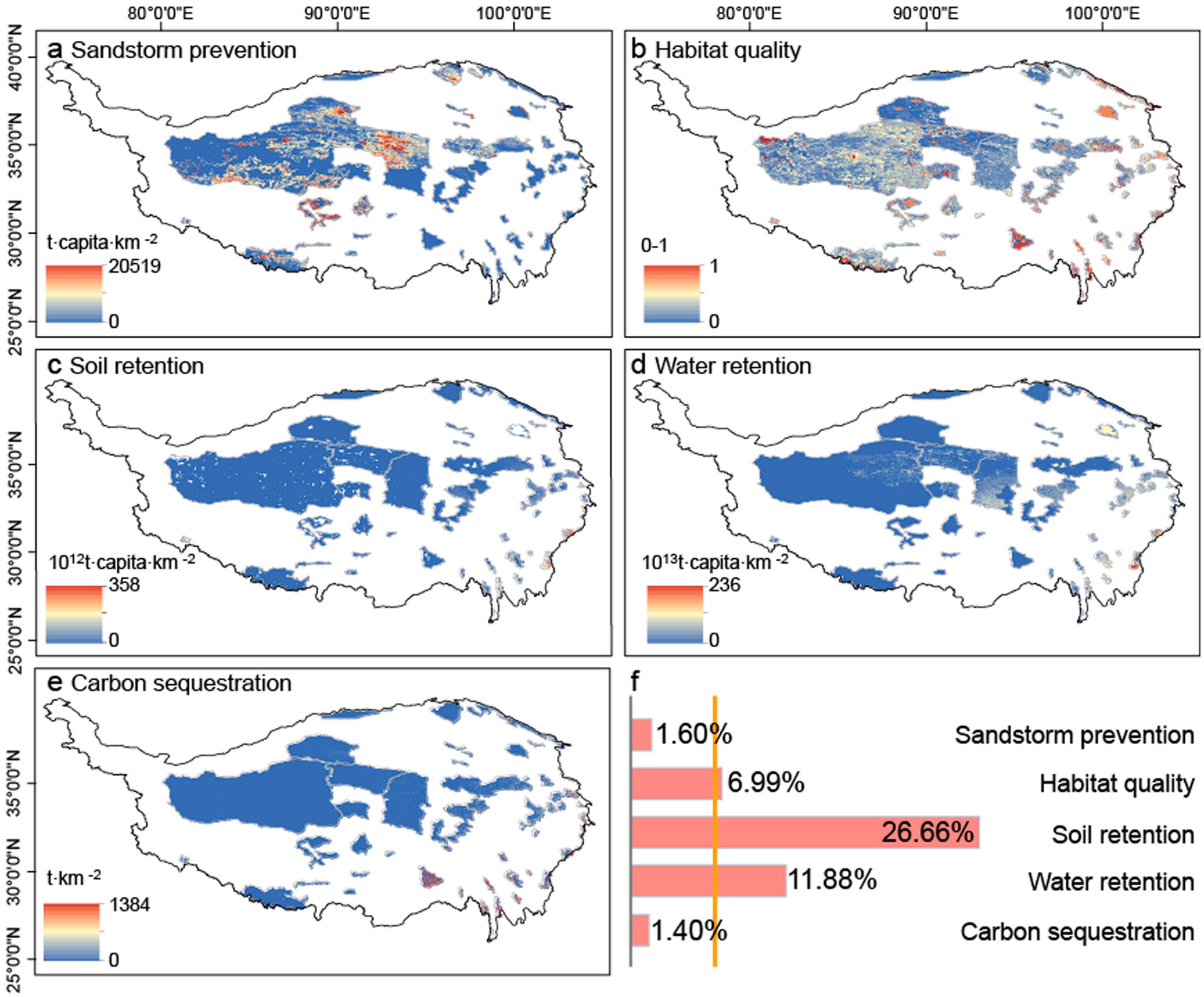

Fig. 5. Distribution of ESs inside NRs on the Qinghai-Tibet Plateau. (a-e) showed the distribution of five types of ESs in NRs. (f) showed the proportion of ESs in NRs under intense human footprint. The vertical orange line indicated the proportion of intense human footprint within the NRs (6.28%). The evaluation of sandstorm prevention, soil retention, water retention, carbon sequestration was derived from Ouyang et al. (2016), and habitat quality was from Hou et al. (2021).

