Machine Learning Approaches in Forecasting Biodiversity Disclosures

Abstract

The growing ecological and financial risks associated with biodiversity loss underscore the need for transparent corporate reporting. This study applies machine learning to examine firm-specific, industry-related, and macroeconomic factors influencing biodiversity disclosures. Analyzing a comprehensive dataset of U.S. firms from 1994 to 2022, we assess the predictive performance of TreeNet® (gradient boosting), Random Forest®, and CART® models. Our results indicate that TreeNet® achieves the highest accuracy, outperforming traditional approaches. Among the key predictors, accounting-related variables—such as asset tangibility, industry competition, and firm size—demonstrate the strongest predictive power, while governance and market factors exhibit moderate influence. The findings highlight the variability of biodiversity disclosures across industries and emphasize the potential of machine learning in sustainability research. By leveraging data-driven insights, this study provides valuable guidance for policymakers, investors, and corporate leaders in improving biodiversity accountability.

Key words: Biodiversity; machine learning; disclosure; environmental risk; sustainability

1. Introduction

Biodiversity, encompassing the diversity of life across species, ecosystems, and genetic resources, is fundamental to ecological stability and human survival (The Guardian, 2018;

United Nations [UN], 2023; United Nations Foundation, 2023; World Wildlife Fund [WWF], 2024a). It underpins critical ecosystem services such as pollination, water purification, and climate regulation, all of which are crucial for global economy (Sherman, 2024). However, biodiversity is declining at an unprecedented rate due to human activities such as deforestation, habitat destruction, and pollution (Ceballos, Ehrlich, & Dirzo, 2017; World Wildlife Fund [WWF], 2024b). The World Wildlife Fund [WWF] (2022) indicates a staggering 69% reduction in global wildlife populations since 1970, raising economic concerns and prompting businesses to recognize their role in biodiversity loss (Blanco-Zaitegi, Álvarez Etxeberria, & Moneva, 2022). Consequently, there is growing demand for corporate biodiversity risk disclosures to enhance transparency and accountability (Ernst & Young [EY], 2022; Price Waterhouse Coopers [PwC], 2024).

In this study, we employ state-of-the-art machine learning techniques to identify the factors driving corporate biodiversity risk disclosure. The contemporary literature highlights machine learning as a powerful tool for processing large datasets, identifying patterns, and making predictive inferences (Mullainathan & Spiess, 2017; Krupa & Minutti-Meza, 2022; Frost, Jones, & Yu, 2023; Kaya, Reichmann, & Reichmann, 2024). Compared to traditional regression methods, machine learning offers superior out-of-sample prediction and reveals complex variable interactions and nonlinear relationships (Jones et al., 2023). Despite its potential, the application of machine learning in biodiversity research remains underexplored.[1] In this study, we aim to address this critical gap in the literature by employing machine learning model to provide deeper insights into the interplay between governance structures, regulatory environments, stakeholder pressures, and firm characteristics in shaping biodiversity reporting practices.

[1] Extant biodiversity literature relies on traditional statistical methods (e.g., Haque & Jones, 2020; Krause, Droste, & Matzdorf, 2021; Carvajal, Nadeem, & Zaman, 2022; Hambali & Adhariani, 2024; Orazalin, Ntim, & Malagila, 2024; Orazalin, Ntim, & Kalimilo Malagila, 2025).

This study is motivated by two key factors. First, biodiversity disclosures are crucial for assessing firms' ecological impacts and environmental accountability (Ernst & Young [EY], 2022; Price Waterhouse Coopers [PwC], 2024), yet current reporting remains limited, inconsistent, and incomplete (Boiral, 2016; Krause et al., 2021). Only 5% of earnings calls and 3.8% of 10-K filings address biodiversity risks (Garel, Romec, Sautner, & Wagner, 2024; Giglio, Kuchler, Stroebel, & Zeng, 2023). Unlike climate risks, which are quantified through standardized metrics like carbon emissions, biodiversity encompasses diverse dimensions, including land use, species richness, and ecosystem functionality (Hoepner et al., 2023; Schimanski et al., 2023). While emerging frameworks such as the Taskforce on Nature-related Financial Disclosures (TNFD) and Iceberg Data Lab's Corporate Biodiversity Footprint (CBF) seek to standardize reporting, challenges persist, including slow adoption, data limitations, and regulatory gaps (Trinh, 2023).

Second, biodiversity loss poses substantial financial risks, with the World Economic Forum [WEF] (2020) identifying it as one of the top five threats to global economic stability, as an estimated $44 trillion of global GDP depends on nature and its services. Firms with high biodiversity impacts often face higher costs of equity and limited access to capital due to heightened regulatory scrutiny and reputational risks (Hoepner et al., 2023; Liu et al., 2024). However, existing ESG frameworks inadequately capture these risks (Xin, Grant, Groom, & Zhang, 2023). The Kunming Declaration and Montreal Agreement highlight biodiversity's growing relevance in investment strategies (Giglio, Kuchler, Stroebel, & Zeng, 2023; Flammer, Giroux, & Heal, 2025). This underscores the need to understand the drivers of corporate biodiversity disclosures. We argue that machine learning models can enhance biodiversity risk disclosure prediction, improving transparency and supporting data-driven sustainability governance. By providing a scalable and systematic approach to assessing disclosures, machine learning aids investors, regulators, and policymakers in evaluating corporate biodiversity risks.

Using a large dataset of U.S. firm-year observations from 1994 to 2022, we assess the predictive performance of machine learning models in forecasting biodiversity risk disclosure. We employ TreeNet® (gradient boosting), Random Forest®, and CART® models. Consistent with Giglio et al. (2023), we define biodiversity risk disclosure as an indicator variable that takes a value of one if a firm's 10-K statement includes at least two sentences about biodiversity risk. Following prior studies (e.g., Haque & Jones, 2020; Krause et al., 2021; Carvajal et al., 2022; Hambali & Adhariani, 2024; Orazalin et al., 2024; Orazalin et al., 2025), we employ more than 80 variables, including firm-level financial characteristics, stock market factors, corporate governance, environmental performance, and industry factors, as predictors of firm-level biodiversity disclosure. In addition to out-of-sample testing, we use marginal effects and partial dependence plots (PDPs) to reveal predictor strength, direction, and possible nonlinear relationships.

We find that the cross-sectional out-of-sample predictive performance of the TreeNet® gradient boosting model (GBM) consistently outperforms alternative approaches, achieving the highest ROC value (0.9266) and the lowest misclassification rates (2.84%). This strong predictive performance is particularly evident in the consumer durables, energy, telephone and television transmission, utility and other industries, as reflected in their AUC scores exceeding 0.9171. When examining the predictive performance across different variable dimensions, we find that the accounting dimension outperforms others in terms of predictive accuracy. Our analysis of the relative variable importance (RVI) suggests that asset tangibility (PPE) is the most critical variable, followed closely by industry competitiveness (Herfindahl index), number of employees and Total Assets. Notably, we observe an overall non-liner impact of these variables in predicting biodiversity disclosure. These results remain robust in longitudinal analysis and across alternative sample periods. Further robustness checks, including stability tests with varying model parameters and cross-validation methods, confirm these findings.

Overall, our study highlights the significance of integrating advanced machine learning techniques with a comprehensive dataset to provide valuable insights for biodiversity disclosure and strategic decision-making.

Our study makes several significant contributions. First, our study is among the first to apply advanced machine learning techniques to biodiversity disclosures, expanding the use of artificial intelligence in sustainability accounting. While prior research relies on traditional statistical models (e.g., logistic regression, fixed effects) to assess corporate disclosure practices (Haque & Jones, 2020; Krause et al., 2021), we leverage machine learning to uncover complex, non-linear relationships between firm-level and industry-level factors and biodiversity disclosures. We show that machine learning models, particularly GBM, outperform traditional methods in identifying key determinants of biodiversity disclosures. By integrating machine learning with a comprehensive dataset, our study advances environmental accountability research and lays the foundation for AI-driven sustainability assessments.

Second, we contribute to the growing literature on biodiversity disclosures. While prior research suggests corporate governance, stakeholder pressures, and regulatory frameworks as key drivers (e.g., Hassan, Roberts, & Atkins, 2020; Carvajal et al., 2022; Ali, García-Sánchez, Aibar-Guzmán, & Rehman, 2024; Treepongkaruna, 2024; Orazalin et al., 2025), few studies systematically compare their relative significance. Using RVI metrics from machine learning models, we find that asset tangibility, industry competitiveness, and firm size are primary determinants of biodiversity disclosures, while market factors and corporate governance mechanisms also play a role. These findings underscore the importance of external monitoring in fostering corporate transparency, reinforcing prior work on the role of regulators, media, and NGOs in promoting accountability and disclosure practices (Boiral, 2016; Haque & Jones, 2020).

Third, we extend emerging machine learning literature in accounting and finance by demonstrating the superior predictive performance of GBM in biodiversity disclosure. This builds on studies showcasing machine learning's effectiveness in predicting financial distress (Jones, 2017), detecting fraud (Bao, Ke, Li, Yu, & Zhang, 2020; Lokanan & Sharma, 2025), forecasting stock returns and profitability (Avramov et al., 2023; Leippold et al., 2022; Jones et al., 2023), and assessing environmental, social and governance (ESG) performance (Zhu & Rahman, 2025). Our finding of non-linear relationships in biodiversity disclosure prediction aligns with extend studies highlighting the importance of capturing complex and non-linear patterns in financial data (Jones, 2017). Moreover, our longitudinal validation supports the reliability of machine learning models over time in financial applications, addressing concerns about temporal stability (Giglio et al., 2021).

Our findings have important policy and managerial implications. For policymakers, the superior predictive performance of machine learning models underscores the potential for AI-driven regulatory monitoring and enforcement in biodiversity disclosures. Regulators can leverage these models to identify firms with inadequate disclosure practices and design targeted interventions to enhance transparency. For managers, our results highlight the critical role of firm characteristics—such as asset tangibility, industry competitiveness, and corporate governance—in shaping biodiversity disclosure outcomes. Firms seeking to improve their sustainability reporting should prioritize governance mechanisms that enhance external monitoring and stakeholder engagement. Additionally, as machine learning reveals complex, non-linear relationships in disclosure practices, companies can integrate AI-driven analytics into their sustainability strategies to anticipate regulatory expectations and strengthen environmental accountability.

2. Theoretical background and literature review

2.1. Theoretical background

Corporate biodiversity disclosure is shaped by multiple theoretical perspectives that provide complementary insights into how firms manage biodiversity disclosures to align with stakeholder expectations, build trust, and mitigate environmental risks. We draw on legitimacy theory, signalling theory, and stakeholder theory to explore the determinants of biodiversity disclosure.

