UNIVERSIDADE FEDERAL DO RIO GRANDE DO SUL
CENTRO DE ESTUDOS E PESQUISAS EM AGRONEGÓCIOS
PROGRAMA DE PÓS-GRADUAÇÃO EM AGRONEGÓCIOS
DOUTORADO EM AGRONEGÓCIOS

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Advancing Holistic Measurement of the Bioeconomy: Proposing the Cyber-Bio-Physical-Social System Framework

Porto Alegre (RS), Brasil
2026

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Tese apresentada como requisito parcial à obtenção do título de doutor em Agronegócios pelo Programa de Pós-graduação em Agronegócios da Faculdade de Agronomia da Universidade Federal do Rio Grande do Sul.
Orientador: Prof. Dr. Edson Talamini - UFRGS

Porto Alegre (RS), Brasil

2026

CIP - Catalogação na Publicação

Leavy, Sebastián
Advancing Holistic Measurement of the Bioeconomy: Proposing the CyberBio-Physical-Social System Framework / Sebastián Leavy. -- 2026.
287 f.
Orientador: Edson Talamini.

Tese (Doutorado) -- Universidade Federal do Rio Grande do Sul, Centro de Estudos e Pesquisas em Agronegócios, Programa de Pós-Graduação em Agronegócios, Porto Alegre, BR-RS, 2026.

1. Medição da Bioeconomia. 2. Bioeconomia Holística. 3. Tecnologias Digitais. 4. Sistemas Ciber-Bio-Físico-Sociais. 5. Contabilidade de Carbono Florestal. I. Talamini, Edson, orient. II. Título.

Elaborada pelo Sistema de Geração Automática de Ficha Catalográfica da UFRGS com os dados fornecidos pelo(a) autor(a).

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Aprovado em: Porto Alegre (RS), Brasil,6 de março de 2026.

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A mi hija Indiana.

AGRADECIMENTOS

O início do meu doutorado coincidiu com a pandemia, logo após meu retorno à cidade natal, alguns meses antes – após 28 anos desde que parti para estudar Agronomia e vivi em diversas cidades da Argentina e do exterior, em universidades orientadas por objetivos de pesquisa. Em primeiro lugar, agradeço à minha filha Indiana pelo tempo compartilhado que sacrificamos mutuamente, a Noelia, e aos meus pais, irmãos, sobrinhos e tios por sua presença constante e apoio incondicional. Com a culminação deste doutorado, aspiro a que se abram novos horizontes na minha trajetória profissional e pessoal, inspirados e impulsionados por esse inestimável respaldo.

Ao meu orientador, Edson Talamini, por sua paciência, espírito nobre e sabedoria. Agradeço-lhe profundamente por toda a ajuda, os ensinamentos e o exemplo que me brindou.

Aos professores das diversas disciplinas: Heinrich Hasenack, Kelly Bruch, Leticia De Oliveira, Glauco Schultz, Verónica Schmidt, Rodrigo Singer, Daniela Callegaro, Jean Philippe Palma Revillion, Sergio Schneider e Elisângela da Silva Rodrigues. E, como sempre, ao grande "Mestre" Homero Dewes, cuja contribuição global e temporal transcende as palavras.

Agradeço profundamente aos membros da banca examinadora do projeto de tese e da tese final, aos professores Profa. Dra. Talita Pinto, Prof. Dr. Antônio Domingos Padula, Dr. Sandro Camargo e Prof. Dr. Feni Agostinho, que prontamente aceitaram participar dessa etapa fundamental de minha formação acadêmica. Suas valiosas contribuições já enriqueceram minha pesquisa de maneira significativa e, sem dúvida, continuarão a aprimorá-la, mesmo após a conclusão desta tese, fortalecendo minha trajetória como pesquisador e inspirando futuros trabalhos na área.

Aos meus colegas de doutorado e mestrado, cuja interdisciplinaridade enriquece as diversas visões da realidade acadêmica.

Aos meus colegas de publicações, já consolidados como especialistas em bioeconomia: Gabriela, Elen, Marcos e Diego.

Ao Centro de Estudos e Pesquisas em Agronegócios (CEPAN), por sua vanguarda no mundo acadêmico.

À Universidad Nacional de Rosario (UNR) e à Universidade Federal do Rio Grande do Sul (UFRGS), por sua institucionalidade positiva que fomenta o desenvolvimento socioeconômico global. Destaco, ademais, ao sindicato de docentes da UNR (COAD), e em particular a Leticia, por seu assessoramento que me permitiu iniciar o doutorado.

Quanto à UFRGS, expresso minha gratidão a todas as suas faculdades e escolas, e de maneira especial novamente ao CEPAN, instituição que sempre se adianta vários passos na pesquisa.

Em memória de Adalberto Medina Málaga, companheiro de mestrado; de Anita Quagliani, docente da cátedra de Comercialização Agropecuária; e do professor Eugenio Ávila Pedrozo, pelos exemplos de vida que nos legaram.

Finalmente, à Coordenação de Aperfeiçoamento de Pessoal de Nível Superior (CAPES), por ter financiado o último período da minha pesquisa, já que sem esse recurso não teria sido possível concluir esta tese.

"Mens humana non potest cum corpore absolute destrui, sed eius aliquid remanet, quod aeternum est." — Baruch Spinoza, Ética, Parte V, Proposição 23.

"L'essentiel est invisible pour les yeux." "Lo esencial es invisible a los ojos"—Antoine de Saint-Exupéry, Le Petit Prince, Reynal & Hitchcock, 1943, p. 83.

RESUMO

A medição holística da bioeconomia (BhBB) é essencial para quantificar suas contribuições ao desenvolvimento sustentável; no entanto, ela enfrenta barreiras como fragmentação conceitual, escassez de dados em tempo real e ausência de integração entre as dimensões biofísica, digital e social. Esta tese de doutorado visa superar essas limitações por meio do desenvolvimento de um framework integrado que explora interconexões entre conceitos, métodos, dados, indicadores, digitalização e sistemas cibernético-bio-físico-sociais, com aplicação empírica na contabilidade de carbono florestal, promovendo assim avaliações adaptáveis e escaláveis alinhadas aos Objetivos de Desenvolvimento Sustentável (ODS). Primeiro, uma revisão de literatura e análise de conteúdo de 84 documentos exploram conexões entre conceitos de bioeconomia (baseadas em biomassa -BmBB, baseadas em biotecnologia -BtBB e baseadas na biosfera-BsBB), métodos (ex.: modelos de input-output), fontes de dados (ex.: contas nacionais), indicadores (ex.: valor agregado, emprego, emissões de GEE) e limitações (ex.: incompletude de dados e incertezas na estimativa de bio-share). Os resultados destacam o domínio da BmBB (94% dos estudos) e clamam por avaliações holísticas. Segundo, análises bibliométricas e de coocorrência mapeiam tecnologias digitais (ex.: IA, ML, IoT, blockchain) no âmbito de sistemas cibernético-físico-sociais (CPSS), revelando sua convergência com elementos da bioeconomia para aprimorar a coleta, o processamento e as métricas de sustentabilidade. Evidências indicam que ferramentas digitais conectam clusters BmBB, BtBB e BsBB – nos quais "biomassa", "genética" e "energia" emergem como elementos conceituais centrais, respectivamente –, enfatizando o papel da digitalização na medição abrangente. Além disso, o conceito de "metabolismo" serve como elo entre ecossistemas e Technosphere, impulsionando avanços em avaliações holísticas da bioeconomia. Terceiro, um novo framework de Sistemas Cibernético-Bio-Físico-Sociais (CBPSS) estende o CPSS ao incorporar realismo biofísico, demonstrado por meio de redes bibliométricas de co-palavras (8.941 documentos do Scopus) e ilustrado na contabilidade de carbono florestal usando dados ForC/MODIS, ML de floresta aleatória (pseudo-R^2: 0.437, redução de incerteza de 64,5%), ajustes REDD+ e valorações emergéticas. Estimativas globais indicam um sumidouro florestal de ~3,63 GtC/ano, valores tradicionais de US$237,14–801,16 bilhões/ano e adições emergéticas holísticas de US$8,49–10,68 trilhões/ano, expondo lacunas de 3.682–4.603% sobre métricas de mercado. A análise de sensibilidade probabilística (índices de Sobol) identifica fatores biofísicos como principais impulsionadores de variância. O CBPSS permite avaliações adaptáveis em tempo real alinhadas aos ODS e aos objetivos do Acordo de Paris, fomentando a convergência biodigital para a governança sustentável em meio a desafios

climáticos. Esta tese de doutorado demonstrou que a integração de conceitos bioeconômicos holísticos com tecnologias digitais e frameworks sistêmicos, como os Sistemas Cibernético-Bio-Físico-Sociais (CBPSS), não apenas supera as limitações de medições fragmentadas, mas também possibilita avaliações adaptáveis e escaláveis, contribuindo assim para a governança sustentável alinhada aos ODS.

Palavras-chave: Medição da Bioeconomia; Bioeconomia Holística; Tecnologias Digitais; Sistemas Ciber-Bio-Físico-Sociais; Contabilidade de Carbono Florestal; Análise de Emergia; Metabolismo; Sustentabilidade.

ABSTRACT

Holistic measurement of the bioeconomy (BhBB) is essential for quantifying its contributions to sustainable development; however, it faces barriers such as conceptual fragmentation, scarcity of real-time data, and lack of integration across biophysical, digital, and social dimensions. This doctoral thesis aims to overcome these limitations through the development of an integrated framework that explores interconnections among concepts, methods, data, indicators, digitalization, and cyber-bio-physical-social systems, with empirical application in forest carbon accounting, thereby promoting adaptive and scalable assessments aligned with the Sustainable Development Goals (SDGs). First, a literature review and content analysis of 84 documents explore connections between bioeconomy concepts (biomass-based -BmBB, biotechnology-based -BtBB, and biosphere-based -BsBB), methods (e.g., input-output models), data sources (e.g., national accounts), indicators (e.g., value added, employment, GHG emissions), and limitations (e.g., data incompleteness and uncertainties in bio-share estimation). The results highlight the dominance of BmBB (94% of studies) and call for holistic assessments. Second, bibliometric and co-occurrence analyses map digital technologies (e.g., AI, ML, IoT, blockchain) within cyber-physical-social systems (CPSS), revealing their convergence with bioeconomy elements to enhance data collection, processing, and sustainability metrics. Evidence indicates that digital tools connect BmBB, BtBB, and BsBB clusters—in which "biomass", "genetics", and "energy" emerge as central conceptual elements, respectively—emphasizing the role of digitalization in comprehensive measurement. Furthermore, the concept of "metabolism" serves as a link between ecosystems and the Technosphere, driving advances in holistic bioeconomy assessments. Third, a novel Cyber-Bio-Physical-Social Systems (CBPSS) framework extends CPSS by incorporating bio-physical realism, as demonstrated by bibliometric co-word networks (8,941 Scopus documents) and illustrated to forest carbon accounting using ForC/MODIS data, random forest ML (pseudo-R^2: 0.437, 64.5% uncertainty reduction), REDD+ adjustments, and emergy valuations. Global estimates indicate a ~3.63 GtC/year forest sink, traditional values of US$237.14–801.16 billion/year, and holistic emergy additions of US$8.49–10.68 trillion/year, exposing 3,682–4,603% gaps over market metrics. Probabilistic sensitivity analysis (Sobol indices) identifies bio-physical factors as primary variance drivers. The CBPSS enables adaptive real-time assessments aligned with the SDGs and the objectives of the Paris Agreement, fostering biodigital convergence for sustainable governance amid climate challenges. This doctoral thesis has demonstrated that the integration of holistic bioeconomic concepts with digital technologies and systemic frameworks, such as Cyber-Bio-Physical-Social Systems (CBPSS), not only

overcomes the limitations of fragmented measurements but also enables adaptive and scalable evaluations, thereby contributing to sustainable governance aligned with the SDGs.

Keywords: Bioeconomy Measurement; Holistic Bioeconomy; Digital Technologies; Cyber-Bio-Physical-Social Systems; Forest Carbon Accounting; Emergy Analysis; Metabolism; Sustainability

SUMÁRIO

CHAPTER 1 - PRESENTATION OF THE THESIS PROPOSAL 13
CHAPTER 2 - MEASURING THE BIOECONOMY ECONOMICALLY: EXPLORING THE CONNECTIONS BETWEEN CONCEPTS, METHODS, DATA, INDICATORS AND THEIR LIMITATIONS 21
1 INTRODUCTION 26
2. MATERIALS AND METHODS 28
3. RESULTS 33
4. DISCUSSION 53
5. CONCLUSIONS 58
CHAPTER 3 - TOWARDS DIGITALIZATION FOR COMPREHENSIVE MEASUREMENT OF THE BIOECONOMY: EXPLORING THE CONVERGENCE BETWEEN ELEMENTS OF THE CYBER-PHYSICAL SOCIAL SYSTEM 76
1 INTRODUCTION 78
2 MATERIALS AND METHODS 81
3 RESULTS 85
4 DISCUSSION 100
5 CONCLUSIONS 104
CHAPTER 4 - A CYBER-BIO-PHYSICAL-SOCIAL SYSTEMS FRAMEWORK FOR HOLISTIC BIOECONOMY MEASUREMENT: A PROPOSAL AND ILLUSTRATION IN FOREST CARBON ACCOUNTING 113
1 INTRODUCTION 116
2 THEORETICAL-CONCEPTUAL PROPOSITION OF THE CBPSS FRAMEWORK 119
4 RESULTS 129
5 DISCUSSION 145
6 CONCLUSIONS 148
CHAPTER 5 - GENERAL CONCLUSIONS AND PERSPECTIVES 158
REFERENCES 162
SUPPLEMENTARY MATERIALS 166
SUPPLEMENTARY MATERIAL FOR ARTICLE 1: “MEASURING THE BIOECONOMY ECONOMICALLY...” 166

SUPPLEMENTARY MATERIAL FOR ARTICLE 2: "TOWARDS DIGITALIZATION FOR COMPREHENSIVE MEASUREMENT..." 191
SUPPLEMENTARY MATERIAL FOR ARTICLE 3: "A CYBER-BIO-PHYSICAL-SOCIAL SYSTEMS FRAMEWORK..." 228

CHAPTER 1 - PRESENTATION OF THE THESIS PROPOSAL

1 GENERAL INTRODUCTION

In a world facing global challenges such as climate change, biodiversity loss, and the depletion of non-renewable resources—what (King; Jones, 2025) term 'polycrisis,' encompassing warfare, resource overexploitation, and human cognitive biases—the bioeconomy could emerge as a transformative paradigm. This approach promises sustainable economic development aligned with principles of circularity, metabolic efficiency, and respect for planetary boundaries (Sterner et al., 2019), provided trade-offs are managed effectively.

This paradigm shift is underscored by scaling laws in complex systems (Kempes; Koehl; West, 2019), as articulated by (Bettencourt et al., 2010; Savage et al., 2007; West, 2017; West; Brown; Enquist, 1999), where superlinear growth in socio-economic metrics—such as innovation and GDP—accelerates societal metabolism but risks systemic collapse without fundamental paradigm shifts beyond technological fixes, echoing (Hagens, 2020) "superorganism" metaphor for humanity's energy-driven expansion and its bio-physical limits. Furthermore, post-normal science and biosemiotics emphasize the need for guided interactions in bio-physical processes, integrating affective, self-referential rules with socio-psychological frameworks to address technical, moral, and ethical dimensions (Giampietro, 2023a, 2024).

The bioeconomy has evolved from its roots in the European Union in 2007, with a focus on a knowledge-based bioeconomy (KBBE) (Patermann; Aguilar, 2018), to become a global strategy adopted by nations such as the United States, Brazil, and China. These strategies integrate biological renewal with technological innovation, fostering transitions toward low-carbon economies and contributing to the United Nations Sustainable Development Goals (SDGs), particularly in areas such as climate action (SDG 13), life on land (SDG 15), and decent work and economic growth (SDG 8) (United Nations, 2015).

The bioeconomy encompasses not only the production of renewable biomass (biomass-based bioeconomy, BmBB), but also advanced biotechnological processes (biotechnology-based bioeconomy, BtBB) and ecosystem functions (biosphere-based bioeconomy, BsBB), culminating in integration into the (holistic bioeconomy, BhBB) that considers socio-ecological, thermodynamic, and digital interactions (Giampietro, 2019, 2023b, 2023a; Leavy et al., 2024, 2026). This holistic vision (BhBB) considers socio-ecological, thermodynamic, and digital interactions, including the integration of biological processes with the Technosphere (Haff, 2014; Mayumi; Giampietro, 2019)—the human-engineered technological sphere—to foster sustainability (Leavy et al., 2026).

West (2017, 2024) emphasizes that such integrations must account for universal scaling principles derived from biology and applied to societies, where sublinear efficiencies in infrastructure contrast with superlinear socio-economic outputs, potentially driving unsustainable acceleration if unmitigated. This could link to endosomatic metabolism in BtBB, which connects genetic editing (e.g., CRISPR; (Kumar et al., 2023)) with cognitive influences via the gut-brain axis (Bastiaanssen et al., 2019), and exosomatic societal metabolism in BsBB, necessitating biodigital tools to capture unconscious decision-making mechanisms (Bechara; Damasio, 2005; Reimann; Bechara, 2010).

Nevertheless, measuring the bioeconomy represents a persistent challenge, constrained by ambiguous definitions and fragmented approaches that underestimate its multidimensional impacts (Leavy et al., 2024). In this context, digitalization—driven by technologies such as artificial intelligence (AI), machine learning (ML), the Internet of Things (IoT), blockchain, and cyber-physical-social systems (CPSS)—emerges as an essential catalyst for overcoming these barriers (Leavy et al., 2026). CPSS, which extend cyber-physical systems (CPS) by incorporating social and human dimensions, represent an evolution toward a human-centered Society 5.0, where bio-digital convergence enables dynamic, adaptive, and scalable measurements (Leavy et al., 2026).

This convergence not only facilitates the integration of real-time data from sources such as MODIS satellites or databases like ForC, but also incorporates bio-physical valuations such as emergy, revealing gaps between traditional and holistic metrics. Furthermore, as highlighted by (Ning et al., 2016; Ning; Liu, 2015), CPSS frameworks bridge physical objects governed by objective laws with social phenomena and cognitive processes, enabling quantitative analysis of organic and inorganic interactions while addressing post-normal science complexities in biosemiotics (Giampietro, 2024), thus enhancing the measurement of metabolic interplays across BmBB, BtBB, and BsBB and promoting equitable stakeholder engagement amid social conflicts (Eversberg; Fritz, 2022; Eversberg; Holz; Pungas, 2023; Villamayor-Tomas et al., 2021).

This doctoral thesis explores this intersection progressively: it begins with a conceptual analysis of limitations in the economic measurement of the bioeconomy (Leavy et al., 2024), advances toward the exploration of digital convergences in CPSS contexts (Leavy et al., 2026), and culminates in the proposal of an integrative framework that links bio-physical realism with computational tools. In this way, it contributes to sustainable governance, aligned with global initiatives such as the FAO's Dashboard on Bioeconomy Strategies and Related Actions for Sustainable Development (updated in 2025) (FAO, 2025) and revisions to the System of

Environmental-Economic Accounting (SEEA) (https://seea.un.org/) in 2025 (United Nations, 2025), fostering equitable transitions in economies.

2 PROBLEMATIC SITUATION

Despite its transformative potential, the bioeconomy confronts a challenging scenario marked by the absence of a precise conceptual definition, which in turn results in a lack of comprehensive, standardized, and dynamic measurement frameworks. Traditional approaches, such as input-output models or social accounting matrices, predominate in the evaluation of BmBB, but largely overlook BtBB and BsBB, resulting in inconsistent metrics that undervalue ecosystem services, metabolic interactions, and biotechnological contributions. Limitations such as incomplete, aggregated, or outdated data, subjectivity in weighting "bio-shares," uncertainty in estimates, and omission of thermodynamic aspects (e.g., emergy in sej/year) perpetuate a partial view, incapable of capturing the holistic value of the bioeconomy in national and global economies.

This fragmentation is further compounded by the risks highlighted by (Bettencourt et al., 2010; Kempes; Koehl; West, 2019; West, 2017), where superlinear scaling in social systems leads to accelerated growth metrics, such as GDP, potentially risking stagnation or collapse—a sophisticated Malthusian trap—unless holistic, adaptive frameworks intervene to realign societal metabolism with planetary limits (Leavy and Talamini, 2024; Giampietro, 2021, 2023b; Hagens, 2020). This aligns with the maximum power principle in behavioral thermodynamics (Hagens, 2025; Odum, 1996), where systems self-organize to maximize short-term energy flows, often leading to ecological overshoot and inefficiencies in resource use, as seen in bioeconomy policies that prioritize rapid throughput over long-term sustainability.

Beyond these biophysical and socioeconomic constraints, the fragmentation is exacerbated by the limited systematic integration of digital technologies, which hold potential to address key deficiencies through real-time data collection, processing, and analysis. Yet, their convergence with core bioeconomic elements (e.g., metabolism, biodiversity, biogeochemical cycles) remains largely underexplored. As a result, current bioeconomy policies—such as the EU's Strategy for a Competitive and Sustainable EU Bioeconomy (2025) (Environment - European Commission, 2025) or Brazil's National Bioeconomy Development Plan revised in 2025 (Ministério do Meio Ambiente e Mudança do Clima, 2025) -lack robust tools to evaluate real impacts, hindering transitions toward circular, equitable, and climate-resilient economies.

The core issue lies in the need for a systemic approach that unifies concepts, methods, data, and indicators, incorporating bio-physical realism into cyber-social systems for adaptive measurements that address inherent uncertainties, such as those derived from spatial variability in carbon sinks or gaps in emergy valuations, and promote inclusive governance aligned with the SDGs (United Nations, 2015).

To overcome these challenges, it is essential to explore: In what ways might the integration of holistic bioeconomic concepts (BmBB, BtBB, and BsBB) with digital technologies within a cyber-bio-physical-social systems (CBPSS) framework address and mitigate the limitations of fragmented and static measurements, thereby facilitating a comprehensive, adaptive, and sustainable evaluation of the bioeconomy?

3 OBJECTIVES

3.1 General Objective

To develop an integrated framework for the holistic measurement of the bioeconomy, exploring connections among concepts, methods, data, indicators, digitalization, and cyber-bio-physical-social systems.

3.2 Specific Objectives

i) To analyze connections among bioeconomy concepts, methods, data, indicators, and limitations to propose a holistic approach (corresponding to Chapter 2).

ii) To explore the convergence between digital technologies and bioeconomy conceptual elements, identifying digitalization's role in enhancing measurement (based on Chapter 3).

iii) To propose and illustrated a Cyber-Bio-Physical-Social Systems (CBPSS) framework for holistic measurement (corresponding to Chapter 4).

4 GENERAL RESEARCH HYPOTHESIS

The integration of holistic bioeconomic concepts (BmBB, BtBB and BsBB) with digital technologies in a framework based on cyber-bio-physical-social systems (CBPSS) enables overcoming the limitations of fragmented and static measurements, facilitating a comprehensive, adaptive, and sustainable evaluation of the bioeconomy that captures metabolic and ecosystemic interactions in real-world applications, reducing uncertainties and revealing gaps in traditional valuations.

5 JUSTIFICATION OF THE THESIS

This doctoral thesis is justified by its academic, social, and practical relevance in a context of accelerated advances in the bioeconomy and digitalization, where holistic measurement has became a global priority for sustainable transitions. Academically, it fills gaps identified in recent literature (2024-2026), such as conceptual fragmentation in economic measurements (Chapter 2), insufficient convergence between the bioeconomy and digital technologies (Chapter 3), and the lack of integrative frameworks like CBPSS for empirical applications (Chapter 4). For instance, while initiatives such as the EU's Strategy for a Competitive and Sustainable EU Bioeconomy (2025) (Biotechnology Innovation Organization, 2025; Circular Bio-Based Europe, 2026) emphasize the "biotechnology revolution" and regulations through 2026, and UNCTAD's contributions to the Bioeconomy Challenge (2025-2028) (UNCTAD -UN, 2025) propose global monitoring, these lack comprehensive tools; This thesis addresses this through BhBB, integrating emergy, AI, and CPSS, contributing to debates in journals such as *Sustainability* and *Technology in Society*.

Socially, it aligns with the SDGs by promoting equity in economies such as Brazil and Argentina, where the bioeconomy can generate employment and reduce poverty (SDGs 1, 8) through biodiversity valorization. In climate crisis scenarios, such as projections of over 350,000 jobs in U.S. biotechnology (Biotechnology Innovation Organization, 2025) and forest carbon deficits (Mo et al., 2023; Yun et al., 2025), CBPSS offers adaptive metrics for inclusive policies, mitigating ethical risks such as indigenous exclusion in REDD+ (Human Rights Watch, 2022).

Practically, it provides actionable innovations: co-occurrence analyses to overcome data limitations (Chapter 2), digital convergence mapping (Chapter 3), and an R-based model that reduces uncertainties and reveals valuation gaps (Chapter 4). In 2025-2026, with investment revisions (Circular Bio-Based Europe, 2026) and programs such as CBE JU's 2026 Work Programme (€170.7 million), this research informs biodigital governance, transforming challenges into sustainable opportunities. Thus, it advances theoretical knowledge and tools for a resilient bioeconomy.

For bioeconomy stakeholders, including industry actors, researchers, and community groups, this thesis offers critical contributions by providing a unified CBPSS framework that enhances decision-making through real-time, data-driven insights into biomass flows, biotechnological innovations, and ecosystem services, thereby facilitating collaborative value chains and reducing risks associated with resource overexploitation. For policymakers, it delivers evidence-based tools for designing equitable strategies, such as integrating emergy

valuations into national accounts to better align bioeconomy policies with SDGs and the Paris Agreement, enabling more effective monitoring, funding allocation, and regulatory adjustments in initiatives like the FAO's Dashboard and SEEA revisions.

6 THESIS STRUCTURE

The thesis is structured in a logical and progressive manner to address the research problem—the fragmentation in bioeconomy measurement and the need for digital and bio-physical integration—establishing connections between the problem, objectives, and results of each chapter/article (Figure 1). This arrangement ensures cohesion, allowing each section to build upon the previous one, from conceptual analysis to applied proposal, culminating in a synthesis that validates the general hypothesis.

Chapter 1: General Introduction. This chapter outlines the overarching context of the thesis, the problem statement, the research hypothesis, the objectives, the justification, and the structure of the thesis.

Chapter 2: This chapter addresses specific objective 1 by examining the interconnections among bioeconomic concepts (e.g., the predominance of the biomass-based bioeconomy, BmBB), methods (e.g., input-output models), data sources (e.g., national accounts and economic activity classification systems), indicators (e.g., value added, employment, and greenhouse gas emissions), and limitations (e.g., incomplete or outdated data, subjectivity in bio-share weighting, and methodological uncertainties). It directly links to the research problem by highlighting the fragmented nature of current measurements. This partiality underscores the need for a holistic framework as a solution to capture multidimensional contributions. The results, derived from a statistical analysis of occurrence and co-occurrence in 84 documents (analyzed via content analysis in QDA Miner), reveal key patterns and constraints, emphasizing the role of digitalization in addressing data gaps and enabling real-time updates. This sets a logical foundation for the subsequent exploration of digital convergences in Chapter 3.

Chapter 3: Digitalization and Convergence in the Bioeconomy (Article: "Towards Digitalization for Comprehensive Measurement..."). Fulfills specific objective 2, analyzing convergences between bioeconomic elements (e.g., biomass. Biotech, metabolism, biodiversity) and digital technologies (e.g., AI, ML, IoT) in CPSS. Links with Chapter 2 by mitigating data limitations through real-time collection, emphasizing applications in BmBB (agriculture), BtBB (health), and BsBB (ecosystems). Results: Co-occurrence maps reveal dominance of data analytics, proposing fusions for comprehensive measurements, preparing the ground for the proposed framework in Chapter 4.

Chapter 4: CBPSS Framework for Holistic Measurement (Article: "A Cyber-Bio-Physical-Social Systems Framework..."). Resolves specific objective 3, proposing CBPSS as an extension of CPSS, integrating biophysics (e.g., emergy) with digital data (e.g., MODIS, ForC) in forest carbon accounting. Connects with previous chapters by addressing conceptual gaps (Chapter 2) and digital convergences (Chapter 3), validating the hypothesis through ML (random forest) and PSA (Sobol). Results: Estimates of carbon sink, holistic valuations, and uncertainty reduction, demonstrating viability for governance.

Chapter 5: General Conclusions and Perspectives. This chapter integrates the results from previous chapters into a cohesive narrative, demonstrating how the CBPSS framework overcomes fragmentation in bioeconomy measurements by enabling adaptive, scalable evaluations aligned with SDGs. It presents integrated conclusions vis-à-vis the specific objectives (5.1), weaving insights on conceptual gaps (e.g., partial focus on BmBB, thermodynamic omissions like emergy), digital convergences (e.g., AI, IoT, ML in CPSS), and framework validation (e.g., uncertainty reduction via ML and PSA in forest carbon accounting).

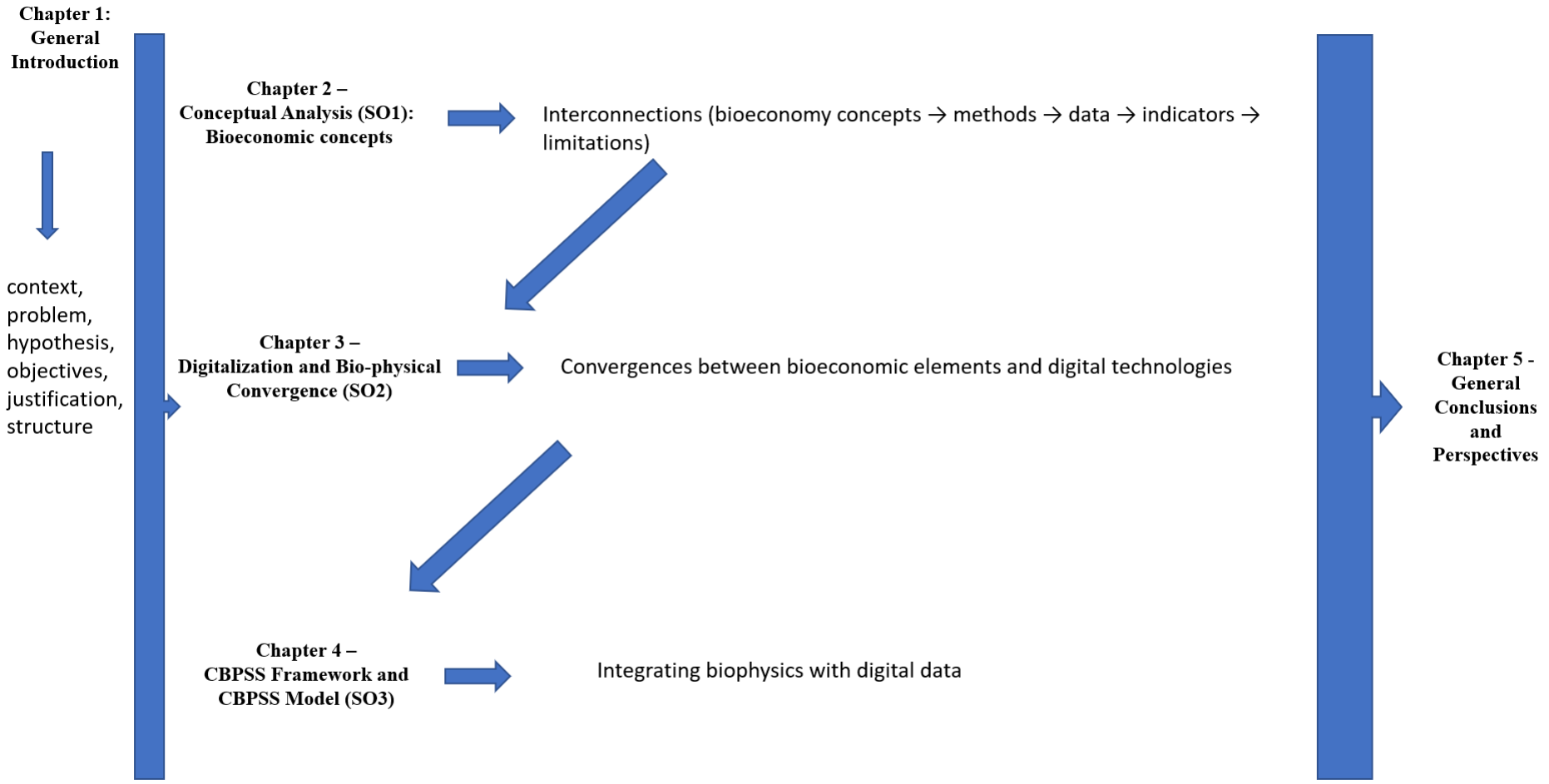


Figure 1: Thesis Structure. Source: Elaborated by author.

CHAPTER 2 - MEASURING THE BIOECONOMY ECONOMICALLY: EXPLORING THE CONNECTIONS BETWEEN CONCEPTS, METHODS, DATA, INDICATORS AND THEIR LIMITATIONS[1]

Abstract

Despite its relevance, measuring the contributions of the bioeconomy to national economies remains an arduous task that faces limitations. Part of the difficulty is associated with the lack of a clear and widely accepted concept of the bioeconomy and moves on to the connections between methods, data and indicators. The present study aims to define the concepts of bioeconomy and to explore the connections between concepts, methods, data, and indicators when measuring the bioeconomy economically and the limitations involved in this process. The bioeconomy concepts were defined based on a literature review and a content analysis of 84 documents selected through snowballing procedures to find articles measuring "how big is the bioeconomy?" The content of the 84 documents was uploaded to the Quantitative Data Analysis (QDA Miner) software and coded according to the bioeconomy concept, the methods or models used, the data sources accessed, the indicators calculated, and the limitations reported by the authors. The results of the occurrence and co-occurrence of the codes were extracted and analyzed statistically, indicating the following: the measurement of the bioeconomy (i) needs to recognize and pursue the proposed concept of a holistic bioeconomy; (ii) rarely considered aspects of a holistic bioeconomy (3.5%); (iii) is primarily based on the concept of biomass-based bioeconomy (BmBB) (94%); (iv) the association with the concept of biosphere (BsBB) appeared in 26% of the studies; (v) the biotech-based bioeconomy (BtBB) was the least frequent (1.2%); (vi) there is a diversity of methods and models, but the most common are those traditionally used to measure macroeconomic activities, especially input-output models; (vii) depending on the prevailing methods, the data comes from various official statistical databases, such as national accounts and economic activity classification systems; (viii) the most frequently used indicators are value added, employment, and Greenhouse Gases (GHG) emissions; (ix) there are various limitations related to the concept, methods and models, data, indicators, and others, like incomplete, missing, or lack of data, aggregated data, outdated data or databases, uncertainty of the estimated values, the subjectivity in the bio-shares weighting procedures, and other limitations inherent to methods and models. We conclude that current

[1] Leavy, S., Allegretti, G., Presotto, E., Montoya, M. A., & Talamini, E. (2024). Measuring the Bioeconomy Economically: Exploring the Connections between Concepts, Methods, Data, Indicators and Their Limitations. *Sustainability*, *16* (20), 8727. https://doi.org/10.3390/su16208727

efforts only partially measure the contributions of the bioeconomy, and efforts should be encouraged toward a full assessment, starting by recognizing that the measurement of a holistic bioeconomy should be pursued.

Keywords: bioeconomics; holistic bioeconomy; bio-based economy; biotechnology; biotechonomy; bioecology; digitalization

Abreviations

A-LCA	Attributional Life Cycle Assessment
ADF	Augmented Dickey–Fuller
AHP	Analytic Hierarchy Process
AIC	Akaike Info Criterion
ARCH	Autoregressive Conditional Heteroscedasticity
ARDL	Autoregressive Distributed Lag
BmBB	Biomass-Based Bioeconomy
BRIC+	Brazil, China, Indonesia, India, Russia, Taiwan
BsBB	Biosphere-Based Bioeconomy
BtBB	Biotechnology-Based Bioeconomy
BTF	Bioeconomy Transition Framework
BTS	Bartlett's test of Sphericity
C-LCA	Consequential Life Cycle Assessment
CAIT	Climate Data Explorer
CAPRI	Common Agricultural Policy Regionalised Impacts
CAS	Complex Adaptive Systems
CAWI	Computer-Assisted Web Interview
CBM	Carbon Budget Model
CED	Cumulative Energy Demand
CEE	Central and Eastern European
CES	Constant Elasticity Substitution
CET	Constant Elasticity Transformation
CGE	Computable General Equilibrium Model
CH Rule	Calinski–Harabasz (CH) rule
CH_4	Methane
CICES	Common International Classification of Ecosystem Services
CNBio	National Bioeconomy Account
CO_2	Carbon Dioxide
CoCo	Complete and Consistent
COFOG	Classification of the Functions of Government
COMEXT	Eurostat Reference Database for International Trade in Goods.
CPA	Statistical Classification of Products by Activity in the European Economic Community
CPC	Central Product Classification
CRF	Common Reporting Format
CSO	Central Statistics Office in Ireland
CUSUMQ	Cumulative Sum of Squares
CZSO	Czech Statistical Office
DEU	Domestic Extraction Used
dFRI	Direct Fossil Resource Intensity
DMI	Domestic Material Input
DNA	Deoxyribonucleic Acid
EAA	Economic Accounts for Agriculture
EC	European Commission
ECT	Error Correction Term
EEIO	Environmental Extended Input-Output Model
EEMRIO	Environmental Extended Multi-Regional Input-Output Model
EFISCEN	European Forest Information Scenario Model
EIA	Energy Information Administration
EPA	Environmental Protection Agency
EU	European Union
EU CSO	European Construction Sector Observatory

EU KLEMS	EU level analysis of capital (K), labour (L), energy (E), materials (M) and services (S) inputs
EXIOBASE	Multi-Regional Environmentally Extended Supply-Use Table (MR-SUT) and Input-Output Table (MR-IOT)
FADN	EU Farm Accountancy Data Network
FAO	Food and Agriculture Organization
FAOSTAT	FAO Statistics
FEA	Forestry Economic Accounts
FLQ	Flegg Location Quotient
ISI	Institute for Systems and Innovation Research
FRC	Fossil Resource Consumption
FRS	Fossil Resource Savings
FU	Functional Unit
GAMS	General Algebraic Modeling System
GDP	Gross Domestic Product
GEIH	Gran Encuesta Integrada de Hogares
GFCF	Gross Fixed Capital Formation
GFN	Global Footprint Network
GFTM	Global Forest Trade Model
GHG	Greenhouse Gases
GINFORS	Global Inter-industry Forecasting System
GMFD	Global Material Flows Database
GPA	Global Positioning System
GRIT	Generation of Regional Input-Output Tables
GST	General System Theory
GTAP	Global Trade Analysis Project
GTAP-AEZ	Global Trade Analysis Project Agro-Ecological Zones
GTAP-AGR	Global Trade Analysis Project-Agriculture
GTAP-E	Global Trade Analysis Project-Energy
GTEM	Global Trade and Environment Model
GWP	Global Warming Potential
HAC	Hierarchical Agglomerative Clustering
HDI	Human Development Index
HEM	Hypothetical Extraction Method
ICT	Information and Communication Technology
IEA	International Energy Agency
IMAG	Integrated Model to Assess the Global Environment
IMPACT	International Model for Policy Analysis of Agricultural Commodities and Trade
IMPLAN	Impact Analysis for Planning
IO	Input-Output
IOM	Input-Output Model
IPCC	Intergovernmental Panel on Climate Change
IRENA	International Renewable Energy Agency
ISIC	International Standard Industrial Classification of All Economic Activities
ISTAT	Istituto Nazionale di Statistica
JCR	Join Commission Research
KEI	Knowledge Economic Index
KMO	Kaiser–Meyer–Olkin
LCA	Life Cycle Assessment
LCIA	Life Cycle Impact Assessment
LFS	Labour Force Survey
LPES	Linear Programming Energy System
LQ	Location Quotient

LULC	Land Use and Land Change
MAGNET	Modular Applied General Equilibrium Tool
MARKAL-NL-UU	Market Allocation-The Netherlands-Energy and Chemical Industry Sectors
MCDA	Multi-Criteria Decision Analysis
MFA	Material Flow Analysis
MRIO	Multirregional Input-Output
N_2O	Nitrous Oxide
NACE	Statistical Classification of Economic Activities in the European Community
NAFTA	North American Free Trade Agreement
NAICS	North American Industry Classification System
NAMEA	National Accounting Matrices including Environmental Accounts
NASEM	The National Academies of Sciences, Engineering, and Medicine
NEAD	National Environmental Accounting Database
NEMO	non-European Major OECD countries
NFS	National Farm Survey
OCDE	Organisation for Economic Co-operation and Development
ORBIS	Open Repository Base on International Strategic Studies
PATSTAT	European Patent Database
PCA	Principal Component Analysis
PKD	Polish Classification of Activities
PP	Phillips–Perron Test
PRODCOM	"PRODuction COMmunautaire" (Community Production)
QDA	Qualitative Data Analysis
R&D	Research and Development
RAS	Methodology to Balance Matrices
rDNA	Recombinant Deoxyribonucleic Acid
REGON	National Official Business Register
RESET	Regression Specification Error
ROW	Rest of World
RPA	Revealed Patent Advantage
SAM	Social Accounting Matrices
SAT-BBE	Systems Analysis Tools Framework for the EU Bio-Based Economy Strategy
SBS	Structural Business Statistics or Survey
SEAI	Sustainable Energy Authority of Ireland
SEEA	System of Environmental-Economic Accounting
SEIB	Socio-Economic Indicator for the Bioeconomy
SIMSIPSAM	Simulation for Social Indicators and Poverty using SAM
SNA	System of National Accounts
SQL	Simple Location Quotient
SSI	Substitution Share Indicator
SSS	State Statistics Service
STECF	Scientific, Technical and Economic Committee for Fisheries
SUTs	Supply and Use Tables
tFRI	Total Fossil Resource Intensity
TOPSIS	Technique for Order Performance by Similarity to Ideal Solution
ToSIA	Tool for Sustainability Impact Assessment
US, BEA	US Department of Commerce's Bureau of Economic Analysis
VEC	Vector Error Correction
WALD Test	Multivariate Generalization Test developed by Wald (1943)
WIOD	World Input-Output Database
WPINDEX	Derwent World Patents Index

1 INTRODUCTION

In the last two decades, the bioeconomy has emerged as the promise of a new paradigm toward developing a sustainable economic system [1]. This expectation is based on the renewability of biological resources and the circulation of chemical elements. Thus, the bioeconomic paradigm is superior to the economic system based on finite resources whose stocks are finite and non-renewable [2]. As new political and economic stimuli have been prospected, new ventures are taking place in the field of bioeconomy, leading various countries to adopt specific programs, strategies, or guidelines to stimulate the bioeconomy.

Although the European Commission (EC) started discussions and the implementation of EU Framework Programmes in biotechnology and life science in the last century (1982), institutionally, the bioeconomy concept first appeared in a proposition by Christian Patermann grounded in knowledge-based bioeconomy (KBBE) as a vision for the European bioeconomy in 2030 [3]. The concept was proposed in 2007 in the Cologne paper "En Route to the Knowledge-Based Bio-Economy (KBBE)". The purpose was to aggregate competitiveness and sustainability into circular bio-based solutions while addressing climate neutrality, environmental performance, safety, and social acceptance by respecting planetary boundaries [4]. The Organization for Economic Co-operation and Development (OECD) followed this approach, proposing an official agenda for promoting bioeconomy in 2009 [5].

In 2012, the European Union launched its strategy for developing a bioeconomy that connected the economy to nature for sustainable growth [6,7]. Since then, national governments worldwide have made efforts to promote bioeconomy activities and boost national economies officially. These include the Netherlands, Sweden, the United States, and Russia in 2012, Malaysia and South Africa in 2013, Germany and Finland in 2014, and France in 2016 [8]. Brazil launched its national bioeconomy program in 2019 [9], while China included the bioeconomy in its 14th five-year plan for 2021–2025 [10]. Currently, dozens of countries have specific or related bioeconomy strategies [11,12].

However, one aspect that differentiates national strategies is the essence of the bioeconomy concept considered when outlining the actions to be stimulated. In the European Union (EU), for example, the concept was updated in 2018 to add sectors and systems that rely on biological resources in addition to those primary sectors that produce renewable biological resources [13,14]. Although it is recognized that there is no widely accepted concept of the bioeconomy [15], in the United States, it can be said that former President Barack Obama's National Bioeconomy Blueprint is based on three main and correlated axes: knowledge,

technology, and innovation [16] From the North American perspective, the bioeconomy is the economic activity driven by research and innovation in life sciences and biotechnology, enabled by technological advances in engineering, computing, and information sciences [15,17]. Genetic engineering, molecular biology, bioinformatics, and synthetic biology are some driving technological platforms. The Bioeconomy Brazil Program focuses on extracting renewable resources and exploring biodiversity as a strategy for the sustainable development of smallholder and indigenous communities [9]. Recently, the Brazilian strategy for bioeconomy has been revised based on a wider concept that includes innovations and technologies to add value and generate work and income sustainably and climate-fair [18].

In scholarly circles, several authors have differentiated bioeconomy approaches by considering the resources, processes, and effects that activities trigger in the economic and bio-physical systems. Bugge et al. [19] classified the bioeconomy into the following: (i) bioresources, indicating products composed wholly or in large part of biomass; (ii) biotechnology—products or processes enabled by innovation in the life sciences; (iii) bioecology based on sustainable processes and sustainably sourced products. Vivien et al. [20] categorized the bioeconomy into the following: (i) Type I—an ecological economy that is compatible with the biosphere constraints; (ii) Type II—a science-based economy driven by industrial biotechnology; (iii) Type III—a biomass-based economy. Befort [21] categorized the visions of the bioeconomy based on socio-technical regimes, proposing the following: (i) a Biotech-bioeconomy, which is technology-driven, spreading biotechnology into health, food, industry, etc., and industrialization of the living; (ii) a Biomass-bioeconomy, whose mission-driven towards the substitution of oil for biomass. Other variants of classifications, typologies, and narratives are explored in the literature, as in [22,23]. However, the classifications cited are sufficient for the following: (i) to show evidence that a widely accepted concept of bioeconomy is lacking; (ii) link the national concepts to the visions of the bioeconomy in the literature, being EU close to bioresources or Type III, US to biotechnology or Type II, and Brazil to bioecology or Type I; (iii) reflect on what are the implications for the measurement of the bioeconomy.

Despite these conceptual differences, stakeholders' interests exist, and there are efforts to show the economic importance of bioeconomy and to monitor indicators to attract investment in bioeconomy-related activities. Although awareness differs between stakeholders, the economic dimension is still relevant [24,25]. In this regard, Ronzon et al. [26] estimated that the bioeconomy contributed 4.7% of the EU-27's Gross Domestic Product (GDP) in 2017. In the US, the contribution of the bio-based bioeconomy to the national GDP in 2016 was 5.1% and could reach 7.4% [15]. Specifically, the biotechnology-based bioeconomy reached 2.0% of

the US GDP in 2012, up from 0.004% in 1980. This is an annual growth rate of over 10% [27]. In Brazil, the bioeconomy value chain accounted for 19.6% of GDP in 2019 [28], which is a higher share than the 13.8% of added value found by [29].

Consequently, one question that arises is as follows: How are concepts, methods, data, and indicators connected in the process of measuring bioeconomy economically, and what are the limitations involved? A relevant study in this regard is the review by [30], which lists the methods, variables, and data used to measure the sustainability of the bioeconomy, including the economic dimension. However, it does not define concepts nor explore the connections between methods, data, and indicators and their limitations. The present study aims to advance in detailing all these connections to measuring "how big is the bioeconomy?" Therefore, the present study aims to define the concepts of bioeconomy and to explore the connections between concepts, methods, data, and indicators when measuring the bioeconomy economically and the limitations involved in this process.

2. MATERIALS AND METHODS

The first step in reaching this study's goal is to define the concepts of bioeconomy. Once the bioeconomy concepts have been defined, the next step is to carry out a content analysis of carefully selected documents. This section describes the methodological procedures used to complete these research steps. The following steps to achieve these goals are explained in detail.

2.1. First Step: Defining the Concepts of Bioeconomy

As mentioned earlier, there is no widely accepted definition for the bioeconomy that incorporates all its idiosyncrasies. However, defining the concept of bioeconomy is crucial for exploring its connections with methods, data, and indicators. A literature review was conducted on scientific articles that reported conceptual analyses, visions, narratives, or approaches to the bioeconomy. The concepts were then organized based on the similarity of their fundamental elements. Three concepts were defined as partial, as they adopted a restricted vision of the bioeconomy. Based on the characteristics and limitations of these partial concepts, the concept of a holistic bioeconomy was proposed that combines many characteristics and elements of partial concepts. This new concept has advantages for measuring the true value of the bioeconomy.

2.2. Second Step: Articles Selection and Content Analysis

This section describes the procedures adopted for searching and selecting articles, building the database, defining the codes, coding the content of articles, and extracting the results.

2.2.1. Searching for Articles

Content analysis requires selecting documents of interest. In this respect, the scope of documents to be retrieved was restricted to measuring bioeconomy economically. The methodological strategy chosen to find documents (scientific articles, technical reports, government reports) fitting to the desired scope follows the snowballing procedures.

Snowballing is a well-established and widely used technique for exploring related documents by identifying articles relevant to your topic of interest from key and cited-by articles [31]. In some cases, snowballing proved to be a more efficient method for retrieving articles of interest than the databases themselves [32], depending on the database [33]. Synthetically, according to Greenhalgh and Peacock [31], snowballing refers to using the reference list of a paper or the citations of a paper to identify additional ones. You have to start with a few articles currently in or around your topic of interest. These articles are referred to as the “start set”. Once the start set is defined, it is time to conduct backward and forward snowballing.

The snowballing procedures followed the steps described by [34–36]. According to Jalali and Wohlin [37], systematic literature studies can be conducted differently regarding the first step. Based on the specificity of this study, we opted to start with the reference lists of a starting set of papers, called the “start set”. The start set of papers was identified in two previous studies by [38,39], which focus on the economic measurement of the bioeconomy. By merging both lists and excluding duplicated papers, a list of 10 papers remains as the start set, as listed in Table 1.

Table 1. List of papers serving as the start set for snowballing procedures.

Document Order and Information	Reference
1. Nowicki P, Banse M, Bolck C, Bos H, Scott E. 2008. Biobased economy. State-of-the-art assessment. Rep., Agric. Econ. Res. Inst., The Hague, The Netherlands.	[40]
2. Vandermeulen V, Prins W, Nolte S, Van Huylenbroeck G. 2011. How to measure the size of a bio-based economy: evidence from Flanders. Biomass Bioenerg. 35: 4368–4375.	[41]
3. Efken J, Banse M, Rothe A, Dieter M, Dirksmeyer W, et al. 2012. Volkswirtschaftliche Bedeutung der biobasierten Wirtschaft in Deutschland. Work. Pap., 07/2012, Johann Heinrich v. Thünen-Inst., Braunschweig, Germany. (*)	[42]
4. Rosegrant MW, Ringler C, Zhu T, Tokgoz S, Bhandary P. 2013. Water and food in the bioeconomy: challenges and opportunities for development. Agric. Econ. 44(s1):139–150.	[43]
5. Golden JS, Handfield RB, Daystar J, McConnell TE. 2015. An economic impact analysis of the U.S. biobased products industry: a report to the Congress of the United States of America. Ind. Biotech. 11(4):201–209.	[44]
6. Ronzon T, Santini F, M'Barek R. 2015. The bioeconomy in the European Union in numbers. Facts and figures on biomass, turnover and employment. Rep., Eur. Comm., Joint Res. Cent., Inst. Prospect. Tech. Stud., Sevilla, Spain.	[45]
7. Heijman W. 2016. How big is the bio-business? Notes on measuring the size of the Dutch bio-economy. NJAS 77:5–8.	[46]
8. Carlson R. 2016. Estimating the biotech sector's contribution to the US economy. Nat. Biotechnol. 34(3):247–255.	[27]
9. Ronzon, T.; Piotrowski, S.; Tamosiunas, S.; Dammer, L.; Carus, M.; M'barek, R. 2020. Developments of Economic Growth and Employment in Bioeconomy Sectors across the EU. Sustainability, 12, 4507.	[26]
10. Kuosmanen, T.; Kuosmanen, N.; El Meligi, A.; Ronzon, T.; Gurria Albusac, P.; Iost, S.; M'Barek, R. 2020. How Big is the Bioeconomy? Reflections from an economic perspective; Publications Office of the European Union: Luxembourg.	[47]

Note: Documents are ordered by publication date. (*) Efken et al. 2012 [42] was included in the start set papers but excluded from content analysis because it is in German. Source: papers selected from [38,39].

We began the backward and forward snowballing procedures from the start set papers. Backward snowballing means using the reference list of a starting set paper to identify new documents to include in the literature review, while forward snowballing refers to identifying new papers based on those papers citing the paper being examined [34]. A series of iterations were conducted during backward and forward snowballing. The following procedures were

carried out to accomplish the first iteration. Firstly, we took each of the papers from the start set and wholly revised the list of references, searching for potentially additional papers to be included in the review database. The question "How big is the bioeconomy?" [47] illustrates the guiding question we sought in the papers. Secondly, we went to the Scopus database, searched for each paper, and accessed the papers citing them. For documents such as reports not indexed in Scopus, we looked for their citation by filing the query within "References" with the document title. In both the backward and forward snowballing process, the title of the cited or citing papers was evaluated, and according to the adherence to the goal of the present study, the papers were pre-selected to compose the review database. Then, the pre-selected papers were revised according to the criteria described in Section 2.2.2—Selecting for articles. The second iteration started from the selected documents, and backward (cited) and forward (citing) snowballing was carried out. This process was repeated in five iterations until no additional papers were selected, as shown in Figure 1. The search for the articles was carried out from August to the end of October 2023.

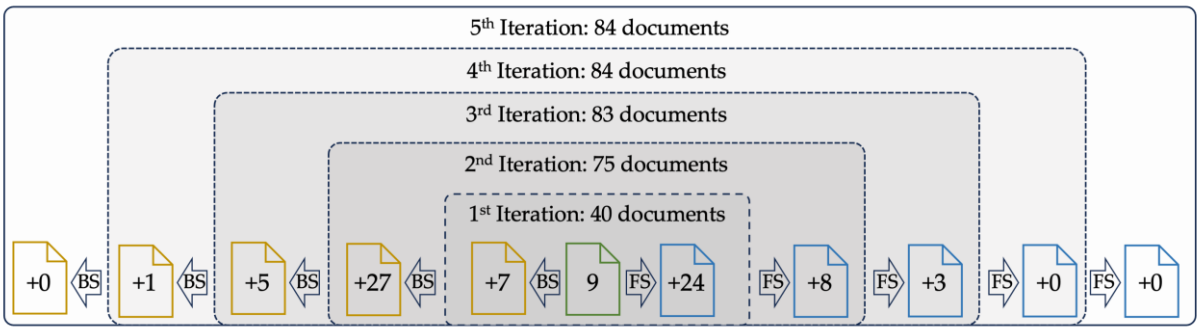


Figure 1. Documents identified and selected during the backward (BS) and forward (FS) snowballing iterations from the seed references. Source: elaborated by the authors based on [36].

2.2.2. Selecting for Articles

The criteria to include an article in the database are as follows: (i) the word "bioeconomy" or "bio-economy" should appear in the title, abstract, keywords, or at least in the introductory contextualization; (ii) the study should measure some economic aspects of a sector or a bioeconomy system within local, regional, national, or multiple countries' economies; (iii) the study should describe a method to measure the bioeconomy share in the economic system. Therefore, studies based on reviews, analyzing national strategies or policies on bioeconomy, describing the bioeconomy based purely on official statistical data or

conceptual frameworks, or assessing only socio-environmental aspects of bioeconomy sustainability were excluded from the analysis.

At the end of the snowballing process, 84 documents, including articles and technical or scientific reports, were selected to have their content analyzed (Table S1 in Supplementary Materials).

2.2.3. Building the Database

The first step to analyzing the documents' content was the construction of an appropriate database. To make the process more reliable, we used the software, Qualitative Data Analysis (QDA Miner), v. 5, provided by Provalis Research (https://provalisresearch.com/products/qualitative-data-analysis-software/, accessed on 25 September 2024). The textual content of each document was uploaded to the QDA Miner environment, and its year of publication and first author name were assigned as related variables. The associated variables are interesting for comparing results over time and by authors. We chose to compare authors and studies in the present study and did not conduct a temporal analysis. At the end of this process, the text content of the documents was electronically stored and coded in the QDA Miner environment using the software's functions.

2.2.4. Defining the Codes

We did not use automated text mining processes in this study. Instead, the content of the documents was personally coded by the authors. The textual content of the documents can be coded using a list of predefined codes or an appropriately designed code structure according to the purpose of this study. Although a list of possible and useful codes could be extracted from the literature in studies like [30,38,39,48–50], we decided to construct a particular code structure.

Considering the purpose of this study, we defined a fundamental root-code structure based on concepts, methods, data, indicators, and limitations. The studies' geographical scope (country, region, etc.) was also considered a root code. Only the codes under the root code "bioeconomy concepts" were predefined based on Sections 2.1 and 4.1. of this article. Thus, only the codes BmBB (biomass-based bioeconomy), BtBB (biotechnology-based bioeconomy), and BsBB (biosphere-based bioeconomy) could be used in the coding process. The codes for the other root codes were defined as the content was analyzed and coded. Thus, new codes were identified and added to the code structure. As the list of codes expanded, the codes began to

repeat themselves, and the occurrence of additional codes ceased. The final code structure can be found in Table S2 in Supplementary Materials.

2.2.5. Coding the Articles' Content

With the textual database and code structure available in the QDA Miner user interface, the next step was to code the content of the documents. The coding process involves linking a given code to a fraction of the corresponding text. For example, if, during the content analysis, a passage of text that characterized the use of the biomass-based bioeconomy concept was identified, this text fragment was selected, and the code "BmBB" was linked to it. The same procedure was applied to the other codes relating to methods, data, indicators, and limitations. Therefore, at the end of the coding process, the content of the 84 documents was coded entirely considering bioeconomy concepts, measurement methods, data used, indicators explored, and any limitations identified. Finally, a complete review of duplicate codes in the same document was completed, and corrections were made where necessary.

2.2.6. Extracting the Results

Using the QDA Miner's statistical resources made it possible to generate some figures directly, and the occurrence and co-occurrence of codes were downloaded so that other figures could be generated in other software.

