





Review

Environmentally Extended Input-Output Models in Agriculture: A Bibliometric Review

Giulio Grassi , Majid Zadmirzaei, Mario Cozzi , Severino Romano  and Mauro Viccaro * 

Department of Agricultural, Forestry, Food and Environmental Sciences, University of Basilicata, 85100 Potenza, Italy; giulio.grassi@unibas.it (G.G.); majid.zadmirzaei@unibas.it (M.Z.); mario.cozzi@unibas.it (M.C.); severino.romano@unibas.it (S.R.)

* Correspondence: mauro.viccaro@unibas.it

Abstract

This review paper synthesizes the application and evolution of environmentally extended input–output (EEIO) analysis in agricultural research, drawing on 647 publications (Scopus and Web of Science, 1978–2025) following the PRISMA method and using the Bibliometrix package in the R statistical computing environment. EEIO has become a leading method for assessing system-level environmental impacts by quantifying direct and indirect flows across complete supply chains. Bibliometric and thematic analyses reveal accelerated growth since 2015 and four principal domains of enquiry: emissions embodied in trade, water-resource management, energy and climate impacts, and the sustainability of agri-food supply chains. EEIO’s principal value lies in its capacity to support production-versus consumption-based accounting and to reveal intersectoral trade-offs that single-sector approaches overlook. However, standard EEIO frameworks remain constrained by fixed technical coefficients, coarse sectoral aggregation, and uncertainty in environmental extensions, which limit their capacity to resolve farm-scale processes, structural change, and feedbacks. To enhance analytical rigor and policy relevance, we advocate hybridization with life-cycle and farm-level data, development of higher-resolution multi-regional EEIO tables, incorporation of stochastic and scenario analyses, dynamic formulations to capture technological change, and adoption of open-data standards with transparent reporting. Advancing these priorities will improve comparability, reproducibility and the practical uptake of EEIO for evidence-based transitions in agricultural systems.

Keywords: agriculture; environmentally extended input–output (EEIO); embodied environmental impacts; Water–Energy–Food (WEF) nexus



Academic Editor: Sanzidur Rahman

Received: 18 February 2026

Revised: 30 March 2026

Accepted: 31 March 2026

Published: 2 April 2026

Copyright: © 2026 by the authors.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and conditions of the [Creative Commons Attribution \(CC BY\) license](https://creativecommons.org/licenses/by/4.0/).

1. Introduction

The environmental impact of agricultural production systems has become an increasing concern for scholars in recent decades [1]. Such emphasis reflects the growing global concerns about sustainability and the urgent necessity for policy frameworks with the potential to address the various challenges arising in agriculture [2]. Agriculture is among the sectors imposing the greatest pressure on the environment, both through direct impacts on ecosystems and through indirect effects that are transmitted along supply chains [3,4].

Modern agriculture affects the environment not only via land use and irrigation water withdrawals, but also through greenhouse-gas emissions, disruptions of biogeochemical cycles, and pressures on environmental quality associated with the use of chemical inputs—such as pesticides and fertilizers—and with production intensification, which can

entail deforestation, destruction of natural habitats, and consequent biodiversity loss [5–7]. In addition, some components of the environmental footprint attributable to agricultural production do not originate solely from on-farm cropping or livestock activities, but rather arise across the broader supply chain [8]. Illustrative examples encompass the industrial production of agrochemicals, including pesticides, fertilizers, and antibiotics, and the post-harvest storage and transportation to processing facilities or final consumers. This complexity and intersectoral interconnectedness imply that analytical approaches confined solely to on-farm activities may underestimate overall environmental impacts, as they neglect the upstream burdens embodied in intermediate inputs and transmitted across supply chains [5,9]. These interconnections are notably evident when examining climate change and the environmental burden of agriculture: a significant portion of emissions associated with agrifood products derive from indirect processes occurring along the value chain, rendering footprint assessments highly sensitive to the delineation of system boundaries [10,11]. Similarly, assessments of water use in agriculture must be beyond direct withdrawals by the agrifood sector; this has led to the growing prominence of concepts such as the water footprint and virtual water, which quantify the water embedded in traded commodities and thereby reveal the spatial redistribution of water demand and associated environmental pressures across geographic regions and economic sectors [12–15]. In this regard, environmentally extended accounting studies indicate that agricultural production and the food industry often dominate both the intensity and the overall magnitude of the water footprint, and that part of the virtually embodied water in produced goods is exported through trade flows—reinforcing the need for analytical tools capable of capturing the economic system as a whole, rather than focusing solely on the point of production [16,17].

