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Research Article

A Comprehensive and Innovative Environmental PSR Model for Biodiversity Priority Conservation Areas

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Abstract: Biodiversity is essential for ecosystem resilience and human well-being, yet it faces accelerating threats from habitat loss, climate change, and human activities. Conservation models often inadequately address the intertwined ecological and socio-economic drivers of biodiversity loss, leaving a gap between theoretical frameworks and real-world implementation. This study introduces an advanced Pressure-State-Response (PSR) model, developed through extensive fieldwork and leveraging Geographic Information Systems (GIS) and remote sensing technologies. The model integrates ecological indicators with socio-economic factors, including stakeholder engagement, education, and local economic conditions, creating a dynamic, context-specific approach to conservation. By adopting a Multi-Criteria Decision Analysis (MCDA) framework, specifically the Analytic Hierarchy Process (AHP), the enhanced PSR model prioritizes biodiversity hotspots based on ecological urgency and socio-economic resilience. It overcomes limitations of traditional models by incorporating customizable criteria and fostering equitable conservation strategies. The approach optimizes resource allocation, ensuring interventions target areas of highest biodiversity value while balancing local development needs. This study provides a replicable and adaptable methodology for conservation planning, addressing 21st-century challenges of biodiversity loss and socio-ecological complexity. By aligning conservation priorities with sustainable development goals, the model advances a transformative framework that bridges science, policy, and practice, offering global applicability for safeguarding biodiversity and ecosystem services.

Keywords: Biodiversity Conservation, Pressure-State-Response (PSR) Model, Multi-Criteria Decision Analysis (MCDA), Geographic Information Systems (GIS), Sustainable Development.

1. Introduction

Biodiversity, encompassing the vast variety of life forms on Earth, is the cornerstone of ecosystem health and human well-being, supporting essential ecosystem services such as food security, climate regulation, and the maintenance of natural environments (DeLong, 1996; Gaston and Spicer, 2004; Yang et al., 2021; Daily, 1997; Folke et al., 2004; Johnson, 2000). These services are critical for sustaining agricultural systems and supporting human livelihoods by enhancing ecosystems' resilience and recovery in the face of environmental challenges, while also maintaining the delicate balance necessary for ecosystem functioning. However, despite the critical importance of biodiversity, its preservation often suffers from a lack of integrated approaches that address both ecological and socio-economic dimensions, creating a disconnect between theoretical frameworks and practical implementation.

Biodiversity is now facing unprecedented threats due to habitat fragmentation, climate change, and increasing human pressures, leading to extinction rates that far exceed natural background levels (Pimm et al., 2014; Díaz et al., 2019; Ceballos et al., 2015). Tackling these urgent challenges requires innovative conservation strategies that prioritize areas for intervention. Conservation priority areas play a crucial role in safeguarding biodiversity by identifying regions critical for species survival and ecosystem service maintenance. These areas are typically determined using various ecological models that assess regions' relative importance based on their biodiversity value, ecological function, and the pressures they face. Despite their utility, traditional ecological models often overlook socio-economic drivers, such as poverty, population density, and stakeholder engagement, which significantly influence conservation outcomes. This gap highlights the need for integrated frameworks that balance ecological priorities with socio-economic realities.

The Pressure-State-Response (PSR) model, originally developed by the OECD, offers a framework for understanding the interactions between human pressures, environmental conditions, and societal responses. However, traditional PSR models have largely overlooked the broader impact of human activities and socio-economic variables on biodiversity (Esmail and Geneletti, 2017). While PSR provides a foundational understanding, its applicability is limited in complex socio-ecological systems where human activities and ecological dynamics interact in non-linear ways. Recognizing this gap, recent studies have emphasized the importance of integrating socio-economic factors into conservation strategies (Esmail and Geneletti, 2017; Jones et al., 2018). Incorporating socio-economic factors—such as stakeholder engagement, poverty levels, and population density—into conservation planning has been shown to significantly enhance biodiversity and livelihoods simultaneously (Mizrahi et al., 2018; Cetas and Yasué, 2017). Nevertheless, practical implementation of such integrated approaches has been hindered by data limitations and methodological challenges, necessitating the development of adaptable and context-specific conservation models. Technological advancements in Geographic Information Systems (GIS) and remote sensing have revolutionized conservation planning, providing precise tools for mapping habitats and species distributions (Saptarshi and Raghavendra, 2009; Gupta et al., 2022). However, the integration of these technologies with socio-economic data remains limited, underscoring the need for comprehensive frameworks that leverage the strengths of both ecological and socio-economic analyses.

The objective of this study is to develop an advanced and comprehensive PSR model that integrates ecological and socio-economic factors through a Multi-Criteria Decision Analysis (MCDA) framework, providing a more holistic and adaptable approach for conservation planning. This model aims to bridge the gap between theoretical conservation frameworks and practical applications by aligning ecological priorities with socio-economic needs, ensuring that conservation efforts are both effective and equitable. By leveraging advanced analytical techniques, fieldwork, GIS, and remote sensing technologies, our refined PSR model will utilize diverse datasets, including socio-economic assessments, to more effectively identify conservation priority areas. This model's interdisciplinary focus, integrating socio-economic criteria such as local community involvement, education, and economic conditions alongside ecological data, allows for conservation strategies that are socially equitable and contextually sustainable. Furthermore, the model incorporates customizable criteria weighting using methods like the Analytic Hierarchy Process (AHP), ensuring its adaptability to specific regional needs and making it operationally viable. By focusing on biodiversity hotspots, the model optimizes conservation resources by targeting areas with the highest biodiversity value and urgency, balancing effective conservation with practical resource constraints. This approach addresses critical gaps in existing conservation models, providing a transformative tool for addressing the socio-ecological complexities of the 21st century.

2. Literature Review

Biodiversity conservation has evolved significantly since the late 20th century, driven by increasing awareness of environmental degradation and species extinction. Soule's (1985) seminal work underscored the urgency of addressing species loss, advocating for an interdisciplinary approach that integrates ecology with conservation strategies to mitigate habitat destruction. This foundational perspective laid the groundwork for conservation biology as a distinct discipline, emphasizing the integration of ecological, genetic, and environmental sciences to address complex conservation challenges.