3. RESULTS

3.1. The Concepts of Bioeconomy: From Partial to Holistic Bioeconomy

In this section, we propose the concept of a holistic bioeconomy based on three partial conceptual approaches discussed in the literature and the recognition that these concepts are not mutually exclusive, in agreement with [17]. We argue that the holistic bioeconomy should be considered and pursued in measuring the bioeconomy.

3.1.1. Biomass-Based Bioeconomy (BmBB)

In line with the work of Bugge et al. [19], Vivien et al. [20], Befort [21], and Giampietro [51], this approach seeks to measure the bioeconomy from a concept that bases the bioeconomy on the primary input, biomass, or bioresources [17]. Biomass is defined as all organic matter produced by photosynthesis convergence of solar energy [52] or primary or secondary organic matter (waste) derived from plants, animals, or microorganisms. It can be used as a renewable input to produce energy, food, fiber, or material [53]. Biorefineries are the technological

platforms for transitioning from fossil to renewable materials and energy [20,53,54]. Measuring the BmBB, therefore, starts by identifying the primary sectors that produce biomass, which could suggest a narrow view of the bioeconomy. Studies, such as that by [55], have identified agriculture, livestock, and forestry as the primary sectors of the BmBB. However, methodological approaches may differ regarding the method, data and indicators used to measure the BmBB. The fact is that even though biomass is essentially produced in three or four economic sectors, it flows between almost all sectors of the economic system, being consumed or transformed with added value (Figure 2). Thus, measuring the BmBB provides information on physical or monetary flows that express how large the BmBB is in terms of an economy's GDP, for example. In national bioeconomy strategies, the BmBB concept is well represented by the European Bioeconomy Strategy [13]. The BmBB is close to an economic system where bioresources and bioproducts are supplied and demanded through the value chains and market structures [56].

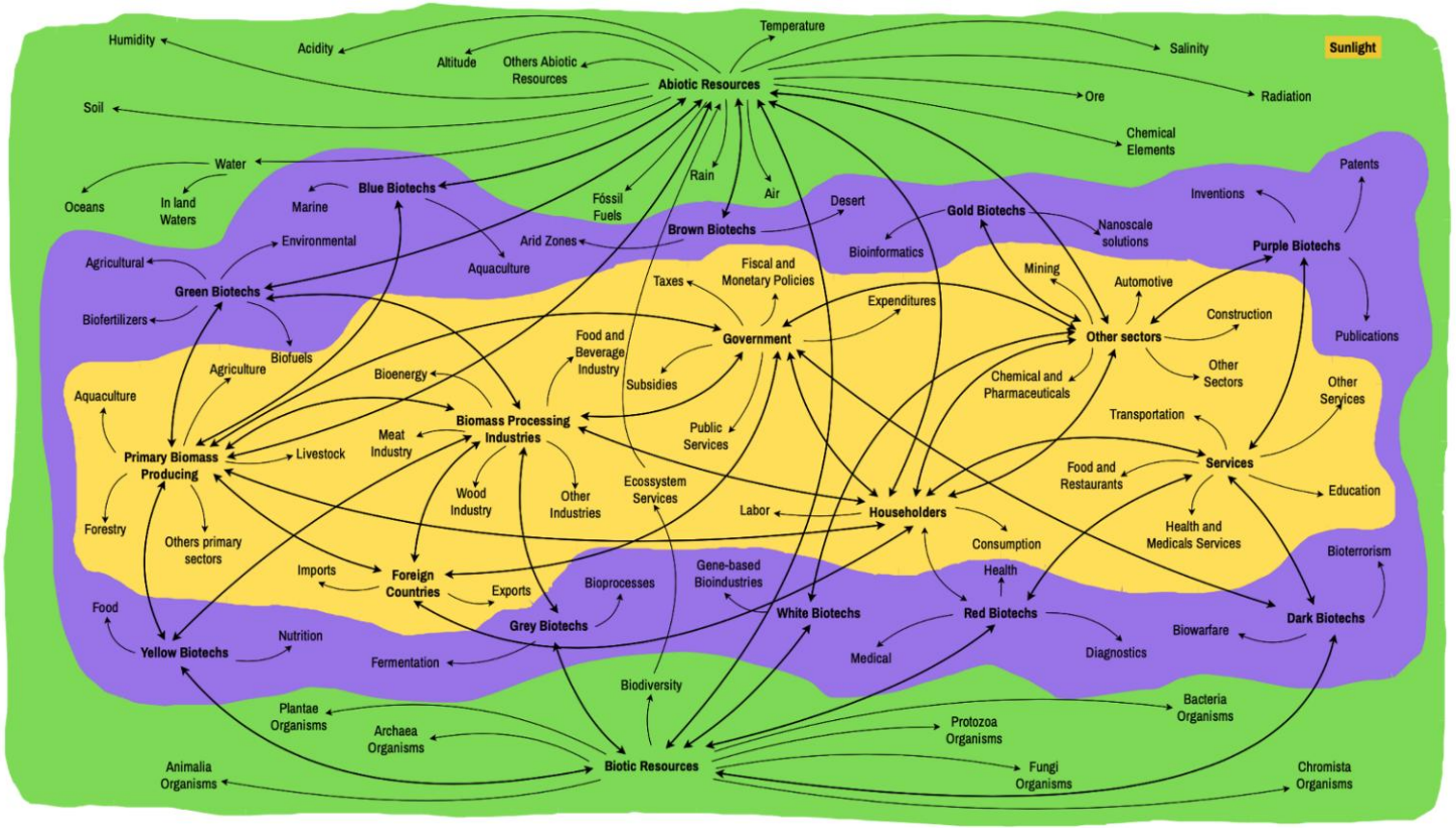


Figure 2. Generic conceptual framework of the holistic bioeconomy based on the hierarchy of partial concepts. In general terms, the central part of the figure (orange) represents the concept of BmBB, indicating the production of biomass as a fundamental input and its intermediate and final flows between the intermediate demand of the economic sectors and the final demand of the government, households, and the external market. The intermediate part (purple) represents the concept of BtBB in its different categories of development of biotechnological solutions. BtBB interfaces with the economic system to which it provides its solutions and receives the knowledge of human capital to apply to the biotic resources of the different kingdoms of nature (BsBB). The outermost part of the figure represents the concept of BsBB (green) or, more specifically, the biosphere where the biotic and abiotic resources are located. The biosphere provides the necessary substrates for maintaining and developing all biodiversity, which underpins the holistic bioeconomy. The scheme, therefore, suggests a hierarchical system structure in which BmBB and BtBB are subsystems within the BsBB system. The arrows with thicker lines illustrate interconnections between bioeconomy concepts and their main elements. The arrows with thinner lines indicate the connections between secondary elements, usually within the same concept. Source: elaborated by the authors.

3.1.2. Biotechnology-Based Bioeconomy (BtBB)

Although some researchers around the world have already nominated biotechnology use for different purposes, we defined the BtBB as the second approach to measuring the bioeconomy. Alternatively, the term "biotechonomy" can be applied to define the scope of this approach [57] or knowledge-based bioeconomy (KBBE), as originally proposed by Christian Patermann [3]. Conceptually, this approach aligns with the view of bioeconomy as synonymous with biotechnology suggested by [17,19,58] and the Type II bioeconomy identified by [20] and reinforced by [21]. The BtBB is based on biotechnologies or bioengineered solutions developed from biological assets (biodiversity) and used to solve society's problems on different fronts: human health and medicine (Red), agriculture (Green), marine (Blue), industry (White), food and nutrition (Yellow), deserts and arid regions (Brown), bioterrorism and biocrime (Black), intellectual properties, patents and publications (Violet), nanobiotechnology and bioinformatics (Gold), and environmental protection (Grey) (see Table 1 in [58]). The BtBB has gained strength from advances in genomics, synthetic biology, genetic engineering, and other modern biotechnology platforms [4,59]. Therefore, while the BmBB is based on raw materials, the BtBB is based on knowledge, innovation, and processes for adding value to biodiversity, including biomass. Measuring the BtBB involves identifying the relevant activities and sectors related to biotechnology, their value, and the value of their application for society and the biosphere. Resources, processes, and products are integrated into the dynamics of the economic system, increasing the added value and contribution of the BtBB in national economies. The intermediate part of Figure 2 represents this conceptual approach. Studies on BtBB measurements suggest investment in research and development (R&D) and the number of biotechnology patents as indicators [60,61]. The aims and scope of the US Bioeconomy Blueprint is an example of a national strategy more aligned with the BtBB concept [16].

3.1.3. Biosphere-Based Bioeconomy—BsBB

The third conceptual approach to the bioeconomy is referred to as the biosphere-based bioeconomy (BsBB). The term "biosphere" is used because it is the part of the Earth's environment in which living organisms are found and interact to produce a steady-state system. Within the biosphere, there are environments and ecosystems. The environment is composed of physical (land, water, air) and biological conditions in which organisms live as well as social, cultural, economic, and political conditions. An ecosystem consists of living and non-living things interacting in an area of the biosphere, where energy and material flow are fundamental

concepts [62]. So, the entire web of life and its trophic hierarchy can be seen as a natural marketplace and thus the bioeconomy itself [63]. Therefore, the biosphere is the broader term that houses the conditioning factors and life itself—the basis of the bioeconomy. While the BmBB and BtBB are closely associated with inputs and the technological means for adding value, respectively, the BsBB is the broadest and most integrative approach of all. The BsBB meets the scope of the bio-ecological or agroecological vision of the bioeconomy by [17,19,64] and the Type I Bioeconomy proposed by [20], which associates economic activity with the limits of the biosphere and the laws of non-equilibrium thermodynamics [51,65–67]. On the political scene, the Brazilian bioeconomy program focused on an economic system based on socio-biodiversity, innovation, and technology is close to the BsBB concept [9,18].

3.1.4. Holistic Bioeconomy

The breakdown of bioeconomy concepts occurs beyond academia. Among policymakers, the association of the bioeconomy with the concepts of BmBB and BtBB is prevalent [21]. In addition to policymakers, other civil society stakeholders have a fragmented view of the bioeconomy. Farmers and forest owners, for example, perceive the bioeconomy to be more associated with the BmBB concept. Industry and commerce members and researchers see the bioeconomy in a more balanced way between the BmBB and BtBB. The media associates the bioeconomy exclusively with the BmBB, while the BsBB concept is more mentioned among citizens and consumers [68]. This behavior may reflect the utopian perception regarding the BsBB. However, the bioeconomy needs to be sketched into the human activities that are genuinely embedded into the local ecosystem and biosphere, where we perpetually communicate with the environment, deliberately or not [63].

The partial view of the bioeconomy has limitations and practical implications, especially for formulating integrative policies and strategies that maximize the potential of the bioeconomy. This is why scientific research must search for a holistic view of the bioeconomy. Other authors recognize the need to reconcile the different bioeconomy concepts [17,21]. In this direction, the adoption of a systemic perspective is proposed [23]—a whole vision from a sector to a system [58] or a holistic system with thinking and planning to integrate the multifaceted sectors interconnected in the circular bioeconomy [69]. In addition, a holistic approach to encompass the relationships between the different concepts, in particular the BmBB-BtBB and BsBB, is advocated by [20,70,71]. The European Bioeconomy University included in its Forum 2023 in the thematic session “Identifying synergies for a holistic Bioeconomy approach” to provide an informative overview of the historical evolution and

diverse concepts within the bioeconomy to overcome the complexity involving a range of visions, values, and narratives [72]. However, the outline of the holistic approach was not clearly stated.

Holism claims that evaluating and measuring the holistic bioeconomy is more important because it highlights the interactions and contributions of and between all the partial concepts. Therefore, advances toward the construction of conceptual and methodological alternatives need to be grounded in General Systems Theory (GST) [73] and Complex Adaptive Systems (CAS) [74]. They recognize, at the very least, the type, hierarchy, boundaries, components, and relationships between the elements of systems and the complexity surrounding systemic dynamics.

In general, the BmBB and BtBB approaches are referred to in the literature more as a closed system model of the economic system, open only to the economy system of other countries. However, the BsBB necessarily means considering the economic system as an open system interacting with the bio-physical system. The biosphere provides the necessary substrates for maintaining and developing all biodiversity and its contributions to society [75]. Biodiversity is the basis for creating value chains in the holistic bioeconomy seeking to increase economic value with the least use of preferably renewable energy and low entropy generation. Therefore, assuming that the partial bioeconomy concepts are open systems and that there is a hierarchy between them, the BmBB and BtBB are subsystems of the BsBB system, as represented in Figure 2.

The BsBB perspective is relevant because it makes it possible to measure the flows from the biosphere into the economic system and vice versa. The BtBB intermediates some of these flows by taking resources from both the BmBB (e.g., knowledge and financial support) and BsBB (e.g., biodiversity and DNA) and providing solutions for the environment and society. Many BtBB contributions to the BmBB may be embodied in the BmBB outputs because of biotechnologies on crop yields, for example. At the same time, other flows are directly exchanged between the BsBB and the BmBB, like externalities (e.g., CO_2 emissions) and ecosystem services (e.g., cycling materials). Therefore, the consumption of flows and stocks and the role of funds for the absorption of waste and pollution become measurable. Sustainability aspects of the bioeconomy can be gauged [51,76], despite the criticism regarding the sustainability labels as bio-based use, CO_2-neutral, or climate-friendly as a consumption stimulus into the economic system. [63].

The holistic measurement of the bioeconomy is challenging since many contributions of nature are provided by the BsBB with no charge for the BtBB and BmBB. Additionally, the

exchange in nature is measured in energy units, while in the economy, it is in monetary terms. In the 1990s, Howard T. Odum proposed a challenging task of aligning ecology and economics through a new method–the emergy analysis. He aimed to assess the value of energy and materials involved in biological or economic processes, converting them into a common unit (sej-solar emjoules). Emergy accounts for all the direct and indirect solar energy required to produce the services and products of ecosystems and the national economies [77]. Within this framework, the emergy-to-money ratio, known as the "emdollar", can be calculated, expressing how much emergy is required to generate one monetary unit (e.g., US$1) in an economy. However, the complexity of this methodology and the lack of an interdisciplinary approach have limited its applications in economic science.

Despite this, the BsBB approach cannot be ignored in the methods developed for measuring national bioeconomies. The bioeconomy's contributions to sustainability and the environment have already been highlighted in studies such as [61,78]. Vivien et al. [20] suggest that the lack of emphasis on the BsBB is due to a hijacking of Georgescu-Roegen's term "bioeconomy" by economic activities that want to convey a sustainability appeal. Therefore, given the distorted use of the term bioeconomy, the public needs to be very critical of all attempts by political or commercial groups to use the concept of sustainability to mask their true interests [63].

On the other hand, the intransigence of the laws of thermodynamics, on which the BsBB is based, makes this approach challenging to measure. Giampietro and Funtowicz [79,80] classified this theoretical fragility as "uncomfortable knowledge" to assess the economy–bio-physical interface [79,80]. Ignoring the impacts of the laws of thermodynamics cannot be a limiting factor for advances in conceptual discussions of the bioeconomy. The challenge lies in developing suitable methods to measure its dimensions and implications. Far from a disciplinary approach grounded in economics, it requires an interdisciplinary or even transdisciplinary engagement supported by post-normal science and biosemiotics [79,81–84].

In the political arena, national strategies are based on partial bioeconomy concepts. Some countries have emphasized the primary input (biomass), while others focus on processes (biotechnology) or natural resources. The concepts assumed in national policies lead to a biased and partial measurement of the contributions of the bioeconomy. National strategies for a holistic bioeconomy would have the potential to stimulate countless other development initiatives. It should be integrated into national accounting and measured as effective contributions of the bioeconomy to national economies.

Therefore, the holistic bioeconomy is an integrated and integral systemic approach to the systems pertaining to each partial concept (BmBB, BtBB and BsBB). Measuring the holistic bioeconomy must consider the hierarchy of systems and subsystems and their boundaries, components, and interactions. The central issue is that the elements of each concept that contribute to the holistic bioeconomy are expressed in different units of measurement. Direct economic measurements of the holistic bioeconomy are unfeasible because their relationships are not always measured in economic terms (monetary value). Therefore, the system represented by the holistic bioeconomy is complex and challenging to measure, but it needs to be considered, as explained by [51,70].

3.2. Authors, Documents and Countries: A Brief Characterization

This section characterizes the set of documents regarding their content similarity and shows the leading countries in the studies on measuring the economic impact of the bioeconomy. Such results are essential to understand the context from which the main results originated.

The first set of results shown in Figure 3 illustrates the clusters of documents grouped by degree of similarity.

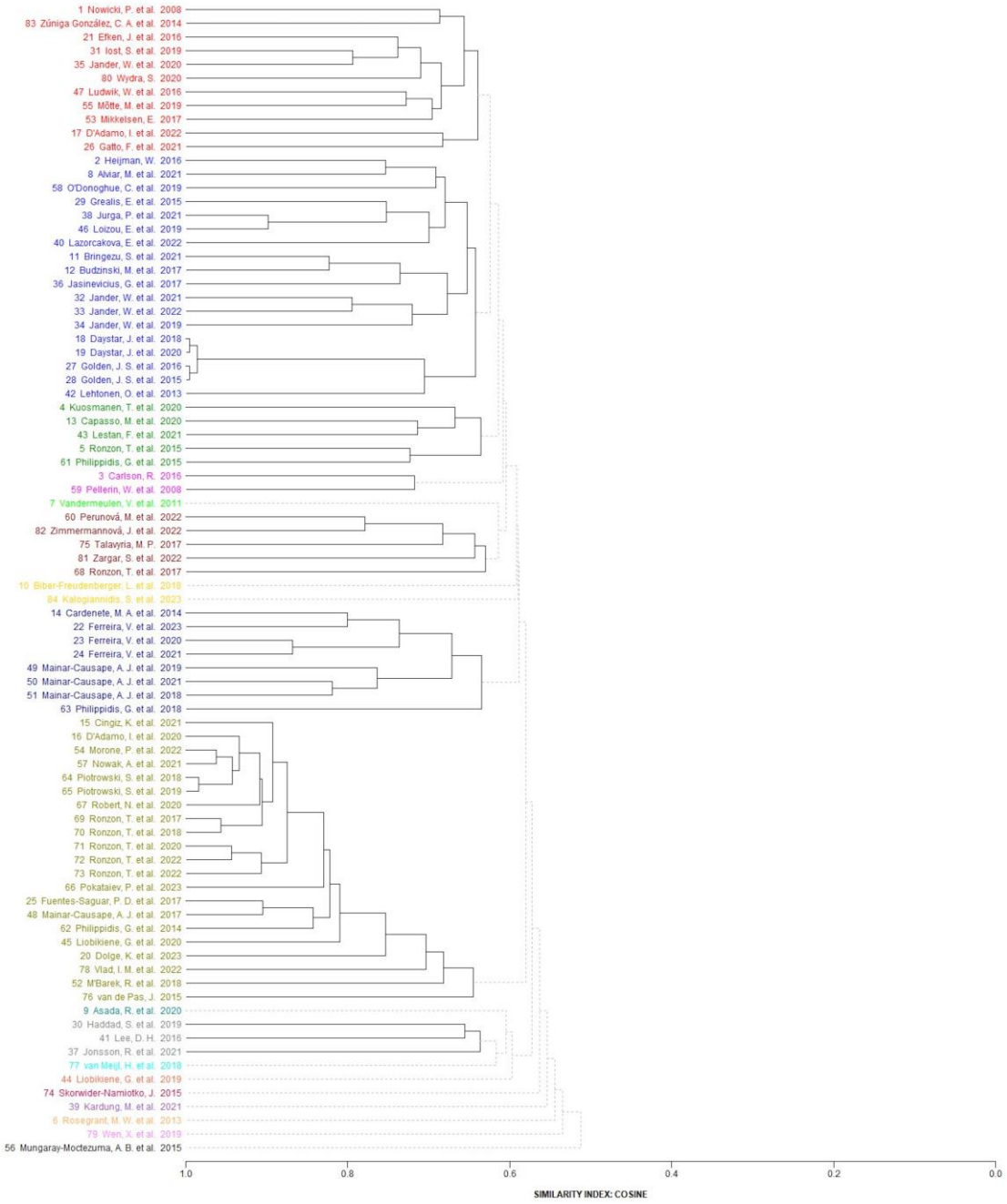


Figure 3. Dendrogram of the documents [1,26,27,39–41,43–47,85–157] clustered by Cosine Similarity Index. Source: elaborated by the authors based on research data.

Cosine similarity is one of the most popular similarity measures applied to text documents, such as in numerous information retrieval applications and document clustering [158]. Cosine similarity is a measure of similarity between two vectors obtained from the cosine angle multiplication value of two vectors being compared [159]. A zero value indicates total dissimilarity between the documents, while a value of one means that the documents are entirely similar. Documents with a Cosine index greater than 0.5 can be considered to have high

similarity. Although Cosine similarity is widely applied in document content analysis, in the case of this study, Cosine similarity is based on the occurrence of codes. Therefore, documents with the same codes would result in a cluster with a Cosine similarity value of one.

A total of 10 main document clusters were considered based on the similarity of code occurrence. Overall, there is a high degree of similarity between the 84 documents, given that the lowest Cosine index value was higher than 0.5 for all documents. In particular, some documents showed very high similarity, with a Cosine index close to one. This is the case, for example, with the documents "18 Daystar, J. et al. 2018" [107], "19 Daystar, J. et al. 2020" [108], "27 Golden, J. S. et al., 2016" [109], and "28 Golden, J. S. et al., 2015" [44]. This group of documents consists of a series of technical reports drawn up by a team of researchers and addressed to the US Congress. These authors co-authored the four documents and each year, the report updates the data using essentially the same method, data, and indicators. Another example is documents 64 and 65 by Piotrowski et al. in 2018 and 2019 [132,133], respectively. Therefore, the high level of similarity is due to the recurrence of the same codes.

Another feature to be highlighted in the formation of clusters is the effect of co-authorship on the grouping of documents. Many of the authors who form the clusters have worked together with the authors of other documents. In this sense, the cluster formed by the documents "15 Cingiz, K. et al. 2021" [39] to "76 van de Pas, J. 2015" [147] is worth highlighting. These clusters represent the efforts of research groups developing joint studies to measure the bioeconomy using relatively similar concepts, methods, data, and indicators.

The high level of similarity between the documents may also have been affected by the geographical scope of the studies. Only 47 countries had data and indicators from their national economies investigated. However, most of the documents report bioeconomy results from countries that are members of the European Union. Germany has the highest number of records, followed by Poland, Spain, the Netherlands, and the Czech Republic (Figure 4). Some documents are specific to one country, while others report results from groups of countries, such as EU-28, EU-27, EU-15, and so on. In these cases, the country code was assigned to the document whenever country-specific results could be identified.

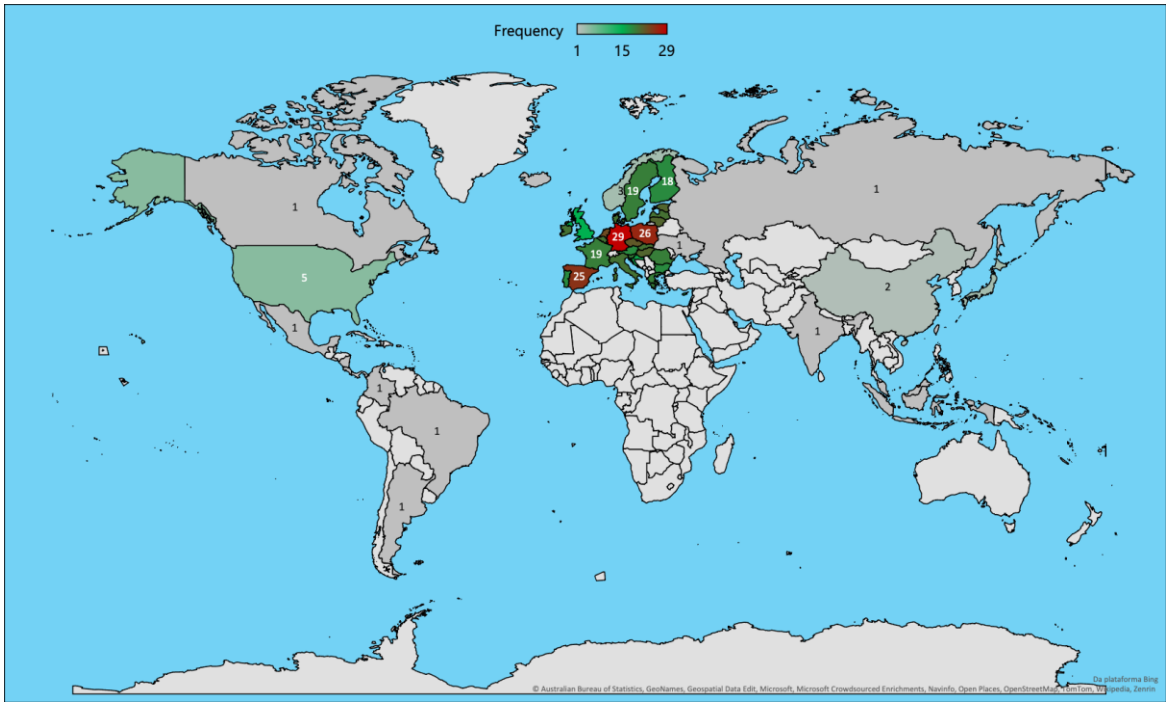


Figure 4. Frequency of studies by country. Source: elaborated by the authors based on research data.

Only some countries outside the EU have been included in studies. Of these, the United States had the highest number of studies on its bioeconomy (5), followed by Japan (3), Norway (3), and China (2). Despite the potential of the bioeconomy, countries in Latin America, Africa, Oceania, and Asia need studies that measure their bioeconomy.

These initial results illustrate a specific pattern in efforts to measure the bioeconomy. Although the studies used various methods, data, and indicators, studies that proposed cutting-edge or significantly innovative methodologies still need to be identified.

3.3. Connections between Concepts, Methods, Data, Indicators and Limitations

Figure 5 gives an overview of the connections between bioeconomy concepts, methods, data, indicators, and limitations through cooccurrence.

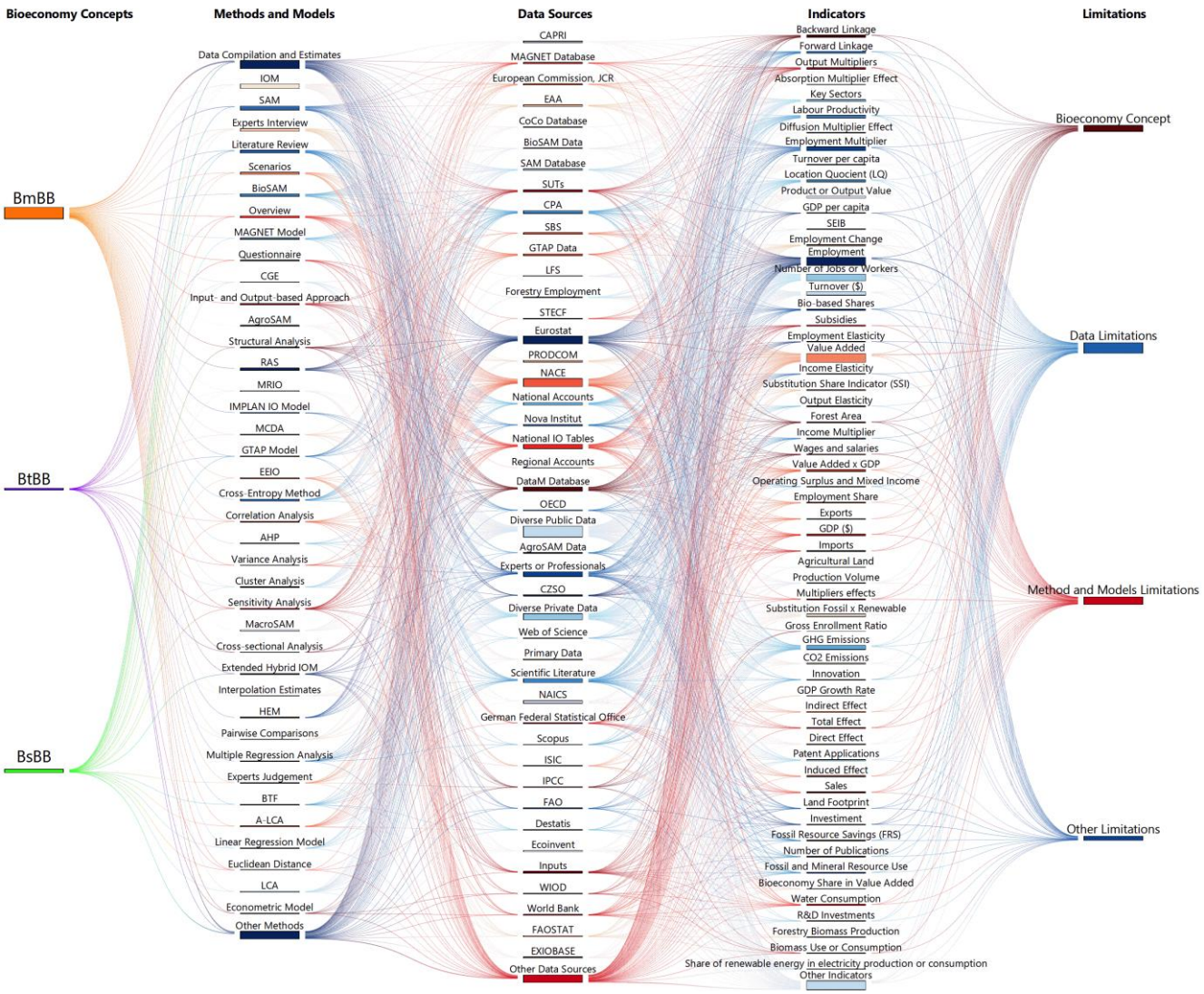


Figure 5. An overview of the connections between bioeconomy concepts, methods and models, data sources, indicators, and limitations. Notes: (i) the bars' thickness corresponds to the occurrence frequency of the codes; (ii) "Other limitations" include those related to indicators; (iii) a list of acronyms and abbreviations shown in figures are available in Abbreviations. Source: elaborated by the authors based on research data.

At this point, a result worth highlighting is that most studies (94%) measured the bioeconomy associated exclusively with the biomass-based bioeconomy (BmBB). This is likely due to the concentration of studies in EU member countries, where the official concept of the bioeconomy is more aligned with the bio-based economy. In 22 documents, economic and environmental aspects were measured together, and these documents were coded with both concepts (BmBB + BsBB). Three documents measured aspects of the three bioeconomy concepts (BmBB + BsBB + BtBB).

As elaborated in Section 3.1, we recognize the existence of at least three conceptual visions of the bioeconomy—BmBB, BtBB, and BsBB—and we consider the holistic bioeconomy results from the integration of the three concepts. However, only a few studies recognized the three partial concepts, like [95], but are limited in measuring the holistic bioeconomy.

The BsBB concept was considered by the authors of approximately one-quarter of the studies but not explicitly grounded in ecological economics. Essentially, the studies are restricted to combining the measurement of specific indicators of environmental impacts or resource use combined with socioeconomic performance, such as [148,149]. Although biotechnology has been advocated as an inclusive and sustainable technological platform for the bioeconomy [160], few studies have been dedicated to measuring the economic impacts of the BtBB. Carlson's [27] was the only study that dealt exclusively with the BtBB, using data compilation to estimate the contribution of biotechnology to the North American economy. Possibly, the lack of structured data that adequately informs the contributions of the BtBB is a limitation. Given this, the few studies considering the BtBB have mainly explored the turnover of biotech industries or aspects related to patent registration. Besides this, human resources training and R&D investments have been used to evaluate knowledge capital, generally associated with KBBE [4].

Figures 6–8 explore more clearly the connections between bioeconomy concepts and methods, data, and indicators, respectively. A miscellaneous 72 methods were coded in the documents analyzed. Figure 6 shows those methods with a frequency of two or more occurrences. The methods that occurred only once were grouped under "Other Methods". This is the case, for example, with Causality Analysis, Case Studies and Cointegration Tests, among others.

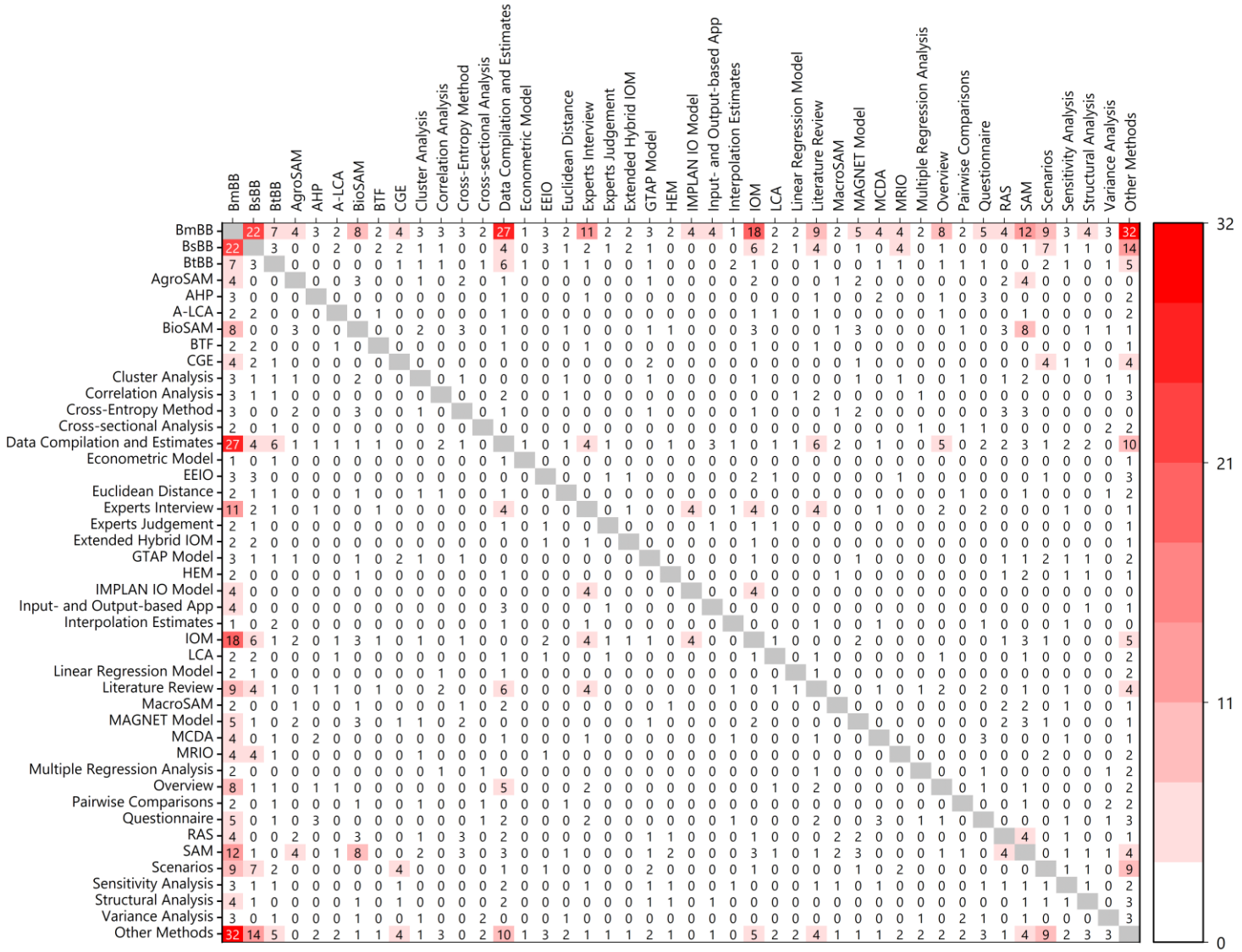


Figure 6. The co-occurrence between concepts of bioeconomy and methods. Source: elaborated by the authors based on research data.

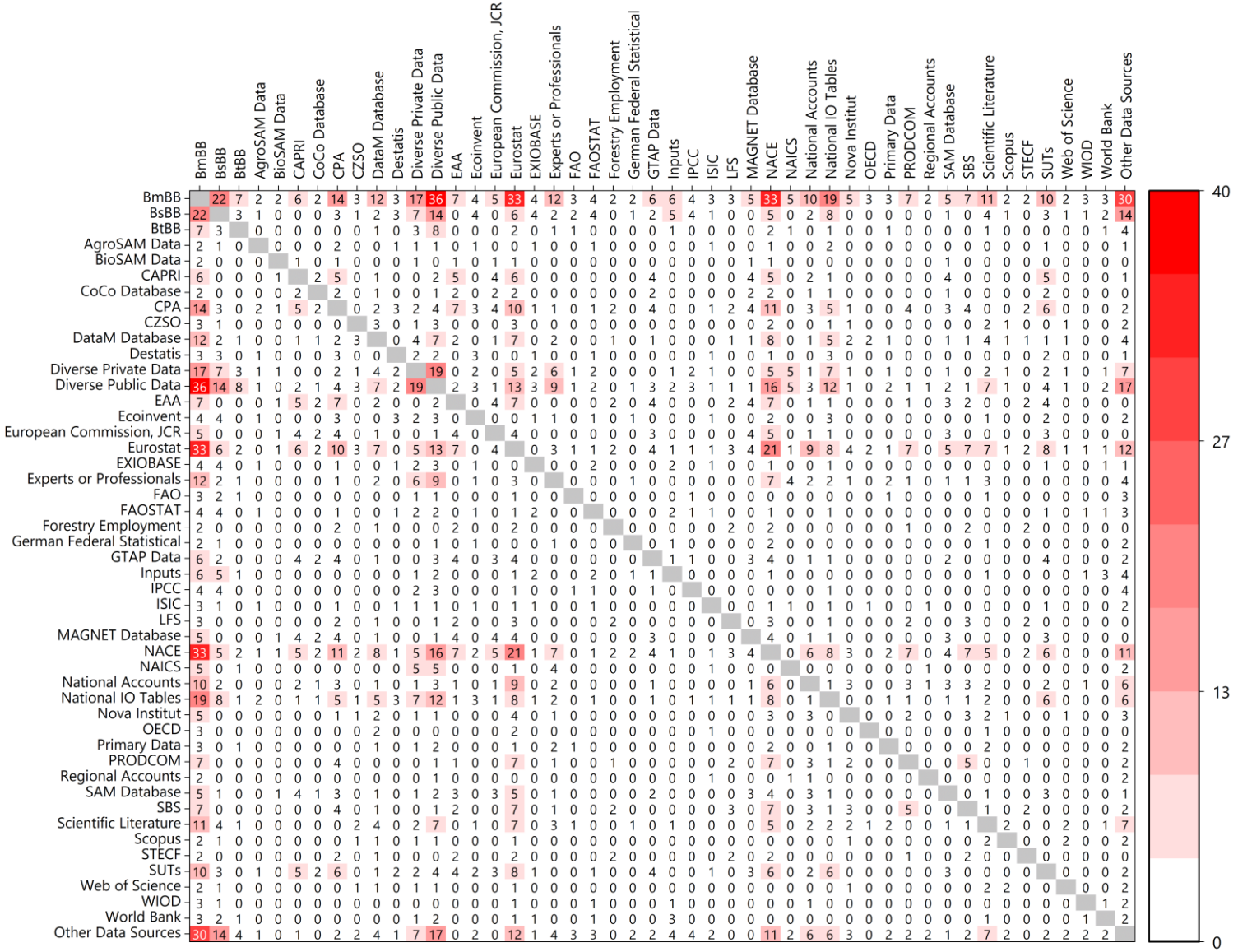


Figure 7. The co-occurrence between concepts of bioeconomy and data sources. Source: elaborated by the authors based on research data.

Macroeconomic studies exploring economic systems' structures and structural changes often resort to input-output models (IOMs). While IOMs measure the interconnections between economic sectors, social accounting matrices (SAMs) are expansions of IOMs that add other agents such as government and households [161]. Together, IOMs and SAMs make it possible to calculate various dimensions of economic activity, such as intermediate and final demand, technical multipliers, and backward and forward linkages, among others.

The studies by [26,39,46,55,98,100,135–137], for example, used input-output models (IOMs). Variations on IOMs, such as the Multiregional Input-Output Model (MRIO) and Environmentally-Extended Input-Output Model (EEIO) or Environmentally-Extended Multiregional Input-Output Model (EEMRIO), were used by [148] to aggregate data and measure environmental aspects associated with the bioeconomy. Complementarily, [156] combined Principal Component Analysis (PCA), Autoregressive Distributed Lag (ARDL), and IOM to identify the key sectors and the short- and long-term effects of the bioeconomy on Japan's GDP.

Measuring the bioeconomy using traditional macroeconomic methods can be justified by using the concept of the bioeconomy restricted to the BmBB, where biomass is the main input and primary production sectors are the key sectors. This sectoral structure makes it possible to use data from national input-output tables and measure the participation of the bioeconomy like any other economic activity. In this sense, the measurement of the BmBB differs little from what is usually measured as agribusiness [162].

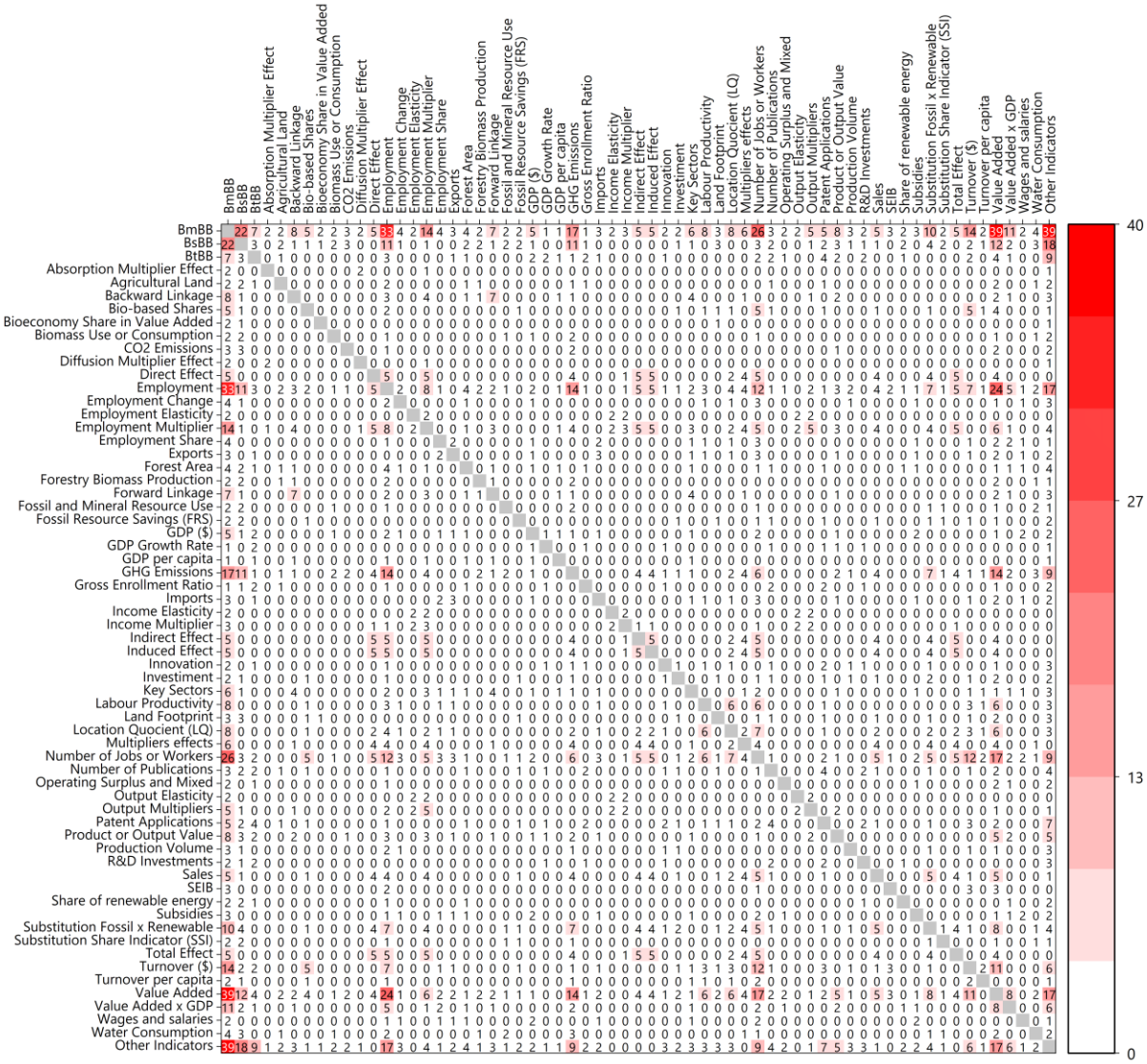


Figure 8. The co-occurrence between concepts of bioeconomy and indicators. Source: elaborated by the authors based on research data.

Similarly, Figure 7 shows the connections between the concepts and the data or data sources used to measure the bioeconomy. Likewise, the data presented in the figure occurred twice or more. Data that only occurred once are grouped under “Other data sources”.

The unavailability of suitable data has been an obstacle to adequately measuring the bioeconomy. Part of this difficulty is related to the conventional structure of the organization of national accounts. There is no classification of specific sectors and the bioeconomy and, as stated in [38], the bioeconomy crosses sectors and cannot be treated as a traditional sector of the economy. Consequently, from the perspective of conventional economic analysis, efforts have been aimed at identifying sectors and activities related to the bioeconomy.

National classification systems for economic sectors and activities have been used alone or in combination to delimit the scope of data representative of the bioeconomy. Thus, coding structures for sectors and activities, such as the Statistical Classification of Economic Activities (NACE) [40,98,100,135–137], Classification of the Functions of Government (COFOG), Common International Classification of Ecosystem Services (CICES) [55], Statistical Classification of Products by Activity in the European Economic Community (PRODCOM) [148], Classification of Products (CPA) [100], in the EU, and the National Income and Product Accounts (NIPAs), North American Industry Classification System (NAICS), North American Product Classification System (NAPCS) [61,163], and Impact Analysis for Planning (IMPLAN) Industry Scheme, in the US, are examples of classification systems used in delimiting the bioeconomy.

The strategy to delimitate the bioeconomy is to estimate the relative share of biomass (bio-share) in the economy’s sectors, activities, or products. Researchers have resorted to using sectoral statistical data, such as *Istituto Nazionale di Statistica* (ISTAT), exploring regional transitions to the bioeconomy using a socio-economic indicator: the cases of Italy [93], PRODCOM [164], and NACE [132,133,135,136]. They also combine statistical data with the biomass content in products reported in the scientific literature [55] or the opinions of sectoral experts collected through interviews. Alternatively, Lazorcakova et al. [100] estimated minimum, maximum, and middle bio-share based on the classification of products provided by the CPA. However, as there is no official data on the subject, determining bio-shares is just as tricky as classifying activities, leaving researchers to use imprecise estimates that compromise the accuracy of the estimated values.

Figure 8 best shows the connections between the concepts and indicators used to measure the bioeconomy. By default, only indicators with a frequency of two or more are listed, while those with a unit frequency are aggregated under “Other Indicators”.

Value added and GDP have been the recurrent measures of the bioeconomy in the literature [26,39,46,55,95,137,156,163]. Other studies have considered the turnover of industries related to the bioeconomy [135]. The socioeconomic contributions of the bioeconomy have also been investigated, mainly through the labor market and jobs [26,55,135–137,163]. The environmental impacts of the bioeconomy have been assessed in terms of GHG emissions [95,100] or natural resources like water and land [149]. These indicators have been calculated and reported in absolute values, such as $ millions, number of employees, and tons of CO_2 from fossil origin, mainly, summed with biogenic, or, in relative terms, such as value added/GDP, turnover/GDP, percentage of jobs/total jobs, and growth rate of these variables over time [26,39,46,55,100,137]. In general, the indicators used to express the contribution of the bioeconomy to national economies are those usually used to measure other economic activities, considering the methods predominantly used.

When analyzing the content of the documents, an effort was made to identify limitations reported by the authors associated with measuring the bioeconomy. In this process, 71 unique limitations were identified and grouped by those related to the bioeconomy concept, data, method, indicators, and others, as shown in Figure 9.

Data limitations were the most frequently reported, accounting for 36.6% of all unique limitations. In this sense, incomplete data, missing or lacking data, aggregated data, outdated data or databases, unavailable data, scarce or limited data, and data quality were the most frequent limitations. As stated by Meyer [165], while statistical data for the primary production of biomass in agriculture, forestry, and fishery are relatively well established, the economic shares of downstream stages in biomass-based value chains are not readily available.

The second position regarding limitations is those associated with methods or models. A total of 25 unique limitations (35.2%) were found in this category. The most frequently reported method limitations were the uncertainty of the estimated values, the linearity assumptions of the models, difficulties in combining models, the subjectivity of some weighting procedures, the absence of supply restrictions in the models, and the assumption of fixed prices [166]. In the same vein, the limitations of the data are closely related to the methods and models used. The limited availability of timely input-output tables is pointed out as a critical limitation of IOM data [167].

The limitations of methods or models and data were the most relevant and accounted for more than 70% of the unique limitations. Among the remaining limitations, the category of other limitations and bioeconomy concepts account for 23.9% of the unique limitations. In this sense, the main limitations related to the concept of the bioeconomy concern the lack of specific

codes in classification systems to measure biotechnology activities or sectors correctly. The existence of different definitions for the term bioeconomy, the criteria used to delimit the scope of the bioeconomy, and the limited definitions of the bioeconomy also were identified. Complementarily, other frequent limitations are associated with the criteria or lack of precision in bio-share estimates, the geographical scope of studies restricted to the borders of a country or region, and limitations related to the measurement of biotechnology (BtBB).

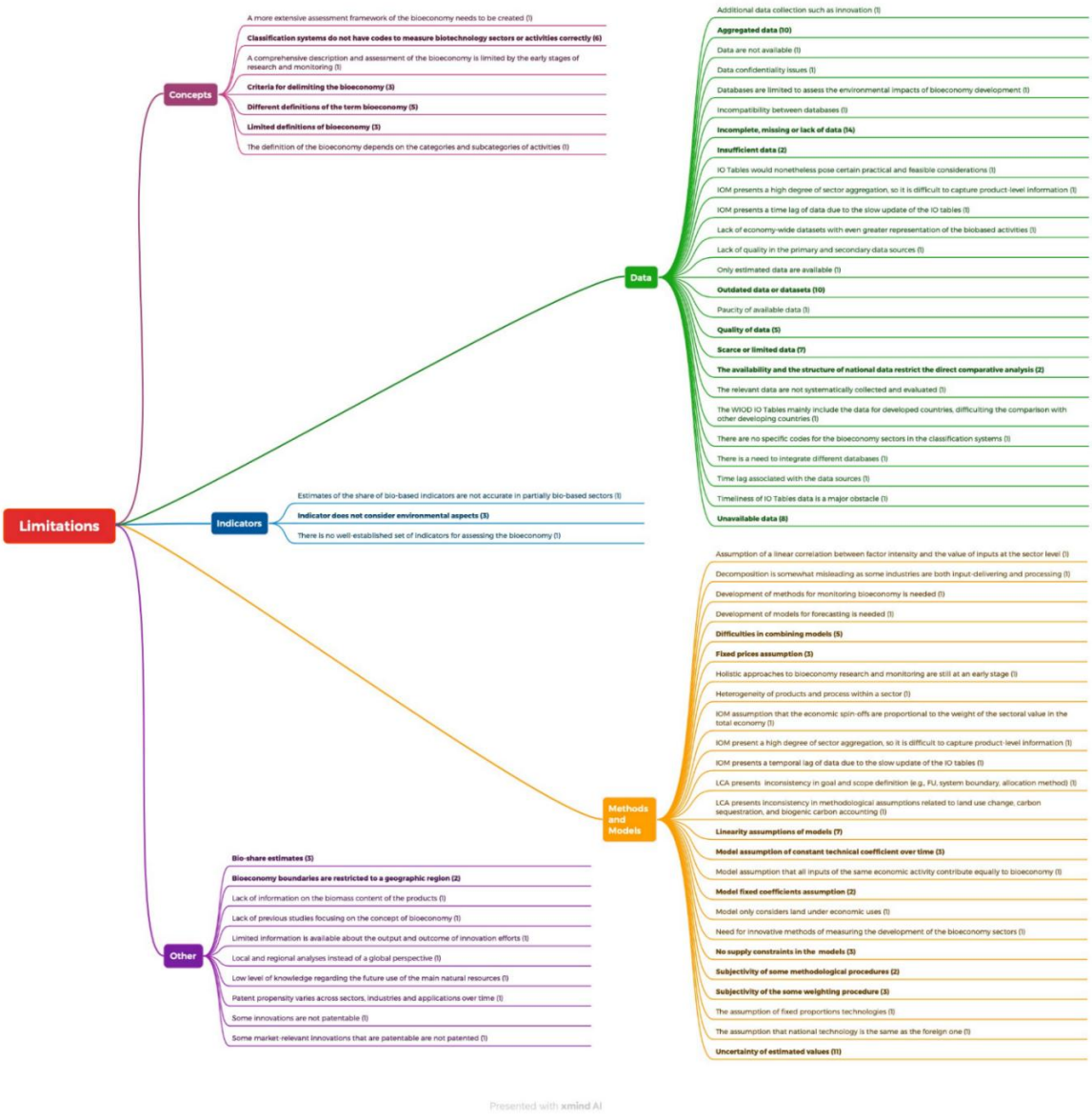


Figure 9. The mind map of limitations in measuring the bioeconomy related to the concepts, data, method and models, indicators, and others. Note: The numbers in parentheses refer to the frequency. The most frequent limitations are in bold. Source: elaborated by the authors based on research data.

The category of limitations related to indicators was the least relevant, with only three unique limitations. These limitations are important to note. They signal concern about the environmental aspects of the BsBB. They also recognize the limitations of the indicator results due to the criteria used for weighting the participation of biological resources in economic activities. Additionally, they highlight the need to develop specific indicators to assess the BsBB.

4. DISCUSSION

4.1. Challenges to Measure the Holistic Bioeconomy Economically

Jander and Grundmann [88] state that monitoring bioeconomy transitions and their effects can be considered a Herculean task, as they cannot be easily captured using current economic statistics. This study's findings reinforce and detail the difficulties and limitations associated with this endeavor. However, it is necessary to move forward, recognizing and confronting the challenges. Of course, many challenges could be listed. Below, we highlight some that are relevant.

The first and perhaps most important question is as follows: Which bioeconomy will be measured? In this sense, recognizing the existence of different conceptual approaches and moving towards measuring the holistic bioeconomy is fundamental. It is necessary to consider the complexity surrounding the etymology of the word "bioeconomy". Efforts to measure the BmBB are valid and commendable but insufficient. Attempts to measure the BsBB use a conceptual perspective restricted to environmental impacts but need to develop an economic approach to these impacts. The few studies that have considered the BtBB concept have come up against inaccurate and inadequate data.

The restricted conceptual scope of bioeconomy measurements may be associated with the structure of national accounts, which implies a deliberate choice between predefined sectors. The proposal of a specific satellite account has been suggested as an alternative to qualifying the measurements of the bioeconomy. Vargas et al. [168] proposed satellite accounts for the bioeconomy of Latin American countries, finding that the bioeconomy represents, on average, 17.2% of the production of the countries analyzed. The creation of a National Bioeconomy Account (CNBio) for Brazil was proposed by [169], while [61] proposed a satellite account structure for the North American bioeconomy. Satellite accounts can be useful for measuring the bioeconomy, even when observing the different concepts of bioeconomy as undertaken by

[61,169]. However, their structure can still be limited to the sectors and activities with data available in the national account structures.

The first challenge inevitably leads to a second: How do you economically measure something with no market and economic parameters? This challenge is strongly associated with the BsBB concept. In particular, there is a market for various abiotic natural resources, such as oil, land, and minerals. So, the market parameters (supply, demand, price) are known, and such resources can be incorporated into the usual models without major difficulties. The same is not true of diverse biotic resources. It performs ecosystem services or serves as the basis for biotechnology applications and the production of bioengineered solutions, such as multiple microorganisms living in the soil, air, and water [170].

Carbon dioxide is an example of an abiotic resource facing challenges in the current economic scenario. Due to the growth of global economies based on nonrenewable energy, anthropogenic activity fosters greenhouse gas emissions, including CO_2, CH_4, and N_2O [171]. As a result, the world's climate change discussions from the Intergovernmental Panel on Climate Change (IPCC) are crucial. To promote the sustainable development of nations, a carbon market can reduce the expenses associated with achieving global emissions targets [172]. However, due to the lack of global market regulation, incorporating carbon accounting into bioeconomic measurement is challenging. Additionally, it is difficult to embed the value of green biotechnologies related to carbon capture and sequestration in bioeconomic measurement. Although only biotic resources fall within the scope of the bioeconomy, abiotic resources are essential as life substrates.

Despite the challenges of measuring aspects associated with the BsBB, the valuation of ecosystem services has been a rapidly developing frontier in recent decades. Although the bioeconomy has not yet been strongly linked to the ecosystem services concept, both deal with sustainability [64]. Perillo et al. [173] state that the ecosystem services approach has become the dominant criterion for studying human and natural relationships. Valuing ecosystem services means finding values, including monetary values, for the benefits of ecosystem services [174]. Therefore, this approach exemplifies alternative approaches to connect the BsBB to BmBB concepts of bioeconomics. The valuation of specific ecosystem services can be carried out using appropriate methods.

Provisioning services include the classes of nutrition (terrestrial plants and foodstuffs, freshwater and animal foodstuffs, marine plants and animal foodstuffs, drinking water), materials (biotic and abiotic materials), and energy (renewable fuels). These ecosystem services can be economically valued using various methods, such as market-based (market prices,

substitute goods, net prices, etc.), cost-based (avoided cost, conversion cost, damage cost, mitigation cost, opportunity cost, etc.), production-based (bioeconomic modeling, factor income, stated preference, choice modeling, etc.), or revealed preference (hedonic price, avoidance behavior, travel cost method, etc.) [174–176]. Vermaat et al. [177] concluded that land use changes from bioeconomy strategies may impact the provisioning, regulating, and cultural ecosystem services differently. An application of the economic valuation of ecosystem services in the Amazon estimated the value of habitat provision for species, carbon sequestration, water regulation, recreation, and ecotourism for local populations at US$ 410 $ha^{-1}yr^{-1}$ [178]. The available and recommended methods can also be used to value other regulating, supporting, and cultural classes of ecosystem services.