The legitimacy theory of biodiversity disclosure posits that firms voluntarily disclose their biodiversity impact to maintain a "social license to operate," and align with societal expectations for transparency (Dowling & Pfeffer, 1975; Haque & Jones, 2020). These disclosures are particularly crucial in high-impact industries such as energy, mining, and agriculture, where they help mitigate external pressures and enhance corporate reputations (Haque & Jones, 2020). Robust biodiversity reporting enhances corporate legitimacy by demonstrating genuine environmental efforts (Jones, 2003), while vague or unverifiable disclosures undermine accountability and stakeholder trust (Clarkson, Li, Richardson, & Vasvari, 2008). Comprehensive disclosures further align firms with global conservation efforts, reinforcing legitimacy among stakeholders and regulators.

The signalling theory suggests that firms voluntarily disclose biodiversity-related information to signal superior environmental performance to stakeholders (Spence, 1973). Firms with strong biodiversity performance use these disclosures to differentiate themselves from peers, demonstrating accountability and proactive risk management (Brooks & Schopohl, 2021). Transparent and detailed reporting reduces information asymmetry, enhances reputation, and provides competitive advantages, such as access to green financing and stronger stakeholder relationships (Braam et al., 2016). Nonetheless, firms with weak biodiversity performance may limit transparency to obscure shortcomings, exacerbating information asymmetry. The board plays a critical role in ensuring the credibility of biodiversity disclosures, overseeing sustainability commitments, and preventing greenwashing (Haque & Jones, 2020; Hambali & Adhariani, 2024; Orazalin et al., 2025).

The stakeholder theory posits that firms disclose biodiversity-related information to address the diverse demands of stakeholders, including regulators, NGOs, investors, and local communities (Freeman, 2010; Ali et al., 2024). Recognizing the growing emphasis on environmental sustainability, companies use biodiversity disclosures to foster trust and demonstrate accountability. Stakeholder pressure encourages firms to integrate biodiversity considerations into their reporting frameworks, enhancing transparency and aligning with global environmental goals. Consequently, firms with strong biodiversity performance are more likely to voluntarily disclose their initiatives to meet stakeholder expectations and sustain collaborative relationships (Gerged et al., 2024).

2.2. Biodiversity literature and determinants

With the growing importance of biodiversity conservation, a growing body of literature examines the factors driving variations in biodiversity disclosure. As with other areas of sustainability reporting, biodiversity disclosures vary significantly across firms and industries, reflecting differences in organizational capabilities and priorities, stakeholder pressures, and regulatory environments (Giglio et al., 2023). In this study we employ a comprehensive set of features influencing biodiversity disclosure practices.

While selecting biodiversity disclosure predictors, we include key determinants from prior literature and other plausible factors, even if they remain explicitly underexplored. This broad approach is warranted by two considerations. First, no clear theoretical or empirical consensus exists on the relative importance of specific determinants, as firm-level characteristics and external factors influencing biodiversity disclosure are often highly correlated. However, prior research and corporate reporting practices suggest that some factors are more influential. Given the ability of GBM to unravel signals from correlated predictors, this study examines how well the model can differentiate among them. Second, incorporating a comprehensive set of predictors allows the model to explore a wide feature space and identify the most influential factors. The findings contribute to the theoretical discourse on biodiversity disclosure drivers and deepen our understanding of corporate sustainability reporting mechanisms.

2.2.1. Accounting dimension (ACCT)

Extant literature suggests that accounting and financial factors significantly shape firms' biodiversity risk disclosure. Larger and mature firms—measured by total assets, sales, employee size and firm age—tend to disclose biodiversity risks due to greater stakeholder scrutiny and resource availability (Ali et al., 2024; Garel et al., 2024). Profitable firms, captured by return on equity (ROE), return on assets (ROA), profit margin, and industry-adjusted ROA, may disclose biodiversity risks to signal financial strength and long-term sustainability commitments (Clarkson et al., 2008; Ali et al., 2024). However, financially distressed firms, indicated by Altman's Z-score, may be less transparent due to resource constraints and short-term financial survival priorities (Beck et al., 2018). Financial leverage also influences biodiversity disclosure, as creditors may pressure highly leveraged firms to adopt risk-averse strategies (Garel et al., 2024).

Investment and operational efficiency also influence biodiversity disclosure. Firms with higher capital expenditures (CAPX) and research and development (R&D) intensity may disclose more due to long-term strategic focus and regulatory compliance requirements (Qian & Chen, 2021; Orazalin et al., 2024). The newness of property, plant, and equipment (PPE) can reflect environmental commitment, potentially influencing disclosure practices (Garel et al., 2024). Market competition, captured by the Herfindahl Index, can shape disclosure strategies, with firms in concentrated industries engaging in greater transparency to differentiate themselves (Benlemlih et al., 2024). Additionally, higher advertising expenses (Advertising Exp.), sales growth (Sales Growth), EPS growth and total assets growth may drive disclosure as part of brand-building strategies (Huang & Kung, 2010; Garel et al., 2024).

Firms with higher cash holdings (Cash), operating cash flow (OCF), and liquidity (current ratio) have more financial flexibility to invest in sustainability initiatives and disclosures (Benlemlih et al., 2024; Orazalin et al., 2024). Dividend paying firms signal stability and commitment to stakeholder, enhancing biodiversity disclosures (Benlemlih et al., 2024). Conversely, financing constraints, measured by the Kaplan-Zingales (KZ) index, limit disclosure due to limited financial resources. Overall, firm-specific financial conditions critically influence biodiversity risk disclosure.

2.2.2 Market-related dimensions (MKT)

Market-related factors influence firms' biodiversity risk disclosure practices by shaping investor expectations, firm valuation, and corporate transparency. Higher share prices and stock returns signal market confidence, incentivizing firms to enhance biodiversity disclosures to maintain investor trust (Cormier & Magnan, 1999). Conversely, firms with high stock return volatility (RET_SD) face greater scrutiny and may enhance environmental disclosures to mitigate risks (Clarkson et al., 2008). Market capitalization (MCap), reflecting firm size and prominence, is positively associated with biodiversity risk disclosure due to heightened public and regulatory expectations (Cormier et al., 2005; Garel et al., 2024).

Capital structure and valuation also influence biodiversity disclosure. Firms raising capital may disclosure biodiversity risk to attract investors and lower financing costs (Cormier et al., 2005; Clarkson et al., 2011). Similarly, the market-to-book ratio (MTB) and its industry-adjusted counterpart (Ind. Adj_MTB) signal growth potential, with high-growth firms disclose more biodiversity risks to align with long-term sustainability trends (Haque & Jones, 2020). Additionally, firms reliant on capital markets (Capital Mkt. Reliance) may disclose biodiversity risks to meet investor demand and secure external financing (Cormier et al., 2005).

Risk and liquidity considerations shape disclosure practices. Systematic risk (BETA) is positively associated with disclosure, as high-risk firms increase transparency to reduce information asymmetry (Cormier et al., 2005). Firms with high trading volume, a proxy for stock liquidity, may enhance disclosures to sustain investor engagement (Cormier et al., 2005; Benlemlih et al., 2024). Overall, financial markets play a critical role in shaping corporate biodiversity reporting.

2.2.3 Corporate governance dimension (GOVERN)

Corporate governance has considerable impact on corporate biodiversity disclosure. Strong governance mechanisms enhance transparency and accountability, compelling firms to disclose more environmental information (Haque & Jones, 2020; Ali et al., 2024). Larger boards (Board Size) bring diverse expertise and foster biodiversity-related disclosures, while independent directors (Board Independence) advocate for responsible environmental practices (Haque & Jones, 2020). Gender Diversity enhances corporate sustainability, leading to higher biodiversity disclosure (Haque & Jones, 2020). High meeting attendance reflects board diligence, reinforcing biodiversity disclosure efforts (Ali et al., 2024). However, CEO Duality can reduce disclosure, as powerful CEOs may resist transparency (Haque & Jones, 2020; Lu & Wang, 2021). Similarly, CEOs with significant ownership (CEO Ownership) stakes may prioritize profitability over sustainability, reducing biodiversity disclosure (Gerged, 2021).

Ownership structure also influences biodiversity risk disclosure. Institutional investors consider environmental risks in investment decisions (Ali et al., 2024), with long-term investors (Dedicated Ownership) exerting stronger pressure than short-term investors

(Transient Ownership). The effect of blockholder ownership (Blockholder Ownership) depends on whether large shareholders perceive biodiversity disclosure as value-enhancing. High institutional ownership concentration may create agency conflicts, leading to selective disclosures that align with dominant investors rather than broader stakeholders (Cormier et al., 2005). Analyst coverage prompts firms to either to enhance biodiversity disclosure to mitigate reputational risks or limit it to avoid regulatory scrutiny (Ali et al., 2024).

With respect to other governance mechanisms, firms audited by a Big4 auditor disclose more biodiversity information due to greater assurance and credibility (Simnett et al., 2009). Strong employee relations and human rights commitments enhance transparency (Mallin et al., 2013). CEO attributes also matter—CEOs with MBAs or female CEOs demonstrate stronger sustainability commitments (Lewis et al., 2014). CEO tenure has a nonlinear effect; experienced CEOs may enhance sustainability or resist change (Haque & Jones, 2020), while younger CEOs are often more open to sustainability initiatives. Media scrutiny pressures firms to disclose biodiversity risks to manage public perception (Clarkson et al., 2011). A newly appointed CEO may use enhanced disclosures to establish credibility and signal a strategic shift from prior leadership (Lewis et al., 2014).

2.2.4 Environmental performance dimension (ENVIRON)

Environmental performance plays a critical role in biodiversity risk disclosure. Firms with lower CO_2 emissions and waste generation signal superior environmental responsibility, incentivizing greater disclose of their biodiversity impact (Orazalin et al., 2024; Garel et al., 2024). Similarly, higher environmental performance correlates with greater biodiversity disclosure due to stronger stakeholder accountability, while higher environmental concerns may either increase disclosure to mitigate reputational risks or reduce disclose due to litigation risks (Cho et al., 2006). Additionally, firms that actively recycle waste or engage in waste reduction initiatives are inclined to disclose biodiversity information as part of their broader environmental commitment (Orazalin et al., 2024).

Corporate sustainability structures also influence biodiversity disclosure. The presence of a CSR committee or an environmental management team strengthens a firm's environmental governance framework, enhancing transparency in biodiversity reporting (Haque & Jones, 2020). Firms receiving environmental fines may disclose biodiversity risks to comply with regulatory requirements or rebuild stakeholder trust (Brammer and Pavelin, 2008). Similarly, firms investing in environmental restoration or sustainability initiatives tend to disclose more to highlight their risk mitigation efforts (Brammer & Pavelin, 2006). Furthermore, firms receiving CSR awards or making environmental investments may disclose biodiversity risks to strengthen their sustainability credentials (Hassan et al, 2020).