Building upon this foundation, Myers (1988) introduced the concept of biodiversity hotspots—regions characterized by high levels of endemism and significant anthropogenic pressures—which became a cornerstone in prioritizing conservation efforts. This methodology acknowledges the necessity of strategic decision-making due to limited conservation resources (Myers et al., 2000; Mittermeier et al., 2011; Radeloff et al., 2013). By focusing on these hotspots, conservation initiatives aim to protect critical habitats and species populations more efficiently. For instance, Myers et al. (2000) and Pimm et al. (2001) estimated that protecting globally identified hotspots could be achieved with a fraction of the global conservation budget, illustrating the cost-effectiveness of this approach (Myers, 2003).

The 1990s marked the formal emergence of conservation biology, with global projects emphasizing biodiversity protection across diverse ecosystems (Woodruff, 1990; Bawa et al., 1990; Jongman, 1995). Researchers explored the sources of pressure on species, with studies like Parsons (1991) highlighting the inherent stressors in nature and the need for resilience in response to climate change. At the same time, the economic value of biodiversity was increasingly recognized, as global ecosystems provide approximately $125 trillion worth of goods and services annually (Costanza et al., 2014). These services are crucial for industries such as agriculture and forestry, which support billions of jobs worldwide (FAO, 2018). For example, forests sustain the livelihoods of over 1.6 billion people, and in India, forest ecosystems contribute significantly to rural communities' livelihoods (World Bank, 2004; Aggarwal et al., 2020).

Despite these advancements, effective biodiversity conservation in developing regions continues to face significant challenges. Chronic poverty, limited access to essential resources, and over-reliance on natural ecosystems often lead to unsustainable exploitation and land-use conflicts, exacerbating threats to biodiversity (Fisher and Christopher, 2007; Ferraro et al., 2011). Socio-economic factors such as limited education, lack of alternative livelihoods, and inadequate governance structures compound these challenges (Barrett et al., 2011; Agrawal and Redford, 2006). Large-scale conservation areas, although critical, frequently encounter logistical, socio-political, and financial challenges, making long-term management difficult (Brandon et al., 1998; Watson et al., 2014). Focusing on biodiversity hotspots offers a more pragmatic and sustainable approach, safeguarding biodiversity while securing community support essential for the success of conservation efforts (Brooks et al., 2006; Klein et al., 2015).

As conservation science progressed into the 21st century, indices that account for biodiversity richness, deforestation rates, and conservation potential became pivotal in refining priorities (Dinerstein and Wikramanayake, 1993; Jetz et al., 2014). The concept of conservation triage emerged, prioritizing areas where interventions can prevent the most significant losses (Wilson et al., 2006; Bottrill et al., 2008). Technological advancements, particularly in GIS and remote sensing, have revolutionized conservation practices by enhancing the precision of habitat mapping and species monitoring (Foody, 2008; Wang et al., 2010). High-resolution satellite imagery, aerial photography, and LiDAR provide precise tools for conservation planning (Pettorelli et al., 2014; Gupta et al., 2022).

Despite these innovations, there remains a critical need for models that integrate socio-economic dimensions into conservation planning to address the complex challenges of biodiversity loss (Polasky et al., 2011; McShane et al., 2011). Socio-economic issues such as poverty, population growth, and resource dependency directly affect conservation outcomes (Balmford and Whitten, 2003; Nielsen et al., 2019). Without considering local community needs and socio-economic contexts, conservation efforts may face resistance and ineffective outcomes (Redpath et al., 2013). Interdisciplinary models that incorporate socio-economic factors alongside ecological data are needed for creating contextually relevant and sustainable conservation strategies.

3. The Pressure-State-Response (PSR) Model

The Pressure-State-Response (PSR) model, developed by the Organisation for Economic Co-operation and Development (OECD) in the early 1990s, is a fundamental framework for analyzing interactions between human activities and environmental impacts (OECD, 1994). Central to sustainable development, the PSR model provides insights into the interconnections between conservation issues, economic activities, and social well-being (Hukkinen, 2003a). At the time of its inception, there was a pressing need for methods to assess interactions across environmental, demographic, social, and developmental parameters. Recognizing this gap, many international organizations launched initiatives to create indicators that capture these complex interrelationships, as noted in Chapter 40 of Agenda 21: “Methods for assessing interactions between different sectoral environmental, demographic, social, and developmental parameters are not sufficiently developed or applied” (CSD, 1992, p. 40.4). The PSR model's three interrelated components—Pressure, State, and Response—offer a structured approach to environmental impact management (Figure 1). It evaluates the pressures of human activities on environmental states and proposes responses to achieve a "desirable state" (OECD, 1994). Figure 1 illustrates the PSR framework, where human-induced pressures affect the state of the environment, prompting societal responses to mitigate or adapt to environmental changes. However, while the PSR model was instrumental as a foundational tool, its linear structure presents limitations in capturing the complexities and feedback loops inherent in modern socio-ecological systems (OECD, 1994).

