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Review

Mapping Human Pressure for Nature Conservation: A Review

Quanxin Luo [1], Shicheng Li [1,2,*], Haifang Wang [3] and Haonan Cheng [1]

[1] Department of Land Resource Management, School of Public Administration, China University of Geosciences, Wuhan 430074, China; luoqx@cug.edu.cn (Q.L.); chenghaonan@cug.edu.cn (H.C.)
[2] Hubei Key Laboratory of Environment and Culture in Yangtze Regions, China University of Geosciences, Wuhan 430074, China
[3] Forestry Investigation and Planning Institute of Hubei, Wuhan 430079, China; wanghaier19@163.com
* Correspondence: lisc@cug.edu.cn

Abstract: The escalating human pressures on natural ecosystems necessitate urgent and effective conservation strategies to safeguard biodiversity and ecosystem functions. This review explored current techniques for mapping human pressure, with a particular focus on their application in nature conservation, especially within protected areas (PAs). Specifically, we analyzed the impacts of seven major types of human pressures on nature conservation within PAs. Additionally, we discussed four key methods for mapping human pressure, including land use intensity, human footprint, digital human footprint, and other proxies, examining their distinct characteristics and respective advantages and disadvantages. Additionally, our research explored the application of human pressure mapping for nature conservation, assessing its suitability for conservation applications and delineating directions for future work. These insights contributed to better support nature conservation and the management of PAs.

Keywords: human pressure; human footprint; protected areas; nature conservation; biodiversity conservation; review

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1. Introduction

Humans have altered terrestrial ecosystems at accelerating rates. Recent reports suggest that more than 75% of Earth's land surface is modified by human activities [1,2]. These modifications, such as deforestation, urbanization, agriculture, and infrastructure development, are recognized as the most important threats to biodiversity, with ongoing habitat fragmentation and ecosystem degradation [3,4]. Around half of a million species will face extinction unless actions are taken to reduce and mitigate the potential to harm nature [5]. Therefore, measuring, mapping, and understanding human pressure change on protected areas (PAs) continues to be a critical component given the pressing need for sustainable development and nature conservation. Mapping these changes is closely pertinent to UN Sustainable Development Goals (SDGs), especially Goal 15 (to protect, restore, and promote sustainable use of terrestrial ecosystems, sustainably manage forests, combat desertification, halt and reverse land degradation, and halt biodiversity loss).

In the age of satellite observations, a wide application of geographic information systems (GISs) with survey data has achieved unprecedented progress in human pressure mapping. Remote sensing images and derived data products have become the ideal proxies for capturing human-induced changes in a spatially explicit way [6–8].

Since the 1980s, the first global human pressure map was produced for identifying wilderness, more comprehensive human pressure maps have been proposed to support land use and conservation planning [9,10], measurement of species extinction risks [11], and remaining wilderness management [12], among other applications. However, human pressure products are still constrained by the inconsistent understanding of human activities, a lack of high-quality remote sensing data, and varying spatiotemporal scales. Recent reviews highlighted the significant impact of human activities on Earth's ecosystems, emphasizing urgent conservation needs. Riggio et al. [13] conducted a comprehensive comparison of global human influence on terrestrial ecosystems, and then highlighted the significant opportunities for conservation. Watson et al. [14] expanded this discussion by mapping the industrial influences on Earth's ecosystems. In the marine context, Clarke et al. [15] investigated the cumulative impacts of human activities on marine environments, with specific reference to international frameworks such as the London Protocol/Convention.

The above studies offer a partial overview of the methods for measuring human pressure but lack comprehensiveness. Firstly, analyzing and comparing specific human stress datasets exclusively may lead to inaccurate conclusions. Secondly, the advantages and disadvantages of various human pressure assessment methods remain unclear, which impedes further innovation. Lastly, current research has yet to synthesize the applications of human pressure for nature conservation in terrestrial PAs. Therefore, a new review is needed to provide a detailed classification and in-depth analysis of human pressure. Several aspects were considered in this review: (1) the major human pressure types for biodiversity threats; (2) the mapping methods; (3) implications for biodiversity conservation; and (4) limitations and future prospects.

2. The Framework of Review

2.1. Definition of Human Pressure

While broader human pressure refers to all direct and indirect human activities, in the context of conservation theory and practice, it generally refers to direct and negative human activities. In this review, we compared the definitions of three key terms: human pressure, human threat, and human impact/influence (Table 1). We did not discuss the indirect effects by humans as a human pressure type (for example, climate change and species invasion). We focused our discussion on quantifiable and mappable human pressures, as this allows for more precise conservation planning and management [16]. Therefore, "human pressure" is the most suitable term to use in our review.

Table 1. Different terms and definitions.

Term	Definition	Examples
Human pressure	Emphasizes the stress exerted by human activities on the environment, culture, or social systems, usually direct and measurable.	Urbanization, agriculture
Human threat	Emphasizes the potential or actual danger and harm posed by human activities or presence to humans, species, or ecosystems, usually direct and urgent.	Climate change and species invasion
Human impact/influence	Encompasses various effects of human activities, both positive and negative, associated with the direct outcomes of specific actions.	Reforestation, habitat loss

2.2. Conceptual Framework

Following calls in SDG 15 of the 2030 Agenda for Sustainable Development, we outlined major human pressure types in the nature conservation sector, and reviewed methodological advances, considering their application to innovate progress in developing a framework (Figure 1). This is particularly important in areas with high diversity, which often have superior natural conditions in tropical and subtropical countries [17].

To define human pressure types, we referred to and modified existing direct threat classifications [18,19]. Seven major and quantifiable human pressures are selected in this review (Figure 2): agriculture, urban development, livestock grazing, transportation infrastructure, light pollution, mining and quarrying, and human population.

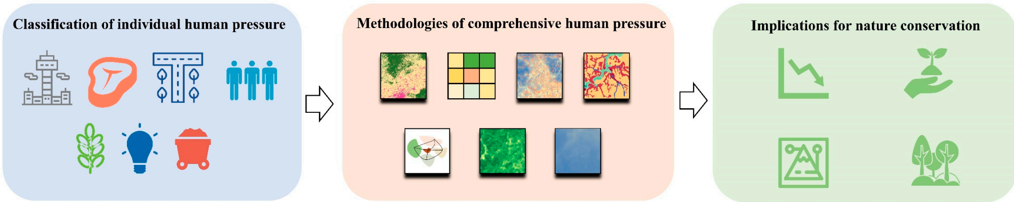

Figure 1. The framework of review.