The challenge in making progress in measuring the contributions of the BsBB lies in obtaining data and developing methods and indicators that capture the contributions of the biosphere (energy) and value these flows (monetary). In this respect, the conventional input-output analysis could be used to measure the metabolic pattern involved in the social-ecological system as a metabolic system [70]. Additionally, using emergy accounting developed by [77] may be a suitable methodological alternative. The results provided by the National Environmental Accounting Database [179] reflect the relationship between emergy and currency for the economies of various countries. Among the indicators produced, the sej/GDP ($) ratio is relevant. According to the most current results available, the sej/GDP ($) ratio for the Chinese economy was in the order of 3.33×10^{12}, while for Germany, Brazil, and the United States, it was 4.80×10^{12}, 2.81×10^{12}, and 1.86×10^{12}. It denotes different intensities of participation of the biosphere (energy) in the wealth produced by these countries [180]. Further development of these analyses includes the integration of emergy accounting and IOMs. This allows for a detailed analysis of the economic activity and the dynamics between sectors and resources, as exemplified by the studies by [181–183]. However, the unavailability of up-to-date data and the lack of standardization of emergy assessments for global analyses are still challenges to overcome.

The United Nations' initiative for developing a System of Environmental-Economic Accounting (SEEA) is promising in data production. The SEEA "is a framework that integrates economic and environmental data to provide a more comprehensive and multipurpose view of the interrelationships between the economy and the environment and the stocks and changes in stocks of environmental assets, as they bring benefits to humanity" [184]. The SEEA system of accounts is integrated with the System of National Accounts-SNA and is currently being developed and implemented in 90 countries [185]. Therefore, the possibilities for broadening

the conceptual scope of the bioeconomy are widening with the development of databases and methods that can connect concepts such as the BsBB and BmBB, for example.

The second challenge gives rise to a third one, which lies at the interface between the BsBB and BtBB: How do we establish the proportionality of the contribution between biological organisms (bio-share) and knowledge (knowledge-share) in the BtBB? Many biotechnological solutions result from applying accumulated human knowledge and physical resources to biological organisms to produce a desired result: food, plant, or medicine. The book "The Genesis Machine: Our Quest to Rewrite Life in the Age of Synthetic Biology" by [186] and the microbial cell factory approach [187] illustrate this relationship well. Would the new route to insulin production be possible only with the knowledge used to map the genetic code? Could Escherichia coli produce insulin voluntarily? Neither. Synthetic insulin production requires the knowledge to map the Escherichia coli genome and genetically modify the bacteria to express insulin production through synthetic biology. The economic value and, therefore, the market price of insulin is known, but the bio-share and knowledge-share are unknown. There are many other examples in this direction. The proposition of a system dynamics model for the so-called "biotechonomy" was proposed by [188], but much work remains to be undertaken.

A fourth challenge is the inclusion of other sectors and economic activities beyond the primary ones. Most studies have measured the bioeconomy based on a restricted set of primary sectors, especially agriculture, livestock, fishing, and forestry. This section assumes that biomass is the bioeconomy's primary input. Although biomass is relevant, other equally valuable biological inputs are produced and used in many sectors. In this sense, sectors such as the biochemical industry, pharmaceuticals, human and animal health, marine, nanobiotechs, and environmental protection are rarely mentioned. However, they should be considered when measuring the holistic bioeconomy.

Lastly, the most daunting challenge is integrating efforts to measure the holistic bioeconomy. The limitations of the methods, data, and indicators used in the restricted measurement of the bioeconomy indicate the difficulty in developing methods, producing data and information, and generating indicators capable of measuring the holistic bioeconomy. The challenge increases when it comes to measuring the bioeconomy economically. Input-output models or even satellite accounts or environmental-economic accounts require a time-consuming and costly process of collecting and recording data. In addition, holistic bioeconomy requires data from the biosphere to be considered. Environmental data can have specific time and place attributes, increasing the difficulty in obtaining reliable and current data. So, how can this be overcome?

The modern world has been marked by increasing digitalization and is moving towards a Society 5.0, marked by a close connection between physical and cyber spaces [189]. Digital integration requires resources that convert facts from the physical world into digital data and then into information. Thus, mechanisms that collect and store those data, integrate and analyze them in an automated way, and communicate relevant information to other devices or stakeholders make up the cyber-structure of the bioeconomy. In this sense, advances in the development of electronic devices, sensors, scanners, drones, a global positioning system (GPS), satellites, wearable devices, digital data storage, digital twins, the internet of things, big data, data analytics, quantum computing, digital platforms, deep and machine learning, artificial intelligence, metaverse, and blockchain are examples of possibilities for advancing recording and measurement of the holistic bioeconomy through digitalization.

4.2. Limitations of This Study

The results reported in the current study were influenced by the scope defined in the purpose and the methodological choices. Consequently, the limitations inherent in the process may have interfered in some way with the outcomes. The main limitations are highlighted below.

Firstly, this study focused on identifying research that measured the economic contribution to the bioeconomy. This delimitation left out other measurements related to the bioeconomy, such as circularity and sustainability in its economic, environmental, and social dimensions. The literature review by [30] presents methods and indicators related to the sustainability of the bioeconomy, including the economic dimension. However, our results are more detailed and include limitations.

The snowballing strategy for identifying and selecting documents for content analysis may have excluded other documents not cited in the literature consulted due to variables such as language or journal indexing base. Examples of this are the works by [190] for the Argentine bioeconomy and by [28,29,191] for the Brazilian bioeconomy. Possibly, other similar studies around the world could have been retrieved, expanding the number of countries measuring their bioeconomy in Figure 4. Therefore, choosing other search strategies could have broadened the spectrum of documents. Although using alternative search strategies could have broadened the range of documents, the additional articles included in the analysis also employed the concepts, methods, data, and indicators outlined in the results of the current study.

No predefined structure was used to code the concepts, methods, data, indicators, and limitations. Instead, the possibility of adding codes as they were identified in the documents

was kept open. In addition, we tried to adopt a nomenclature that was as faithful as possible to that used by the authors. These choices may have resulted in a long list of codes; some could have been aggregated, resulting in different values. This is the case, for example, with the codes “IOM”, “MRIO”, and “EEIO”, which, alternatively, could have been merged into the code “IOM”.

The researcher’s subjectivity can bias qualitative studies. For this reason, it would be advisable for two or more researchers to code the documents. The QDA Miner software has resources for coding by a team of researchers and statistically comparing the coding results. However, due to restrictions on the number of licenses for the software and the researchers’ access to the licensed equipment, coding was only carried out by one senior researcher.

5. CONCLUSIONS

This study aimed to define the bioeconomy and explore the links between concepts, methods, data, and indicators, along with the limitations of measuring it economically. Based on the findings, we conclude that efforts to measure the economic contributions of the bioeconomy in terms of national economies, although important, are essentially restricted to the concept of biomass-based bioeconomy. Thus, the estimates on how big the bioeconomy is are only partially assessed. The economic contributions of the bioeconomy have mostly been measured by economists, whose theoretical and econometric backgrounds are grounded in the disciplinary field of economics.

To fully explore the contributions of the bioeconomy, the concept of a holistic bioeconomy should be considered. In addition, the adaptation of conventional methods, data, and indicators from macroeconomic analysis imposes several limitations that shorten the real contribution of the bioeconomy. Several challenges stand in the way of developing new methods, obtaining suitable data, and creating indicators. Although some progress is being made, it is necessary to step up efforts in this direction, starting by recognizing that the bioeconomy is made up of a set of complex and hierarchical systems. The contributions of economists are fundamental to the process, but we need to be open to a transdisciplinary dialog with researchers from other areas of knowledge. Advances in digitalization technologies and processes can contribute to a more accurate measurement of the bioeconomy’s contributions.

This study reinforces the diversity of bioeconomy concepts and introduces the holistic bioeconomy as a broader, interdisciplinary approach to measurement. In addition, the findings detail the connections between the methods, data, and indicators used to measure each

bioeconomy concept. In doing so, numerous limitations are identified, providing a research agenda so that the measurement of the bioeconomy can be increasingly better evaluated.

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CHAPTER 3 - TOWARDS DIGITALIZATION FOR COMPREHENSIVE MEASUREMENT OF THE BIOECONOMY: EXPLORING THE CONVERGENCE BETWEEN ELEMENTS OF THE CYBER-PHYSICAL SOCIAL SYSTEM[2]

Abstract

The bioeconomy is an evolving concept that faces measurement challenges due to the scarcity of up-to-date, structured, and comprehensive data. We argue that digital technologies—including artificial intelligence (AI), machine learning (ML), automation, sensors and biosensors, blockchain and the Internet of Things (IoT)—can enhance the bioeconomy measurement. However, there is currently no clear evidence linking digital technologies to conceptual scopes of bioeconomy. This study explores the convergence between digital technologies and the conceptual elements of bioeconomy. Firstly, independent literature reviews were conducted using Biblioshiny and VOSviewer to (i) define the core terms in the scope of bioeconomy concepts and (ii) map the digital technologies. Secondly, we coded and analyzed the literature content with QDA Miner and WordStat to examine the co-occurrence of digital technologies and the conceptual elements of the bioeconomy. The results indicate that the Biomass-Based Bioeconomy (BmBB), Biotechnology-Based Bioeconomy (BtBB), and Biosphere-Based Bioeconomy (BsBB) possess distinct clusters of conceptual elements but also integrative domains, like metabolism. Our findings reveal that digital technologies within categories of data science and analytics, computing and software, and imaging and sensing have been the most prevalent in the bioeconomy context. Evidence has surfaced regarding the interactions between the bioeconomy concepts and digital technologies, illustrating the role of digitization in enhancing data collection, storage, processing and communication across various aspects of the bioeconomy. This evidence underscores the potential of digitalization for a comprehensive measure of the bioeconomy. Ultimately, this research provides valuable insights for improving bioeconomy assessment and supports sustainability goals by integrating emerging digital technologies with the bioeconomy development.

Keywords: Digital technologies, Society 5.0, Cyber-technologies, Artificial intelligence, Sustainability.

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[2] Sebastián Leavy, Gabriela Allegretti, Elen Presotto, Marco Antonio Montoya, Edson Talamini (2026). Towards digitalization for comprehensive measurement of the bioeconomy: exploring the convergence between elements of the cyber-physical social system. *Technology in Society*, v. 84, 103101. https://doi.org/10.1016/j.techsoc.2025.103101.

Abbreviations

AI Artificial Intelligence

AR Augmented Reality

BhBB Holistic Based Bioeconomy

BmBB Biomass-Based Bioeconomy

BsBB Biosphere-Based Bioeconomy

BtBB Biotechnology-Based Bioeconomy

CPS Cyber-Physical Systems

CPSS Cyber-Physical Social Systems

CRISPR Clustered Regularly Interspaced Short Palindromic Repeats

DL Deep Learning

DNA Deoxyribonucleic Acid

DT Digital Technology

Dt Digital twin

EG Economic Growth

GIS Geographic Information System.

IoT Internet of Thing

LIDAR Light Detection and Ranging

ML Machine Learning

PDB Protein Data Bank

RNA Ribonucleic Acid

SD Sustainable Development

SDG Sustainable Development Goal

SM Supplementary Material

SME Small and Medium-Enterprise

UAV Unmanned Aerial Vehicle

1 INTRODUCTION

The bioeconomy has been advocated as a new socio-technical-economic paradigm towards a more sustainable society. However, the bioeconomy remains an emerging concept lacking a universally accepted definition, which compounded by other data, methodological, and metrics constraints, hinders the comprehensive measurement of its societal contributions (Papadopoulou et al., 2022, Leavy et al., 2024). From a social sciences perspective, Sanz-Hernández et al. (2019) describe it as a political-economic initiative aimed at replacing fossil resources with biological alternatives. To clarify its diverse applications, Bugge et al. (2016) and Vivien et al. (2019) classify the bioeconomy into three approaches: biomass-based, biotechnology-based (science), and biosphere-based (ecological). Building on these perspectives, Leavy et al. (2024) propose the holistic bioeconomy (BhBB), which integrates these approaches to enable more comprehensive measurement.

The biomass-based bioeconomy (BmBB) emphasizes sustainable biomass sourcing from agriculture, forestry, and livestock sectors, employing input-output models to quantify gross value added, employment, and emissions. However, persistent data gaps hinder accurate estimation of the "bio-share" (Béfort et al., 2019; Béfort & Nieddu, 2020; Bugge et al., 2016; Giampietro, 2019, 2022, 2023a, 2023b, 2023c; Leavy et al., 2024; Vivien et al., 2019). The biotechnology-based bioeconomy (BtBB) centers on micro-scale biological processes, like genetic engineering and synthetic biology, which are tracked through R&D investments and patent analyses, though it is constrained by the scarcity of structured data (Patermann & Aguilar, 2018; Giampietro, 2022; Leavy et al., 2024). The biosphere-based bioeconomy (BsBB) prioritizes ecosystem cycles, utilizing tools such as Odum's emergy analysis to monetize unpriced services (e.g., carbon sequestration). Similarly, it faces challenges in translating ecological functions into comparable economic metrics (Georgescu-Roegen, 1971; Giampietro, 2019, 2022; Lucia & Grisolia, 2021).

Worldwide, bioeconomy initiatives are increasingly viewed as strategic pathways for achieving the United Nations Sustainable Development Goals (SDGs), as they link renewable resource management to innovation and social inclusion (Rowan et al., 2022). High-income countries often focus on advanced biotechnology and circular production to promote good health and well-being, cut carbon emissions and foster responsible consumption (SDGs 3, 9, 12, and 13) (Aguilar et al., 2019). Emerging economies leverage biomass-based value chains to generate employment and reduce poverty, contributing to No Poverty (SDG 1), Zero Hunger (SDG 2) and Decent Work and Economic Growth (SDG 8) (Blair et al., 2021; Luhas & Mikkilä,

2025). In biodiversity-rich regions of the Global South, bioecological strategies support ecosystem restoration and community-based resource management, reinforcing Life on Land (SDG 15) and Sustainable Cities and Communities (SDG 11). Adapting these strategies to local contexts positions the bioeconomy as a flexible driver of low-carbon growth, social equity, and long-term sustainability.

On the other hand, the progress in digital technologies development is contributing decisively to monitor the SDGs achievement. Artificial Intelligence (AI) enhances predictive models for climate action (SDG 13), precision agriculture (SDG 2), and public health (SDG 3), while also enabling disaster prediction through large-scale data analysis (Albahri et al., 2024). Internet of Things (IoT) networks deliver real-time monitoring that improves energy efficiency (SDG 7) and supports smart cities (SDG 11) (Nižetić et al., 2020). Big-data analytics generate actionable insights for environmental and economic systems, aiding climate-risk assessment and boosting agricultural productivity (SDG 2). Remote sensing and GIS further expand measurement capacity by mapping deforestation, evaluating drought severity, and managing water resources (SDGs 6, 14, 15), with Albahri et al. (2024) demonstrating how satellite data and social-media inputs refine forecasts of floods and landslides.

Despite its potential, measuring the contributions of the bioeconomy widely remains challenging. Key obstacles include fragmented and updated data standards, limited interoperability among biological, economic, and social models, unidimensional approaches that ignore systemic interactions, and the omission of governance and equity considerations (Eastwood et al., 2023; Leavy et al., 2024). Many existing frameworks also lack actionable metrics. Addressing these gaps requires integrated approaches capable of capturing complex interactions across multiple scales—an objective advanced by the holistic bioeconomy framework (BhBB) (Leavy et al., 2024).

Digital technologies offer promising tools to meet these challenges. They can enhance bioeconomy data collection, storage, processing, sharing, and monetization (Tetere & Zeverte-Rivza, 2023). Digital technologies are transforming system optimization through artificial intelligence (AI), machine learning (ML), and emerging tools such as cognitive computing, blockchain, automation, and genome editing, all developed with attention to cybersecurity and sustainability (Arya et al., 2023; Delanoë et al., 2023; Simionescu et al., 2024). Despite the large volume of data that digital technologies allow us to access, advances in quantum computing suggest the advent of unprecedented data processing capabilities (Goyal et al., 2024; Memon et al., 2024).

These technologies underpin Cyber-Physical Systems (CPS), which integrate sensing and computing with physical processes to interact rapidly with the environment (Lee, 2015; Zhuang et al., 2021). Yet a purely technological focus overlooks the social dimension critical to sustainable development. Cyber-Physical-Social Systems (CPSS) extend CPS by incorporating social actors and governance dynamics into networks of interconnected systems (Sobb et al., 2023). By merging physical elements and digital technologies and processes with social participation, CPSS supports the vision of a people-centered Society 5.0, where interactions among humans, robots, and AI drive innovation (Beniiche et al., 2022). CPSS uses a network of physical devices, like sensors, to collect and digitalize data which can be used in almost all areas for desired objectives. For instance, the CPSS approach is transforming research in ecology and sustainability in ways that align closely with bioeconomy approaches (Y. Wang et al., 2023).

Governments have embraced the bioeconomy as a pillar of sustainable growth, yet quantifying its contributions remains difficult due to data gaps, weak interoperability, and limited incentives for data sharing (Interagency Working Group on Data for the Bioeconomy, 2023). Integrating heterogeneous, multi-scale data for applications such as bioprocess optimization and biorefinery design adds to these challenges (Heck et al., 2024). Although previous studies have examined specific elements—such as biomass flows (Montoya et al., 2024; Ronzon et al., 2020, 2021) or socio-technical transitions (Fox et al., 2020)—they lack a holistic framework that unites technical, societal, and biological dimensions (Leavy et al., 2024; Onyeali et al., 2023; Moustakas, K., & Loizidou, M. (2023).

This study is grounded in the CPSS approach to outline the methodological framework with the aim of addressing the following research question: How does digitalization link digital technologies and conceptual elements to enable a comprehensive measurement of bioeconomy? Therefore, the present study aims to explore the use of digital technologies associated with defining elements of the concepts of bioeconomy and the digitalization setting in which they have been employed. To achieve this objective, a literature review was designed following three steps: (i) the identification of the core elements defining the concepts of bioeconomy, (ii) the mapping of digital technologies employed in the scope of the bioeconomy, and (iii) the analysis of the co-occurrence between digital technologies and core elements of bioeconomy concepts, illustrating their applications in the direction of data and information digitalization.

2 MATERIALS AND METHODS

The study commenced with a comprehensive literature review to identify the essential elements of bioeconomy concepts, as developed by Leavy et al. (2024). Subsequently, articles that focus on digital technologies within the bioeconomy were selected for analysis. The third step involved linking the elements of bioeconomy concepts with the digital technologies by constructing databases. Through an analysis of this data, the study aimed to explore the cooccurrence of digital technologies and conceptual elements of bioeconomy and describe the digitalization setting where they are employed. Figure 1 shows the methodological framework grounded in CPSS approach, illustrating the main steps and procedures.

It is worth noting that the physical dimension of CPSS is normally associated with hardware devices involved in the collection and transformation of analogical to digital data. In the context of this study, the "cyber" dimension encompasses both the hardware devices and the software used in the collection, storage, and processing of digital data, while the physical dimension expresses the substantive elements associated with the concept of bioeconomy.

2.1. Step 1: Selecting articles to identify the conceptual elements of Bioeconomy

We followed the framework proposed by Leavy et al. (2024) to identify the physical elements associated with bioeconomy concepts. In July 2024, we conducted a literature search on Scopus, limiting results to articles published between 2000 and 2024. Due to Scopus download limit, we downloaded the 20,000 most cited and 20,000 most recent articles for each bioeconomy concept and processed them using VOSviewer (1.6.20). Duplicates were removed in R studio (2025.05.0), and Biblioshiny was used to extract and analyze keywords (Aria & Cuccurullo, 2017).

Keyword extraction and filtering were performed using the Bibliometrix R-package (version 4.1.4) on bibliographic datasets retrieved from Scopus, focusing on titles, abstracts, and author keywords for each bioeconomy concept (BmBB, BtBB, and BsBB). This involved quantifying unique words and their co-occurrences to reveal underlying thematic structures (Table 1).

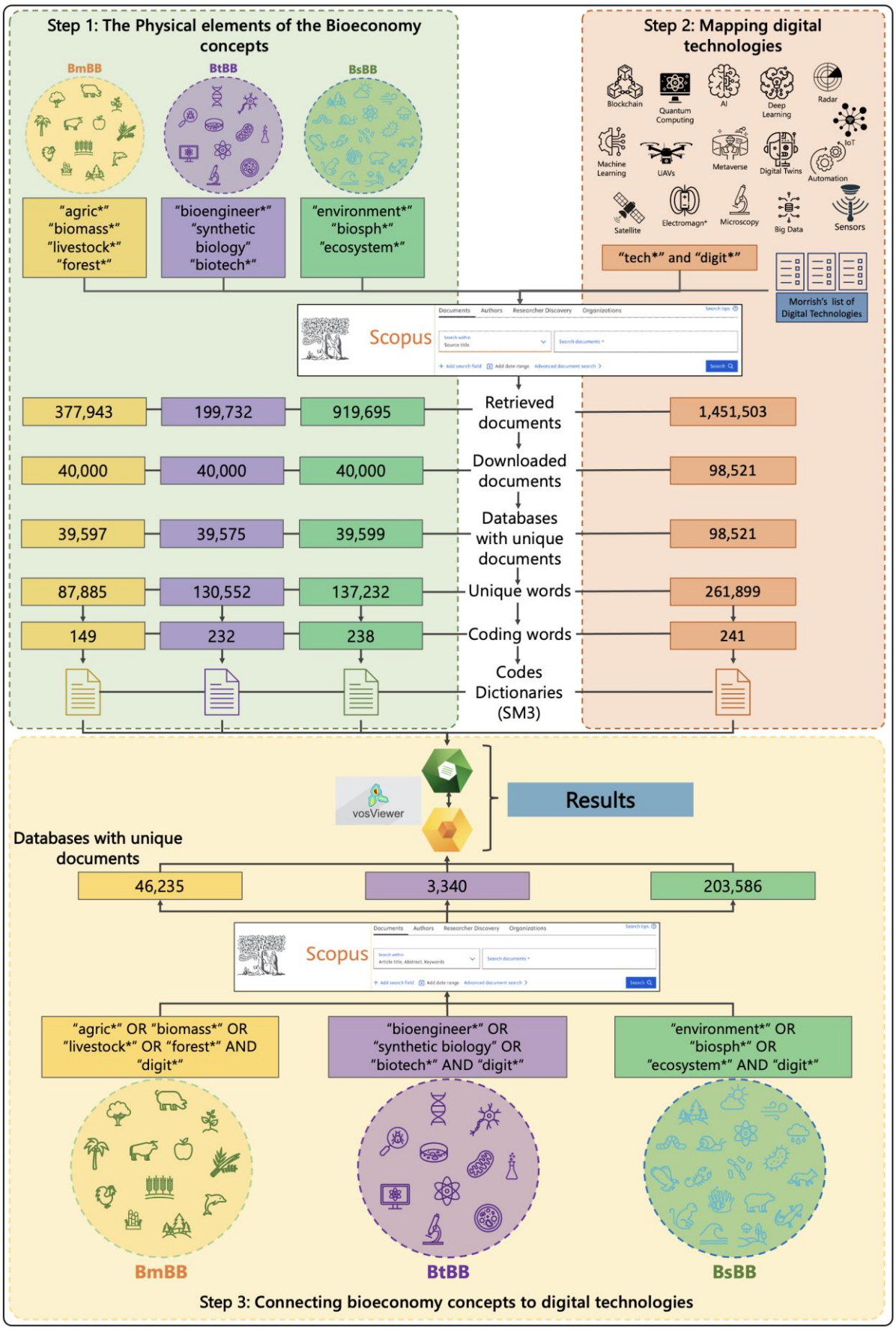


Figure 1: CPSS grounded methodology for integrating the concepts of bioeconomy and digital technologies. Source: Developed by the authors based on research data.

Table 1. Search parameters and dataset characteristics for bioeconomy concepts

Bioeconomy Concept	Keywords (Source Title)	Total Retrieved Documents	Unique Documents After Deduplication*	Unique Words Extracted
Biomass-based Bioeconomy (BmBB)	"biomass*" OR "agric*" OR "livestock*" OR "forest*"	377,943	39,597	87,885
Biotechnology-Based Bioeconomy (BtBB)	"bioengineer*" OR "synthetic biology" OR "biotech*"	199,732	39,575	130,552
Biosphere-based Bioeconomy (BsBB)	"environment*" OR "biosph*" OR "ecosystem*"	919,695	39,599	137,232

*Note: after the deduplication, the title, abstract and keywords of the 20,000 most cited + 20,000 most recent articles downloaded from Scopus. Source: Elaborated by the authors.

To operationalize Pareto's law, we first confirmed a Zipfian distribution in word frequencies—a power-law pattern typical in natural language corpora where a small subset of terms dominates occurrences (Piantadosi, 2014). Power laws appear widely in physics, biology, earth and planetary sciences, economics and finance, computer science, demography, and the social sciences (Alstott et al., 2014; Clauset et al., 2009; Newman, 2006; West, 2024). We generated log-log plots of ranked word frequencies to visualize the distribution and manually identified the point of slope change, indicating diminishing returns in explanatory power (i.e., where additional keywords contribute marginally to network density or conceptual coverage). This visual inspection targeted the inflection where the curve transitions from steep to gradual decline, approximating the Pareto threshold (e.g., capturing ~80% of cumulative frequency with minimal terms) while ensuring interpretability for the bioeconomy concepts.

In a list of 87,885 unique words with total occurrences accounting 721,741 times in the 39,597 documents related to the BmBB concept, the slope changes in rank-frequency plots occurred at ~176 words. For BtBB, the top 262 most frequent words were selected from a list of 130,552 unique words accounting for a total occurrence of 1,536,224 times in the database composed by 39,575 documents. The same procedure was applied to select 275 most frequent words for BsBB, which came from the list of 137,232 unique words that occurred 1,435,073 time in the 39,599 documents. Using this criterion, we selected the top 1% most relevant words from the top 20% of extracted terms. Thresholds were cross-validated for semantic coherence

through co-occurrence networks (visualized with VOSviewer) and alignment with bioeconomy concepts' physical elements (e.g., biomass feedstocks in BmBB).

The set of the 1% most relevant words for each concept of bioeconomy was used to compile the code dictionary in WordStat. The WordStat package refers to the list of terms (codes) used by the software to perform qualitative analysis of databases as a “dictionary”. The dictionary of codes representative of each bioeconomy concept is available in the supplementary materials (SM2).

After identifying the set of main conceptual elements regarding bioeconomy concepts, the next step was to map the digital technologies being applied within the bioeconomy contexts.

2.2. Step 2: Selecting articles to map digital technologies used in the bioeconomy

In August 2024, a thorough search was performed in the Scopus database to identify trends in cybertechnological advancements and digitalization, guided by the framework proposed by (Morrish et al., 2024) (see Supplementary Material SM1). This search resulted in a total of 1,451,503 documents. All documents published in 2025 were retrieved, along with a maximum of 20,000 documents per annum from the years 2020 to 2024. Subsequently, these documents were merged using R, yielding a consolidated dataset consisting of 98,521 documents. The dataset was then processed using Biblioshiny, which generated a total of 261,899 words.

Applying the same procedures adopted in section 2.1, a list of the most relevant 1% of terms was selected to compose the dictionary of codes associated with digital technologies (DT codes). The original list of terms was revised to group terms with the same root. For example, using “*” for terms in the singular and plural (e.g., “ALGORITHM*” counts both the occurrence of the word “algorithm” and “algorithms”). The digital technologies dictionary consists of 241 codes and is available in SM3 of the supplementary material.

2.3 Step 3: Connecting bioeconomy concepts to digital technologies

The databases for each bioeconomy concept—BmBB, BtBB, and BsBB—were created utilizing the same keywords outlined in Section 2.1 (Table 1). Additionally, the term “digit*" was incorporated to encompass both cyber and physical elements, resulting in the following:

a. BmBB: We broadened the Scopus search to encompass article titles, abstracts, and keywords within the databases that involve the interaction of physical and digital elements. On August 10th, a comprehensive literature search was performed using the following key terms: "agric*", "biomass*", "livestock*", "forest*", and "digit*". From the Scopus database, a

total of 53,087 documents were retrieved. After initial processing, 52,262 of these documents were successfully uploaded into the R software environment for further analysis. After merging the datasets and removing duplicates, we retained 46,235 documents in the BmBB and digit* databases.

b. BtBB: On August 13, 2024, a Scopus search for "bioengineer*" or "biotech*" or "synthetic biology" and "digit*" returned 3,406 documents. R eliminated 32 duplicates, resulting in the BtBB database containing 3,340 documents.

c. BsBB: On August 13, 2024, a Scopus search for "environment*" or "biosph*" or "ecosystem*" and "digit*" yielded 218,761 documents. After eliminating duplicates, the BsBB database had a total of 203,586 documents.

2.3.1 Co-occurrence of conceptual elements of bioeconomy and digital technologies

The final step of the study sought to analyze the joint occurrence of conceptual elements of the bioeconomy and digital technologies. In addition, some of the most frequent cases of co-occurrence were described to illustrate how certain digital technologies are being employed in the context of the bioeconomy. To do so, the conceptual elements of each bioeconomic concept were systematically coded to enhance their integration with digital technologies by running the dictionary of codes to read the databases within WordStat software package. The final dictionary of codes includes 149 codes related to BmBB, 232 codes related to BtBB, 238 codes related to BsBB, and 241 codes related to digital tecnologies. These codes were meticulously compiled in a 'dictionary of codes' created using WordStat (v.2024.0.1), while the corresponding databases were uploaded into QDA Miner (v.2024.0.5), provided by Provalis Research (https://provalisresearch.com/products/qualitative-data-analysis-software/). All dictionary of codes are accessible in Supplementary Material SM3. Following this, the conceptual and digital technologies codes for each database were cross-referenced in WordStat, which integrates smoothly with QDA Miner.

3 RESULTS

The results are structured into three sections. First, we delineate the core elements defining the bioeconomy, enhancing the conceptual understanding by aligning with the framework proposed by Leavy et al. (2024) and establishing the foundation for further analysis of co-occurrence with digital technologies. The second section categorizes and quantifies the primary digital technologies, detailing their frequency of occurrence within the databases for

each bioeconomy concept. Finally, the third section presents the co-occurrence analysis between the conceptual elements of the bioeconomy and digital technologies.

3.1 Conceptual elements of Bioeconomy

The analysis of a scientific database focused on BmBB identified five distinct clusters of terms that define its conceptual scope (Figure 2-A). Two clusters are particularly associated with vegetal and animal biomass production, derived from primary sectors such as agriculture, livestock, and forestry. The red cluster, centered on "forestry" and "plants," is grounded in aspects related to vegetal biomass production and the natural environment (ecosystems). It includes terms like wildfires, ecosystems, and species diversity, reflecting ecological and conservation dimensions, and represents a bioeconomy framework rooted in biomass resource management and biodiversity preservation. The green cluster suggests a focus on animal biomass production, with terms such as chemistry, metabolism, molecular docking, antioxidants, enzymes, and genes, indicating a biochemical research domain that emphasizes molecular and chemical innovations in animal biomass utilization.

The purple cluster, anchored by "soils" and encompassing crop yield, cultivation, soybean, farms, nitrogen, soil carbon, soil moisture, and water use efficiency, highlights a botanical and physiological perspective, representing the foundational abiotic resources and biological processes supporting the biomass-based bioeconomy (BmBB). The blue cluster links vegetal and animal biomass, prominently featuring "biomass" alongside terms such as fermentation, pyrolysis, drying, gasification, hydrolysis, yeast, and essential oils, suggesting a focus on biomass biorefinery processes. This cluster encapsulates the transformation and valorization of biomass through advanced processing techniques, underscoring its role in sustainable production systems. Surprisingly, the yellow cluster, dominated by "agriculture," "crops," "fruits," and terms like deep learning, machine learning, learning systems, remote sensing, satellite data, LiDAR, and unmanned aerial vehicles (UAVs), anticipates the integration of digital technologies in agricultural practices, suggesting an agritech-driven bioeconomy segment. Collectively, these clusters provide a comprehensive view of the multidimensional nature of biomass-based bioeconomy, integrating ecological, biological, technological, biochemical, and botanical dimensions.

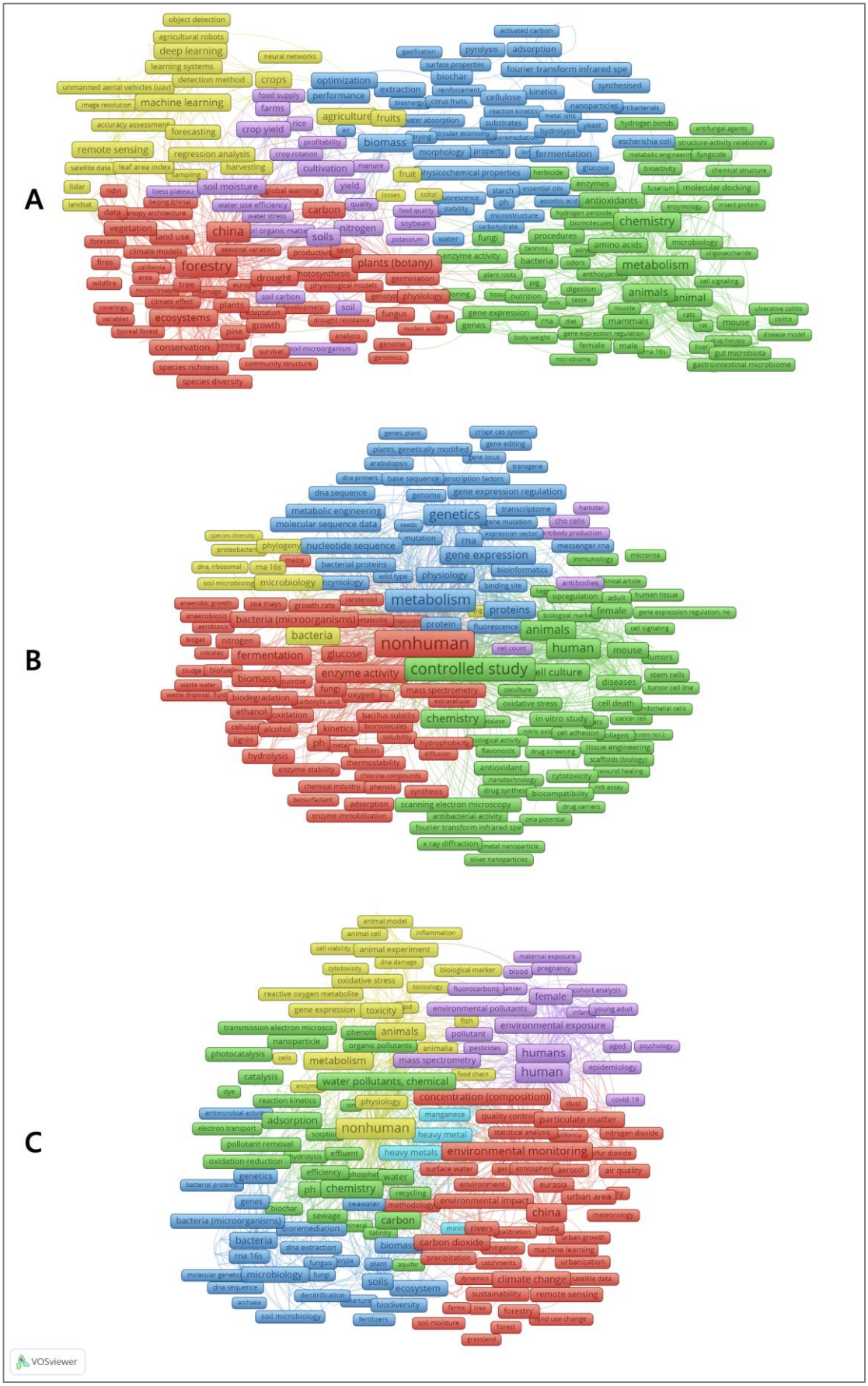


Figure 2. Clusters of conceptual elements of bioeconomy: (A) BmBB, (B) BtBB and (C) BsBB. Source: Elaborated by the authors based on research data extracted with VOSViewer.

The analysis of a scientific database focused on BtBB identified five distinct clusters of terms delineating this concept (Figure 2-B). However, the scope of BtBB is predominantly shaped by the blue, red, and green clusters. The blue cluster, centered on "genetics" and including terms such as gene expression, mutation, transcription, and CRISPR-Cas system, highlights a domain focused on genetic engineering, synthetic biology, and molecular biology, with an emphasis on advancements in genome editing and gene regulation. The frequent occurrence of "metabolism" suggests its relevance to flow of information and energy use and efficiency in bioengineering interventions (Jeong et al., 2023; Yang & Lu, 2025; Zhang et al., 2020).

The red and green clusters differ based on the application domains of biotechnology research and solutions. The red cluster, dominated by "nonhuman" biotechnologies, features terms such as bacteria, microorganisms, fungi, fermentation, oxidation, enzyme activity, and glucose, indicating a biochemical and metabolic engineering focus. This cluster underscores the transformation of biological processes for biotechnological innovation, particularly in biomass substrates to produce energy solutions like ethanol, biofuels, and biogas. Conversely, the green cluster, grounded in applications for "human" and "animal" health, encompasses terms such as controlled study, diseases, tumors, cancer cells, drug synthesis, drug carriers, and immunology, representing a biomedical research perspective focused on health-related applications of biotechnology tools highlighted in the blue cluster.

Less prominent are the yellow and purple clusters. The yellow cluster, anchored by "soil microbiology" and including species diversity, proteobacteria, DNA, and RNA, reflects a microbiological and ecological perspective, representing the role of soil microbial communities in biotechnological applications. The purple cluster is dedicated to antibodies and antibodies production. Collectively, these five clusters provide a comprehensive view of the multidimensional nature of BtBB, integrating genetic, microbiological, biochemical, chemical, and biomedical dimensions with interfaces to other bioeconomy concepts.

The analysis of a scientific database focused on BsBB identified six distinct clusters of terms that delineate its conceptual framework (Figure 2-C). The red cluster emphasizes the bio-physical environment as the broader landscape of the biosphere. This cluster, centered on "environmental monitoring" reflects concerns regarding atmospheric pollution (air quality, nitrogen dioxide, particulate matter) and its environmental impacts (climate change, meteorology, precipitation) across various societal and natural landscapes (urban area, urbanization, forestry, grassland). The cluster's scope embodies an environmental management

perspective, emphasizing the assessment, regulation, and sustainability of ecological conditions.

The green cluster is particularly focused on water resources (water, aquifer, sewage, effluent), pollution sources (organic pollutants, chemical pollutants, phenols), and treatment methods (adsorption, pollutant removal, hydrolysis, oxidation-reduction, electron transport, reaction kinetics, nanoparticle). The anchor term, "chemistry," may be associated with both the chemical characteristics of water (pH, mineral, salinity, phosphate) and the pollutants and treatment methods applied to water resources. The blue cluster explores the microbiological biodiversity available within ecosystems (microbiology, microorganisms, bacteria, fungus, fungi, archaea) at the genetic level (genetics, gene, DNA extraction, molecular genetics, DNA sequence, bacterial proteins), with origins or applications potentially associated with plants, soils, biomass, seawater, and bioremediation.

The purple cluster is grounded in analyses of human exposure (human, humans) and specific social groups (female, infant, young adult, aged, pregnancy) to environmental pollution (environmental exposure, pollutant, environmental pollutants, fluorocarbons, pesticides) and its health consequences (cancer, epidemiology, COVID-19, psychology). Conversely, the yellow cluster is centered on biochemical analyses in nonhuman living systems (nonhuman, animals, animalia, fish), where aspects related to energy efficiency (metabolism, food chain) have been explored at the cellular level (cells, cell viability, animal cell, gene expression, DNA damage).

The ensemble of clusters provides a comprehensive view of BsBB, integrating aspects of the bio-physical environment and its abiotic resources, the diversity of biotic resources encompassing microorganisms to the human species, and the reciprocal impacts of interactions between society and the biosphere.

3.2 The occurrence of digital technologies across bioeconomy concepts

A word frequency analysis was conducted using Biblioshiny, resulting in the identification of 155 terms associated with digital technologies (SM1). To address the general nature of certain terms, 241 codes were defined to link these terms to specific digital technologies, which were ultimately consolidated into 193 DT Codes (SM3).

The digital technologies linked to each bioeconomy concept were analyzed using QDA Miner and WordStat. The reported values indicate the percentage of the documents where digital technologies occurred within the dataset (refer to Supplementary Material SM4). Categories were established to group the digital technologies and synthesize the results. The eleven categories, along with their respective number of digital technologies (in parentheses),

are as follows: (i) Networking and Communication (32); (ii) Computing and Software (15); (iii) Imaging and Sensing (33); (iv) Data Science and Analytics (47); (v) Bioinformatics and Biotechnology (6); (vi) Cyber-Physical Systems (CPS) (33); (vii) Enterprise and Manufacturing (6); (viii) Semantic Technologies (8); (ix) Blockchain and Cryptography (8); (x) Quantum Computing (3); and (xi) Cybersecurity (2) (see Figure 3).

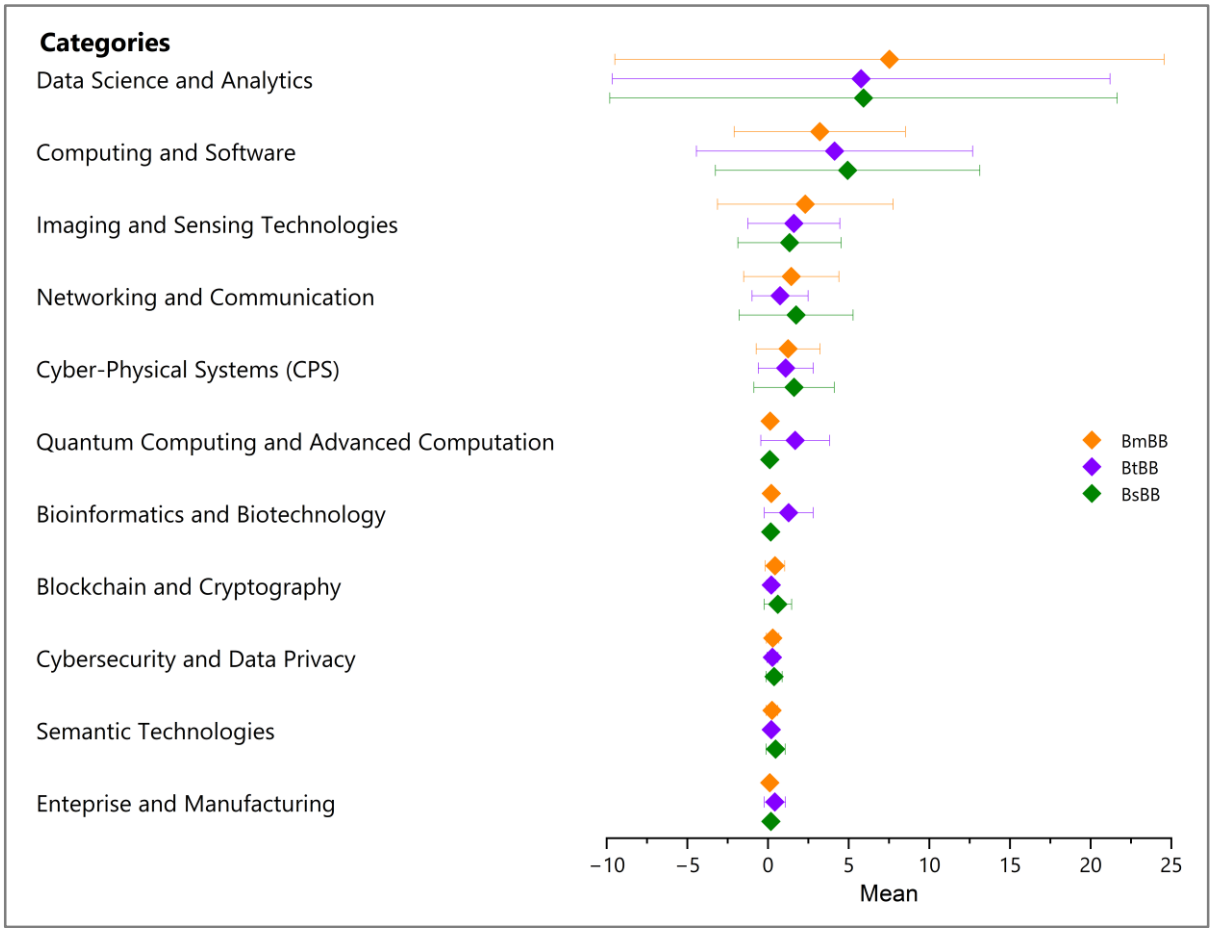


Figure 3. Main categories of digital technologies occurring across bioeconomy concepts. Mean percentage (diamond dots) and standard deviation (horizontal lines) relating to the percentage of cases (documents) in which each category was mentioned. Source: Elaborated by the authors based on research data.

The category of Data Science and Analytics occupies the uppermost position in the figure, demonstrating the strongest associations across all bioeconomy concepts, with mean co-occurrence rates clustering around 6.40% of the documents analyzed. Notably, the BmBB exhibits the highest mean, approaching 7.5%, which underscores a substantial linkage in documents focused on biomass production, processing, and utilization. In these contexts, analytics tools enable the optimization of resource flows, predictive modeling, and decision-making informed by big data. The BtBB and BsBB display comparably robust integrations, with means near 5.7% and 5.9%, respectively, highlighting their relevance in biotechnology-

oriented research as well as ecosystem and environmental analyses. Prominent terms associated with digital technologies in this category include "digit*", "data", "information", "sign*", "digital image*", "algorithm", "machine learning" and "neural network" reflecting an emphasis on data processing, algorithmic computation, and artificial intelligence applications.

The Computing and Software category follows, with mean co-occurrence rates ranging from approximately 3.2% to 4.9% across the documents. Here, BsBB registers the highest mean, indicative of software's pivotal role in environmental and ecosystem modeling. BtBB and BmBB present slightly lower yet commensurate associations, emphasizing the utility of computational tools in areas such as computational biology and integrated system simulations. Key digital technology terms within this category encompass "comput*", "software*", "hardware*", "code*" and "programming" which collectively suggest the deployment of hardware-software infrastructures for advanced programming solutions tailored to bioeconomy challenges.

Additional categories warrant attention for their relevance across bioeconomy concepts, including Imaging and Sensing Technologies, Networking and Communication, and Cyber-Physical Systems (CPS), which collectively represent critical enablers of real-time data acquisition, connectivity, and hybrid system integration. Among the less prevalent categories, Quantum Computing and Advanced Computation, along with Bioinformatics and Biotechnology, are particularly noteworthy in the BtBB context, appearing in 1.7% and 1.3% of documents, respectively. These associations highlight specialized applications, such as “bioinformatics” in genetic analyses involving "gene expression" and "CRISPR" technologies.

In aggregate, the results delineate a hierarchical structure in which data-centric and computational technologies predominate in associations with bioeconomy concepts. By contrast, emerging domains such as blockchain, cryptography, cybersecurity, data privacy, and semantic technologies exhibit attenuated linkages, attributable potentially to their nascent maturity or inherent domain-specific constraints. These observations elucidate prospective avenues for technological innovation, particularly in advancing digitalization processes that support the development, evaluation, and quantification of bioeconomy frameworks.

3.3 Digitalization in the Context of the Bioeconomy

This section delineates the outcomes of the co-occurrence analysis between bioeconomy concepts and digital technologies. Multiple clusters were discerned from the dedicated databases and code dictionaries pertaining to bioeconomy concepts and digital technologies (SM5, SM6, SM7). Predominantly, these clusters comprise groupings of terms specific to either

bioeconomy concepts or digital technologies. Nonetheless, within each bioeconomy concept, at least one cluster manifests where both domains co-occur, signifying zones of digitalization in bioeconomy. The subsequent subsections delve more profoundly into the contextual underpinnings of these clusters.

3.3.1 The application of Digital Technologies (DT) in the Biomass-based Bioeconomy (BmBB)

Prior analyses indicate that the production, transformation, and consumption of biomass constitute the predominant framework for defining the bioeconomy from the BmBB perspective. Accordingly, this approach emphasizes aspects of agriculture, livestock, and forestry, along with their interactions within the bio-physical environments supporting these socioeconomic activities, as depicted in the cluster in Figure 4. Terms such as "BM\Agric*", "BM\Forest", "BM\Tree", "BM\Soil" and "BM\Water" are among the most frequent, complemented by occurrences of "BM\Crop" "BM\Plant" "BM\Food" "BM\Biomass" and "BM\Ecosystem" which collectively delineate the scope of the BmBB.

Concurrently, the cluster reveals frequent co-occurrences between elements of the BmBB and various digital technologies. Prominent among these are "DT\Digit*," "DT\Data", "DT\Image", "DT\Sens*", "DT\Information", "DT\Algorithm*", "DT\Sign*", "DT\Machine_Learning", "DT\Compt*" and "DT\Satellite*". The prevalence of these cyber components underscores the deployment of hardware and software systems for data acquisition, analysis, and transmission within the BmBB domain.

For a more granular examination, the highlighted subcluster in Figure 4 elucidates the most frequent co-occurrences between specific BmBB elements and digital technologies, illustrating key digitalization processes in the bioeconomy. Term groupings are derived from agglomeration based on the Jaccard coefficient, accounting for joint appearances within the same paragraph. This subcluster emphasizes the utilization of digital technologies, such as sensors, for gathering data and deriving insights pertinent to agricultural practices. Furthermore, satellite imagery is employed for monitoring forestry-related parameters.

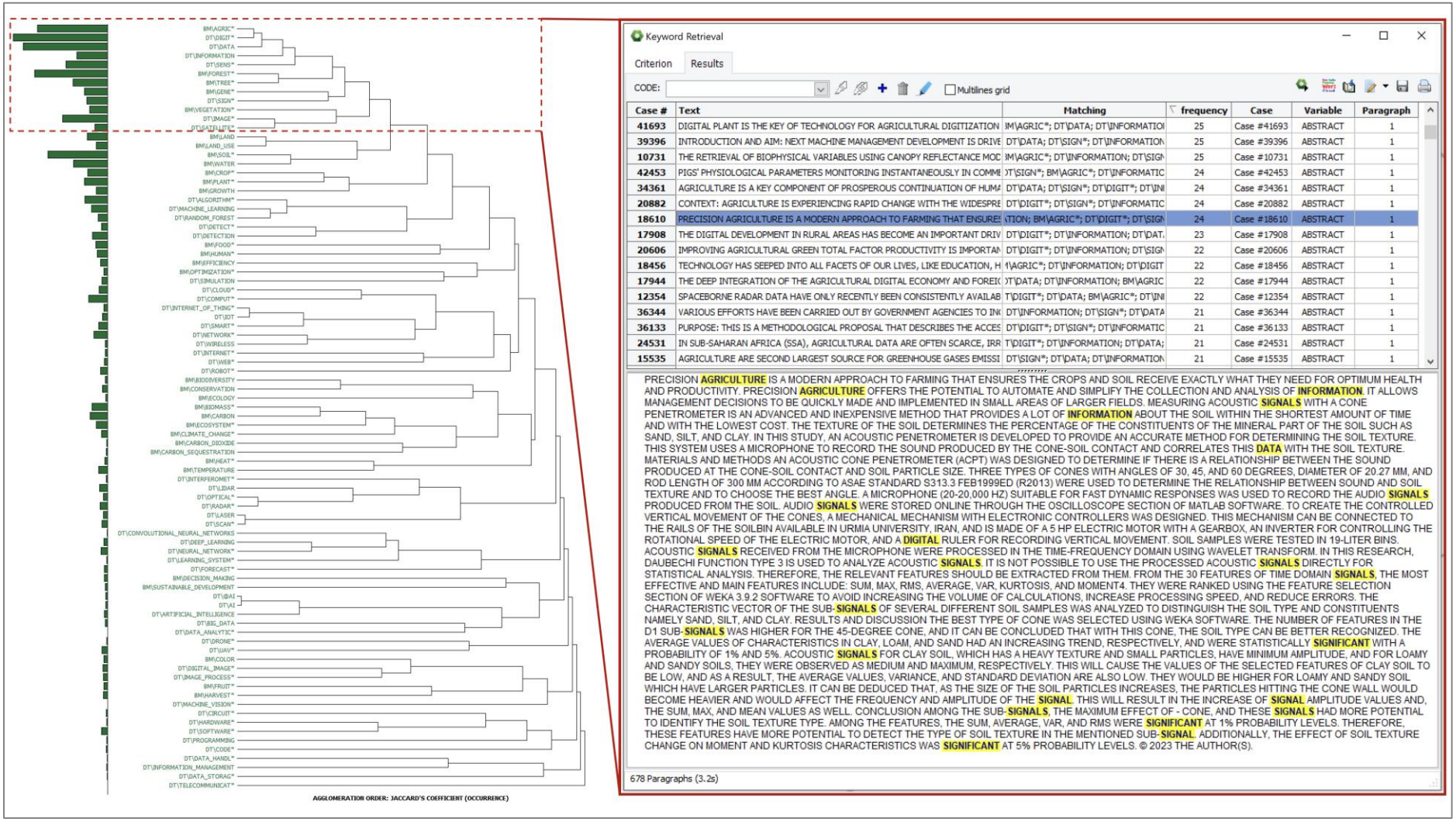


Figure 4. Primary cluster of co-occurring codes associated with the Biomass-based Bioeconomy (BmBB) concept and digital technology (DT). The highlighted subcluster features codes with the highest co-occurrence frequencies, complemented by contextual paragraphs retrieved from the database. Source: Prepared by the authors based on research data.

To delve further into the applications of digital technologies and to evaluate the potential of digitalization in measuring the BmBB, the right-hand panel in Figure 4 presents paragraphs featuring co-occurrences of terms from the highlighted subcluster. In total, 678 such paragraphs were retrieved. For example, case #18610 describes an acoustic signal device designed to assess soil texture and composition, which supports precision agriculture management (Azar et al., 2023). Additional technologies focus on monitoring crop morphology and growth. The case #41693, for instance, introduces a cost-effective 3D digital plant model utilizing a time-of-flight (TOF) depth sensor and a dedicated algorithm (Xia et al., 2018). Beyond abiotic resource and crop monitoring, digitalization extends benefits to biomass-based supply chains. Case #17944 investigates the integration of agriculture into the digital economy within international trade, demonstrating how digitalization bolsters agricultural exports to the advantage of producers and consumers (Y. Liu et al., 2024).

The co-occurrence of bioeconomy elements and digital technologies within the BmBB scope signifies substantial progress in the digitalization of agricultural, forestry, and resource management processes. This integration, leveraging sensors, satellite imagery, and algorithms, optimizes data collection and analysis, thereby improving the monitoring of crops, soils, and ecosystems while enhancing supply chains and international trade, as evidenced by the examined cases.

3.3.2 The application of Digital Technologies (DT) in the Biotechnology-based Bioeconomy (BtBB)

The BtBB is rooted in knowledge generated from research and development, which propels innovations via biotechnological platforms at the micro- and molecular scales. The co-occurrence analysis, as depicted in Figure 5, identifies a principal cluster comprising conceptual codes such as “BT\Biotechnology”, “BT\Human”, “BT\Model”, and “BT\Disease” which frequently intersect with digital technologies including “DT\Digit*”, “DT\Data”, “DT\Comput*”, “DT\Sign*”, “DT\Information”, “DT\Algorithm” and “DT\Model”. This interplay underscores the capability of digital technologies to detect biological signals, generate data, perform computational processing, and construct predictive models, thereby exemplifying a profound convergence between bio-physical and digital realms within the BtBB.

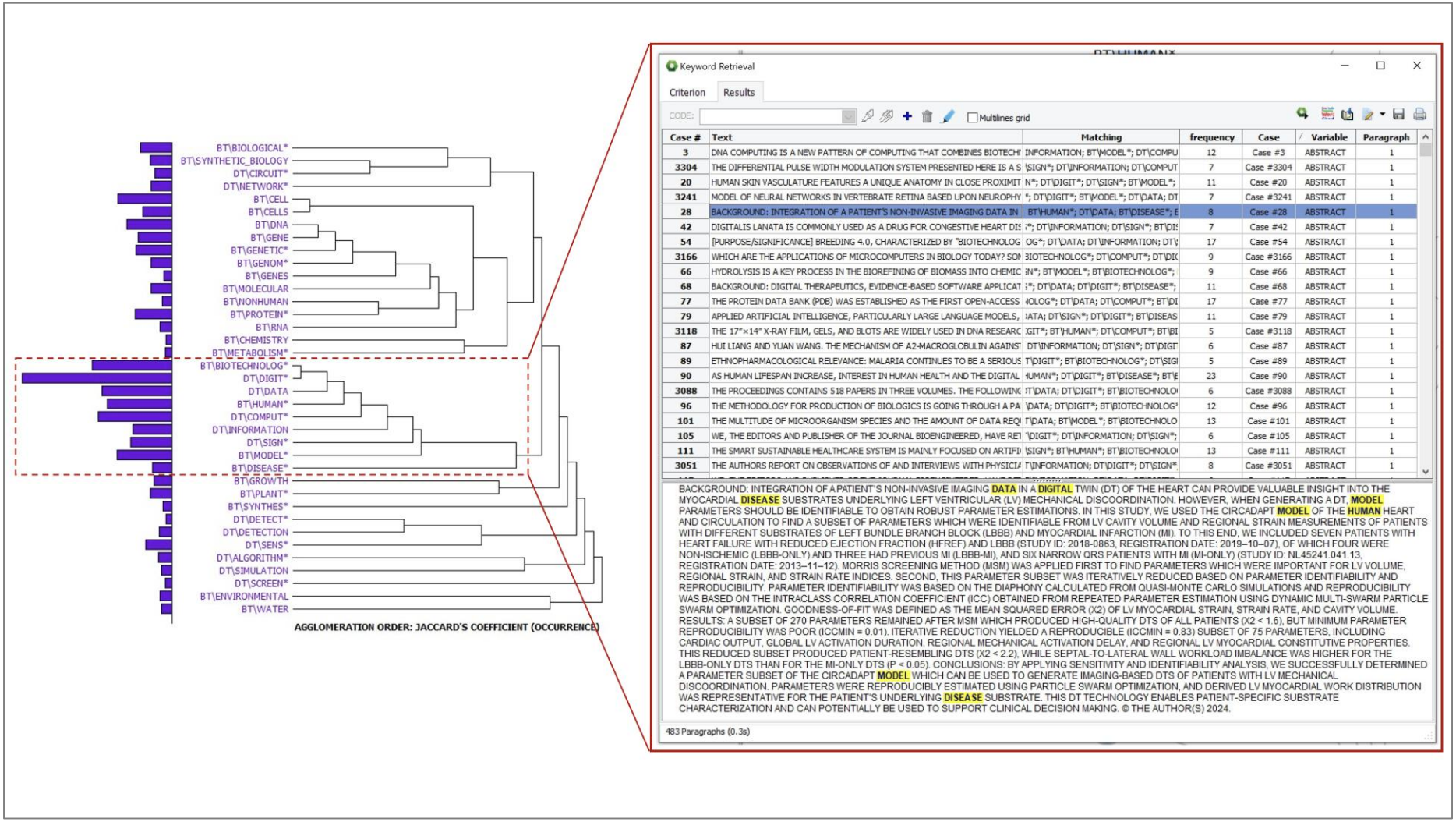


Figure 5. Primary cluster of co-occurring codes associated with the Biotechnology-based Bioeconomy (BtBB) concept and digital technology (DT). The highlighted subcluster features codes with the highest co-occurrence frequencies, complemented by contextual paragraphs retrieved from the database. Source: Prepared by the authors based on research data.

