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Research Article

Rethinking Factor Inputs in Green Economy Growth: Capital, Labour or AI?

Oleksii Lyulyov, Tetyana Pimonenko, and Ruoxi Li

Abstract. As climate change and resource scarcity intensify, the pursuit of green economic growth has become a central policy priority across Europe. Understanding how different factors, particularly digitalization, institutional adaptation, and technological progress, interact to shape eco-productivity is essential for guiding sustainable transformation. This study explores the evolving dynamics of green economic growth across European countries, emphasizing the importance of technological change, institutional adaptation, and digital integration in driving sustainable development. While the literature has advanced the measurement of eco-productivity, gaps remain in understanding how digital capital interacts with traditional productivity models and environmental efficiency components. This research aims to address these gaps by evaluating green growth trajectories via a combination of entropy-based undesirable composite indicators and total factor productivity change (TFPCH) under both baseline and digital model specifications. Using panel data from 2005-2023, the study applies decomposition techniques to assess technological progress (TECH) and efficiency change (TECCH), complemented by nonparametric tests to determine statistical significance. The results show a general decline in environmental burdens across most EU countries, alongside modest but heterogeneous improvements in green productivity. While the TFPCH indicator remained stable between models, notable divergences emerged in its components: the digital model reported lower TECH values, indicating slower frontier advancement, but higher TECCH values, suggesting stronger catch-up dynamics when digital capital is accounted for. Countries such as Sweden, Finland, and Estonia led in reducing undesirable outputs, whereas others, including Poland, Ireland, and Ukraine, presented persistent challenges in improving relative eco-efficiency. These findings contribute to a deeper understanding of the structural factors underlying green growth and reveal the transformative potential of digitalization when appropriately integrated. The study concludes that while green economic growth is underway in many European regions, its pace and composition vary widely, requiring targeted policy responses.

Keywords: sustainable development; green development; renewable energy; green growth; AI.

Authors:

Oleksii Lyulyov
Institute for Sustainable Development and International Relations, WSB University, 1C Zygmunt Cieplak Street, 41-300 Dabrowa Gornicza, Poland; Department of Marketing, Sumy State University, 116, Kharkivska St, Sumy, 40007, Ukraine
E-mail: alex_lyulev@econ.sumdu.edu.ua
https://orcid.org/0000-0002-4865-7306

Tetyana Pimonenko
Institute for Sustainable Development and International Relations, WSB University, 1C Zygmunt Cieplak Street, 41-300 Dabrowa Gornicza, Poland; Department of Marketing, Sumy State University, 116, Kharkivska St, Sumy, 40007, Ukraine
E-mail: tetyana_pimonenko@econ.sumdu.edu.ua
https://orcid.org/0000-0001-6442-3684

Ruoxi Li
Department of Marketing, Sumy State University, 116, Kharkivska St, Sumy, 40007, Ukraine
E-mail: li.ruoxi@aspd.sumdu.edu.une
https://orcid.org/0009-0006-1597-7502

Corresponding Author: Tetyana Pimonenko, tetyana_pimonenko@econ.sumdu.edu.ua

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1. Introduction

In the current context of climate change, resource depletion, and digital transformation, the global scientific community is placing increasing emphasis on green economic growth—a development model that promotes improved well-being without compromising environmental sustainability [1]. One of the key challenges in this regard is the creation of a methodologically sound system for assessing green growth—one that accounts not only for traditional production factors but also for emerging digital drivers capable of influencing both resource efficiency and environmental impact [2–12].

According to neoclassical growth theory [13], economic growth is explained through a production function comprising three main inputs: capital, labor, and the use of natural resources. While this model captures the essence of industrial development, it reveals significant limitations in the context of the environmental crisis. Growth is often achieved through the extensive exploitation of natural resources, leading to a range of negative consequences, such as environmental degradation, increased CO_2 emissions, and biodiversity loss [14; 15].

Concurrently, the growing prominence of digital technologies is shaping a new paradigm of economic development. Within this digital (postindustrial) economic model, artificial intelligence (AI) is regarded as a novel productivity factor that enables more efficient resource utilization, loss minimization, logistics optimization, production automation, and emission reduction through more precise energy management [16-18]. With proper regulation and ethical implementation, digital technologies have the potential to significantly reduce or even neutralize adverse environmental impacts [9]. However, academic discourse also highlights the potential risks and limitations of the digital green growth model. AI is not environmentally neutral; data centers consume vast amounts of energy, and the infrastructure depends on rare earth metals, introducing new environmental challenges [19]. Moreover, the digital model may exacerbate global inequality: countries with access to advanced technologies, skilled labor, and data gain strategic advantages in developing “digital capital,” while developing nations risk being excluded from the process of sustainable development [20–24].

In this context, the OECD’s methodology for assessing green growth assumes particular significance. It is grounded in a comprehensive set of environmental and economic indicators designed to monitor progress toward sustainable development. The OECD green growth indicator framework encompasses four key dimensions: (1) environmental and resource productivity, (2) the natural asset base, (3) environmental quality of life, and (4) economic opportunities and policy responses. This methodology includes both production- and consumption-based indicators, such as CO_2 and greenhouse gas emission intensities, material and energy productivity, and environmentally adjusted multifactor productivity. By integrating these indicators with macroeconomic data (e.g., GDP, national income), the system facilitates the evaluation of countries' progress toward sustainable growth. Although the OECD methodology enables cross-country comparisons, it faces several significant limitations that reduce its analytical and practical effectiveness. First and foremost, this approach does not account for the core production processes that link resource use, economic output generation, and associated environmental externalities. Furthermore, within this framework, economic growth and environmental impact are treated as parallel but methodologically unconnected trajectories. A formalized mechanism for assessing eco-efficiency or the trade-offs between productivity and environmental constraints is lacking.

This approach is also limited in its ability to capture dynamic changes in total factor productivity under increasing environmental pressure. It does not distinguish between productivity shifts driven by technological innovation (i.e., outwards shifts in eco-efficiency frontiers) and those resulting from relative efficiency improvements (i.e., catching up). Moreover, undesirable production outcomes are not considered factors that influence the boundaries of feasible output. As a result, the OECD's indicator system does not offer an integrated, process-oriented evaluation of green economic growth. Additionally, the methodology insufficiently accounts for modern digital drivers, particularly investments in artificial intelligence, big data, and the Internet of Things, which already play crucial roles in advancing green innovations and ecoefficient management [9–12]. Its scope is limited primarily to the national level, neglecting intraregional disparities that are especially relevant for countries with significant territorial differentiation [14]. Given these shortcomings, contemporary challenges demand a rethinking of traditional economic growth models and the adaptation of assessment tools to the realities of digital transformation [24]. The integration of natural resources with digital technologies is creating new pathways for green growth with a minimal environmental footprint. Moreover, there is a growing need for an updated methodology capable of delivering a comprehensive, ethically grounded, and adaptive system for monitoring and managing sustainable development [25; 26].

This paper addresses these conceptual and methodological gaps by proposing an integrated approach to measuring green economic growth, grounded in production theory and responsive to the structural dynamics of digital transformation. The aim of this study is to provide a quantitative assessment of green economic growth on the basis of conventional (industrial) and digital (postindustrial) configuration model specifications followed by a comparative evaluation of their outcomes via the Malmquist–Luenberger productivity index (TFPCH) framework. The main contribution of the paper lies in the development and application of an extended TFPCH model that integrates both traditional production inputs (capital, labor, renewable energy) and intangible digital capital (venture capital in artificial intelligence), alongside a composite undesirable output index constructed via the entropy method. This dual-model design allows for a structural comparison of how digitalization affects eco-productive performance across European countries and Ukraine over the period 2005–2023.

To overcome the limitations of indicator-based approaches, this study applies the directional distance function framework of the TFPCH, which enables a decomposition of green growth into its core components: technological progress (frontier shift), efficiency change (catch-up), and total factor productivity change. By explicitly including undesirable outputs, the method captures the environmental costs embedded in economic activity. Moreover, the digital specification introduces a postindustrial perspective by incorporating AI-linked investment as a proxy for technological absorption capacity. This allows for an evaluation of eco-productivity under real-world conditions of structural transformation, environmental pressure, and intangible capital expansion. The findings reveal asymmetries in how different economies integrate digital inputs into their production frontiers, with implications for both the direction and speed of green convergence. By offering a process-oriented, flexible, and empirically validated framework, the study contributes to the evolving literature on green growth measurement and provides an operational tool for monitoring sustainability transitions in the digital age.

The paper has the following structure: the literature review explores the theoretical background on green economic growth and capital, labour and AI; the data and methods explore the data sources, methods and instruments used to chale the hypotheses of the study; the results describe the core empirical results; the discussion provides a comparison of the obtained results with those of previous studies; and the conclusion summarizes the core results of the study.