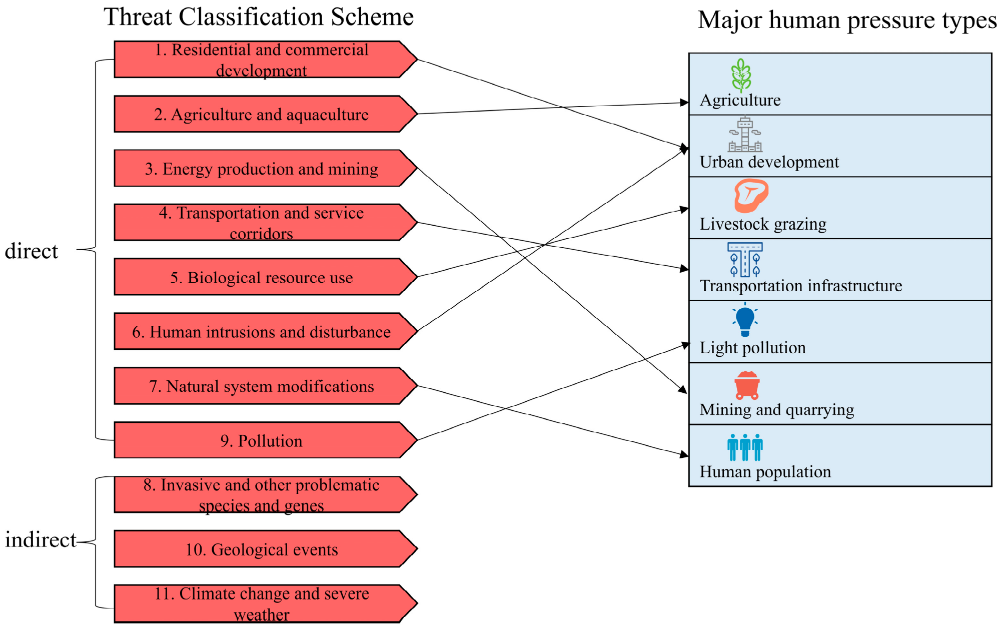

Figure 2. Structure of the classification of human pressure used in our study.

The comprehensive human mapping methodologies were conducted according to the research literature strategy (Supplementary Material). Then, we summarized their applications for nature conservation.

3. Classification of Individual Human Pressure

3.1. Agriculture

Agriculture is a leading driver of terrestrial biodiversity loss [20] and directly threatens Red List threatened species [21]. Recent research indicates that cropland accounts for 18% of all human pressures within PAs [22]. With growing global demands for food, feed, bioenergy, and bio-feedstocks, the impact of agriculture in these areas is expected to increase [23,24]. Food and Agriculture Organization of the United Nations (FAO) estimates approximately 70 million hectares of cropland expansion by 2050 [25].

Two strategies to increase agricultural production are employed: cropland expansion and intensification [26,27]. Cropland expansion reduces biodiversity through direct habitat loss and fragmentation, depriving many species of foraging and nesting spaces [28,29]. Most expansion occurs in the biodiversity hotspots, particularly in tropical countries [17] and their PAs [30]. The current study from these regions suggested that better land allocation and improved intensification practices may benefit biodiversity [31]. Cropland intensification is promoted to spare land for nature while meeting agricultural needs [31,32]. In addition, combining agricultural production with conservation can balance food security and nature preservation [33,34]. However, cropland intensification could still threaten biodiversity due to habitat homogenization [35]. If induced by new market opportunities, it could increase forest conversion to cropland, thereby offsetting the effect [36,37].

3.2. Urban Development

Urbanization represents a major driver of biodiversity loss. Global urban growth is projected to increase by 1 km^2, resulting in significant habitat loss, particularly within critical biodiversity hotspots [38]. Urban expansion also causes habitat fragmentation and isolation. It introduces environmental changes such as increased chemical pollution, heightened pollutant levels, and altered local microclimates [39,40].

As urban areas move closer to PAs, the impact on biodiversity conservation becomes more severe [41]. This threat is intensified by a research bias toward developing countries, where current urban expansion rates are lower but have high growth potential. By 2030, urban land near PAs is expected to increase significantly, particularly in regions like China [42]. Recent studies also indicated that strategic green infrastructure planning and informed conservation zoning can enhance connectivity between PAs and help maintain urban biodiversity [38,43]. Consequently, effective planning and management strategies are crucial to ensure sustainable urban development and minimize the negative effects on biodiversity [44].

3.3. Livestock Grazing

Livestock grazing is the most widespread form of land use [45], exerting both positive and negative influences on biodiversity conservation. Properly managed grazing can support grassland ecosystems, fostering diverse plant and animal communities [46]. It can also help mitigate wildfire risks and control the spread of invasive species [47]. However, intensive and prolonged grazing practices can lead to landscape degradation, negatively affecting key species and undermining conservation objectives [48,49]. Despite its significance, there is a scarcity of empirical data on grazing's impact on PAs, largely due to the unreliability and unavailability of existing grazing data [50]. Limited studies suggest that establishing sustainable grazing thresholds is vital for effective PA management [51–53], though this has not yet been addressed.

Pastoralist behavior also plays a crucial role in shaping grazing impacts on biodiversity. Factors like financial capacity and socio-economic conditions influence their decisions regarding grazing practices [54]. Effective grazing management in PAs requires scientific planning and continuous monitoring to safeguard the ecological integrity. This may involve implementing measures such as limiting livestock numbers, rotating grazing locations, restoring degraded habitats, and controlling invasive species. Striking a balance between livestock management and biodiversity conservation is essential for achieving sustainable outcomes that benefit both livestock and wildlife [55].

3.4. Transportation Infrastructure

Transportation infrastructure poses a significant threat to biodiversity through the process of habitat fragmentation [56]. These infrastructures lead to land use change and promote human activities such as mining [57], and their ecological footprint extends up to about 10 km from their immediate vicinity [58,59]. For instance, studies in the Amazon showed that nearly 95% of deforestation occurred within 5.5 km of roads or 1 km of rivers [57]. The expansion of transportation networks also increased noise pollution [60]. Additionally, the road pressure on biodiversity is contingent upon various factors such as traffic intensity, the distance and type of the road, and its location [61,62]. With global road and railway networks expected to expand by 36% and 45%, respectively, between 2000 and 2050 [63], there is an urgent need for comprehensive global strategies to mitigate negative impacts on biodiversity [64].