The co-occurrences illuminate tangible applications of digital technologies in the BtBB, wherein bioeconomic elements (e.g. endosomatic metabolism and knowledge) are interwoven with digital tools to facilitate precise quantification, simulation, and optimization.

These interactions span various scales, from internal organ systems in animal organisms to molecular processes, as conceptualized by Giampietro (2023a) in terms of endosomatic metabolism. For instance, case #218 employs a digital twin model encompassing 75 parameters to simulate myocardial diseases, thereby enabling high-precision clinical diagnostics (Koopsen et al., 2024). Similarly, case #3 by (Z. C. Wang et al., 2024) advances DNA computing as an integrative paradigm merging biotechnology with information technology to tackle combinatorial optimization problems, demonstrating its transformative implications for the BtBB.

Leveraging such foundational resources, case #77 highlights the Protein Data Bank (PDB), an open-access repository containing over 210,000 three-dimensional structures of proteins and nucleic acids, augmented by annotations for disease-associated mutations that advance fields in biology, biomedicine, and biotechnology (Burley et al., 2024). From these databases, multifaceted applications emerge across animal and human systems, as illustrated in case #90, which examines biomodels for translational research (Park, 2024). Analogously, case #68 elucidates how digital therapeutic devices, integrated with real-time monitoring, are positioned to transform healthcare through a patient-centered ecosystem (Young Park, 2024). Complementing these examples, case #79 introduces a biomimetic digital twin ecosystem that incorporates phenotype classification algorithms and machine learning to expedite bias-free biomarker discovery in biomedical research (Kearns et al., 2024).

Collectively, these cases emphasize there is an important digitalization progress integrate to the biotechnology-related activities. Such technologies not only augment capabilities for detailed measurement and analysis at endosomatic levels but also pave new avenues for clinical translation, computational optimization, and scalable management of biological data, thereby enhancing value creation within the bioeconomy.

3.3.3 The application of Digital Technologies (DT) in the Biosphere-Based Bioeconomy (BsBB)

The BsBB frames the bioeconomy as an integrated system that encompasses matter and energy cycles within the biosphere, incorporating biotic and abiotic resources, biodiversity, and ecological functions while respecting thermodynamic constraints.

BsBB-related codes, such as “BS\Environment*,” “BS\Model,” and “BS\Human,” are illustrated in Figure 6 as interacting with digital elements including “DT\Digit*”, “DT\Data”, “DT\Information”, “DT\Comput*”, “DT\Sign*”, “DT\Sens*”, “DT\Network*”, “DT\Artificial_Intelligence” and “DT\Algorithm*”. The right-hand panel of the figure displays paragraphs where terms from the highlighted subcluster co-occur. In total, 117 such paragraphs were retrieved.

The following cases exemplify the deployment of digital technologies to augment the monitoring and management of natural resources, such as soil and water. For instance, case #39080 assesses the precision of satellite image classification techniques for land cover mapping, thereby enhancing hydrological modeling and elucidating interactions between biotic and abiotic elements (Palamuleni et al., 2007). In advancing image acquisition and management, encryption technologies provide robust data authentication protocols for image-centric applications. Case #200995 applies encryption technology in medical and environmental contexts, bolstering the integrity of bio-physical data streams (T. Liu et al., 2024).

Energy flows in natural living systems parallel monetary circulation in economic systems, with metabolism denoting the energy efficiency of processes across various hierarchical levels. At the micro metabolic scale, case #164179 develops hybrid RNA-DNA circuits within cell-free biosensors to execute logic computations and analog-to-digital signal conversions, thereby refining the quantification of molecular interactions (Jung et al., 2022). Similarly, case #176824 advances cell-free biosensors through a self-powered enzyme-based biofuel cell (EBFC-SPS) augmented by ultrasonically dispersed graphene, enabling ultra-trace detection of atrazine, an endocrine-disrupting herbicide that perturbs bio-physical cycles (Du et al., 2023). This innovation attains exceptionally low detection thresholds in ambient waters, ensuring high selectivity and stability while safeguarding biotic integrity and advancing bioeconomy sustainability. Transitioning from molecular to crop scales, case #161849 examines high-throughput phenotyping platforms that integrate unmanned aerial vehicles (UAVs), multispectral sensors, and big data analytics to delineate genotype-environment-phenotype interrelations (Fu & Jiang, 2022). This methodology expedites crop enhancement and refines sustainable bioeconomy metrics via real-time, non-destructive data collection spanning cellular to field levels.

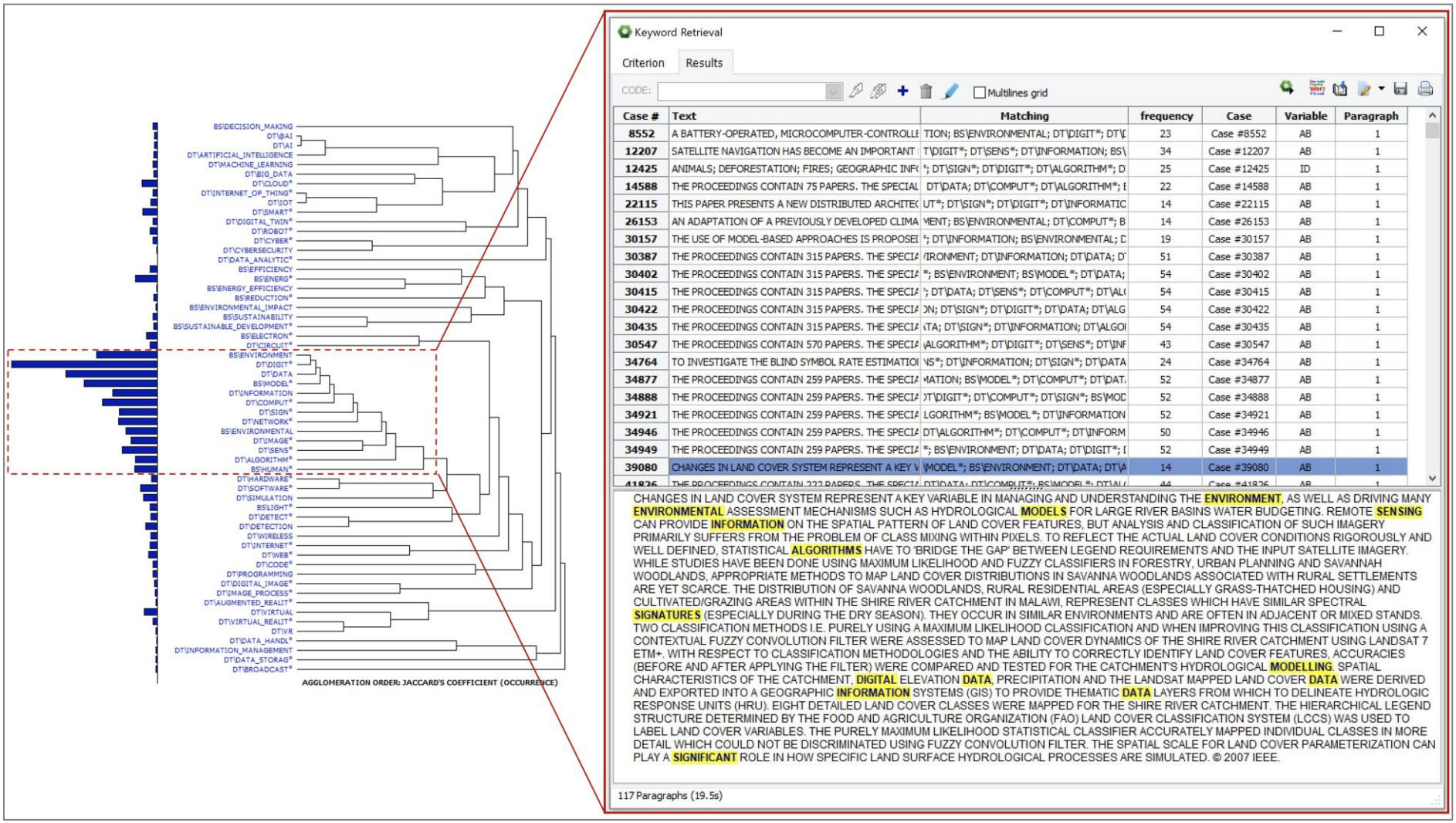


Figure 6. Primary cluster of co-occurring codes associated with the Biosphere-based Bioeconomy (BsBB) concept and digital technology (DT). The highlighted subcluster features codes with the highest co-occurrence frequencies, complemented by contextual paragraphs retrieved from the database. Source: Prepared by the authors based on research data.

At the meso metabolic scale, extending Internet of Things (IoT) architectures with edge computing (e.g. case #179694) facilitates Kirigami triboelectric edge computing sensors (K-TECS) for real-time monitoring and management of bio-physical resources, predictive forecasting, proactive interventions, and optimized information flows across firms or supply chain (Reinhart & Watson, 2023). Finally, at the macro metabolic scale, artificial intelligence (AI) bolsters decision-making, natural language processing (NLP), and robotic automation, among other capabilities (case #198614; Latha & Malini (2024). This integration aligns with progress in regenerative architecture, where digital twins and biofilm sensors monitor metabolic signals to foster biodiversity and socioeconomic resilience in urban ecosystems (case #196330; Bühler et al. (2024)).

The primary inner subcluster interfaces with the inner-upper cluster, with the bio-physical element "BS\Energ*" proving particularly salient for bioeconomy quantification. In this context, case #163215 scrutinizes the energy trilemma encompassing security, equitable access, and environmental sustainability, alongside transitions to sustainable energies. The analysis reveals that such transitions foster long-term economic growth and environmental quality, albeit with the trilemma exerting a negative influence on the latter (H. Liu et al., 2022). Consequently, it advocates for policymakers to pursue integrated measures that advance energy security, environmental strategies, and investments in technological innovation, thereby enabling a clean energy transition that maximizes social and economic benefits while upholding environmental sustainability.

In summary, the deployment of digital technologies across the BsBB framework elevates the quantification, management, and sustainability of bio-physical resources across micro-, meso-, and macrometabolic scales. Applications of sophisticated biosensors and high-throughput phenotyping to edge computing, artificial intelligence, and digital twins enhance data precision and real-time decision-making, while confronting thermodynamic limitations and energy trilemma challenges to facilitate efficient energy transitions. By fostering resilience in ecological and socioeconomic systems and supporting biodiversity, BsBB leverages digital innovations to drive a regenerative bioeconomy that ensures long-term environmental sustainability and equitable resource utilization.

The co-occurrence analysis of conceptual elements and digital technologies across the BmBB, BtBB, and BsBB underscores the pervasive role of digitalization in the bioeconomy. In the BmBB, digital tools such as sensors, satellite imagery, and algorithms optimize agricultural and forestry processes, thereby improving resource monitoring, ecosystem management, and

supply chain efficiency. The BtBB employs computational models, data repositories, and machine learning for detailed endosomatic analyses, fostering innovations in disease simulation, biomarker discovery, and bio-computational optimization. The BsBB extends these integrations to broader scales via biosensors, AI-driven phenotyping, edge computing, and digital twins, addressing thermodynamic constraints, energy transitions, and ecological resilience to promote sustainable stewardship of biotic and abiotic cycles. Collectively, these patterns indicate there is an ongoing digitalization in course that may evolve to unify these concepts, thereby enabling comprehensive measurement of a holistic bioeconomy in the future.

4 DISCUSSION

This study elucidates the convergence of digital technologies with bioeconomy concepts through a CPSS lens, illustrating how cyber elements facilitate targeted data collection, processing, and analysis across BmBB, BtBB and BsBB concepts. Aligning with the research objective, bibliometric keyword extraction and co-occurrence analyses identified core conceptual clusters (e.g., vegetal/animal production and biorefinery processes in BmBB (Figure 2-A)), genetic engineering and biomedical applications in BtBB (Figure 2-B), and bio-physical monitoring with human-ecological interfaces in BsBB (Figure 2-C) while mapping 193 digital technology (DT) codes into 11 categories, dominated by Data Science and Analytics (mean occurrence ~6.4%) and Computing and Software (~4%). Co-occurrence clusters (Figures 4–6) highlight domain-specific digitalization applications: sensors and satellite imagery supporting precision monitoring in BmBB (e.g., soil texture assessment; Azar et al., (2023)), computational models and data repositories aiding endosomatic simulations in BtBB (e.g., digital twins for disease modeling; Koopsen et al. (2024)), and biosensors with AI enabling metabolic-scale resource tracking in BsBB (e.g., high-throughput phenotyping; Fu & Jiang, (2022). These patterns indicate DTs' potential to address data gaps and interoperability barriers in specific contexts (Leavy et al., 2024; Eastwood et al., 2023), suggesting pathways toward holistic bioeconomy (BhBB) measurement, although not yet realizing.

The findings extend Leavy et al.'s (2024) BhBB by demonstrating CPSS-mediated digital convergence as a mechanism to support multi-scale bioeconomy metrics in targeted applications, addressing definitional fluidity and unidimensionality critiqued in the introduction (Papadopoulou et al., 2022; Giampietro, 2022). A key point of convergence across BmBB, BtBB, and BsBB lies in Data Science and Analytics, which facilitates the processing of heterogeneous bio-physical and economic data in domain-specific ways through tools like algorithms and machine learning, as evidenced by its dominant co-occurrence rates (~6.4%;

Figure 3). Complementing this, metabolism emerges as another conceptual convergence, particularly bridging BtBB and BsBB through hierarchical energy flows (Giampietro, 2019; Georgescu-Roegen, 1971), where DTs such as biosensors and predictive modeling enable targeted quantification of energy flows at various levels in ecosystemic processes (e.g., RNA-DNA circuits for molecular detection; (Jung et al., 2022)). In BmBB, the integration of imaging/sensing DTs (e.g., LiDAR and UAVs in the yellow cluster) with biomass clusters facilitates algorithmic optimization of soil/crop parameters in precision agriculture, bridging physical (abiotic resources) and cyber (data analytics) dimensions per Zhuang et al. (2021). This approach may aid "bio-share" estimation (Befort, 2021) through real-time valorization of select services, such as water use efficiency, though broader systemic integration remains nascent.

BtBB's emphasis on bioinformatics and computational modeling (e.g., CRISPR-linked neural networks) supports endosomatic metabolism analyses (Giampietro, 2019) via digital twins, as in Wang et al.'s (2024) DNA computing for combinatorial tasks. Notably, co-occurrence patterns reveal a pronounced focus on health-sector applications, such as disease simulation, drug synthesis, and immunology (green cluster, Figure 2-B), where DTs like data repositories and machine learning enable targeted biomedical advancements (e.g., digital therapeutics; Young Park (2024); biomodels; (Park, 2024)). This convergence tempers reductionist biotechnology views Patermann (2015), with ~1.7% quantum computing co-occurrences hinting at specialized molecular simulations amid data scarcity, although highlighting the need for expanded structured repositories. Critically, such health-centric associations remain undervalued in bioeconomy measurement analysis, which often overlook biotechnology-based contributions to societal well-being in favor of industrial metrics, limiting holistic valuation of BtBB's potential.

BsBB findings most profoundly illustrate CPSS holism (Sobb & Moustafa, 2023), where DT clusters interface bio-physical cycles across metabolic hierarchies in domain-specific ways, with biodiversity serving as a pivotal element for ecosystem resilience. At micrometabolic levels, hybrid RNA-DNA biosensors (Jung & Archuleta, 2022) and enzyme-based biofuel cells (Du et al., 2023) enable analog-to-digital conversions for targeted detection (e.g., atrazine), refining thermodynamic efficiency per Georgescu-Roegen (1971) while supporting microbial diversity in biotic resources (blue cluster, Figure 2-C). Mesometabolic IoT-edge computing (Reinhart & Watson, 2023) and macrometabolic AI (Latha et al., 2024) aid regenerative ecosystems, as in Bühler and Hollenbach's (2024) digital twins for urban biodiversity monitoring, where remote sensing and genomic tools enhance species diversity

assessments. This convergence tempers challenges in translating ecological functions into metrics (Lucia & Grisolia, 2021), facilitating targeted enhancements to biodiversity stewardship, although underscoring persistent gaps in valuing diverse biotic interactions amid thermodynamic constraints. The energy trilemma subcluster Liu et al. (2022) underscores bio-physical "BS\Energ*" relevance, where DTs support mitigation of security-equity-sustainability tensions, advancing Odum's emergy analysis (Giampietro, 2022) through predictive tools, while underscoring gaps in holistic ecological-economic translation. Collectively, these integrations suggest DTs can unify BmBB/BtBB/BsBB elements toward BhBB in focused domains, transforming select metrics into more interconnected indicators with social participation (Beniiche et al., 2022; Wang et al., 2023).

4.1 Implications for Practice and Policy

The identified convergences offer actionable insights for bioeconomy stakeholders, aligning with SDG priorities outlined in the Introduction while recognizing DTs' current focus on specific applications. In high-income contexts, BtBB's digital twins and PDB repositories (Burley et al., 2024), particularly in health-sector domains like biomarker discovery and patient-centered ecosystems (Kearns et al., 2024; Young Park & Jin, 2024), can aid SDG 3 (health) through targeted, equitable innovations, addressing the sub valuation of biomedical metrics in bioeconomy assessments. This emphasis could recalibrate strategies to integrate health outcomes into gross value-added calculations, fostering inclusive R&D. Meanwhile, BmBB's satellite-algorithm tools support SDG 12 (responsible consumption) in biomass supply chains (Liu et al., 2024). For emerging economies, BsBB's phenotyping platforms (Fu & Jiang, 2022) bolster SDG 2 (zero hunger) and SDG 8 (decent work) via equitable crop enhancements and trade facilitation, with biodiversity-focused DTs (e.g., genomic monitoring; (Holmes et al., 2025) enabling community-based conservation in diverse ecosystems.

Globally, CPSS-driven DTs can address governance omissions (Eastwood et al., 2023) by incentivizing data-sharing in niche areas (Interagency Working Group on Data for the Bioeconomy, 2023) and blockchain for secure bio-physical data (Liu et al., 2024), reducing greenwashing risks in SDG 13 (climate action) and SDG 15 (life on land). This holds particular promise for North-South relations: BtBB-developed countries (e.g., EU and USA biotech leaders) could collaborate with biodiversity-rich Global South nations (e.g., Brazilian hotspots; Barbosa et al. (2025) through shared digital platforms for genomic biodiversity analytics, alleviating financing burdens on the South and promoting equitable bioeconomy transitions (e.g., Kunming-Montreal-aligned metrics; Danielsen et al., (2024).

Policymakers might explore hybrid metrics, like emergy-calibrated input-output models incorporating health indicators (Heck et al., 2024) for EU and UN strategies, prioritizing interoperability in select domains via open-access platforms like PDB. Innovators could advance quantum/ML applications Memon et al. (2024) for biorefineries, with attention to equity in Global South biodiversity contexts (Rowan et al., 2022). Overall, these domain-specific leverages position digitalization as a supportive tool for low-carbon, inclusive growth, embedding social participation in Society 5.0 while pathways to holistic measurement evolve (Tetere & Zeverte-Rivza, 2023).

4.2 Limitations and Future Research Directions

While robust, this study's reliance on Scopus (2000–2025) introduces citation biases toward English-language, high-impact works, potentially underrepresenting Global South perspectives (e.g., indigenous bioecological strategies; Blair et al. (2021). Downloads limited by Scopus (20,000 cited/recent per concept) and Pareto thresholds (~1% word selection) ensured feasibility but may overlook niche terms, as Zipfian distributions approximate rather than exhaust semantic coverage (Piantadosi, 2014). Co-occurrence via Jaccard coefficients captures paragraph-level links but risks overlooking causal dynamics absent in bibliometric data. The "digit*" filter broadens scope yet conflates cyber-physical elements, per CPSS framing, what could be refined by future qualitative validations. Furthermore, the cases retrieved from co-occurrence paragraphs and explored in Section 3.3, primarily illustrate contextual applications of DTs within each bioeconomy concept, potentially introducing a selection bias from author-chosen "random" exemplars. This illustrative focus enriches qualitative insights but may limit the breadth of represented digitalization pathways, as non-selected cases could reveal alternative associations.

To further refine the conceptual foundation, future work could propose alternative frameworks to CPSS with a bioeconomy-specific bias, such as sustainability-integrated models emphasizing social life cycle assessments or multi-dimensional governance structures that better capture bio-physical and economic synergies. Additionally, studies might integrate digital data generated for other specific purposes (e.g., real-time monitoring in agriculture or environmental) to measure specific bioeconomy contributions, like ecosystem services in BsBB, thereby bridging data silos toward targeted valuation. Advances in fusing such domain-specific data with official databases (e.g., precision agriculture yields from IoT sensors integrated with national agricultural statistics) could explore scalable integration protocols, enhancing interoperability for bioeconomy metrics.

5 CONCLUSIONS

This CPSS-grounded bibliometric analysis illuminates how digital technologies converge with bioeconomy concepts to facilitate targeted measurement across biomass-, biotechnology- and biosphere-based frameworks, addressing the research question on digitalization's linking role. Through co-occurrence mapping, key convergences emerge: Data Science and Analytics as a transversal enabler for processing heterogeneous bio-physical data (~6.4% dominance), metabolism as a hierarchical bridge for energy flow quantification (Giampietro, 2019, 2023c), and biodiversity as a resilience pivot in ecosystem stewardship (Figure 2-C). These patterns reveal domain-specific applications, such as algorithmic precision in BmBB agriculture, health-centric simulations in BtBB, and AI-driven phenotyping in BsBB, that mitigate data gaps and interoperability barriers yet underscore the provisional nature of holistic integration amid selection biases in illustrative cases.

By extending Leavy et al.'s (2024) holistic bioeconomy (BhBB), this study advances theoretical recalibration, foregrounding undervalued dimensions like endosomatic health contributions in BtBB and biodiversity's role in BsBB, which traditional metrics often overlook in favor of industrial biomass. Digitalization holds substantial potential to transform bioeconomy measurement through seamless data integration, fusing domain-specific streams (e.g., IoT yields from precision agriculture with genomic biodiversity repositories), and the elaboration of innovative methods, such as AI-augmented emergy analyses. This could yield multi-dimensional indicators that comprehensively evaluate the bioeconomy's societal impacts: economic valorization via real-time and geographical-specific bio-share tracking, environmental resilience through metabolic cycle modeling, and social equity via inclusive access metrics. Such advancements would recalibrate policy and innovation toward a sustainable societal transition.

As digitalization accelerates in an era of socio-ecological complexity, interdisciplinary efforts must prioritize alternative frameworks with bioeconomy-specific biases, such as sustainability-integrated governance, and scalable data fusions (e.g., precision agriculture yields with official statistics) to realize comprehensive measurement. Ultimately, this convergence charts equitable pathways toward a people-centered bioeconomy, fostering resilient innovation that honors thermodynamic constraints and global interdependencies.

Declaration of generative AI and AI-assisted technologies in the writing process

The authors used ChatGPT (OpenAI, free version) exclusively to refine the English-language wording. All scientific content was rigorously validated and remains the sole responsibility of the authors.

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CHAPTER 4 - A CYBER-BIO-PHYSICAL-SOCIAL SYSTEMS FRAMEWORK FOR HOLISTIC BIOECONOMY MEASUREMENT: A PROPOSAL AND ILLUSTRATION IN FOREST CARBON ACCOUNTING

Abstract

The bioeconomy promises sustainable solutions to climate change and biodiversity loss, yet fragmented measurement frameworks constrain its potential. This study proposes the Cyber-Bio-Physical-Social Systems (CBPSS) framework, extending Cyber-Physical-Social Systems (CPSS) to integrate bio-physical realism with digital and social dimensions for holistic bioeconomy (BhBB) assessment. CBPSS addresses gaps in biomass-based (BmBB), biotechnology-based (BtBB), and biosphere-based (BsBB) domains via a modular Digital Integrated Platform (DIP) fusing real-time data, emergy analysis, and network metrics. Applied to forest carbon accounting, it illustrates the proposed structure through bibliometric co-word network analysis of 8,941 Scopus documents (1936–2025), revealing interconnections (e.g., forestry bridging layers). An R-based model operationalizes CBPSS using ForC database, MODIS data, random forest ML (pseudo-R^2: 0.437, 64.5% uncertainty reduction), REDD+ adjustments, and emergy valuations. Results estimate a ~3.63 GtC/year global forest sink, traditional values of U$S237.14–801.16 billion/year ($14.80–50/tCO2e), and holistic emergy additions of U$S 8.49–10.68 trillion/year, with 3,682–4,603% gaps over market metrics. Probabilistic sensitivity analysis (Sobol indices) identifies bio-physical factors as key variance drivers. CBPSS surpasses static models like SEEA or EXIOBASE, enabling adaptive measurements for SDGs and Paris Agreement goals. By embedding bio-physical metabolism in cyber-social systems, it advances biodigital convergence for sustainable governance amid climate challenges.

Keywords: Bioeconomy Measurement; CBPSS Framework; Forest Carbon Accounting; Emergy Analysis; Sustainability

Abbreviations

- AFOLU: Agriculture, Forestry, and Other Land Use
- AI: Artificial Intelligence
- ANPP: Aboveground Net Primary Productivity
- AR6: Sixth Assessment Report (IPCC)
- BhBB: Holistic Bioeconomy
- BIO-SES: Bioeconomy Sustainability Evaluation System
- BmBB: Biomass-based Bioeconomy
- BNPP: Belowground Net Primary Productivity
- BsBB: Biosphere-based Bioeconomy
- BtBB: Biotechnology-based Bioeconomy
- BWI: Bioeconomic Welfare Index
- CBPSS: Cyber-Bio-Physical-Social Systems
- CIDAR: Cybernetics, Informatics, Design, Automation, and Robotics
- COD: Chemical Oxygen Demand
- CoWordNet: Co-occurrence Word Network
- CPBS: Cyber-Physical-Biological Systems
- CPSS: Cyber-Physical-Social Systems
- CPS: Cyber-Physical Systems
- DIASCA: Digital Integration of Agricultural Supply Chains Alliance
- DIP: Digital Integration Platform
- DSC-TG: Differential Scanning Calorimetry-Thermogravimetry
- EmDollar: Emergy Dollar
- EmGDP: Emergy-Adjusted GDP
- FAO: Food and Agriculture Organization
- ForC: Global Forest Carbon Database
- G4M: Global Forest Model
- GBMF: Global Bioeconomy Monitoring Framework
- GCAM: Global Change Assessment Model
- GHG: Greenhouse Gases
- GIS: Geographic Information System
- GPP: Gross Primary Productivity
- GtC: Gigatonnes of Carbon
- GtCO2e: Gigatonnes of CO2 Equivalent
- IPCC: Intergovernmental Panel on Climate Change
- IoT: Internet of Things
- IPO: Input-Processing-Output
- LAI: Leaf Area Index
- LiDAR: Light Detection and Ranging
- LLM: Large Language Model
- MAP: Mean Annual Precipitation
- MAPD: Mean Absolute Percentage Deviation
- MASL: Meters Above Sea Level
- MAT: Mean Annual Temperature
- ML: Machine Learning
- MODIS: Moderate Resolution Imaging Spectroradiometer

- NACE: Nomenclature of Economic Activities
- NAICS: North American Industry Classification System
- NEAD: National Environmental Accounting Database
- NEE: Net Ecosystem Exchange
- NEP: Net Ecosystem Production
- NeRF: Neural Radiance Fields
- NH4+-N: Ammonium Nitrogen
- NMR: Nuclear Magnetic Resonance
- NPP: Net Primary Productivity
- NSF: National Science Foundation
- P: Phosphorus
- PES: Payments for Ecosystem Services
- PSA: Probabilistic Sensitivity Analysis
- R&D: Research and Development
- RAG: Retrieval-Augmented Generation
- RCP4.5: Representative Concentration Pathway 4.5
- REDD+: Reducing Emissions from Deforestation and Forest Degradation
- RF: Random Forest
- RMSE: Root Mean Square Error
- RMPs: Recommended Management Practices
- SD: Standard Deviation
- SDGs: Sustainable Development Goals
- SEEA: System of Environmental-Economic Accounting
- sej: Solar Emergy Joules
- SOC: Soil Organic Carbon
- SOM: Soil Organic Matter
- SM: Supplementary Material
- tC: Tonnes of Carbon
- tCO2e: Tonnes of CO2 Equivalent
- UNCTAD: United Nations Conference on Trade and Development
- UNEP-FI: United Nations Environment Programme Finance Initiative
- USD: United States Dollar

1 INTRODUCTION

The bioeconomy, leveraging sustainable biological resources and ecosystems, promises solutions to climate change and biodiversity loss—but fragmented measurement hinders its potential. It spans three interdependent domains: (i) the biomass-based bioeconomy (BmBB), focused on renewable biological resources such as agriculture and forestry; (ii) the biotechnology-based bioeconomy (BtBB), driven by biotechnological processes; and (iii) the biosphere-based bioeconomy (BsBB), addressing ecosystem functions, biodiversity, and biogeochemical cycles (Ronzon et al., 2020). Integrating these into a holistic bioeconomy (BhBB) (Leavy et al., 2024) demands a socio-ecological paradigm that promotes circular, resource-efficient metabolism within planetary boundaries, while accounting for socio-technical and cultural co-evolution.

Each domain poses distinct measurement challenges: BmBB struggles with estimating the "bio-share" in national accounts due to data gaps; BtBB lacks structured data on contributions; and BsBB faces difficulties translating ecological functions into economic or bio-physical units. Traditional approaches—such as input-output models, social accounting matrices, and sectoral statistics (e.g., NACE or NAICS)—focus on indicators like value added, employment, sales, linkage coefficients, and greenhouse gas emissions for BmBB. BtBB relies on R&D investments, patent counts, and human capital metrics, while BsBB draws on thermodynamic frameworks (e.g., emergy analysis in solar emjoules, seJ) or ecosystem service valuations (e.g., System of Environmental-Economic Accounting, SEEA).

Complementary indicators, such as Emergy-Adjusted GDP (EmGDP), which converts economic output to bio-physical emergy units (seJ/year) using national ratios (Brown; Ulgiati, 2016), and the Bioeconomic Welfare Index (BWI), which adjusts GDP for ecosystem services and environmental degradation (Coscieme et al., 2020), mitigate some limitations of conventional GDP. However, ongoing issues—fragmented data, conceptual ambiguities, and inadequate tools—result in inconsistent metrics, underreported value chains, and poor integration of ecological, social, and technological dimensions, constraining the bioeconomy's sustainable potential (Marvik & Philp, 2020; Ronzon et al., 2021; Leavy et al., 2024; Thomchick et al., 2024).

Although prior studies have investigated the integration of digital technologies with the bioeconomy (Eastwood et al., 2023), furthermore via cyber-physical-social systems (CPSS) (Clauser et al., 2022), these approaches often lack explicit bio-physical

realism. The 'physical' component typically prioritizes measurement devices over biological elements, overlooking thermodynamic constraints and ecosystem metabolism essential for transitioning from static to holistic bioeconomy assessments.

Forests exemplify this nexus, supplying biomass for bio-products while delivering ecosystem services like carbon sequestration. Global assessments estimate potential living tree carbon stocks in natural forests at ~600 GtC (range: 487–712 GtC), with a current deficit of 217 GtC (153–267 GtC) due to human disturbance; ~61% (138 GtC) of recoverable stocks outside urban/agricultural areas offers conservation potential (Mo et al., 2023). However, global mean surface temperature is rising above 1.5 °C relative to pre-industrial levels, and recent updates indicate higher deficits due to events such as the 2024 Amazon fires (Yun et al., 2025). The forest carbon application is timely, with 2025 updates confirming ~18-24% global terrestrial carbon depletion, and potential for 20-35x carbon credit supply growth by 2050 (Ganzenmüller et al., 2025). Models like the Global Biosphere Management Model (GLOBIOM) and the Global Forest Model (G4M) simulate harvest-trade dynamics under bioenergy scenarios, highlighting the need for integrated accounting (Augustynczik et al., 2025; Frank et al., 2018; Lauri et al., 2014).

Information technology and biology are converging synergistically, transforming economies through biodigitalism (e.g., bioelectronics, genetic manipulation) (Peters, 2023). Advancements in quantum computing (Alexeev et al., 2025; Memon et al., 2024), blockchain, metaverses, demetaverses (X. Wang et al., 2023), and tokenization offer market solutions for balancing bioeconomy systems (Wang et al., 2023b). Vertical connections among scientific knowledge, patents, and business activities highlight network dynamics in genome editing (Laibach; Bröring, 2022), while catalysts like AI, digital knowledge management, and innovation networks drive progress (Smolinski, 2024).

Digitalization enables convergence for improved measurement (Leavy et al., 2024, 2026), as seen in the European Union’s Bioeconomy Monitoring System (updated October 2025), hybrid models like EXIOBASE-3 (Exiobase- Home, 2025), and SEEA revisions (2025) (https://seea.un.org/). Initiatives like FAO's open-access tools for deforestation-free supply chains (FAO, 2025; (“Open Foris”, *[S.d.]*)), Knowledge Centre for Bioeconomy EU (Knowledge Centre for Bioeconomy, 2025) and the Digital Integration of Agricultural Supply Chains Alliance (DIASCA) (DIASCA-SASI, 2025); emphasize transparent data.

Adetoyinbo; Trienekens; Otter (2023) integrate a contingent resource-based view with the netchain approach to examine how food netchain organization (supply chain networks with horizontal and vertical interactions across multiple tiers, such as producer and processor levels) impacts firm performance, proposing metrics for efficiency, sustainability, and transparency—including indicators of coopetition (competition-cooperation), digital innovation, and environmental/social impacts—applied to modern agrifood chains to reduce uncertainties in sustainability. This framing aligns with multi-level systems perspectives (Geels, 2019), where resource heterogeneity and interdependencies are analyzed at micro (firm), meso (network), and macro (ecosystem) levels (Adetoyinbo; Trienekens; Otter, 2023; Leavy et al., 2024; Qiu; Liu; Wu, 2023; Wang et al., 2022).

To address these gaps, we propose a Cyber-Bio-Physical-Social Systems (CBPSS) framework, extending Cyber-Physical-Social Systems (CPSS) to bioeconomy measurement. Unlike prior CPSS applications, CBPSS explicitly incorporates bio-physical realism, enabling dynamic quantification absent in static models. CBPSS integrates cyber, bio-physical, and social layers via a modular Digital Integrated Platform (DIP), using bibliometric network metrics for transparent modeling (Qu et al., 2025). Applied to forest carbon accounting, it demonstrates dynamic, cross-layers quantification.

The development and implementation of the CBPSS framework and model are justified by the pressing need to bridge gaps in current bioeconomy assessments, which often overlook dynamic interactions between bio-physical processes, digital technologies, and social governance, thereby enabling more accurate, sustainable decision-making in the face of global challenges like climate change and resource depletion. Our hypothesis is that cybernetic convergence with bio-physical and social systems, through a cybernetic-bio-physical -social systems (CBPSS) framework, enables holistic and scalable measurement of the bioeconomy, overcoming the limitations of fragmented approaches by integrating real-time data, bio-physical flows, and social dynamics, resulting in more accurate and adaptable assessments. Therefore, the objectives are: i) to illustrate the structure of the CBPSS framework by analyzing the co-occurrence of its core elements in the literature on forest carbon accounting; and (ii) to apply this framework through a computational model that quantifies both traditional market-based values and emergy-based holistic values in forest carbon accounting.

2 THEORETICAL-CONCEPTUAL PROPOSITION OF THE CBPSS FRAMEWORK

Digital transformation, driven by rapid technological advancements, has exponentially increased the volume and diversity of data generated by interconnected systems. This evolution has progressed from mechatronics and embedded systems to Cyber-Physical Systems (CPS), the Internet of Things (IoT), and ultimately to Cyber-Physical-Social Systems (CPSS), which integrate physical sensors, computational servers, a social layer for human interactions, and bidirectional information flows (Fig. 1 a,b)) (De et al., 2017; Reine et al., 2021; Pasandideh et al., 2022)

The CBPSS framework builds on systems science paradigms to meet holistic bioeconomy (BhBB) demands. Cyber-Physical Systems (CPS) integrate computation with physical environments for real-time monitoring in manufacturing and energy (Oks et al., 2022). CPS emphasizes sensor-actuator-algorithm feedback but overlooks social dynamics. Cyber-Physical-Social Systems (CPSS) extend CPS by adding a social layer, focusing on human behaviors, institutions, and governance in complex ecosystems (Sobb; Turnbull; Moustafa, 2023). For example, CPSS supports urban planning and disaster response via IoT and AI-driven platforms (Zhao et al., 2023). CPSS architecture features interconnected layers: cyber (data analytics), physical (sensors/infrastructure), and social (policy/feedback), forming adaptive sustainability loops. This structure aligns with digitalization, as emerging technologies like AI, IoT, and blockchain enable seamless data flows and interactions across layers, enhancing CPSS's capacity for real-time decision-making and system optimization (Leavy et al., 2026).

However, conventional CPSS models treat the physical layer in a generic manner, often lacking explicit integration of bio-physical elements critical for tracking biomass flows, biodiversity dynamics, and planetary boundaries. Unlike (Ostrom, 2009) socio-ecological systems (SES) framework- which examines sustainability through interactions between resource systems, users, and governance structures but relies on static diagnostics without real-time adaptation enabled by cybernetics- the proposed CBPSS framework enables the incorporation of dynamic digital tools for continuous feedback loops. De Schutter et al. (2019) advanced the integration of social and ecological dimensions in the BIO-SES framework, focusing primarily on qualitative governance aspects. Our CBPSS extends this by shifting toward quantitative bio-physical valuation,

applying thermodynamic principles—such as emergy analysis—to bioeconomy measurement.

Similarly, cyber-physical-biological systems (CPBS) in bioengineering—such as BioCPS for engineering living cells via synthetic biology and micron-scale robotics (e.g., CIDAR Lab, 2025 www.cidarlab.org) collaborative research on BioCPS, NSF-funded projects, McIntyre, David et al 2025) ("Cooperative Agreement 2452693", *[S.d.]*; NSF, 2025) —focus on embedded control at cellular scales but often neglect broader socio-economic integration. BhBB spans BmBB, BtBB, and BsBB, necessitating a dedicated bio-physical layer for interactions like carbon sequestration and water cycles. CBPSS extends CPSS by inserting this layer, enabling dynamic BhBB quantification.

The CBPSS extension of CPSS is novel, now bolstered by 2025 real-world parallels (e.g., FAO's Open Foris tools for digital monitoring align with the DIP concept; https://openforis.org/). The interdisciplinary scope (bibliometrics + dynamics modeling) has potential impact for SDGs/Paris Agreement. CBPSS provides scalable metrics integrating ecological limits with economic/social goals, surpassing fragmented approaches like SEEA or EXIOBASE (Exiobase- Home, 2025; Pan et al., 2017; Wang et al., 2025) by handling uncertainties better—e.g., through modular real-time simulations that incorporate machine learning to reduce prediction errors in ecosystem flows compared to static valuations, as demonstrated in adaptive forest models. CBPSS's modularity supports bio-specific feedbacks (e.g., AI-linked climate-policy simulations), fostering planetary-scale sustainable development.

The CBPSS is structured in three interdependent layers: bio-physical (based on natural processes such as biomass stocks and carbon flows), cybernetic (digital core for AI-driven processing and modeling), and social (which translates results into policies and equity considerations), which converge in the BhBB. Metabolism unifies these elements, analyzing macro-scale flows (e.g., regional carbon cycles) and micro-scale processes (e.g., cellular nutrient efficiency) (Giampietro and Funtowicz, 2020; Leavy et al., 2024, 2026).

The bio-physical layer grounds CBPSS in natural processes from BmBB, BtBB, and BsBB (Leavy et al., 2024,2025), categorizing stocks (e.g., biomass, patents), flows (e.g., net primary productivity, CO_2 emissions), and auxiliaries (e.g., emergy in seJ for valuation). It quantifies bioeconomic metabolism, coupling yields with ecosystem services.

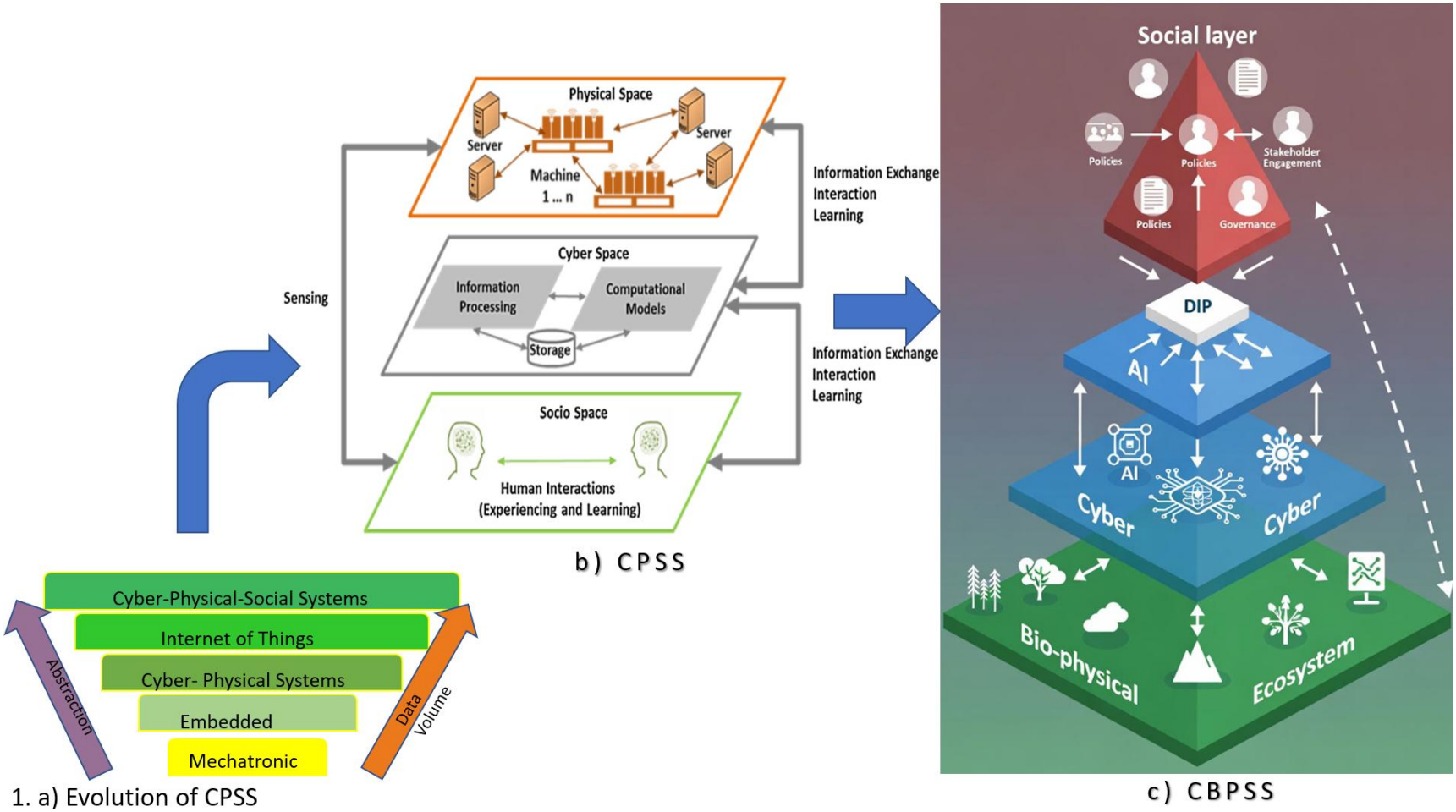


Figure 1: a) Evolution of CPSS, adapted from (De et al., 2017).; b) CPSS from (Ansari et al., 2018); c) Proposition of the CBPSS Framework. Source: Elaborated by the author

The cyber layer, the digital core, uses artificial intelligence, machine learning, and remote sensing for processing and modeling (Wang et al., 2023b), managing sensor/satellite inputs for real-time simulations (e.g., land use forecasting using random forests) and scalability. Cyber includes both physical devices and digital elements.

The social layer translates outputs into decisions, policies, and equity—e.g., payments for ecosystem services or SDG governance (Le et al., 2023)—ensuring bidirectional flows where bio-physical data shapes policy and social inputs refine cyber models, for instance, through REDD++ which extends REDD+ frameworks to incentivize broader reductions in deforestation, degradation, and emissions while valuing carbon stocks, biodiversity conservation, and sustainable land management via financial mechanisms.

To enhance representation, we incorporated the netchain concept from agribusiness (Adetoyinbo; Trienekens; Otter, 2023), integrating vertical supply chains (e.g., forest-to-carbon markets) with horizontal networks (e.g., stakeholder data sharing). CBPSS is a modular DIP unifying heterogeneous data, tools, and governance for transparent representation (Fig. 1c). Its architecture uses an input-processing-output (IPO) framework with three interdependent layers.

Via DIP, CBPSS drives adaptive measurement. This embeds bio-physical realism in CPSS, enabling dynamic assessments balancing economy, innovation, and ecology for BhBB sustainability.

3 METHODS AND DATA

In the context of CBPSS, we define a framework as a conceptual and methodological structure that integrates bio-physical, cybernetic and social layers, establishing levels of abstraction for collecting, processing, and transforming data into actionable knowledge.

The research architecture employs a tripartite sequential pipeline to formalize the CBPSS framework and its computational operationalization. Phase I entails a bibliometric synthesis to delineate the taxonomic and conceptual landscape of forest carbon accounting within the bioeconomy, pinpointing key cross-domain interactions and emergent metrics. Phase II integrates this foundational knowledge into the CBPSS structural architecture, defining protocols for multi-domain data fusion and integrated measurement. Phase III culminates in the assembly and calibration of the CBPSS model (Figure 2).

Forest carbon accounting was selected as a validation case for its encapsulation of holistic bioeconomy (BhBB) domains—BmBB for biomass processes, BtBB for biotechnological integration, and BsBB for biosphere functions—along with its multi-scale dynamics (e.g., from cellular metabolism to global cycles), rich data availability (e.g., remote sensing datasets), and alignment with global sustainability goals, such as the UN Sustainable Development Goals (SDGs) and Paris Agreement targets (Lauri et al., 2014; Mo et al., 2023).

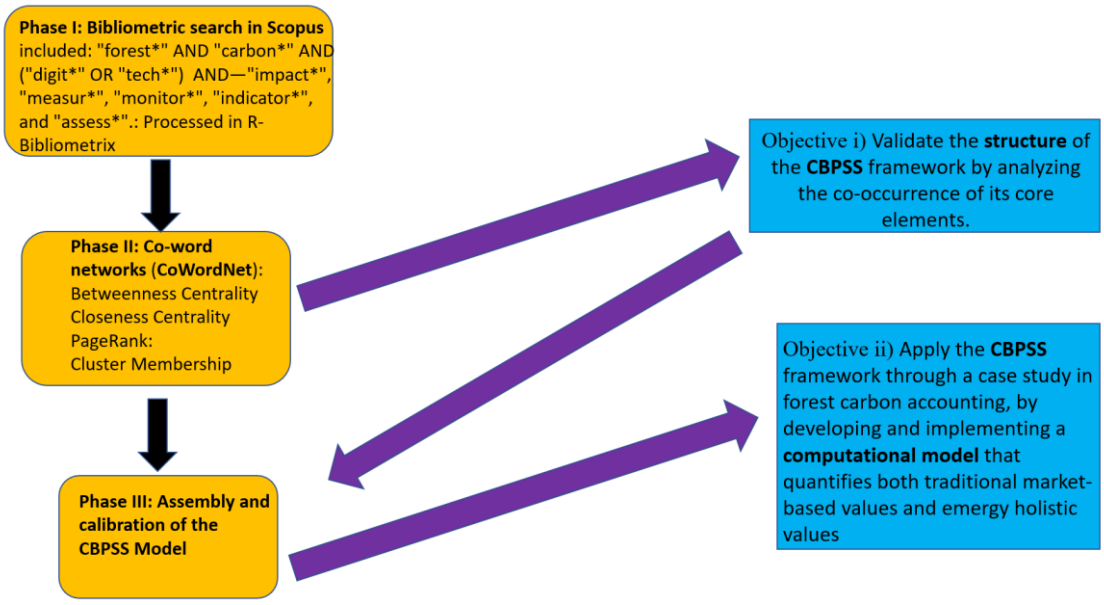


Figure 2: Methodological design.
Source: Elaborated by the author

3.1 Operational Dimensions and the CBPSS Framework

Implementation begins according to the interests of the stakeholder(s), defining the bio-physical element (e.g., forest and carbon), selecting metrics (e.g., emergy in seJ), and identifying keywords aligned with the CBPSS layers. Territorial (from local to global) and temporal scopes guide data integration, transforming heterogeneous inputs into composite indicators that minimize subjectivity through digital technologies and transdisciplinary approaches.

3.1.1 Bibliometric Data Collection and Processing

To apply the CBPSS to forest carbon accounting, we conducted a focused bibliometric search to identify key concepts, interactions, and metrics at the intersection

of forestry, carbon dynamics, and enabling technologies. The strategy targeted studies integrating bio-physical processes (e.g., carbon sequestration in forests) with cyber tools (e.g., remote sensing, data analytics) and social factors (e.g., policy and stakeholder decisions). The query in Scopus (Timespam 1936-2025) included: "forest*" AND "carbon*" AND ("digit*" OR "tech*"). To prioritize measurement-oriented research, we incorporated terms from (Ferreira et al., 2022)—"impact*", "measur*", "monitor*", "indicator*", and "assess*". The search yielded 9,056 documents from the Scopus database. After removing duplicates, 8,941 unique records were retained and analysed in R (v. 4.4.1) using the Biblioshiny web interface of the Bibliometrix package (Aria; Cuccurullo, 2017) Supplementary Material (SM) - (SM I.1 Main Information Bibliometrix). This enabled the construction of co-word networks (CoWordNet) based on author keywords, keywords plus, titles, and abstracts.

Processing steps:

Extracted keywords, abstracts, and metadata to build CoWordNets, where nodes represent concepts (e.g., "remote sensing" for cyber, "carbon sequestration" for bio-physical) and edges denote co-occurrences, revealing relations like bridges between "AI" (cyber) and "policy incentives" (social).

Classified nodes into CBPSS layers manually with validation via cluster analysis: bio-physical (e.g., "forest"); cyber (e.g., "machine learning"); social (e.g., "sustainable development"). This mapping directly connects query terms to framework elements—e.g., "forest* AND carbon*" nodes cluster in bio-physical, while "digit*/tech*" co-occurrences link to cyber-social integrations like AI-enabled governance.

Classifications aligned with bioeconomy archetypes: BmBB (bio-physical approach), BtBB (innovation or technology-based), BsBB (ecological), and BhBB (holistic synthesis).

3.1.2 Analytical Framework: From CoWordNetworks to CBPSS Framework Application

CoWordNets visualized conceptual interconnections with term relations demonstrating CBPSS layer synergies—bio-physical flows informed by cyber tools, modulated by social policies. This reframes CoWordNets as "netchain layers" within CBPSS: bio-physical as foundational chains, cyber as enabling data networks, and social as relational ties, graphically depicting interconnected systems (e.g., satellite monitoring linked to community reforestation).

CBPSS interactions were parameterized data-driven via network metrics from CoWordNets (calculated in Biblioshiny with igraph backend; (Lv et al., 2024):

Betweenness Centrality: Quantifies bridging roles. High values (e.g., >0.01) prioritize inter-layer couplings, like "forestry" bridging bio-physical to social in adjacency matrices for simulating netchain flows.

Closeness Centrality: Measures proximity. Uniform values (~0.02) modulate diffusion in differential equations for rapid propagation (e.g., policy impacts on carbon dynamics). Analyses under various clustering algorithms (Walktrap, Louvain, Leiden) yielded identical closeness values, but Louvain generated 4 clusters (vs. 2 with Walktrap and 1 with Leiden), making it optimal for modular CBPSS sub-models and selected herein.

PageRank: Assesses importance. Values >0.02 weight influential nodes (e.g., "carbon sequestration") in sub-models.

Cluster Membership: Identifies thematic clusters, defining modular sub-models for scalability and emergent behaviors like carbon market feedbacks.

These metrics ensure term relations (e.g., co-occurrences) translate to CBPSS dynamics, enabling simulations of holistic bioeconomy metrics like EmGDP.

While Closeness Centrality is ideally recognized for measuring the speed with which a node can interact with the rest of the network, its direct interpretation can be compromised within the context of a large-scale co-occurrence analysis. This is primarily because the underlying graph may contain multiple disconnected components, or the network analysis software's normalization procedures may introduce artifacts in the calculation of geodesic distances. Given the uniformity of the Closeness values obtained, and in order to maintain methodological robustness, our structural analysis is grounded in the Betweenness Centrality and PageRank indicators. These metrics demonstrated significant variance and are considered more robust for characterizing the brokerage and influence roles, respectively, within this thematic network.

The bibliometric analysis and dynamic systems modeling phases are complementary, bridging conceptual mapping with operational quantification to achieve a holistic CBPSS framework. The bibliometric phase deconstructs fragmented knowledge domains (BmBB, BtBB, BsBB) into interconnected netchains, providing transparent, evidence-based metrics (e.g., betweenness centrality for bridging roles) that address gaps in traditional static models like SEEA or EXIOBASE by incorporating bio-physical

realism and socio-technical dynamics (Ronzon et al., 2020; Leavy et al., 2024; Adetoyinbo et al., 2023).

This complements the modeling phase by supplying parameterized interactions for scalable simulations, ensuring modularity and interoperability across layers—e.g., cyber tools refine bio-physical flows while social feedbacks adapt outputs—thus enabling emergent behaviors like real-time EmGDP adjustments that unify economic, ecological, and innovative dimensions for BhBB sustainability, as hypothesized in our framework extension of CPSS.

3.2 Validation of the CBPSS Model for Forest Carbon Accounting

To address the second objective—applying and validating the CBPSS framework through a forest carbon accounting case study—we developed a computational model in R (version 4.4.1) that provides a comprehensive, holistic valuation of global forest contributions to the bioeconomy. This model operationalizes the CBPSS layers (bio-physical, cyber, social) within a digital integrated platform (DIP), demonstrating adaptive interactions among bioeconomic concepts: biomass-based bioeconomy (BmBB) for biomass flows, biotechnology-based bioeconomy (BtBB) for technological integration, and biosphere-based bioeconomy (BsBB) for systemic sustainability. It integrates bio-physical quantification of carbon fluxes, cybernetic machine learning for uncertainty reduction, social policy adjustments, and dollar-integrated emergy metrics for bio-physical energy accounting, extending traditional carbon credit valuations by incorporating emergy analysis to quantify the embodied solar energy in ecosystem processes (Brown & Ulgiati, 2004; Nightingale et al., 2019; Odum, 1996; Campbell D E et al., 2024).

The model starts by using the ForC database (Anderson-Teixeira et al., 2018) for site-specific bio-physical data (available at https://github.com/forc-db/ForC) and MODIS satellite imagery for global NPP estimation.

The model is structured in four sequential steps, each corresponding to a CBPSS layer, with global parameters configured as follows: forest area = 4 × 10^9 ha (FAO, 2020); base carbon price =U$S14.80/tCO2e (Ecosystem Marketplace, 2023), alternative =U$S50/tCO2e ((IPCC, 2006; MSCI Carbon Markets, 2024); policy factor = 1.2 (REDD+ uplift) (Wheeler et al., 2026)); transformities = 1.5 × 10^8 sej/g (Odum, 1996) and 1.2 × 10^8 sej/g (Campbell, 2016; Campbell et al., 2024); biomass per tC = 2 × 10^6 g (IPCC, 2022); global emergy baseline = 1.2 × 10^25 sej/yr; global GDP =U$S100 ×

10^12 (World Bank, 2023) (World Bank, 2023); NEP/NPP ratio = 0.1 (Pan et al., 2011). Logging was enabled to track execution, and results were exported as tables and figures.

Step 1: Bio-Physical Layer (BmBB/BsBB Core): Forest stocks and fluxes were quantified using ForC data (n = 5241 geolocated sites). Measurements were filtered for relevant variables (e.g., NPP, GPP, NEP, respiration) and merged with site metadata (latitude, longitude, elevation, MAT, MAP). Summary statistics were computed for initial flux assessment (SM I.2: Table 1: Summary of Bio-Physical Variables from ForC Database). Upon processing the carbon sequestration rates derived from the ForC measurements dataset, they did not align with the values reported in the scientific literature. Hence, net sequestration rates were primarily derived from MODIS MOD17A3HGF NPP data (2022–2024) extracted at ForC coordinates using MODISTools, scaled to tC/ha/yr, and adjusted by the NEP factor to approximate net ecosystem production. Fallback to ForC-based calculation (NPP minus heterotrophic respiration where available) was implemented if MODIS failed. To enhance bio-physical realism, explicit solar insolation data (ALLSKY_SFC_SW_DWN, annual climatological average in kW-hr/m²/day) were fetched for each site using the nasapower package, accessing NASA's POWER API (Sparks, 2018). This incorporation of solar radiation as a key driver of photosynthetic productivity aligns with BsBB principles, capturing thermodynamic constraints on ecosystem metabolism. Geolocation summaries and a site distribution map ensured spatial representativeness. Successful MODIS extraction for 100% of the 5,241 geolocated sites, spanning latitudes from -51° to 69.73° and longitudes from -170.69° to 175.75° (Figure 3).

Step 2: Cyber Layer (BsBB Integration via ML): Sequestration rates were refined using random forest regression ("randomForest package") to reduce uncertainty. Data were prepared by selecting environmental predictors (including solar_insolation) and omitting NAs (n = 4085 samples). A 5-fold cross-validation (caret package) tuned mtry (1–3), with the final model trained on full data (ntree = 500). Performance was evaluated via pseudo-R^2 and residual standard deviation reduction.