2. Literature Review

2.1. Green Economic Growth and Capital

Many scientists have focused on the assessment and modelling of green economy development, particularly in the context of local governance, regional disparities, and methodological innovations in evaluation frameworks. Dmuchowski et al. [14] examine the role of Polish local authorities in fostering and sustaining the conditions necessary for green economic growth. The studies [27–33] underscore the importance of municipal engagement in environmental investments, the implementation of eco-innovations, and the formulation of local environmental policies. Dmuchowski et al. [14] argued that enhancing institutional coordination and monitoring mechanisms is essential for maintaining long-term trajectories of green growth at the subnational level. Expanding this perspective, Misztal & Dziekański [34] analyse the determinants of green capital across Polish districts over the period 2010–2020, with a particular emphasis on waste management systems. Employing a synthetic indicator approach, the study models green capital development and reveals marked regional heterogeneity. The findings highlight the significant role of efficient resource management and environmental governance in shaping local capacities for green economy growth, emphasizing the strategic importance of integrating ecological considerations into regional planning. From a methodological standpoint, Wu & Liao [35] propose an innovative multicriteria decision-making (MCDM) framework complemented by conflict analysis to evaluate the performance of the green economy. This approach enables the resolution of trade-offs among competing criteria, such as economic efficiency versus environmental sustainability, and facilitates a more robust comparative analysis across national or regional contexts. The model enhances the accuracy and comprehensiveness of green economy assessments, offering valuable decision-support tools for policymakers. Similarly, Zheng [36] developed a system dynamics-based model designed to simulate the complex interdependencies among economic growth, environmental protection, and energy consumption within the green economy framework. This model provides a dynamic platform for evaluating the long-term implications of various policy interventions, enabling the identification of feedback loops and threshold effects.

The studies [37–42] underscore the multifaceted nature of green economic growth and offer methodological and policy-relevant pathways to measure and accelerate its advancement. Çapar & Arslanoğlu [37] highlight the role of the Sustainable Development Goals (SDGs) in driving the expansion of medical tourism, illustrating how sustainability objectives can foster sector-specific growth that aligns with environmental and social priorities. Duong [39] and Titko et al. [40] explored the psychological foundations of sustainable entrepreneurship, emphasizing the motivational mechanisms that encourage individuals to pursue green ventures, which are vital for fostering a sustainable business ecosystem. Kwilinski [41] investigated the nonlinear impact of digital technology on CO_2 emission reduction, offering an empirical perspective on how technological innovation contributes to environmental efficiency. Scholars [42] have presented a forecasting model for green competitiveness, positioning it as a critical tool for evaluating and steering business transformation in line with green growth imperatives. Vovk et al. [43] complement this perspective through a systematic review of the circular economy in the European Union, applying the PRISMA methodology to assess progress, barriers, and success factors in implementing circular models. This review provides a critical lens for evaluating policy effectiveness and the structural readiness of economies to transition toward resource efficiency and reduced environmental impact. Building on the entrepreneurial dimension of green growth, Zhao et al. [44] explore the determinants of green entrepreneurial intentions among SMEs in the electric vehicle component industry.

Sattarov & Choi [45] developed advanced deep Q-network algorithms for Bitcoin trading strategies, illustrating the power of AI in optimizing financial systems. Although focused on cryptocurrency, the underlying AI models have implications for broader financial efficiency and green investment portfolio optimization. Subramaniam et al. [46] analyse how personality traits and employee dynamic capabilities mediate performance during digital transformation, highlighting the role of human-AI interaction in productivity gains and operational sustainability. Scholars [47–49] have discussed how digital culture and AI-infused communication technologies support the achievement of the SDGs, demonstrating how digital tools enable more informed decision-making, participation, and social innovation.

Studies [50–55] have shown that green economy growth depends not only on the volume of capital mobilized but also on institutional design, spatial dynamics, investment quality, governance structures, and international capital flows. Bartelega & de Mendonça [50] emphasize the strategic role of public financial institutions, particularly the Brazilian Development Bank (BNDES), in channeling capital toward green economy initiatives. Their analysis underscores how institutional frameworks and targeted disbursement policies can significantly influence the scale and direction of green investments. In contrast, Zheng et al. [51] focused on the spatial dimension of finance, highlighting how financial agglomeration in China fosters green growth through increased access to capital, improved financial services, and concentrated knowledge spillovers. Ge et al. [52] examine infrastructure investment as a potential catalyst for green growth. Their findings suggest that while infrastructure spending can stimulate economic activity, only investments explicitly aligned with environmental goals yield sustainable outcomes. This aligns with the broader argument that the effectiveness of capital deployment depends heavily on the quality and orientation of investment [56–61], not merely its quantity. Li & Xu [62] introduce a governance lens by analysing how fiscal decentralization impacts green development. They argue that empowering local governments with financial autonomy can support green innovation and localized environmental initiatives, provided that there is sufficient institutional capacity and regulatory oversight. This decentralized approach provides a counterpoint to centralized financial control, as seen in the BNDES model. Song et al. [63] examine the influence of foreign direct investment (FDI) on green economic performance. They reveal that the environmental impact of FDI depends on its alignment with national green policies and the regulatory environment. When strategically directed, FDI can facilitate technology transfer and green innovation, reinforcing the positive effects observed in both domestic financial agglomeration and public investment strategies.

Ekayani et al. [64] examine how access to capital mediates the relationships among financial literacy, inclusion, and SME sustainability. Their findings underline the importance of equitable financial systems and support mechanisms in enabling small businesses to adopt sustainable practices—an essential pillar of inclusive green growth. Chen et al. [65] analyse the effects of digital transformation on tax compliance in the Chinese industrial sector, linking financial governance improvements with increased industrial efficiency and transparency, which are fundamental for mobilizing green investments and public trust. Ismail et al. [66] provide a framework for converting innovation into market-ready solutions, emphasizing how collaborative models enhance the return on public and private R&D investments, which is vital for scaling up green technologies. Kwilinski and Kardas [67] further contributed by assessing the efficiency of factorial designs in quality management, with practical relevance for optimizing production processes and resource use, which is key to reducing industrial environmental footprints.

Peng & Sun [68] address the primary structural and institutional challenges impeding China's green economy transition. This paper identifies key barriers such as insufficient policy coordination, weak regulatory enforcement, and the dominance of resource-intensive industrial models. It proposes strategic countermeasures, including improving legal frameworks, enhancing environmental governance capacity, and promoting green technologies to support a systemic shift toward sustainability. By offering a more comprehensive evaluation of China's green development trajectory, scholars [69] built on their earlier analysis, emphasizing the need for integrated policy reform. The study highlights strategic priorities such as optimizing energy structures, increasing investment in green industries, and fostering public awareness. It also stresses the importance of aligning environmental objectives with economic growth goals through institutional innovation and cross-sectoral collaboration. Reference [70] focused on the methodological development of a measurement system for green economy progress in China. Through empirical analysis, this study constructs a multidimensional indicator framework encompassing economic, environmental, and social variables. This system is intended to enable more accurate assessment and monitoring of green development performance across regions, providing a quantitative foundation for evidence-based policymaking.

Scholars [71–73] underscore that the effectiveness of environmental regulation in advancing green economic growth is conditioned by regulatory design, industrial readiness, and innovation capacity. Lu et al. [71] provide a nuanced analysis of the heterogeneous effects of various environmental regulatory instruments on green economic development in China. Lu et al. [71] revealed that regulatory efficacy varies significantly across sectors and regions, contingent upon factors such as institutional capacity, industrial composition, and local governance frameworks. Shao et al. [72] examine the interdependencies among environmental regulation, industrial transformation, and green economic growth. The authors [72] demonstrated that well-calibrated environmental policies can catalyze structural shifts in industry toward cleaner and more efficient production models. Through empirical assessment, the authors highlight how stringent, yet innovation-enabling, regulations serve as drivers for long-term green industrial development. Zhao et al. [15] investigate the interaction between environmental regulation and the stages of innovation development, with a particular focus on the moderating role of absorptive capacity. The study reveals that regulatory impacts on green growth are significantly enhanced when firms or regions possess advanced capabilities to assimilate and apply external knowledge. This suggests that the effectiveness of environmental regulation is dependent not only on policy formulation but also on innovation maturity and knowledge infrastructure within regulated entities. Nadiroh & Emilkamayana [73] evaluate the policy efficiency of environmental governance in supporting green economy objectives within the Indonesian context.

Studies [74–76] have demonstrated the tensions and synergies among economic valuation, governance structures, and ecological integrity in operationalizing natural capital within the context of green economy growth. Boehnert [74] explored the conceptual foundations of the green economy by reframing the idea of the natural commons forms of natural capital. Boehnert [74] argues that while integrating natural systems into economic frameworks can support environmental valuation, it also risks a commodifying nature in ways that may undermine ecological integrity. Dehm [75] investigated the evolving landscape of environmental governance under the influence of green economy principles, particularly through the lens of natural capital stewardship. The study highlights how governance frameworks are being reshaped to accommodate market-based instruments, property rights, and resource accounting, which in turn affect how environmental responsibilities are distributed and managed. Ducoing [76] focused on the practical challenges and opportunities associated with managing natural capital in green economy models. This paper provides an overview of methodologies and tools for assessing natural resource use and integrating ecological assets into economic planning. The results of the analysis identify the critical gaps in institutional coordination, resource allocation, and performance monitoring that constrain the implementation of green policies.