3.5. Light Pollution

Artificial light pollution has emerged as a critical environmental issue, particularly impacting biodiversity and ecosystem functioning. It acts as a proxy for broader anthropogenic activities, including urban expansion [65], economic development measured by gross domestic product (GDP) [66], energy production [67], and fire incidences [68]. This has drawn increasing attention in conservation science. Mu et al. [69] highlighted this trend, but also noted that nations like Japan and the United States have implemented stringent conservation policies, leading to a decline in artificial light pollution within their PAs. Similarly, Xiang & Tan [70] found that strategic policies effectively mitigated light pollution in China, despite global increases.

The primary datasets for quantifying light pollution include the Operational Linescan System (OLS) and the Visible Infrared Imaging Radiometer Suite (VIIRS). While these data sources provide valuable insights, they are constrained by variations in spatial resolution, sensor sensitivity, and temporal coverage [71,72]. Addressing these methodological challenges is imperative for refining the assessment of light pollution dynamics and advancing evidence-based conservation strategies.

3.6. Mining and Quarrying

Mining and quarrying pose significant threats to nature conservation [73], contributing to habitat loss, fragmentation [74], and facilitating deforestation and hunting activities [75]. As the demand for minerals and metals is projected to surge over the next decade [76], the detrimental impact of mining is expected to intensify. According to the World Resources Institute, 75% of active mines and exploration zones globally overlap with regions of high conservation value, and over 25% are situated within 10 km of PA boundaries [77]. In 2003, the International Council on Mining and Metals (ICMM) pledged to refrain from mining in World Heritage Sites and committed to mitigating the environmental impact of mining in PAs. However, the organization has faced accusations of repeatedly breaching these commitments [74].

The ongoing conflict between mining activities and PAs remains a contentious topic [78]. Kobayashi et al. [79] developed a quantitative index called MiBiD, utilizing data on land cover, PAs, and mining operations. This index provides a measure of the impact of mining on biodiversity. Wanghe et al. [80] refined the MiBiD index, revealing a decline in mining activities within panda habitats since 2016. Despite these advancements, accurately quantifying the full scope of mining's pressure remains a complex challenge.

3.7. Human Population

The rapid growth of the global human population is widely recognized as a significant driver of biodiversity loss. Over the next 30 years, the world's population is expected to increase from 7.7 billion to 9.7 billion [81]. However, the relationship between population growth and nature conservation remains debated. Forester and Machlis [82] argued that global biodiversity loss is not directly correlated with human population changes. Wittemyer et al. [83] found that population growth occurs near the edges of 306 PAs in 45 countries. Joppa et al. [84] disputed this, finding no significant correlation between population growth and PAs, and argued that Wittemyer's datasets were incompatible, resulting in flawed conclusions. Recent studies suggest a new dynamic: a decline in rural populations near PAs may paradoxically benefit biodiversity conservation [85,86].

4. Methodologies of Comprehensive Human Pressure

Human pressure techniques provide a comprehensive characterization of human-induced activities, analyzing them across multiple dimensions (such as intensity and spatial scale) and across different sectors (like agriculture, urbanization, and transportation infrastructure). These methods enable the quantification by assigning precise numerical values, which are then further analyzed and synthesized through advanced combinatorial methodologies (Figure 3).

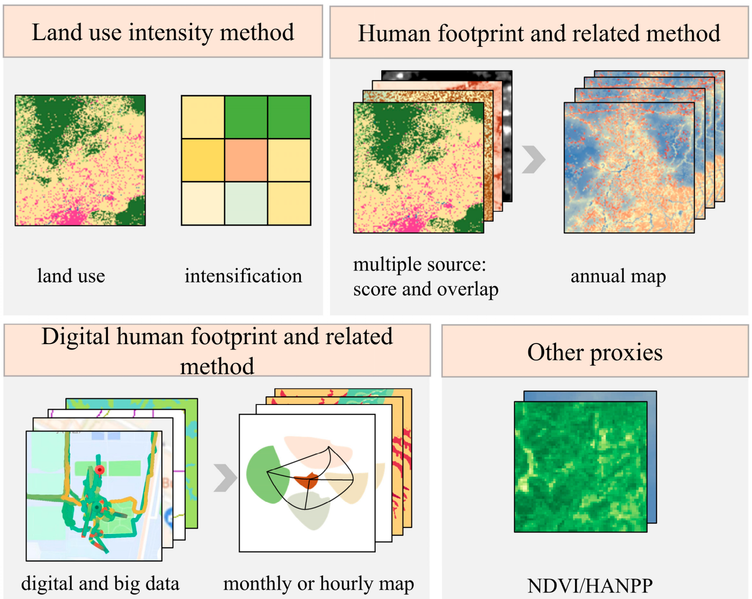

Figure 3. Four methodologies of comprehensive human pressure.

4.1. *Land Use Intensity Method*

Land use intensity is a method used to measure the degree of land intensification by assigning specific values to different land use types based on their level of intensification [87]. This process involves classifying land into categories such as agricultural, forested, and urban areas, and assigning each a value that reflects its intensity, such as higher values for heavily mechanized agriculture and lower values for natural forests [88]. The intensity for a region is calculated by taking a weighted average of these values, considering the area occupied by each land use type. This method helps policymakers and researchers compare land use patterns over different regions and periods, thereby aiding in the analysis of trends and the environmental impact of land use decisions, ultimately guiding more sustainable land management practices.

In an alternative aspect, land use intensity generally describes the extent to which land is utilized, focusing on the distribution and physical changes of different land types within a specific area, such as the conversion of forests to agricultural land. Intensification, on the other hand, emphasizes internal changes in land use without altering the land's purpose, such as increasing the level of mechanization in farming or the use of fertilizers [89]. Combining land use intensity and intensification provides a more comprehensive land use intensity assessment. This combined approach can be applied not only at the macro level for regional and national analyses but also at the micro level for specific projects. Within the framework of global sustainable development goals, such a deep understanding of land use can foster the optimized allocation of resources, minimizing environmental impacts while meeting economic development needs.