This emerging need aligns with the systems approach that is increasingly promoted internationally to transform agrifood systems. The FAO has explicitly advocated this perspective, underscoring that a systems approach is essential to analyze and manage intersectoral interdependencies, cascading effects, and trade-offs among environmental, economic, and social objectives [18,19]. Such an approach recognizes that interventions at one stage of the value chain can propagate and generate unexpected consequences elsewhere in the production system and across other sectors [20]. In doing so, there is a clear need for analytical tools able to capture intersectoral interdependencies by tracking production from its origin to final consumption. Among the available models, Environmentally Extended Input–Output (EEIO) models provide a framework capable of representing intersectoral linkages while attributing environmental pressures not only to direct production processes but also to the indirect supply-chain activities activated by final demand [21–23]. Indeed, EEIO analysis originated from extending Wassily Leontief’s 1930s input-output economic model by attaching environmental data—such as resource use or pollutant emissions—to industrial sectors. It evolved to bridge the gap between traditional monetary economic transactions and physical environmental flows, enabling analysis of environmental impacts across supply chains. In the agrifood context, this approach helps clarify how agrifood production and consumption activate energy, chemical, and material inputs across the entire supply chain, and how these inputs contribute to emissions, resource use, and overall pollution [5,16]. Consequently, the use of EEIO models is now well established for footprint estimation and environmental accounting, and is widely applied to analyze emissions embodied along global value chains [24,25]. EEIO approaches enable the analysis of material flows embodied in goods by reconstructing all stages of the supply chain and identifying the points at which environmental pressures are generated most intensively [26,27]. Such studies highlight the pivotal role of agriculture in the use of water and land, whereas construction and industrial activities are often responsible for

higher energy requirements—creating trade-off configurations that require intersectoral analytical tools to be interpreted correctly. In addition, the relevance of EEIO models is further reinforced by growing interest in the Water–Energy–Food (WEF) nexus, which seeks to investigate interdependencies among water resources, energy systems, and food production and consumption [28].

Despite the maturity of EEIO modelling and its expanding application across sectors, there remains a need to clarify how EEIO approaches have been applied to agricultural systems and how these applications have evolved over time. The growing corpus of studies on footprints, the water–energy–food nexus, and related themes makes it timely to map EEIO applications in order to identify dominant research topics, methodological shifts, and emerging trajectories shaped by recent empirical and technical developments. At the same time, the rising demand for economy-wide analyses to inform international policy agendas underscores the importance of understanding how EEIO has been used—and how it can be further used—as a systems-oriented tool to support the sustainable transformation of agrifood systems. In this respect, bibliometric studies are especially useful, as they provide a structured way to monitor the development of a research field and to trace how scholarly debates have evolved. The main objective of this study is to analyze the literature on EEIO applications to agricultural systems through a bibliometric approach. Specifically, the study aims to reconstruct the evolution of scientific output in this domain, identify the key authors and institutions that have shaped it, map the thematic and methodological trajectories that have defined the use of EEIO approaches in agriculture, and—through keyword co-occurrence analysis combined with thematic clustering of the assembled literature—identify the principal domains in which EEIO methodologies are currently applied within agricultural contexts (emissions trading, water management, energy-climate impacts, and agri-food chain sustainability). In fulfilling these aims, the analysis clarifies how EEIO evidence has been generated and how it can more effectively support research and policy for the sustainable transformation of agrifood systems.

The remainder of the paper is organized as follows. Section 2 introduces the EEIO framework that forms the analytical foundation of the study. Section 3 outlines the methodological approach and describes the data sources utilized in the analysis. Section 4 presents the empirical results, followed by Section 5, which interprets the findings and situates them within the broader literature and policy context. Section 6 concludes the paper by summarizing the key contributions and identifying directions for future research.

2. Environmentally Extended Input-Output Models: A General Overview

The Input-Output model, introduced by Nobel Prize winner Wassily Leontief at the end of the thirties [29,30], analyzes economic systems by quantifying the direct and indirect interdependencies among sectors in satisfying final demand [31]. By tracing flows of goods and services from primary inputs through successive stages of intermediate production to final consumption, the model enables the reconstruction of economic value chains. When extended to incorporate environmental or resource accounting—often termed environmentally extended input-output analysis—it can adopt a “cradle-to-grave” perspective, following economic activity from raw material extraction to end-use disposal. The primary concept of this analysis lies in the definition of the economic system as a set of sectors that produce goods and services, with each sector purchasing production inputs from the other sectors that make up the economic system [32,33]. The classical IO approach supposes that the inputs used in production are in fixed proportions and consequently there are constant returns to scale. This assumption leads to the definition of the matrix of technical coefficients $A = [a_{ij}]$ and to express the system as $x = Ax + f$, where x is the vector of the outputs and f is the vector of the final demand. Rearranging the terms yields the

fundamental Leontief equation: $x = (I - A)^{-1}f$, where $(I - A)^{-1}$ is the Leontief inverse, conventionally denoted by L in the literature. This matrix captures the whole production needs, both direct and indirect, necessary to satisfy any final demand shock [22].

The IO framework is widely used to measure, to understand sectoral interdependencies and analyze the effects that new policies or exogenous demand shocks can have on the economic system and how these propagate within the various sectors with which the economy is described [34–36]. Despite its analytical power, the monetary-only IO framework proved insufficient for capturing biophysical realities such as resource scarcity and environmental pressures—a limitation that motivated scholars in the 1960s–70s to integrate physical flows of energy, materials, and emissions into the model. This extension yielded EEIO analysis, which quantifies the direct and indirect ecological burdens associated with economic activity [37,38]. The EEIO model links environmental satellite accounts to the economic structure of the IO model that allow to estimate the environmental impact of all production sectors and consequently also the impact that can be generated by any demand shocks with the same mechanism explained in the previous studies.