2.2. Green Economic Growth and Labour

The studies [77–92] underscore the significant role of human, intellectual, and social capital in shaping the trajectory of green economic growth and the transformation of labor markets. Huo & Liu [77] examine the dynamic interrelationship between intellectual property rights (IPR) and green economic development in China, suggesting that robust IPR protection incentivizes green innovation and supports the expansion of employment in environmentally sustainable sectors. Pawlewicz & Cieślak [78] explore the influence of social capital on green economy outcomes across Polish voivodeships, revealing that higher levels of trust, civic engagement, and cooperative behavior are positively associated with green policy adoption and labor market readiness for the green transition. Their findings outlined the social embeddedness of green growth and its reliance on collective social norms and institutions. Kozera-Kowalska [79] focused on the strategic importance of human capital in enabling green economic growth, highlighting that the development of environmentally relevant skills, education, and workforce adaptability is essential for supporting the evolving demands of green labor markets. The study advocates for the integration of sustainability competencies into human capital development frameworks. Szczepanska-Woszczyna et al. [80] and Tsiskaridze et al. [81] emphasized the contribution of higher education as a foundational pillar in fostering innovation, both in the short and long term. Their findings underscore how universities act as catalysts for green growth by generating knowledge, nurturing human capital, and facilitating research–industry collaboration that supports sustainable innovation ecosystems. Berg & Spicka [82] explore how political trust among farm workers is shaped by misinformation exposure, highlighting how social dynamics and institutional trust impact labour engagement in the agricultural sector. This is particularly relevant to green economic transformation, as trust in institutions can determine the effectiveness of sustainable labour policies and the willingness of workers to participate in ecological reforms. In parallel, studies [83-85] have investigated stakeholder-oriented value in family businesses, revealing how internal cultural values and brand strategies influence labour relationships and sustainability priorities, thereby affecting the long-term resilience and adaptability of labour-driven green enterprises.

Studies [86; 87] have examined the influence of green human resource (HRM) practices on ecological employee behavior, highlighting how organizational strategies can increase environmental responsibility in the workplace. Scholars [88] analyse the consequences of human capital misallocation across Chinese urban agglomerations and find that inefficiencies in labour allocation hinder the performance of the green economy. Their empirical analysis underscores the necessity of aligning skill distribution with regional environmental priorities to increase green productivity and labor utilization. Studies [21; 89] have demonstrated that high levels of human capital significantly contribute to environmental sustainability and the expansion of green economic activities. The study affirms that investment in education and human development is fundamental to supporting labor market transitions in the context of sustainable development. Tao et al. [9] investigated the synergistic effects of education-driven human capital and environmental regulation on the efficiency of the green economy in China. Their findings indicate that higher educational attainment enhances the effectiveness of environmental policies by fostering a more competent and adaptive labour force. Wang et al. [90] provide robust empirical evidence from 30 Chinese provinces, demonstrating that human capital accumulation has a significant positive effect on green economy indicators such as energy efficiency, technological adoption, and renewable sector employment. Angheluţă [91] articulates the foundational role of education in developing human capital for the green economy, stressing the importance of environmental awareness, specialized training, and curricular innovation in preparing future professionals for green-sector engagement. Shah et al. [92] analyse the role of corporate social responsibility (CSR) in facilitating green economic development in developing countries. Their study argues that CSR initiatives can stimulate green employment by promoting sustainability-driven organizational practices and investments in employee development aligned with environmental goals. Misztal & Ratajszczak [93] argue that integrating sustainability-focused management practices into workforce operations improves resource efficiency, employee engagement, and long-term competitiveness, which are foundational aspects of green transition in the business sector.

By demonstrating how knowledge-based assets improve resource efficiency in agriculture and positioning universities as key innovation hubs, scholars [94; 95] have highlighted the role of intellectual and institutional capital in green economy growth. Past studies [96] have investigated how religious values influence food waste behavior, revealing how deeply held social beliefs affect sustainable consumption patterns, which are critical for shaping labor and citizen practices in green transitions. Scholars [97] explore the intersection of country-of-origin perceptions, consumer ethnocentrism, and environmentalism, offering implications for green marketing strategies and labor engagement through culturally sensitive approaches. Zimbroff [98] emphasized the importance of adaptive and diverse extension programming postpandemic, which supports human capital development and environmental literacy, which is key to building resilient labor forces. van Deventer et al. [99] validated a behavioral model of consumer loyalty in banking, providing insights into how service design and trust can influence green financial behavior.

The results of the analysis revealed that green innovation, policy implementation, and sustainable development are significantly influenced by factors such as intellectual property rights, educational attainment, workforce adaptability, and social trust. Several scholars confirm that efficient labour allocation, skills development, and human capital investment are essential to enhancing green productivity and supporting transitions towards environmentally sustainable employment. Furthermore, the studies underline the importance of measuring labour-related impacts as central determinants of a successful green economy. This underscores the necessity of systematically estimating the contributions of labour and human capital to green growth strategies to ensure inclusive, resilient, and innovation-driven sustainability transitions.

2.3. Green Economic Growth and AI

Studies [16; 17; 100–102] have highlighted the growing importance of AI in enhancing environmental sustainability and supporting green economic growth. Kumar et al. [16] examine how the development of AI capabilities can improve environmental performance, emphasizing the moderating role of green knowledge management in translating technological potential into measurable sustainability outcomes. Doran et al. [17] complement this by offering policy recommendations aimed at guiding AI-driven industries toward the achievement of sustainable development goals, with a focus on regulatory frameworks and strategic alignment. Research [100] provides a conceptual analysis of the transformative capacity of AI to accelerate sustainable transitions across sectors, portraying AI as a critical enabler of green innovation and systemic change. Sivakumar et al. [101] proposed advanced AI-driven strategies for green network management and software-defined networking, contributing to the development of sustainable digital infrastructure. Gotsch et al. [102] underscore the broader contributions of data science and AI to green economic development, demonstrating their utility in optimizing resource efficiency, reducing environmental footprints, and supporting evidence-based decision-making in ecological planning.

These studies [103–105] suggest that the intersection of AI, digital technologies, and sustainable innovation within the context of green economy development. Benabdellah et al. [103] proposed an ontology-based knowledge management model that leverages AI tools to support green product design, facilitating more efficient decision-making and the integration of environmental criteria into early-stage product development. Montresor & Vezzani [104] investigate the relationship between digital technologies and ecoinnovation across Italian firms, revealing how digitalization acts as a catalyst for sustainable industrial transformation and competitiveness. Zribi et al. [105] introduced a computer vision-based quality assessment system designed to automate and optimize the management of consumables in analytical laboratories, contributing to resource efficiency and environmental sustainability through AI-enhanced process control. Osinubi et al. [106] underscore how digital tools facilitate access to finance, improve market connectivity, and foster innovation among entrepreneurs especially in underresourced regions thereby unlocking capital for green ventures and inclusive growth. The sholar [19] investigates how the integration of blockchain and AI technologies enhances transparency, traceability, and efficiency in sustainable investment processes, aiming to optimize capital flows toward environmentally responsible projects. Si Mohammed et al. [107] analyse the role of AI and fintech in fostering eco-friendly investments while preventing greenwashing, emphasizing the regulatory and technological mechanisms that ensure authenticity in sustainable finance. Bohn et al. [108] focused on the evolving governance landscape of sustainability reporting, examining stakeholder perceptions and the legitimacy of the International Sustainability Standards Board in the digital era. In the educational domain, Ferk et al. [26] explore how AI integration in higher education supports the achievement of sustainable development goals (SDGs), particularly by promoting digital literacy, innovation, and green competencies. Scholars [109–111] have examined the behavioural factors influencing the adoption of electronic health information systems and have assessed their broader implications for green economic efficiency, particularly in reducing resource consumption and operational waste. Jetha et al. [112] analyse how digital transformation and AI-driven changes in the nature of work may fragment labor markets and increase vulnerabilities among certain worker populations, raising critical questions about the inclusivity and equity of green and digital transitions. Du et al. [113] provide a comprehensive review of financial sentiment analysis techniques, showing how AI-driven tools can enhance decision-making in financial markets. These insights are critical for assessing green investments and risk perception, enabling more informed capital allocation toward environmentally sustainable assets.

Maldonado-Canca et al. [114] highlighted how AI applications support strategic communication, consumer engagement, and brand positioning, all of which are crucial for promoting sustainable products and environmental awareness. Melnychenko [115] leverages AI models to analyse the relationship between battlefield developments during the Russian-Ukrainian war and fluctuations in stock market values. Although conflict-centered, this paper contributes to green economic thinking by illustrating how AI-powered analytics can enhance risk management and financial resilience, which is key for mobilizing green investments in volatile environments.