Given these aspects, the land use intensity method offers various advantages and certain limitations in its application:

- Advantages: The land use intensity method is known for its simple structure and great flexibility. Its simplicity allows researchers and policymakers to apply it easily without needing complex technical tools or extensive expertise. This method's flexibility lets users adjust intensity parameters to fit specific regional or study needs, making it more applicable for various analyses. This adaptability ensures that the method can be easily integrated into existing decision-making processes, offering a practical tool for various stakeholders in land management and policy planning.
- Disadvantages/limitations: Despite its benefits, the land use intensity method has several limitations. It requires accurate and extensive data collection, which can be resource-intensive and challenging to obtain. The complexity of the method may

demand specialized knowledge for implementation and interpretation of results. Additionally, the method may not fully capture rapid or unforeseen changes in land use or intensification patterns. There is also an element of subjectivity in assigning intensity values to different land use types, which may vary by context and affect the consistency of results.

A summary table with some representative land use intensity work performed is presented in Table 2.

Table 2. Representative land use intensity studies.

Ref.	Year	Study Area	Land Use Intensity Methods	Main Findings
[90]	2014	Global PAs	Use the naturalness of land use to assign values.	The effectiveness of worldwide PAs is anticipated to decline by 54% by 2050 in light of the land-use intensity.
[91]	2015	Biodiversity conservation priority areas across China	Construct an Ecosystem Comprehensive Anthropogenic Disturbance Index (ECADI): categorizing land use types into four distinct indexes ranging from 0 to 3 and standardizing.	From 1990 to 2010, ECADI values showed increasing trends in areas designated as moderately important, important, and very important for biodiversity conservation.
[92]	2022	Global	Use HANPP and the land use intensity metric to measure land use intensity.	Two land use intensity sets showed a significant correlation, and land conversion and land use intensity have similar effects on habitat loss.
[93]	2024	Europe	Define the suitability of land use classes as habitats for each species	Land use intensity leads to a significant improvement compared with that only included land cover.

4.2. Human Footprint and Related Methods

Since the introduction of the human footprint concept in the 2000s, various human pressure data products have been developed. Table 3 summarizes these methodologies' characteristics.

Table 3. The concepts of human footprint and related methods.

Methods	Ref.	Description
Human footprint (HF)	[12]	Reassign and overlay different categories of spatial human pressure data.
Anthropogenic biomes/Anthromes	[94]	Analyze human and biological systems together, and integrate potential natural vegetation cover with categories that represent various types of human activity and levels of intensity.
Spatial human footprint index (SHFI)	[95]	Develop a quantitative spatial human footprint indicator under three dimensions, including land use intensity, intervention time, and biophysical vulnerability of the impacted ecosystems.
Human modification (HM)	[1]	Distinguish human pressure into intensity and spatial distribution, using "fuzzy algebraic sum" to reduce covariance of individual human pressure and provide a comprehensive index.
Temporal human pressure index (THPI)	[96]	Only select human pressure data that change with temporal and spatial, then reassign and overlay them.
Low-impact areas (LIAs)	[97]	Categorize human pressure data and identify low human pressure areas.
Chronic anthropogenic disturbance (CAD)	[98]	Identify and quantify the main sources of single chronic anthropogenic disturbance (refer to ongoing or long-term human activities) using data with varying precision, categorizing these sources into general disturbance pressures and creating indices for each, then integrating these indices into a comprehensive index.

Although these methods focus on different aspects, their core feature lies in classifying and quantifying human pressures, resulting in a numerical indicator or a categorization of the natural environment. It helps us better understand and manage the impact of human activities on the environment.

In 2002, Sanderson et al. [12] first introduced the concept of the human footprint representing the sum total of human ecological footprints. It effectively measured human pressures by considering the additive effects of nine individual pressures, such as population density, land transformation, accessibility, and electrical infrastructure [12].

From another perspective, Ellis and Ramankutty [94] developed the framework of anthromes, using cluster analysis to identify significant patterns combining human activities (using land use and human population density) and biological systems (using potential natural vegetation cover with classes). They created 21 categories representing different human pressures in the natural environment (e.g., dense settlements, villages, croplands, and residential rangelands) [94].

Building on the foundational concept of the human footprint, Etter et al. [95] developed a new index called the spatial human footprint index (SHFI), incorporating indicators on intervention time and biophysical vulnerability of the impacted ecosystems with a human footprint (land use intensity). Some researchers believed it was a more comprehensive human pressure than the human footprint [99]. Geldmann et al. [96] introduced the Temporal Human Pressure Index (THPI) to address data consistency issues by only selecting human pressure data that change with temporal and spatial.

Further advancing the study of human pressure, Theobald [100] introduced the human modification method, which carefully distinguishes the intensity and spatial distribution of human pressure. By using the "fuzzy algebraic sum", this method minimizes covariance issues among diverse human pressures and provides a nuanced analysis of cumulative human modification. However, its complexity hindered its widespread applications.

Compared with other methods, Low Impact Areas introduced a classified dataset to identify areas with minimal human influence by utilizing high-resolution and publicly available global data, such as population, livestock density, forest changes, land cover, and nighttime lights [97].

Chronic Anthropogenic Disturbance (CAD) focuses on the gradual yet persistent human pressures like livestock grazing and hunting [101]. This approach employs weighted methods or principal component analysis (PCA) to create a comprehensive measure of human pressure. Data collection for this method occasionally requires conducting field surveys in natural environments [102].

Table 4 presents a comparison of each method, outlining their respective advantages and disadvantages.

Table 4. Comparisons of different methods.

Methods	Advantages	Disadvantages
Human footprint (HF)	Provide a broad and unified measure of diverse human pressures, facilitating different regions' comparisons.	Simplify complex ecological interactions and pressures, potentially leading to less precise conclusions.
Anthropogenic biomes/Anthromes	Capture a wide range of human-environment interactions, highlighting diverse anthropogenic pressures.	Highly complex; requires substantial data, which can be difficult to compile and standardize.
Spatial human footprint index (SHFI)	Integrate human pressure with ecological vulnerability, offering a comprehensive perspective.	The complexity of the index may restrict its usability in practical assessments and decision-making; lack of intervention time data.
Human modification (HM)	Consider temporal dynamics, enhancing data relevance and accuracy over time.	Data limitations, particularly regarding high-resolution temporal and spatial variability, may impair its effectiveness.