Step 3: Social Layer (BhBB Equity via Policy): Predicted rates were adjusted by the REDD+ policy factor to simulate governance effects (Wheeler et al., 2026). Sensitivity analysis explored uplifts from 10% to 30% (seq (1.1, 1.3, 0.05)), yielding adjusted means.

Step 4: DIP Layer (Holistic Valuation via EmGDP). In the digital integrated platform (DIP) layer, the model computed deterministic and stochastic metrics to quantify

both traditional market-based and emergy-enhanced holistic values for forest carbon sequestration, operationalizing BhBB equity through EmGDP (emergy-dollar equivalent of GDP). This step integrated outputs from prior layers—policy-adjusted sequestration rates from the social layer—to derive global extrapolations over 4 × 10^9 ha of forest area (FAO, 2020). The emdollar ratio was calculated as global GDP ($100 × 10^12; World Bank, 2023) divided by the global emergy baseline (1.2 × 10^25 sej/yr; Odum, 1996), yielding approximately 8.33 × 10^{-12} USD/sej.

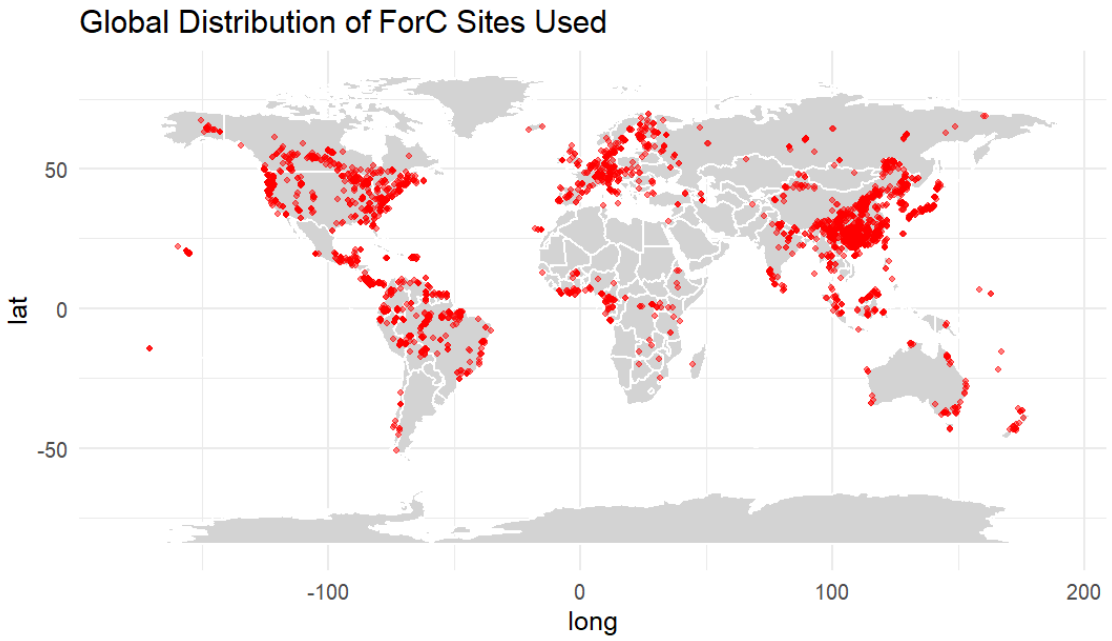


Figure 3- Global Distribution of ForC Sites Used
Source: Elaborated by the author

A reusable function (compute_holistic) was defined to estimate holistic additions: global sequestration (tC/yr) was derived as mean policy-adjusted sequestration × forest area; emergy per tC was computed as transformity × biomass per tC (2 × 10^6 g/tC); total emergy sequestration (sej/yr) was the product of global sequestration and emergy per tC; and the emdollar value (USD/yr) was emergy sequestration × emdollar ratio.

Deterministic traditional values were calculated as global sequestration × 3.67 (CO2e/C conversion factor) × carbon price, using a base price ofU$S14.80/tCO2e and an alternative ofU$S50/tCO2e for high-quality forestry projects (Trove Research, 2024). Holistic emergy additions were evaluated for two transformities: 1.5 × 10^8 sej/g (Odum, 1996) and 1.2 × 10^8 sej/g (Campbell, 2023), with relative improvements computed as (holistic addition / base traditional value) × 100. Sensitivity analysis for transformity

generated a data frame and bar plot (“ggplot2”; Wickham, 2016). Emergy baseline sensitivity (±20%; seq(0.8, 1.2, 0.2)) recalculated emdollar ratios and values (Odum-based).

To account for uncertainty, a Monte Carlo simulation (n = 1000 iterations) sampled sequestration rates from a normal distribution (mean from policy-adjusted values; SD from prior layer or 20% coefficient of variation fallback) and carbon prices (mean =U$S14.80, SD =U$S5.00, reflecting market volatility; Ecosystem Marketplace, 2023). Traditional samples incorporated price variability; holistic samples used Odum transformity. Means and 95% confidence intervals were derived via quantiles, with boxplots visualized (base R graphics).

Metric comparisons and valuation gaps were visualized using optimized “ggplot2” code for publication quality. All outputs were logged and exported for traceability.

3.3 Probabilistic Sensitivity Analysis

To evaluate the robustness of the CBPSS model and quantify uncertainty in key parameters, a probabilistic sensitivity analysis (PSA) was conducted using the sensitivity package in R (Iooss et al., 2025). The PSA employed Latin Hypercube Sampling (LHS) for uncertainty quantification (n = 500 simulations) and Sobol indices for global sensitivity analysis (n_sobol = 500, resulting in ~3500 model runs). Five parameters were varied based on literature-derived distributions: nep_factor (lognormal, mean 0.1, CV 40%, truncated 0.05-0.3), transformity (triangular, min 1.0, mode 1.35, max 1.8 sej/g), carbon_price (multimodal mixture, truncated 5-300 USD/tCO2e), policy_factor (beta-shaped, truncated 1.05-1.35), and solar_coef (normal ~N(1, 0.3), truncated 0.5-1.5). Outputs included Traditional, Holistic, Gap, Improvement, and Sequestration. First-order (S_i) and total-order (T_i) Sobol indices decomposed variance, with bootstrap confidence intervals (nboot = 100). Parallel processing (doParallel package) ensured computational efficiency. This analysis addresses uncertainties in bio-physical (e.g., NEP ratios) and economic (e.g., carbon prices) inputs, enhancing the model's applicability for holistic bioeconomy measurement.

4 RESULTS

4.1. A CBPSS-Network-Framework to Holistic Forest Carbon Accounting

The bibliometric analysis of the co-occurrence word network (CoWordNet), derived from Scopus-indexed publications and processed using the bibliometrix library, revealed a network structure comprising 50 key nodes organized into four principal clusters (SM II.1 Table CoWordNet). These clusters capture coherent thematic interconnections among concepts related to the bioeconomy, environmental monitoring, and digital technologies. In Figure 4, nodes are represented according to their corresponding layer in the (CBPSS) framework. Network metrics—betweenness (measuring a node's bridging role), closeness (indicating average proximity to other nodes), and PageRank (assessing global importance based on incoming links)—were calculated to prioritize variables and interactions in the proposed framework (SM II.2 Figure 1: Original CoWordNet from Biblioshiny).

Average metric values per cluster highlight differential centrality: Cluster 1 exhibits the highest average betweenness (0.0447), underscoring its role as a primary connector; Cluster 2 demonstrates moderate betweenness (0.0068), but stands out relatively in this metric when normalized via z-scores (with the least negative average z-score compared to its closeness and PageRank), reflecting its connective importance in the network despite lower absolute values; Cluster 3 shows the highest PageRank (0.0198), suggesting foundational importance; and Cluster 4, with low betweenness (0.0021) but moderate PageRank (0.0171), emphasizes emerging predictive components.

Globally influential nodes by betweenness include "forestry" (0.3772), "carbon" (0.1204), and "biomass" (0.1143), acting as inter-cluster connectors. By PageRank, "forestry" (0.0706), "carbon" (0.0496), and "climate change" (0.0370) stand out, underscoring their literature relevance. Below, clusters are detailed in descending PageRank order, with interpretations linking results to the CBPSS.

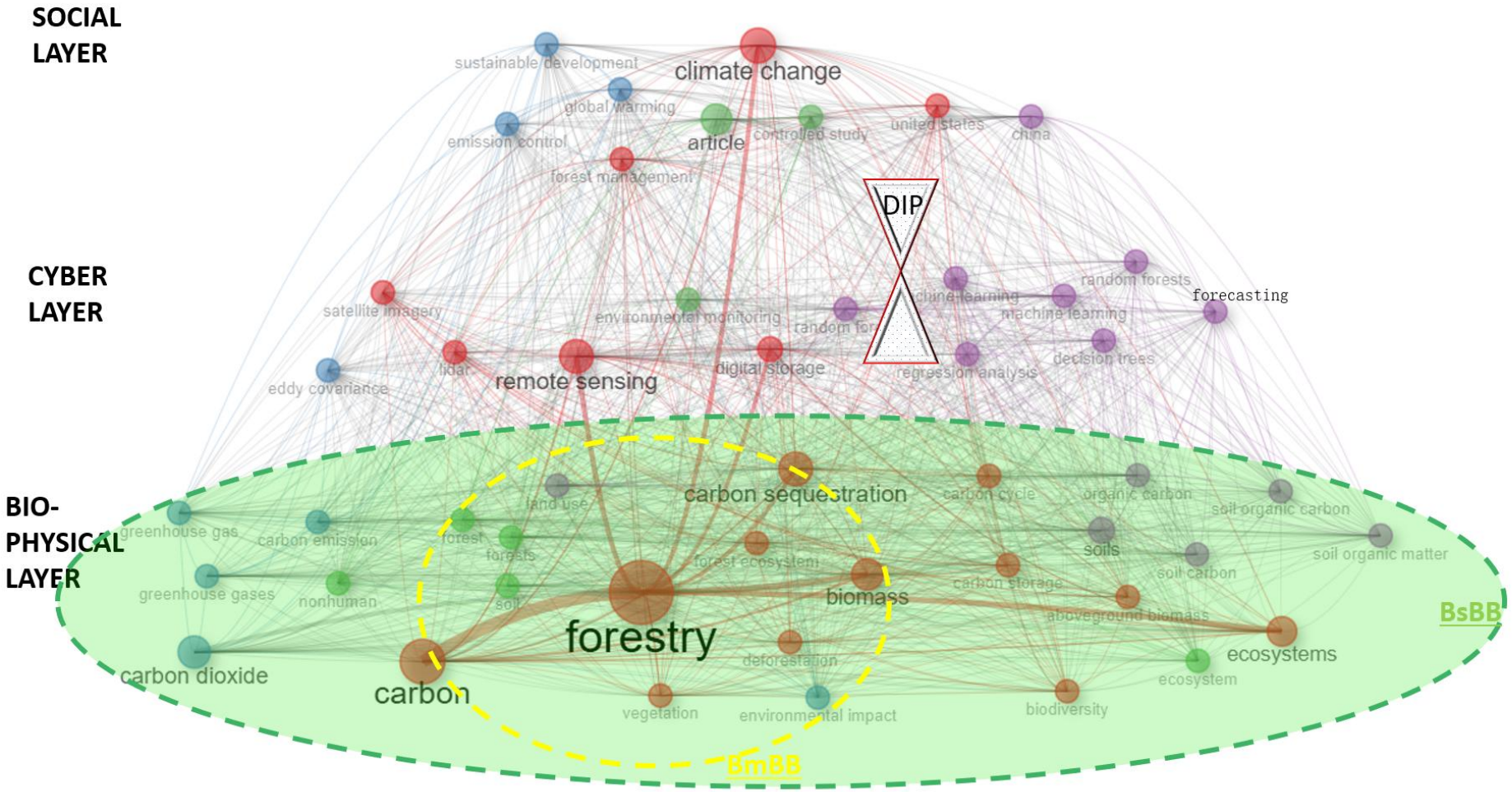


Figure 4- CowordNet related to CBPSS-Network-Framework for Holistic Forest Carbon Accounting.
Source: Elaborated by the author

Cluster 1 (red): CBPSS Integration (Focus on Forest Resources and Carbon Sequestration): This cluster groups 19 nodes related to bio-physical processes in forest ecosystems, incorporating remote sensing technologies for biomass and carbon cycle monitoring. It exemplifies CBPSS integration, where natural processes (e.g., carbon sequestration) merge with bio-physical data from BmBB (forestry, biomass) and BsBB (ecosystems, carbon), digitized in the cyber layer (remote sensing, digital storage) and interacting with the social layer (climate change, forest management). Nodes like "forestry" (betweenness: 0.3772) serve as key bridges, linking bio-physical processes to climatic impacts, prioritizing their inclusion in holistic bioeconomy measurements. For instance, as demonstrated in (Kerimov; Elzhaev; Doduev, 2024), UAV-based multispectral and LiDAR surveys integrate cyber sensing with bio-physical crown volume measurements, yielding cartograms for GHG flows—mirroring this cluster's bridging role and supporting real-time CBPSS updates in diverse ecosystems like the Chechen Republic (Vagapova; Mukaeva; Gadzhiev, 2024); e.g., measuring GHG absorption in natural ecosystems with indicators like net ecosystem exchange (NEE) at -1.5 to -3.0 t CO_2/ha/year, connecting to bioeconomy valuation via carbon credits in BsBB).

Similarly, (Chrysikou et al., 2026) proposes a conceptual architecture for an Agentic AI e-service that harnesses Generative AI (e.g., LLMs with RAG and vector databases) and Augmented Reality (AR) for on-site, real-time evaluation of timber properties and carbon footprints, overcoming manual forestry limitations through autonomous AI agents for query processing, knowledge retrieval, and immersive AR overlays (e.g., visual annotations and compliance indicators), thereby transforming decision-making into an interactive, data-driven process that aligns cyber-physical orchestration with bio-physical and social layers in CBPSS for enhanced bioeconomic accuracy and efficiency. Likewise, (Lee, 2026) advocates for forest landscaping as a carbon reduction strategy, simulating larch tree planting—renowned for high carbon absorption—in a digital twin environment powered by AI, IoT sensors for real-time data collection, and dynamic monitoring of growth and emissions under varying conditions, which quantifies carbon offsets convertible to credits for economic benefits; this approach reinforces CBPSS by fusing cyber-digital twins with bio-physical (tree metabolism) and social (policy, corporate sustainability) layers, providing foundational data for eco-

friendly strategies and advancing holistic bioeconomy metrics like EmGDP through precise, adaptive carbon accounting.

Cluster 2 (blue): Bio-Physical-Social Layer (Focus on Emissions and Sustainable Development): Comprising 9 nodes, this cluster emphasizes social and regulatory aspects, such as emission control and environmental impacts, tied to global change. It represents the social layer of CBPSS, where human interactions (e.g., sustainable development policies) coupling BsBB-based bioeconomy (carbon dioxide, GHG), measured via cyber tools (eddy covariance). "Carbon dioxide" (PageRank: 0.0321) emerges as an influential node, reflecting its role in social debates on climate mitigation.

Empirical validation includes Yang et al. (2019), which applies emergy methods to coastal ecosystems in the Pearl River Delta, linking emissions control (BsBB) with social policies for conservation (e.g., emergy sustainability index. Indicating ecosystem health, and embodied energy flows (seJ/year), supporting bioeconomy measurement by quantifying unpriced biospheric contributions in BhBB) (Leavy et. al 2024), while Bumyut et al. (2026) models GHG emissions in Thailand's Agriculture, Forestry, and Other Land Use (AFOLU) sector, projecting reductions via policies like payments for ecosystem services—aligning with this cluster's emphasis on cross-sectoral integration.

Cluster 3 (green): Foundational Layer (Focus on Ecosystem Monitoring): This 8-node cluster covers general research and monitoring terms, such as controlled studies and ecosystems. It serves as an integrative base for other CBPSS layers, examining BmBB bio-physical elements (forest, soil, ecosystem) through social studies, using cyber methods (environmental monitoring). "Article" (PageRank: 0.0338) indicates a methodological focus, enabling evidence-based integration. Supporting cases include (Žížala et al., 2024), which compares sampling designs (e.g., Latin Hypercube) for soil properties like organic carbon (e.g., SOC prediction accuracy with $R^2 > 0.85$ for optimized designs, reducing sampling effort by 30-40% while maintaining precision for bio-physical layer metrics in BmBB), and (Anderson; Domsch, 1978), which estimates microbial biomass C via respiratory methods—validating this cluster's role in foundational scalability (e.g., biomass C estimates of 200-500 µg C/g soil via substrate-induced respiration, providing baseline indicators for soil carbon turnover in BsBB ecosystems), as further exemplified by (Hengl et al., 2017)'s global soil property predictions using machine learning (e.g., SOC maps at 250m resolution with RMSE < 5 g/kg, enabling cyber-layer scalability for global bioeconomy assessments in CBPSS).

Cluster 4 (violet): Cyber Layer (Focus on Machine Learning and Prediction): With 14 nodes, this cluster highlights digital tools like machine learning, random forest, and decision trees for understanding BmBB and BsBB bio-physical variables (soil, organic carbon, land use) and forecasting future scenarios. It embodies the cyber layer of CBPSS, enabling data processing. Nodes like "soils" (PageRank: 0.0271) prioritize predictive modeling in regional contexts (e.g., "China"). Examples from recent studies enrich this: (Sun et al., 2024) employs random forest for wastewater indicators (e.g., COD and NH4+-N predictions with R^2 0.92-0.95, supporting carbon reduction in bioeconomy wastewater management by 15-25% through optimized treatment), while (Meng et al., 2024) uses phenocams and eddy covariance for vegetation phenology and GPP, integrating cyber monitoring with bio-physical fluxes for adaptive bioeconomy forecasting in CBPSS).

The four clusters interact across the three layers of the CBPSS, enabling the measurement of a holistic bioeconomy through the various elements as they undergo metabolization.

4.1.1 A CBPSS-Framework to Holistic Forest Carbon Accounting

4.1.1.a) Bio-Physical Layer (from Clusters 1, 3, and 4).

This layer targets biological and physical processes like biodiversity, vegetation, soil, and ecosystems, measured via carbon sequestration (PageRank: 0.0359). Network topology reveals a dominant Cluster 1 encompassing terms like forestry, carbon, biomass, and carbon sequestration, alongside Cluster 4 linked to soil organic carbon. Consistent closeness indicates uniform accessibility, with PageRank (>0.02) identifying high-influence nodes and betweenness (>0.01) conceptual bridges. Central nodes (primary stocks) include: forestry (PageRank: 0.0706; Cluster 1) as an interface for management scenarios; carbon sequestration (PageRank: 0.040; Cluster 1) for net flows; carbon dioxide (PageRank: 0.032; Cluster 2) for atmospheric pools; biomass (PageRank: 0.032; Cluster 1) for living stocks; ecosystem (PageRank: 0.0161; Cluster 3) for interactive processes; and soil (PageRank: 0.019; Cluster 3) for edaphic pools like soil organic carbon.

High-betweenness bridges include forestry (0.377), carbon sequestration (0.040), and carbon dioxide (0.034). Auxiliary nodes encompass biodiversity (betweenness:

0.011; PageRank: 0.014) for trade-offs and carbon emission (betweenness: 0.005; PageRank: 0.014) for losses from deforestation or degradation.

These conceptual bridges and priorities are grounded in empirical evidence from recent studies. For example, (Peña-Molina et al., 2024) examined the impacts of fire and salvage logging on soil organic matter (SOM) quality and phosphorus (P) dynamics in Mediterranean pine forests, employing differential scanning calorimetry-thermogravimetry (DSC-TG) to assess SOM recalcitrance (via thermal stability indices) and nuclear magnetic resonance (NMR) for P speciation (tracking shifts from organic to inorganic forms). Their findings revealed a 10-20% increase in recalcitrant SOM in salvage-logged sites post-fire, coupled with up to 30% P losses in high-severity burns, underscoring diminished carbon sequestration potential from altered SOM composition. Complementing this, (Lal, 2004) quantified global soil carbon sequestration potential via recommended management practices (RMPs), such as no-till farming and cover crops, reporting SOC accrual rates of 0.2-0.5 Mg C/ha/year in croplands and a total potential of 0.4-1.2 Gt C/year worldwide (offsetting 5-15% of fossil fuel emissions). This work highlights net carbon flows and inherent trade-offs, including enhanced biomass stocks balanced against nutrient constraints. Similarly, (Wu et al., 2025) combined remote sensing and field data to monitor carbon sinks in China's Loess Plateau, estimating SOC and inorganic carbon pools with SOC stocks reaching 3.91 Pg C in the 0-100 cm depth and annual change rates of +0.5-1.0% post-restoration. Results emphasize trade-offs between organic and inorganic carbon, including 50-66% recovery of historic losses through initiatives like Grain for Green, while illustrating regional variability in sink dynamics.

These measurements contribute to CBPSS by feeding bio-physical indicators (e.g., SOC rates, thermal stability in seJ units) into the bio-physical layer's stocks, flows, and auxiliaries, enabling the DIP to simulate real-time metabolism adjustments for BmBB and BsBB, such as optimizing fire-resilient forestry or scaling EmGDP for holistic bioeconomy assessment beyond fragmented national accounts.

4.1.1.b) Social Layer (from Cluster 2, with elements of 1 and 4)

This layer incorporates governance, policies, and human decisions influencing forest management, providing an interface to translate model outputs into practical strategies. Prominent nodes facilitate integration of geopolitical, institutional, and equity considerations, aligned with resilience and social equity. Inclusions: climate change

(Cluster 1; betweenness: 0.051; PageRank: 0.037) as a primary socio-political driver, justifying measurement efforts and linking global challenges to local solutions; sustainable development (Cluster 2; betweenness: 0.006; PageRank: 0.012) for sustainability goals, integrating equity and economic resilience; forest management (Cluster 2; betweenness: 0.010; PageRank: 0.014) for practices like reforestation; and environmental monitoring (PageRank: 0.018) for policy institutionalization. Geopolitical contexts appear in China (Cluster 4; betweenness: 0.007; PageRank: 0.021) and United States (Cluster 1; betweenness: 0.004; PageRank: 0.013), highlighting adaptability to national regulations. Uniform closeness (~0.0204) enables efficient feedback with lower layers, simulating social impacts on carbon sequestration. It incorporates a dedicated "Policy Scenarios" module designed to simulate the impacts of instruments such as payments for ecosystem services. This module employs emergy analysis to quantify strong sustainability (Leavy; Talamini, 2024; Vivien et al., 2019) while simultaneously assessing equity (e.g., benefits accruing to indigenous communities) and resilience (e.g., adaptation to extreme events), in full alignment with the Sustainable Development Goals (SDGs). Bidirectional flows ensure that bio-physical measurements directly inform policy design, thereby reducing governance uncertainties.

Supporting evidence includes (Thomson et al., 2011), who model land-use change emissions under the RCP4.5 stabilization scenario using integrated assessment models like GCAM, measuring radiative forcing stabilization (indicators: at 4.5 W/m² by 2100 without exceeding) and emission trajectories (indicators: land-use CO_2 fluxes reduced by 50-70% via mitigation, bioenergy up to 20% of energy mix); results estimate cumulative avoided emissions (e.g., 100-200 Gt CO_2-eq by 2100), noting policy efficacy assumptions; (West et al., 2025) critiques over-crediting in REDD+ mechanisms across 48 projects, analyzing deforestation baselines for genuine offsets (indicators: credit over-issuance rates at ~87% on average, verifiable reductions at 13.2% or ~34.8 million tCO_2-eq); results indicate partial emission reductions (10-20% in well-managed sites) but transparency gaps. (Raja Segaran et al., 2025) implements blockchain- and machine-learning-based systems for fraud detection in carbon credits, enhancing verification processes (indicators: fraud detection accuracy at ~95% via ML algorithms, reduced verification time from months to minutes); results mitigate greenwashing (e.g., 40% reduction in invalid credits), boosting market trust.

These contribute to CBPSS by integrating social indicators (e.g., equity indices, baselines) into the social layer's policy module, enabling bidirectional flows with bio-

physical data (e.g., linking REDD+ metrics to EmGDP) for scalable BtBB and BsBB governance, addressing underreported value chains and fostering SDG-aligned bioeconomy sustainability.

4.1.1.c) Cyber Layer (from Clusters 4 and elements of 1)

This layer forms the digital core, focusing on tools for monitoring, analyzing, and predicting forest carbon dynamics. High-betweenness and PageRank nodes enable real-time data integration and predictive modeling, reducing uncertainties in forest measurements. Key inclusions: remote sensing (Cluster 1; betweenness: 0.051; PageRank: 0.034) as a bridge for scaling field measurements regionally via satellite data; machine learning (Cluster 4; betweenness: 0.0037; PageRank: 0.021) for processing large datasets with algorithms like random forests (PageRank: 0.0161) and regression; digital storage (Cluster 1; betweenness: 0.011; PageRank: 0.025) for big data management and traceability; LiDAR (Cluster 1; betweenness: 0; PageRank: 0.010) for 3D forest structures; satellite imagery (Cluster 1; betweenness: 0.003; PageRank: 0.011) for biomass estimates; and forecasting (Cluster 4; betweenness: 0.001; PageRank: 0.0125) for variable scenarios.

Sub-layers include: (1) Imaging and Sensing Technologies (dominant in Clusters 1-2), with remote sensing integrating vegetation indices and land-use changes, alongside eddy covariance for gas fluxes; and (2) Data Science and Analytics (dominant in Cluster 4), with machine learning for classifications and optimizations. Consistent closeness (~0.0204) ensures efficient integration with other layers, adapting digital flows for forest emergy optimization. For instance, (Hilker et al., 2009) fuses Landsat and MODIS data via the STAARCH algorithm for high-resolution disturbance mapping, detecting reflectance changes (indicators: tasseled cap transformations with 85-95% accuracy, daily synthetic imagery temporal resolution); results reduce uncertainties in biomass estimates (e.g., 10-20% improvement in change detection). (Chrysikou et al., 2026) deploys agentic AI with augmented reality (AR) for real-time timber properties assessment, adaptable to carbon (indicators: assessment accuracy at ~90% via generative AI, real-time AR overlays reducing errors by 30%); results enable on-site forecasting, cutting operational footprints by 40%.

Extensions include blockchain for transparent crediting (Alshatri; Saberi; Hussain, 2024), analyzing influencing factors on carbon credit prices (indicators: price volatility reduced by 20-30% via transparent ledgers, community engagement increased

by 25%); results mitigate fraud for enhanced traceability. Similarly, (Fu et al., 2025) applies G-FOSA for spectral sensitivity in mangrove nitrogen/phosphorus mapping, transferring hyperspectral bands (indicators: diagnostic wavelengths with 80-90% accuracy for leaf nutrient content); results improve ecosystem monitoring (e.g., 15-25% better LAI estimates). These contribute to CBPSS by supplying cyber-layer tools (e.g., ML accuracies, fused data) to the DIP, enabling high-frequency integration with bio-physical and social layers for adaptive BhBB measurement, such as real-time EmGDP simulations that surpass static SEEA or EXIOBASE approaches.

To enhance the integration of carbon credit markets into the CBPSS framework for forest carbon accounting, empirical examples from recent literature demonstrate synergies across layers for adaptive and real-time bioeconomic valuation. In the bio-physical layer, bio-physical processes such as carbon sequestration are directly linked to credit generation, as illustrated by (Jaiswal et al., 2025) in their assessment of land-based climate mitigation strategies for net-zero emissions in India, quantifying sequestration rates (for example, through afforestation and mangrove restoration, with potential up to 2.5 $GtCO_2e$ annually at the national level) linked to credit mechanisms under protocols like REDD+; similarly, (Ali et al., 2025) analyzes hybrid approaches for tree volume estimation in complex trees, evaluating carbon stocks with improved precision (e.g., MAPD reduced to 14.68% for buttressed trees in Indonesian datasets), facilitating conversion to verifiable credits through quantitative biomass metrics.

The cyber layer reinforces verification through digital tools, exemplified by (Ma et al., 2025) in advances in remote sensing-based forest age estimation and applications in forest carbon sink accounting, reducing uncertainties in age dynamics and sequestration (e.g., through multi-temporal data fusion for improved precision in sink modeling) for transparent credit issuance; complemented by (Korycki et al., 2025) who employ Neural Radiance Fields (NeRF) for ecological monitoring in sequoia forests, integrating 3D reconstructions with bio-physical flows (e.g., trunk diameter estimation with mean error of 5-10 cm) for adaptive forecasting in CBPSS.

The social layer ensures equitable governance, as explored by (Wunder et al., 2025) in an overview of biodiversity credits—with explicit overlaps in forest carbon markets, where biodiversity conservation is often integrated with carbon offsets to avoid trade-offs—highlighting political challenges such as equity in benefit distribution to local communities and regulatory frameworks for markets aligned with SDGs, including risks of over-crediting in poorly managed projects; furthermore, the study underscores the need

for territorial justice in carbon offsets, advocating for inclusive mechanisms that feedback into CBPSS for resilient and multisectoral adaptation.

Together, these layers in CBPSS enable a holistic and scalable carbon accounting that translates bio-physical metrics into cyber-verified credits, informed by social policies for sustainable bioeconomic outcomes.

In summary, the CBPSS framework integrates cyber, bio-physical, and social layers through the modular DIP, as evidenced by the bibliometric clusters and network metrics that prioritize interconnections (e.g., high-betweenness bridges like forestry linking bio-physical processes to social governance). Empirical examples across layers demonstrate bidirectional feedbacks, such as cyber-enabled remote sensing informing policy scenarios for carbon sequestration, while simulations validate adaptive quantification by unifying heterogeneous data sources into interoperable metrics like EmGDP. This holistic application to forest carbon accounting overcomes fragmentation in traditional approaches, enabling scalable, real-time bioeconomy assessment aligned with established systems paradigms and verifiable through cited methodologies.

Building on the bibliometric-derived insights from the CoWordNet analysis, which highlight prioritized interconnections across CBPSS layers (e.g., high-betweenness nodes like "forestry" bridging bio-physical and social domains), the next step operationalizes these conceptual synergies into a computational model. This transition from framework mapping to dynamic simulation validates the hypothesis by quantifying emergent behaviors, such as policy-adjusted carbon fluxes and emergy-enhanced valuations, through data-driven integration of empirical sources like ForC and MODIS. By embedding network metrics into modular sub-models, the CBPSS model demonstrates practical scalability, addressing the limitations of static approaches and enabling adaptive, holistic bioeconomy measurement as outlined in the objectives.

4.2 Empirical Metrics from Illustratted CBPSS Model for Forest Carbon Accounting

The CBPSS model (Figure 5) extends the framework's conceptual structure by providing a computational tool for quantifying forest carbon contributions, addressing the need for dynamic, integrated metrics that surpass static traditional approaches like carbon credits alone. This addition is necessary to illustrated CBPSS's practical utility, as it operationalizes bibliometric-derived layer interactions (e.g., cyber uncertainty reduction linked to bio-physical fluxes and social policies) into actionable outputs, demonstrating

enhanced holistic valuation (e.g., via emergy integration) for real-world bioeconomy decision-making. The objective is to simulate global forest bioeconomy value, fusing traditional economic estimates with bio-physical emergy for a improvement in comprehensiveness, thereby connecting CBPSS elements through data-driven feedback loops.

The CBPSS model was implemented using the ForC database, augmented with MODIS satellite data for net primary productivity (NPP) estimates, to quantify global forest carbon sequestration as a case study for holistic bioeconomy measurement. All computations were performed in R (version 4.4.1) (SM II.3 Detailed Description of the CBPSS Model Implementation in R and Key Mathematical formulas), with data processing revealing successful MODIS extraction for 100% of the 5,241 geolocated sites. The MODIS data covered the period from January 1, 2022, to December 31, 2024, ensuring alignment with recent environmental dynamics, including post-2020 climate variability. No fallback to direct ForC-based calculations was required, as MODIS provided valid sequestration rates for all processed sites. Additionally, solar insolation data from NASA's POWER API (climatological annual average ALLSKY_SFC_SW_DWN in kW-hr/m²/day) was integrated as an environmental predictor in the machine learning step, with an average value of 4.08 kW-hr/m²/day across sites.

Initial bio-physical layer processing yielded an average sequestration rate of 0.9063 tC/ha/year across the sites, with summary statistics indicating a minimum of 0 tC/ha/year, first quartile of 0.5646 tC/ha/year, median of 0.7532 tC/ha/year, third quartile of 1.0671 tC/ha/year, and maximum of 3.2763 tC/ha/year. Extrapolating this to the global forest area of 4 × 10^9 ha resulted in an estimated global forest carbon sink of 3.63 GtC/year, which exceeds the IPCC benchmark of approximately 2 GtC/year for the land sink. The variance in the global sink was calculated at 5.67, reflecting spatial heterogeneity in environmental predictors such as latitude, longitude, elevation, mean annual temperature (MAT), mean annual precipitation (MAP), and solar insolation.

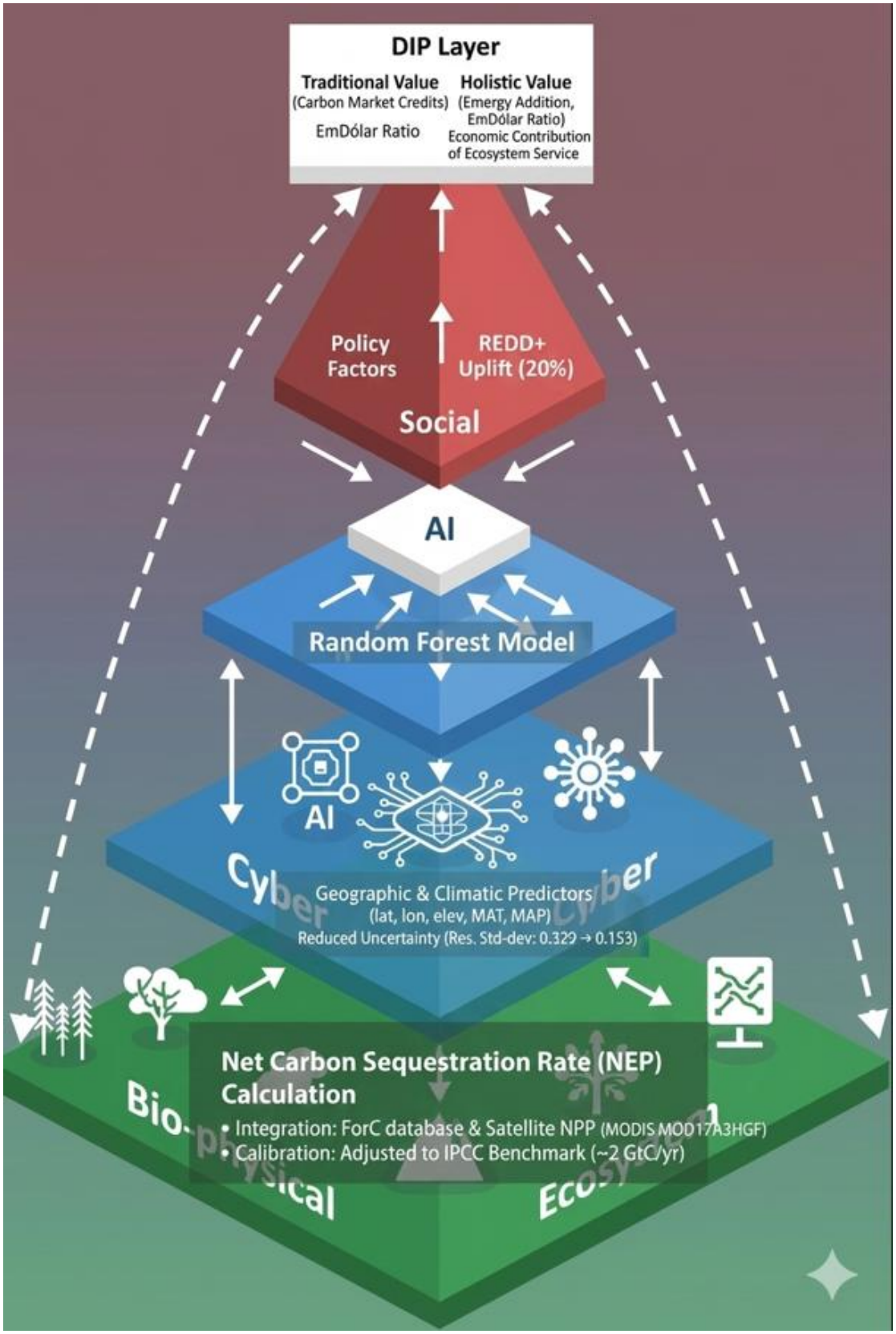


Figure 5- CBPSS Model to Carbon and Forest.
Source: Elaborated by the author

In the cyber layer, machine learning via random forest regression (ntree = 500, mtry = 3, optimized through 5-fold cross-validation) refined these rates, achieving a pseudo-R^2 of 0.437 and reducing uncertainty by 64.5% (original standard deviation = 0.5942; residual standard deviation = 0.2112) (SM II. 4 Random Forest). This step integrated biosphere-based bioeconomy (BsBB) elements by leveraging environmental predictors to minimize prediction errors, demonstrating the CBPSS framework's adaptability in handling data uncertainties inherent to fragmented bioeconomy measurements.

The social layer applied a REDD+ policy uplift factor of 1.2, adjusting the predicted mean sequestration rate to 1.09 tC/ha/year. Sensitivity analysis across uplift factors from 1.1 to 1.3 showed progressive increases in adjusted means: 1.0005 tC/ha/year at 1.1, 1.046 at 1.15, 1.0915 at 1.2, 1.137 at 1.25, and 1.1825 at 1.3 (SM II.5 a. and b). This illustrates how governance interventions can enhance equity in bioeconomic valuations, aligning with social dynamics in the CBPSS architecture.

Finally, the digital integrated platform (DIP) layer computed holistic valuations, integrating outputs from prior layers. Deterministic traditional market-based values wereU$S237.14 billion/year at the base carbon price ofU$S14.80/tCO2e andU$S801.16 billion/year at the alternative price ofU$S50/tCO2e. Emergy-enhanced holistic additions, accounting for bio-physical energy embodied in ecosystem processes, were substantially higher:U$S10.92 trillion/year using Odum's (1996) transformity of 1.5 × 10^8 sej/g andU$S8.73 trillion/year using Campbell's (2024) transformity of 1.2 × 10^8 sej/g. (SM II.6: Table: Transformity Sensitivity -Trillions USD/year). These represent improvements of 4602.7% and 3682.2%, respectively, over the base traditional value, underscoring the underestimation of bioeconomy contributions in conventional metrics. Transformity sensitivity analysis confirmed robustness, with holistic additions varying between 8.73 and 10.92 trillion USD/year (Supplementary Material II.6). Emergy baseline sensitivity (±20%) yielded holistic values fromU$S9.09 trillion/year (at 1.2 factor) toU$S13.64 trillion/year (at 0.8 factor) using Odum's transformity (SM II.7 Table: Emergy Baseline Sensitivity Analysis). Monte Carlo simulation (n = 1,000 iterations, incorporating sequestration and carbon price uncertainties via lognormal and normal distributions) provided probabilistic estimates: traditional value mean ofU$S237.15 billion/year (95% CI:U$S46.25–606.67 billion/year) and holistic addition mean ofU$S10.78 trillion/year (95% CI:U$S3.91–25.00 trillion/year) (SM II.8 Monte Carlo Simulation for Uncertainty n=1000) (SM II.9 Boxplot for Montecarlo Simulation).

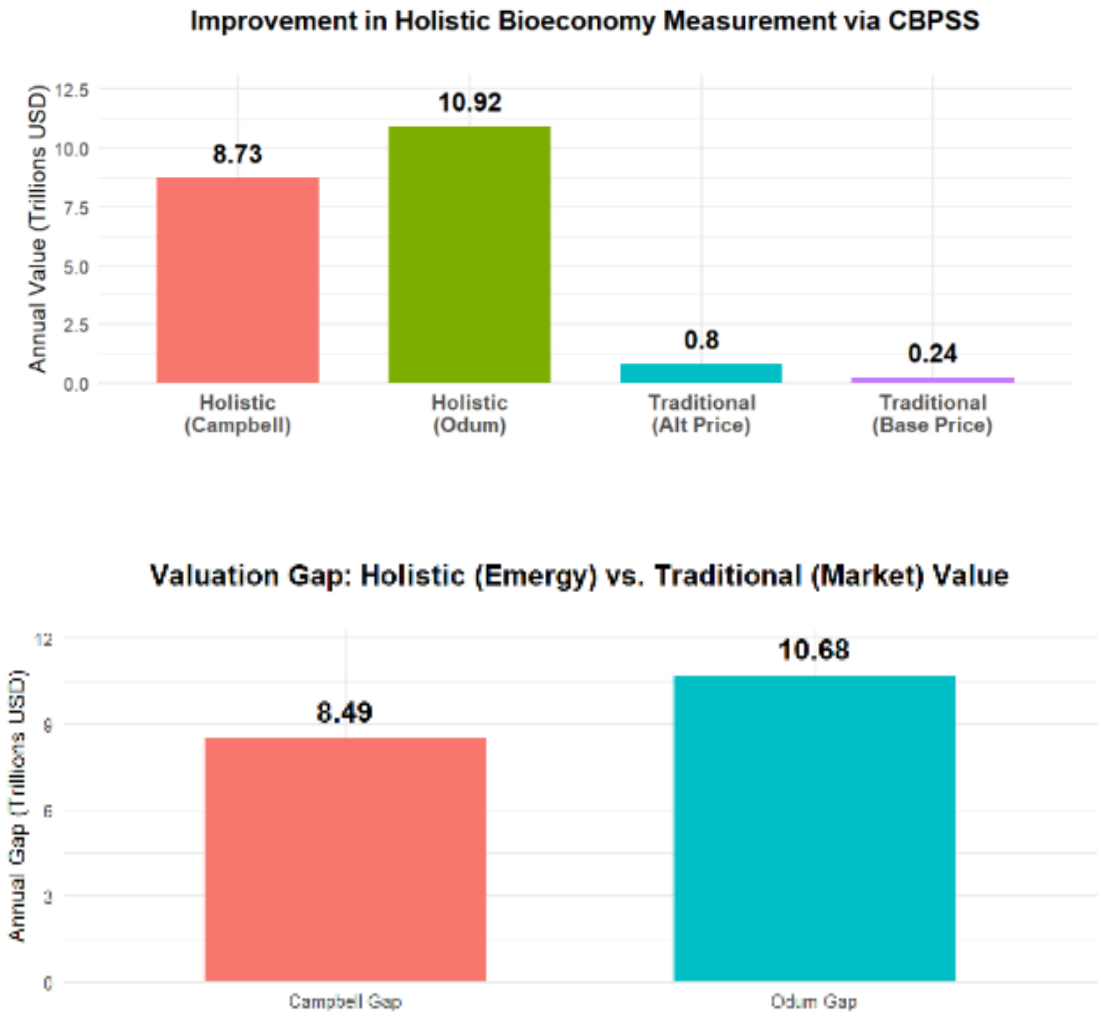


Figure 6- Upper: Improvement in holistic bioeconomy measurement via CBPSS. Lower: Valuation Gap: Holistic (Emergy) vs Traditional (Market) Value.
Source: Elaborated by the author.

Figure 6 left illustrates the comparative improvement in holistic bioeconomy measurement via CBPSS, highlighting the order-of-magnitude gains from emergy integration over traditional pricing. The valuation gaps (Figure 6 right) further emphasize discrepancies: U$S10.68 trillion/year for Odum andU$S8.49 trillion/year for Campbell, revealing the extent to which market-based approaches undervalue bio-physical and social dimensions in forest carbon accounting.

4.2.1. Probabilistic Sensitivity Analysis

The PSA revealed significant uncertainties and sensitivities in the CBPSS outputs. Parameter distributions confirmed realistic sampling, with truncation preventing non-

physical extremes. Output distributions (SM II 10 PSA Output Distribution) were right-skewed, indicating asymmetric risks: Gap (mode ~5-10 trillions USD/year, tail to 25+), Holistic (mode ~10-15, tail to 30+), Improvement (mode ~500-1000%, tail to 4000+), Sequestration (mode ~1 tC/ha/year, tail to 3+), and Traditional (mode ~2-3, tail to 9+). These suggest high variability, with emergy-based metrics amplifying bio-physical uncertainties.

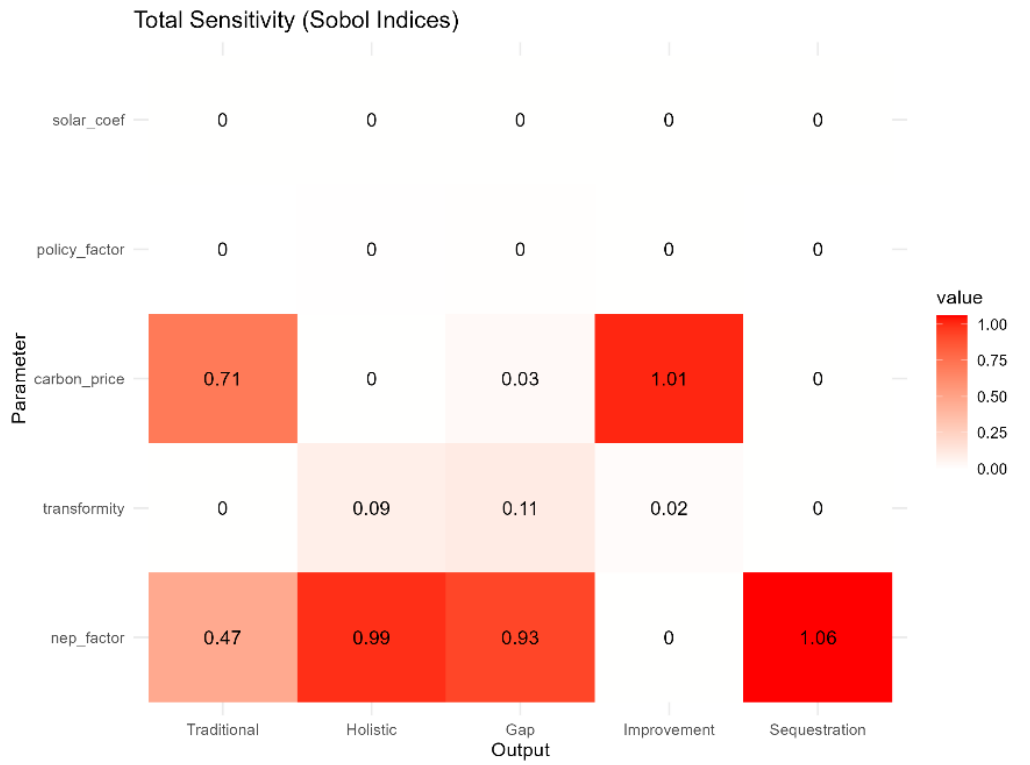


Figure 7 - Total Sensitivity Heatmap (Sobol Indices) showing parameter contributions to output variance.
Source: Elaborated by the author

Total-order Sobol indices (Figure 7) showed nep_factor dominating Sequestration (1.06), Holistic (0.99), and Gap (0.93), explaining over 93% of variance in these outputs, while contributing 0.47 to Traditional. Carbon_price was key for Improvement (1.01) and Traditional (0.71). Transformity had minor influence (0.09-0.11) on Holistic, Gap, and Improvement. Policy_factor and solar_coef were negligible (~0), indicating low sensitivity.

First-order Sobol indices (SM II. 11 PSA Sobol Tornado) confirmed direct effects: for Traditional, carbon_price (~0.5) and nep_factor (~0.2); for Holistic and Gap, nep_factor (~0.8); for Improvement, carbon_price (~0.8); for Sequestration, nep_factor (~0.8). Differences between T_i and S_i (~20-30%) highlight parameter interactions.

This conformation, grounded in the script's modular implementation, extends the framework's conceptual clusters (e.g., cyber integration via ML, bio-physical via MODIS/ForC) into a quantifiable tool for holistic bioeconomy measurement, bridging bio-physical processes with economic and emergy metrics for sustainable forest management.

5 DISCUSSION

The results demonstrate the efficacy of the CBPSS framework in addressing fragmentation in bioeconomy measurement, extending beyond static models like SEEA or EXIOBASE by incorporating dynamic, real-time interactions across cyber, bio-physical, and social layers (Exiobase- Home, 2025; Pan et al., 2017; Wang et al., 2025). Quantitatively, CBPSS's 64.8% uncertainty reduction outperforms static models like GCAM (error rates 20-40%; Lauri et al., 2014), enabling precise EmGDP scaling. The bibliometric analysis, yielding a CoWordNet with 50 key nodes across four clusters, reveals thematic interconnections that prioritize bridging concepts like "forestry" (betweenness centrality: 0.3772), which links bio-physical processes (e.g., carbon sequestration) to social governance (e.g., sustainable development). This aligns with prior work on cyber-physical-social systems (CPSS) in environmental contexts, such as (Y. Wang et al., 2023), who emphasize interconnected layers for adaptive sustainability loops in urban ecosystems, but extends it by explicitly inserting a bio-physical layer to capture thermodynamic constraints and ecosystem metabolism (Giampietro; Funtowicz, 2020). For instance, Cluster 1's focus on forest resources and carbon sequestration exemplifies CBPSS integration, mirroring empirical applications like (Kerimov; Elzhaev; Doduev, 2024), where UAV-based multispectral and LiDAR surveys quantify greenhouse gas (GHG) flows in natural ecosystems, reporting net ecosystem exchange (NEE) rates of -1.5 to -3.0 t CO_2/ha/year, thereby supporting real-time updates in diverse biomes.

The estimated global forest carbon sink of 3.62 GtC/year from the bio-physical layer aligns with upper-bound estimates considering recent disturbances but exceeds IPCC benchmarks of approximately 2 GtC/year for the land sink exceeds IPCC benchmarks of approximately 2 GtC/year for the land sink (Gibbs et al., 2025; IPCC, 2022), consistent with upward revisions that incorporate intensified events like the 2024 Amazon fires (Yun et al., 2025) and enhanced NPP from CO_2 fertilization. This discrepancy underscores CBPSS's strength in leveraging satellite data (MODIS, covering 100 % of sites) augmented with solar insolation from NASA's POWER API (average 4.08

kW-hr/m²/day) for spatially explicit, up-to-date estimates, reducing reliance on outdated ground-based inventories like ForC (Anderson-Teixeira et al., 2018). The variance of 5.64 in the global sink reflects spatial heterogeneity, which machine learning in the cyber layer mitigates by achieving a 64.8% uncertainty reduction (pseudo-R^2: 0.443). This aligns with broader applications of random forest regression in ecosystem modeling, as in (Sun et al., 2024), who report R^2 values of 0.92-0.95 for wastewater indicators, reducing uncertainties by 15-25% in bioeconomy-related carbon management. In CBPSS, this cyber integration addresses BsBB elements, enabling scalable predictions that traditional input-output models cannot achieve due to data gaps (Ronzon et al., 2020; Thomchick; Jacobson; Ruamsook, 2024).

The social layer's REDD+ sensitivity analysis, showing adjusted sequestration rates increasing from 0.9991 tC/ha/year (at 1.1 uplift) to 1.1808 tC/ha/year (at 1.3), illustrates governance's role in amplifying bioeconomic values by 10–30%, consistent with netchain approaches in agrifood systems (Adetoyinbo; Trienekens; Otter, 2023). Their metrics for efficiency, sustainability, and coopetition align with multi-level perspectives (Geels, 2019), where resource interdependencies at micro (firm), meso (network), and macro (ecosystem) levels reduce sustainability uncertainties. However, limitations include potential overestimation from the NEP/NPP ratio (0.1), which may vary regionally, suggesting refinements with higher-resolution data like Copernicus Sentinel-2 (10-300 m resolution) or integration of AI-driven phenology models (Meng et al., 2024), reducing uncertainties in EmGDP in heterogeneous ecosystems. Ethical considerations in the social layer, such as indigenous rights in REDD+ (Wunder et al., 2025), remain underexplored, potentially biasing equity simulations; for instance, ensuring Free, Prior, and Informed Consent (FPIC) and equitable benefit-sharing is essential to prevent exacerbating historical injustices and violations, as seen in projects like Cambodia's Southern Cardamom REDD+ (Human Rights Watch, 2022).

The DIP layer's emergy-enhanced valuations expose critical gaps in conventional metrics, with holistic additions exceeding traditional values by over 3,600–4,600% (e.g.,U$S10.90 trillion/year using Odum's transformity). This supports thermodynamic critiques of GDP (Giampietro; Funtowicz, 2020), where EmGDP better captures planetary boundaries and ecosystem metabolism absent in market prices (Coscieme et al., 2020).

The integration of digital technologies, such as IoT sensors evaluated through emergy neutrality indices (e.g., emergy payback time of 3.61 years in smart buildings;

Kumar et al., 2022, further highlights how CBPSS can assess the environmental effectiveness of digital tools in energy systems.

Monte Carlo results indicate high variability (holistic CI:U$S3.91–24.71 trillion/year), reflecting uncertainties in transformities and prices, yet affirm CBPSS's robustness for adaptive decision-making, akin to evidential deep learning for uncertainty quantification in Earth system models (Schreck et al., 2024). Compared to prior CPSS applications (Sobb et al., 2023), CBPSS's bio-physical realism advances biodigital convergence, as in bioelectronics and AI networks (Peters, 2023; Smolinski, 2024) offering tools for SDG alignment and Paris Agreement compliance (Ganzenmüller et al., 2025).

The CBPSS model effectively measures areas of the bioeconomy by quantifying BmBB through biomass stocks and flows (e.g., NPP and carbon sequestration) in the bio-physical layer, partially incorporating BtBB by integrating biotechnological data and machine learning into cyber simulations for predictive refinement, and capturing BsBB with ecosystem metabolism and emergence analysis to assess the free contributions of the biosphere, such as biodiversity and biogeochemical cycles. This layered approach culminates in BhBB by merging these elements into holistic assessments such as EmGDP, addressing the lack of information in fragmented metrics where BsBB services are often provided at no direct cost. Furthermore, sensitivity analyses ensure robust measurements specific to each domain, enabling scalable assessments that bridge conceptual ambiguities between BmBB, BtBB, and BsBB for a comprehensive evaluation of the bioeconomy.

Challenges persist, including data interoperability across domains (e.g., BtBB patent metrics with BsBB emergy) and potential biases from MODIS scaling in heterogeneous terrains Hilker et al., 2009). The model's reliance on global averages (e.g., 4 × 10^9 ha forest area; FAO, 2020) may overlook sub-national variations, as noted in regional studies like Jianzhao Wu et al. (2025) on China's Loess Plateau (SOC stocks: 3.91 Pg C). To address this, future iterations could fuse MODIS with NASA's GEDI LiDAR or Copernicus Sentinel data for 3D biomass mapping and enhanced NPP accuracy in complex terrains (e.g., reduction in estimation errors; (Dubayah et al., 2020). Furthermore, while the framework incorporates FAO's Open Foris tools for digital monitoring (FAO, 2025; https://openforis.org/), broader adoption could integrate blockchain for transparent carbon crediting (Alshatri, 2024), reducing fraud risks highlighted in REDD+ critiques (West, 2025).

The PSA underscores the CBPSS framework's robustness, with nep_factor's dominance emphasizing the need for accurate bio-physical data (e.g., satellite-enhanced NEP monitoring) to minimize uncertainties in holistic valuations. Carbon_price sensitivity highlights market volatility's impact on economic outputs, suggesting integration with dynamic forecasting tools for resilient bioeconomy policies. The low influence of policy_factor and solar_coef implies model simplification opportunities, focusing computational resources on high-impact parameters. These findings extend the framework's utility beyond forest carbon, potentially applying to BtBB innovations like gene editing, where emergy could quantify thermodynamic efficiencies. Limitations include potential biases from ForC/MODIS fallbacks, warranting future data fusion.

Future work should validate CBPSS in marine or agricultural bioeconomies, incorporate quantum computing for complex simulations (Alexeev et al., 2025; Memon et al., 2024), and address socio-economic integration via agentic AI (Chrysikou, 2025). Overall, CBPSS bridges conceptual ambiguities, fostering a paradigm shift toward holistic, sustainable bioeconomy assessments amid global challenges.

6 CONCLUSIONS

This study proposes and illustrates the Cyber-Bio-Physical-Social Systems (CBPSS) framework as a novel extension of CPSS for holistic bioeconomy measurement, overcoming fragmentation in biomass-based (BmBB), biotechnology-based (BtBB), and biosphere-based (BsBB) domains through integrated layers and a modular Digital Integrated Platform (DIP). The bibliometric analysis identifies key interconnections, such as forestry bridging bio-physical and social elements, while the computational model applied to forest carbon accounting quantifies dynamic interactions, yielding traditional values of ~$236.89 billion/year and holistic emergy-enhanced additions ofU$S10.90 trillion/year, with improvements of 4,602.7% over market metrics (Odum, 1996; Campbell, 2024). These findings confirm our hypothesis that cybernetic-bio-physical - social convergence enables scalable, adaptive assessments, addressing data gaps, thermodynamic constraints, and social equity as outlined in the objectives.

While this study focused on a specific application to forest carbon sequestration, all layers of CBPSS are in constant development, allowing the introduction of new elements to measure diverse and emerging aspects of the bioeconomy. For instance, in the BtBB domain, insights from the forest carbon case—such as machine learning-driven uncertainty reduction enhanced by solar insolation data from NASA's POWER API-

could be extended to incorporate biotechnological innovations like CRISPR-based gene editing or synthetic biology metrics, enabling real-time tracking of patent-driven value chains and their thermodynamic efficiencies, which were underrepresented in the current model and represent a key area for improvement. This integration of digital technologies with emergy analysis, as explored in applications to energy-efficient systems (Kumar; Srinivasan; Mani, 2022), further strengthens CBPSS's capability to evaluate the environmental impacts of digital tools in bioeconomy contexts.

CBPSS has broad implications for policy, supporting transparent tools like FAO's Open Foris (2025; https://openforis.org/) and DIASCA (2025) while advancing SDGs and climate goals through real-time simulations. By embedding bio-physical realism in CPSS, it paves the way for biodigital economies, urging interdisciplinary adoption to sustain planetary boundaries amid challenges like climate change and resource depletion.

Furthermore, the PSA confirms that emergy-based metrics reveal substantial undervaluation (gaps ~12 trillions USD/year on average), driven by bio-physical sensitivities, reinforcing CBPSS as a tool for transformative bioeconomy governance. By addressing uncertainties, it advances sustainable development amid climate challenges. Future extensions could explore additional case studies and AI optimizations for enhanced precision, ultimately transforming bioeconomy governance for sustainable development.