The sholar [2] explores the application of integrated methodological approaches—potentially incorporating AI-based modelling—for the assessment of sustainable development strategies within the green economy framework. This study emphasizes the need for multidimensional evaluation tools that capture the environmental, economic, and social dimensions of sustainability, offering a more holistic and data-driven basis for policy formulation and long-term planning. From a complementary perspective, Silagadze et al. [24] conduct a comparative analysis of how leading global economies, including the U.S., the EU, and post-Soviet countries, have adapted their economic policies in response to the converging pressures of digital transformation and green transition. The study highlights policy convergence and divergence across geopolitical contexts, shedding light on strategic shifts in fiscal, industrial, and innovation policies aimed at supporting a dual digital–green agenda in the face of evolving global economic realities.

Studies [116; 117] explore two critical areas: cybersecurity awareness and the implementation of e-proctoring technologies in education. Scholars have identified key organizational and behavioural factors influencing employee cybersecurity awareness—an essential element for securing digital infrastructures that underpin green technologies and smart systems. In addition, they evaluate the institutional readiness and sustainability implications of digital surveillance tools in higher education, offering insights into how digitalization supports continuity, monitoring, and efficiency in learning environments aligned with green competencies.

Chahid et al. [18] proposed an integrated framework that combines AI and Internet of Things (IoT) technologies to reduce CO_2 emissions and strengthen environmental protection measures, highlighting the potential of smart systems for real-time monitoring and sustainable resource management. Ruiz-Real et al. [118] conducted a comprehensive review of AI applications in agriculture, emphasizing their role in enhancing environmental sustainability and productivity through precision farming, crop monitoring, and optimized resource use. Huang et al. [119] explored the use of AI for detecting and analysing controversial topics within the green energy sector, offering insights into how artificial intelligence contributes to social sustainability by informing public discourse and facilitating it.

3. Data and methods

Following the OECD's Green Growth Measurement Framework [1], which defines green growth as the pursuit of economic progress while ensuring environmental sustainability, this study applies the Malmquist–Luenberger Productivity Index (TFPCH) to measure country-level green economic growth. While the OECD framework provides a broad set of environmental and economic indicators, it remains largely descriptive and does not offer a direct linkage to the underlying production process or to the dynamics of total factor productivity under environmental constraints. The TFPCH addresses this limitation by enabling a production-theoretic operationalization of green growth. It allows for the dynamic assessment of productivity changes over time while explicitly incorporating both desirable outputs and undesirable outputs.

In the production context, the input vector is denoted as $x_t \epsilon R_+^N$, the desirable output vector as $y_t \epsilon R_+^M$, and the undesirable output vector as $b_t \epsilon R_+^J$, all observed at time t. The production possibility set $P(x_t)$ represents all feasible combinations of outputs producible with inputs x_t. The directional distance function $\vec{D}(\cdot)$ evaluates the maximum feasible expansion of desirable outputs and the simultaneous contraction of undesirable outputs in a given direction (g_y, g_b). It is formally defined as:

$$\vec{D}\left(x_t, y_t, b_t;\ g_y, g_b\right) = sup\{\beta : (y_t +\ \beta g_y, b_t\ - \beta g_b) \epsilon P(x_t)\} \tag{1}$$

The TFPCH is then calculated between two consecutive time periods t and t+1 as follows:

$$\mathrm{TFPCH}^{t\to t+1} = 1 + \frac{1}{2}\left[\vec{D}^t(x^{t+1}, x^{t+1}, b^{t+1}) - \vec{D}^t(x^t, x^t, b^t) + \right.$$
$$\left. + \vec{D}^{t+1}(x^{t+1}, x^{t+1}, b^{t+1}) - \vec{D}^{t+1}(x^t, x^t, b^t)\right] \tag{2}$$

Formula (2) allows for the assessment of productivity evolution under ecological constraints and can be multiplicatively decomposed into two interpretable components:

$$\mathrm{TFPCH} = \mathrm{TECH}\ \times\ \mathrm{TECCH} \tag{3}$$

where TECH r represents technological change, corresponding to a shift in the eco-productive frontier between periods, and where TECCH represents efficiency change, reflecting a country's movement toward or away from that frontier.

On the basis of formula (2), two empirical model specifications are constructed to analyse green economic growth across 27 EU member states and Ukraine over the period 2005–2023. The European Union provides a diverse yet integrated regional context for examining the evolution of green growth under common environmental goals and market frameworks, such as the European Green Deal and Fit for 55 initiatives. Ukraine is included as a transition economy with distinct structural challenges and increasing alignment with EU environmental and energy standards, particularly following the EU-Ukraine Association Agreement. These two models differ in terms of input configuration, allowing for a comparative evaluation of green productivity under traditional and digitally enhanced production structures.

The baseline model is grounded in a classical production structure that includes labor and capital as core inputs, which is consistent with the neoclassical framework of total factor productivity analysis [120]. Labour (L) is measured as total employment relative to the working-age population, capturing the available human input in the production process [121]. Capital (K) is represented by gross fixed capital formation in current US dollars, reflecting cumulative investments in physically productive assets and infrastructure [122]. In addition to these conventional inputs, the model incorporates renewable energy (RE), specified as its share of total final energy consumption. While not part of the traditional production function, this variable is introduced as an environmentally relevant input in line with the OECD Green Growth Measurement Framework [1], which emphasizes the role of energy system transformation in sustainable productivity. The inclusion of renewable energy captures structural adjustments in resource use and energy efficiency that influence green economic performance [123–130].

The digital model modifies the input configuration by replacing labor and capital with an intangible input reflecting digital technological capacity. Specifically, venture capital investment in artificial intelligence (AI) is used to proxy a country's absorptive capacity for digital innovation and structural transition toward knowledge-intensive production. This specification is consistent with emerging models of postindustrial productivity, where intangible capital plays a pivotal role in frontier movement [131–133]. Renewable energy is retained in both models to preserve analytical consistency and ensure comparability of the environmental input structures.

The desirable output is gross domestic product (GDP), measured in current US dollars. The GDP serves as an indicator of economic performance and output in the productivity and growth literature [134]. All the input and output variables are transformed into natural logarithms to align with the log-linear formulation of Model (2).

To incorporate environmental degradation, five undesirable outputs are selected on the basis of their theoretical significance within ecological economics and their presence in empirical green growth models. Carbon dioxide emissions represent long-term climate impacts and are the principal global pollutant considered in eco-productivity analyses [121]. PM2.5 air pollution captures human health-related externalities associated with energy-intensive production. Water stress reflects overexploitation of renewable freshwater resources and is particularly relevant in agriculture- and industry-intensive contexts. Fertilizer consumption serves as a proxy for land-based environmental pressure through nutrient runoff. Forest loss, operationalized as the inverse of forest area loss, accounts for ecosystem degradation and terrestrial carbon sink depletion [135]. These indicators are aggregated into a single environmental burden index via the entropy weighting method, which assigns objective weights on the basis of the statistical dispersion of each variable across countries and time periods [136]. This method avoids subjective assumptions and supports the construction of a composite indicator that is consistent with information theory-based approaches in sustainability assessment.

The descriptive statistics of all the variables are presented in Table 1. All data were obtained from the Sustainable Development Report [137], the OECD. AI [138] and the World Bank database [139].

Table 1. Summary of the Undesirable Composite Indicators (without Log Transformation).

Variable	Abbriviation	Mean	SD	Min	Max
Inputs					
Employment to population ratio, total (%)	L	53.34468	5.400475	37.289	65.184
Gross fixed capital formation, current US$	K	1.15×10^{11}	1.82×10^{11}	1.29×10^{9}	9.73×10^{11}
Renewable energy share in total final energy consumption, %	RE	18.23263	12.1444	0.1	59.21348
VC investments in AI, US$ millions	AI	175.7623	623.6486	1	5852.4
Desirable Output					
GDP, current US$	GDP	25.99101	1.489314	22.5322	29.1407
Undesirable Outputs					
CO_2-emissions	CO_2	123.8109	169.1986	1.3653	863.7247
PM2.5 air pollution, mean annual exposure (micrograms per cubic meter)	AirPollution	14.61654	5.115434	3.6271	27.76174
Level of water stress: freshwater withdrawal as a proportion of available freshwater resources	Water	21.31811	19.35073	0.9929	91.28713
Fertilizer consumption (kilograms per hectare of arable land)	Fertilizer	184.246	204.4167	16.4180	1497.291
Forest area (% of land area)	Forest	33.89166	16.94112	1.09375	73.82427

Source: Developed by the Authors.

