Review

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Assessing Human Influence on Ecological Dynamics: A Study of Anthropogenic Ecology and Impact Measurement

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Abstract: The current epoch, known as the Anthropocene, is characterized by significant human impact on the global ecological system, including altered species survival and distribution patterns due to global warming resulting from industrialization. Accurately quantifying and assessing the extent of human impact on the environment is of utmost importance. To this end, four primary methods have been developed to measure human impact: (1) ecological footprint, (2) Human appropriation of net primary production (HANPP), (3) Planetary boundary, and (4) Living Planet Index. In this paper, we aim to provide a comprehensive understanding of these methods, including their strengths and weaknesses, to evaluate their efficacy in accurately assessing the impact of human activities on the global ecosystem. Furthermore, we explore the potential of utilizing novel machine learning modelling for future predictions in this area. By analyzing and comparing these methods, we can gain insight into the ways in which human activities impact the environment and use this knowledge to inform future policies and practices to mitigate negative effects.

Keywords: anthropocene; ecological system; human impacts; artificial intelligence; machine learning

1. Introduction

The Anthropocene, the current geological era, has seen humans become a significant force shaping the biosphere, with their influence growing over time [1]. For instance, the total carbon biomass of wild mammals was approximately 0.04 gigatons (Gt) in 100,000 BP, while today it has plummeted to about 0.005 Gt C biomass. Meanwhile, the combined biomass of humans and livestock has surged to around 0.165 Gt C [2]. These changes highlight the profound impact humans have had on the biosphere, with consequences for ecological systems around the world [3].

Among the many consequences of human impact on the biosphere, climate change caused by industrialization is perhaps the most significant [4]. The ecological effects of human activity are therefore of crucial importance for ecological research [5,6]. In this essay, we will describe four primary methods for measuring the ecological impact of human activity: the ecological footprint, human appropriation of net primary production, planetary boundaries, and the Living Planet Index.

The first method, ecological footprint, measures the impact of human activities on the environment by calculating the biologically productive land and water area required to produce the resources that humans consume and absorb the waste that they produce. This method helps identify the specific areas and activities that contribute most to human ecological impact. The second method, human appropriation of net primary production, quantifies the fraction of net primary production that humans use for their own purposes, including consumption, trade, and waste. This method provides insight into the extent to which humans are altering ecosystem functions and services and helps identify the drivers of ecosystem change. The third method, planetary boundaries, assesses the potential impacts of human activities on the Earth's biophysical systems, including the atmosphere, oceans, and land. This method identifies a set of nine key planetary boundaries that, if exceeded, could lead to catastrophic ecological consequences. The fourth method, the Living Planet Index assesses changes in the abundance of thousands of species over time. This method provides a comprehensive and integrated view of the impact of human activities on biodiversity and helps identify the specific species and regions most at risk.

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The four methods discussed above are crucial tools for assessing the ecological impact of human activity. They enable ecologists to gain a better understanding of the complexity of human impacts on the biosphere, identify areas that need attention, and take steps to mitigate negative ecological consequences [7]. By using these methods, we can work towards achieving a sustainable future where human activities are in harmony with the natural world [8].

2. Measuring Human Impact on the Environment

Ecological Footprint

The ecological footprint method is a valuable tool for measuring the impact of human activities on the environment. The ecological footprint is calculated by taking into account several factors such as developed land, forest, grazing land, cropland, fishing grounds, and carbon dioxide emissions related to energy and the atmosphere [9,10]. By measuring these factors, the ecological footprint method provides a comprehensive understanding of how human activities affect the environment.

Human use of land and oceans has remained relatively constant from 1961 to 2006 [10]. However, during this period, the atmospheric component of the ecological footprint (carbon dioxide emissions) increased by a factor of six. This increase in carbon dioxide emissions is directly linked to the industrialization and expansion of human activity. These findings confirm that human activity has had a significant impact on the ecosystem through increased carbon dioxide emissions, leading to a variety of environmental problems such as global warming.