Table 4. *Cont.*

Methods	Advantages	Disadvantages
Temporal human pressure index (THPI)	Offer nuanced insights by minimizing covariance among different pressure sources, enhancing analysis precision.	High complexity and data demands limit its application and broader adoption.
Low impact areas (LIAs)	Easy to implement using readily available data, helps biodiversity conservation by identifying regions of low human pressure.	Might miss out on capturing subtle, localized pressures that are not well-represented in existing datasets.
Chronic anthropogenic disturbance (CAD)	Effectively measure gradual and chronic pressures, adaptable to diverse field conditions and datasets.	It often requires detailed and costly field surveys to gather.

A summary table with some representative human footprint-related work performed is presented in Table 5.

Table 5. Representative human footprint-related studies.

Ref.	Year	Study Area	Human Footprint and Related Methods	Main Findings
[9]	2008	Northern Appalachian/Acadian ecoregion	Mapped the HF at a 90 m resolution using the best available data on human settlement, access, land use change, and electrical power infrastructure.	Correlation between HF scores decreased with smaller compared areas.
[103]	2017	Trans-Mexican Volcanic System in Michoacán (TMVS), Mexico	The SHFI was enhanced by incorporating fragmentation and habitat loss, alongside the original components: land use intensity, duration of human intervention, and biophysical vulnerability.	Over 60% of TMVS shows high SHFI values, reducing habitat connectivity for all species. Human impact on connectivity is especially significant for species with limited dispersal capacity (100–500 m).
[104]	2017	South Ecuador	Mapped HF at 100 m resolution, combining human population density, land transformation, power infrastructure distribution, and human access.	Human pressure has increased, and wild areas has decreased since 1982. Notable "hotspots of changes" were found in western seasonally dry forests and eastern premontane evergreen forests. Different human proxies contributed variably to HF values.
[105]	2024	Northern subtropical forests in China	Calculated a CAD index for each plot based on livestock grazing intensity, wood extraction, and miscellaneous resource use.	CAD was linked to more trees and stem proliferation, and increased resprouting in seedlings, but had no effect on adult forests.
[106]	2024	Qinghai-Tibetan Plateau, China	Current human pressure: using the human modification method and employing six categories (human settlement, agriculture, transportation, energy production and mining, electrical infrastructure, and air pollution). Future human pressure: using the future human population density, built-up areas, cropland, air pollution, and other types of human pressure employed the latest current data.	It is predicted that human modification will threaten half of all plateau's land vertebrates.

4.3. Digital Human Footprint and Related Methods

The advent of big (geo) data has revolutionized our understanding of human pressure on the natural environment. Compared to traditional data, big social data have attracted significant attention due to their rapid expansion in usage, also known as the digital human footprint [107].

This digital footprint emerges from a diverse range of sources, including social media platforms, mobile location services, and other online activities [108]. It encompasses three categories (Figure 4): (1) social media data, which includes posts, comments, likes, and shares from platforms such as Twitter, Facebook, WeChat, and Weibo; (2) human mobility data, which consist of geolocation information gathered through GPS and other positioning technologies; and (3) online activity data, which comprise browsing histories, search queries, and online transaction records. This comprehensive digital record provides valuable insights into personal behaviors and preferences, presenting significant implications for privacy, data governance, and the ethical management of information in the digital age [109,110].

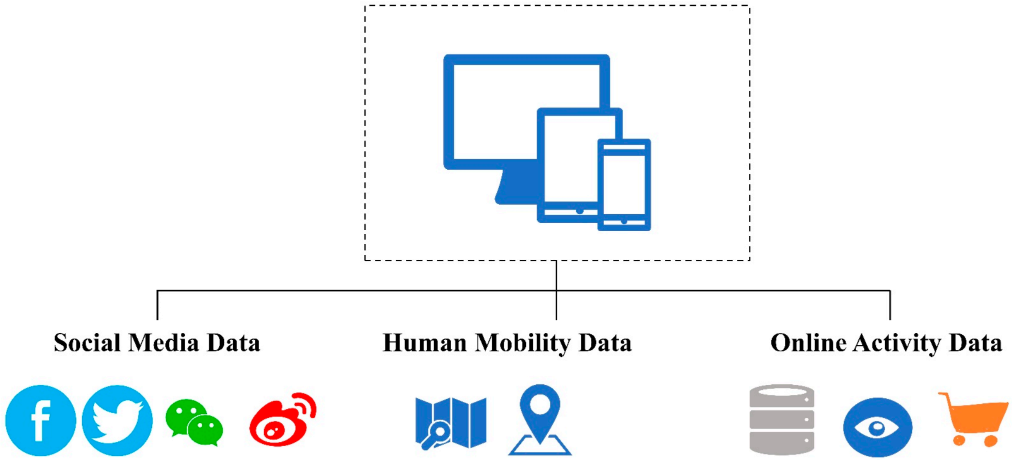

Figure 4. Commonly used human digital big data.

Given these aspects, the method offers various advantages and certain limitations in its application:

- Advantages: The method's ability to leverage large volumes of real-time data means it can provide timely and relevant insights, allowing stakeholders to react quickly to emerging situations. This real-time aspect is crucial for dynamic environments where conditions change rapidly. Additionally, the method enables the analysis of patterns and trends across extensive geographic areas, offering a broad perspective that can be critical for understanding complex phenomena. By integrating diverse data sources, such as social media and mobile applications, the method enhances the robustness and accuracy of the findings, leading to more reliable conclusions and informed decision-making.
- Disadvantages/limitations: Publicly accessible crowdsourced geographic data, such as those from social media or mobile applications, are often limited due to privacy restrictions, data aggregation issues, and sampling biases [111].

A summary table with some representative digital human footprint-related work performed is presented in Table 6.

Table 6. Representative digital human footprint-related studies.

Ref.	Year	Study Area	Digital Human Footprint and Related Methods	Main Findings
[108]	2018	Hawaii Volcanoes National Park (HVNP)	Used geotagged Flickr photos to model temporal and spatial patterns of visitors within HVNP.	Highlighted the potential of social media data to reveal visitation patterns that can inform management strategies for preserving biodiversity and minimizing human impact.