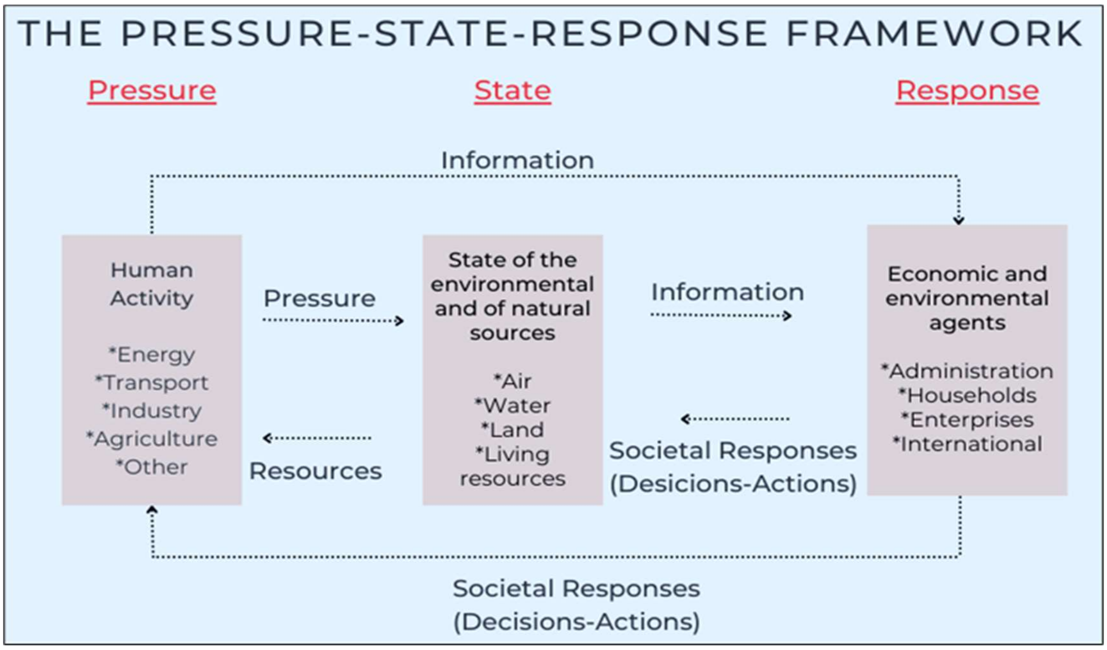

Figure 1. The Pressure-State-Response (PSR) framework model (OECD, 1994).

Pressure represents human activities and natural forces that exert stress on the environment, including industrial production, urban expansion, agricultural practices, and transportation networks. These pressures contribute to habitat destruction, pollution, and climate change, exacerbating natural disasters and further compromising biodiversity and ecosystem resilience (Liu, 2007). State reflects the current conditions of environmental systems, integrating diverse data to assess factors such as biodiversity, air and water quality, soil health, and ecosystem integrity, which are crucial for identifying at-risk areas and guiding conservation and restoration (Wolfslehner and Vacik, 2008). Response encompasses societal actions to mitigate environmental pressures, including policymaking, regulatory measures, conservation initiatives, and community engagement. However, categorizing an activity solely as a "pressure" can inadvertently assign responsibility to specific stakeholders, leading to conflicts rather than fostering constructive dialogue among local communities. To better facilitate interactions and negotiations, the PSR framework requires adaptation within the social context of conservation activities. Widely adopted in environmental reports and scientific programs for its intuitive structure, the PSR model has also faced criticisms for its theoretical limitations, especially in oversimplifying complex social and ecological interactions (Briassoulis, 2001; Hukkinen, 2003a; Zaccaï, 2002; CNDD, 2003). For example, the interplay of fallow land encroachment and increasing tourism reveals ambiguous effects on biodiversity, challenging the classification of these activities as mere pressures (Levrel and Bouamrane, 2008). Such activities can have both beneficial and adverse impacts, and their net effect is often uncertain, suggesting the need for a nuanced approach to manage interconnected socio-ecological issues. To address the complexity of environmental, social, and economic indicators, various adaptations of the PSR framework have emerged. These include the Driver-Pressure-State-Impact-Response (DPSIR) model used by the European Environment Agency (European Environment Agency, 2003), the Driving Force-State-Response (DSR) indicators by the Commission on Sustainable Development (United Nations, 2001), and the Pressure-State-Use-Response-Capacity (PSURC) model by the Convention on Biological Diversity (Convention on Biological Diversity, 2003). Each adaptation builds upon the PSR's core components and incorporates additional dimensions to capture nuanced socio-ecological interactions (Figure 1). Despite these adaptations, few studies provide empirical assessments of such indicators in field applications. The key question, “how is it possible to use the PSR framework as an operational tool for managing social–ecological interactions,” remains underexplored (Levrel, 2007). Effective response indicators should reflect the iterative social processes and negotiations inherent in conservation strategies. Field observations, especially within biosphere reserves, indicate that responses are often the product of collective efforts and stakeholder negotiations, rather than unilateral control by protected area administrators (Mohedano et al., 2019). Without considering these social processes, response indicators risk becoming overly technical and detached from practical, on-the-ground realities.

3.1. Comparative analysis of environmental frameworks for biodiversity conservation

Environmental management frameworks have evolved to address the complex interplay between human and ecological systems. The original Pressure-State-Response (PSR) model, developed and supported by the Organisation for Economic Co-operation and Development (OECD) and its member countries, provided a foundational structure for understanding environmental issues by linking human-induced pressures to changes in the state of the environment and subsequent societal responses (OECD, 1994). The PSR model embodies an institutional and international approach, reflecting the collaborative efforts of OECD countries to address environmental concerns on a global scale, thereby facilitating standardized methods for environmental reporting and policymaking across different nations (Wurzel et al., 2013).