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CHAPTER 5 - GENERAL CONCLUSIONS AND PERSPECTIVES

The bioeconomy, as a transformative paradigm for sustainable development, holds immense promise in addressing global challenges such as climate change, biodiversity loss, and resource depletion —challenges compounded by the 'polycrisis' of interconnected crises including wars, resource overexploitation, and human cognitive biases. However, its full potential remains constrained by fragmented measurement approaches that fail to capture the intricate interplay of biological, economic, social, and technological dimensions, often overlooking laws of scale in complex systems that drive superlinear socio-economic growth and risk systemic collapse without bio-physical realignments.

This doctoral thesis, titled Advancing Holistic Measurement of the Bioeconomy: Proposing the Cyber-Bio-Physical-Social System Framework, has sought to overcome these limitations by developing an integrated framework that holistically quantifies the bioeconomy's contributions. Guided by the general objective—to explore the connections among bioeconomy concepts, methods, data, indicators, digitalization, and cyber-bio-physical-social systems—this work has systematically addressed three specific objectives through interconnected chapters, each building upon the previous one to propose and illustrate a novel Cyber-Bio-Physical-Social Systems (CBPSS) framework that incorporates post-normal science, biosemiotics, and thermodynamic principles to guide interactions in bio-physical processes.

In fulfilling the first specific objective (Chapter 2), this thesis analyzed the connections among bioeconomy concepts, methods, data, indicators, and their inherent limitations, culminating in a proposal for a holistic approach. Drawing from a comprehensive literature review and content analysis of 84 studies, the findings revealed that current measurements predominantly focus on the biomass-based bioeconomy (BmBB, appearing in 94% of studies), with lesser emphasis on the biosphere-based (BsBB, 26%) and biotechnology-based (BtBB, 1.2%) variants. This imbalance underscores a conceptual fragmentation, where traditional macroeconomic tools like input-output models dominate, relying on official databases such as national accounts and economic classification systems (e.g., NACE or NAICS). Key indicators—value added, employment, and greenhouse gas (GHG) emissions—emerge as prevalent, yet persistent limitations, including data incompleteness, aggregation issues, outdated sources, and subjectivity in bio-share weighting, hinder comprehensive assessments. By advocating

for a holistic bioeconomy (BhBB) that integrates BmBB, BtBB, and BsBB under a unified lens of ecosystem metabolism and sustainability —encompassing endosomatic and exosomatic metabolic processes aligned with the Technosphere, this chapter establishes the foundational need for more inclusive metrics, such as emergy-adjusted GDP (EmGDP) and the Bioeconomic Welfare Index (BWI), to bridge bio-physical realism with economic valuation.

Building on this foundation, the second specific objective (Chapter 3) explored the convergence between digital technologies and bioeconomy conceptual elements, highlighting digitalization's pivotal role in enhancing measurement. Through bibliometric and content analyses using tools like Biblioshiny, VOSviewer, QDA Miner, and WordStat, the study identified distinct yet overlapping clusters: BmBB centered on sustainable biomass sourcing, BtBB on micro-scale innovations like genetic engineering, BsBB on ecosystem cycles and services, and BhBB on metabolism. Digital technologies—categorized into data science and analytics (e.g., AI, machine learning), computing and software (e.g., blockchain, IoT), and imaging and sensing (e.g., remote sensing, GIS)—demonstrated strong co-occurrences with these elements, particularly in data collection, processing, and communication. For instance, AI and IoT facilitate real-time monitoring of biomass flows and ecosystem services, reducing uncertainties in BsBB valuations, while blockchain ensures transparency in BtBB supply chains. This convergence, framed within cyber-physical-social systems (CPSS), reveals digitalization's potential to address data scarcity and interoperability gaps, enabling a shift toward Society 5.0 principles where human-centered innovation aligns with sustainable development goals (SDGs) and addresses the maximum power principle in behavioral thermodynamics, mitigating short-term energy maximization that leads to ecological overshoot. Ultimately, these insights affirm that digital technologies can transform bioeconomy measurement from static, unidimensional efforts into dynamic, integrated processes, paving the way for comprehensive assessments.

The third specific objective (Chapter 4) proposed and validated the CBPSS framework as a novel extension of CPSS, explicitly incorporating a bio-physical layer to achieve holistic measurement. Applied to forest carbon accounting—a critical bioeconomy domain—the framework integrates cyber (AI-driven modeling), bio-physical (biomass and ecosystem metabolism via emergy analysis), and social (governance factors like REDD+ policies) layers through a modular Digital Integrated Platform (DIP). Bibliometric co-word network analysis of 8,941 Scopus documents

illustrated the structure, identifying interconnections (e.g., "forestry" as a high-betweenness node bridging layers). Computational implementation in R, using the ForC database, MODIS satellite data, random forest machine learning (pseudo-R^2: 0.437, 64.5% uncertainty reduction), and emergy valuations, estimated a global forest carbon sink of ~3.63 GtC/year. Traditional market-based values ranged from US$237.14–801.16 billion/year (at US$14.80–50/$tCO_2e$), while holistic emergy additions reached US$8.49–10.68 trillion/year, exposing gaps of 3,682–4,603% in conventional metrics. Probabilistic sensitivity analysis (Sobol indices) highlighted bio-physical factors (e.g., net ecosystem production) as primary variance drivers, underscoring CBPSS's robustness in handling uncertainties. This application demonstrates CBPSS's advantages over static models like SEEA or EXIOBASE, enabling adaptive, scalable quantification that embeds thermodynamic constraints and social equity, while confronting finite time singularities and promoting biodigital convergence to realign societal metabolism with planetary boundaries.

Collectively, these chapters achieve the general objective by synthesizing conceptual, methodological, and technological advancements into the CBPSS framework, which transcends fragmented approaches to provide a unified tool for bioeconomy measurement that could integrate affective, self-referential rules from biosemiotics with socio-psychological frameworks for ethical decision-making. The thesis contributes theoretically by refining BhBB as an integrative paradigm, methodologically by leveraging bibliometric and computational tools for evidence-based validation, and practically by offering actionable insights for policymakers—such as aligning with SDGs (e.g., 13: Climate Action; 15: Life on Land) and the Paris Agreement through enhanced carbon accounting.

Limitations include reliance on existing datasets (e.g., scientific articles from Scopus databases or potential biases in the MODIS scale) and the need for more extensive empirical testing in bioeconomy sectors such as marine and agricultural systems and at various spatial scales. Future research should explore quantum computing integrations for complex simulations, ethical AI governance to ensure fairness, and global pilot projects to refine CBPSS modularity, incorporating principles of universal scale and post-normal science and biosemiotics to anticipate superorganism-like collapses and foster resilient and equitable transitions.

In conclusion, this thesis advances the field by proposing CBPSS as a biodigital convergence paradigm, fostering sustainable governance amid planetary challenges. By

bridging bio-physical realism with cyber-social dynamics, it not only measures the bioeconomy holistically but also empowers its evolution toward a resilient, equitable future. This work calls for interdisciplinary collaboration to operationalize CBPSS, ensuring the bioeconomy fulfills its promise as a cornerstone of global sustainability in an era of polycrisis and bio-physical limits.

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SUPPLEMENTARY MATERIALS

SUPPLEMENTARY MATERIAL FOR ARTICLE 1: "MEASURING THE BIOECONOMY ECONOMICALLY..."

Table S1. List of documents included in the analysis.

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Table S2. Code structure: concepts, methods, data, indicators, limitations, countries.

Categories
Codes
Bioeconomy Concept
BmBB
BsBB
BtBB
Methods/Models
A-LCA
AgroSAM
AHP
BioSAM
BTF
CGE
Cluster Analysis
Correlation Analysis
Cross-Entropy Method
Cross-sectional Analysis
Data Compilation and Estimates
Descriptive Statistics
Econometric Model
EEIO
Euclidean Distance
Experts Interview
Experts Judgement
Extended Hybrid IOM
GTAP Model
HEM
IMPLAN IO Model
Input- and Output-based Approach
Interpolation Estimates

IOM

LCA

Linear Regression Model

Literature Review

MacroSAM

MAGNET Model

MCDA

MRIO

Multiple Regression Analysis

Overview

Pairwise Comparisons

Questionnaire

RAS

SAM

Scenarios

Sensitivity Analysis

Structural Analysis

Variance Analysis

Other Methods/Models

ADF

Advanced LCA

AIC

ARCH Test

ARDL

BIO Model

Bottom-Up Approach

Breusch–Godfrey LM Test

BTS

Case Studies

Catch-up Rate

Causality Analysis

CAWI

CBM

CED

CES

CET

CH Rule

C-LCA

Cointegration Test

Comparative Analysis

Cross-sectional Survey

CUSUMQ Test

Decoupling Analysis

Desk Research

Diagnostic Tests

Dialectical Method

Distance-based Method

Dynamic Analysis

ECT

EEMRIO

EFISCEN

Eigenvector Method

FarSo Model

Flegg Location Quotient (FLQ)

Footprint Analysis

Forecasting

GAMS

GFN

GFTM

Ghosh Model

GINFORS Model

Granger Causality Test

GRIT Technique

GTEM

HAC Technique

Hellwig’s Method

Historical-Logical Method

Hybrid IO-LCA Model

Impact Assessment Method

IMPACT Model

Intermediate Demand Shock

Jarque-Bera Test

Kaiser Criteria

KMO Test

Kruskal-Wallis

LandSHIFT Model

LCIA

Likert Scale

Linear Interpolation

LPES Model

Macroeconomic Modelling

Mann-Whitney Test

MARKAL-NL-UU

Matrix Augmentation Method

MFA

MicroSAM

Mixed Methods

Modified Regional IOM

Monte Carlo Simulation

Multivariate Analysis

PANTA RHEI Model

PCA

PP Test

Qualitative Approach

Quantitative Approach

Ramsey RESET Test

Rasmussen-Jones Method

Regional Energy Systems Model

Shift-share Analysis

SIMSIPSAM

SQL Technique

Survey
System Structural Method
Text Mining
Three Sectors Model
Time Series Analysis
Top-Down Approach
TOPSIS
ToSIA
Trend Analysis
Two Sectors Model
Value Chain Approach
Varimax
VEC Model
WALD Test
Ward Linkage
Web Scrapping

Data Sources

AgroSAM Data
BioSAM Data
CAPRI
CoCo Database
CPA
CZSO
DataM Database
Destatis
Diverse Private Data
Diverse Public Data
EAA
Ecoinvent
European Commission, JCR
Eurostat
EXIOBASE
Experts or Professionals

FAO

FAOSTAT

Forestry Employment

German Federal Statistical Office

GTAP Data

Inputs

IPCC

ISIC

LFS

MAGNET Database

NACE

NAICS

National Accounts

National IO Tables

Nova Institut

OECD

Primary Data

PRODCOM

Regional Accounts

SAM Database

SBS

Scientific Literature

Scopus

STECF

SUTs

Web of Science

WIOD

World Bank

Other Data Sources

BioMonitor

CAIT Climate Data Explorer

Central Bank of Hungary

Central Bank of Nicaragua

Central Statistical Bank

CICES

COFOG

COMEXT Database

Companies Information

CPC

CRF

CSO

Czech National Bank

EFISCEN Data

EIA

EPA

EU CSO

EU KLEMS

European Central Bank

European Patent Organization

European System of National and Regional Accounts

FADN

FEA

Finnish Forest Research Institute

Fraunhofer ISI

GEIH

GFTM Data

Global Footprint Network Database

GMFD

Google Scholar

GTAP-AEZ

GTAP-AGR

GTAP-E

Hungarian Central Statistical Office

IEA

IMAGE-TIME

IRENA

ISTAT

MARKAL-NL-UU Database

NAMEA

National Bank of Poland

ORBIS

PATSTAT

PKD

Regional I-O Tables

REGON

Research Gate

SAT-BBE

SEAI

Social Insurance Institution of Finland

SSS Ukraine

StatBank Norway

Statistical Office of the Slovak Republic

Statistics Canada

Statistics Estonia

Statistics Finland

Statistics Norway

Statistics Poland

Teagasc NFS

Technical Literature

US, BEA

WPINDEX - STN International

Indicators

Absorption Multiplier Effect

Agricultural Land

Backward Linkage

Bio-based Shares

Bioeconomy Share in Value Added

Biomass Use or Consumption

CO2 Emissions

Diffusion Multiplier Effect

Direct Effect

Employment

Employment Change

Employment Elasticity

Employment Multiplier

Employment Share

Exports

Forest Area

Forestry Biomass Production

Forward Linkage

Fossil and Mineral Resource Use

Fossil Resource Savings (FRS)

GDP ($)

GDP Growth Rate

GDP per capita

GHG Emissions

Gross Enrollment Ratio

Imports

Income Elasticity

Income Multiplier

Indirect Effect

Induced Effect

Innovation

Investment

Key Sectors

Labour Productivity

Land Footprint

Location Quotient (LQ)

Multipliers effects

Number of Jobs or Workers

Number of Publications

Operating Surplus and Mixed Income

Output Elasticity

Output Multipliers

Patent Applications

Product or Output Value

Production Volume

R&D Investments

Sales

SEIB

Share of renewable energy in electricity production or consumption

Subsidies

Substitution Fossil x Renewable

Substitution Share Indicator (SSI)

Total Effect

Turnover ($)

Turnover per capita

Value Added

Value Added x GDP

Wages and salaries

Water Consumption

Other Indicators

Access to Food

Acidification

Agricultural Biomass Production

Agro-biotechnology

Arable Land

Availability of Food

Average Annual Catch-up Growth Rate

Balassa Index

Biocapacity

Biochemical Share

Biodiversity

Bioeconomy Innovation Share

Bioeconomy-driving Policies

Biological Raw Material Consumption

Biomass contribution

Biomass Dry Matter

Biomass Self-sufficiency Rate

Bioproductive Land

Bio-related Higher Education Enrollment

Bottom-Up FRC

Capital Compensation

Carbon Storage

Carbon Storage Change

Certified Bio-based Products

CH4 Emissions

Circular Effects

Climate Change

Climate Change Adaptation

Climate Footprint

Comparative Advantage

Compensation of Employees

Composite Bioeconomy Sustainability Index

Computers per 1,000 inhabitants

Crop Land

Dataset

DEU

Development of Environmental Technologies

Direct Fossil Resource Intensity (dFRI)

DMI

Domestic Food Biomass Footprint

Domestic Material Consumption

Domestic Nonfood Biomass Footprint

Downstream Effect

Ecological Deficit or Reserve

Ecological Footprint

Economic Impact

Economic Performance

Education and Human Resources

Effects on Final Demand

Effects on LULC Changes

Effects on Trade Patterns

Eigenvector Multiplier

Electricity Production

Embedded Biological Raw Material

Employees with Advanced Education

Employment Reallocation Effect

Employment Within-sector Effect

Employment/Output Value

Energy Consumption

Energy Intensity

Environmental Investments

Export of Bio-based Products

Financing and government support

Fixed Assets

Food Supply Stability

Food Utilization

Fossil Chemical Share

Fossil Resource Consumption (FRC)

Freshwater ecotoxicity

Freshwater Eutrophication

GFCF

Global Innovation Index

Grass Land

Gross Margin

GWP

HEM Multiplier

High-Education Offer

Hours Worked

Human Development Index (HDI)

Human Toxicity - cancer effects

Human Toxicity - no cancer effects

ICT

Import of Bio-based Products

Imported Food Biomass Footprint

Imported Nonfood Biomass Footprint

Input Saving

Institution Regimen Index

International Co-publications

Ionising Radiation

Knowledge Economic Index (KEI)

Labor Compensation

Labor Productivity Growth

Land Cover

Land Intensity per Employees

Land Transformation

Literate Population

Manufactured Exports

Marine Eutrophication

Market Size

Market Value ($)

Material Footprint

Material Intensity per employees

Material Use Efficiency

N2O Emissions

Number of Bioeconomy Strategies

Number of employees per biotechnology company

Number of Research Groups

Number of sectoral economic entities per 10,000 inhabitants

Open Effects

Output Changes

Own Effects

Ozone Depletion

Particulate Matter

Percentage of recycled waste

Photochemical Ozone Formation

Prevalence of Undernurishment

Price Changes

Prices

Primary Biomass Production

Private Property Rights

Product Quantity

Production Change

Proportion of industrial innovative companies

Public Expenditure in Education

Public Funding Attractiveness Capacity

Rasmussen-Jones Multiplier

Recycling of biowaste

Recycling rate of wooden packing

Regulation

Relative advantage in environmental technologies

Renewable Energy Share

Residues Valorization

Resource Depletion

Resource sustainability

Resources productivity

Revenues

Revenues x GDP

Road Transport Fuel Share

RPA

Rural Population

Share of GFCF in the gross total expenditure

Share of land cultivated with certified organic farms

Share of new or significantly improved in the total sales

Skilled Labor

Socioeconomic impact

Students and Graduates

Sustainability of Bioeconomy Technology

Sustainable Resource Use

Synthetic Indicator of Bioeconomy Development

Telephones per 1,000 inhabitants

Terrestrial Eutrophication

Time

Top-Down FRC

Total Fossil Resource Intensity (tFRI)

Trade Balance

Turnover Growth Rate

Unemployment Rate

Upstream Effect

Users of Internet per 1,000 inhabitants

Value Added Growth

Value Added Multiplier

Value Added/Land-Use

Value Added/Material Consumption

Wage Costs

Water Resource Depletion

Workers Growth Rate

Public R&D x GDP

Turnover x GDP

Geographic area

All Countries

Antioquia

Argentina

Asia

Austria

Baltics

Belgium

Brazil

BRIC+

Bulgaria

Canada

CEE Countries

China

Colombia

Costa Rica

Croatia

Cyprus

Czech Republic

Denmark

Developed Countries

Developing Countries

East Asia and Pacific

Estonia

EU

EU Isles + Luxembourg

EU-10

EU-12

EU-13

EU-15

EU-2

EU-22

EU-24

EU-25

EU-26

EU-27

EU-28

EU-3

Europe and Central Asia

Europe Developed

Finland

Flanders

France

Germany

Greece

Hungary

Iceland

India

Indonesia

Ireland

Italian Regions

Italy

Japan

Korea

Latin America and Caribbean

Letonia

Lithuania

Lombardy Province

Lubelskie Region

Luxembourg

Main Eastern EU

Malaysia

Malta

Mediterranean EU

Mexico

Middle East and North Africa

NAFTA

NEMO

Nicaragua

Nordic Countries

North America

Northen & Central EU

Noruegian Counties

Norway

Poland

Portugal

Romania

ROW

Russia

Slovakia

Slovenia

South Asia

Spain

Sub-Saharan Africa
Suutela Village, Kontiolahti
Sweden
Taiwan
The Netherlands
U.S. States
Ukraine
United Kingdom
United States
Visegrad Countries
World

SUPPLEMENTARY MATERIAL FOR ARTICLE 2: "TOWARDS DIGITALIZATION FOR COMPREHENSIVE MEASUREMENT..."

1. Supplementary Material SM1. Keywords used in selecting articles on digital technologies

On August 9, 2024 we searched in Source: title, abstract and keywords: telematics OR "machine to machine" OR "iot platforms" OR "industry 4.0" OR "industry 5.0" OR " operational AND technology " OR "smart AND factory " OR "sensors" OR " 5g " OR " lte " OR " 3g" OR " 2g" OR "narrowband" OR "LoRa" OR "Sigfox" OR "NB-IoȚ" OR "NFV/SDN" OR "Visible Light Communications" OR "Private networks" OR "Bluetooth" OR "fibre" OR "wifi" OR " wifi6 AND wifi AND halow " OR " personal AND area AND networks " OR " rfid " OR " ar " OR "vr" OR " screens " OR "video AND processing " OR "neural AND sensing AND haptics " OR "natural AND language AND processing" OR " quantified AND self AND motion AND control " OR " proactive AND interfaces " OR " exoskeletons " OR " machine AND learning" OR "deep AND learning" OR "machine AND vision" OR "cognitive AND computing" OR "semantic AND web" OR "artificial AND narrow AND intelligence " OR "artificial AND general AND intelligence" OR "superintelligence" OR "neural AND networks" OR "data AND ontologies " OR "distributed AND data AND storage " OR "blockchain" OR "proof-of-work" OR "smart AND contracts" OR "big AND data " OR " date AND lake " OR "data AND analytics " OR "data AND exchanges" OR "data AND trading AND platforms" OR "security-by-design" OR "privacy AND trust" OR "personal AND digital AND information AND management" OR "data AND sovereignty AND data AND streams" OR "data AND anonymization" OR "digital AND identities" OR "digital twin" OR "manufacturing AND process AND management" OR "cad/cam" OR "knowledge-based AND engineering" OR "predictive AND engineering AND analytics" OR "system AND modelling" OR "incremental AND materialization" OR "physical AND twin" OR "circular AND economy" OR "task AND automation" OR "virtual AND assistants" OR "bots" OR "erp" OR "crm" OR "ai-assisted AND rpa" OR "Cloud" OR " hybrid" OR " on-premises " OR "compute AND edge" OR "device AND edge" OR "fog AND computing" OR "software AND containers" OR "hypervisors" OR "datastream AND processing" OR "autonomous AND driving" OR "nanobots" OR "drones" OR "uavs" OR "swarm AND robotics" OR "precision AND robotics " OR "agile AND production" OR

"nano-factories" OR "biological AND printing" OR "perishable AND goods AND printing" OR "molecular AND assembly" OR "rapid AND prototyping" OR "graphene" OR "quantum AND computing" OR "human AND re-engineering" OR "superconductivity" OR "nano AND particles" OR "smart AND materials" OR "olfactory AND technology" OR "energy AND harvesting" OR "smart AND dust" OR "digit*" OR "llm" OR "large language model*" OR "detection" OR "fluorence" OR "learning system*" OR "fluorescence" OR "information retrieval" OR "codes" OR cybersecurity OR "Semantic Interoperability" OR "Information Sharing Platforms" OR "Information Dissemination" OR "Cybernetics" OR "NIRS" OR "RFID" OR "Convolutional Neural Networks" OR "Reinforcement Learning" OR "semantic*" OR "biosemantic*" OR "Nuclear Magnetic Resonance Imaging" OR "Data Handling" OR "Object Detection" OR "gene expression" OR "protein expression" OR "predictive model*" OR "forecast" OR "sens*" OR "detect*" OR "sign*" OR "Robonomics" OR "Social System*" OR "Industrial Revolution" OR "Technological Trends" OR "Social Human-robot Interactions" OR "Man Machine Systems" OR "Internet Protocols" OR "Internet Of No Things" OR "Decentralized Architecture" OR "crypto*" OR "biometrics" OR "Non-fungible Token" OR "Ethereum" OR "multiverse*" OR "Quantum Cosmology" OR "String Theory" OR "biomimetic*" OR "Consciousness" OR "ubiquitous" OR "digit* infrastructure" OR "Middleware" OR "interoperabil*" and were found documents found source: 1,451,503 documents found

2. Supplementary Material SM2. Coding words related to the physical concepts of bioeconomy

BmBB	**BtBB**	**BsBB**
adsorption	acetic acid	activated carbon
agric*	adsorption	adsorption
amino acid*	alcohol	aerosol*
animal*	algae	aged
animalia	amino acid sequence	agric*
anthocyanin*	amino acid*	air pollutant*
antioxidant*	ammonia	air pollution
ascorbic acid	animal cell	air quality
bacteria	animal experiment	ammonia
biochemistry	animal model	animal experiment
biodiversity	animal tissue	animal tissue
biomass*	animal*	animal*
biosynthesis	anti-bacterial agent*	animalia
carbon	antibod*	antibiotic resistance
carbon dioxide	antiinfective agent*	antibiotic*
carbon sequestration	antioxidant*	aquatic environment
catechin	apoptosis	aqueous solution
cattle*	arabidopsis	arsenic
cell line	aspergillus	atmospheric pollution
cellulose	aspergillus niger	bacteri*
chemical analysis	bacillus subtilis	bioaccumulation
chemical composition	bacillus*	bioavailability
chemical structure	bacterial	biochar*
chemistry	bacterial gene*	biochemistry
climate change*	bacterial growth	biodegradation
color	bacterial protein*	biodiversity
coniferous*	bacterial strain*	biomass*
conservation	bacteriology	bioremediation
crop production	bacterium	cadmium
crop yield	bacterium culture	carbon

crop*	base sequence	carbon dioxide
cultivation	biochemistry	carbon emission
deciduous tree	biocompatibilit*	carbon sequestration
decision making	biodegradation*	catalysis
deforestation	biofilm*	catalyst activity
development and aging	biofuel*	catalyst*
diet	biological*	charcoal
digestion	biomass*	chemical
drought	bioreactor*	chemical analysis
drug effect	bioremediation*	chemical composition
drug stability	biosynthesis	chemical oxygen demand
ecology	biotechnolog*	chemistry
ecosystem*	biotransformation*	chlorine compound*
efficiency	blood	chlorophyll
enzyme activity	carbon dioxide	chromium
escherichia coli	carbon source	climate change*
ethanol	carbon*	coal
evapotranspiration	catalysis	combustion*
fatty acid*	cell	concentration*
fermentation	cell culture	contamination*
fertilizer application	cell culture techniques	copper
fertilizer*	cell death	crop*
fire*	cell differentiation	decision making
flavonoid*	cell growth	degradation*
food analysis	cell line	denitrification*
food contamination	cell proliferation	dissolution*
food handling	cell survival	dna
food preservation	cell viability	drinking water
food*	cells	drug effect*
forest ecosystem	cellulase	dust*
forest management	cellulose	ecology
forest*	chemical synthes*	economic development*
fruit*	chemistry	ecosystem*

fungi	chitosan	efficiency
gas chromatography	cloning	effluent*
gene expression*	concentration	electrode*
gene*	corynebacterium glutamicum	electron*
genetic*	cricetulus	emission control*
glucose	culture med*	energy efficiency
glycine max	cultured	environment
growing season	cytology	environmental
growth	cytotoxicity	environmental exposure
growth rate	degradation	environmental factor
harvest*	development and aging	environmental impact
heat*	disease*	environmental management
human*	dna	environmental monitoring
hydrogen-ion concentration	dna sequence	environmental policy
hydrolysis	drug effect	environmental pollutants
irrigation*	electrophoresis	environmental protection
isolation and purification	environmental	enzyme activity*
kinetic*	enzyme activity	escherichia coli
land	enzyme stability	eutrophication
land use	enzyme*	fish*
lignin	enzymology	fluid*
lipid peroxidation	escherichia coli	fluorescence
liquid chromatography	ethanol	forest*
maize	fatty acid*	fourier transform infrared spectroscopy
mammal*	fermentation	fresh water
mass spectrometry	flow cytometry	gene
meat	fluorescence	gene expression*
metabolism	fourier transform infrared spectroscopy	genes
mice	fung*	genetic*

microbiology	fungal strain*	geographic distribution
milk	gene	geologic sediment*
moisture	gene deletion	global warming
mouse	gene editing	greenhouse gas*
nitrogen	gene expression	ground water
nonhuman	gene expression profiling	groundwater
nuclear magnetic resonance spectroscopy	gene expression regulation	growth
numerical model	gene overexpression	health hazard*
nutrient*	gene sequence	health risk*
odor*	genes	heavy metal*
optimization*	genetic engineering	human*
oxidation-reduction	genetic*	hydrogen
oxidative stress	genetically modified	hydrogen peroxide
particle size	genom*	hydrogen-ion concentration
ph	genotype	iron*
phenol derivative	glucose	kinetic*
phenol*	glycerol	lake*
phosphorus	glycosylation	land use*
photosynthesis	gmo*	leaching
physiology	growth	lead
plant extract*	growth rate	light*
plant seed*	human cell	limit of detection*
plant*	human*	liquid chromatography
polyphenols	hydrogen	major clinical study
protein*	hydrogen peroxide	manganese
pyrolysis	hydrogen-ion concentration	manure*
quality control	hydrolysis	marine environment*
rat*	hydrophobicity	mercury
reforestation	in-vitro	metabolism*
rice	isolation and purification	metal*

risk assessment	kinetic*	methane
seed*	lactic acid*	microbial community
silviculture	lactobacillus	microbiology
soil moisture	lignin	microorganism*
soil water	lipid*	microplastic*
soil*	mammal*	model*
solubility	messenger rna	molecular sequence data
soybean	metabolic engineering	mortalit*
spectrometry	metabolism*	nanoparticle*
starch	metabolites	nickel
sustainable development	metal nanoparticle*	nitrate
taste	methane	nitrogen
tea	methanol	nitrogen dioxide
temperature	mice	nitrogen oxides
timber	microbial communit*	nonhuman
tree*	microbiology	nucleotide sequence*
triticum aestivum	microorganism*	numerical model*
tropics	microscopy	organic carbon
unclassified drug	model*	organic compound
vegetable oil*	molecular	organic matter*
vegetation*	molecular biology	organic pollutant*
vitis	molecular cloning	oxidation
volatilization	molecular docking	oxidation reduction reaction
water	molecular dynamic*	oxidation-reduction*
water management	molecular genetics	oxidative stress*
water supply	molecular sequence data	oxygen
water use efficiency	molecular weight	ozone
wheat	mouse	particle size*
wine*	mutagenesis	particulate matter
wood*	mutation	performance assessment*
zea mays	nanoparticle*	pesticide*
	nitrogen	ph

	nonhuman	phenol*
	nucleotide sequence	phosphorus
	optimizat*	photocatalysis
	oxidation	photodegradation*
	oxidative stress*	photosynthesis
	oxygen	phylogeny
	particle size	physical chemistry
	pathology	physiology
	peptide*	plant*
	ph	plastic*
	phenotype	pollutant removal
	photosynthesis	pollutant*
	phylogeny	pollution
	physiology	pollution exposure
	plant extract*	polymer*
	plant leaf	precipitation*
	plant protein*	prediction*
	plant*	pregnanc*
	plasmid	principal component analysis
	polyacrylamide gel electrophoresis	public health
	polymerase chain reaction*	pyrolysis
	polysaccharide*	quality control*
	probiotic*	quantitative analys*
	productivity	rain*
	promoter region	reaction kinetic*
	protein binding	reactive oxygen metabolite*
	protein engineering	reactive oxygen species
	protein expression	recycling
	protein*	reduction*

	proteomic*	ribosomal
	pseudomonas	risk assessment*
	pseudomonas aeruginosa	risk factor*
	purification	river pollution
	quantitative analys*	river*
	rat*	rna
	real time polymerase chain reaction	rna 16s
	recombinant protein*	runoff
	ribosomal	salinit*
	rna	seasonal variation*
	rna 16s	seawater*
	saccharification	sediment*
	saccharomyces cerevisiae	sensitivity analysis
	sequence alignment*	sequence analysis
	sequence analysis	sewage*
	sewage	silver
	signal transduction*	soil microbiology
	sodium chloride	soil moisture
	solubility	soil pollutant
	staphylococcus aureus	soil pollutants
	starch*	soil pollution
	stem cell*	soil*
	streptomyce*	spatiotemporal analysis
	substrate specificity	sulfate
	substrate*	sulfur compound*
	synthes*	surface water*
	synthetic biology	sustainability
	temperature	sustainable development*
	thermostability	temperature
	time factor*	titanium
	tissue engineering	titanium dioxide
	tissue*	toxicity

	tobacco	unclassified drug*
	transcription	urban area*
	transcriptome	urbanization*
	transgenic plant	vegetation*
	transmission electron microscopy	volatile organic compound*
	tumor*	waste disposal*
	unclassified drug	waste management*
	upregulation	waste water management*
	virus*	waste water*
	wastewater treatment*	wastewater treatment*
	water	wastewater*
	western blotting	water contamination*
	x ray	water management*
	xylose	water pollutant*
	yeast*	water pollution*
	zea mays	water purification*
		water quality
		water supply
		water treatment*
		water*
		x ray
		zinc

3. Supplementary Material SM3. Final dictionary of conceptual and digital technologies codes uploaded to the WordStat

Bioeconomy Codes Code			**DT Codes**
BM Codes (BmBB)	**BT Codes (BtBB)**	**BS Codes (BsBB)**	
ADSORPTION	"RAT"	ACTIVATED_CARBON	2G
AGRIC*	ACETIC_ACID	ADSORPTION	3G
AMINO_ACID	ADSORPTION	AEROSOL*	4G
ANIMAL*	ALCOHOL	AGED	5G
ANIMALIA	ALGAE	AGRIC*	6G
ANTHOCYANIN*	AMINO_ACID_SEQUENCE	AIR_POLLUTANT*	@AI [AI NOT NEAR /HA /A /S5]
ANTIOXIDANT*	AMINO_ACID*	AIR_POLLUTION	AGILE_PRODUCTION
ASCORBIC_ACID	AMMONIA	AIR_QUALITY	AGRI_TECH
BACTERIA	ANIMAL*	AMMONIA	AI
BIOCHEMISTRY	ANIMAL_CELL	ANIMAL*	AI-ASSISTED_RPA
BIODIVERSITY	ANIMAL_EXPERIMENT	ANIMALIA	ALGORITHM*
BIOMASS*	ANIMAL_MODEL	ANIMAL_EXPERIMENT	ARTIFICIAL_GENERAL_INTELLIGENCE
BIOSYNTHESIS	ANIMAL_TISSUE	ANIMAL_TISSUE	ARTIFICIAL_INTELLIGENCE
CARBON	ANTI-BACTERIAL_AGENT*	ANTIBIOTIC_RESISTANCE	ARTIFICIAL_NARROW_INTELLIGENCE
CARBON_DIOXIDE	ANTIBOD*	ANTIBIOTIC*	AUGMENTED_REALIT*
CARBON_SEQUESTRATION	ANTIINFECTIVE_AGENT*	AQUATIC_ENVIRONMENT	AUTONOMOUS_DRIVING

CATECHIN	ANTIOXIDANT*	AQUEOUS_SOLUTION	BACKSTEPPING
CATTLE*	APOPTOSIS	ARSENIC	BIG_DATA
CELL_LINE	ARABIDOPSIS	ATMOSPHERIC_POLLUTION	BIOCOMPUT*
CELLULOSE	ASPERGILLUS	BACTERI*	BIOINFORM*
CHEMICAL_ANALYSIS	ASPERGILLUS_NIGER	BIOACCUMULATION	BIOLOGICAL_PRINTING
CHEMICAL_COMPOSITION	BACILLUS_SUBTILIS	BIOAVAILABILITY	BIOMARKER
CHEMICAL_STRUCTURE	BACILLUS*	BIOCHAR*	BIOMETRI*
CHEMISTRY	BACTERIAL	BIOCHEMISTRY	BIOMIMETIC*
CLIMATE_CHANGE*	BACTERIAL_GENE*	BIODEGRADATION	BIOSEMANTIC*
COLOR	BACTERIAL_GROWTH	BIODIVERSITY	BLOCKCHAIN*
CONIFEROUS*	BACTERIAL_PROTEIN*	BIOMASS*	BLUETOOTH
CONSERVATION	BACTERIAL_STRAIN*	BIOREMEDIATION	BOTS
CROP*	BACTERIOLOGY	CADMIUM	BROADCAST*
CROP_PRODUCTION	BACTERIUM	CARBON	CAD
CROP_YIELD	BACTERIUM_CULTURE	CARBON_DIOXIDE	CAM
CULTIVATION	BASE_SEQUENCE	CARBON_EMISSION	CIRCUIT*
DECIDUOUS_TREE	BIOCHEMISTRY	CARBON_SEQUESTRATION	CLOUD*
DECISION_MAKING	BIOCOMPATIBILIT*	CATALYSIS	CODE*

DEFORESTATION	BIODEGRADATION*	CATALYST_ACTIVITY	COGNITIVE_COMPUTING
DEVELOPMENT_AND_AGING	BIOFILM*	CATALYST*	COMPUT*
DIET	BIOFUEL*	CHARCOAL	COMPUT*_EDGE
DIGESTION	BIOLOGICAL*	CHEMICAL	CONVOLUTIONAL_NEURAL_NETWORKS
DROUGHT*	BIOMASS*	CHEMICAL_ANALYSIS	CRISPR
DRUG_EFFECT*	BIOREACTOR*	CHEMICAL_COMPOSITION	CRM
DRUG_STABILITY	BIOREMEDIATION*	CHEMICAL_OXYGEN_DEMAND	CRYPTO*
ECOLOGY	BIOSYNTHESIS	CHEMISTRY	CYBER*
ECOSYSTEM*	BIOTECHNOLOG*	CHLORINE_COMPOUND*	CYBERNETIC*
EFFICIENCY	BIOTRANSFORMATION*	CHLOROPHYLL	CYBERSECURITY
ENZYME_ACTIVITY	BLOOD	CHROMIUM	DATA
ESCHERICHIA_COLI	CARBON*	CLIMATE_CHANGE*	DATASTREAM_PROCESSING
ETHANOL	CARBON_DIOXIDE	COAL	DATA_ANALYTIC*
EVAPOTRANSPIRATION	CARBON_SOURCE	COMBUSTION*	DATA_ANONYMIZATION
FATTY_ACID*	CATALYSIS	CONCENTRATION*	DATA_EXCHANG*
FERMENTATION	CELL	CONTAMINATION*	DATA_HANDL*

FERTILIZER_APPLICATION	CELLS	COPPER	DATA_ONTOLOG*
FERTILIZER*	CELLULASE	CROP*	DATA_SOVEREIGNTY_DATA_STREAMS
FIRE*	CELLULOSE	DECISION_MAKING	DATA_STORAG*
FLAVONOID*	CELL_CULTURE	DEGRADATION*	DATA_TRADING_PLATFORM*
FOOD*	CELL_CULTURE_TECHNIQUES	DENITRIFICATION*	DATE_LAKE
FOOD_ANALYSIS	CELL_DEATH	DISSOLUTION*	DECENTRALIZED_ARCHITECTURE
FOOD_CONTAMINATION	CELL_DIFFERENTIATION	DNA	DEEP_LEARNING
FOOD_HANDLING	CELL_GROWTH	DRINKING_WATER	DETECT*
FOOD_PRESERVATION	CELL_LINE	DRUG_EFFECT*	DETECTION
FOREST*	CELL_PROLIFERATION	DUST*	DEVICE_EDGE
FOREST_ECOSYSTEM	CELL_SURVIVAL	ECOLOGY	DIGIT*
FOREST_MANAGEMENT	CELL_VIABILITY	ECONOMIC_DEVELOPMENT*	DIGIT*_INFRASTRUCTURE
FRUIT*	CHEMICAL_SYNTHES*	ECOSYSTEM*	DIGITAL_IDENTITIES
FUNGI	CHEMISTRY	EFFICIENCY	DIGITAL_IMAGE*
GAS_CHROMATOGRAPHY	CHITOSAN	EFFLUENT*	DIGITAL_INFORMATION
GENETIC*	CLONING	ELECTRODE*	DIGITAL_TWIN*

GENE_EXPRESSION*	CONCENTRATION	ELECTRON*	DISTRIBUTED_DATA_STORAGE
GENE*	CORYNEBACTERIUM_GLUTAMICUM	EMISSION_CONTROL*	DRONE*
GLUCOSE	CRICETULUS	ENERGY_EFFICIENCY	E-LEARNING
GLYCINE_MAX	CULTURE_MED*	ENVIRONMENT	EDGE_DETECT*
GROWING_SEASON	CULTURED	ENVIRONMENTAL	EDIT*
GROWTH	CYTOLOGY	ENVIRONMENTAL_EXPOSURE	ELECTROMAGN*
GROWTH_RATE	CYTOTOXICITY	ENVIRONMENTAL_FACTOR	ENERGY_HARVESTING
HARVEST*	DEGRADATION	ENVIRONMENTAL_IMPACT	ERP
HEAT*	DEVELOPMENT_AND_AGING	ENVIRONMENTAL_MANAGEMENT	ETHEREUM
HUMAN*	DISEASE*	ENVIRONMENTAL_MONITORING	EXOSKELETON*
HYDROGEN-ION_CONCENTRATION	DNA	ENVIRONMENTAL_POLICY	EYE_TRACK*
HYDROLYSIS	DNA_SEQUENCE	ENVIRONMENTAL_POLLUTANTS	FIBRE
IRRIGATION*	DRUG_EFFECT	ENVIRONMENTAL_PROTECTION	FLOW_MEASURE*
KINETIC*	ELECTROPHORESIS	ENZYME_ACTIVITY*	FLUORENCE
LAND	ENVIRONMENTAL	ESCHERICHIA_COLI	FLUORESCENCE
LAND_USE	ENZYME*	EUTROPHICATION	FOG_COMPUT*

LIGNIN	ENZYME_ACTIVITY	FISH*	FORECAST*
LIPID_PEROXIDATION	ENZYME_STABILITY	FLUID*	GENE_EXPRESSION
LIQUID_CHROMATOGRAPHY	ENZYMOLOGY	FLUORESCENCE	GEOSTAT*
MAIZE	ESCHERICHIA_COLI	FOREST*	GEOTECHN*
MAMMAL*	ETHANOL	FOURIER_TRANSFORM_INFRARED_SPECTROSCOPY	GESTURE_RECOGNITION
MASS_SPECTROMETRY	FATTY_ACID*	FRESH_WATER	GOLD_NANOPARTIC*
MEAT	FERMENTATION	GENE	GOOD*_PRINTING
METABOLISM	FLOW_CYTOMETRY	GENETIC*	GPR
MICROBIOLOGY	FLUORESCENCE	GENE_EXPRESSION*	GPS
MILK	FOURIER_TRANSFORM_INFRARED_SPECTROSCOPY	GENES	GRAPH_NEURAL_NETWORK*
MOISTURE	FUNG*	GEOGRAPHIC_DISTRIBUTION	HARDWARE*
NITROGEN	FUNGAL_STRAIN*	GEOLOGIC_SEDIMENT*	HEURISTIC*
NONHUMAN	GENE	GLOBAL_WARMING	HIGH_TECH
NUCLEAR_MAGNETIC_RESONANCE_SPECTROSCOPY	GENES	GREENHOUSE_GAS*	HUMAN_RE-ENGINEERING
NUMERICAL_MODEL	GENETIC*	GROUND_WATER	HYBRID

NUTRIENT*	GENETICALLY_MODIFIED	GROUNDWATER	HYPERVISOR*
ODOR*	GENETIC_ENGINEERING	GROWTH	IMAGE*
OPTIMIZATION*	GENE_DELETION	HEALTH_HAZARD*	IMAGE_PROCESS*
OXIDATION-REDUCTION	GENE_EDITING	HEALTH_RISK*	INCREMENTAL_MATERIALIZATION
OXIDATIVE_STRESS	GENE_EXPRESSION	HEAVY_METAL*	INDUSTRIAL_REVOLUTION
PARTICLE_SIZE	GENE_EXPRESSION_PROFILING	HUMAN*	INDUSTRY_4.0
PH	GENE_EXPRESSION_REGULATION	HYDROGEN	INDUSTRY_5.0
PHENOL_DERIVATIVE	GENE_OVEREXPRESSION	HYDROGEN_PEROXIDE	INDUSTRY_6.0
PHENOL*	GENE_SEQUENCE	HYDROGEN-ION_CONCENTRATION	INFORMATION
PHOSPHORUS	GENOM*	IRON*	INFORMATION_DISSEMINATION
PHOTOSYNTHESIS	GENOTYPE	KINETIC*	INFORMATION_MANAGEMENT
PHYSIOLOGY	GLUCOSE	LAKE*	INFORMATION_RETRIEVAL
PLANT*	GLYCEROL	LAND_USE*	INFORMATION_SHARING_PLATFORMS
PLANT_EXTRACT*	GLYCOSYLATION	LEACHING	INFRARED*
PLANT_SEED*	GMO*	LEAD	INTERFEROMET*

POLYPHENOLS	GROWTH	LIGHT*	INTERNET*
PROTEIN*	GROWTH_RATE	LIMIT_OF_DETECTION*	INTERNET_OF_NO_THINGS_
PYROLYSIS	HUMAN_CELL	LIQUID_CHROMATOGRAPHY	INTERNET_OF_THING*
QUALITY_CONTROL	HUMAN*	MAJOR_CLINICAL_STUDY	INTERNET_PROTOCOL*
REFORESTATION	HYDROGEN	MANGANESE	INTEROPERABIL*
RICE	HYDROGEN_PEROXIDE	MANURE*	IOT
RISK_ASSESSMENT	HYDROGEN-ION_CONCENTRATION	MARINE_ENVIRONMENT*	IOT_PLATFORM*
SEED*	HYDROLYSIS	MERCURY	IRIS_RECOGNITION
SILVICULTURE	HYDROPHOBICITY	METABOLISM*	KNOWLEDGE-BASED_ENGINEERING
SOIL*	IN-VITRO	METAL*	LARGE_LANGUAGE_MODEL*
SOIL_MOISTURE	ISOLATION_AND_PURIFICATION	METHANE	LASER
SOIL_WATER	KINETIC*	MICROBIAL_COMMUNITY	LEARNING_SYSTEM*
SOLUBILITY	LACTIC_ACID*	MICROBIOLOGY	LIDAR
SOYBEAN	LACTOBACILLUS	MICROORGANISM*	LLM
SPECTROMETRY	LIGNIN	MICROPLASTIC*	LORA
STARCH	LIPID*	MODEL*	LTE
SUSTAINABLE_DEVELOPMENT	MAMMAL*	MOLECULAR_SEQUENCE_DATA	LTE_NETWORK*

TASTE	MESSENGER_RNA	MORTALIT*	MACHINE_LEARNING
TEA	METABOLIC_ENGINEERING	NANOPARTICLE*	MACHINE_TO_MACHINE
TEMPERATURE	METABOLISM*	NICKEL	MACHINE_VISION*
TIMBER	METABOLITES	NITRATE	MAGNETI*
TREE*	METAL_NANOPARTICLE*	NITROGEN	MANUFACTURING_PROCESS_MANAGEMENT
TRITICUM_AESTIVUM	METHANE	NITROGEN_DIOXIDE	MAN_MACHINE_SYSTEM*
TROPICS	METHANOL	NITROGEN_OXIDES	MICROSCOPY
UNCLASSIFIED_DRUG	MICE	NONHUMAN	MICROWAVE
VEGETABLE_OIL*	MICROBIAL_COMMUNIT*	NUCLEOTIDE_SEQUENCE*	MIDDLEWARE
VEGETATION*	MICROBIOLOGY	NUMERICAL_MODEL*	MOLECULAR_ASSEMBLY
VITIS	MICROORGANISM*	ORGANIC_CARBON	MOVIE*
VOLATILIZATION	MICROSCOPY	ORGANIC_COMPOUND	MULTIVERSE*
WATER	MODEL*	ORGANIC_MATTER*	NANO-FACTOR*
WATER_MANAGEMENT	MOLECULAR	ORGANIC_POLLUTANT*	NANOBOT*
WATER_SUPPLY	MOLECULAR_BIOLOGY	OXIDATION	NANO_PARTICLE*
WATER_USE_EFFICIENCY	MOLECULAR_CLONING	OXIDATION_REDUCTION_REACTION	NARROW_BAND

WHEAT	MOLECULAR_DOCKING	OXIDATION-REDUCTION*	NATURAL_LANGUAGE_PROCESSING
WINE*	MOLECULAR_DYNAMIC*	OXIDATIVE_STRESS*	NB-IOȚ
WOOD*	MOLECULAR_GENETICS	OXYGEN	NETWORK*
ZEA_MAYS	MOLECULAR_SEQUENCE_DATA	OZONE	NEURAL*
	MOLECULAR_WEIGHT	PARTICLE_SIZE*	NEURAL_NETWORK*
	MOUSE	PARTICULATE_MATTER	NEURAL_SENSING_HAPTICS
	MUTAGENESIS	PERFORMANCE_ASSESSMENT*	NFV
	MUTATION	PESTICIDE*	NIRS
	NANOPARTICLE*	PH	NLP
	NITROGEN	PHENOL*	NON-FUNGIBLE_TOKEN*
	NONHUMAN	PHOSPHORUS	NUCLEAR_MAGNETIC_RESONANCE_IMAGING
	NUCLEOTIDE_SEQUENCE	PHOTOCATALYSIS	OBJECT_DETECTION*
	OPTIMIZAT*	PHOTODEGRADATION*	OLFACTOR*_TECHNOLOGY
	OXIDATION	PHOTOSYNTHESIS	OPERATIONAL_TECHNOLOG*
	OXIDATIVE_STRESS*	PHYLOGENY	OPTICAL*
	OXYGEN	PHYSICAL_CHEMISTRY	PERSONAL_AREA_NETWORK*

	PARTICLE_SIZE	PHYSIOLOGY	PERVASIVE
	PATHOLOGY	PLANT*	PHOTOVOLTAIC
	PEPTIDE*	PLASTIC*	PHYSICAL_TWIN*
	PH	POLLUTANT_REMOVAL	PRECISION_ROBOTIC*
	PHENOTYPE	POLLUTANT*	PREDICTIVE_ENGINEERING_ANALYTIC*
	PHOTOSYNTHESIS	POLLUTION	PREDICTIVE_MODEL*
	PHYLOGENY	POLLUTION_EXPOSURE	PRIVACY_TRUST
	PHYSIOLOGY	POLYMER*	PRIVATE_NETWORK*
	PLANT*	PRECIPITATION*	PROACTIVE_INTERFACE*
	PLANT_EXTRACT*	PREDICTION*	PROGRAMMING
	PLANT_LEAF	PREGNANC*	PROOF-OF-WORK*
	PLANT_PROTEIN*	PRINCIPAL_COMPONENT_ANALYSIS	PROTEIN_EXPRESSION*
	PLASMID	PUBLIC_HEALTH	QUANTIFIED_SELF_MOTION_CONTROL*
	POLYACRYLAMIDE_GEL_ELECTROPHORESIS	PYROLYSIS	QUANTUM_COMPUTING
	POLYMERASE_CHAIN_REACTION*	QUALITY_CONTROL*	QUANTUM_COSMOLOGY

	POLYSACCHARIDE*	QUANTITATIVE_ANALYS*	RADAR*
	PROBIOTIC*	RAIN*	RADIOMETER*
	PRODUCTIVITY	REACTION_KINETIC*	RADIOWAVE*
	PROMOTER_REGION	REACTIVE_OXYGEN_METABOLITE*	RANDOM_FOREST
	PROTEIN*	REACTIVE_OXYGEN_SPECIES	RAPID_PROTOTYPING
	PROTEIN_BINDING	RECYCLING	REINFORCEMENT_LEARNING
	PROTEIN_ENGINEERING	REDUCTION*	RFID
	PROTEIN_EXPRESSION	RIBOSOMAL	ROBONOMIC*
	PROTEOMIC*	RISK_ASSESSMENT*	ROBOT*
	PSEUDOMONAS	RISK_FACTOR*	SATELLITE*
	PSEUDOMONAS_AERUGINOSA	RIVER_POLLUTION	SCAN*
	PURIFICATION	RIVER*	SCANNING_ELECTRON_MICROSCOPY
	QUANTITATIVE_ANALYS*	RNA	SCREEN*
	RATS	RNA_16S	SDN
	REAL_TIME_POLYMERASE_CHAIN_REACTION	RUNOFF	SECURITY-BY-DESIGN*
	RECOMBINANT_PROTEIN*	SALINIT*	SEMANTIC*

	RIBOSOMAL	SATELLITE_IMAG*	SEMANTIC_INTEROPERABILITY
	RNA	SEASONAL_VARIATION*	SEMANTIC_WEB
	RNA_16S	SEAWATER*	SENS*
	SACCHARIFICATION	SEDIMENT*	SIGFOX
	SACCHAROMYCES_CEREVISIAE	SENSITIVITY_ANALYSIS	SIGN*
	SEQUENCE_ALIGNMENT*	SEQUENCE_ANALYSIS	SIMULATION
	SEQUENCE_ANALYSIS	SEWAGE*	SMART*
	SEWAGE	SILVER	SMARTHPHONE*
	SIGNAL_TRANSDUCTION*	SOIL*	SMART_CONTRACT*
	SODIUM_CHLORIDE	SOIL_MICROBIOLOGY	SMART_DUST
	SOLUBILITY	SOIL_MOISTURE	SMART_FACTORY_SENSOR*
	STAPHYLOCOCCUS_AUREUS	SOIL_POLLUTANT	SMART_MATERIAL*
	STARCH*	SOIL_POLLUTANTS	SOCIAL_HUMAN-ROBOT_INTERACTION*
	STEM_CELL*	SOIL_POLLUTION	SOCIAL_SYSTEM*
	STREPTOMYCE*	SPATIOTEMPORAL_ANALYSIS	SOFTWARE*

	SUBSTRATE_SPECIFICITY	SULFATE	SOFTWARE_CONTAINER*
	SUBSTRATE*	SULFUR_COMPOUND*	SPATIAL_INFORMATION
	SYNTHES*	SURFACE_WATER*	SPECTROSCOP*
	SYNTHETIC_BIOLOGY	SUSTAINABILITY	SUPERCONDUCT*
	TEMPERATURE	SUSTAINABLE_DEVELOPMENT*	SUPERINTELLIGENCE
	THERMOSTABILITY	TEMPERATURE	SWARM
	TIME_FACTOR*	TITANIUM	SWARM_ROBOTIC*
	TISSUE_ENGINEERING	TITANIUM_DIOXIDE	SWITCH*
	TISSUE*	TOXICITY	SYNCHRONIZATION
	TOBACCO	UNCLASSIFIED_DRUG*	SYSTEM_MODELLING
	TRANSCRIPTION	URBAN_AREA*	TASK_AUTOMATION
	TRANSCRIPTOME	URBANIZATION*	TECHNOLOGICAL_TREND*
	TRANSGENIC_PLANT	VEGETATION*	MACHINE_TO_MACHINE
	TRANSMISSION_ELECTRON_MICROSCOPY	VOLATILE_ORGANIC_COMPOUND*	TELECOMMUNICAT*
	TUMOR*	WASTEWATER*	TELEMATIC*
	UNCLASSIFIED_DRUG	WASTEWATER_TREATMENT*	TEXT_MINING

	UPREGULATION	WASTE_DISPOSAL*	TOKEN*
	VIRUS*	WASTE_MANAGEMENT*	UAV*
	WASTEWATER_TREATMENT*	WASTE_WATER_MANAGEMENT*	UBIQUITOU*
	WATER	WASTE_WATER*	ULTRASO*
	WESTERN_BLOTTING	WATER*	VIDEO
	X_RAY	WATER_CONTAMINATION*	VIDEO_PROCESSING
	XYLOSE	WATER_MANAGEMENT*	VIRTUAL
	YEAST*	WATER_POLLUTANT*	VIRTUAL_ASSISTANT*
	ZEA_MAYS	WATER_POLLUTION*	VIRTUAL_REALIT*
		WATER_PURIFICATION*	VISIBLE_LIGHT_COMMUNICATION*
		WATER_QUALITY	VR
		WATER_SUPPLY	WARPING
		WATER_TREATMENT*	WEARABLE
		X_RAY	WEB*
		ZINC	WIFI*
			WIFI6_WIFI_HALOW
			WIRELESS
			X-RAY

4. Supplementary Material SM4. Occurrence of categories and digital technologies within the bioeconomy concepts context, % of cases within which the codes occur

Categories	**Codes**	**BmBB**	**BtBB**	**BsBB**
Data Science and Analytics	Digit*	94,32	95,9	93,87
Data Science and Analytics	Data	60,26	36,02	46,06
Data Science and Analytics	Big_data	2,63	2,6	2,65
Data Science and Analytics	Text_mining	0,15	0,12	0,12
Data Science and Analytics	Sign*	28,08	28,56	28,11
Data Science and Analytics	Image*	26,39	12,63	12,44
Data Science and Analytics	Detection*	11,85	7,25	6,88
Data Science and Analytics	Detect*	9,29	5,99	6,15
Data Science and Analytics	Algorithm*	18,32	8,44	12,6
Computing and Software	Comput*	20,18	33,59	32,14
Networking and Communication	Network*	11,66	9,07	18,43
Networking and Communication	Satellite*	11,68	0,6	3,93
Cyber-Physical Systems (CPS)	Smart*	6,75	3,95	7,28
Imaging and Sensing Technologies	Radar*	6,57	0,12	2,14
Data Science and Analytics	Neural_network	5,76	2,54	2,44
Computing and Software	Software*	7,75	8,83	11,66
Imaging and Sensing Technologies	Scan	4,99	3,26	2,83
Cyber-Physical Systems (CPS)	Uav*	3,37	0,15	0,9
Data Science and Analytics	Digital_image	6,75	3,83	3,33

Imaging and Sensing Technologies	Optical*	6,37	5,36	4,06
Data Science and Analytics	Forecast*	4,94	1,89	2,06
Networking and Communication	Web*	3,56	2,63	5,9
Imaging and Sensing Technologies	Infrared*	2,97	0,87	1,23
Cyber-Physical Systems (CPS)	Hybrid	2,17	2,84	2,76
Imaging and Sensing Technologies	Interferomet*	1,17	0,3	0,48
Computing and Software	Circuit*	1,71	6,47	4,56
Networking and Communication	Gps	2,11	0,24	1,11
Data Science and Analytics	Video	1,88	2,04	4,03
Imaging and Sensing Technologies	Spectroscop*	1,76	2,13	1
Cyber-Physical Systems (CPS)	Cyber*	1,37	1,68	2,48
Computing and Software	Code*	2,04	2,78	3,7
Data Science and Analytics	Screen*	1,96	4,67	2,08
Cyber-Physical Systems (CPS)	Learning_system*	3,4	1,11	2,24
Computing and Software	Hardware*	1,9	2,31	4,94
Cyber-Physical Systems (CPS)	Drone*	1,33	0,27	0,43
Semantic Technologies	Semantic*	1,08	0,48	1,59
Computing and Software	Programming	1,87	3,17	4,02
Data Science and Analytics	Edit*	2,35	8,83	2,53
Imaging and Sensing Technologies	Magneti*	0,75	2,81	1,13
Cyber-Physical Systems (CPS)	E-learning	1,51	1,08	3,2
Data Science and Analytics	Predictive_model*	1,1	0,36	0,34
Data Science and Analytics	Geostat*	0,76	0	0,26
Imaging and Sensing Technologies	Radiometer*	1,04	0,03	0,27