Furthermore, the human footprint on the Qinghai-Tibet Plateau has increased by 22% since 2000. The changing pattern follows the "Matthew effect," which states that the higher the initial human pressure, the faster the rising rate. This was evident in the differences in the two provincial capitals and the sparsely populated northwest region (Fig. 2). In contrast, the global human footprint increased by only 9% between 1993 and 2009 (Venter et al., 2016). Similarly, the Tibetan Autonomous Region experienced a 32% increase in human pressure between 1990 and 2010 (Li et al., 2018b). These findings show that the Qinghai-Tibet Plateau is a hotspot of increasing human pressure.

4.2. The role of NRs in reducing human disturbance

PAs are the primary societal tools to conserve biodiversity, ESs and avoid vegetation loss (Gonçalves-Souza et al., 2021). Our findings revealed that PAs have a beneficial effect in lowering human pressure. The mean human footprint in NRs was lower than unprotected land in the entire Qinghai-Tibet Plateau (Fig. 3). Furthermore, a small proportion (6.28%) of the NRs was under intense human footprint. This is a very positive signal regarding the effectiveness of NRs from the perspective of conservation planning. Having a substantial number of NRs with little human disturbance is critical for habitat and biodiversity conservation (Venter et al., 2016; Watson et al., 2018; Williams et al., 2020).

The overall effectiveness of NRs did not offset the localised human footprint. Over 70% of the area of several NRs, especially in the south and southeast of the Qinghai-Tibet Plateau, was under intense human pressure. From 2000–2020, the proportion of intense human footprint increased by more than 10% in 22 NRs and that for human footprint is 28. Satellite images demonstrate that road construction and agriculture extension have encroached on natural ecosystems inside NRs' boundary (Fig. 3). Aside from the loss of natural habitats, calculations revealed that intense human pressure is degrading the protected land with high ES values, especially soil and water retention (Fig. 5). Intense human pressure, including road construction and overgrazing, destroyed the vegetation growth, accelerated habitat loss and fragmentation, soil nutrient loss, or increased impervious surfaces, replacing natural landscapes dominated by vegetation. This may weaken the existing or future ESs supply, and this may raise concerns about the performance of NRs in safeguarding biodiversity and ecosystems.

The human footprint was low in large NRs and high in small ones (Fig. 4). This is attributed to massive NRs in areas with low agricultural value (Struhsaker et al., 2005). The human demand for land resources is reduced in these areas. Large-scale NRs' conservation success has been generally recognised (Butchart et al., 2012; Jones et al., 2018; Gonçalves-Souza et al., 2021). Furthermore, the NRs located in less harsh climatic conditions were less affected by human activities, and they are more favourable to human settlement due to the more suitable climate conditions for human living. However, there was no significant linear association between human pressure and NRs construction period (Fig. 4g-h), which is different from the cognition that more effective conservation of the old NRs (Gonçalves-Souza et al., 2021). Long-term operations and early placement of NRs did not imply low human stress. This might be because Qinghai-Tibet Plateau NRs are often located at high altitudes and rugged terrain, making the management difficult or absent.

4.3. Implications for NRs management

A higher proportion of ESs (e.g. 28.66% of soil retention and 11.88% of water retention) in NRs are exposed to intense human pressure, putting them in danger of loss (Fig. 5). Apart from the intense human footprint, prediction models also revealed a statistically significant association between low human footprint scores ($\leq$3) and the extinction risk of terrestrial mammals (Di Marco et al., 2018). Besides, some NRs (e.g. Gaoligong Mountain, Baimaxueshan, and Mangkam Yunnan Golden monkey NR) faced high climate vulnerability (Shrestha et al., 2021). Climate change may even have a disproportional impact on mountain biomes as exemplified by current melting glaciers and permafrost (Gobiet et al., 2014), which might reduce the benefits of PAs (Hoffmann et al., 2019; Asamoah et al., 2021). These cases highlighted that, despite the low pressure in the Qinghai-Tibet Plateau NRs, it is essential to improve NRs' management and conservation efforts.