As environmental challenges became more complex and intertwined with socio-economic factors, subsequent models like DPSIR (Driver-Pressure-State-Impact-Response) and DSR (Driving Force-State-Response) were introduced to capture broader socio-economic dynamics and feedback mechanisms. The DPSIR framework extends the PSR model by adding "Drivers," representing underlying socio-economic forces such as economic growth, and "Impacts," referring to effects on ecosystems and human well-being. This model has been valuable for assessing large-scale environmental issues by tracing how socio-economic drivers lead to environmental pressures, altering the state of the environment, impacting ecosystems and human health, and necessitating societal responses. Despite its utility, the linear structure of DPSIR may oversimplify complex feedback loops and lacks support for adaptive, community-centered management (Maxim et al., 2009). Similarly, the DSR model focuses on "Driving Forces," "State" changes, and "Responses," making it effective for applications like evaluating the impact of urban expansion on water resources (Thibaut and Connolly, 2013). Yet, its simplicity may limit its ability to capture the nuanced interdependencies of socio-ecological systems where community engagement and stakeholder participation are essential. Our enhanced PSR model builds on these frameworks by incorporating community engagement and educational indicators into the "Response" category, thereby directly involving local stakeholders in conservation strategies. Furthermore, the integration of Geographic Information Systems (GIS) and remote sensing data enhances the spatial and temporal analysis of environmental pressures and states, providing high-resolution insights that traditional models may overlook. This technological advancement allows for precise mapping and monitoring of environmental changes, facilitating data-driven decision-making and adaptive management aligned with real-time field data and socio-economic contexts. For instance, consider a scenario where both logging and tourism activities impact a protected forest ecosystem. Traditional frameworks like DPSIR might categorize logging as a "Pressure" and tourism as a "Driver," focusing primarily on their negative impacts on biodiversity and guiding regulatory responses to mitigate these effects. However, such approaches may overlook the potential socio-economic benefits of sustainable tourism, such as funding for conservation and community development. In contrast, our enhanced PSR model treats logging and tourism as interconnected factors, acknowledging both the pressures they exert and the benefits they may provide. By utilizing GIS and remote sensing technologies, we can accurately assess the spatial extent and intensity of these activities, as well as their impacts on forest cover and biodiversity indices. This spatially explicit analysis enables a more nuanced understanding of environmental dynamics and helps identify priority areas for conservation (Karadeniz, 2023). Moreover, by incorporating local education initiatives and community-driven indicators, the model supports the development of tailored conservation strategies that align with local needs and values. This approach fosters community engagement and promotes sustainable practices, enhancing the effectiveness and resilience of conservation efforts. Thus, while the PSR, DPSIR, and DSR frameworks have significantly contributed to environmental management, they often lack the adaptability, spatial specificity, and stakeholder focus required for effective biodiversity conservation in complex socio-ecological systems. Our enhanced PSR model bridges these gaps by integrating institutional support from OECD principles, a broader range of criteria, community involvement, and advanced spatial analysis techniques. This holistic and context-sensitive approach ensures that conservation strategies are ecologically robust, socially equitable, and capable of addressing the multifaceted challenges of contemporary environmental issues.

3.2. Advancing the PSR framework: developing a contextualized, multi-criteria model

Our study builds upon the foundational PSR framework by integrating seven additional criteria, creating a more comprehensive model suited to the complex challenges of biodiversity conservation. This enhanced model directly addresses the need for an operational tool in managing social–ecological interactions, as previously identified by researchers (Hukkinen, 2003b; Wolfslehner and Vacik, 2008). Grounded in extensive field observations and land surveys, our model incorporates ecological and socio-economic data, providing a contextually relevant, empirically validated approach. Among the additional criteria, logging and hunting are included due to their significant impacts on biodiversity. Logging leads to habitat destruction and fragmentation, while hunting affects species populations, threatening sustainability (Ripple et al., 2016; Benítez-López et al., 2017). Geological features and soil types are added to the State category, as they influence habitat integrity and are crucial for understanding species distribution and resilience (Wardle et al., 2004; Bonan and Shugart, 1989). Relict plants are introduced as a criterion, representing species confined to specific areas that create unique habitats and serve as biodiversity hotspots (Hampe and Jump, 2011). Our model emphasizes education and local community involvement as critical Response criteria—elements often underrepresented in other models. Engaging local leaders and educational institutions is essential for sustainable conservation, particularly in areas with high human-nature interaction (Pretty and Smith, 2004; Berkes, 2007). This human-centric approach aligns conservation strategies with community interests and socio-economic realities, increasing the likelihood of success (Levrel and Bouamrane, 2008). Enhanced communication and the inclusion of interaction indicators capturing economic and social dimensions, such as tourism income and land use for agriculture, help balance biodiversity conservation trade-offs (Figure 2).