Firms with greater climate exposure may disclose biodiversity risks as part of their broader climate strategy (Sautner et al., 2023). Higher climate change sentiment, reflecting greater awareness and concern about climate-related issues, prompts firms to increase transparency regarding biodiversity risks. Additionally, firms reporting reduction in biodiversity impact and land use impact tend to disclose more biodiversity information to signal a proactive environmental stewardship (Clarkson et al., 2008).

2.2.5. Other dimension (others)

Other firm- and industry-level characteristics also affect biodiversity risk disclosure. Sectoral differences in environmental exposure and regulatory pressures shape disclosure practices. High-impact industries (e.g., energy, materials) face greater scrutiny and disclose more about biodiversity, whereas service sectors generally disclose less (Giglio et al., 2023; Garel et al., 2024). Technology firms **(**HITECH), despite having less direct environmental impacts, may disclose biodiversity risks to maintain legitimacy and investor confidence. Multinational operations (Foreign Operation) also drive disclosure as these firms navigate diverse regulatory frameworks and stakeholder expectations (Benlemlih et al., 2024). Finally, while economic crises (Crisis) can constrain voluntary reporting resources, they simultaneously intensify market demands for biodiversity transparency.

2.3. Machine learning method in accounting and finance

Machine learning has become increasingly important in accounting and finance due to its ability to analyze complex datasets, enhance predictive accuracy, and support evidenced-based decision-making (Krupa & Minutti-Meza, 2022). Unlike traditional models – such as linear regression and logistic models—that require strict assumptions and prior variable selection, machine learning methods can process large-scale, heterogeneous data and identify nonlinear relationships without succumbing to overfitting (Geertsema & Lu, 2023). Importantly, machine learning model autonomously identify the most pertinent predictors and model their interactions, uncovering insights that may remain undetected when using conventional techniques (Jones, 2017).

Advanced machine learning methods, such as gradient boosting machine (GBM) and random forests, leverage ensemble learning to integrate multiple models, thereby reducing error margins and enhancing predictive reliability. Furthermore, these approaches help mitigate the risk of *p*-hacking—a common issue in traditional statistical research—by prioritizing predictive performance over exclusive reliance on statistical significance (Ohlson, 2022). This methodological shift not only improves reproducibility but also bolsters the overall credibility of research findings.

Contemporary research in accounting and finance has increasingly employed machine learning models to predict various financial and accounting outcomes. For example, Bao et al. (2019) demonstrate that machine learning models, specifically RUSBoost, outperform conventional techniques such as logistic regression and support vector machines in detecting accounting fraud. Similarly, Bertomeu et al. (2020a) find that GBM is effectively identify accounting misstatements when financial, audit, and market data were integrated. Ding et al. (2020) show that machine learning yields more accurate estimates of insurance loss reserves than those reported by managers, facilitating the detection of both unintentional errors and deliberate misreporting. Extending this line of research, Jiang et al. (2024) use machine learning to forecast stock price crash risks in China's stock market, attaining superior accuracy compared to conventional methods. Furthermore, Jones et al. (2023) demonstrate that machine learning can reveal complex relationships among profitability indicators using the DuPont decomposition model, while Jones (2017) finds that gradient boosting outperforms logistic regression in predicting corporate bankruptcies. Building on this growing body of literature, in this study we employ machine learning to predict biodiversity risk disclosure.

3. Research methods

3.1. Data and sample

We construct our sample by integrating data from multiple sources: financial information from Compustat, stock price and return data from the Center for Research in Security Prices (CRSP), stock ownership data from Thomson Reuters Institutional Holdings (13F) database, executive-level information from Execucomp, board-level data from Institutional Shareholder Services (ISS) and BoardEx, and environmental, social, and governance (ESG) data from MSCI and Refinitiv ESG. We exclude financial firms (SIC codes 6000–6999). All continuous variables are winsorized at the 1st and 99th percentiles to mitigate the impact of extreme outliers. The final sample consists of 14,948 US firm-year observations covering the period from 1994 to 2022.

3.2. Measurement

We quantify firm-level biodiversity risk disclosure through a novel 10K-biodiversity-count score, derived from a rigorous textual analysis of corporate 10-K filings. Leveraging a sophisticated methodology developed by Giglio et al. (2023), our approach employs a specialized biodiversity dictionary with meticulously refined taxonomic terms to systematically identify and extract biodiversity-related sentences. The analysis is implemented via the Seekinf platform's (https://www.seekinf.com/) advanced natural language processing capabilities, which implement targeted regular expression searches to precisely locate and extract sentences referencing biodiversity risk.

We ensure methodological rigor through a multi-stage filtering process that eliminates contextually irrelevant mentions. The comprehensive biodiversity vocabulary and specific terminological criteria are exhaustively documented in Appendix OA.1. This innovative metric serves as a nuanced proxy for corporate biodiversity awareness, capturing the depth and complexity of firms' engagement with and reporting on biodiversity-related risks. For our analysis, following Giglio et al. (2023), we classify biodiversity risk disclosure as a binary variable equal to one if the 10-K statement contains at least two sentences addressing biodiversity, and 0 otherwise.

3.3. Prediction model

In this study, we use three tree-based machine learning models for analysis: classification and regression trees (CART) (Breiman et al., 1984), random forests (Breiman, 2001), and gradient boosting machines (GBM) (Friedman, 2001). All these models share a tree-based foundation but differ in construction, complexity, and predictive performance.

CART: CART is a fundamental decision tree model that recursively splits data based on significant variables to predict outcomes. CART is simple and interpretable but prone to overfitting with complex datasets. Nonetheless, it serves as a baseline model for evaluating the incremental power of other advanced ensemble models discussed below.

Random Forests: Random forests extend CART by constructing multiple decision trees using random subsets of data and features ("bagging") (Breiman, 2001). Predictions are aggregated through majority voting for classification or averaging for regression. This ensemble approach reduces overfitting and provides variable importance scores, which are useful for feature selection.

GBM: Gradient boosting machines, a more sophisticated ensemble approach, construct trees sequentially, with each tree learning from the errors of the previous one to minimize a specified loss function (Friedman, 2001). This iterative process captures non-linear patterns and complex interactions effectively. Although computationally intensive, GBM provides superior performance, making it popular for predictive modeling (Hastie et al., 2009; Jones et al., 2023).

We compare these models based on their prediction accuracy and error rates. We use TreeNet® for GBM, Salford Predictive Modeler version of Random Forest®, and CART® for evaluating their predictive accuracy (Minitab, 2024)[2].

4. Findings

4.1. Summary statistics

We present the mean level of biodiversity risk disclosures and the distribution of firms during the sample period in Table 1. Starting at a modest 0.032 in 1994, the mean values remain

[2] We use the term GBM and TreeNet® interchangeably throughout this paper.

relatively low through the 1990s, fluctuating between 0.014 and 0.033. This period likely reflects limited corporate focus on biodiversity risks, as environmental issues had not yet gained significant traction in the business or regulatory landscapes. From the early 2000s, there is a gradual increase in the mean, with a more pronounced rise observed in the latter half of the 2000s. The mean levels rise steadily through the 2010s, reaching their highest point at 0.100 in 2017. This peak suggests that during this period, companies intensified their efforts to disclose biodiversity-related risks, potentially driven by stronger regulations, investor demand, and public scrutiny. Interestingly, after the peak in 2017, the mean levels plateau and slightly decline, fluctuating between 0.076 and 0.095 through 2022. Overall, the increase in mean biodiversity risk disclosure levels over time reflects a growing recognition of the importance of biodiversity in corporate risk management.

The number of firms in the sample exhibits interesting temporal variations, starting with 1,553 firms in 1994. The frequency of observations is highest during the late 1990s and early 2000s, with a gradual decline in later years. However, the consistent mean increases despite this decline suggest a stronger focus on biodiversity risk reporting in corporate disclosures among the remaining sample. The total mean disclosure across all years is 0.047, based on 133,618 observations.

[Table 1]

Table 2 reports the mean level of biodiversity risk disclosure across the Fama-French twelve industry classifications. We observe the highest mean disclosure levels in the energy (0.252) and utilities (0.233) sectors, indicating that firms in these industries are more proactive in disclosing biodiversity risks, likely due to the direct environmental impact of their operations. In contrast, consistent with prior studies (Skouloudis et al., 2019), the telecommunications and business equipment sectors show minimal engagement, with mean disclosure levels of 0.003 and 0.008, respectively, suggesting lower prioritization of biodiversity concerns. The frequency distribution indicates that the business equipment sector has the highest number of firms (28,542), whereas consumer durables (2,845) have fewer firms. This highlights how biodiversity risk disclosure practices vary not only in intensity but also in the representation of firms across different industries.

[Table 2]

4.2. Cross-sectional predictive performance of various machine learning models

Table 3 presents the results evaluating the cross-sectional predictive performance of different machine learning models for biodiversity risk disclosure[3]. We observe that TreeNet® demonstrates superior performance across all metrics, emerging as the most suitable model in predicting biodiversity risk disclosure in both the in-sample (training) and out-of-sample (testing) data. It achieves exceptional ROC scores of 0.9990 (training) and 0.9266 (testing), compared to lower ROC scores for Random Forest® (0.9095 training, 0.9241 testing) and CART® (0.8293 training, 0.8218 testing). In terms of average log-likelihood, TreeNet® also achieved the best performance with values of 0.0241 (training) and 0.0936 (testing), far superior to Random Forest® and CART®. Finally, TreeNet® shows the lowest misclassification rates, 0.0047 (training) and 0.0284 (testing), in contrast to higher rates for Random Forest® (0.0366 training, 0.0355 testing) and CART® (0.4291 training, 0.4461 testing). Overall, these results clearly indicate that ensemble methods, particularly TreeNet®, are more effective than simpler decision tree approaches for predicting biodiversity risk disclosure, with TreeNet® demonstrating the most promising combination of accuracy, stability, and predictive power. Therefore, in our subsequent analyses, we focus on the TreeNet® model.

[3] The cross-sectional sample is constructed using a standard random allocation method, with 80% of the observations assigned to the training sample and the remaining 20% allocated to the test sample.

[Table 3]

4.3. Out of sample predictive performance across industries

We present the cross-sectional out-of-sample predictive performance of the TreeNet® (gradient boosting) model for biodiversity risk disclosure across industries in Table 4. The model demonstrates strong overall predictive performance for biodiversity risk disclosure across different industries, with particularly robust results in consumer durables (FF2), energy (FF4), telephone and television transmission (FF7), utility (FF8) and other industries (FF12) as evidenced by their high AUC scores (0.9753, 0.9362, 0.9929, 0.9478, and 0.9171 respectively). The superior performance in these sectors can be attributed to their more standardized and regulated environmental reporting practices, especially in the energy and utility sectors where biodiversity impacts are well-documented and closely monitored (Giglio et al., 2023).