In most Qinghai-Tibet Plateau NRs, the pressure state and the proportion of intense pressure were not high (Fig. 3). These areas are not populated, and urban development is limited. Therefore, there is no need to alter NRs management dramatically. Further efforts are needed in the NRs located at the south and southeastern, where the proportion of intense human footprint is higher than 30%, and major roads fragmented the NRs. Therefore, appropriate management practices should emphasise reducing human pressure, such as regulating grazing intensity, and traffic flow. The Chinese government enforced Grazing Withdraw Program (GWP) in 2003, implementing fencing degrading grassland and ecological compensation (Chen et al., 2014). In 2011, the government reinforced the policy to achieve pasture–livestock equilibrium by compensating for prohibitions on grazing (Cui et al., 2017). These measures have already shown initial outcomes (Zhang et al., 2021a), and much of future success depends on policy continuity. Besides, according to the Chinese national railway planning guideline, "The Mid- and Long-term Railway Network Plan", many new railroads are in the pipeline, including Sichuan-Tibet Railway and Yunnan-Tibet Railway (The Central Government of China-CGC, 2016). The design of additional NRs requires an optimised layout, avoiding being disturbed by excessive human activities. Since large-size NRs are more efficient in minimising human pressure, merging several neighbouring and fragmented small NRs can be an option.

The Convention on Biological Diversity (CBD) has set an ambitious goal of expanding PAs to cover 30% of the Earth by 2030 to consolidate the protection effectiveness. Under the wave of expansion of PAs, increasing human pressure seems to limit the outcomes of PAs (Fig. 5). In particular, some older NRs have not demonstrated a function in lowering human pressure that corresponds to the establishment period (Fig. 4). Therefore, instead of blindly expanding PAs, it is preferable to examine the effectiveness of existing PAs, especially in regions with high PAs' coverage, such as the Qinghai-Tibet Plateau. This may be a more cost-effective option. For PAs with an intense human footprint and high ecological benefits, further targeted ecological restoration measures should be taken to reconcile the conflicts between humans and the environment (Sun et al., 2020). Also, integrating local communities as stakeholders of PAs into planning and management has simultaneously improved the performance of PAs (Nelson et al., 2011; Gonçalves-Souza et al., 2021) and enhanced human well-being (Sarkar and Montoya, 2011). It emphasised that the human presence in the natural environment is not necessarily incompatible with the conservation effort.

Sustainable Development Goals 15 (Life on Land), 15.5 (*Take urgent and significant action to reduce the degradation of natural habitats, halt the loss of biodiversity and, by 2020, protect and prevent the extinction of threatened species*) and 15.9 (*by 2020, integrate ecosystems and biodiversity values into national and local planning, development processes and poverty reduction strategies, and accounts*) called for immediate actions to restore ecosystems and their services, as well as incorporating these goals into national and local planning (UN, 2015). PAs, properly managed, can be a solution to advance these goals.

4.4. Uncertainty, limitations and future direction

Our work is subject to four limitations. Our calculations did not consider all human pressure types, and we did not quantify pressure that is hard to detect at the resolution we worked on, such as logging or illegal hunting (Hu et al., 2021). Secondly, there are some inconsistencies in datasets time used owing to availability. For instance, the nighttime lights and grazing intensity datasets are not available for 2020 (data from 2018 and 2015 were used instead). Also, the data with different resolutions were used, especially the resolution of nighttime lights (30 s) and Globeland30 (30 m). Using data from different years and resolutions may cause some uncertainties (Gomes et al., 2021). Thirdly, we used visual interpretation to validate the evaluation of human footprint with the support of high-resolution images following Venter et al. (2016). Visual interpretation is often limited by expert knowledge and the selection of validation points. Fourthly, the method developed is focused more on measuring human pressure rather than the realised response of the ecosystem to human pressure. Due to variances in sensitivity and resilience, ecosystems may react differently to the same exposure to human stress (Li et al., 2018a; Qi et al., 2020; Sun et al., 2020). Therefore, future work needs to investigate more human disturbances at a higher resolution. In addition, the interaction between human footprint and ecosystems and possible consequences under intense human footprint needs to be considered. Finally, a more collaborative survey of local stakeholders should be considered to map the human footprint better and understand its influences.

5. Conclusion

Excessive human activities may result in the loss of biodiversity and ESs supply and negate the benefits of PAs. Based on various human activities, we traced the pattern and change of human footprint on the Qinghai-Tibet Plateau and the NRs in this region since 2000. Our results indicated a widespread and uneven growth of human footprint that can undermine the role of NRs and ESs supply. It highlighted the urgency to strengthen and increase the effectiveness of the PA network on the Qinghai-Tibet Plateau. In practice, this small-size / high-ESs NRs with intensive human footprint should be given management priority. In addition, integrating several neighbouring and fragmented small NRs can be viable solutions to minimise human pressure. Future management of the PAs network on the Qinghai-Tibet Plateau should be well planned, executed, and financially supported to secure long-time benefits and protect key vulnerable areas.

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.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.gecco.2022.e02053.

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