Table 6. *Cont.*

Ref.	Year	Study Area	Digital Human Footprint and Related Methods	Main Findings
[112]	2021	Qinghai–Tibet Plateau and its PAs	Analyzed Tencent's location-request data to track digital human footprint trends within PAs.	Revealed distinct U-shaped and N-shaped temporal patterns during major festivals, demonstrating the utility of digital data in capturing fluctuations during significant periods.
[113]	2021	Brazilian PAs	Combined Wikipedia page views with developmental pressure indices to assess the political vulnerability of PAs.	Exemplified how digital data sources can be used to understand human visitation patterns and the socio-political context affecting PAs, capturing complex human-environment interactions.
[114]	2022	Qinghai Lake National Nature Reserve, China	Provided insights into the spatial distribution and intensity of digital human footprints within the reserve.	Offered valuable data for future conservation efforts.
[115]	2023	Qinghai–Tibet Plateau and its PAs	Explored seasonal variation of human activity in PAs.	Showed that these areas experienced significantly higher human pressure in summer compared to winter.

4.4. Other Proxies

By using proxies such as NDVI and HANPP, they enable detailed analysis of land use intensity and its ecological impacts. They can more accurately identify areas under human pressure, enhancing the potential for targeted nature conservation efforts. NDVI can be useful in forest and grassland ecosystems, and other factors can easily interfere with their effects [116]. HANPP is directly considered a comprehensive metric to map land use intensity, which refers to the difference between potential plant NPP and total biomass NPP [117].

Given these aspects, the method offers various advantages and certain limitations in its application:

- Advantages: They provide comprehensive metrics that offer a broader understanding of ecosystem changes over time.
- Disadvantages/limitations: Proxies like NDVI are primarily effective in specific types of ecosystems (forest and grassland) and can be easily influenced by external factors such as cloud cover and land management practices, which may skew results. Concerns about the accuracy and limitations of spatial data can impact the reliability of conclusions drawn from these analyses. Furthermore, the high data requirements and complexity may limit their accessibility and usability for broader applications in conservation planning.

A summary table with some representative digital human footprint-related work performed is presented in Table 7.

Table 7. Other representative proxies studies.

Ref.	Year	Study Area	Other Proxies Methods	Main Findings
[116]	2012	114 worldwide PAs	Used NDVI to quantify vegetation-cover heterogeneity and as an indicator of land-cover homogeneity.	PAs with low human pressure were more isolated than those with high levels.
[118]	2016	Czech Republic	Created spatial distribution of HANPP as an indicator for human pressure.	HANPP is negatively related to both biodiversity and ecosystem services.
[119]	2018	Tibet, China	Applied clustering analysis to explore county-level dynamics of HANPP components.	Increase in HANPP was mainly driven by the commercialization of animal husbandry and ecological conservation policies.

5. Implications for Nature Conservation

In this section, we provide an overview of the major nature conservation applications of human pressure maps. We categorized these applications into four topics: (1) ecological monitoring, (2) effectiveness evaluation, (3) spatial identification of wilderness, and (4) optimization of protected areas.

5.1. Ecological Monitoring

Human pressure maps serve as powerful tools for monitoring ecological changes. Through the use of remote sensing technologies and monitoring systems, environmental managers can track the extent and intensity of human activities across various landscapes. For example, national forest inventories in the European Union are utilized to evaluate forest health and track deforestation or degradation caused by human interventions. In China, the Ministry of Ecology and Environment (MEP) has developed a comprehensive human pressure monitoring program to assess the impact of anthropogenic activities on key ecological zones [120,121]. Such programs allow authorities to respond proactively to environmental degradation, providing essential data for adaptive management and policy-making.

5.2. Effectiveness Evaluation

Another important area of human pressure map application for biodiversity conservation is evaluating the effectiveness of conservation strategies, particularly for PAs [122–125]. Studies have used a time series of human pressure data to conduct before/after comparisons to illustrate the effectiveness. For instance, Fan et al. [126] conducted an analysis of China’s national PAs by calculating trends in land cover conversion, which provided insights into the effectiveness of these areas in preserving natural habitats. Similarly, Sieber et al. [127] used Landsat satellite imagery to assess forest pressure in Russia’s PAs, demonstrating that two of these areas significantly reduced human pressure on forests. Such studies underscore the importance of using human pressure maps to inform conservation policy, adapt management strategies, and ensure that conservation goals are being met.

Directly comparing PAs and non-PAs may reveal inherent differences in various environmental variables [128]. Andam et al. [129] indicated that matching methods are a good tool for measuring the effectiveness of PAs. However, using matching, Geldmann et al. [124] found that global PAs did not reduce human pressure compared with non-PAs.

5.3. Spatial Identification of Wilderness

Wilderness areas, as defined by the International Union for the Conservation of Nature (IUCN), represent large, intact regions of natural land or sea that are minimally influenced by human activity [130]. These areas are often remote, with little to no permanent human settlements, and are protected to maintain their pristine condition. The identification of such wilderness areas is crucial for global conservation efforts, as they provide important ecological functions and biodiversity benefits that are often absent in more human-dominated landscapes [131] (Figure 5).

The development of the first quantitative wilderness map marked a significant advance in understanding the spatial distribution of wilderness areas relative to human pressure. Mccloskey and Spalding [132] created one such map by analyzing jet navigation charts, identifying regions that were at least 6 km away from developed features. In further research, Caver [133,134] used a set of indicators to quantify wilderness areas, including naturalness, human pressure, remoteness, and ruggedness. These factors are often combined using a weighted linear combination method, where higher scores indicate areas with more wilderness qualities, and lower scores reflect regions with greater human modification.

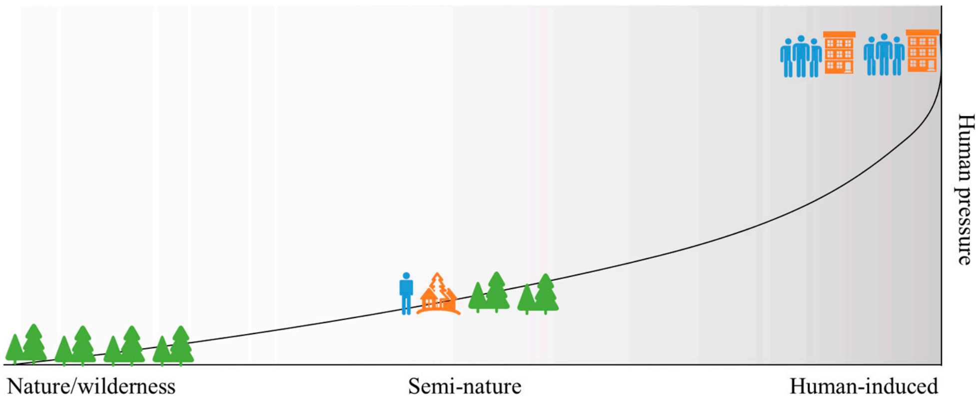

Figure 5. Identification of wilderness based on human pressure.