However, the model shows relatively weaker performance in business equipment (FF6) and healthcare (FF10) sectors, with lower AUC scores of 0.7819 and 0.8275 respectively. This reduced predictive power may be explained by the more diverse and less standardized nature of biodiversity risk reporting in these industries, as they typically have less direct environmental impacts compared to extractive or manufacturing industries (Skouloudis et al., 2019).

[Table 4]

4.4. Out of sample predictive performance across feature dimensions

Table 5 demonstrates the predictive performance of the TreeNet® (gradient boosting) model in forecasting biodiversity risk disclosure using five - dimensions: accounting (ACCT), market (MKT), governance (GOVERN), environmental (ENVIRON), and other (OTHERS) dimensions. The ACCT features outperform other dimensions in terms of predictive accuracy with an AUC of 0.9018 and a low misclassification rate of 0.0324. This suggests that accounting-related metrics contribute significantly to accurate biodiversity risk predictions, likely due to their quantifiable and structured nature, which aligns well with machine learning model capabilities. This is followed by the OTHERS, GOVERN and MKT dimensions with an AUC of 0.8286, 0.7964 and 0.7884. The relatively higher predictive performance in GOVERN dimension may be driven by the formalized nature of corporate governance reporting requirements.

The model shows relatively moderate performance ENVIRON dimension, with AUC values of 0.6535. These lower performance metrics likely stem from the complex, evolving and often qualitative nature of environmental features that present challenges in data standardization and model training. Studies such as Li et al. (2021) emphasize that machine learning models generally perform better when handling structured, numerical data as opposed to unstructured, nuanced environmental data. Nevertheless, the overall predictive performance remains robust across all dimensions, with consistently low misclassification rates (below 5%) and strong lift values. Taken together, our results suggest that machine learning approaches can effectively predict biodiversity risk disclosures, though their effectiveness varies based on the standardization and structure of the underlying reporting frameworks in each dimension.

[Table 5]

4.5. Relative variable of importance

Table 6 presents the Relative Variable Importance (RVI) scores for the biodiversity risk prediction model, derived using the TreeNet® model with all predictor variables outlined in Appendix A. The RVI scores, ranging from 0 to 100, quantify the contribution of each variable to the model's predictive accuracy, with a score of 100 representing the most influential predictor and all other variables scaled relative to it. Variables with a score of 0 are excluded due to their lack of significant contribution to the prediction.

The results consistently identify financial metrics as the most significant predictors of biodiversity risk. The asset tangibility (PPE) emerges as the most critical variable, achieving a RVI score of 100, followed closely by industry competitiveness (Herfindahl index) (96.1), Employees (65.7) and Total Assets (61.2). Other notable predictors include Shareholders Number, PPE Newness, and BVPS, all with RVI scores above 50, indicating their substantial contribution to the model's predictive power.

These findings are strongly supported by existing literature, which emphasizes the influence of financial metrics on biodiversity risk. For instance, Garel et al. (2024) and Xin et al. (2023) demonstrate that firms with higher levels of property, plant, and equipment (PPE) contribute more to biodiversity degradation. Similarly, research suggests that the Herfindahl index, a measure of market concentration, often reduces competitive pressure, potentially weakening firms' incentives to adopt sustainable practices and thereby increasing biodiversity risk (Benlemlih et al., 2024). Additionally, the number of employees and total assets, proxies for firm size, play a critical role. Larger firms may exert a greater spatial impact, heightening biodiversity risk, or they may possess greater resources, leading to a more pronounced environmental disclosure (Ali et al., 2024; Benlemlih et al., 2024; Garel et al., 2024).

These results underscore the intricate interplay between a firm's financial characteristics and its biodiversity risk profile. Financial metrics not only serve as indicators of a firm's operational health but also provide critical insights into its broader environmental impact, including biodiversity risks.

[Table 6]

4.6. Comparison with logit

We compare gradient boosting and logit models using top 20 variables derived by RVI from the GBM model (see Table 6). Both models are re-run with these variables for a fair comparison. As shown in table 7, GBM outperforms the logit model with higher ROC (Area Under Curve) score (0.9970 for training and 0.9085 for testing) compared to the logit model (0.8436 for training and 0.8290 for testing). GBM also achieves lower misclassification error rates (0.0079 for training and 0.0304 for testing) than the logit model (0.0615 for both training and testing). Additionally, GBM shows lower average loglikelihood and higher lift, indicating superior predictive performance.

[Table 7]

We assess the stability of both models. The logit model exhibits parameter estimation issues (see Table 8), with a few variables having large coefficients while most contribute minimally, reflecting limited explanatory power. Furthermore, many top variables in the logit model, such as Herfindahl Index, PPE Newness, BVPS, are statistically insignificant, likely due to multicollinearity, which reduces the model's effectiveness. In contrast, GBM effectively addresses multicollinearity and heteroscedasticity, as evidenced by more evenly distributed RVIs across variables and its ability to extract meaningful signals from correlated inputs. Furthermore, its marginal effects (discussed in the next section) align with expected variable-outcome relationships, enhancing both interpretability and practical relevance.

[Table 8]

4.7. Marginal effects

Partial Dependency Plots (PDPs) provide crucial insights when exploring complex relationships between predictor variables and outcomes. While traditional models, such as logit regression, offer interpretability, they often fail to capture non-linear patterns in complex datasets (Jones et al., 2015). PDPs overcome this limitation by revealing both the direction and magnitude of variable effects in machine learning models, allowing researchers to understand the relationships even when using “black box” algorithms (Friedman, 2001; Jones, 2017). In this analysis, we examine the top five influential variables and their relationships with biodiversity disclosure.

Figure 1 exhibit a positive relationship between asset intensity (PPE) and biodiversity disclosure, particularly in the mid-range values (0.2 – 0.8). Firms with higher asset intensity face greater environmental scrutiny, driving increased transparency. However, this relationship plateaus at very high PPE values (> 0.8), suggesting diminishing returns where additional factors may influence disclosure decisions.

Figure 2 demonstrates a non-linear relationship between the Herfindahl Index, a measure of market concentration, and the likelihood of firm-level biodiversity disclosure. Firms in highly competitive markets (very low index values) exhibit a sharp increase in disclosure probability, followed by a relatively flat relationship across moderate concentration levels (0.1 – 0.8). In highly concentrated markets (> 0.8), disclosure probability decreases slightly, indicating reduced transparency incentives when competition is limited.

In Figure 3, firm size, measured by the natural log of the number of employees, exhibit a U-shaped relationship. Small firms show a higher likelihood of disclosure, which decreases as firms grow to medium size. The relationship then flattens, with a slight upward trend emerging for very large firms (employee size ≈ 6+). This pattern suggests that while medium-sized firms may have fewer disclosure incentives, very large organizations face increased stakeholder expectations and scrutiny.

Figure 4 reveals a non-linear relationship between total assets (log) and biodiversity disclosure. Smaller firms (assets < 3) demonstrate minimal disclosure association, followed by a significant upward trend for mid-to-large firms (assets 3 – 10). Importantly, the largest firms (assets >11) show a sharp decline in disclosure likelihood, potentially reflecting different strategic priorities or reporting approaches.

Figure 5 presents the PDP showing the relationship between the natural log of the number of shareholders (Shareholders Number) and biodiversity disclosure. Firms with fewer shareholders (< 2) show lower disclosure rates, while those with moderate shareholder bases (2 – 4) demonstrate increased disclosure likelihood, possibly due to stronger governance pressures. Beyond this threshold, additional shareholders do not further increase disclosure probability, suggesting potential dilution of governance incentives in widely held firms.

Finally, the three-dimensional surface plot in Figure 6 exhibits the interaction between market concentration (Herfindahl Index) and asset intensity (PPE) on biodiversity disclosure. Firms in highly concentrated markets with moderate asset intensity show the highest disclosure likelihood. However, this relationship diminishes at very high asset intensity levels, while firms in less concentrated markets maintain consistently lower disclosure levels regardless of asset intensity. Overall, these findings highlight the complex, non-linear relationships between firm characteristics and biodiversity disclosure practices.

[Figures 1 – 6]

5. Sensitivity analysis

5.1. Longitudinal analysis

In the baseline analysis, we used a cross-sectional approach using a traditional random allocation of data splits. However, incorporating the time dimension is crucial for predictive modeling, particularly when temporal order may influence patterns or relationships. Literature suggests that training on earlier periods and testing on later periods better simulates realistic forecasting scenarios, where future outcomes are predicted based on past information (Jones, 2017).

In this section, we evaluate the performance of TreeNet®, Random Forest®, and CART® models using longitudinal data splits. Instead of random splits, we use data from 1994 to 2018 for training and 2019 to 2022 for testing to avoid look-ahead bias. The results in Table 9 show that TreeNet® consistently outperforms Random Forest® and CART® across all metrics for both training and testing datasets. Specifically, TreeNet® archives ROC values of 0.9740 (training) and 0.8969 (testing), outperforming Random Forest® (0.8617 for training and 0.8688 for testing) and CART® (0.7816 for training and 0.7885 for testing). Although the testing ROC for TreeNet® decreases slightly from 0.9266 (cross-sectional analysis) to 0.8969 (longitudinal analysis), this decline is expected due to the inherent challenges of temporal predictions. Despite this drop, TreeNet® maintains strong predictive power, with a testing ROC close to 0.90, significantly outperforming random guessing (0.50). In untabulated results, we repeat predictive performance across different industries and feature dimensions and obtain qualitatively similar results. Furthermore, our RVI analysis confirm the robustness of our conclusions These findings confirm that TreeNet® continues to demonstrate robust performance under the more stringent conditions of longitudinal data, further validating its reliability and predictive superiority over alternative models.

[Table 9]

5.2. Alternative sample period (2002 – 2022)

We now assess the performance of our main machine learning model using an alternative sample period. While tree-based models are generally resilient noise, including missing values, TreeNet® demonstrates superior performance due to its built-in mechanisms for handling missing data, ensemble learning approach, regularization to mitigate overfitting, and sequential improvements (Freedman, 2010; Jones, 2017). These features enhance its robustness compared to traditional machine learning models in noisy data environments.

Our main analysis covers the period from 1994 to 2022. However, certain data sources, such as Refinitiv ESG, provide data only from 2002 onward. To test the robustness of our findings, we re-estimate key analyses using the 2002–2022 sample. As shown in Appendix OA.2A, TreeNet® consistently outperforms alternative models (for TreeNet® ROC value = 0.9999 for training and 0.939 for testing), achieving a ROC value of 0.9999 for training and 0.939 for testing, with predictive metrics aligning with baseline results for the full sample (Table 3).

Furthermore, we assess model performance across different dimensions (Appendix OA.2B) and find that the results remain consistent with those obtained from the full sample (Table 5). For example, the ACCT dimension exhibits a ROC of 0.9043, followed by OTHERS (0.8414), GOVERN (0.7879), and MKT (0.7825). Finally, we conduct a RVI analysis for this sub-sample (see Appendix OA.3)[4]. Notably, the ranking and significance of predictors largely align with the full sample results (Table 6). These findings confirm the robustness of our main conclusion, even in the presence of missing data.