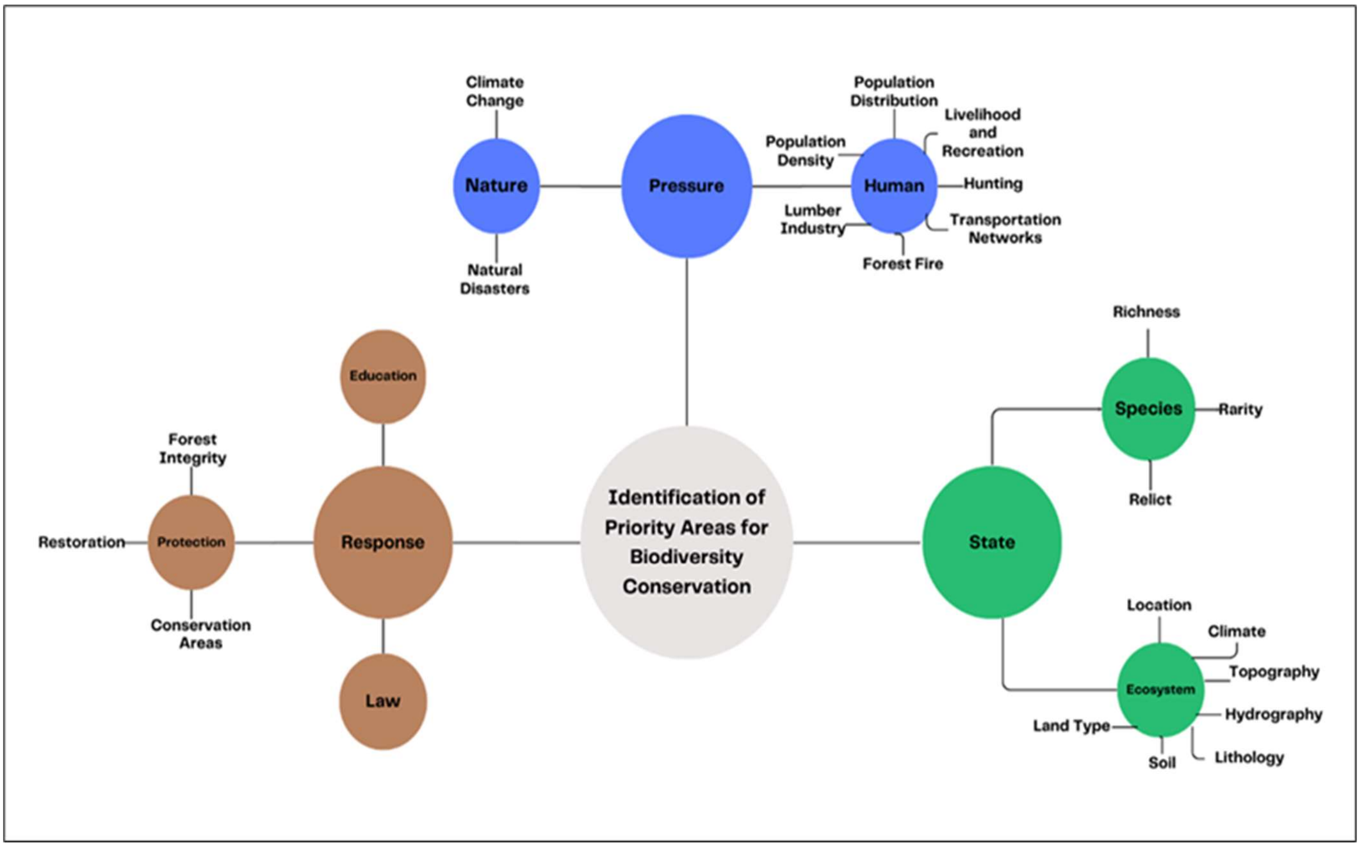

Figure 2. Enhanced PSR framework, incorporating socio-economic and ecological dimensions essential for modern conservation (adapted from Liu, 2007; Wolfslehner and Vacik, 2008; Vu, 2020; Karadeniz, 2024).

This adapted PSR model functions as a multi-criteria decision-making framework, dynamically adjusting the weight of criteria based on specific study area characteristics. A key strength of this approach is its context-specific design, enriched by field observations, allowing for a more accurate alignment with the unique environmental and socio-economic conditions of the region, thereby enhancing the relevance and effectiveness of conservation efforts. By transcending generalized approaches, our study integrates a diverse range of ecological, socio-economic, and environmental factors, presenting a comprehensive and adaptable framework for biodiversity conservation. This holistic, context-sensitive methodology addresses previous limitations, ensuring that conservation strategies are ecologically sound, socially equitable, and economically viable (Adams et al., 2004; Berkes, 2007). By developing an operational tool for managing complex social–ecological interactions, we aim to bridge the theoretical gaps in the PSR framework and provide a practical approach for real-world biodiversity management (Levrel and Bouamrane, 2008).

4. An Overview of Decision-Making Techniques for Environmental Management

Environmental decision-making often involves navigating complex and conflicting objectives that span ecological, economic, social, and cultural dimensions (Guerrero et al., 2020; Peng et al., 2023). Traditional decision-making tools frequently struggle to provide comprehensive and balanced outcomes in such multifaceted contexts. To address these challenges, Multi-Criteria Decision Analysis (MCDA) has emerged as a powerful tool, offering a structured framework for evaluating diverse alternatives and facilitating more informed decisions (Beaudrie et al., 2021). MCDA's strength lies in its flexibility to incorporate both qualitative and quantitative data, making it particularly suitable for situations marked by uncertainty and incomplete information (Pelissari et al., 2021). One of the most widely used methods within MCDA is the Analytic Hierarchy Process (AHP), developed by Thomas L. Saaty in the 1980s. AHP assists decision-makers in systematically comparing criteria and alternatives, even when information is incomplete or subjective. This paper explores the application of MCDA, particularly AHP, in environmental decision-making, discussing how these tools can enhance the robustness and transparency of decisions. Furthermore, modern advancements such as the integration of spatial statistics, fuzzy logic, and artificial intelligence (AI) into MCDA methodologies are examined to highlight their contributions to the field.

4.1. Applying multi-criteria decision analysis (MCDA) techniques in environmental decision-making

MCDA is particularly valuable in environmental contexts characterized by complexity, uncertainty, and conflicting objectives. Its key strength lies in its ability to incorporate a wide range of criteria—ecological, economic, social, and cultural—essential for comprehensive environmental assessments (Esmail and Geneletti, 2017). This holistic approach enables decision-makers to evaluate trade-offs in a structured and transparent manner, facilitating well-informed and balanced decisions that reflect multiple considerations (Geneletti, 2010; Geneletti and Ferretti, 2015). Additionally, MCDA supports stakeholder engagement by integrating diverse perspectives and preferences into the decision-making process, enhancing the legitimacy and acceptance of outcomes, especially in contexts where decisions impact stakeholders with differing values (Pullin et al., 2016; Etxano et al., 2015; Ianni and Geneletti, 2010; Mukherjee et al., 2015). The flexibility of MCDA in handling both qualitative and quantitative data makes it well-suited for addressing complex environmental issues where data might be incomplete or uncertain (Geneletti and Ferretti, 2015; Linkov and Moberg, 2012). Its ability to explore "what-if" scenarios through sensitivity analysis further strengthens decision robustness by assessing the impact of changes in criteria weights or alternative performances, which is particularly valuable in dynamic situations where conditions and priorities may shift (Saltelli et al., 2000; Linkov et al., 2006). Determining the weight of each criterion in MCDA is crucial and should be based on a combination of fieldwork, spatial correlation of variables using zonal statistics methods, and expert opinions. Fieldwork is often the most influential factor, providing direct and context-specific insights critical for accurate decision-making. As discussed in subsequent sections, weighting ratios can also be determined using various methods, depending on the context and specific requirements of the study.