Imaging and Sensing Technologies	Electromagn*	0,75	0,75	1,14
Imaging and Sensing Technologies	Ultraso*	0,45	1,35	0,48
Imaging and Sensing Technologies	Microwave	0,6	0,33	0,43
Bioinformatics and Biotechnology	Gene_expression	0,43	4,28	0,3
Networking and Communication	Telecomminicat*	1,01	0,96	3,22
Networking and Communication	Switch*	0,69	2,01	1,88
Data Science and Analytics	Machine_vision*	0,59	0,12	0,17
Data Science and Analytics	Spatial_information	0,82	0,15	0,35
Cyber-Physical Systems (CPS)	Wearable	0,38	0,93	0,71
Data Science and Analytics	Information_retrieval	0,72	1,14	0,84
Cyber-Physical Systems (CPS)	Cad	0,35	1,02	0,7
Cyber-Physical Systems (CPS)	Augmented_realit*	0,33	0,69	1,44
Bioinformatics and Biotechnology	Biometri*	0,32	0,6	0,29
Semantic Technologies	Interoperabil*	0,42	0,42	1,16
Data Science and Analytics	Digital_information	0,46	1,14	0,91
Data Science and Analytics	Neural*	0,3	1,11	0,37
Enteprise and Manufacturing	Industrial_revolution	0,38	1,56	0,54
Cyber-Physical Systems (CPS)	Ubiquitou*	0,45	0,72	1,53
Networking and Communication	Broadcast*	0,27	0,12	1,37
Imaging and Sensing Technologies	Gpr	0,14	0	0,06
Computing and Software	Synchronization	0,26	0,24	0,73
Imaging and Sensing Technologies	Fibre	0,17	0,24	0,22
Computing and Software	Fog_comput*	0,14	0	0,26

Computing and Software	Difit*_infraestrure	0,26	0,12	0,34
Data Science and Analytics	Geotechn*	0,18	0,03	0,17
Bioinformatics and Biotechnology	Biomarker	0,2	0,84	0,12
Cyber-Physical Systems (CPS)	High_tech	0,23	0,72	0,24
Cyber-Physical Systems (CPS)	Pervasive	0,21	0,3	0,68
Semantic Technologies	Information_dissemination	0,18	0,57	0,39
Imaging and Sensing Technologies	Cam	0,12	0,27	0,15
Imaging and Sensing Technologies	Nuclear_magnetic_resonance_imaging	0,21	0,96	0,16
Computing and Software	Middleware	0,08	0,15	0,38
Bioinformatics and Biotechnology	Crispr	0,06	0,93	0,02
Networking and Communication	Narrow_band	0,1	0,06	0,1
Data Science and Analytics	Movie*	0,08	0,27	0,23
Imaging and Sensing Technologies	Nirs	0,06	0	0,01
Imaging and Sensing Technologies	Flow_measure*	0,09	0,15	0,07
Bioinformatics and Biotechnology	Protein_expression*	0,1	0,06	0,1
Bioinformatics and Biotechnology	Biomimetic*	0,08	0,96	0,13
Networking and Communication	Telematic*	0,05	0,09	0,06
Computing and Software	Superconduct*	0,05	0,06	0,12
Cyber-Physical Systems (CPS)	Exosqueleton*	0,02	0,06	0,04
Data Science and Analytics	Warping	0,05	0,03	0,06
Enteprise and Manufacturing	Agro_tech	0,06	0	0
Cyber-Physical Systems (CPS)	Cybernetic*	0,06	0,66	0,26

Cyber-Physical Systems (CPS)	Machine_to_Machine	0,06	0	0,06
Cyber-Physical Systems (CPS)	Man_machine_system	0,07	0,45	0,17
Enteprise and Manufacturing	Rapid_prototyping	0,04	0,87	0,24
Semantic Technologies	Social_system	0,05	0	0,08
Data Science and Analytics	Graph_neural_network*	0,03	0,03	0,03
Imaging and Sensing Technologies	Gold_nanopartic*	0,02	0,27	0,03
Semantic Technologies	Bots	0,03	0	0,04
Data Science and Analytics	Large_language_model*	0,03	0,03	0,05
Cyber-Physical Systems (CPS)	Technological_trend	0,04	0	0,04
Blockchain and Cryptography	Non_fungible_token*	0,03	0,03	0,07
Networking and Communication	Private_network	0,02	0	0,07
Data Science and Analytics	Cognitive_computing	0,02	0	0,03
Computing and Software	Hypervisor*	0,01	0	0,05
Blockchain and Cryptography	Proof-of-work	0,02	0	0,04
Networking and Communication	Nfv	0,01	0	0,03
Enteprise and Manufacturing	Operational_technolog*	0,01	0,03	0,05
Data Science and Analytics	Llm	0,01	0	0,02
Blockchain and Cryptography	Decentralized_architecture	0,01	0	0
Semantic Technologies	Digital_identities	0,01	0	0,06
Networking and Communication	Lte*networks	0,01	0	0,01
Networking and Communication	Radiowave*	0,01	0	0,01
Data Science and Analytics	Backstepping	0,01	0	0,01
Computing and Software	Hardware	4,94	2,31	4,94

Networking Communication	and	2g	0,06	0,03	0,02
Networking Communication	and	3g	0,07	0	0,12
Networking Communication	and	4g	0,11	0,03	0,1
Networking Communication	and	5g	0,34	0,24	0,52
Networking Communication	and	6g	0,06	0	0,16
Networking Communication	and	Lte	0,06	0	0,14
Networking Communication	and	Wifi*	0,12	0,06	0,16
Networking Communication	and	Bluetooth	0,14	0,18	0,26
Networking Communication	and	Rfid	0,3	0	0,37
Networking Communication	and	Lora	0,15	0	0,06
Networking Communication	and	Visible_light_communication*	0,01	0	0,06
Networking Communication	and	Personal_area_network*	0,01	0	0,03
Networking Communication	and	Wireless	2,17	1,11	3,91
Networking Communication	and	Internet	3,18	3,08	5,91
Networking Communication	and	Internet_of_thing*	4,13	2,13	3,81
Networking Communication	and	Internet_protocol*	0,13	0,03	0,44

Networking and Communication	Iot	3,59	0,9	3,12
Networking and Communication	Iot_platform*	0,14	0,03	0,1
Networking and Communication	Sdn	0,08	0	0,15
Blockchain and Cryptography	Blockchain*	1,68	0,66	1,81
Blockchain and Cryptography	Ethereum	0,15	0	0,16
Blockchain and Cryptography	Crypto*	1	0,66	2,11
Blockchain and Cryptography	Smart_contract*	0,38	0,21	0,4
Blockchain and Cryptography	Token*	0,12	0,03	0,24
Data Science and Analytics	Artificial_intelligence	4,33	6,35	3,74
Data Science and Analytics	AI	2,05	2,07	1,88
Data Science and Analytics	Machine_learning	11,28	3,59	3,05
Data Science and Analytics	Deep_learning	3,5	1,17	1,63
Data Science and Analytics	Reinforcement_learning	0,15	0,06	0,44
Data Science and Analytics	Nlp	0,22	0	0,1
Data Science and Analytics	Natural_language_processing	0,43	0,15	0,26
Data Science and Analytics	Convolutional_neural_networks	1,41	0,12	0,38
Data Science and Analytics	Random_forest	12,1	0,21	0,64
Data Science and Analytics	Heuristic*	0,38	0,21	0,53
Computing and Software	Cloud*	6,51	1,59	6
Computing and Software	Edge_detect*	0,33	0,12	0,18
Data Science and Analytics	Data_analytic*	0,64	0,42	0,66
Data Science and Analytics	Data_exchang*	0,19	0,27	0,38
Data Science and Analytics	Data_handl*	1,72	1,08	1,67
Data Science and Analytics	Data_storag	1,46	2,72	2,18
Data Science and Analytics	Information	31,06	25,75	28,26

Data Science and Analytics	Information_management	2,4	1,17	2,79
Data Science and Analytics	Information_sharing_platforms	0,01	0	0,01
Cyber-Physical Systems (CPS)	Comput*_edge	0,05	0,03	0,06
Cyber-Physical Systems (CPS)	System_modelling	0,03	0	0,03
Cyber-Physical Systems (CPS)	Simulation	6,61	7,63	10,23
Cyber-Physical Systems (CPS)	Physical_twin*	0,01	0	0,03
Cyber-Physical Systems (CPS)	Digital_twin*	1,56	1,41	2,62
Cyber-Physical Systems (CPS)	Industry_4.0	0,84	1,26	1,63
Cyber-Physical Systems (CPS)	Industry_5.0	0,06	0,18	0,16
Cyber-Physical Systems (CPS)	Smart_material*	0,01	0,12	0,03
Cyber-Physical Systems (CPS)	Robot*	6,71	5,33	3,11
Cyber-Physical Systems (CPS)	Autonomous_driving	0,08	0	0,24
Cyber-Physical Systems (CPS)	Swarm	0,42	0,12	0,38
Cyber-Physical Systems (CPS)	Swarm_robotic*	0,02	0	0,01
Imaging and Sensing Technologies	Lidar	4,73	0,03	1,1
Imaging and Sensing Technologies	Sens*	30,41	14,82	18,33
Imaging and Sensing Technologies	Image_process*	5,99	4,19	2,91
Imaging and Sensing Technologies	Object_detection*	0,49	0,09	0,36
Imaging and Sensing Technologies	Eye_track*	0,05	0,09	0,15
Imaging and Sensing Technologies	Iris_recognition	0,02	0	0,02
Imaging and Sensing Technologies	Video_processing	0,03	0	0,07
Imaging and Sensing Technologies	Nano_particle*	0,01	0,03	0,01

Imaging and Sensing Technologies	Energy_harvesting	0,09	0,03	0,21
Imaging and Sensing Technologies	Photovoltaic	0,39	0,03	0,54
Imaging and Sensing Technologies	Laser	3,33	2,43	1,84
Imaging and Sensing Technologies	Microscopy	0,61	4,94	0,74
Imaging and Sensing Technologies	X-ray	0,81	2,31	0,81
Imaging and Sensing Technologies	Scan_elect_microscopy	0,3	0,81	0,35
Imaging and Sensing Technologies	Fluorescence	0,55	3,77	0,42
Cyber-Physical Systems (CPS)	Vr	0,23	0,18	1,13
Cyber-Physical Systems (CPS)	Virtual_assistant*	0,01	0,09	0,04
Cyber-Physical Systems (CPS)	Virtual	2,15	3,05	8,32
Cybersecurity and Data Privacy	Cybersecurity	0,56	0,51	0,72
Cybersecurity and Data Privacy	Privacy_trust	0,01	0,03	0,02
Enteprise and Manufacturing	Erp	0,07	0,03	0,15
Enteprise and Manufacturing	Crm	0,04	0,03	0,08
Semantic Technologies	Semantic_web	0,15	0,03	0,33
Semantic Technologies	Semantic_interoperability	0,01	0,03	0,04
Quantum Computing and Advanced Computation	Quantum_computing	0,04	0,3	0,07
Quantum Computing and Advanced Computation	Bioinform*	0,34	4,13	0,23
Quantum Computing and Advanced Computation	Biocomput*	0,01	0,6	0,01

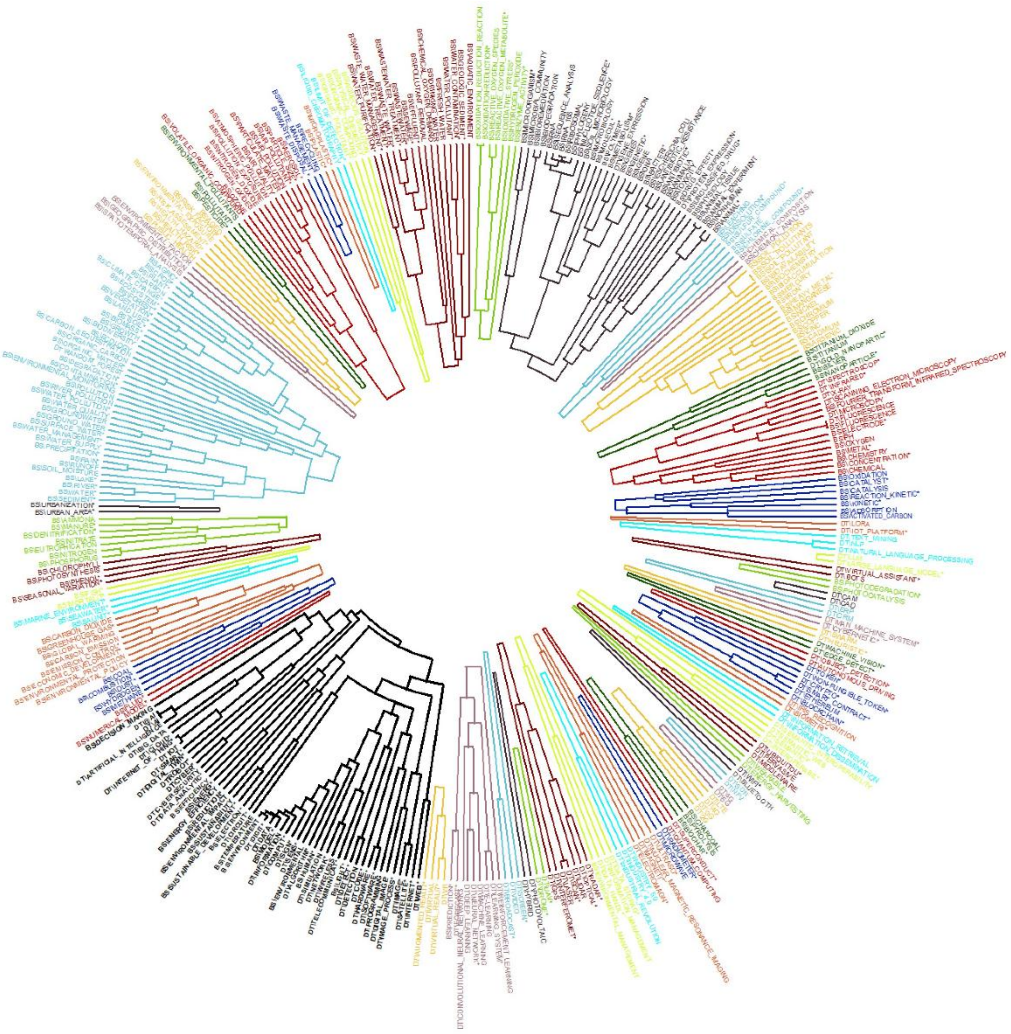
5. Supplementary Material SM5. All clusters of cyber-physical elements of the biomass-based bioeconomy



6. Supplementary Material SM6. All clusters of cyber-physical elements of the biotechnology-based bioeconomy



7. Supplementary Material SM7. All clusters of cyber-physical elements of the biosphere-based bioeconomy



SUPPLEMENTARY MATERIAL FOR ARTICLE 3: "A CYBER-BIO-PHYSICAL-SOCIAL SYSTEMS FRAMEWORK..."

SM I) METHODOLOGY

SM I.1) Main Information Bibliometrix

Description	Results
MAIN INFORMATION ABOUT DATA	
Timespan	1936:2025
Sources (Journals, Books, etc)	2450
Documents	8941
Annual Growth Rate %	7,5
Document Average Age	7,79
Average citations per doc	33,58
References	0
DOCUMENT CONTENTS	
Keywords Plus (ID)	34753
Author's Keywords (DE)	20073
AUTHORS	
Authors	29918
Authors of single-authored docs	451
AUTHORS COLLABORATION	
Single-authored docs	549
Co-Authors per Doc	5,4
International co-authorships %	32,43
DOCUMENT TYPES	
article	6860
article article	60
article book	1
article book chapter	3
article conference paper	10
article conference review	2
article review	7

book	36
book chapter	326
book chapter article	2
conference paper	1015
conference paper article	6
conference paper conference paper	3
conference paper review	1
conference review	59
data paper	18
editorial	8
erratum	2
letter	7
note	11
retracted	5
review	490
review article	3
review conference paper	1
short survey	5

SM I.2) Table 1: Summary of Bio-Physical Variables from ForC Database

Variable Name	Average Value	Standard Deviation
ANPP_0_C	4.66	4.61
ANPP_0_OM	12.18	7.37
ANPP_1_C	4.14	2.82
ANPP_1_OM	10.34	5.16
ANPP_2_C	4.28	3.42
ANPP_2_OM	8.21	6.00
ANPP_foliage_C	1.77	1.09
ANPP_foliage_OM	4.19	2.20
ANPP_folivory_C	0.30	0.29
ANPP_folivory_OM	0.41	0.21
ANPP_litterfall_0_C	2.69	2.54
ANPP_litterfall_0_OM	7.41	2.81
ANPP_litterfall_1_C	3.35	1.57
ANPP_litterfall_1_OM	7.83	2.61
ANPP_litterfall_2_OM	7.60	3.50
ANPP_repro_C	0.74	1.71
ANPP_repro_OM	0.66	0.39
ANPP_woody_C	2.70	2.13
ANPP_woody_OM	6.47	2.42
ANPP_woody_branch_C	0.53	0.51
ANPP_woody_branch_OM	1.16	0.89
ANPP_woody_stem_C	2.68	1.87
ANPP_woody_stem_OM	5.50	3.70
BNPP_root.turnover_fine_C	1.69	1.51
BNPP_root_C	2.16	1.57
BNPP_root_OM	3.94	3.50
BNPP_root_coarse_C	0.67	0.76
BNPP_root_coarse_OM	0.94	0.39
BNPP_root_fine_C	1.69	1.22

BNPP_root_fine_OM	3.33	3.48
GPP_C	15.52	7.76
GPP_cum_C	10.16	3.86
NPP_0_C	7.77	7.01
NPP_0_OM	17.77	9.45
NPP_1_C	6.94	4.38
NPP_1_OM	17.73	7.30
NPP_2_C	6.18	3.36
NPP_2_OM	13.47	8.54
NPP_3_C	7.63	2.72
NPP_3_OM	17.58	NA
NPP_4_C	8.88	2.18
NPP_5_C	8.96	2.83
NPP_litter_C	3.33	2.30
NPP_understory_C	0.49	0.88
NPP_understory_OM	1.13	0.26
NPP_woody_C	4.52	3.38
R_het_soil_C	4.59	2.85
R_soil_C	8.84	5.37
biomass_ag_C	98.40	103.63
biomass_ag_OM	101.79	111.59
biomass_ag_foliage_C	4.71	3.69
biomass_ag_foliage_OM	5.57	4.86
biomass_ag_understory_C	1.53	2.34
biomass_ag_understory_OM	6.57	7.48
biomass_ag_woody_C	112.61	113.87
biomass_ag_woody_OM	125.29	118.36
soil_C	101.04	135.05
soil_C2N	18.28	8.34

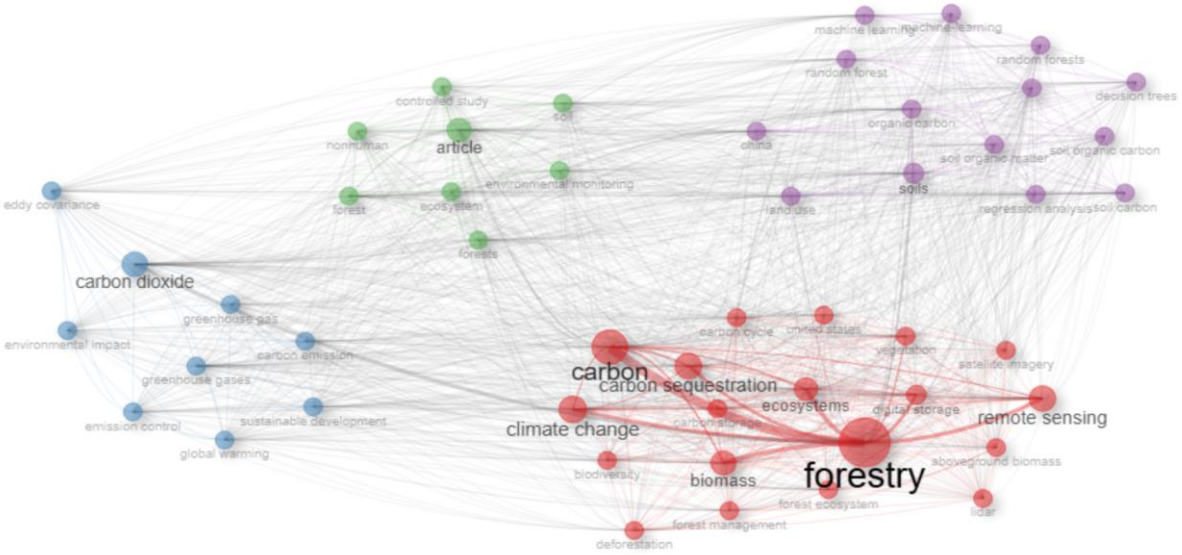
SM II. RESULTS

SM II.1 Table CoWordNet

Node	Cluster	Betweenness	Closeness	PageRank
forestry	1	0,37722828	0,02040816	0,07062805
carbon	1	0,12039878	0,02040816	0,04961516
climate change	1	0,05083504	0,02040816	0,0369585
remote sensing	1	0,0514296	0,02040816	0,0348899
carbon sequestration	1	0,04015416	0,02040816	0,03585057
biomass	1	0,11428329	0,02040816	0,03237868
ecosystems	1	0,02238101	0,02040816	0,0312907
digital storage	1	0,01146655	0,02040816	0,025358
vegetation	1	0,01125421	0,02040816	0,02055143
deforestation	1	0,00613673	0,02040816	0,01278616
carbon storage	1	0,0068587	0,02040816	0,01705932
forest ecosystem	1	0,00286664	0,02040816	0,01422906
forest management	1	0,01003323	0,02040816	0,01437185
carbon cycle	1	0,00350367	0,02040816	0,01496043
biodiversity	1	0,01086137	0,02040816	0,01410014
united states	1	0,00400268	0,02040816	0,01305701
aboveground biomass	1	0,00286664	0,02040816	0,01242282
lidar	1	0	0,02	0,01028918
satellite imagery	1	0,00327009	0,02040816	0,01186168
carbon dioxide	2	0,03370954	0,02040816	0,03213598
greenhouse gases	2	0,00853621	0,02040816	0,01687909
carbon emission	2	0,00502192	0,02040816	0,0140294
sustainable development	2	0,00603056	0,02040816	0,01223351
global warming	2	0,00249504	0,02040816	0,01170504
greenhouse gas	2	0,00174122	0,02040816	0,01336712
emission control	2	0,0031533	0,02040816	0,01130019
eddy covariance	2	0,00021234	0,02040816	0,00794416
environmental impact	2	0	0,02	0,01045336
article	3	0,01932326	0,02040816	0,03382958
forest	3	0,01575589	0,02040816	0,02291632

soil	3	0,0020385	0,02040816	0,01945024
forests	3	0,00732585	0,02040816	0,01879383
environmental monitoring	3	0,00668882	0,02040816	0,01794307
ecosystem	3	0,00338688	0,02040816	0,01610697
controlled study	3	0,00305775	0,02040816	0,01503995
nonhuman	3	0,00254812	0,02040816	0,0142507
machine learning	4	0,00373725	0,02040816	0,0210102
soils	4	0,00286664	0,02040816	0,02708309
china	4	0,00659327	0,02040816	0,0209455
land use	4	0,00675252	0,02040816	0,02377083
organic carbon	4	0,00140147	0,02040816	0,02393285
random forest	4	0,00138023	0,02040816	0,01605967
soil carbon	4	0,0006795	0,02040816	0,01556285
soil organic matter	4	0,00055209	0,02040816	0,0146698
decision trees	4	0,00080691	0,02040816	0,01328942
random forests	4	0,00055209	0,02040816	0,01305333
regression analysis	4	0,00159258	0,02040816	0,01311906
forecasting	4	0,00100863	0,02040816	0,01258524
soil organic carbon	4	0,0003716	0,02040816	0,01308381
machine-learning	4	0,00084937	0,02040816	0,01079721

II.2) Figure 1: Original CoWordNet from Biblioshiny



II.3) Detailed Description of the CBPSS Model Implementation in R and Key Mathematical formulas

Computations utilized the following packages: “dplyr” (Wickham et al., 2023) for data manipulation; “readr” (Wickham et al., 2023) for efficient data import; “reshape2” (Wickham, 2007) for data reshaping; “randomForest” (Liaw and Wiener, 2002) for machine learning regression; “caret” (Kuhn, 2020) for cross-validation; “sensitivity” (Iooss et al., 2024) for global sensitivity analysis; “lhs” (Carnell, 2024) for Latin Hypercube Sampling; “ggplot2” (Wickham, 2016) for data visualization; “gridExtra” (Auguie, 2017) for arranging multiple plots; “knitr” (Xie, 2015) for dynamic reporting and table generation; “kableExtra” (Zhu, 2024) for advanced table formatting; “moments” (Komsta and Novomestky, 2022) for statistical moments calculation; “MODISTools” (Tuck et al., 2014) for satellite data extraction; “nasapower” (Sparks, 2018) for solar insolation data; “maps” (Becker et al., 2023) for site mapping; “pbapply” (Solymos and Zawadzki, 2019) for parallel processing with progress bars; “doParallel” (Microsoft and Weston, 2022) and “foreach” (Microsoft and Weston, 2022) for parallel computing. All code and data are available at (Script) for reproducibility

The Cyber-Bio-Physical-Social System (CBPSS) model is a multilayered framework designed to provide a comprehensive, holistic valuation of forest carbon sequestration. It integrates four interconnected layers: the Bio-Physical layer for quantifying carbon stocks and fluxes; the Cyber layer for applying machine learning to reduce uncertainties; the Social layer for incorporating policy-driven adjustments; and the Digital-Information-Physical (DIP) integration layer for synthesizing emergy-based and economic metrics. This model leverages empirical datasets, remote sensing data, machine learning algorithms, policy scenarios, and emergy analysis to align with bioeconomy principles, emphasizing the non-market values of ecosystems such as embodied solar energy. By bridging bio-physical processes with socio-economic and digital tools, the CBPSS model enables scalable assessments from site-specific to global levels, supports sensitivity analyses, and quantifies uncertainties through probabilistic simulations. The model's outputs include traditional market-based valuations (e.g., in USD) and holistic emergy-equivalent valuations (e.g., in EmUSD), facilitating applications in climate policy, REDD+ initiatives, and sustainable forest management.

Step 1: Bio-Physical Layer (Quantification of Stocks and Fluxes)

The Bio-Physical layer forms the empirical foundation by quantifying carbon stocks and fluxes using integrated datasets. It begins by loading the ForC database (Anderson-Teixeira et al., 2018), which includes site-specific measurements of forest carbon dynamics. Data merging

and filtering focus on key variables such as aboveground biomass (AGB), belowground biomass (BGB), gross primary productivity (GPP), net primary productivity (NPP), net ecosystem productivity (NEP), and ecosystem respiration (Re). Summary statistics, including averages and standard deviations, are compiled in (SM. I.2- Table 1: Summary of Bio-Physical Variables from ForC Database) to provide an overview of data distribution.

Geospatial coordinates from ForC sites are extracted to enable remote sensing integration. Solar insolation is retrieved via NASA's POWER API, providing climatological annual averages of all-sky surface shortwave downward radiation (ALLSKY_SFC_SW_DWN) in kW-hr/m²/day, which serves as a proxy for energy inputs driving photosynthesis. Additionally, MODIS NPP data (MOD17A3HGF product, averaged over 2022-2024) are scaled to tC/ha/yr and adjusted to estimate NEP (approximately 0.1 × NPP, accounting for respiration). In cases where MODIS data are unavailable or unreliable, the model falls back to ForC-derived values, prioritizing direct NEP measurements, followed by NPP minus heterotrophic respiration (Rh), or NPP × 0.1 as a conservative estimate.

Validation is performed by scaling site-level estimates to global forest sinks (3.63), benchmarked against IPCC reports (~2-3 GtC/yr net forest sink, excluding land-use change). A site distribution map is generated using geospatial plotting tools. This layer ensures accurate, globally representative bio-physical inputs for subsequent modeling, capturing spatial variability in carbon sequestration driven by climate, soil, and vegetation factors.

Step 2: Cyber Layer (Machine Learning for Uncertainty Reduction)

The Cyber layer employs machine learning to refine sequestration estimates by reducing inherent uncertainties in bio-physical data. Input features include latitude (lat), longitude (lon), elevation, mean annual temperature (MAT), mean annual precipitation (MAP), and solar insolation, with the target variable being the sequestration rate (tC/ha/yr, derived from NEP).

A Random Forest regressor is implemented with 5-fold cross-validation for hyperparameter tuning (mtry ranging from 1-3, ntree=500). Model performance is evaluated using metrics such as mean squared error (MSE) and out-of-bag (OOB) error, with pseudo-R^2 calculated as 1 - (OOB MSE / variance of target). Uncertainty reduction is quantified as the ratio of residual standard deviation to the original data's standard deviation, achieving approximately 64.8% reduction in variability. The full model is then trained on the entire dataset for predictions.

For sites with fewer than 10 data points, the model defaults to the dataset average to avoid overfitting. This layer enhances the reliability of sequestration estimates by accounting for environmental covariates, providing a data-driven bridge between raw bio-physical observations and policy-adjusted valuations.

Step 3: Social Layer (Policy Application and Sensitivity)

The Social layer incorporates governance and policy factors to adjust sequestration rates, emphasizing equity and incentives in the bioeconomy. A REDD+ uplift factor (default 1.2) is applied to predicted rates, simulating enhanced carbon storage through reduced deforestation and degradation programs.

Sensitivity analyses explore uplift ranges (1.1-1.3), presented in Table 2 and visualized as line plots to illustrate policy impacts (e.g., elevating mean sequestration from 1.00 to 1.18 tC/ha/yr). This accounts for socio-political interventions, such as community-based management or international financing, which amplify bio-physical potentials. The layer ensures the model reflects real-world dynamics where policies can mitigate threats like illegal logging or climate stressors, thereby integrating human dimensions into valuation.

Step 4: DIP Integration (Metric Calculation and Monte Carlo Uncertainty Analysis)

The DIP integration layer synthesizes outputs from prior layers into holistic metrics, combining digital emergy analysis with physical and economic valuations. First, the emdollar ratio is computed as global GDP divided by the planetary emergy baseline (e.g., 1.68 × 10^25 sej/yr from Odum, 1996), converting sej to EmUSD.

The core holistic function scales policy-adjusted sequestration rates to global levels, converts to emergy using transformities (sej/tC), and derives EmUSD values. Deterministic comparisons contrast traditional market valuations (sequestration × 3.67 tCO2e/tC × carbon price) with holistic emergy-based approaches (using Odum or Campbell transformities). Sensitivity analyses vary transformities and emergy baselines (±20%), with results in tables and figures to assess robustness.

Uncertainty is quantified via Monte Carlo simulations (n=1000 iterations), assuming lognormal distributions for sequestration rates (to capture positive skewness) and normal distributions for carbon prices. Outputs include 95% confidence intervals, boxplots for distribution visualization, and comparison graphs highlighting gaps between traditional and holistic valuations. This probabilistic approach ensures robust estimates, accounting for variability in inputs.

Overall, the CBPSS model advances bioeconomy measurement by seamlessly integrating market-oriented and emergy-based paradigms, with direct applications in REDD+ policy design, climate mitigation strategies, and sustainable resource accounting. Its modular structure allows for extensions, such as incorporating additional remote sensing datasets or advanced ML techniques, to further refine holistic valuations.

Global Parameter Configuration (Social/DIP Layer)

This foundational section establishes key constants and parameters that underpin the model's valuation processes, linking bio-physical fluxes to both economic and emergy-based metrics. The purpose is to standardize inputs for consistency across layers, enabling sensitivity analyses and the calculation of holistic indicators such as EmGDP (emergy-based gross domestic product). Key parameters include:

Global forest area: Set at 4 × 10^9 hectares, derived from FAO estimates, to extrapolate site-level sequestration rates to global aggregates.

Carbon prices: Two scenarios are used—$14.80/tCO2e (based on voluntary carbon market averages from Ecosystem Marketplace, 2023) and $50/tCO2e (reflecting premium credits from Trove Research, 2024)—to represent market variability and policy-driven pricing.

Transformities: Sourced from emergy literature (Odum, 1996; Campbell, 2024), these conversion factors (e.g., 1.68 × 10^15 sej/tC for biomass) quantify the solar emjoules (sej) embodied in carbon sequestration, accounting for upstream energy inputs in ecosystem processes.

NEP factor: A default value of 0.1 (from Pan et al., 2011) is applied to approximate net ecosystem production (NEP) from gross primary productivity (GPP) or net primary productivity (NPP), reflecting typical heterotrophic respiration losses in forests.

These parameters are configurable to allow for scenario testing, such as varying carbon prices or transformities, and ensure the model's adaptability to different bioeconomic contexts.

Key Mathematical Formulas of the CBPSS Model:

The model bridges the gap between Ecological Science and Holistic Economics through three main calculations.

1. Carbon-to-CO_2 Conversion (Traditional Metric)

Before valuing the carbon, the model converts raw Carbon (C) into Carbon Dioxide equivalent (CO_2e), which is the standard unit for international markets.

$$Value_{Traditional} = (NEP \times 3.67) \times Price_{Market}$$

NEP: Net Ecosystem Production (The actual carbon "captured" by the forest).

3.67: The molecular ratio used to convert 1 ton of Carbon into 1 ton of CO_2.

Price: The current market price per carbon credit (e.g., $14.80).

Simple Logic: "How much is the market willing to pay for the CO_2 this forest removed from the atmosphere?"

---

2. Emergy Valuation (The Holistic Wealth)

This formula calculates the "True Value" based on the work done by the biosphere. It uses Transformity, which represents the solar energy required to create one gram of biomass.

$$Emergy_{Total} = (NEP \times BiomassRatio) \times Transformity$$

Biomass Ratio: Converts Carbon tons into grams of total organic matter.

Transformity: A scientific constant (e.g., 1.5×10^8 sej/g) that acts as a "quality factor" for the energy stored in the forest.

---

3. Emdollar Ratio (The Economic Bridge)

Since the global economy runs on dollars but the biosphere runs on energy (Emergy), we need a "exchange rate" to compare them.

$$Ratio_{Emdollar} = \frac{Global\ GDP\ (USD)}{Global\ Emergy\ Baseline\ (sej)}$$

Global GDP: Total human economic output (approx. $100 Trillion).

Global Emergy: Total energy work of the Earth (wind, rain, sun, minerals).

The Final Holistic Value is then:

$$Value_{Holistic} = Emergy_{Total} \times Ratio_{Emdollar}$$

Simple Logic: "If the entire Earth's work supports the entire human economy, what is the fair dollar share of this specific forest's energy work?"

---

4. Uncertainty Reduction (The AI Performance)

The model calculates how much "better" the AI is compared to simple guessing.

$$Reduction\% = \left(1 - \frac{\sigma_{Residual}}{\sigma_{Original}} \right) \times 100$$

$\sigma_{Original}$: The standard deviation (variation) of the raw field data.

$\sigma_{Residual}$: The error remaining after the Random Forest model makes its prediction.

Simple Logic: "How much 'doubt' did we remove from our estimation by using NASA satellites and Artificial Intelligence?"

SM II.4) Random Forest

4084 samples

6 predictor

No pre-processing

Resampling: Cross-Validated (5 fold)

Summary of sample sizes: 3267, 3267, 3267, 3268, 3267

Resampling results across tuning parameters:

mtry	RMSE	Rsquared	MAE
1	0.5988158	0,118384	0,3899774
2	0.5972089	0,1735784	0,3881337
3	0.5926675	0,1952549	0.3823999

RMSE was used to select the optimal model using the

smallest value.

The final value used for the model was mtry = 3.

[1] "Random Forest Pseudo-R^2: 0.437"

[1] "Uncertainty Reduction via ML: Original SD = 0.5942 ; Residual SD = 0.2112 ; Reduction = 64.5 %"

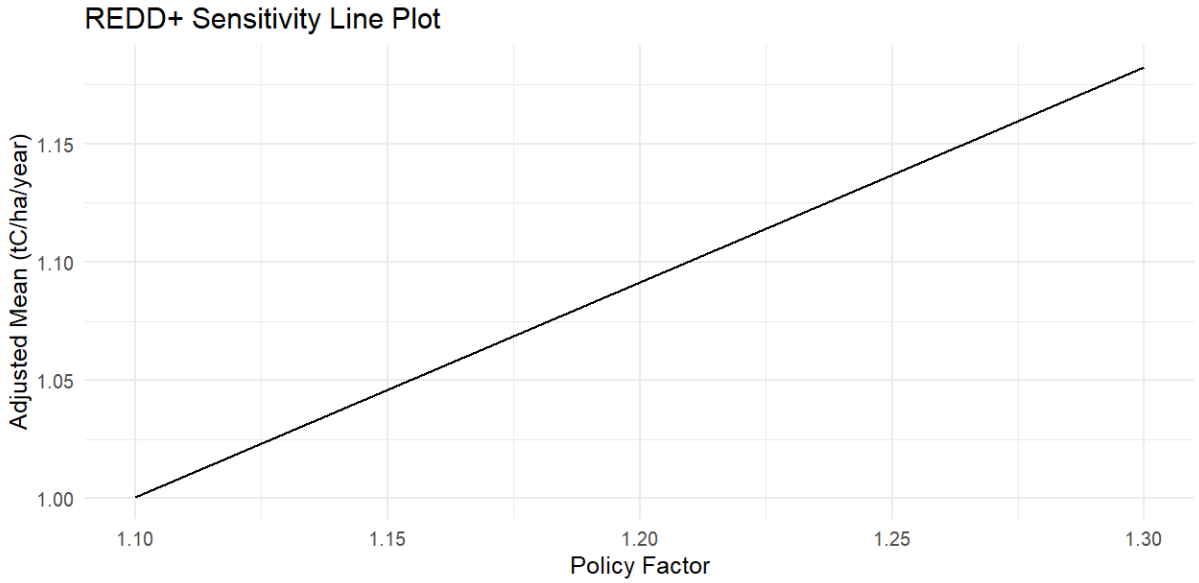
SM II.5 a) Social Layer:

Policy Factor Application

> ml_data$policy_adjusted_sequestration <- ml_data$predicted_sequestration * policy_factor

Policy Factor	Adjusted Mean (tC/ha/year)
1.10	10005
1.15	1046
1.20	10915
1.25	11377
1.30	11825

SM II.5 b) Figure Social Layer



SM II.6: Table: Transformity Sensitivity (Trillions USD/year)

Source	Transformity	Holistic_Addition
Odum (1996)	1.5e+08	10.92
Campbell (2023)	1.2e+08	8.73

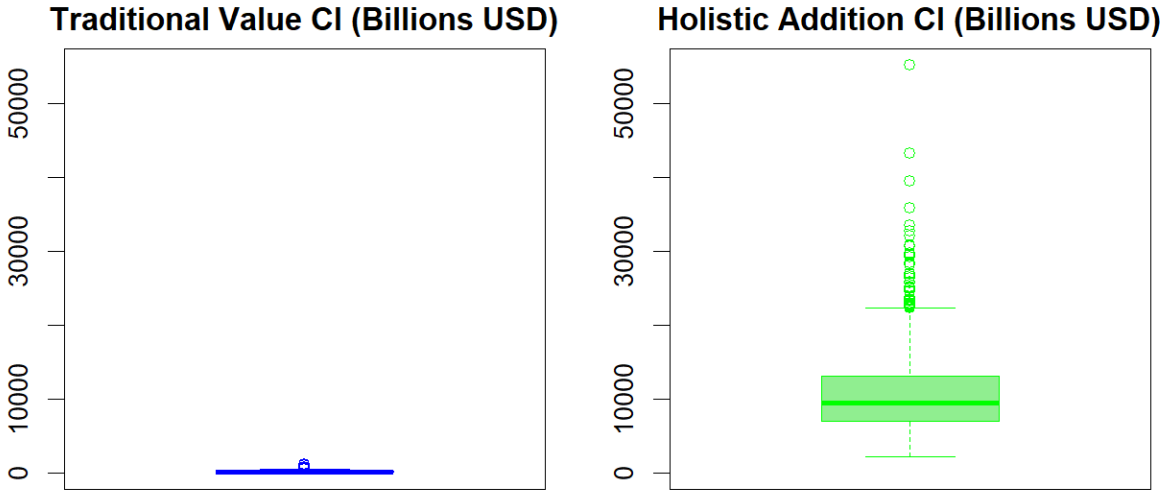
SM II.7) Table: Emergy Baseline Sensitivity Analysis

Baseline Factor	Holistic Addition (USD/year)
0.8	$13643.83
1.0	$10915.07
1.2	$9095.89

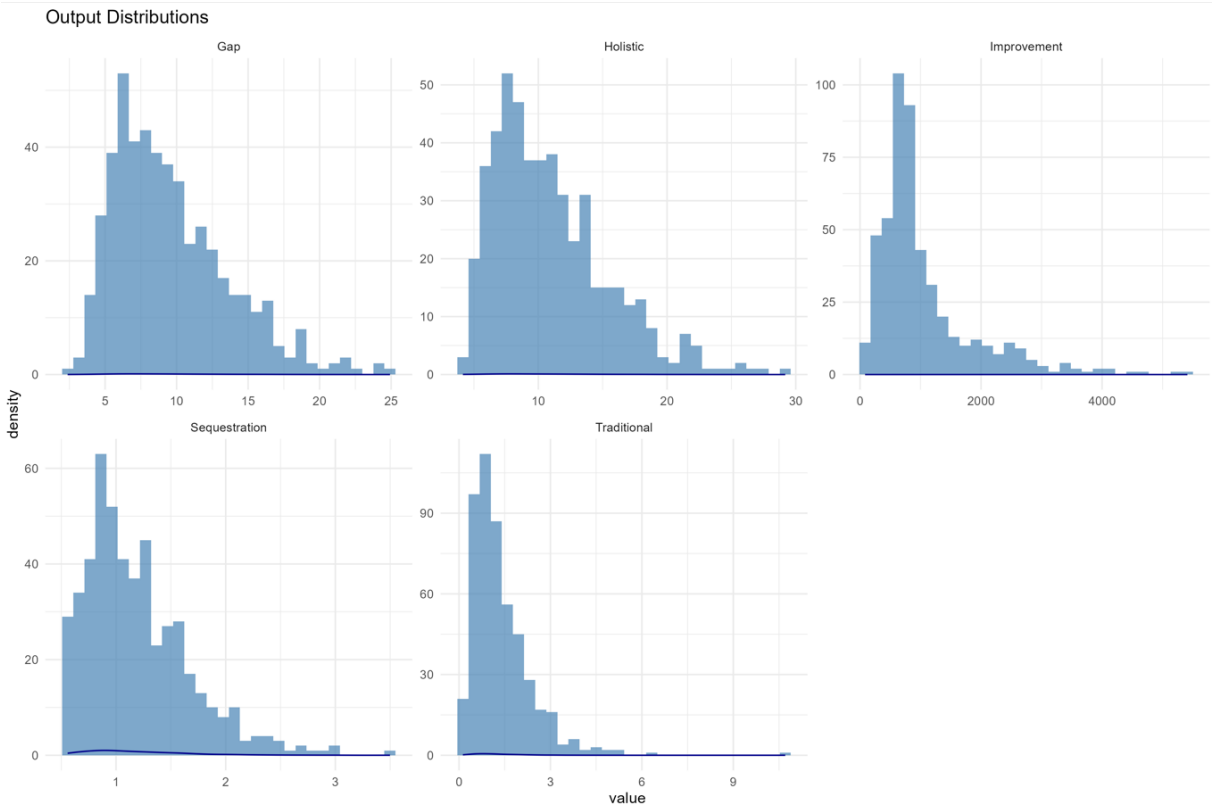
SM II.8) Monte Carlo Simulation for Uncertainty (n=1000)

Métrica	Media (Mean)	IC 95% Inferior	IC 95% Superior
Traditional Value	$232154450839	$46258628998	$606675999239
Holistic Addition	$10785100947732	$3915809549989	$25002560183724

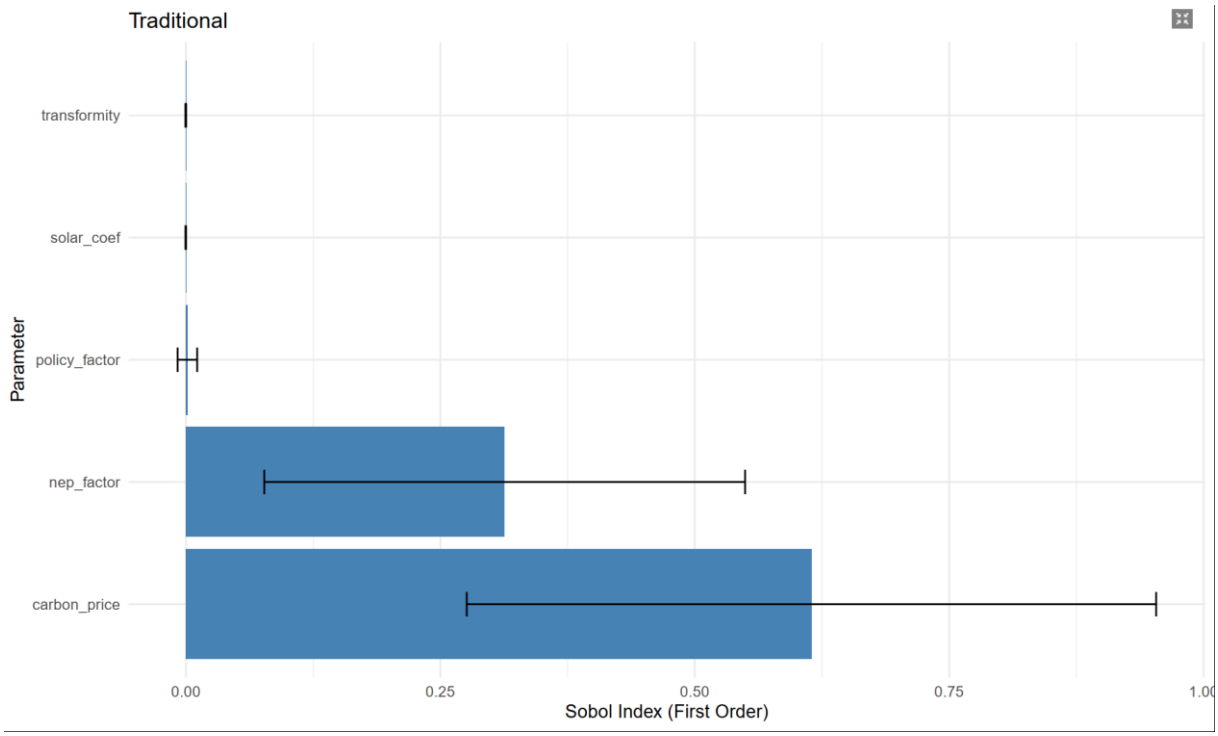
SM II.9: Boxplot for Montecarlo Simulation

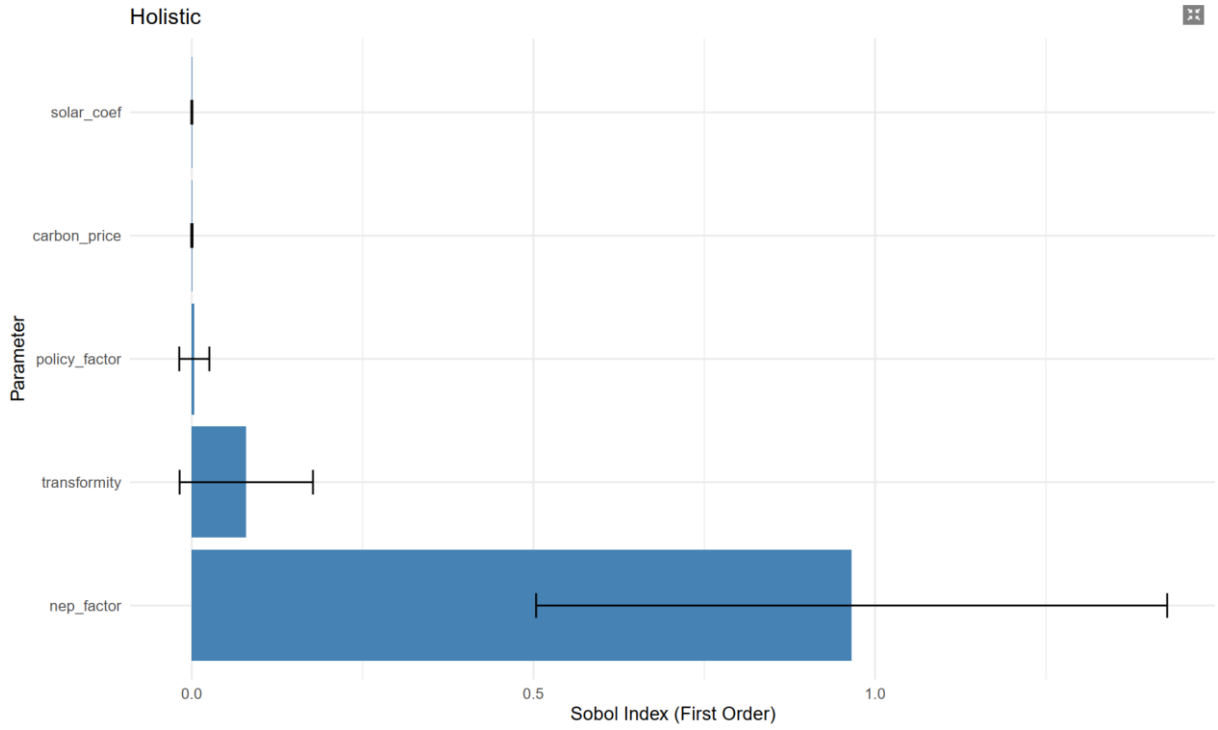


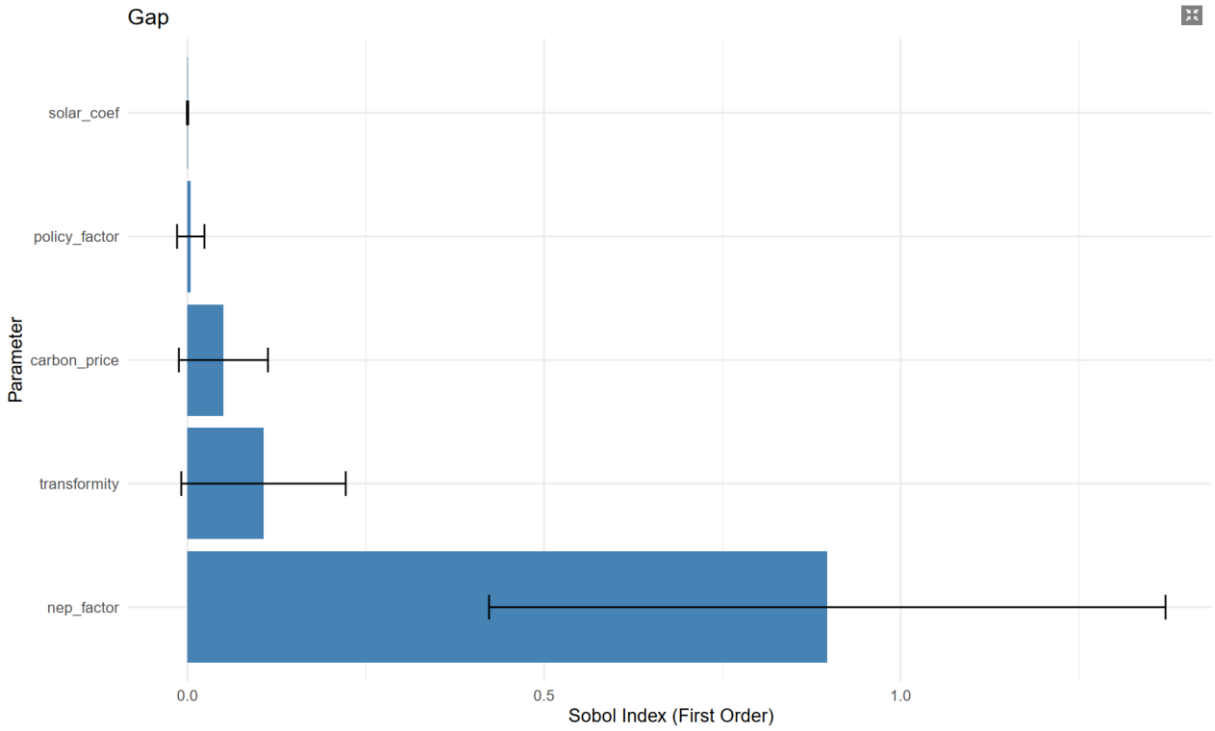
SM II.10: PSA Output Distribution

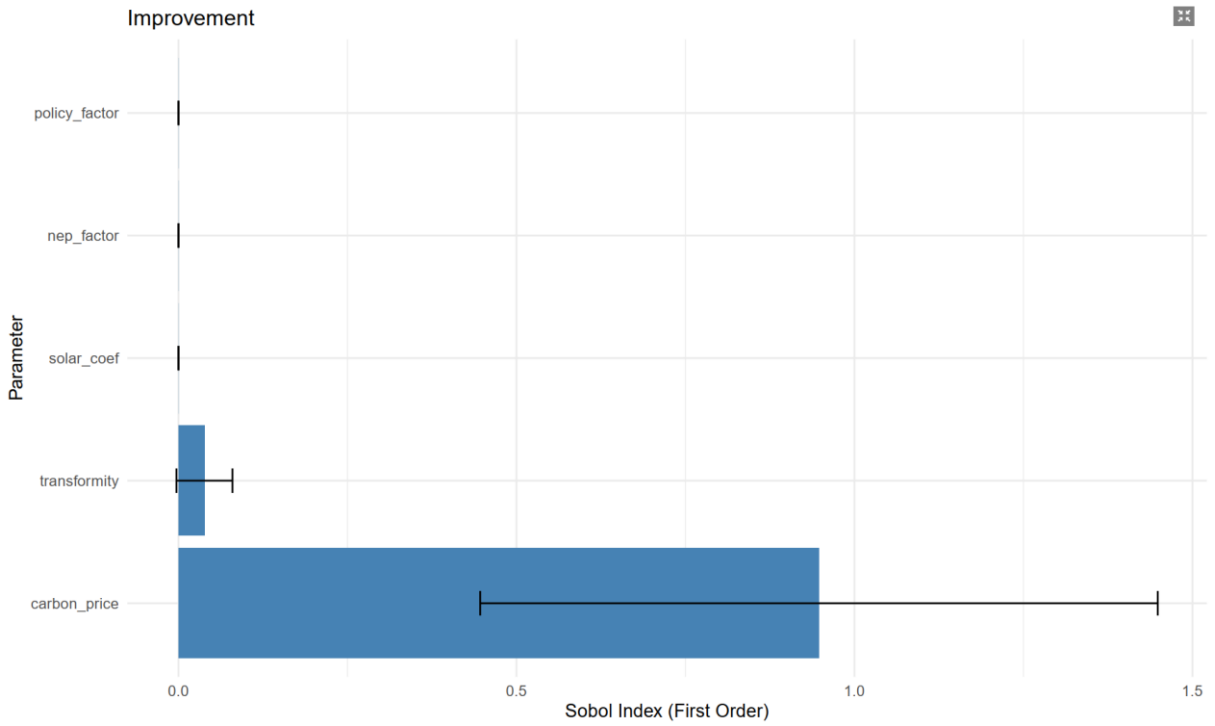


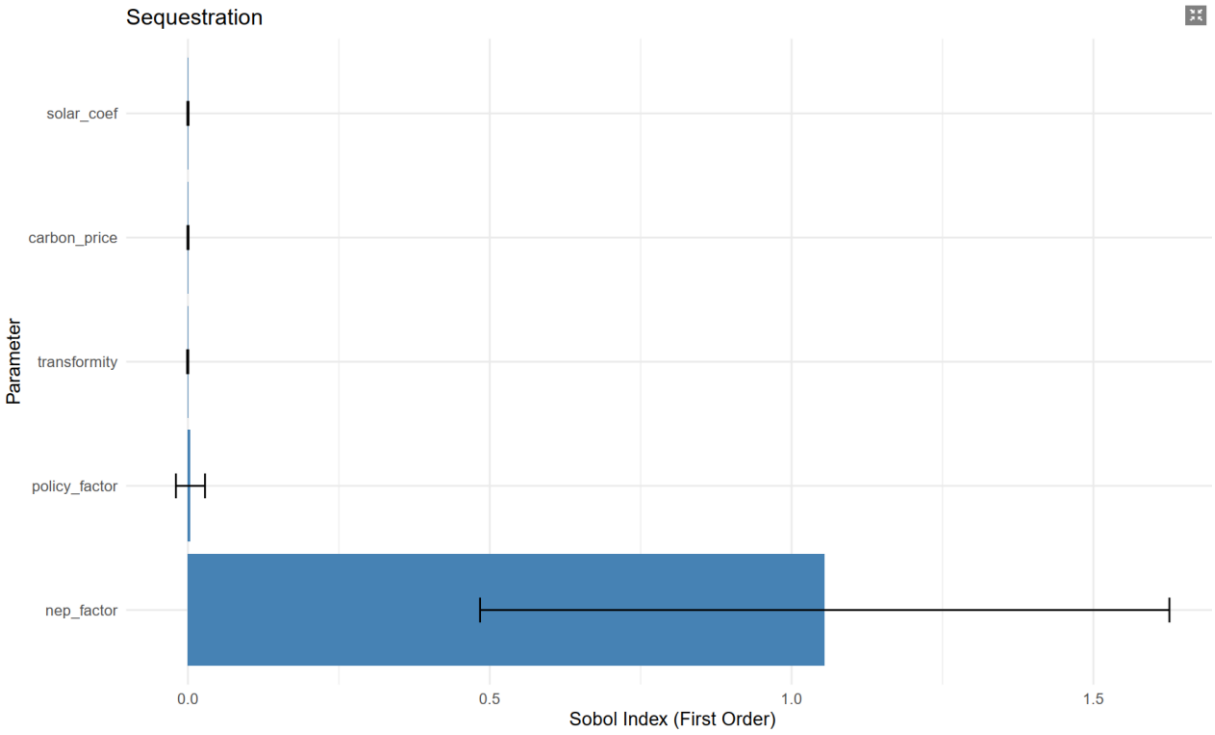
SM II. 11: PSA Sobol Tornado






Gap
solar_coef
policy_factor
carbon_price
transformity
nep_factor
Parameter
0.0
0.5
1.0
Sobol Index (First Order)


Improvement
policy_factor
nep_factor
solar_coef
transformity
carbon_price
Parameter
0.0
0.5
1.0
1.5
Sobol Index (First Order)


Sequestration
solar_coef
carbon_price
transformity
policy_factor
nep_factor
Parameter
0.0
0.5
1.0
1.5
Sobol Index (First Order)

SCRIPT

#5ene2026

Sink output to log file at the beginning (captures all console output)

sink("_log.txt", append = FALSE, split = TRUE) # append=FALSE to start fresh; split=TRUE to also show on console

Original code starts here, with existing logging enhanced where needed

- Logging for ForC vs. MODIS usage, including proportion.