5.3. Robustness of gradient boosting model

We now examine the reliability and generalisability of the GBM. By evaluating performance under varying conditions, we can confirm the model's stability and reliability across diverse settings. This can strengthen our confidence that the model is just not overly dependent on specific hyperparameter values, making it more reliable and applicable to unseen data.

[4] For brevity, we only present the top 20 variables.

We first run the TreeNet® model with different k-fold cross validations[5], followed by tests with varying learning rates and subsample fractions[6]. As shown in Table 10, the TreeNet® model maintains consistently strong performance across the different k-fold cross-validations (k=5, k=10, k=15), with ROC value (testing: 0.936–0.938) and low misclassification rates (testing: 0.0276–0.0283). These results indicate significant stability and predictive power across different validation strategies.

[Table 10]

Next, we evaluate different learning rates and subsample fractions. Table 11 shows that the TreeNet® model remains robust with learning rates of 0.001, 0.010, 0.100, as well as subsample fractions of 0.5 and 0.7. The ROC values (0.862–0.926) and misclassification rates (0.028–0.039) consistently support the model's performance stability under these hyperparameters variations.

[Table 11]

6. Conclusion

This paper predicts biodiversity risk disclosure using machine learning techniques to examine the firm-level, industry-level and macro-economic factors that influence corporate reporting on biodiversity risks. It leverages three machine learning models—TreeNet® (gradient

[5] K-fold cross-validation is a resampling procedure where the dataset is divided into *k* equally sized subsets (folds). The model is trained on *k-1* folds and tested on the remaining fold, then this process it repeated until every fold has used as the testing set once. This procedure ensures a more comprehensive evaluation, as the model is tested on multiple subsets of the data.

[6] Learning rate is a key hyperparameter in gradient boosting that determines the step size for updating model parameters during training. A smaller learning rate often leads to more gradual learning and requires a higher number of iterations, while a larger learning rate accelerates learning which increases the risks of "overshooting" the optimal predictive scenario. Subsample fraction, on the other hand, represents the proportion of the training data used to fit each individual tree, which play an important role in model building by introducing randomness as well reducing overfitting, thereby enhances robustness of predictive model.

boosting), Random Forest®, and CART®—to uncover patterns in corporate biodiversity disclosure using structured financial and governance data as well as unstructured textual analysis of corporate reports. This approach is novel in biodiversity disclosure research, which has traditionally relied on conventional statistical methods. The study demonstrates the superiority of machine learning in capturing complex, nonlinear relationships and identifying key disclosure drivers, thereby addressing critical gaps in sustainability accounting research.

The findings indicate that biodiversity disclosure has increased over time, particularly among firms in resource-intensive industries such as energy and utilities, which exhibit higher reporting levels due to regulatory scrutiny and stakeholder pressure. Additionally, the machine learning models outperform traditional approaches in predicting disclosure patterns, demonstrating strong predictive accuracy across different validation techniques. Accounting features emerge as the most influential predictors of biodiversity disclosure, while governance and market factors have a moderate impact. Key accounting determinants include asset tangibility, the level of industry competition, and firm size.

Overall, this study makes significant contributions to the field of biodiversity disclosure by illustrating how machine learning can enhance transparency and accountability in corporate sustainability reporting. It offers policymakers data-driven insights for designing more effective regulatory frameworks and industry-specific guidelines. Moreover, the findings have practical implications for investors, regulators, and corporate leaders seeking to evaluate firms' biodiversity commitments and mitigate biodiversity-related financial risks. In light of global sustainability initiatives, such as the Kunming-Montreal Global Biodiversity Framework, this research provides timely insights into improving biodiversity accountability and integrating AI-driven analysis into sustainability policymaking.

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Appendix A. Variable definitions

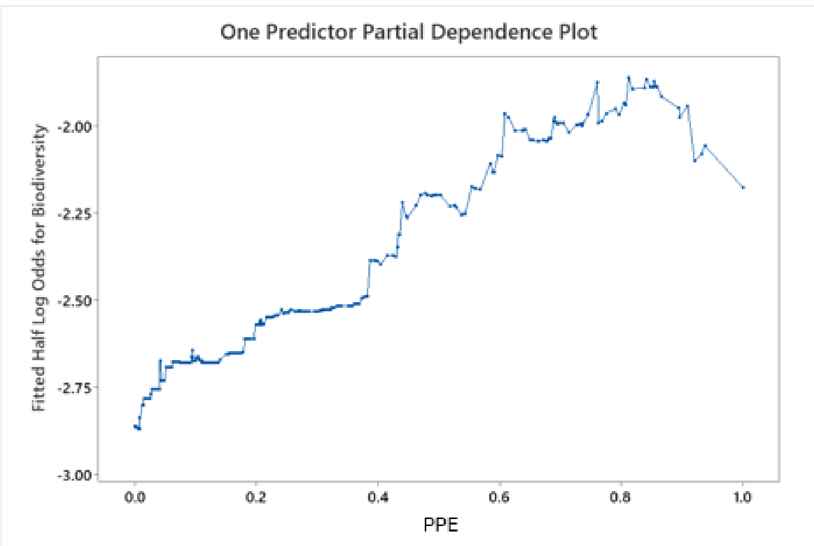
Variable	Definition and measurement	Source
Accounting		
Total Assets	The natural logarithm of the book value of total assets at fiscal year end	Compustat
Sales	The natural logarithm total sales	Compustat
ROE	Return on equity measured as earnings before interest and tax divided by common shareholders' equity	Compustat
ROA	Return on assets measured as earnings before interest and tax divided by total assets	Compustat
Ind_Adj_ROA	Industry (SIC2)-year adjusted ROA	Compustat
Profit Margin	Profit margin measured as earnings before interest and tax divided by sales	Compustat
Leverage	Financial leverage measured as Total debt divided by total assets	Compustat

Cash	Cash holdings divided by total assets	Compustat
CAPX	Capital expenditure divided by total assets	Compustat
PPE Newness	The ratio of net property, plant, and equipment to gross ratio related to property, plant, and equipment	Compustat
PPE	Net property, plant and equipment divided by total assets	Compustat
Herfindahl Index	Herfindahl Index, a measure of market concentration and competition within an industry	Compustat
R&D	The ratio of a firm's research and development expenses to its total assets	Compustat
Advertising Exp.	The ratio of a firm's advertising expenses to its total assets	Compustat
Sales Growth	The percentage change in a firm's sales revenue	Compustat
EPS Growth	The growth in a firms' earnings per share	Compustat
Total Assets Growth	The growth in a firms' total assets	Compustat
Distress	Financial distress, measured using Altman (1968) model	Compustat
Current Ratio	Current assets over current liabilities	Compustat
OCF	Operating cashflow over total assets	Compustat
Employees	The natural logarithm of the number of employees in a firm	Compustat
Dividend	A binary variable that indicates whether a firm has paid dividends during a given period (1) or not (0)	Compustat
Inventory Turnover	Cost of goods sold scaled by average inventory level	Compustat
BVPS	The natural logarithm of book value per share at the end of the year	Compustat
Financial Const	Financing constraints measured using KZ index (Kaplan and Zingales, 1997)	Compustat
Firm Age	The natural logarithm of firm age	Compustat
Market		
Share Price	The natural logarithm of a firm's stock price measured at the end of the fiscal year	Compustat
Stock Returns	The 12-month buy-and-hold stock returns, calculated by compounding monthly returns over the fiscal year	CRSP
RET_SD	The standard deviation of daily stock returns calculated over the fiscal year	CRSP
MCap	The natural logarithm of market capitalization at the year end	Compustat
Capital Issue	Capital issue, measured as net debt and equity issue in year t scaled by total assets	Compustat
MTB	The market-to-book ratio	Compustat
Ind. Adj_MTB	Industry-adjusted market-to-book ratio	Compustat
Capital Mkt. Reliance	Capital market reliance is a binary variable equal to 1 if the firm has issued public securities in the previous three years, and 0 otherwise	Compustat
BETA	The systematic risk of a firm	CRSP
Trading Volume	Trading Volume is calculated as the total annual trading volume divided by shares outstanding	CRSP
Governance		

Shareholders Number	Shareholder Base is measured as the natural logarithm of the total number of shareholders	Execucomp
Duality	Duality is a binary variable equal to 1 if the CEO also serves as the Chairman of the Board, and 0 otherwise	ISS
Board Size	Board Size is measured as the total number of directors serving on the board	ISS
Board Independence	Board Independence is measured as the proportion of independent directors on the board relative to total board size	ISS
Meeting Attendance	A binary variable equal to 1 if the director attended more than 75% of board meetings, and 0 otherwise	ISS
Gender Diversity	The proportion of male directors on the board	BoardEx
Institutional Ownership	The percentage of a firm's outstanding shares owned by institutional investors	13F
Inst. Ownership Concentration	The Herfindahl-Hirschman Index of institutional ownership	13F
Analyst Following	The number of financial analysts covering a firm	IBES
CEO MBA	A binary variable equal to 1 if the CEO holds a Master of Business Administration (MBA) degree and 0 otherwise	BoardEx
New CEO	A binary variable equal to 1 if the firm has appointed a new CEO within past three years and 0 otherwise	Execucomp
Dedicated Ownership	The proportion of shares held by long-term institutional investors	13F
Transient Ownership	The proportion of shares held by short-term institutional investors	13F
Blockholder Ownership	The percentage of a firm's shares owned by large shareholders (blockholders)	13F
CEO Ownership	he percentage of the firm’s shares directly owned by the CEO	Execucomp
Big4	A binary variable equal to 1 if the firm is audited by one of the Big Four accounting firms (Deloitte, EY, KPMG, or PwC), and 0 otherwise	Compustat
Employee Relations	Employee relations performance score from MSCI	MSCI
Human Rights	Human rights performance score from MSCI	MSCI
CEO Tenure	The natural logarithm of the CEO's tenure	Execucomp
Media Coverage	The natural logarithm of one plus the number of news published about a firm in year t	RavenPack
CEO Age	The natural logarithm of the CEO's age	Execucomp
CEO Female	A binary variable that equals 1 if the CEO is female and 0 otherwise	Execucomp
Environment		
Total CO2 Emissions	The natural logarithm of a firm's total CO_2 emissions	Refinitiv ESG
Total Waste Generation	The natural logarithm of a firm's total waste generation	Refinitiv ESG