4.2. Understanding the role of the analytic hierarchy process (AHP) in multi-criteria decision-making

The Analytic Hierarchy Process (AHP), developed by Thomas L. Saaty in 1980, is a structured decision-making technique that systematically organizes and analyses complex processes by integrating both quantitative and qualitative criteria (Saaty, 1980). AHP facilitates the evaluation of alternatives by helping decision-makers represent and measure the relative importance of decision criteria and the performance of alternatives (Saaty, 2008). Implemented through a multi-level hierarchical structure consisting of goals, criteria, sub-criteria, and alternatives, AHP allows decision-makers to break down a complex problem into more manageable sub-problems, each of which can be analysed independently (Thakkar, 2021). At the core of AHP is the pairwise comparison process, where elements at each level of the hierarchy are compared with respect to their impact on an element in the level above. These comparisons are typically based on the decision-maker's judgment and are quantitatively expressed using a relative importance scale. After the pairwise comparisons are made, numerical priorities are derived for each decision element. These priorities are then used to calculate a weighted total score for each decision alternative, ultimately identifying the most suitable option. AHP has significantly contributed to the literature as a method for defining priorities and offering systematic solutions to complex decision-making processes. Due to its simplicity and robustness, AHP is widely used by decision-makers and researchers across various scenarios, including policy formulation, risk assessment, resource allocation, and strategic planning (Forman and Gass, 2001). The hierarchical structure of the AHP methodology allows for the measurement and synthesis of various factors in a complex decision-making process, facilitating the integration of the parts into a cohesive whole (Russo and Camanho, 2015). In AHP, the weights of criteria are calculated based on the Saaty scale and the pairwise comparison matrix. Modern extensions and integrations of AHP have further expanded its applicability and effectiveness. One prominent enhancement is Fuzzy AHP, which addresses the inherent uncertainty and vagueness in decision-makers' judgments by incorporating fuzzy logic. This allows for more nuanced evaluations in situations where precise data may be lacking. Another significant development is the Analytic Network Process (ANP), which extends AHP by allowing for interdependencies among decision criteria, offering a more dynamic and interconnected framework for complex decisions (Saaty, 2001). The integration of AHP with Geographic Information Systems (GIS) has also proven particularly useful in spatial decision-making contexts, such as land-use planning and environmental management, where spatial data and criteria weighting are crucial (Malczewski, 2000; Geneletti, 2004; Vizzari, 2011). The synergy between AHP and GIS enhances the decision-making process by allowing for the visualization and analysis of spatial relationships, leading to more informed and effective environmental management strategies (Chowdary et al., 2013; Chandio et al., 2013).

4.3. Integration of multi-criteria decision-making and spatial statistics in environmental analysis

Spatial statistics provide a probabilistic framework necessary for integrating spatial location information with data to address specific queries scientifically (Moores, 2012). This methodology is grounded in the principle of spatial dependence, as described by Tobler's first law of geography, which posits that spatially proximate entities tend to be more similar than those further apart (Tobler, 1969). This fundamental observation underlies the analysis of geographical data and emphasizes the concept of spatial autocorrelation, which describes the clustering or dispersion of spatial data based on distances. Spatial autocorrelation can be categorized as positive or negative, depending on the nature of the relationship between the data and its surroundings. Various spatial autocorrelation indices have been developed to evaluate the spatial dependency between values of the same variable in different locations. These indices are crucial for testing the significance of defined spatial features (Salima and Bellefon, 2018; Perihanoğlu and Yeler, 2021). In this study, both global and local Moran's I and Getis-Ord G* statistics were utilized (Griffith, 2021). Global spatial autocorrelation provides a single measure of spatial correlation for the entire study area, while local spatial autocorrelation measures the spatial correlation of individual features, identifying spatial patterns while considering relationships among these features. The integration of AHP with spatial statistics in biodiversity conservation facilitates the identification of the relative importance or priority values of spatial parameters within the AHP framework. Practically, the application of spatial statistical analyses is simplified through the use of Geographic Information System (GIS) software such as ArcGIS Pro (Milek et al., 2023). This software integrates these complex statistical methods into a user-friendly interface, allowing researchers to visualize data spatially, perform spatial queries, and conduct sophisticated statistical analyses that inform conservation strategies. For instance, ecologists employ spatial autocorrelation analysis to delineate critical habitats and identify potential areas for biodiversity conservation by examining vegetation patterns and animal species distributions (Negret et al., 2020; Diniz-Filho et al., 2002). By integrating the Analytic Hierarchy Process (AHP) with spatial statistical methods, decision-makers can systematically prioritize conservation areas based on the spatial significance of ecological patterns and the relative importance of diverse environmental criteria (Estoque, 2012). This combined approach facilitates more informed and balanced conservation strategies, ensuring that both spatial dependencies and multi-criteria considerations are adequately addressed.

4.4. Utilizing fuzzy logic to enhance multi-criteria decision analysis and spatial statistical approaches

Fuzzy logic plays a critical role in enhancing MCDA and spatial analysis, particularly in addressing the uncertainties inherent in environmental data and decision-making processes. By allowing for more nuanced and flexible modeling of criteria and decision alternatives, fuzzy logic is especially valuable when dealing with imprecise or incomplete data. Although fuzzy logic techniques were not directly applied in this study, their potential for modelling uncertainties cannot be overlooked. In future research, these methods could be integrated into the PSR model to improve the accuracy of multi-criteria analyses. In environmental decision-making, fuzzy logic has been effectively applied to various spatial analysis contexts, often outperforming traditional models like Boolean logic and weighted means. For instance, Moreira et al. (2004) evaluated the performance of fuzzy logic in spatial analysis for mineral prospecting and found it superior in identifying potential areas for radioactive mineral occurrences. This highlights fuzzy logic's ability to handle the complexities and uncertainties in geological data, such as favorable lithology, structural features, and gamma-ray intensity. Similarly, in environmental management, the application of fuzzy logic in spatial analyses could yield more robust results, particularly in areas characterized by high levels of uncertainty. While no such application was conducted in this study, the use of this methodology could be explored in future iterations of the model. In the context of GIS, fuzzy logic techniques have been integrated into MCDA to enhance decision-making precision. Morris et al. (2001) developed a prototype system called FOOSBALL, which implemented fuzzy set membership and methods for criteria weighting and geographic preferences, addressing the weaknesses of classical GIS systems. This approach allows for a more precise representation of decision alternatives and geographic preferences, enabling spatial decision-makers to make more informed and accurate decisions. Within the context of the PSR model, integrating fuzzy logic into spatial analyses could provide greater precision in evaluating regional priorities. When combined with geographic information systems, this approach could significantly contribute to managing spatial uncertainties. Moreover, the integration of fuzzy logic with AI in MCDA and spatial analysis further enhances decision-making processes by combining the strengths of both approaches. While AI can efficiently process large datasets and identify patterns, fuzzy logic excels in managing the uncertainties and imprecise information often present in environmental data. This hybrid approach facilitates more robust and flexible decision-making, particularly in complex and uncertain environments.