- Geolocation summary and optional world map plot for sites.

- Increased ntree=500 in Random Forest, with pseudo-R^2 and cross-validation (via caret).

- Transformity sensitivity: Odum (1.5e8 sej/g) vs. Campbell (1.2e8 sej/g).

- Alternative carbon price: $50/tCO2e (from Trove Research 2024; IPCC AR drafts for high-quality forestry).

- Additional: CV for RF, global sink variance, logging to file, results export, BhBB comments.

- Enhanced filtering for all NPP components (sum per site/year for total NPP; exclude stocks).

- Expanded unit normalization with more patterns; handle more data points.

- Integrated MODIS MOD17A3HGF for global-representative NPP extraction at ForC sites, adjusted to approximate NEP (net sequestration) using calibrated factor ~0.1 (adjusted from literature: Pan et al. 2011 ratio ~0.11 for global forests; previous 0.055 was too low).

- Added validation vs. IPCC benchmarks (~2 GtC/year net forest sink).

- Fixed fallback logic: Check for valid rates (not just nrow==0) to handle empty/NA data from MODIS.

- Fixed join in fallback: Use consistent column names ("sites.sitename" = "site_name").

- Proper CV: Use train() for metrics only; final model on full data.

- Monte Carlo: Added uncertainty to carbon price (normal dist, mean=14.8, sd=5 based on market volatility).

- Expanded filter to include respiration variables (R_het_soil_C, R_soil_C) for direct NEP calculation where possible.

- In fallback, prioritize direct NEP if available, else calculate as NPP - Rh if Rh present, else use factor; group by site only to avoid date issues.

- Fixed predicted_sequestration in else: Create as vector rep(avg_sequestration, nrow(ml_data)).

```
# - Added final "Gap de Valoración" graph: Difference between traditional (base) and holistic (Odum/Campbell).
# - Expected outcome: Average sequestration rate (NEP approx.) ~1 tC/ha/year with new factor; global sink ~2 GtC/year alignment; holistic addition in trillions USD/year.
# - Modification: Added explicit solar insolation data using nasapower package from NASA's POWER API. Fetched climatological annual average ALLSKY_SFC_SW_DWN (kW-hr/m²/day) for each site and included as a predictor in ML model.

# Install packages if necessary
if (!require("dplyr")) install.packages("dplyr")
if (!require("randomForest")) install.packages("randomForest")
if (!require("ggplot2")) install.packages("ggplot2")
if (!require("readr")) install.packages("readr")
if (!require("knitr")) install.packages("knitr")
if (!require("MODISTools")) install.packages("MODISTools")
if (!require("pbapply")) install.packages("pbapply")
if (!require("caret")) install.packages("caret")  # For cross-validation
if (!require("maps")) install.packages("maps")  # For site map
if (!require("nasapower")) install.packages("nasapower")  # For NASA's POWER API solar data

library(dplyr)
library(randomForest)
library(ggplot2)
library(readr)
library(knitr)
library(MODISTools)
library(pbapply)
library(caret)
library(maps)
library(nasapower)

# Start logging (define early to avoid reference errors; but since sink is active, this will go to log)
```

```
log_file <- "cbpss_log.txt"  # Keeping original for specific cats, but main log is _log.txt via sink
cat("CBPSS Model Run - January 05, 2026\n", file = log_file)

# Create results directory if it doesn't exist
dir.create("results", showWarnings = FALSE)

# --- GLOBAL PARAMETER CONFIGURATION (Social/DIP Layer) --- [Links to BsBB/BmBB for valuation]
global_forest_area_ha <- 4e9  # Approx. global forest area (ha)
carbon_price_usd_base <- 14.80  # Base average carbon credit price (USD/tCO2e; Ecosystem Marketplace 2023)
carbon_price_usd_alt <- 50.00  # Alternative from literature (Trove Research 2024; IPCC AR7 drafts for high-quality forestry)
carbon_price_sd <- 5.00  # SD for Monte Carlo uncertainty (based on market volatility)
policy_factor <- 1.20  # REDD+ policy adjustment factor (Base +20%)
transformity_sej_per_g_biomass_odum <- 1.5e8  # Odum (1996)
transformity_sej_per_g_biomass_campbell <- 1.2e8  # Campbell (2023) alternative
biomass_per_tC <- 2e6  # Grams of biomass per ton of Carbon (g/tC)
global_emergy_baseline <- 1.2e25  # Global Emergy baseline (sej/year)
global_gdp_usd <- 100e12  # Approx. Global GDP (USD)
nep_factor <- 0.1  # Adjusted NEP/NPP ratio from literature (Pan et al. 2011 ~0.11; typical 0.1-0.3 for forests)

# --- Step 1: Bio-Physical Layer (Quantification of Stocks and Fluxes) --- [Core for BmBB/BsBB metabolism]
# Load local data (assuming 'data/' contains the files)
sites <- read_csv("data/ForC_sites.csv", show_col_types = FALSE)
print(problems(sites))  # Inspect parsing issues
measurements <- read_csv("data/ForC_measurements.csv", show_col_types = FALSE)
print(problems(measurements))  # Inspect parsing issues

# 1.1 Merging and Variable Filtering (Expanded to include respiration for NEP)
data_forc <- measurements %>%
  left_join(sites %>% select(sites.sitename, lat, lon, masl, mat, map), by = "sites.sitename")
```

```
forest_data <- data_forc %>%

filter(grepl("biomass_ag|soil_C|C_organic_soil|GPP|NPP|R_het_soil|R_soil|NEP|NEE|biomass_root|litter_C", variable.name)) %>%
  mutate(mean = as.numeric(mean)) %>%
  filter(!is.na(mean))

# 1.2 Initial Stock/Flux Summary (For Table S1)
bio_physical_summary <- forest_data %>%
  group_by(variable.name) %>%
  summarise(avg_mean = mean(mean, na.rm = TRUE),
            sd_mean = sd(mean, na.rm = TRUE))
print("Bio-Physical Summary Table:")
print(kable(bio_physical_summary, caption = "Summary of Bio-Physical Variables from ForC Database",
            col.names = c("Variable Name", "Average Value", "Standard Deviation"),
            digits = 2))
write.csv(bio_physical_summary, "results/Table1_BioPhysical_Summary.csv")

# 1.3 Improved Sequestration Rate Calculation (NPP Proxy with MODIS Integration, adjusted to NEP approx.)
# First, prepare sites coords (unique, non-NA)
sites_coords <- sites %>%
  filter(!is.na(lat) & !is.na(lon)) %>%
  select(site_name = sites.sitename, lat, lon, masl, mat, map) %>%
  distinct()

# Optional: Limit sites for faster testing (uncomment for full run; e.g., head(100) for testing)
# sites_coords <- head(sites_coords, 100) # For quick testing

# Fetch explicit solar insolation data using nasapower (NASA POWER API)
cat("Starting solar insolation extraction via NASA's POWER API...\n", file = log_file, append = TRUE)
```

```
print("Extracting climatological annual solar insolation (ALLSKY_SFC_SW_DWN) for ForC sites with progress bar...")
get_solar_single <- function(row) {
  tryCatch({
    solar_data <- get_power(
      community = "re",
      lonlat = c(row$lon, row$lat),
      pars = "ALLSKY_SFC_SW_DWN",
      temporal_api = "climatology"
    )
    solar_data$ANN  # Return annual average (kW-hr/m²/day)
  }, error = function(e) {
    cat(paste("Error extracting solar for site", row$site_name, ":", e$message, "\n"), file = log_file, append = TRUE)
    return(NA_real_)
  })
}
solar_list <- pblapply(split(sites_coords, 1:nrow(sites_coords)), get_solar_single)
sites_coords$solar_insolation <- unlist(solar_list)

num_valid_solar <- sum(!is.na(sites_coords$solar_insolation))
num_failed_solar <- nrow(sites_coords) - num_valid_solar
print(paste("Número de sitios con insolación solar válida:", num_valid_solar, "de", nrow(sites_coords)))
print(paste("Número de sitios fallidos en extracción solar:", num_failed_solar))
cat(paste("Número de sitios con insolación solar válida:", num_valid_solar, "de", nrow(sites_coords), "\n"), file = log_file, append = TRUE)
cat(paste("Número de sitios fallidos en extracción solar:", num_failed_solar, "\n"), file = log_file, append = TRUE)

cat("Solar insolation extraction complete. Average solar:", mean(sites_coords$solar_insolation, na.rm = TRUE), "kW-hr/m²/day\n", file = log_file, append = TRUE)
```

```
# Extract MODIS NPP with progress bar (loop over sites)
cat("Starting MODIS extraction...\n", file = log_file, append = TRUE)
print("Extracting MODIS NPP for ForC sites with progress bar...")
get_npp_single <- function(row) {
  tryCatch({
    mt_subset(
      product = "MOD17A3HGF",
      band = "Npp_500m",
      lat = row$lat,
      lon = row$lon,
      start = "2022-01-01",
      end = "2024-12-31",
      km_lr = 0, km_ab = 0,
      site_name = row$site_name,
      internal = TRUE
    )
  }, error = function(e) {
    cat(paste("Error extracting for site", row$site_name, ":", e$message, "\n"), file = log_file,
append = TRUE)
    return(NULL)
  })
}
npp_list <- pblapply(split(sites_coords, 1:nrow(sites_coords)), get_npp_single)

# Filter out NULLs from errors
npp_list <- npp_list[!sapply(npp_list, is.null)]

# Check if any data was fetched before binding
if (length(npp_list) > 0) {
  npp_modis <- do.call(rbind, npp_list)
  cat("MODIS extraction succeeded for some sites. Using MODIS for calculations.\n", file =
log_file, append = TRUE)
} else {
  npp_modis <- data.frame() # Empty df to trigger fallback
```

```
  cat("MODIS extraction failed completely. Falling back to ForC for calculations.\n", file = log_file, append = TRUE)
}

# Process MODIS data: Apply scale and convert kgC/m²/yr to tC/ha/yr, then adjust to NEP approx.
sequestration_data <- npp_modis %>%
  mutate(sequestration_rate = as.numeric(value) * as.numeric(scale) * 10) %>% # kgC/m²/yr to tC/ha/yr
  filter(!is.na(sequestration_rate)) %>%
  group_by(site) %>% # Fixed: Use 'site' column from MODISTools output
  summarise(sequestration_rate = mean(sequestration_rate, na.rm = TRUE)) %>%
  mutate(sequestration_rate = sequestration_rate * nep_factor) %>% # Adjusted NEP factor
  left_join(sites_coords %>% select(site_name, lat, lon, masl, mat, map, solar_insolation), by = c("site" = "site_name"))
data_source <- "MODIS" # Default

# Improved Fallback Logic: Trigger if no valid rates (handles empty data or all NA)
if (nrow(sequestration_data) == 0 || all(is.na(sequestration_data$sequestration_rate))) {
  cat("Using ForC fallback for 100% of calculations.\n", file = log_file, append = TRUE)
  print("MODIS extraction failed or no valid data; falling back to improved ForC NPP...")
  # Prioritize direct NEP/NEE if available
  nep_data <- forest_data %>%
    filter(grepl("NEP|NEE", variable.name)) %>%
    mutate(sequestration_rate = mean) %>% # Direct NEP
    group_by(sites.sitename) %>%
    summarise(sequestration_rate = mean(sequestration_rate, na.rm = TRUE)) %>%
    left_join(sites_coords, by = c("sites.sitename" = "site_name"))

  if (nrow(nep_data) > 0 && !all(is.na(nep_data$sequestration_rate))) {
    sequestration_data <- nep_data
    cat("Using direct NEP from ForC.\n", file = log_file, append = TRUE)
  } else {
    # Calculate NEP = NPP - Rh if Rh available
```

```
  npp_data <- forest_data %>%
    filter(grepl("NPP", variable.name)) %>%
    mutate(original.units.cleaned = tolower(gsub("[^a-z0-9/]", "", gsub("\\s+", "", original.units)))) %>%  # Corrigido: "\\s+"
    filter(grepl("yr|year|ann|peryear|yr1|yr-1|annual|peryr", original.units.cleaned)) %>%
    filter(!is.na(original.units) & original.units != "NA" & original.units != "NAC") %>%
    mutate(component_rate = case_when(
      grepl("gc/m2/yr|gc/m2yr|g/m2/yr|g/m2yr|gcm2yr1|gcm-2yr-1|gcm2yr|gcm-2yr|gcm-2a-1|gcm-2year-1|gc/m2/ann|gc/m2annual", original.units.cleaned) ~ mean / 100,
      grepl("mgc/ha/yr|mgc/hayr|mg/ha/yr|mg/hayr|mgcha-1yr-1|mgcha1yr1|mgc/ha/ann|mgc/haannual", original.units.cleaned) ~ mean,
      grepl("kgc/ha/yr|kgc/hayr|kg/ha/yr|kg/hayr|kgcha-1yr-1|kgcha1yr1|kgc/ha/ann|kgc/haannual", original.units.cleaned) ~ mean / 1000,
      grepl("tc/ha/yr|tc/hayr|tcha-1yr-1|tcha1yr1|tc/ha/ann|tc/haannual",  original.units.cleaned) ~ mean,
      grepl("kgc/m2/yr|kgc/m2yr|kg/m2/yr|kg/m2yr|kgcm2yr1|kgcm-2yr-1|kgc/m2/ann|kgc/m2annual", original.units.cleaned) ~ mean * 10,
      TRUE ~ NA_real_
    )) %>%
    filter(!is.na(component_rate)) %>%
    group_by(sites.sitename) %>% # Group by site only to avoid date issues
    summarise(npp_rate = mean(component_rate, na.rm = TRUE)) # Average across components/dates

  rh_data <- forest_data %>%
    filter(grepl("R_het_soil|R_soil", variable.name)) %>%
    mutate(original.units.cleaned = tolower(gsub("[^a-z0-9/]", "", gsub("\\s+", "", original.units)))) %>%  # Corrigido: "\\s+"
    filter(grepl("yr|year|ann|peryear|yr1|yr-1|annual|peryr", original.units.cleaned)) %>%
    filter(!is.na(original.units) & original.units != "NA" & original.units != "NAC") %>%
    mutate(component_rate = case_when(
      grepl("gc/m2/yr|gc/m2yr|g/m2/yr|g/m2yr|gcm2yr1|gcm-2yr-1|gcm2yr|gcm-2yr|gcm-2a-1|gcm-2year-1|gc/m2/ann|gc/m2annual", original.units.cleaned) ~ mean / 100,
```

```
      grepl("mgc/ha/yr|mgc/hayr|mg/ha/yr|mg/hayr|mgcha-1yr-
1|mgcha1yr1|mgc/ha/ann|mgc/haannual", original.units.cleaned) ~ mean,
      grepl("kgc/ha/yr|kgc/hayr|kg/ha/yr|kg/hayr|kgcha-1yr-
1|kgcha1yr1|kgc/ha/ann|kgc/haannual", original.units.cleaned) ~ mean / 1000,
      grepl("tc/ha/yr|tc/hayr|tcha-1yr-1|tcha1yr1|tc/ha/ann|tc/haannual",  original.units.cleaned)
~ mean,
      grepl("kgc/m2/yr|kgc/m2yr|kg/m2/yr|kg/m2yr|kgcm2yr1|kgcm-2yr-
1|kgc/m2/ann|kgc/m2annual", original.units.cleaned) ~ mean * 10,
      TRUE ~ NA_real_
    )) %>%
    filter(!is.na(component_rate)) %>%
    group_by(sites.sitename) %>%
    summarise(rh_rate = mean(component_rate, na.rm = TRUE))

  # Join and calculate NEP
  sequestration_data_forc <- npp_data %>%
    left_join(rh_data, by = "sites.sitename") %>%
    mutate(sequestration_rate = ifelse(!is.na(rh_rate), npp_rate - rh_rate, npp_rate *
nep_factor)) # Use calculated or factor

  sequestration_data <- sequestration_data_forc %>%
    left_join(sites_coords, by = c("sites.sitename" = "site_name"))
  data_source <- "ForC"
  cat("Using calculated NEP from ForC components.\n", file = log_file, append = TRUE)
 }
} else {
 cat(paste("Using MODIS for 100% of calculations (", nrow(sequestration_data), "sites).\n"),
file = log_file, append = TRUE)
}
# Geolocation Summary
num_sites <- nrow(sequestration_data)
min_lat <- min(sequestration_data$lat, na.rm = TRUE)
max_lat <- max(sequestration_data$lat, na.rm = TRUE)
min_lon <- min(sequestration_data$lon, na.rm = TRUE)
```

```
max_lon <- max(sequestration_data$lon, na.rm = TRUE)
print(paste("Final number of sites:", num_sites))
print(paste("Sites span latitudes:", min_lat, "to", max_lat, "; longitudes:", min_lon, "to", max_lon))
cat(paste("Sites:", num_sites, "from global map (lat", min_lat, "-", max_lat, "; lon", min_lon, "-", max_lon, ")\n"), file = log_file, append = TRUE)

# Optional: Plot site map
world <- map_data("world")
ggplot() +
  geom_map(data = world, map = world, aes(long, lat, map_id = region), fill = "lightgray", color = "white") +
  geom_point(data = sequestration_data, aes(x = lon, y = lat), color = "red", size = 1, alpha = 0.5) +
  labs(title = "Global Distribution of ForC Sites Used") +
  theme_minimal()
ggsave("results/Fig_Site_Map.png", width = 10, height = 6)

# Debug: Print stats
print(paste("Number of sites with valid NPP:", num_sites))
avg_sequestration <- mean(sequestration_data$sequestration_rate, na.rm = TRUE)
print(paste("Improved Average Sequestration Rate (t C/ha/year):", round(avg_sequestration, 2)))

# Validation: Global extrapolation vs. IPCC (~2 GtC/year land sink)
global_sink_gtC_year <- avg_sequestration * global_forest_area_ha / 1e9 # GtC/year
global_sink_variance <- var(sequestration_data$sequestration_rate, na.rm = TRUE) * (global_forest_area_ha / 1e9)^2 # Approximate variance
print(paste("Estimated Global Forest Sink (GtC/year):", round(global_sink_gtC_year, 2), "(should align with ~2 GtC/year)"))
print(paste("Global Sink Variance:", round(global_sink_variance, 2)))


# Check MODIS access and date range (flexible based on extraction parameters)
```

```
if (data_source == "MODIS" && "calendar_date" %in% colnames(npp_modis)) {
  extracted_dates <- unique(npp_modis$calendar_date[!is.na(npp_modis$calendar_date)])
  if (length(extracted_dates) > 0) {
    date_range_min <- min(as.Date(extracted_dates))
    date_range_max <- max(as.Date(extracted_dates))
    print(paste("MODIS extracted date range:", date_range_min, "to", date_range_max))
    cat(paste("MODIS extracted date range:", date_range_min, "to", date_range_max, "\n"), file = log_file, append = TRUE)

    # Expected dates (hardcoded here, but you can change to match your start/end when testing/expanding)
    expected_start <- as.Date("2022-01-01")
    expected_end <- as.Date("2024-12-31")  # Adjust this when starting with one year (e.g., "2022-12-31")

    if (date_range_min >= expected_start && date_range_max <= expected_end) {
      print("MODIS data covers the expected period successfully.")
      cat("MODIS data covers the expected period successfully.\n", file = log_file, append = TRUE)
    } else {
      print("Warning: MODIS dates do not fully match expected period; partial data or error.")
      cat("Warning: MODIS dates do not fully match expected period; partial data or error.\n", file = log_file, append = TRUE)
    }
  } else {
    print("No valid dates in MODIS data; check extraction.")
    cat("No valid dates in MODIS data; check extraction.\n", file = log_file, append = TRUE)
  }
} else if (data_source == "MODIS") {
  print("MODIS data fetched but no 'calendar_date' column; unable to verify period.")
  cat("MODIS data fetched but no 'calendar_date' column; unable to verify period.\n", file = log_file, append = TRUE)
} else {
  print("Using ForC fallback; no MODIS date check needed.")
```

```
  cat("Using ForC fallback; no MODIS date check needed.\n", file = log_file, append = TRUE)
}

# Calculate proportion of MODIS vs. ForC (based on successful extractions)
total_sites_attempted <- nrow(sites_coords)
modis_successful_sites <- length(npp_list)  # Number of sites with successful extraction (pre-binding)
forc_sites_used <- if (data_source == "ForC") nrow(sequestration_data) else 0  # If fallback, all from ForC
proportion_modis <- (modis_successful_sites / total_sites_attempted) * 100
proportion_forc <- (forc_sites_used / total_sites_attempted) * 100  # 0 if MODIS fully used
print(paste("Proportion of sites using MODIS:", round(proportion_modis, 2), "% (", modis_successful_sites, "of", total_sites_attempted, ")"))
print(paste("Proportion of sites using ForC fallback:", round(proportion_forc, 2), "% (", forc_sites_used, "of", total_sites_attempted, ")"))
cat(paste("Proportion of sites using MODIS:", round(proportion_modis, 2), "% (", modis_successful_sites, "of", total_sites_attempted, ")\n"), file = log_file, append = TRUE)
cat(paste("Proportion of sites using ForC fallback:", round(proportion_forc, 2), "% (", forc_sites_used, "of", total_sites_attempted, ")\n"), file = log_file, append = TRUE)

# Additional pertinent check: Summary of sequestration rates (to spot data issues early)
if (nrow(sequestration_data) > 0) {
  print(summary(sequestration_data$sequestration_rate))
  cat("Summary of sequestration rates:\n", file = log_file, append = TRUE)
  capture.output(summary(sequestration_data$sequestration_rate), file = log_file, append = TRUE)
} else {
  print("No sequestration data available; check data sources.")
  cat("No sequestration data available; check data sources.\n", file = log_file, append = TRUE)
}
```

```
#
==========================================================================
===========
# --- Step 2: Cyber Layer (Machine Learning for Uncertainty Reduction) ---
# [BsBB integration via ML]
#
==========================================================================
===========
# 2.1 Data Preparation for ML
ml_data <- sequestration_data %>%
  select(lat, lon, masl, mat, map, solar_insolation, sequestration_rate) %>%
  na.omit() %>%
  rename(elevation = masl)
# 2.2 Random Forest Training and Prediction (ntree=500 for speed, limited mtry to prevent
errors)
if (nrow(ml_data) >= 10) {

  set.seed(123)

  # Proper CV for metrics: Split data for evaluation
  train_index <- createDataPartition(ml_data$sequestration_rate, p = 0.8, list = FALSE)
  train_data <- ml_data[train_index, ]
  test_data <- ml_data[-train_index, ]

  # Configuration for Cross-Validation with limited mtry (1-3, since p=5 predictors; sqrt(5)~2
for regression)
  control <- trainControl(method = "cv", number = 5, allowParallel = TRUE) # Enable parallel
  tune_grid <- expand.grid(mtry = c(1, 2, 3)) # Limit to avoid mtry > p error

  cat("Starting RF CV...\n", file = log_file, append = TRUE)

  # Training with caret for Cross-Validation metrics
  rf_cv <- train(sequestration_rate ~ lat + lon + elevation + mat + map + solar_insolation,
                 data = train_data,
```

```
            method = "rf",
            ntree = 500,
            trControl = control,
            tuneGrid = tune_grid) # Added to limit mtry

  print(rf_cv)

  # Logging CV results
  cat(paste("CV RMSE:", round(rf_cv$results$RMSE[1], 4), "\n"), file = log_file, append = TRUE)
  cat("RF CV complete.\n", file = log_file, append = TRUE)

  # Final model on full data for predictions
  cat("Training final RF...\n", file = log_file, append = TRUE)
  rf_model <- randomForest(sequestration_rate ~ lat + lon + elevation + mat + map + solar_insolation,
                           data = ml_data,
                           ntree = 500,
                           mtry = rf_cv$bestTune$mtry) # Use best mtry from CV

  ml_data$predicted_sequestration <- predict(rf_model, ml_data)

  # 2.2.1 Pseudo-R² from Out-of-Bag (OOB) error
  pseudo_r2 <- 1 - (mean(rf_model$mse) / var(ml_data$sequestration_rate))
  print(paste("Random Forest Pseudo-R²:", round(pseudo_r2, 3)))
  cat(paste("RF Pseudo-R²:", round(pseudo_r2, 3), "\n"), file = log_file, append = TRUE)

  # 2.3 Adaptability Metric (Uncertainty Reduction)
  original_sd <- sd(ml_data$sequestration_rate)
  predicted_sd <- sd(ml_data$sequestration_rate - ml_data$predicted_sequestration)

  uncertainty_reduction <- (1 - (predicted_sd / original_sd)) * 100

  # Print and Log Results
```

```
  message_uncer <- paste("Uncertainty Reduction via ML: Original SD =", round(original_sd,
4),
                         "; Residual SD =", round(predicted_sd, 4),
                         "; Reduction =", round(uncertainty_reduction, 1), "%")

  print(message_uncer)
  cat(paste("Uncertainty Reduction:", round(uncertainty_reduction, 1), "%\n"), file = log_file,
append = TRUE)
} else {

  # Fallback logic for insufficient data
  print("Insufficient data for ML; using average rate as prediction.")
  # Note: Ensure 'avg_sequestration' is calculated in Step 1
  ml_data$predicted_sequestration <- rep(mean(ml_data$sequestration_rate, na.rm = TRUE),
nrow(ml_data))
}
# Final Check of ML Results
head(ml_data)

#
================================================================
=======
# --- Step 3: Social Layer (Policy Application and Sensitivity) --- [Social governance for BhBB
equity]
#
================================================================
=======
# 3.1 Policy Factor Application
ml_data$policy_adjusted_sequestration <- ml_data$predicted_sequestration * policy_factor

# 3.2 Sensitivity Analysis for REDD+ Factor
print("--- Sensitivity Analysis for REDD+ Uplift (10-30%) ---")
sensitivity_df <- data.frame(factor = numeric(), adjusted_mean = numeric())
for (factor in seq(1.10, 1.30, 0.05)) {
```

```
  adjusted <- ml_data$predicted_sequestration * factor
  mean_adj <- mean(adjusted, na.rm = TRUE)
  print(paste("Policy factor", factor, ": Adjusted mean =", round(mean_adj, 4), "tC/ha/year"))
  sensitivity_df <- rbind(sensitivity_df, data.frame(factor = factor, adjusted_mean = mean_adj))
}
print("Table 2: REDD+ Sensitivity")
print(kable(sensitivity_df, caption = "REDD+ Uplift Sensitivity Analysis", digits = 4))
write.csv(sensitivity_df, "results/Table2_REDD.csv")
ggplot(sensitivity_df, aes(x = factor, y = adjusted_mean)) +
  geom_line() +
  labs(title = "REDD+ Sensitivity Line Plot", x = "Policy Factor", y = "Adjusted Mean (tC/ha/year)") +
  theme_minimal()
ggsave("results/Fig2_REDD_line.png", width = 6, height = 4)

#
=======================================================================
=======
# --- Step 4: DIP Integration (Metric Calculation and Monte Carlo) --- [Holistic BhBB via EmGDP]
#
=======================================================================
=======

# 4.1 Emdollar Ratio Calculation (USD/sej)
emdollar_ratio <- global_gdp_usd / global_emergy_baseline

# Function for holistic calculation (reusable for sensitivity)
compute_holistic <- function(mean_adj, transformity) {
  global_sequestration_tC_year <- mean_adj * global_forest_area_ha
  emergy_per_tC <- transformity * biomass_per_tC # sej/t C
  emergy_sequestration <- global_sequestration_tC_year * emergy_per_tC
  emdollar_value <- emergy_sequestration * emdollar_ratio
  return(emdollar_value)
```

```
}

# 4.2 Deterministic Metrics (Base)
mean_adjusted_sequestration <- mean(ml_data$policy_adjusted_sequestration, na.rm = TRUE)

# Traditional Metric (Base and Alternative Price)
traditional_value_base <- mean_adjusted_sequestration * global_forest_area_ha * 3.67 * carbon_price_usd_base
traditional_value_alt <- mean_adjusted_sequestration * global_forest_area_ha * 3.67 * carbon_price_usd_alt
print(paste("Traditional Value (Base Price $14.80/tCO2e, USD/year):", format(traditional_value_base, scientific = FALSE)))
print(paste("Traditional Value (Alt Price $50/tCO2e, USD/year):", format(traditional_value_alt, scientific = FALSE)))
cat(paste("Traditional Base:", format(traditional_value_base, scientific = FALSE), "\n"), file = log_file, append = TRUE)
cat(paste("Traditional Alt:", format(traditional_value_alt, scientific = FALSE), "\n"), file = log_file, append = TRUE)
getwd()

# Holistic Emergy Addition (Odum vs. Campbell)
holistic_emgdp_addition_odum <- compute_holistic(mean_adjusted_sequestration, transformity_sej_per_g_biomass_odum)
holistic_emgdp_addition_campbell <- compute_holistic(mean_adjusted_sequestration, transformity_sej_per_g_biomass_campbell)
print(paste("Holistic Addition via Emergy (Odum 1.5e8 sej/g, USD/year):", format(holistic_emgdp_addition_odum, scientific = FALSE)))
print(paste("Holistic Addition via Emergy (Campbell 1.2e8 sej/g, USD/year):", format(holistic_emgdp_addition_campbell, scientific = FALSE)))
print(paste("Total Improvement (Odum): EmGDP increases by", round((holistic_emgdp_addition_odum / traditional_value_base) * 100, 1), "% over traditional metric"))
```

```
print(paste("Total Improvement (Campbell): EmGDP increases by", round((holistic_emgdp_addition_campbell / traditional_value_base) * 100, 1), "% over traditional metric"))

# Transformity Sensitivity Table/Plot
transformity_sensitivity_df <- data.frame(
  Source = c("Odum (1996)", "Campbell (2024)"),
  Transformity = c(1.5e8, 1.2e8),
  Holistic_Addition = c(holistic_emgdp_addition_odum / 1e12, holistic_emgdp_addition_campbell / 1e12) # In trillions
)
print(kable(transformity_sensitivity_df, caption = "Transformity Sensitivity (Trillions USD/year)", digits = 2))
write.csv(transformity_sensitivity_df, "results/Table_Transformity_Sensitivity.csv")
ggplot(transformity_sensitivity_df, aes(x = Source, y = Holistic_Addition)) +
  geom_bar(stat = "identity", fill = "blue") +
  labs(title = "Transformity Sensitivity Comparison", y = "Holistic Addition (Trillions USD/year)") +
  theme_minimal()
ggsave("results/Fig_Transformity_Sensitivity.png", width = 6, height = 4)

# 4.3 Sensitivity Analysis for Emergy Baseline (±20%)
print("--- Sensitivity Analysis for Emergy Baseline (±20%) ---")
emergy_sensitivity_df <- data.frame(factor = numeric(), holistic_addition = numeric())
baseline_factors <- seq(0.8, 1.2, 0.2)
# Fix: Define emergy_sequestration for Odum before the loop
global_sequestration_tC_year <- mean_adjusted_sequestration * global_forest_area_ha
emergy_sequestration <- global_sequestration_tC_year * (transformity_sej_per_g_biomass_odum * biomass_per_tC)
for (factor in baseline_factors) {
  emdollar_ratio_new <- global_gdp_usd / (global_emergy_baseline * factor)
  emdollar_value_new <- emergy_sequestration * emdollar_ratio_new # Using Odum from earlier
```

```
 print(paste("Baseline factor", factor, ": Holistic Addition (USD/year) =", format(emdollar_value_new, scientific = FALSE)))
 emergy_sensitivity_df <- rbind(emergy_sensitivity_df, data.frame(factor = factor, holistic_addition = emdollar_value_new / 1e9))
}
print("Table 3: Emergy Baseline Sensitivity (Billions USD)")
print(kable(emergy_sensitivity_df, caption = "Emergy Baseline Sensitivity Analysis", digits = 2))
write.csv(emergy_sensitivity_df, "results/Table3_Emergy.csv")

# Asegura que la carpeta results exista
dir.create("results", showWarnings = FALSE)

# 4.4 Monte Carlo Simulation (95% CI for Global Extrapolation) - With carbon price uncertainty
if (nrow(ml_data) > 1) {
 print("--- Monte Carlo Simulation for Uncertainty (n=1000) ---")
 n_sim <- 1000
 sequestration_sd <- sd(ml_data$policy_adjusted_sequestration, na.rm = TRUE)

 if (is.na(sequestration_sd) || sequestration_sd == 0) {
  sequestration_sd <- mean_adjusted_sequestration * 0.2 # Assume 20% CV if SD=0
 }

 # Use lognormal for samples to ensure non-negative values
 cv <- sequestration_sd / mean_adjusted_sequestration # Coefficient of variation
 sdlog <- sqrt(log(1 + cv^2))
 meanlog <- log(mean_adjusted_sequestration) - sdlog^2 / 2

 samples <- rlnorm(n_sim, meanlog, sdlog)
 price_samples <- pmax(rnorm(n_sim, carbon_price_usd_base, carbon_price_sd), 0) # Truncate negative prices to 0

 # Calculate traditional value samples (with variable price)
```

```
  traditional_samples <- samples * global_forest_area_ha * 3.67 * price_samples

  # Calculate holistic addition samples (Odum transformity)
  global_sequestration_samples <- samples * global_forest_area_ha
  emergy_sequestration_samples <- global_sequestration_samples * (transformity_sej_per_g_biomass_odum * biomass_per_tC)
  holistic_samples <- emergy_sequestration_samples * emdollar_ratio

  # Summary: Mean and 95% CI
  traditional_ci <- quantile(traditional_samples, c(0.025, 0.975))
  holistic_ci <- quantile(holistic_samples, c(0.025, 0.975))

  print(paste("Traditional Value Mean (USD/year, with price uncertainty):", format(mean(traditional_samples), scientific = FALSE)))
  print(paste("Traditional Value 95% CI:", format(traditional_ci[1], scientific = FALSE), "to", format(traditional_ci[2], scientific = FALSE)))
  print(paste("Holistic Addition Mean (USD/year):", format(mean(holistic_samples), scientific = FALSE)))
  print(paste("Holistic Addition 95% CI:", format(holistic_ci[1], scientific = FALSE), "to", format(holistic_ci[2], scientific = FALSE)))

  # Calcular límites comunes para la escala Y (Same scale)
  common_min <- min(c(traditional_samples / 1e9, holistic_samples / 1e9), na.rm = TRUE)
  common_max <- max(c(traditional_samples / 1e9, holistic_samples / 1e9), na.rm = TRUE)

  # Plot to screen (with colors) - (pane Plots de RStudio)
  par(mar = c(3, 3, 2, 1)) # Reduced margins to avoid 'figure margins too large' error; adjust further if needed
  par(mfrow = c(1, 2)) # Divide the window into 1 row, 2 columns
  boxplot(traditional_samples / 1e9,
          main = "Traditional Value CI (Billions USD)",
          ylab = "Value",
          col = "lightblue",
          border = "blue",
```

```
        ylim = c(common_min, common_max))
  boxplot(holistic_samples / 1e9,
        main = "Holistic Addition CI (Billions USD)",
        ylab = "Value",
        col = "lightgreen",
        border = "green",
        ylim = c(common_min, common_max))

  # Fig. 3: Boxplot for Monte Carlo CI (saved to PDF, no colors for simplicity)
  pdf_file <- "results/Fig3_MonteCarlo_box.pdf"
  pdf(pdf_file, width = 8, height = 4)
  par(mar = c(3, 3, 2, 1)) # Reduced margins here too for consistency
  par(mfrow = c(1, 2))
  boxplot(traditional_samples / 1e9, main = "Traditional Value CI (Billions USD)", ylab =
"Value", ylim = c(common_min, common_max))
  boxplot(holistic_samples / 1e9, main = "Holistic Addition CI (Billions USD)", ylab = "Value",
ylim = c(common_min, common_max))
  dev.off()

  # Confirmation
  if (file.exists(pdf_file)) {
    print(paste("PDF generado exitosamente en:", pdf_file))
  } else {
    print("Error al generar PDF - verifica permisos o ruta.")
  }
} else {
  print("Insufficient data for Monte Carlo simulation.")
}
# 4.5 Visualization: Metric Comparison - OPTIMIZADO
comparison_df <- data.frame(
  Metric = c("Traditional\n(Base Price)", "Traditional\n(Alt Price)",
             "Holistic\n(Odum)", "Holistic\n(Campbell)"),
  Value_USD_trillions = c(traditional_value_base / 1e12,
                          traditional_value_alt / 1e12,
```

```
                holistic_emgdp_addition_odum / 1e12,
                holistic_emgdp_addition_campbell / 1e12)
)

ggplot(comparison_df, aes(x = Metric, y = Value_USD_trillions, fill = Metric)) +
  geom_bar(stat = "identity", width = 0.7) +
  # 1. We add the numbers on the bars
  geom_text(aes(label = round(Value_USD_trillions, 2)),
            vjust = -0.8, size = 4.5, fontface = "bold") +
  # 2. We expanded the Y axis by 20% to make room for the number and title
  scale_y_continuous(expand = expansion(mult = c(0, 0.2))) +
  # 3. We prevent R from cutting off numbers that stick out
  coord_cartesian(clip = "off") +
  labs(title = "Improvement in Holistic Bioeconomy Measurement via CBPSS",
       y = "Annual Value (Trillions USD)", x = "") +
  theme_minimal() +
  # 4. Science aesthetic adjustments
  theme(
    plot.title = element_text(hjust = 0.5, size = 13, face = "bold", margin = margin(b = 20)),
    axis.text.x = element_text(size = 10, face = "bold"), # Texto del eje X más claro
    plot.margin = margin(t = 40, r = 20, b = 10, l = 20), # Margen superior generoso
    legend.position = "none"
  )

# Save with dimensions that prevent distortion
ggsave("results/Fig4_Metric_Comparison.png", width = 9, height = 5, dpi = 600)



# New: Gap de Valoración Graph - Right for Science
gap_df <- data.frame(
  Metric = c("Odum Gap", "Campbell Gap"),
  Gap_USD_trillions = c((holistic_emgdp_addition_odum - traditional_value_base) / 1e12,
                        (holistic_emgdp_addition_campbell - traditional_value_base) / 1e12)
```

```
)

ggplot(gap_df, aes(x = Metric, y = Gap_USD_trillions, fill = Metric)) +
  geom_bar(stat = "identity", width = 0.6) +
  # 1. We expanded the Y axis by 15% upwards so that the number does not collide with the edge
  scale_y_continuous(expand = expansion(mult = c(0, 0.15))) +
  labs(title = "Valuation Gap: Holistic (Emergy) vs. Traditional (Market) Value",
       y = "Annual Gap (Trillions USD)",
       x = "") +
  # 2. We adjust vjust and add a more professional format
  geom_text(aes(label = round(Gap_USD_trillions, 2)),
            vjust = -0.8,
            size = 5,
            fontface = "bold") +
  # 3. We disable clipping (clip="off") so that the text is visible even if it extends beyond the area
  coord_cartesian(clip = "off") +
  theme_minimal() +
  # 4. We add extra margin at the top of the graph (plot.margin)
  theme(
    plot.title = element_text(hjust = 0.5, size = 14, face = "bold", margin = margin(b = 20)),
    plot.margin = margin(t = 30, r = 10, b = 10, l = 10), # 't' es top (margen superior)
    legend.position = "none" # Opcional: quita la leyenda si los nombres ya están en el eje X
  )

# Save in high resolution
ggsave("results/Fig_Gap_Valoracion.png", width = 8, height = 6, dpi = 600)



# End logging
cat("Model run complete.\n", file = log_file, append = TRUE)

# Close the sink at the end to stop redirecting output
```

sink()

```
#############
#Probabilistic Sensitivity Analysis
############
# Install packages if necessary (only once)
required_packages <- c("sensitivity", "ggplot2", "gridExtra", "dplyr", "doParallel", "foreach",
"reshape2", "moments", "kableExtra", "lhs", "randomForest")
for (pkg in required_packages) {
  if (!require(pkg, character.only = TRUE)) install.packages(pkg)
}
library(sensitivity)
library(ggplot2)
library(gridExtra)
library(dplyr)
library(doParallel)
library(foreach)
library(reshape2)
library(moments)
library(kableExtra)
library(lhs)
library(randomForest)

# Clean up any existing parallel backends to avoid connection errors
foreach::registerDoSEQ()

#------------------------------------------------------------------------------
# 0. INITIAL CONFIGURATION (Customizable)
#------------------------------------------------------------------------------
n_samples <- 500 # Number of LHS samples for uncertainty analysis
n_sobol <- 500   # For paper-quality precision (total runs ~3500)
n_cores <- max(1, detectCores() - 1) # Ensures at least 1 core
seed_value <- 123 # Seed for reproducibility
log_file <- "results/PSA_log.txt" # Log file
dir.create("results", showWarnings = FALSE) # Create directory if it does not exist
```

```
# Initialize log
cat("PSA Start -", format(Sys.time(), "%Y-%m-%d %H:%M:%S"), "\n", file = log_file)
# Load data from the main model if not present
if (!exists("ml_data") || !exists("global_forest_area_ha")) {
  rds_file <- "results/model_data.rds"
  if (file.exists(rds_file)) {
    loaded_data <- readRDS(rds_file)
    list2env(loaded_data, .GlobalEnv)
    cat("Data loaded from", rds_file, "\n", file = log_file, append = TRUE)
  } else {
    stop("Execute the main model first or generate 'results/model_data.rds'.")
  }
} else {
  # Save for future executions
  saveRDS(list(ml_data = ml_data, global_forest_area_ha = global_forest_area_ha,
               global_emergy_baseline = global_emergy_baseline, global_gdp_usd =
global_gdp_usd,
               biomass_per_tC = biomass_per_tC, nep_factor = nep_factor),
"results/model_data.rds")
}
#------------------------------------------------------------------------------
# 1. MODEL FUNCTION (Wrapper for PSA) - Optimized with variance check
#------------------------------------------------------------------------------
model_cbpss_psa <- function(params) {
  # Extract parameters with defaults if missing
  nep_factor_psa <- params$nep_factor
  transformity_psa <- params$transformity * 1e8 # sej/g
  carbon_price_psa <- params$carbon_price
  policy_factor_psa <- params$policy_factor
  solar_coef_psa <- params$solar_coef
  # 1.1 Bio-Physical Layer: NEP Adjustment
  sequestration_rate_adj <- ml_data$sequestration_rate * (nep_factor_psa / nep_factor)
  # Check for zero variance in response (common cause of failure in RF)
  if (sd(sequestration_rate_adj, na.rm = TRUE) == 0 || all(is.na(sequestration_rate_adj))) {
```

```
  return(rep(NA, 5))
 }
 # 1.2 Cyber Layer: RF with weighted solar insolation (reduced ntree for speed)
 ml_data_psa <- ml_data
 ml_data_psa$solar_weighted <- ml_data_psa$solar_insolation * solar_coef_psa
 rf_psa <- randomForest(sequestration_rate_adj ~ lat + lon + elevation + mat + map +
solar_weighted,
                        data = ml_data_psa, ntree = 50, importance = FALSE)
 predicted_sequestration <- predict(rf_psa, ml_data_psa)
 # 1.3 Social Layer: Policy Adjustment
 policy_adjusted <- predicted_sequestration * policy_factor_psa
 mean_adj_seq <- mean(policy_adjusted, na.rm = TRUE)
 # 1.4 DIP Layer: Metrics (includes check for division by zero)
 traditional_value <- mean_adj_seq * global_forest_area_ha * 3.67 * carbon_price_psa / 1e12
# Trillions USD
 global_seq_tC_year <- mean_adj_seq * global_forest_area_ha
 emergy_per_tC <- transformity_psa * biomass_per_tC
 emergy_seq <- global_seq_tC_year * emergy_per_tC
 emdollar_ratio <- global_gdp_usd / global_emergy_baseline
 holistic_value <- emergy_seq * emdollar_ratio / 1e12 # Trillions USD
 valuation_gap <- holistic_value - traditional_value
 percent_improvement <- if (traditional_value == 0) NA else (holistic_value / traditional_value
- 1) * 100
 sequestration_mean <- mean_adj_seq
 return(c(Traditional = traditional_value, Holistic = holistic_value, Gap = valuation_gap,
          Improvement = percent_improvement, Sequestration = sequestration_mean))
}
#------------------------------------------------------------------------------
# 2. PARAMETER DISTRIBUTION DEFINITION - Enhanced with validation and truncation
#------------------------------------------------------------------------------
# Truncated to avoid extremes/NA: nep_factor 0.05-0.3, carbon_price 5-300, etc.
param_distributions <- list(
 nep_factor = function(n) pmin(pmax(rlnorm(n, meanlog = log(0.1) - 0.5 * log(1 + 0.4^2),
sdlog = sqrt(log(1 + 0.4^2))), 0.05), 0.3),
```

```
  transformity = function(n) {
    min_val <- 1.0; mode_val <- 1.35; max_val <- 1.8
    u <- runif(n)
    ifelse(u <= (mode_val - min_val) / (max_val - min_val),
           min_val + sqrt(u * (max_val - min_val) * (mode_val - min_val)),
           max_val - sqrt((1 - u) * (max_val - min_val) * (max_val - mode_val)))
  },
  carbon_price = function(n) {
    components <- sample(1:3, n, replace = TRUE, prob = c(0.3, 0.5, 0.2))
    prices <- numeric(n)
    idx1 <- components == 1
    if (any(idx1)) prices[idx1] <- pmin(pmax(rlnorm(sum(idx1), log(35) - 0.5 * log(1 + 0.4^2),
sqrt(log(1 + 0.4^2))), 5), 100)
    idx2 <- components == 2
    if (any(idx2)) prices[idx2] <- pmin(pmax(rnorm(sum(idx2), 75, 15), 50), 100)
    idx3 <- components == 3
    if (any(idx3)) prices[idx3] <- pmin(pmax(rlnorm(sum(idx3), log(150) - 0.5 * log(1 + 0.3^2),
sqrt(log(1 + 0.3^2))), 100), 300)
    prices
  },
  policy_factor = function(n) pmin(pmax(rbeta(n, 8, 2) * 0.3 + 1.05, 1.05), 1.35),
  solar_coef = function(n) pmin(pmax(rnorm(n, 1, 0.3), 0.5), 1.5)
)
param_q <- list(
  nep_factor = function(p) pmin(pmax(qlnorm(p, meanlog = log(0.1) - 0.5 * log(1 + 0.4^2),
sdlog = sqrt(log(1 + 0.4^2))), 0.05), 0.3),
  transformity = function(p) {
    min_val <- 1.0; mode_val <- 1.35; max_val <- 1.8
    ifelse(p <= (mode_val - min_val) / (max_val - min_val),
           min_val + sqrt(p * (max_val - min_val) * (mode_val - min_val)),
           max_val - sqrt((1 - p) * (max_val - min_val) * (max_val - mode_val)))
  },
  carbon_price = function(p) {
    large_sample <- param_distributions$carbon_price(100000)
```

```
    quantile(large_sample, p, na.rm = TRUE)
  },
  policy_factor = function(p) pmin(pmax(qbeta(p, 8, 2) * 0.3 + 1.05, 1.05), 1.35),
  solar_coef = function(p) pmin(pmax(qnorm(p, 1, 0.3), 0.5), 1.5)
)
# Generate LHS samples for uncertainty
set.seed(seed_value)
param_names <- names(param_distributions)
X <- randomLHS(n_samples, length(param_names))
param_df <- as.data.frame(X)
colnames(param_df) <- param_names
for (i in seq_along(param_names)) {
  param_df[[param_names[i]]] <- param_distributions[[param_names[i]]](n_samples)
}
# Validation: Parameter histograms
pdf("results/PSA_Param_Distributions.pdf")
par(mfrow = c(2, 3))
for (param in param_names) {
  data <- param_df[[param]]
  if (is.numeric(data)) {
    hist(data, main = param, xlab = "Value", col = "lightblue")
  } else {
    cat("Warning: Column", param, "is not numeric. Class:", class(data), "\n", file = log_file,
append = TRUE)
  }
}
dev.off()
cat("Parameter distributions saved in results/PSA_Param_Distributions.pdf\n", file = log_file,
append = TRUE)
#------------------------------------------------------------------------------
# 4. PSA EXECUTION (Uncertainty with LHS) - Parallelized and robust
#------------------------------------------------------------------------------
cat("Executing PSA (n=", n_samples, ")...\n", file = log_file, append = TRUE)
cl <- makeCluster(n_cores)
```

```
registerDoParallel(cl)
results <- foreach(i = 1:n_samples, .combine = rbind, .packages = c("randomForest")) %dopar% {
  params <- as.list(param_df[i, ])
  tryCatch(model_cbpss_psa(params), error = function(e) {
    cat("Error in simulation", i, ":", e$message, "\n", file = log_file, append = TRUE)
    rep(NA, 5)
  })
}
stopCluster(cl)
colnames(results) <- c("Traditional", "Holistic", "Gap", "Improvement", "Sequestration")
# Handle NAs: Impute with mean if >5% NAs, log rate
na_prop <- colMeans(is.na(results))
cat("NA proportions per output:", paste(names(na_prop), round(na_prop, 3), collapse = "; "), "\n", file = log_file, append = TRUE)
if (any(na_prop > 0.05)) warning("High proportion of NAs; imputing means.")
for (col in 1:ncol(results)) {
  if (na_prop[col] > 0) {
    col_mean <- mean(results[, col], na.rm = TRUE)
    if (is.na(col_mean)) col_mean <- 0 # Fallback if all NA
    results[is.na(results[, col]), col] <- col_mean
  }
}
psa_results <- cbind(param_df, as.data.frame(results))
cat("PSA completed. Total NAs after imputation:", sum(is.na(psa_results)), "\n", file = log_file, append = TRUE)
#------------------------------------------------------------------------------
# 5. SENSITIVITY ANALYSIS (SOBOL INDICES) - With custom sampling
#------------------------------------------------------------------------------
cat("Computing Sobol indices...\n", file = log_file, append = TRUE)
# Generate Sobol design (uniform [0,1])
set.seed(seed_value + 1) # Different seed
X1 <- randomLHS(n_sobol, length(param_names))
colnames(X1) <- param_names # Ensures names for row.names in indices
```

```
X2 <- randomLHS(n_sobol, length(param_names))
colnames(X2) <- param_names
x <- sobol2007(model = NULL, X1 = X1, X2 = X2, nboot = 100)
# Transform to parameter scale
full_design_u <- x$X
full_param_df <- as.data.frame(full_design_u)
colnames(full_param_df) <- param_names
for (i in seq_along(param_names)) {
  full_param_df[[param_names[i]]] <- param_q[[param_names[i]]](full_design_u[, i])
}
# Execute model on complete design
cat("Executing Sobol (n=", nrow(full_param_df), ")...\n", file = log_file, append = TRUE)
cl <- makeCluster(n_cores)
registerDoParallel(cl)
results_sobol <- foreach(i = 1:nrow(full_param_df), .combine = rbind, .packages = c("randomForest")) %dopar% {
  params <- as.list(full_param_df[i, ])
  tryCatch(model_cbpss_psa(params), error = function(e) {
    cat("Error in Sobol simulation", i, ":", e$message, "\n", file = log_file, append = TRUE)
    rep(NA, 5)
  })
}
stopCluster(cl)
colnames(results_sobol) <- c("Traditional", "Holistic", "Gap", "Improvement", "Sequestration")
# Handle NAs for Sobol
na_prop_sobol <- colMeans(is.na(results_sobol))
cat("NA proportions per Sobol output:", paste(names(na_prop_sobol), round(na_prop_sobol, 3), collapse = "; "), "\n", file = log_file, append = TRUE)
if (any(na_prop_sobol > 0.05)) warning("High proportion of NAs in Sobol; imputing means.")
for (col in 1:ncol(results_sobol)) {
  if (na_prop_sobol[col] > 0) {
    col_mean <- mean(results_sobol[, col], na.rm = TRUE)
    if (is.na(col_mean)) col_mean <- 0 # Fallback if all NA
```

```
    results_sobol[is.na(results_sobol[, col]), col] <- col_mean
  }
}
# Compute indices with checks
sobol_list <- list()
for (var in colnames(results_sobol)) {
  y <- results_sobol[, var]
  sobol_obj <- x # Copy of the design
  # Check for length mismatch or all NA/zero variance
  if (length(y) != nrow(sobol_obj$X) || all(is.na(y)) || sd(y, na.rm = TRUE) == 0) {
    err_msg <- paste("Invalid y for", var, ": length", length(y), "sd", sd(y, na.rm = TRUE))
    cat(err_msg, "\n", file = log_file, append = TRUE)
    next # Skip this variable
  }
  # Wrap tell in tryCatch to handle internal errors
  tryCatch({
    tell(sobol_obj, y)
    sobol_list[[var]] <- sobol_obj
  }, error = function(e) {
    cat("Error in tell for", var, ":", e$message, "\n", file = log_file, append = TRUE)
  })
}
# If sobol_list is empty, note it
if (length(sobol_list) == 0) {
  cat("No Sobol indices computed due to errors; check log for details.\n", file = log_file, append
= TRUE)
}
#------------------------------------------------------------------------------
# 6. PROFESSIONAL VISUALIZATIONS (Science-ready) - Expanded
#------------------------------------------------------------------------------
# (No changes, but skip if sobol_list is empty or data invalid)
if (length(sobol_list) > 0) {
  cat("Generating visualizations...\n", file = log_file, append = TRUE)
  # 6.1 Tornado for First-Order Indices
```

```
  plot_sobol_tornado <- function(sobol_obj, title) {
    si <- sobol_obj$S[, 1] # First order
    si_sd <- sobol_obj$S[, 3] # Confidence interval
    df <- data.frame(Parameter = rownames(sobol_obj$S), Sensitivity = si, Lower = si - 1.96 *
si_sd, Upper = si + 1.96 * si_sd)
    df <- df[order(abs(df$Sensitivity), decreasing = TRUE), ]
    df$Parameter <- factor(df$Parameter, levels = df$Parameter)
    ggplot(df, aes(x = Parameter, y = Sensitivity)) + geom_bar(stat = "identity", fill = "steelblue")
+
      geom_errorbar(aes(ymin = Lower, ymax = Upper), width = 0.2) + coord_flip() +
      labs(title = title, x = "Parameter", y = "Sobol Index (First Order)") + theme_minimal()
  }
  pdf("results/PSA_Sobol_Tornado.pdf", width = 10, height = 6)
  lapply(seq_along(sobol_list), function(i) print(plot_sobol_tornado(sobol_list[[i]],
names(sobol_list)[i])))
  dev.off()
  # 6.2 Total Sensitivity Heatmap
  total_sens <- sapply(sobol_list, function(s) s$T[, 1])
  rownames(total_sens) <- rownames(sobol_list[[1]]$T)
  melted_total <- melt(total_sens)
  ggplot(melted_total, aes(x = Var2, y = Var1, fill = value)) + geom_tile() +
scale_fill_gradient(low = "white", high = "red") +
    geom_text(aes(label = round(value, 2))) + labs(title = "Total Sensitivity (Sobol Indices)", x
= "Output", y = "Parameter") + theme_minimal()
  ggsave("results/PSA_Total_Sensitivity_Heatmap.png", width = 8, height = 6, dpi = 300)
}
# 6.3 Output Distributions (always, from uncertainty) - With check for valid data
if (nrow(psa_results) > 0 && sum(!is.na(psa_results$Traditional)) > 0) {  # Check for data
  output_summary <- psa_results %>% select(Traditional:Sequestration) %>%
pivot_longer(everything())
  tryCatch({
    ggplot(output_summary, aes(x = value)) + geom_histogram(bins = 30, fill = "steelblue",
alpha = 0.7) + geom_density(color = "darkblue") +
```

```
    facet_wrap(~name, scales = "free") + labs(title = "Output Distributions") + theme_minimal()
   ggsave("results/PSA_Output_Distributions.png", width = 12, height = 8, dpi = 300)
  }, error = function(e) {
   cat("Error in distributions plot:", e$message, "\n", file = log_file, append = TRUE)
  })
} else {
  cat("Skipping distributions plot: Insufficient valid data.\n", file = log_file, append = TRUE)
}
# 6.4 Scatters for Top Parameters (skip if no Sobol)
if (length(sobol_list) > 0) {
  top_params <- names(sort(abs(sobol_list[["Improvement"]]$S[, 1]), decreasing = TRUE))[1:3]
  scatters <- lapply(top_params, function(p) {
   ggplot(psa_results, aes(x = .data[[p]], y = Improvement)) + geom_point(alpha = 0.3) + geom_smooth(method = "lm") +
    labs(title = paste(p, "vs Improvement")) + theme_minimal()
  })
  grid.arrange(grobs = scatters, ncol = 2)
  ggsave("results/PSA_Scatter_Top_Params.png", width = 10, height = 6, dpi = 300)
}
#------------------------------------------------------------------------
# 7. RESULTS REPORT (Tables for paper) - Expanded
#------------------------------------------------------------------------
output_stats <- output_summary %>% group_by(name) %>%
  summarise(Mean = mean(value, na.rm = TRUE), SD = sd(value, na.rm = TRUE),
            CI_lower = quantile(value, 0.025, na.rm = TRUE), CI_upper = quantile(value, 0.975, na.rm = TRUE),
            CV = SD / Mean * 100, Skewness = skewness(value, na.rm = TRUE), Kurtosis = kurtosis(value, na.rm = TRUE))
kable(output_stats, "latex", booktabs = TRUE, caption = "PSA Output Statistics") %>%
  save_kable("results/PSA_Output_Stats.tex")
if (length(sobol_list) > 0) {
  sobol_summary <- do.call(rbind, lapply(names(sobol_list), function(out) {
```

```
    data.frame(Output = out, Parameter = rownames(sobol_list[[out]]$S),
               First_Order = paste(round(sobol_list[[out]]$S[, 1], 3), "±",
round(sobol_list[[out]]$S[, 3], 3)),
               Total_Order = paste(round(sobol_list[[out]]$T[, 1], 3), "±",
round(sobol_list[[out]]$T[, 3], 3)))
  }))
  kable(sobol_summary, "latex", booktabs = TRUE, caption = "Sobol Indices") %>%
    save_kable("results/PSA_Sobol_Summary.tex")
}
#------------------------------------------------------------------------------
# 8. SAVE COMPLETE RESULTS
#------------------------------------------------------------------------------
saveRDS(psa_results, "results/PSA_Complete_Results.rds")
if (length(sobol_list) > 0) saveRDS(sobol_list, "results/PSA_Sobol_Indices.rds")
write.csv(psa_results, "results/PSA_Results_Table.csv", row.names = FALSE)
cat("PSA completed successfully.\n", file = log_file, append = TRUE)
```

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