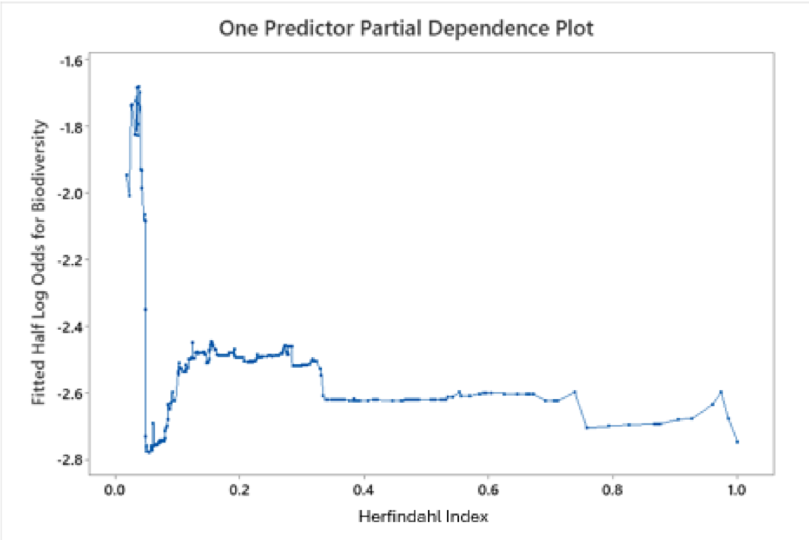
Environmental Performance	A firm's environmental performance score, as reported by MSCI.	MSCI
Environmental Concerns	A firm's environmental concerns score, as reported by MSCI	MSCI
Waste Recycled	The natural logarithm of the amount of waste recycled by a firm	Refinitiv ESG
CSR Committee	A dummy variable that equals one if a firm has a CSR committee and zero otherwise	Refinitiv ESG
Environmental Mgt. Team	A dummy variable that equals one if a firm has an environmental management team and zero otherwise	Refinitiv ESG
Environmental Fines	The natural logarithm of environmental fines reported by the company	Refinitiv ESG
Environmental Restore	A dummy variable that equals one if a firm undertakes environmental restoration initiatives and zero otherwise.	Refinitiv ESG
Environmental Investment	The natural logarithm of a firm's environmental investment	Refinitiv ESG
Climate Change Exposure	A measure of a firm’s exposure to climate change risk, as defined by Sautner et al. (2023)	Sautner et al. (2023)
Climate Change Risk	A measure of a firm’s climate change risk, as defined by Sautner et al. (2023)	Sautner et al. (2023)
Climate Change Sentiment	A measure of climate change sentiment, as defined by Sautner et al. (2023)	Sautner et al. (2023)
CSR Award	A dummy variable that equals one if a firm has received a CSR award and zero otherwise	Refinitiv ESG
Biodiversity Impact Reduction	A dummy variable that equals one if a firm reports efforts to reduce its biodiversity impact and zero otherwise	Refinitiv ESG
Waste Reduction Initiative	A dummy variable that equals one if a firm implements waste reduction initiatives and zero otherwise	Refinitiv ESG
Environmental Invest. Initiative	A dummy variable that equals one if a firm undertakes initiatives specifically aimed at environmental investment and zero otherwise	Refinitiv ESG
Land Env. Impact Reduction	A dummy variable that equals one if a firm reports on initiatives to reduce the environmental impact of land it owns, leases, or manages for production activities or extractive use, and zero otherwise	Refinitiv ESG
Others		
FF	Fama-French 12 industry classifications	Compustat
HITECH	A dummy variable that equals one if a firm operates in any of the following 3-digit SIC code industries: 372, 371, 481, 482, 489, 363, 366, 369, 781, 783, 791, 351–356, 357, 381, 383, 384, 387, and 491, 493, and zero otherwise.	Compustat
Foreign Operation	A dummy variable that equals one if a firm has foreign operations and zero otherwise	Compustat
Crisis	A dummy variable that equals one for the years 2008–2009 and 2020, representing periods of financial and economic crises, and zero otherwise.	

Figure 1: Partial dependence plot for Property, Plant, and Equipment (PPE)



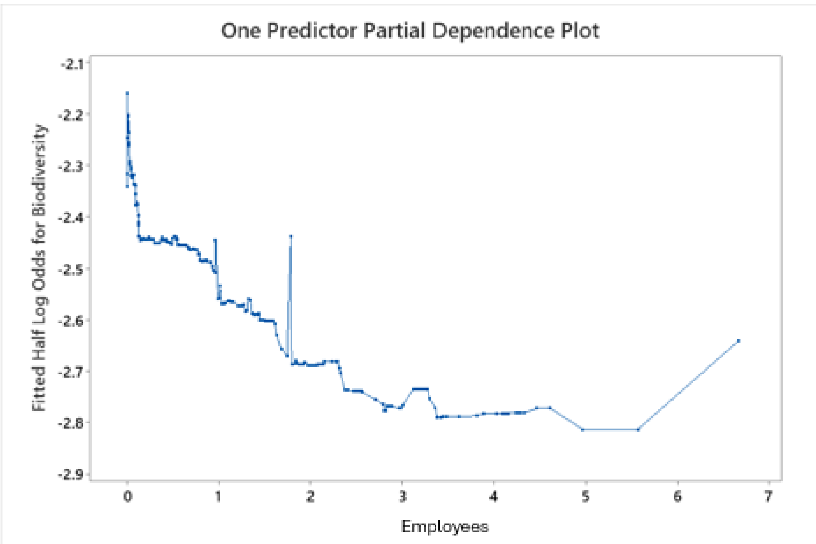
Notes: This partial dependence plot illustrates the relationship between PPE (property, plant, and equipment) and the fitted half log odds for biodiversity of the TreeNet® (gradient boosting) model while averaging out the effects of all other variables. The x-axis represents PPE, while the y-axis shows the corresponding fitted log odds.

Figure 2: Partial dependence plot for Herfindahl Index



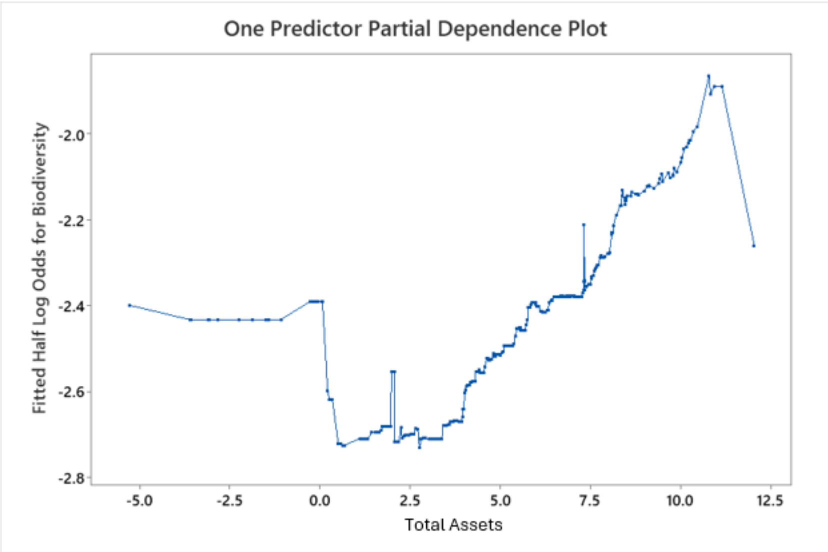
Notes: This partial dependence plot illustrates the relationship between Herfindahl Index and the fitted half log odds for biodiversity of the TreeNet® (gradient boosting) model while averaging out the effects of all other variables. The x-axis represents Herfindahl Index, while the y-axis shows the corresponding fitted log odds.

Figure 3: Partial dependence plot for Number of Employees



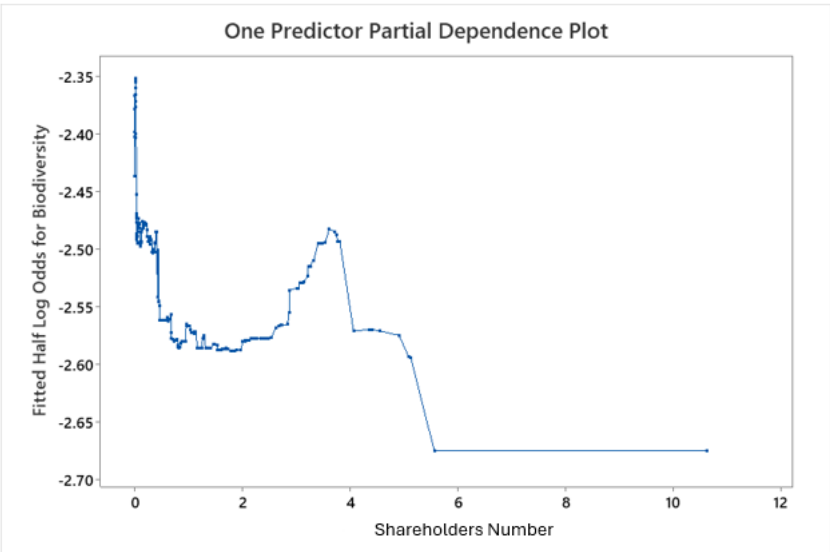
Notes: This partial dependence plot illustrates the relationship between number of employees and the fitted half log odds for biodiversity of the TreeNet® (gradient boosting) model while averaging out the effects of all other variables. The x-axis represents number of employees, while the y-axis shows the corresponding fitted log odds.

Figure 4: Partial dependence plot for Total Assets.



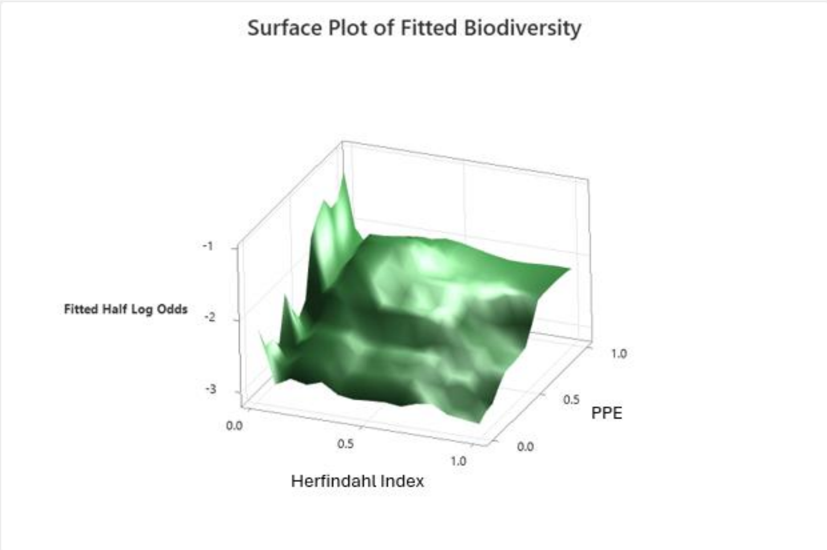
Notes: This partial dependence plot illustrates the relationship between total assets and the fitted half log odds for biodiversity of the TreeNet® (gradient boosting) model while averaging out the effects of all other variables. The x-axis represents total assets, while the y-axis shows the corresponding fitted log odds.