Overall, the ecological footprint method provides valuable insight into the impact of human activities on the environment. It helps us identify the specific areas and activities that contribute most to human ecological impact, and it helps us understand the complex relationship between human activity and the environment. By using this method, we can take steps to mitigate negative ecological consequences and move towards a more sustainable future.

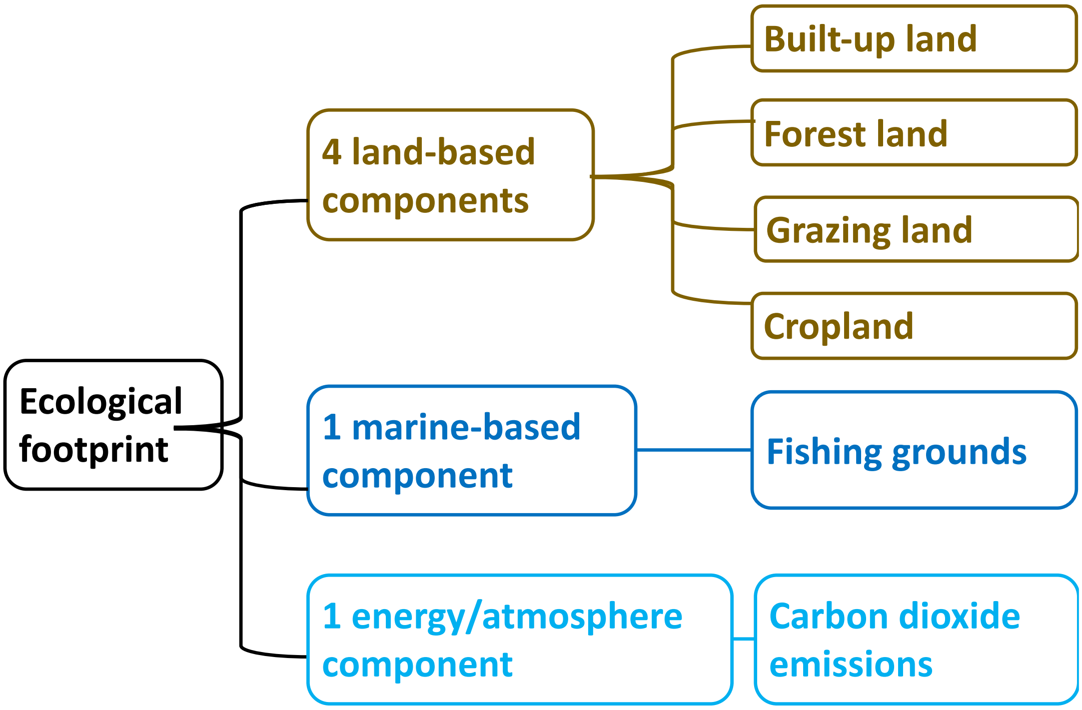

Figure 1. Ecological footprint. The information was from [10] and the figure was replotted by this study.

Human Appropriation of Net Primary Production (HANPP)

The Human Appropriation of Net Primary Production (HANPP) is a vital socioecological indicator that measures the human-induced ecological impacts of production [11]. As human activity

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continues to impact land and biomass, the composition and energy flow of the biosphere are being altered. To better understand how human activity affects land productivity and harvests, Vitousek et al. introduced the concept of HANPP, which quantifies the human impact on productivity and harvests in the ecosystem [12]. Three methods for calculating the HANPP were proposed by Vitousek et al. The first is to measure the biomass used directly by society, such as food or timber. In the second method, the total net primary production (NPP) of human-dominated ecosystems, such as cropland, is calculated. In the third method, NPP is calculated in terms of losses due to human-induced changes in ecosystem productivity, such as forest degradation. By calculating these three aspects, Vitousek et al. can determine the HANPP and understand the human impact on the ecosystem [12].

Haberl et al. conducted a systematic quantification and mapping of the HANPP in the earth's terrestrial ecosystems [13]. By using vegetation modeling, agricultural statistics, forestry data, and geographical information systems, Haberl et al. calculated a global HANPP value of 15.6 Pg C/yr, which is 23.8% of potential net primary productivity [14]. Of this, 53% was due to crop growth, 40% to changes in productivity due to land use, and 7% to human-induced fires. They conclude that human activity can significantly affect the planet and that human impact might increase still more in the future. They recommend a large-scale reassessment of biomass and fuel usage to ensure that human impacts will not exceed the limits that the planet can withstand.