Wilderness mapping efforts have been instrumental in several developed countries [134–139], guiding conservation priorities and ensuring long-term ecological sustainability. However, developing countries often lack detailed wilderness mapping, which can hinder their ability to identify key conservation areas. There is a growing need for further wilderness mapping initiatives in these regions to enhance global conservation efforts and provide valuable data for maintaining natural landscapes.

5.4. Optimization of Protected Areas

Human pressure maps are also invaluable for optimizing the design and management of PAs. One common approach to optimizing PAs is gap analysis, which compares the spatial overlap between existing PAs and regions of high conservation priority. This analysis helps identify gaps in protection and areas where conservation efforts could be expanded or intensified. For example, Yang et al. [140] found that nearly two-thirds of areas under low human pressure are considered high-priority conservation zones based on overlap analysis. This suggests that many areas with minimal human impact may still be underrepresented in current conservation frameworks.

In addition, Li et al. [141] applied a representativeness-vulnerability framework to evaluate conservation priorities in the Qinghai–Tibet Plateau, a region characterized by its unique biodiversity and ecological importance. By integrating human pressure data, this framework provides a more comprehensive understanding of which areas are most vulnerable to human activities and thus in greater need of protection. Such optimization strategies are essential for improving the efficiency and effectiveness of PAs, ensuring that conservation resources are allocated where they are needed most.

6. Fitness-for-Use Discussion

The process of mapping human pressure involves classifying human pressure categories, measuring various individual human pressures, and calculating comprehensive proxies [2]. The quality and accuracy of the input data, the resolution of the resulting gridded dataset, and the methodologies employed to identify and quantify human pressure are all critical determinants of the quality of such spatial datasets. While much progress has been made in recent years regarding data quality research, discussions on the relative quality or fitness for use of data are still needed. Given the diversity in underlying data, methodologies, and applications among different human pressure datasets, assessing whether a specific comprehensive data method is suitable for a particular purpose is crucial. Thus, in this section, we explore several key factors to assist data users in evaluating the fitness of the use of human pressure data for nature conservation.

6.1. Consistency Issues of Human Pressure Data

To effectively map and analyze changes in human pressure on the environment, it is crucial to have access to consistent and comparable data sources. However, achieving this objective remains a challenge due to various technical and policy constraints. Even when dealing with similar types of human pressure, differences in processing methodologies and interpretive frameworks arise based on specific needs and intended uses, resulting in a wide range of interpretations and outcomes.

For example, when considering land use data, the European Space Agency Climate Change Initiative (ESA-CCI) land cover product from 1992 to 2015, with a resolution of 300 m, classifies land use into 22 categories [142]. In addition, the GlobeLand30 data divide the Earth's surface into 10 categories and report an overall classification accuracy of over 80.33% [143]. The FROM-GLC includes two levels of land cover classes: 10 Level-1 classes and 29 Level-2 classes. The overall accuracy for Level-1 FROM-GLC is 53.88–64.89%, while the overall accuracy for Level-2 FROM-GLC is 52.76% [144]. Additionally, several regional datasets have emerged, including the China land cover dataset (CLCD) [145], land-use/cover datasets (CLUDs) [146], and the National Land Cover Database (NLCD) for the USA [147].

It is important to note that the following: (1) Due to inconsistencies in the databases used for validation, accuracy cannot be directly compared across datasets. (2) Differences in processing methodologies can result in varying levels of accuracy for specific land cover classes within a given map. For instance, certain datasets might exhibit high accuracy for identifying forested areas but lower accuracy for distinguishing between different types of urban land use. (3) Global maps often exhibit regional variations in accuracy. Generally, regional maps can achieve higher levels of accuracy and detail compared to their global counterparts, primarily due to their ability to focus on specific geographical areas and utilize more localized data sources. (4) Higher-resolution maps often contain more information, enabling more detailed changes in human pressure. (5) Available global or regional data are constrained by limitations in temporal and spatial resolution. When mapping historical human pressure, we frequently rely on data sources like HYDE3.1 [148] and HYDE3.2 [149], which have ~10 km resolution. However, these limitations are inherent and unavoidable until more advanced historical data products emerge.

Human population data and other data also face issues of consistency and comparability. Digital data, as a special type of data leveraging new technologies, are generally only available for the past decades [107]. Furthermore, their availability is often further limited due to privacy concerns and other restrictions. These factors necessitate a focus on data timeliness and compliance with legal standards to ensure the accuracy and efficacy of analyses.

6.2. Comprehensive Methods of Uncertainty

The processing methods are fundamental to the production of human pressure, yet they inherently introduce various forms of uncertainty [150]. When raw data are converted into formats suitable for analysis, it often requires a series of assumptions and simplifications. Integrating disparate datasets requires careful alignment and harmonization to ensure compatibility and coherence.

However, even with rigorous methods, inherent differences in data collection, definitions, and spatial resolutions can create disparities that are difficult to reconcile, leading to increased uncertainty in the aggregated dataset [151]. Different models and methodologies might be based on varying assumptions and theories, leading to diverse interpretations and predictions of the data. The selection and application of these models, therefore, demand careful evaluation of their suitability and reliability. This precautionary approach is crucial to avoid introducing additional uncertainty stemming from the inherent limitations or biases of the models themselves.

Lastly, it is imperative to emphasize that while uncertainty is an inherent aspect of human pressure data production, it can be mitigated through the adoption of scientific methods and technologies. For example, utilizing more advanced data collection tools and techniques can enhance the accuracy and completeness of the data. Similarly, employing more complex data processing and analytical methods can reveal hidden patterns and information within the data, thereby reducing uncertainty. Concurrently, continuous improvement and optimization of models can lead to more precise predictions, further minimizing the impact of uncertainty on our understanding of human pressures [152].