Figure 5: Partial dependence plot for Number of Shareholders.



Notes: This partial dependence plot illustrates the relationship between number of shareholders and the fitted half log odds for biodiversity of the TreeNet® (gradient boosting) model while averaging out the effects of all other variables. The x-axis represents number of shareholders, while the y-axis shows the corresponding fitted log odds.

Figure 6: Surface plot for biodiversity with Property, Plant, and Equipment, and Herfindahl Index.



Notes: This surface plot shows the three-dimensional relationship between Property, Plant, and Equipment (PPE), Herfindahl Index, and the fitted half log odds for biodiversity in the TreeNet® (gradient boosting) model. The x-axis represents PPE, the y-axis represents the Herfindahl Index, and the z-axis displays the fitted half log odds for biodiversity. The plot helps to understand how biodiversity predictions vary based on different levels of PPE and Herfindahl Index. Areas with higher elevations on the surface indicate conditions where the model predicts higher biodiversity, while lower regions suggest lower predicted values.

Table 1

Biodiversity disclosure over the sample period.

Year	Mean	Freq.	Year	Mean	Freq.
1994	0.032	1,553	2009	0.053	4,204
1995	0.017	3,156	2010	0.056	4,171
1996	0.015	5,757	2011	0.065	4,097
1997	0.015	6,239	2012	0.076	4,131
1998	0.016	6,393	2013	0.080	4,182
1999	0.014	6,597	2014	0.092	4,101
2000	0.019	6,559	2015	0.091	3,968

2001	0.023	6,183	2016	0.094	3,859
2002	0.023	5,769	2017	0.100	3,744
2003	0.026	5,349	2018	0.095	3,703
2004	0.026	5,192	2019	0.086	3,676
2005	0.033	5,052	2020	0.078	3,836
2006	0.033	4,887	2021	0.076	4,133
2007	0.038	4,722	2022	0.080	4,069
2008	0.044	4,336	Total	0.047	133,618

Note: This table provides a frequency distribution of biodiversity risk disclosure for U.S. listed firms over the period of 1994 - 2022.

Table 2

Industry-level biodiversity disclosure.

FF	Mean	Freq.
FF1	0.027	7,356
FF2	0.011	3,845
FF3	0.029	14,571
FF4	0.252	6,833
FF5	0.035	3,957
FF6	0.008	28,524

FF7	0.003	4,303
FF8	0.233	6,531
FF9	0.024	13,972
FF10	0.009	21,218
FF12	0.066	22,508

Note: This table provides a frequency distribution of Fama & French 12 industries (FF1 – FF12) classification for biodiversity risk disclosure over the sample period.

Table 3

Summary of cross-sectional predictive performance of alternative machine learning models for the biodiversity disclosure.

Metric	**TreeNet®**		**Random Forest®**		**CART®**	
	Training	**Testing**	**Training**	**Testing**	**Training**	**Testing**
Average LogLikelihood	0.0241	0.0936	0.3498	0.1813	0.1499	0.1585
ROC (Area Under Curve)	0.9990	0.9266	0.9095	0.9241	0.8293	0.8218

Lower Confidence Limit ROC	0.9986	0.9169	0.9043	0.9148	0.6291	0.6095
Upper Confidence Limit ROC	0.9994	0.9363	0.9147	0.9335	1.0000	1.0000
Lift	9.9508	8.0709	7.5607	7.8210	5.0983	5.1094
Misclassification rate	0.0047	0.0284	0.0366	0.0355	0.4291	0.4461

Notes: This table provides cross-sectional predictive performance of three alternative machine learning models (TreeNet®, Random Forest®, CART®) for the biodiversity risk disclsoure. Five different metrics are used for the evaluative purposes: Average LogLikelihood, ROC (Area Under Curve), Lower and Upper Confidence Limit of ROC, Lift, and Misclassification rate.

Table 4

Summary of out-of-sample predictive performance of TreeNet® (gradient boosting) model for biodiversity disclosure across industry groups.

	Fama-French 12 industry classifications										
Metric	FF 1	FF 2	FF 3	FF 4	FF 5	FF 6	FF 7	FF 8	FF 9	FF 10	FF 12
Average LogLikelihood	0.0764	0.0421	0.0816	0.2619	0.1161	0.0439	0.0079	0.2468	0.0711	0.0415	0.1183
ROC (Area Under Curve)	0.8873	0.9753	0.8887	0.9362	0.8845	0.7819	0.9929	0.9478	0.8670	0.8275	0.9171
Lower Confidence Limit ROC	0.8130	0.9478	0.8411	0.9206	0.8102	0.7104	0.9791	0.9342	0.8072	0.7548	0.8944
Upper Confidence Limit ROC	0.9617	1.0000	0.9363	0.9518	0.9589	0.8533	1.0000	0.9613	0.9267	0.9001	0.9399
Lift	8.0851	9.0000	7.4713	3.8943	7.0588	5.4717	10.0000	3.9678	7.3239	5.5000	7.6779
Misclassification rate	0.0210	0.0119	0.0241	0.1001	0.0356	0.0090	0.0012	0.1012	0.0178	0.0090	0.0367

Notes: This table provides cross-sectional out of sample predictive performance of TreeNet® (gradient boosting) model for biodiversity risk disclosure across Fama & French 12 industries (FF1 – FF12) classification. Five different metrics are used for the evaluative purposes: Average LogLikelihood, ROC (Area Under Curve), Lower and Upper Confidence Limit of ROC, Lift, and Misclassification rate.

Table 5

Summary of cross sectional out-of-sample predictive performance of TreeNet® (gradient boosting) model for biodiversity disclosure across dimensions.

Metric	**ACCT**	**MKT**	**GOVERN**	**ENVIRON**	**OTHERS**
Average LogLikelihood	0.1068	0.1546	0.1502	0.1719	0.1481
ROC (Area Under Curve)	0.9018	0.7884	0.7964	0.6535	0.8286
Lower Confidence Limit ROC	0.8908	0.7745	0.7822	0.6374	0.8171
Upper Confidence Limit ROC	0.9129	0.8024	0.8105	0.6696	0.8402
Lift	7.3372	4.5095	4.8228	3.1418	5.2540
Misclassification rate	0.0324	0.0439	0.0426	0.0446	0.0454

Note: This table provides cross-sectional out of sample predictive performance of TreeNet® (gradient boosting) model for biodiversity risk disclosure across five dimensions: Accounting, Market, Governance, Environment, and Others. Five different metrics are used for the evaluative purposes: Average LogLikelihood, ROC (Area Under Curve), Lower and Upper Confidence Limit of ROC, Lift, and Misclassification rate.

Table 6
RVIs for TreeNet® (gradient boosting) model.

Variables	RVIs Scores	RVIs Strengths
PPE	100	
Herfindahl Index	96.1	
Employees	65.7	
Total Assets	61.2	
Shareholders Number	55.6	
PPE Newness	55.2	
BVPS	50.9	
FF4	49.1	
Cash	46.4	
Inventory Turnover	46.1	
CAPX	44.9	
Firm Age	44.7	
Climate Change Exposure	44.2	
Current Ratio	43.9	
Gender Diversity	43.7	
Sales	42.6	
Leverage	42.4	
Ind_Adj_ROA	40.1	
Profit Margin	38.8	
Ind. Adj_MTB	38.3	
Inst. Ownership Concentration	35.8	
ROE	35.5	
ROA	35.4	
Share Price	35	
Distress	34.7	
Institutional Ownership	33.5	
Media Coverage	33.2	
Sales Growth	32.7	
MTB	32.1	
MCap	31.7	
OCF	31.2	
FF12	31.1	
Capital Issue	31	
Advertising Exp.	30.8	
FF8	30.7	
Fin_Const	30.6	
Total_Assets_Growth	29.8	
Trading Volume	29.5	
BETA	29.5	
EPS Growth	28.6	
R&D	25.9	
Transient Ownership	25.7	

Analyst Following	25.6
Climate Change Risk	23.6
Dedicated Ownership	22.9
RET_SD	22.8
CEO Age	22.4
CEO Ownership	21.1
Stock Returns	20.8
Total Waste Generation	19.7
Blockholder Ownership	19.2
Total CO2 Emissions	18.4
CEO MBA	18.1
FF1	17.4
FF3	16
Environmental Concerns	16
Dividend Payment	15.9
Board Size	15.9
CEO Tenure	15.6
FF9	14.2
Environmental Fines	13.6
Big4	13.2
Board Independence	13
Land Env. Impact Reduction	12.7
Climate Change_Sentiment	12.5
Human Rights	11.9
HITECH	11.7
FF10	10.9
Employee Relations	10.9
FF5	10.8
CSR Committee	9.7
Environmental Invest. Initiative	9.5
Environmental Investment	9.3
Waste Recycled	9.1
Biodiversity Impact Reduction	9
Meeting Attendence	8.4
FF6	7.9
Crisis	7.2
Environmental Mgt. Team	6.9
Cap Mkt. Reliance	6.6
FF7	5.3
CEO Female	5.1
CSR Award	5
Duality	4.1
Environmental Performance	3.4
FF2	3
Waste Reduction Initiative	2.5
Environmental Restore	1.8

Notes: This table shows the relative variable importances (RVIs) of the TreeNet (gradient boosting) model using all the variables outlined in the appendix. Only the variables with RVI scores greater than zero are presented here. RVI measures a variable's contribution to the model by weighting its split frequency by the squared improvement it provides, averaged across all trees. The most important variable is assigned 100, with others scaled accordingly.

Table 7

Comparisons of predictive performance between TreeNet® (gradient boosting) model and logit model on cross-sectional out-of-sample data for the top 20 variables.

Metric	**TreeNet®**		**Logit**	
	Training	**Testing**	**Training**	**Testing**
Average LogLikelihood	0.0324	0.1018	-0.1738	0.1687
ROC (Area Under Curve)	0.9970	0.9085	0.8436	0.8290
Lower Confidence Limit ROC	0.9962	0.8973	0.8435	0.8289
Upper Confidence Limit ROC	0.9978	0.9196	0.8437	0.8291
Lift	9.8937	7.5927	5.6518	5.8176
Misclassification rate	0.0079	0.0304	0.0615	0.0615

Notes: This table provides comparisons of predictive performance between TreeNet® (gradient boosting) model and logit model on cross-sectional out-of-sample data for the top 20 variables identified in table 6. Five different metrics are used for the evaluative purposes: Average LogLikelihood, ROC (Area Under Curve), Lower and Upper Confidence Limit of ROC, Lift, and Misclassification rate.

Table 8

Logit parameter estimation based on top 20 most important predictors from TreeNet® (gradient boosting) cross-sectional model.