4.5. Enhancing multi-criteria decision analysis and spatial analysis through AI

In recent years, Artificial Intelligence (AI) has emerged as a transformative addition to the MCDA process, particularly in optimizing conservation decisions and improving the accuracy of spatial analysis. AI technologies, such as machine learning algorithms and artificial neural networks (ANNs), significantly enhance the ability to process and analyze complex environmental data, enabling more accurate, efficient, and robust decision-making (Zhang et al., 2019; Ivić, 2019; Hill et al., 2005). Although AI techniques were not directly employed in this study, their advantages in big data analysis and managing spatial dynamics present significant opportunities for future research. AI-based tools could enable the PSR model to handle larger datasets and provide deeper insights. AI's role in MCDA is multifaceted. For instance, AI can automate the determination of criteria importance, a critical step in the decision-making process. Traditionally, methods like direct weighting or pairwise comparison (as used in AHP) relied heavily on expert judgment, which could introduce subjectivity and bias. AI-driven approaches, particularly those leveraging machine learning, can analyze large datasets to identify patterns and relationships that might not be evident through human analysis alone (Zhang et al., 2019). These methods continuously learn from data, refining the weighting process over time and allowing for more objective and data-driven decision-making (Malczewski, 2010; Greene et al., 2011). AI-based learning algorithms, in particular, could serve as powerful tools to reduce human biases in multi-criteria decision analysis and enable objective, data-driven analyses. Although this study did not employ such methods, their potential contribution in analyzing larger datasets could be explored in future research. Moreover, AI can enhance spatial statistics by improving the accuracy of analyses like spatial autocorrelation. By handling large datasets more efficiently and identifying subtle patterns, AI provides more precise insights into spatial relationships, leading to better conservation outcomes (Hill et al., 2005; Ferretti, 2011). The use of AI in improving the accuracy of spatial statistics, particularly in large-scale conservation strategies, could be highly effective.

While this was not applied in this study, AI-driven spatial analysis methods could be considered for future projects. AI-driven tools can also automate parts of the MCDA process, making it more accessible and reducing the time required to reach decisions (Eldrandaly et al., 2012). The integration of AI with MCDA and spatial analysis not only improves computational efficiency but also enhances the quality of environmental decision-making. By leveraging AI's capabilities in data processing and pattern recognition, environmental managers can develop more effective and adaptive strategies that respond to the complexities of ecological systems. When integrated with the PSR model, AI techniques are anticipated to significantly enhance the evaluation of spatial dynamics and adaptability to ecological complexities. This could make environmental decision-making processes more robust and effective.

5. Environmental Decision-Making and Weighting Techniques: Insights from the Analytic Hierarchy Process (AHP)

In environmental decision-making, assigning weights to various criteria is a critical process that directly influences the outcomes of the decision model. The Analytic Hierarchy Process (AHP) provides a systematic and hierarchical approach to weighting, ensuring that decision-making is both structured and transparent (Laskar, 2003). The process begins with pairwise comparisons of criteria, where each criterion is evaluated relative to others based on its importance to the decision context. This method employs a standardized scale ranging from 1 (indicating equal importance) to 9 (indicating extreme importance), allowing decision-makers to prioritize criteria based on both subjective judgment and empirical data, making it highly suitable for complex environmental contexts. Building upon this methodology, our study is grounded in extensive fieldwork, comprehensive land surveys, and a thorough review of existing literature. These efforts enabled us to develop a highly detailed and context-specific weighting system, ensuring that the criteria and sub-criteria reflect the unique environmental and socio-economic conditions of the study area. By integrating field observations and stakeholder input with established methodologies, we constructed one of the most exhaustive and inclusive tables of criteria and sub-criteria available in the literature. Table 1 provides a foundational tool for our analysis, detailing the comprehensive range of pressures, states, and responses that encompass both socio-economic and ecological dimensions critical to biodiversity conservation in our region of interest. Despite the robustness of AHP, recent literature has highlighted several challenges associated with weighted decision models. Herson (1977) discusses the limitations of such models, particularly the assumption of unanimous values among stakeholders, which might not hold true in complex environmental contexts. This suggests that in certain scenarios, alternative methods like trade-off analysis may be more suitable for addressing divergent stakeholder objectives. These limitations underscore the importance of adapting and refining traditional models to better accommodate the diverse perspectives and contextual realities inherent in environmental decision-making. After constructing the pairwise comparison matrix in AHP, normalization is performed to convert the comparisons into a proportionate scale. The principal eigenvector of the normalized matrix is then calculated to determine the relative weights of each criterion, reflecting their significance within the overall decision model and ensuring that more critical factors are prioritized. In our study, we identified key criteria such as "Pressure," with significant sub-criteria including "Human" activities and "Nature" impacts. "State" was another important criterion, focusing heavily on "Ecosystem" characteristics, while "Response" emphasized "Education" and "Law" as pivotal elements. These criteria and sub-criteria are outlined in Table 1, providing a comprehensive overview used in our analysis.

Table 1. Detailed breakdown of the enhanced PSR framework, listing specific criteria within the Pressure, State, and Response categories to comprehensively address socio-economic and ecological dimensions in conservation planning (Karadeniz, 2024).

Criterion		**PSR**	**Main Criteria**
No	Class	Class	Class
1	Pressure	Human	Livelihood and Recreation
2			Population Distribution
3			Population Density
4			Transportation Networks
5			Forest Fires
6			Hunting
7			Timber Industry/Logging
8		Nature	Natural Disasters
9			Climate Change
10	State	Ecosystem	Location
11			Climate
12			Topography
13			Hydrography
14			Lithology (Karst)
15			Soil
16			Land Type
17		Species	Rarity
18			Richness
19			Relic
20	Response	Education	Education
21		Law	Law
22		Conservation	Conservation Areas
23			Forest Integrity
24			Restoration

In practice, the selection of weighting methods can greatly impact decision outcomes. For example, Hajkowicz et al. (2000) found that decision-makers in community-based natural resource management often preferred simpler ordinal ranking approaches over fixed-point scoring, emphasizing the need to align the complexity of the weighting method with the capabilities and preferences of decision-makers. The reliability of AHP is largely dependent on the consistency of the pairwise comparisons, quantified through the Consistency Ratio (CR). A CR value below 0.1 is typically considered acceptable, indicating that the judgments are logically consistent and that the resulting weights are reliable. However, Steele et al. (2009) caution that the final ranking of alternatives can be sensitive to the choice of performance scoring scales, even when criteria weights remain constant. This sensitivity underscores the importance of carefully selecting and standardizing scoring scales to prevent unintended biases in the decision-making process.