To assess whether the baseline and digital model configurations yield statistically distinct estimates of green economic growth and its components, the analysis employs the Wilcoxon signed-rank test. This nonparametric test is designed for matched-pair data structures and does not require the assumption of normality in the underlying distribution. In the context of this study, each observation for a given country-year under the baseline model is paired with the corresponding observation from the digital model for the same period. The Wilcoxon signed-rank test evaluates the null hypothesis that the median difference between the two models is zero:

$$H_0 : \mathrm{TFPCH}_{baseline} = \mathrm{TFPCH}_{digital} \quad (4)$$

The procedure is applied separately to each component of model (3): TFPCH, TECH, and TECCH. The analysis yields test statistics, including the number of positive and negative differences, the sum of signed ranks, the standardized z statistic, and the corresponding p value. Prior to applying the Wilcoxon test, the Shapiro–Wilk test is conducted to examine the distributional properties of the indicators under both model specifications.

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4. Results

The results of the entropy method used to evaluate the undesirable composite indicator are presented in Table 2.

Table 2. Summary of the Undesirable Composite Indicators.

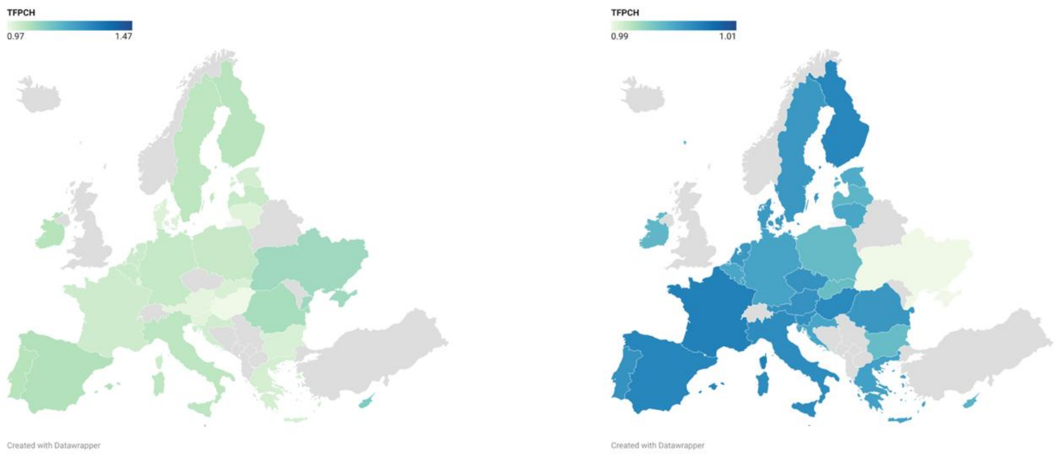
Country	Mean	Min	Max	Country	Mean	2005	2023
Austria	0.2086	0.1657	0.2479	Italy	0.4329	0.3508	0.5254
Belgium	0.4501	0.3824	0.5361	Latvia	0.1524	0.1253	0.1814
Bulgaria	0.3855	0.3131	0.4403	Lithuania	0.2010	0.1403	0.2611
Croatia	0.2639	0.2110	0.3133	Luxembourg	0.1980	0.1602	0.2291
Cyprus	0.3460	0.3208	0.3711	Malta	0.5154	0.4886	0.5425
Czechia	0.3360	0.2638	0.3802	Netherlands	0.3731	0.3162	0.4211
Denmark	0.3072	0.2927	0.3257	Poland	0.4701	0.3591	0.5268
Estonia	0.1353	0.0696	0.1637	Portugal	0.2242	0.1732	0.2606
Finland	0.0644	0.0416	0.0980	Romania	0.2804	0.2333	0.3145
France	0.3611	0.3002	0.4218	Slovakia	0.2391	0.1818	0.2746
Germany	0.5325	0.4164	0.6265	Slovenia	0.1836	0.1366	0.2232
Greece	0.3199	0.2750	0.3675	Spain	0.3786	0.3215	0.4436
Hungary	0.3018	0.2558	0.3362	Sweden	0.0675	0.0521	0.1061
Ireland	0.3536	0.3231	0.3976	Ukraine	0.3947	0.3367	0.4665

Source: Developed by the Authors.

In most European Union countries, a gradual decline in the composite undesirable indicator has been observed, reflecting improvements in environmental conditions. The decreasing values of the indicator signify a reduction in harmful emissions, improved air quality, and more efficient management of natural resources. Sweden, in particular, recorded the lowest value of the indicator in 2023 (0.052), highlighting the successful implementation of policies related to sustainable development, renewable energy, and environmental protection. Similarly, positive outcomes were also observed in Finland and Estonia. Central and Eastern European countries have gradually reduced their levels of undesirable effects throughout the study period. However, in comparison with those of Northern European countries, their values remain relatively higher, indicating the need for further modernization of environmental policy.

The high value of Ukraine's undesirable composite indicator in 2004 (0.466) points to a significant ecological burden, characteristic of post-Soviet economies with high energy intensity, a heavy industrial base, and limited application of environmental technologies. Nonetheless, a consistent downwards trend was recorded over the following two decades, with the indicator decreasing to 0.320 by 2023. This change resulted from a combination of internal structural transformations and external geopolitical factors. Since the mid-2000s, Ukraine's economy has gradually begun to shift away from the dominance of energy-intensive heavy industry, particularly after the 2008 global financial crisis and the political events of 2014. The partial shutdown of metallurgical enterprises, reductions in coal extraction and processing, and lower CO_2 emissions in industry have contributed to a decrease in environmental pressure in several regions. Following the signing of the EU-Ukraine Association Agreement in 2014, the country adopted a trajectory toward institutional and regulatory harmonization with EU environmental law. These processes have supported the rise of environmental awareness at the state level, increased transparency in environmental governance, and stimulated the development of new initiatives in the renewable energy sector.

Figure 1 presents the spatial distribution and temporal evolution of green economic growth across chosen European countries under the baseline model.



a) **b)**

Figure 1. Green Economic Growth Levels in European Countries, Evaluated under the Baseline Model For a) 2005 and b) 2023.
Source: Developed by the Authors.

In 2005, the distribution of TFPCH values indicates that most European economies were positioned below the productivity-neutral threshold of 1. This pattern reflects limited progress in simultaneously achieving economic output and environmental improvements. Bulgaria (0.9906), Croatia (0.9908), and Ireland (0.9942) exhibited relatively low performance, underscoring structural inefficiencies in integrating sustainability into growth processes. Greece (1.0038), France (1.001), and Portugal (1.0009) recorded marginally positive scores; these values suggest that truly green productivity gains were nascent and geographically uneven. By 2023, the spatial configuration of TFPCH values reveals significant improvements in green productivity across multiple regions. Malta (1.0116), Slovenia (1.0018), Finland (1.0032), and France (1.004) demonstrated advances, indicative of greater alignment between economic transformation and environmental efficiency. These improvements are attributed to a combination of policy interventions, investments in renewable technologies, and institutional adaptation to climate governance mechanisms. However, the persistence of subunity values in Poland (0.9960) and Ireland (0.9965) points to ongoing challenges in sustaining long-term eco-productivity. Ukraine's TFPCH declined to 0.9856, the lowest value among the assessed countries. Overall, the observed shift between 2005 and 2023 reflects an ongoing transition from an economic model based primarily on conventional inputs toward one that is gradually internalizing sustainability imperatives. While the pace and magnitude of progress remain heterogeneous, the data suggest the emergence of green growth trajectories in select economies, with Central and Southern Europe showing the most dynamic improvements.

Table 3 presents the results for the TECH component under the baseline model and reflects the shift in the eco-productive frontier.

Table 3. Summary of the Variable TECH under the Baseline Model.

Country	Mean	2005	2023	Δ2023-2005	Country	Mean	2005	2023	Δ2023-2005
Austria	0.9997	1.0009	1.0005	-0.0004	Italy	1.0000	1.0000	1.0000	0.0000
Belgium	0.9998	0.9992	1.0049	0.0057	Latvia	1.0001	0.9933	0.9967	0.0034
Bulgaria	0.9998	0.9918	1.0062	0.0144	Lithuania	0.9997	0.9955	0.9992	0.0037
Croatia	0.9998	0.9969	1.0018	0.0049	Luxembourg	1.0000	1.0000	1.0000	0.0000
Cyprus	0.9996	0.9980	1.0085	0.0105	Malta	1.0000	1.0000	1.0000	0.0000
Czechia	0.9998	0.9989	1.0066	0.0077	Netherlands	1.0002	0.9993	1.0000	0.0007
Denmark	0.9993	0.9973	1.0038	0.0065	Poland	0.9999	1.0000	1.0039	0.0039
Estonia	1.0003	0.9958	0.9964	0.0006	Portugal	1.0001	0.9994	1.0012	0.0018
Finland	1.0000	0.9981	1.0000	0.0019	Romania	0.9995	0.9977	1.0003	0.0026
France	1.0000	1.0000	1.0000	0.0000	Slovakia	1.0002	0.9947	1.0006	0.0059
Germany	1.0000	1.0000	1.0000	0.0000	Slovenia	1.0003	0.9953	1.0023	0.0070
Greece	1.0004	1.0058	1.0000	-0.0058	Spain	1.0005	0.9983	1.0020	0.0037
Hungary	0.9994	0.9999	1.0069	0.0070	Sweden	1.0000	1.0000	1.0000	0.0000
Ireland	1.0001	0.9943	1.0067	0.0124	Ukraine	1.0003	1.0016	1.0000	-0.0016

Source: Developed by the Authors.