In examining changes in land use in India from 1700 to 2007, DeSouza et al. calculated the HANPP based on the Food and Agriculture Organization's (FAO) dataset for India [15]. They found that the HANPP as a percentage of potential NPP increased from 29% (1700) to 73% (2007), indicating that human activity has significantly impacted the ecosystem. A slow increase in the HANPP was observed from 1700 to 1900, followed by a quick increase from 1961 to 2007 [16]. The study concluded that the impact of human activity on ecosystems in India is rapidly increasing [15,17].

Krausmann et al. found that the global HANPP doubled in the 20th century [18]. Throughout the last century, the HANPP increased from 13% to 25% of global NPP. The primary factors contributing to the HANPP were cropland, grassland, woodland, developed land, and fires. Different regions have different trends: Latin America and Africa had low HANPPs in 1910 that have increased in recent years. Europe has had a high, stable HANPP from 1910 to the present. Russia also had a high HANPP in 1910, which has decreased in recent years. Krausmann et al. recommend careful planning of the energy economy of land-based resources and control of the human impact on global ecosystems to ensure sustainable use of natural resources.

Planetary Boundary

The planetary boundary framework is a useful tool for measuring the impact of human activity on the planet, as suggested by Steffen et al. They propose using this framework to guide human development in order to maintain the earth's resilience and protect human life worldwide [19]. By examining and regulating human behaviour, the planetary boundary framework can help maintain the balance of the planet's ecosystem [19].

Rockström et al. conducted a study examining the global boundaries of several processes [20]. They found that stratospheric ozone depletion, global freshwater use, changes in land use, ocean acidification, and the phosphorus cycle (biogeochemical flow boundary) were at safe levels. However, climate change was at a dangerous level and might exceed the planetary boundary. The nitrogen cycle (biogeochemical flow boundary) and biodiversity loss had already exceeded the planetary boundary and required control (see Figure 2). The study did not quantify atmospheric aerosol loading and chemical pollution. The authors recommend careful monitoring of climate change, biodiversity conservation, and the nitrogen cycle in the future.

Mace et al. proposed a method to calculate the planetary boundary for biodiversity [21]. According to them, biodiversity is crucial in maintaining a safe operating space for humanity. They suggest evaluating the planetary boundary of biodiversity by considering three factors: the genetic library of life, functional type diversity, and biome condition and extent. They also suggest ways to

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measure these three factors and how changes would affect human societies. Additionally, they highlight important conservation areas that scientists and policymakers should focus on.

Newbold et al. studied the impact of land use on biodiversity [22]. They established a safe limit for biodiversity loss, which might have already been exceeded. Human land use has already caused a decline of 10% in biotic intactness on around 65% of the terrestrial surface, which is the planetary boundary identified in their paper. The most significantly impacted areas are grasslands and biodiversity hotspots.