Variable	Coefficients	S.E.	T-ratio	P-value	RVIs	Pearson's correlation with Biodiversity
const	-5.2397	0.3906	-13.4137**	0.0001	n/a	n/a
PPE	2.7553	0.1754	15.7095**	0.0001	100.0	0.3314**
Herfindahl Index	-0.1662	0.1812	-0.9169	0.3592	96.1	-0.0991**
Employees	-0.5298	0.0428	-12.3815**	0.0001	65.7	-0.0481**
Total Assets	0.6117	0.0491	12.4501**	0.0001	61.2	0.1385**
Shareholders Number	-0.0924	0.0259	-3.5705**	0.0004	55.6	0.0377**
PPE Newness	-0.2739	0.2252	-1.2165	0.2238	55.2	0.1879**
BVPS	0.0013	0.0455	0.0277	0.9779	50.9	0.0937**
FF4	0.9225	0.0954	9.6737**	0.0001	49.1	0.2892**
Cash	-2.6154	0.3465	-7.5475**	0.0001	46.4	-0.1410**
Inventory Turnover	-0.0002	0.0003	-0.7829	0.4337	46.1	0.0005
CAPX	-1.3882	0.4932	-2.8145**	0.0049	44.9	0.1956**
Firm Age	-0.2537	0.0367	-6.9198**	0.0001	44.7	-0.0252**
Climate Change Exposure	39.5753	7.0503	5.6133**	0.0001	44.2	0.1474**
Current Ratio	0.0513	0.0176	2.9134**	0.0036	43.9	-0.0914**
Gender Diversity	0.1349	0.2923	0.4614	0.6445	43.7	-0.0024
Sales	-0.1776	0.0481	-3.6946**	0.0002	42.6	0.0677**
Leverage	0.0714	0.2050	0.3482	0.7277	42.4	0.1185**
Ind_Adj_ROA	-0.0035	0.0087	-0.4006	0.6887	40.1	-0.0111
Profit Margin	0.0001	0.0017	0.0480	0.9617	38.8	0.0049
Ind_Adj_MTB	-0.0004	0.0002	-2.4556*	0.0141	38.3	-0.0375**

Notes: This table presents logit parameter estimates for the top 20 most important variables identified in Table 6. The first column lists the variables, followed by coefficients and standard errors in the second and third columns. The next two columns display t-ratios and their corresponding p-values. The second-to-last column reports RVIs for each of the top 20 variables, while the final column shows Pearson's correlation between each explanatory variable and biodiversity. *Sig < 0.05; **Sig < 0.01

Table 9

Summary of predictive performance of longitudinal analysis.

Metric	TreeNet®		Random Forest®		CART®	
	Training	Testing	Training	Testing	Training	Testing
Average LogLikelihood	0.0560	0.1686	0.7492	0.7579	0.1461	0.2353
ROC (Area Under Curve)	0.9740	0.8969	0.8617	0.8688	0.7816	0.7885
Lower Confidence Limit ROC	0.9713	0.8861	0.8554	0.8561	0.3077	0.3020
Upper Confidence Limit ROC	0.9768	0.9077	0.8680	0.8815	1.0000	1.0000
Lift	9.1862	6.6428	6.9952	6.3451	4.6013	4.6122
Misclassification rate	0.0155	0.0579	0.0344	0.0655	0.4832	0.4619

Notes: This table provides longitudinal predictive performance of three alternative machine learning models (TreeNet®, Random Forest®, CART®) for the biodiversity disclosure prediction. Five different metrics are used for the evaluative purposes: Average LogLikelihood, ROC (Area Under Curve), Lower and Upper Confidence Limit of ROC, Lift, and Misclassification rate.

Table 10

TreeNet® (gradient boosting) model stability test with different k-fold cross-validation.

Metric	K=5		K=10		K=15	
	Training	Testing	Training	Testing	Training	Testing
Average LogLikelihood	0.0285	0.0905	0.0282	0.0895	0.0282	0.0903
ROC (Area Under Curve)	0.9977	0.9362	0.9978	0.9379	0.9978	0.9361
Lower Confidence Limit ROC	0.9972	0.9322	0.9973	0.9340	0.9973	0.9321
Upper Confidence Limit ROC	0.9982	0.9402	0.9983	0.9417	0.9983	0.9400
Lift	9.8964	8.2367	9.9015	8.2306	9.9015	8.2077
Misclassification rate	0.0063	0.0282	0.0062	0.0276	0.0062	0.0283

Notes: This table provides TreeNet® (gradient boosting) model stability test with different three different k-fold cross-validation (k=5, k=10, and k=15). Five different metrics are used for the evaluative purposes: Average LogLikelihood, ROC (Area Under Curve), Lower and Upper Confidence Limit of ROC, Lift, and Misclassification rate.

Table 11

TreeNet® (gradient boosting) model stability test with different learning and subsample fraction on out-of-sample data.

Model	Optimal Number of Trees	Average LogLikelihood	ROC (Area Under Curve)	Misclassification Rate	Learning Rate	Subsample Fraction
1	5000	0.128657	0.862867	0.0399895	0.001	0.5
2	5000	0.110326	0.901200	0.0346775	0.010	0.5
3	4803	0.095874	0.924212	0.0291785	0.100	0.5
4	5000	0.128741	0.862677	0.0399521	0.001	0.7
5	5000	0.109732	0.902688	0.0341912	0.010	0.7
6	4851	0.093631	0.926635	0.0283555	0.100	0.7

Notes: This table provides TreeNet® (gradient boosting) model stability test with different learning (0.001, 0.010, and 0.100) rates and subsample fractions (0.5 and 0.7) on out-of-sample data. Three different metrics are used for the evaluative purposes: Average Log Likelihood, ROC (Area Under Curve), and Misclassification rate

Online Appendix

Appendix OA.1

Biodiversity dictionary

We use the following biodiversity dictionary to comprehensively collect biodiversity-related terms as referenced in corporate disclosures (Giglio et al., 2023). This dictionary includes terms that reflect key concepts such as biodiversity loss, habitat destruction, species extinction, and ecosystem services, among others.

Ecosystem(s): Ecosystem + climate, Ecosystem + coast, Ecosystem + forest, Ecosystem + micro, Ecosystem + natur, Ecosystem + public + health, Ecosystem + sustaina, Ecosystem + water

Marine: Marine + biodiversity, marine + ecosystem, marine + environment, marine + life, marine + species

Tropical: tropical + biodiversity, tropical + ecosystem, tropical + environment, tropical + forest, tropical+ species

Species: Species + aquatic, Species + biodiversity, Species + bird, Species + endanger, Species + environment, Species + fish, Species + habitat, Species + invasive, Species + list, Species + marine, Species + protect, Species + threat, Species + ESA, Species + EPA

Appendix OA.2

Alternative sample period (2002 – 2022)
Appendix OA.2A

Summary of cross-sectional predictive performance of machine learning models for the biodiversity disclosure from 2002 to 2022.

Metric	**TreeNet®**		**Random Forest®**		**CART®**	
	Training	**Testing**	**Training**	**Testing**	**Training**	**Testing**
Average LogLikelihood	0.0203	0.1088	0.1911	0.1628	0.1660	0.2081
ROC (Area Under Curve)	0.9999	0.9390	0.9339	0.9345	0.8593	0.8339
Lower Confidence Limit ROC	0.9999	0.9298	0.9294	0.9253	0.6763	0.6301
Upper Confidence Limit ROC	1.0000	0.9482	0.9383	0.9438	1.0000	1.0000
Lift	9.9978	8.1569	7.7037	7.8362	5.6512	5.6552
Misclassification rate	0.0025	0.0354	0.0449	0.0442	0.3731	0.4096

Notes: This table provides cross-sectional predictive performance of three machine learning models (TreeNet®, Random Forest®, CART®) for the biodiversity risk disclosure from 2002 to 2022. Five different metrics are used for the evaluative purposes: Average LogLikelihood, ROC (Area Under Curve), Lower and Upper Confidence Limit of ROC, Lift, and Misclassification rate.

Appendix OA.2B

Summary of cross sectional out-of-sample predictive performance of TreeNet® (gradient boosting) model for biodiversity disclosure across dimensions from 2002 to 2022.

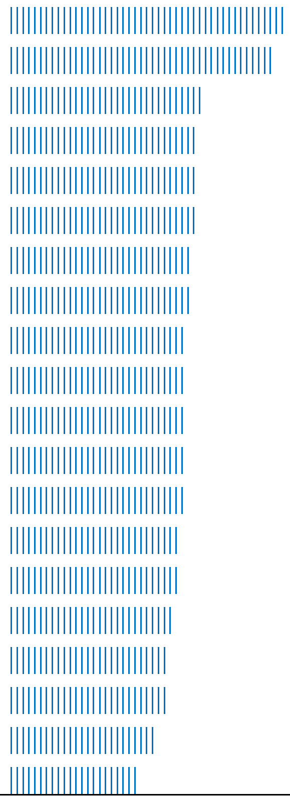
Metric	**ACCT**	**MKT**	**GOVERN**	**ENVIRON**	**OTHERS**
Average LogLikelihood	0.1315	0.1920	0.1864	0.2125	0.1756
ROC (Area Under Curve)	0.9043	0.7825	0.7879	0.6786	0.8414
Lower Confidence Limit ROC	0.8923	0.7674	0.7723	0.6628	0.8298
Upper Confidence Limit ROC	0.9164	0.7977	0.8036	0.6944	0.8531
Lift	7.3084	4.3339	4.7445	2.8467	5.2420
Misclassification rate	0.0422	0.0592	0.0558	0.0600	0.0601

Note: This table provides cross-sectional out of sample predictive performance of TreeNet® (gradient boosting) model for biodiversity risk disclosure across five dimensions from 2002 to 2022: Accounting, Market, Governance, Environment, and Others. Five different metrics are used for the evaluative purposes: Average LogLikelihood, ROC (Area Under Curve), Lower and Upper Confidence Limit of ROC, Lift, and Misclassification rate.

Appendix OA.3

RVIs for TreeNet® (gradient boosting) model for biodiversity disclosure from 2002 to 2022.

Variables	RVIs Scores	RVIs Strengths
PPE	100	
Herfindahl Index	98.0	
Total Assets	58.2	
Employees	56.6	
Shareholders Number	49.4	
PPE Newness	48.7	
CAPX	47.0	
BVPS	45.7	
FF4	44.4	
Firm Age	43.7	
Inventory Turnover	43.4	
Cash	42.3	
Current Ratio	41.9	
Sales	41.8	
Leverage	39.6	
Ind_Adj_ROA	38.0	
Distress	37.7	
Profit Margin	37.4	
Climate Change Exposure	34.8	
Share Price	34.2	



Notes: This table shows the relative variable importances (RVIs) of the TreeNet (gradient boosting) model using all the variables outlined in the appendix. For brevity, we only present top 20 variables. RVI measures a variable's contribution to the model by weighting its split frequency by the squared improvement it provides, averaged across all trees. The most important variable is assigned 100, with others scaled accordingly.