The results demonstrate that the average TECH values across most countries are close to 1.0000, indicating general stability in the eco-productive frontier across Europe during the observed period. The most significant pgositive changes in TECH are observed in Bulgaria (Δ = +0.0144), Ireland (Δ = +0.0124), Cyprus (Δ = +0.0105), Czechia (Δ = +0.0077), Slovenia, and Hungary (each Δ = +0.0070). These countries experienced measurable improvements in their eco-productive potential, indicating a forward shift in the frontier toward more sustainable efficiency levels. In contrast, Greece (Δ = –0.0058) and Ukraine (Δ = –0.0016) show a decline in TECH values. This indicates a regression in the formation of the eco-productive frontier, reflecting a reduced capacity to achieve better outcomes without increasing environmental impacts. In France, Germany, Italy, Luxembourg, Malta, and Sweden, the TECH indicator remained constant at 1.0000 throughout the period. This reflects the stability of the frontier in terms of the combination of economic and environmental efficiency.

The empirical results demonstrate substantial variation in TECCH across countries (Table 4).

Table 4. Summary of the Variable TECCH under the Baseline Model.

Country	Mean	2005	2023	Δ2023-2005	Country	Mean	2005	2023	Δ2023-2005
Austria	1.0006	1.0000	1.0010	0.0010	Italy	1.0000	1.0000	1.0024	0.0024
Belgium	0.9989	0.9971	0.9939	-0.0032	Latvia	1.0005	1.0033	1.0001	-0.0032
Bulgaria	1.0001	0.9988	0.9898	-0.0090	Lithuania	1.0009	1.0040	0.9996	-0.0044
Croatia	1.0002	0.9938	0.9971	0.0033	Luxembourg	0.9999	0.9989	0.9989	0.0000
Cyprus	1.0000	1.0003	0.9885	-0.0118	Malta	0.9995	1.0000	1.0116	0.0116
Czechia	1.0004	1.0008	0.9950	-0.0058	Netherlands	0.9995	0.9983	1.0008	0.0025
Denmark	1.0005	1.0013	0.9968	-0.0045	Poland	0.9992	0.9985	0.9921	-0.0064
Estonia	1.0005	1.0031	1.0016	-0.0015	Portugal	1.0006	1.0015	1.0004	-0.0011
Finland	1.0003	1.0007	1.0032	0.0025	Romania	1.0006	0.9998	1.0006	0.0008
France	1.0005	1.0010	1.0040	0.0030	Slovakia	1.0003	1.0013	0.9950	-0.0063
Germany	0.9987	0.9987	0.9992	0.0005	Slovenia	1.0006	1.0038	0.9995	-0.0043
Greece	1.0005	0.9980	0.9997	0.0017	Spain	1.0000	0.9995	1.0014	0.0019
Hungary	1.0004	0.9973	0.9958	-0.0015	Sweden	1.0002	1.0023	1.0008	-0.0015
Ireland	0.9996	0.9999	0.9898	-0.0101	Ukraine	0.9998	0.9980	0.9856	-0.0124

Source: Developed by the Authors.

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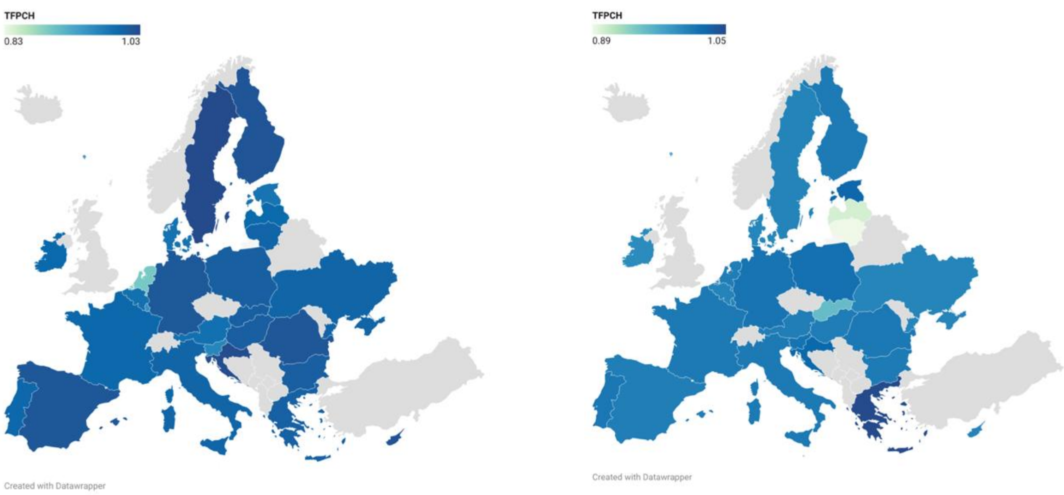
Several countries recorded a decline in their catch-up efficiency, indicating a widening gap between their current production practices and the best achievable eco-productive performance. The most significant declines are observed in Ukraine (Δ = –0.0124), Cyprus (Δ = –0.0118), Ireland (Δ = –0.0101), Bulgaria (Δ = –0.0090), and Poland (Δ = –0.0064). These results reflect a weakening of eco-efficiency relative to the frontier, suggesting deterioration in the ability of these countries to convert inputs into GDP while minimizing environmental pressures.

In contrast, positive changes in TECCH are noted in several other economies. The most notable improvements are observed in Malta (Δ = +0.0116), Italy (Δ = +0.0024), Finland and the Netherlands (each Δ = +0.0025), Spain (Δ = +0.0019), and Greece (Δ = +0.0017). These countries demonstrated better convergence toward the eco-productive frontier, reflecting improved relative efficiency in combining inputs and controlling the ecological burden. For the majority of EU countries, the TECCH values remained close to one, indicating overall stability in terms of relative eco-efficiency. France, Austria, Romania, and Germany experienced modest gains, whereas countries such as Luxembourg, Slovakia, and Czechia experienced minor declines. Ukraine's TECCH value decreased from 0.9980 in 2005 to 0.9856 in 2023, representing the largest negative change among all the observed countries. This result reflects a measurable decline in the country's relative eco-efficiency, indicating an increasing gap between Ukraine and the best-performing eco-productive frontier. The data confirm that, over the study period, Ukraine demonstrated a reduced capacity to maintain or improve its position relative to the most efficient countries in terms of resource use and environmental impact.

Figure 2 presents the results obtained from the application of the digital model for assessing green economic growth.



a) b)

Figure 2. Level of Green Economic Growth across European Countries, Assessed via the Digital Model Based on TFPCH: (a) Year 2013; (b) Year 2023.
Source: Developed by the Authors.

In 2013, green growth was recorded in less than half of the EU countries. Notably, leaders in that year included Sweden (1.0284), Croatia (1.0256), Cyprus (1.0190), Finland (1.0167), Romania (1.0160), Germany (1.0139), and Spain (1.0149). These countries have effectively integrated renewable energy and emerging digital capital into their production systems under environmental constraints. However, a significant number of countries registered TFPCH values below 1, indicating declining eco-productivity, including Malta (0.8314), the Netherlands (0.8956), Luxembourg (0.9538), and Denmark (0.9861). By 2023, a broader group of countries achieved TFPCH values above 1. The most prominent growth was observed in Greece (1.0507), Estonia (1.0253), Poland (1.0169), Slovenia (1.0148), Germany (1.0143), and Portugal (1.0112). These results reflect increased eco-productive performance, which may be attributed to more consistent integration of renewable technologies and digital innovation over the decade. At the same time, several countries showed stagnation or decline in TFPCH values. Latvia and Lithuania demonstrated the sharpest regressions, with TFPCH dropping to 0.9005 and 0.8874, respectively, in 2023, despite being close to the threshold in 2013. The Slovak Republic declined from 1.0062-0.9516. Compared with 2013, Malta, although improving, still remained below the threshold (0.9835). Ukraine maintained a stable TFPCH of 1.0000 in both years, reflecting neither improvement nor regression in its eco-productivity level over the analysed period.

The values of the TECH component indicate that in 2013, a substantial number of countries recorded TECH values greater than one, corresponding to a forward shift in the eco-productive frontier (Table 5).

Table 5. Summary of the Variable TECH under the Digital Model.