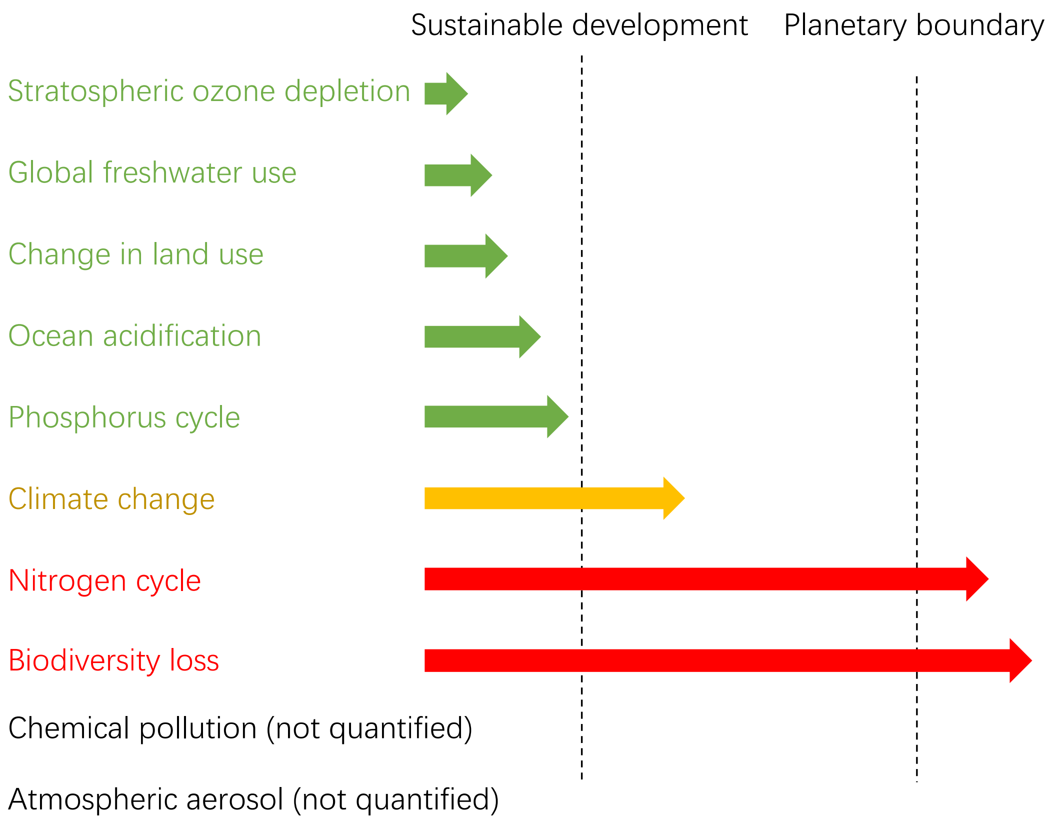

Figure 2. A schematic illustration of planetary boundary. The data were estimated via the previous papers [20,23] and the figure was replotted by the author of this paper. The nitrogen cycle and the biodiversity loss already surpass the planetary boundary.

Living Planet Index

The Living Planet Index (LPI) is an essential tool for measuring human impact on the planet, specifically on the Earth's biodiversity [24,25]. Developed by the Living Planet Database (LPD), the LPI provides insights into the state of the planet's ecosystem and the welfare of its inhabitants. This index uses data from more than 18,000 populations of over 3,600 species of mammals, birds, fish, reptiles, and amphibians worldwide, making it one of the most comprehensive measures of biodiversity trends in the world [25,26].

The LPD, which collects data on the populations of various species around the world, has been a valuable resource in developing the LPI. It tracks changes in the size of populations for each species, using a standardized methodology that allows for comparisons across different types of animals and ecosystems. The LPI, therefore, provides an indication of the health of biodiversity across three ecosystems: terrestrial, marine, and freshwater systems.

The LPI has shown that the overall state of the planet's biodiversity has significantly decreased from 1970 to 2012. The terrestrial LPI has been declining rapidly, indicating that human activities pose the most significant threat to the terrestrial system. The marine LPI decreased from 1970 to 1990 and then remained stable from 1990 to 2012. In contrast, the freshwater LPI decreased from 1970 to 2007 but increased from 2007 to 2012 [25].

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This decline in the LPI is mainly due to human activities such as habitat destruction, pollution, and overfishing. Habitat destruction is a major threat to biodiversity, especially in the terrestrial system. Forests, for instance, are cleared to make way for agriculture and urbanization, leading to a decline in the populations of species living in these areas. Polluted water bodies pose another significant threat to freshwater biodiversity. Overfishing, on the other hand, has led to the decline of marine biodiversity.

In conclusion, the LPI is an essential tool for monitoring and evaluating the state of the planet's biodiversity [27]. It provides valuable insights into the health of ecosystems and the welfare of their inhabitants. The decline in the LPI highlights the urgent need for more sustainable practices to protect the planet's biodiversity. It is crucial to take action to conserve and restore habitats, reduce pollution and overfishing, and promote sustainable practices to ensure the long-term survival of the planet's biodiversity.