6.3. Data Validation

The validation of human pressure data has consistently been a challenge, for a straightforward reason. The validation of land use intensity methods depends heavily on land use verification datasets. However, high-resolution validation data are rarely available, as gathering such data requires extensive fieldwork to accurately record actual land use categories for comparison with alternative datasets [153]. Validating human footprint-related methods, on the other hand, demands considerable volunteer effort, specifically involving volunteers assessing human pressure values from remote sensing images and comparing these with the values produced by the dataset [1]. It is evident that relying on the subjective judgment of volunteers is often questioned. Additionally, digital footprints and other proxies typically do not engage in concrete data validation processes.

6.4. Usage Guideline

When handling and analyzing human pressure datasets aimed at nature conservation, making informed and effective decisions is crucial. The following guidelines can help users assess the suitability and utility of these methodologies:

- Define the objective and scope: Clearly define the purpose of the dataset. Are you assessing the impact of urbanization, agricultural expansion, pollution, or another type of human pressure on the environment? Specify the geographical area (local, regional, or global) covered by the dataset.
- Evaluate data quality: Understand the methods of data collection, sources, and whether the data are original or aggregated to ensure accuracy and reliability. Check for consistency across datasets, especially if multiple datasets are being integrated for comprehensive analysis.
- Consider temporal and spatial resolution: Ensure the dataset's temporal and spatial resolution matches the scale of your conservation efforts. Fine-scale data may be needed for local management, while coarser data might suffice for broader regional assessments.
- Assess usability and compatibility: confirm that the data are in a usable format and compatible with the analytical tools you are using.
- Ethical and legal considerations: ensure compliance with ethical standards and legal requirements regarding the use of data, especially digital data if they include sensitive or proprietary information.

By adhering to these guidelines, users can effectively utilize human pressure datasets to enhance nature conservation efforts, leading to better-informed decisions and outcomes.

7. Future Work

7.1. Advanced Modeling Techniques

The evolving capabilities of remote sensing provide more opportunities for developing a novel framework for mapping human pressure. By using remote sensing techniques such as satellite imagery and aerial photography, we can gain comprehensive insights into the dynamic changes of human pressure [154]. Furthermore, combining datasets from multiple sources can enhance the accuracy of human pressure measurements [96]. Recent advancements in machine learning technologies have facilitated the construction of more accurate datasets utilizing very high-resolution images, such as those provided by World View and SPOT-5 [155–157]. The amalgamation of machine learning algorithms with these models can elevate their predictive accuracy, particularly in understanding how diverse land-use patterns and management strategies impact nature over time.

Future research efforts should be directed towards refining geographic simulation models, including landscape-driven patch-based cellular automata, to better anticipate dynamic changes in human pressures [158,159]. Exploring the interactions between human and natural systems at different scales will be crucial in fine-tuning these models.

7.2. Integration of Remote Sensing and Big Data

With the emergence of geospatial big data, driven by advancements in mobile positioning, wireless communication, and the Internet of Things [160], the integration of remote sensing and big data has become increasingly critical. For instance, OpenStreetMap (OSM) is widely recognized as an important form of spatial big data. It has been used in many human pressure mapping models combining remote sensing [1,135,151]. Mobile phone data, traffic data, social media data, and smart card data can help to capture digital human activities. How to use these data with remote sensing for human pressure mapping needs further studies. In this context, data access is a key challenge. We call on using more big data and building data-sharing platforms. Future research should focus on improving human pressure quality mapping and filling data gaps, prioritizing the greatest data deficiencies. Taking grazing data as an example, we urgently need to understand better mapping grazing extent, especially grazing distribution among different vegetation types [50].

7.3. Addressing Data Gaps and Enhancing Accessibility

Identifying and addressing data gaps, particularly in underserved areas such as the impacts of grazing across different vegetation types, remain critical priorities. Future efforts should focus on establishing robust data-sharing platforms that facilitate the exchange and accessibility of high-quality data among researchers, policymakers, and practitioners. This task demands not only technical support but also international collaboration to bolster data collection efforts in resource-limited settings, especially in developing countries. By enhancing data accessibility and interoperability, we can ensure more comprehensive and accurate information for global ecological management and decision-making.

7.4. Policy Implications and Collaborative Strategies

While monitoring human pressure is essential, it is not sufficient to achieve conservation goals in isolation. Future research should explore how these data-driven insights can be translated into practical policy measures. This requires strengthening collaboration among academic researchers, conservation organizations, governments, and local communities. It is imperative to ensure that conservation strategies are not only scientifically sound but also socially equitable and economically viable. To this end, an interdisciplinary approach that integrates knowledge from ecology, sociology, economics, and other fields is necessary to develop comprehensive solutions. Collaborative efforts among stakeholders are crucial for the formulation and implementation of strategies that effectively mitigate the negative impacts of human activities on biodiversity and enhance the overall ecological resilience of communities.

8. Conclusions

In this review, we provide a comprehensive and in-depth analysis of human pressure mapping for nature conservation, primarily for PAs. First, we considered seven human pressures in detail, including agriculture, urban development, livestock grazing, transportation infrastructure, light pollution, mining and quarrying, and human population, which pose serious threats to the ecological integrity and biodiversity of PAs. Through a deeper understanding of these individual human pressures, we were able to better assess their actual pressures for nature conservation, thus providing an important basis for the development of effective conservation strategies.

Subsequently, we summarized commonly used quantifiable human pressure mapping methodologies. These methodologies include land use intensity, human footprint and related, digital human footprint and related methods, and other proxies. They can help us visualize the distribution of human pressures on PAs, and thus provide scientific decision support for policy makers.

In addition, we outlined the application of human pressures in nature conservation, including ecological monitoring, effectiveness evaluation, spatial identification of wilderness, and optimization of protected areas. Human pressure maps provide a powerful toolset for enhancing both the strategic planning and operational management of conservation efforts, ultimately contributing to more effective biodiversity preservation and ecosystem management.

Moreover, we discussed the fitness-for-use of human pressures in nature conservation. We highlighted the inherent uncertainties in data processing methods and the challenges associated with data validation. To assist users, we provided a set of guidelines to evaluate the applicability and practicality of human pressure data methodologies.

Finally, we outlined future directions, including developing advanced modeling techniques, integrating remote sensing and big data, addressing data gaps, improving accessibility, and considering policy implications and collaborative strategies. Through these efforts, human pressure data can be utilized more effectively to enhance conservation work, leading to more informed decisions and better outcomes.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/rs16203866/s1, Figure S1: Number of publications on human pressure mapping literature.

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