Country	Mean	2013	2023	Δ2023-2013	Country	Mean	2005	2023	Δ2023-2013
Austria	1.0077	1.0397	1.0084	-0.0313	Italy	1.0177	1.0968	1.0148	-0.0820
Belgium	1.0177	1.1390	1.0110	-0.1280	Latvia	0.9964	1.0000	0.9614	-0.0386
Bulgaria	1.0192	1.1527	1.0232	-0.1295	Lithuania	1.0094	1.0427	1.0000	-0.0427
Croatia	1.0227	1.1609	1.0698	-0.0911	Luxembourg	1.0000	1.0000	1.0069	0.0069
Cyprus	1.0198	1.3119	1.0296	-0.2823	Malta	1.0051	1.0000	1.0000	0.0000
Denmark	1.0058	1.0399	0.9969	-0.0430	Netherlands	1.0001	0.9773	1.0000	0.0227
Estonia	1.0014	1.0000	1.0541	0.0541	Poland	1.0344	1.3826	1.0462	-0.3364
Finland	1.0000	1.0000	1.0000	0.0000	Portugal	1.0087	1.0501	1.0170	-0.0331
France	1.0181	1.0323	1.0055	-0.0268	Romania	1.0107	1.1284	1.0010	-0.1274
Germany	1.0194	1.0685	1.0117	-0.0568	Slovakia	1.0172	1.1304	1.0000	-0.1304
Greece	1.0234	1.2078	1.1221	-0.0857	Slovenia	0.9999	1.0000	1.0099	0.0099
Hungary	1.0209	1.1343	1.0646	-0.0697	Spain	1.0173	1.0466	1.0069	-0.0397
Ireland	1.0082	1.1103	0.9947	-0.1156	Sweden	0.9977	1.0000	1.0001	0.0001
					Ukraine	1.0000	1.0000	1.0000	0.0000

Source: Developed by the Authors.

By 2023, a majority of countries experienced a decline in the TECH indicator, indicating a slowdown in the pace of frontier advancement. The most notable reductions were observed in Poland, Cyprus, Slovakia, Bulgaria, Belgium, Ireland, and Croatia, where the decrease in TECH between 2013 and 2023 ranged from 0.09-0.34. Although the TECH values remained above one in most of these cases, the reduced magnitude confirms a weakening dynamic of eco-productive improvement relative to the earlier period. A limited number of countries, including Estonia, the Netherlands, and Slovenia, presented TECH values greater than one in both 2013 and 2023, which indicates the continuous advancement of the eco-productive frontier. In contrast, Finland, Malta, Sweden, and Ukraine recorded TECH values equal to one in both years, indicating a stable frontier with no net progression or regression throughout the observed period.

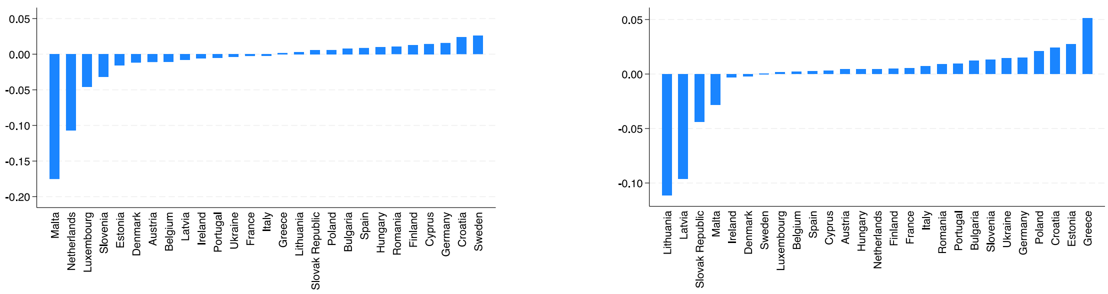
The TECCH values from 2013-2023 indicate clear variation in the pace of convergence toward the eco-productive frontier across European countries (Table 6). In 2013, most countries recorded TECCH values below one, reflecting an initial efficiency gap. By 2023, the majority had increased their TECCH scores, indicating a measurable reduction in this gap. Poland (+0.2443), Cyprus (+0.1948), and Malta (+0.1521) exhibited the strongest gains, whereas countries such as Denmark, France, Germany, the Netherlands, Romania, and Slovenia reached or exceeded full convergence (TECCH $\geq$ 1). In contrast, Latvia, Lithuania, and Sweden recorded negative changes, indicating a decline in relative efficiency. Ukraine maintained a stable value of 1.0000 throughout the period, representing constant alignment with the eco-productive frontier.

Table 6. Summary of Variables: TECCH under the Digital Model.

Country	Mean	2013	2023	Δ2023-2013	Country	Mean	2005	2023	Δ2023-2013
Austria	0.9933	0.9505	0.9974	0.0469	Italy	0.9860	0.9120	0.9950	0.0830
Belgium	0.9841	0.8679	0.9900	0.1221	Latvia	0.9927	0.9948	0.9367	-0.0581
Bulgaria	0.9895	0.8734	0.9855	0.1121	Lithuania	0.9898	0.9594	0.8874	-0.0720
Croatia	0.9845	0.8834	0.9565	0.0731	Luxembourg	0.9903	0.9538	0.9937	0.0399
Cyprus	0.9872	0.7767	0.9715	0.1948	Malta	0.9695	0.8314	0.9835	0.1521
Denmark	0.9914	0.9483	1.0016	0.0533	Netherlands	0.9829	0.9164	1.0054	0.0890
Estonia	0.9966	0.9846	0.9727	-0.0119	Poland	0.9937	0.7278	0.9721	0.2443
Finland	1.0030	1.0167	1.0081	-0.0086	Portugal	0.9917	0.9500	0.9943	0.0443
France	0.9855	0.9659	1.0039	0.0380	Romania	0.9909	0.9004	1.0087	0.1083
Germany	0.9860	0.9489	1.0026	0.0537	Slovakia	0.9880	0.8901	0.9516	0.0615
Greece	0.9874	0.8318	0.9364	0.1046	Slovenia	0.9971	0.9660	1.0049	0.0389
Hungary	0.9833	0.8877	0.9458	0.0581	Spain	0.9864	0.9698	0.9992	0.0294
Ireland	0.9851	0.8969	0.9989	0.1020	Sweden	1.0035	1.0284	1.0008	-0.0276
					Ukraine	0.9791	1.0000	1.0000	0.0000

Source: Developed by the Authors.

Figure 3 illustrates the intermodel differential in green economic growth levels (TFPCH) between the digital and baseline specifications for 2013 (panel a) and 2023 (panel b).



a) b)

Figure 3. Differences in Green Economic Growth Levels across European Countries, Estimated under the Digital And Baseline Models: (a) 2013; (b) 2023.
Source: Developed by the Authors.

In 2013, the magnitude of divergence between the two models was moderate and structurally concentrated. A small cluster of countries (Malta, the Netherlands, and Luxembourg) exhibited positive differentials under the digital model, indicating early-stage productivity gains linked to digital capital. In contrast, a wider set of economies, such as Estonia, Croatia, Cyprus, and Bulgaria, showed negative differentials, suggesting that conventional input structures remained dominant and that digital investments had not yet been absorbed into frontier-shifting processes. By 2023, the divergence had deepened and became structurally differentiated. Lithuania, Latvia, and Ireland recorded the largest negative differentials, reflecting limited technological absorption and a potential mismatch between digital investment and eco-productive outcomes. On the other hand, countries such as Estonia, Croatia, Poland, and Greece exhibited significant positive differentials, implying that digital capital was effectively integrated into their production systems, contributing to green total factor productivity under the digital specification. These dynamics reflect the emergence of two distinct clusters: one characterized by successful digital frontier expansion, and another marked by persistent reliance on traditional growth trajectories.

Table 7 presents the results of the Shapiro–Wilk test for normality, which is applied to the green productivity indicators under both the baseline and digital model specifications. For all variables (TFPCH, TECH, and TECCH), the test yields W statistics significantly below 1 and p values of 0.00000, indicating strong evidence against the null hypothesis of normality. These results confirm that the data distributions are nonnormal in both models, justifying the use of a nonparametric Wilcoxon signed-rank test.

Table 7. The Shapiro–Wilk W Test Was Used for Normally Distributed Data.

Variable	baseline model				digital model			
	W	**V**	**z**	**Prob>z**	**W**	**V**	**z**	**Prob>z**
TFPCH	0.85294	31.053	8.061	0.00000	0.80108	42.004	8.770	0.00000
TECH	0.84835	32.022	8.133	0.00000	0.79640	42.993	8.824	0.00000
TECCH	0.92799	15.205	6.385	0.00000	0.89231	22.741	7.330	0.00000

Source: Developed by the authors.

Table 8 presents the results of the Wilcoxon signed-rank test, which evaluates whether the distributions of the green growth indicators obtained from the baseline and digital model specifications differ significantly across countries and time periods.

Table 8. Wilcoxon Signed-Rank Test.

Sign	Obs	Sum ranks	Expected	z	Prob > |z|
		TFPCH			
Positive	139	22405	22126		
Negative	157	21847	22126	0.188	0.8506
Zero	1	1	1		
		TECH			
Positive	89	15584	21538.5		
Negative	160	27493	21538.5	-4.029	0.0001
Zero	48	1176	1176		
		TECCH			
Positive	182	27904.5	22125		
Negative	113	16345.5	22125	3.902	0.0001
Zero	2	3	3		

Source: Developed by the authors.