Table 1. Summary of different methods calculating human impacts to global ecology.

Methods	Basic concept	Main components	Unit	Advantages	Limitations	Reference
Ecological footprint	Human activities measured in terms of productive land	Land, marine, and atmosphere	Hectare (ha)	General view of ecology	Difficulty during calculation of mixed land areas	[28-30]
HANPP	Human contribution fraction based on net primary production	Potential NPP, ecosystem NPP, land use NPP, harvest NPP	annual carbon exchange fluxes (Pg C/yr)	Trackable data; Good understanding of land use	Lack of considering the land differences	[31-33]
Planetary boundaries	9 major indicators representing earth system's limit	Climate change, ozone depletion, biodiversity loss, etc	Different units for different indicators	Easy understanding to public	Controversial view during defining the limits	[20,34,35]
Living planet index	The complex index calculating the planet condition	Terrestrial index, marine index, freshwater index	No unit	Clear figure and trend	Questionable calculating methods	[25,36,37]

3. Big Data and Machine Learning on Human Activity Prediction

In recent years, there has been a growing trend in utilizing big data and machine learning techniques to predict outcomes in complex systems. This trend has been observed across various scientific fields, such as ecology, biology, and environmental science [38-40]. Big data and machine learning algorithms enable scientists to input various factors and predict outcomes with greater accuracy and efficiency.

In ecology, machine learning has been used to predict ecological footprints, which is an important metric that provides insight into the impact of human activities on the environment. For example, one study utilized machine learning to predict ecological footprints in China, which helped identify key factors that contribute to the ecological footprint, such as population density, urbanization, and industrialization [41,42].

Similarly, machine learning may be used to predict the Human Appropriation of Net Primary Productivity (HANPP), which is another important metric that measures the extent to which human activities impact the productivity of ecosystems. For instance, a recent study utilized machine learning to model HANPP in Europe, which helped identify the key drivers of HANPP, such as land use change and population density [43,44].

Moreover, machine learning algorithms can be used to predict planetary boundaries, which are the critical thresholds that define a safe operating space for humanity. By utilizing machine learning,

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scientists can identify key drivers of planetary boundaries, such as climate change, biodiversity loss, and land use change. This knowledge can inform policy decisions and help to mitigate the impacts of human activities on the environment [45-47].

Furthermore, machine learning has been used to predict the Living Planet Index, which is an important measure of the state of the world's biodiversity. By analyzing big data sets, scientists can identify patterns in biodiversity loss and gain insights into the drivers of these trends. For example, a recent study utilized machine learning to analyze the Living Planet Index, which helped identify key drivers of biodiversity loss, such as habitat loss, climate change, and overexploitation [48,49].

The application of big data and machine learning has transformed our capability to forecast outcomes in intricate systems. By utilizing these advanced technologies, scientists have gained a deeper understanding of critical environmental indicators such as ecological footprints, HANPP, planetary boundaries, the Living Planet Index, and human behaviour. This improved understanding enables policymakers to make more informed decisions regarding environmental governance [50,51]. As an illustration, the utilization of machine learning techniques to achieve more accurate predictions can empower policymakers to formulate more effective strategies for addressing various environmental issues, including chemical pollutants [52-56] and biological concerns in waterways or porous media [57-59]. By doing so, policymakers can take proactive measures to mitigate the negative impacts that humans have on the environment [60-62]. This can ultimately help to ensure the sustainability of natural resources for future generations [63-65].

4. Conclusion

In the era of the Anthropocene, human activities are exerting increasingly significant impacts on the natural environment. As a result, accurately quantifying the extent of these impacts is of paramount importance. This paper has examined four major quantifying methods (ecological footprint, HANPP, planetary boundaries, living planet index) that have been widely used in previous research. It has become evident that each method has its own advantages and limitations, and it is essential for researchers to carefully evaluate and select the appropriate method based on the specific research targets and requirements. By doing so, we can gain a better understanding of the complex relationship between humans and the environment and develop more effective strategies for achieving sustainable development.

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