Once the weights are determined, they are applied within Geographic Information Systems (GIS) to integrate and analyse spatial data, thereby producing an overall score for each spatial unit. This method enables the identification of priority areas for conservation or other environmental management objectives. In our case, the criteria and sub-criteria were applied to create a detailed, spatially explicit conservation prioritization model, incorporating elements such as transportation networks, forest integrity, and species richness. For instance, in the context of biodiversity conservation, the relative importance of criteria such as ecological pressure, habitat state, and conservation responses can vary, and these variations are reflected in the analysis. The literature suggests that traditional weighted models may need to be supplemented or adapted to better fit specific decision-making contexts. Rowley et al. (2012) highlight the subjectivity and uncertainty introduced when aggregating sustainability indicators using multi-criteria decision analysis (MCDA) methods, arguing that the choice of weighting method should be context-specific and transparent. Additionally, AHP facilitates the inclusion of diverse stakeholder perspectives by allowing for separate weighting exercises for different groups. Bengtsson (2000) emphasizes the importance of involving decision-makers in the modelling and interpretation processes, particularly in life-cycle assessments, to ensure that the weights reflect their values and objectives. Furthermore, Odu (2019) discusses the trade-offs between subjective and objective approaches in multi-criteria decision-making. The integration of these approaches through meta-weighting methods, as proposed by Huppes et al. (2012), can address inconsistencies and provide a more balanced and adaptable framework for environmental decision-making. Our model, which integrates extensive field data, stakeholder input, and comprehensive literature analysis, exemplifies this approach, ensuring that the weighting process is both scientifically sound and practically applicable. Overall, while AHP offers a robust method for weighting criteria, the literature underscores the need for flexibility, stakeholder engagement, and careful consideration of context to ensure that the decision-making process is both scientifically rigorous and responsive to the diverse values of stakeholders.

6. Discussion and Conclusion

Our study significantly advances biodiversity conservation by enhancing the traditional Pressure-State-Response (PSR) model through the integration of Multi-Criteria Decision Analysis (MCDA), specifically utilizing the Analytic Hierarchy Process (AHP). This innovative approach, grounded in extensive fieldwork, detailed geographic observations, and comprehensive literature review, has resulted in one of the most contextually relevant criteria selection frameworks currently available. By integrating 24 criteria that encompass both biological and socio-economic factors, our methodology surpasses previous studies that often relied solely on remote sensing and survey data without direct field validation. This dual focus not only addresses the ecological dimensions of conservation but also embeds the socio-economic context, thereby increasing its applicability to real-world scenarios.

By emphasizing biodiversity hotspots, our framework aligns with broader conservation strategies that prioritize regions exhibiting high species diversity, concentrations of endemic species, and significant vulnerability to anthropogenic threats. The hotspot approach is not only cost-effective but also ensures the protection of critical habitats and species while garnering necessary community support for sustainable conservation efforts. This strategy is particularly crucial in developing regions, where economic challenges and chronic poverty intensify conservation difficulties. By concentrating efforts on areas where interventions can prevent the most significant biodiversity losses, our approach effectively balances conservation needs with the practicalities of limited resources. Our findings underscore the critical importance of integrating both ecological and socio-economic factors into conservation planning. Unlike models such as that of Vu et al. (2022), which may not fully incorporate socio-economic dimensions, our comprehensive framework demonstrates the value of detailed fieldwork coupled with rigorous data analysis. This methodological rigor ensures that conservation priorities are scientifically robust and practically applicable, thereby representing a significant advancement in the field.

In conclusion, this study presents a robust and adaptable framework for biodiversity conservation that is capable of addressing the complex challenges of conservation planning on a global scale. The integration of a broader range of factors into conservation planning, as demonstrated, is essential for enhancing the effectiveness and sustainability of conservation efforts worldwide. Future research should aim to refine this model further, incorporating emerging data and advanced techniques to increase its precision and applicability. By providing a tool that is both scientifically rigorous and practically relevant, our framework has significant implications for policymakers and conservation practitioners seeking to optimize resource allocation and conservation outcomes. Furthermore, the integration of advanced technologies such as Geographic Information Systems (GIS), remote sensing, and artificial intelligence (AI) has been pivotal in enhancing the accuracy and precision of identifying priority conservation areas. These technologies have facilitated a comprehensive analysis of pressures, states, and responses, enabling the development of scientifically grounded and effective conservation strategies. Our findings highlight the necessity of incorporating these technologies into conservation planning to optimize resource use and ensure effective biodiversity protection. By significantly advancing the PSR model through the incorporation of a comprehensive and contextually relevant framework, our study provides a robust foundation for effective biodiversity conservation strategies. The integration of socio-economic factors, coupled with a rigorous criteria selection process grounded in detailed fieldwork, literature review, and cutting-edge technologies, underscores the critical impact of human activities on biodiversity and the importance of ecosystem integrity.

Our results highlight the necessity of strong educational and legal frameworks to support conservation efforts. Moreover, given that ecosystems contribute trillions of dollars in goods and services globally, addressing the challenges of poverty and ensuring that conservation efforts do not exacerbate economic inequalities are essential for the long-term sustainability of both conservation initiatives and human livelihoods. Overall, the enhanced PSR model we developed serves as a strategic tool for addressing complex environmental and socio-economic challenges. Its adaptability to diverse conditions of the 21st century makes it a valuable asset for real-world conservation projects, particularly in regions facing significant biodiversity threats. By bridging the gap between scientific rigor and practical applicability, our framework has the potential to significantly influence conservation policies and practices, contributing to the preservation of biodiversity and the well-being of human societies globally.

Conflicts of Interests
Authors declare that there is no conflict of interests

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Statement contribution of the authors
This study's experimentation, analysis and writing, etc. all steps were made by the authors.

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