For the total factor productivity change, the test yields a z value of 0.188 with a p value of 0.8506, indicating that there is no statistically significant difference between the baseline and digital models. This result supports the null hypothesis, suggesting that, at the aggregate level, the overall measure of green economic growth remains stable across specifications. Despite notable cross-country variation observed in the graphical analysis (Figure 3), these differences balance out in the aggregate, yielding no systemic shift between models in total productivity terms. In contrast, the decomposition components exhibit statistically significant differences. For TECH, which captures technological change or frontier shift, the test returns a z value of -4.029 and a p value of 0.0001. The negative sign indicates that the digital model produces consistently lower values of frontier shift relative to the baseline. This implies that the incorporation of digital capital reveals a more conservative estimate of technological progress, potentially reflecting the lagged diffusion of digital inputs into the eco-productive frontier. For TECCH, which measures efficiency change or catch-up to the frontier, the test produces a z value of 3.902 and a p value of 0.0001. The positive result indicates that the digital model yields significantly greater catch-up effects than the baseline model does. This suggests that when digital capital is included, more countries appear to be moving closer to the frontier, reflecting either improved absorption capacity or a recalibrated benchmark under the expanded model specification. These results demonstrate that while total productivity remains statistically equivalent across models, the underlying mechanisms driving green growth are fundamentally altered when intangible digital factors are introduced. This finding reinforces the value of model decomposition in revealing the structural asymmetries and latent drivers of eco-productive change under digital transformation.

5. Discussion

This study aimed to measure and compare the dynamics of green economic growth across 27 EU member states and Ukraine using the Malmquist–Luenberger productivity index (TFPCH) under two specifications: a baseline model with conventional inputs (labor, capital, renewable energy) and a digital model incorporating intangible capital (AI investment). The findings reveal that while total factor productivity change remains stable across models, the decomposition into technological change and efficiency change shows significant variation, indicating structural asymmetries in how countries internalize green and digital transformations.

The observed divergence is consistent with theoretical expectations from the green growth literature, which emphasize the multidimensional nature of sustainability performance [1; 140]. The relatively lower values of TECH in the digital model suggest that digital capital does not automatically translate into frontier expansion. This aligns with findings from Tao [100] and Kumar et al. [16], who argue that AI-driven productivity gains are often nonlinear and highly context dependent, requiring institutional and technological readiness to fully manifest. In contrast, the higher TECCH scores in the digital model support the hypothesis that digital inputs can enhance relative efficiency through process optimization and better environmental management, even in the absence of technological breakthroughs [17; 26].

These patterns also echo findings in the DEA and MLPI literature, where efficiency improvements often precede or outweigh frontier shifts in response to structural changes [33; 72; 122; 134]. Countries such as Poland, Croatia, and Greece, which demonstrate stronger

TECCH under the digital model, appear to benefit from institutional adaptation and policy environments conducive to absorbing digital inputs. Conversely, countries such as Lithuania and Latvia display stagnation or regression in both dimensions, pointing to persistent structural rigidities or underinvestment in innovation ecosystems.

Ukraine represents a structurally differentiated case within the sample. Under both model specifications, the country demonstrates a stable level of TFPCH, indicating a neutral trajectory in terms of green economic growth during the analysed period. However, the decomposition of TFPCH reveals significant variation between the models. In the baseline specification, a decline in the efficiency change component suggests that Ukraine's capacity to convert conventional inputs such as capital, labor, and renewable energy into environmentally adjusted output has weakened over time. This result reflects long-standing challenges associated with outdated industrial infrastructure, low capital renewal rates, and inefficiencies in institutional arrangements governing labor and energy markets [141]. In contrast, the digital specification produces a more stable profile. Despite relatively limited AI-related investment in absolute terms, Ukraine does not exhibit deterioration in either TFPCH or TECCH under the digital model. This outcome indicates a relative alignment with postindustrial eco-productive dynamics, particularly in terms of efficiency convergence. These results correspond to Ukraine's gradual institutional alignment with European Union standards following the signing and implementation of the EU-Ukraine Association Agreement [142]. Advancements in digital infrastructure, such as the Diia public services platform, along with reforms in environmental governance and integration into European digital and energy frameworks, have contributed to increasing institutional adaptability [1]. Nonetheless, structural constraints persist. The economy continues to rely on energy-intensive and extractive sectors, and the consequences of military conflict, including large-scale destruction of capital stock and disruption of labor force dynamics, are likely to inhibit both technological advancement and frontier expansion [143]. The relative stabilization observed in the digital model may therefore reflect compensatory effects, in which inefficiencies in traditional inputs are mitigated through limited but targeted investments in intangible assets and renewable technologies within a constrained resource environment.

6. Conclusions

The analysis reveals a general decline in undesirable composite indicators across most EU countries, indicating reduced environmental burdens due to reforms, technological upgrades, and efficient resource use. Countries such as Sweden, Finland, and Estonia lead in terms of environmental performance, reflecting strong governance and investment in renewables. Green productivity, measured through TFPCH, improved notably between 2005 and 2023, especially in Southern and Central Europe, although Poland and Ukraine continue to face challenges. TECH values remained relatively stable but improved in countries such as Bulgaria and Czechia, suggesting progress in technological advancement and cleaner production. In contrast, TECCH has declined in several countries, including Ukraine and Cyprus, pointing to widening gaps in efficiency relative to the frontier. The digital model highlighted different growth dynamics and lower frontier shifts but stronger catch-up effects, underscoring the transformative role of digital capital. Countries such as Greece and Estonia benefited from digital integration, whereas Latvia and Lithuania lagged behind. Ukraine showed progress in reducing emissions but remained the lowest in terms of the green productivity indicators.

Statistical tests confirm stable overall productivity but with significant divergence in the drivers of growth when digital inputs are considered. These findings emphasize the need to address structural disparities and invest in digital and clean technologies to support inclusive green economic growth.

On the basis of the research findings, the following policy implications for enhancing green economy growth can be outlined:

- To accelerate the growth of the green economy, a strategic focus on digital infrastructure and innovation ecosystems is essential. Investments in smart grids, AI-powered environmental monitoring, and digital energy management systems can significantly increase both technological advancement and catch-up efficiency. These digital tools not only enable real-time data analysis and more precise decision-making but also foster eco-innovations that can be scaled across sectors and regions.
- Institutional reforms must be prioritized, especially in countries exhibiting persistent eco-efficiency gaps, such as Ukraine and Cyprus. Strengthening governance frameworks through increased transparency, regulatory alignment with EU standards, and more effective enforcement of environmental legislation could create a more conducive environment for sustainable transformation. Building administrative capacity and reducing institutional fragmentation are key to enhancing policy implementation and attracting sustainable investments.
- Regional convergence mechanisms, including EU cohesion funds, Just Transition initiatives, and dedicated green transition platforms, should be expanded to bridge disparities between high-performing and lagging countries. By promoting knowledge transfer and providing tailored technical and financial support, these mechanisms can help less advanced economies emulate the best practices of sustainability leaders such as Sweden, Finland, and Estonia.
- Public–private partnerships (PPPs) should be actively encouraged to drive sustainability-oriented research and development. Collaborations among governments, universities, and businesses can stimulate innovation in renewable energy, sustainable agriculture, and circular economy solutions. These partnerships can also derisk green investments and enhance market readiness for clean technologies.
- Fiscal policies and financial instruments must be aligned with each country’s green performance metrics. Incentives such as tax credits, green bonds, and subsidies should be designed on the basis of specific national and sectoral TECH and TECCH outcomes, ensuring that support is directed where it can yield the most significant environmental and economic returns. Performance-based financing can motivate industries to adopt greener practices and invest in efficiency-enhancing innovations.
- Targeted education and training programs in digital literacy, green entrepreneurship, and sustainable technology application are crucial for developing a workforce that can thrive in the emerging green digital economy. Emphasis should also be placed on upskilling workers in traditional sectors to enable just and inclusive transitions.
- National sustainability strategies should adopt integrated modelling approaches such as those based on digital TFPCH metrics to identify inefficiencies, monitor progress, and inform dynamic policy adjustments. These tools could help policymakers understand the interactions between technological innovation, capital deployment, and labor market

transformation, allowing for more responsive and evidence-based governance in pursuit of green economic growth.

This study, while comprehensive, is limited by its reliance on entropy-based composite indicators and TFP decomposition, which may not fully capture qualitative aspects of environmental policy implementation and societal behavioral shifts. The analysis is constrained by data availability and uniformity across countries, particularly with respect to intangible digital capital and real-time environmental metrics. Moreover, the digital model assumes linear integration of digital capital into eco-productivity, which may oversimplify complex interactions in innovation diffusion. Future research should explore sector-specific dynamics of green growth, especially in emerging economies and postconflict contexts such as Ukraine. The integration of machine learning techniques and firm-level data to better assess microeconomic drivers and regional disparities in green transformation trajectories is also recommended.

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