In the EEIO implementation, the direct environmental intensities are represented by the coefficients d_{kj} , which constitute the intensity matrix D . Its each element quantifies the amount of environmental pressure k —such as cubic meters of water consumed, hectares of land occupied, or tons of CO₂ emitted—generated per monetary unit of output by sector j [22]. By combining the direct environmental intensity matrix D —whose elements d_{kj} represent environmental pressure k per monetary unit of sector j output—with the Leontief inverse L , the EEIO framework captures both direct and indirect environmental impacts embedded in final demand. The product $D^* = DL$ yields the matrix of total environmental intensities, where each element reflects the full supply-chain burden (direct plus upstream indirect) associated with one unit of final demand. Hence, multiplying D by a final demand vector f gives the total environmental pressure p attributable to that demand; i.e., $p = D^*f = DLf$ [39].

The EEIO model is particularly well-suited for assessing environmental implications across the entire economy precisely because it accounts for sectoral interdependencies. By tracing supply-chain linkages through the Leontief inverse, the model captures both direct and upstream indirect impacts, thereby providing a comprehensive and accurate quantification of the environmental footprint embedded in production and final demand [26]. In the literature, the EEIO model is widely used to calculate impact coefficients for emissions propagating them throughout the production chain [40], for example an application on the economy of Croatia reflects how the carbon footprint changes when emissions are attributed to sectoral output compared to when they are attributed to final demand, highlighting the role played by indirect emissions that are incorporated in the intermediate inputs used for the production of the final output needed to meet final demand [41]. Moreover, recent research demonstrates that EEIO-based footprint estimates, with their economy-wide coverage, effectively complement bottom-up approaches by capturing upstream supply-chain impacts that would otherwise be omitted or truncated in process-based assessments [42].

When the analytical focus shifts to agri-food systems, the value of a framework capable of estimating aggregate environmental pressures becomes evident. Agricultural production draws heavily on natural capital and is tightly integrated with energy, chemical, manufacturing and logistics activities; consequently, a systems-level perspective that quantifies embodied resource use and emissions is essential [43]. The EEIO model permits estimation of water, energy, land and pollutant burdens embedded in intersectoral flows associated with production, processing, transport, distribution and final consumption, thereby furnishing a rigorous basis for policy appraisal across the food supply chain [44,45]. Empirical applications attest to the method's versatility; for instance, EEIO studies have quantified

the water consumption and greenhouse-gas emissions embodied in food waste, providing an evidential foundation for assessing anti-waste interventions [46]. In another related work, ref. [47] reconstructed virtual grey-water flows within interprovincial agricultural exchanges, enabling the identification of critical nodes for water-quality management. Investigations of urban supply chains that integrate carbon and water accounting reveal that agriculture often displays a high intensity of embodied water even when aggregate emission profiles are dominated by other sectors, thereby underscoring the necessity of multi-indicator evaluations [48,49]. Therefore, the primary contribution of this review is to provide a consolidated, evidence-based roadmap that both clarifies how EEIO has been employed in agri-food research and guides future methodological refinement and policy translation. These findings aim to inform researchers and decision-makers on where EEIO analysis can most effectively support sustainable food-system governance and where further methodological development is required.

3. Research Methodology

3.1. Methods

Bibliometric analysis is a highly useful tool for researchers, as it allows us to quantitatively examine the evolution of scientific production and to assess techniques, methodologies and research trends within a given topic. Through the systematic analysis of publications over time, it enables the identification of correlations, collaboration networks, development trajectories and emerging trends, thereby offering a clear and structured overview of the state of the art in a specific field. One of the main advantages of these approaches, as highlighted by [50], is their capacity to facilitate reproducible and dependable processes, thereby minimizing errors associated with manual and qualitative analyses of extensive datasets. Bibliometric analysis also supports the definition of research objectives, the delimitation of the field of inquiry and the identification of atypical results or gaps and trajectories that warrant further investigation. Building on these advantages, this study employs a bibliometric methodological framework to offer a comprehensive analysis of publication trends over time, identify the most influential authors, journals, and articles, and perform citation, collaboration, and keyword analyses.

3.2. Data Collection, Cleaning and Preprocessing

A systematic literature search for studies applying EEIO models in agriculture was conducted using two major bibliographic databases: Web of Science and Scopus. These complementary resources were chosen to maximize coverage across disciplines and publication venues, given their extensive, heterogeneous collections and established editorial standards. Results retrieved from both platforms were merged and deduplicated using Digital Object Identifiers (DOIs) so that each study was represented only once in the final corpus. This approach reduced redundancy and helped ensure the integrity of the dataset used to characterize the contemporary research landscape [51,52]. The PRISMA framework was used to report transparently the identification and selection of bibliographic records included in the final dataset. In this bibliometric review, PRISMA served to outline the main stages of the workflow rather than to support a qualitative appraisal of the full text of individual studies. These stages comprised database identification, application of eligibility filters, removal of duplicate records, and final inclusion. Figure 1 summarizes the record selection process and provides an overview of how the bibliometric dataset was assembled.

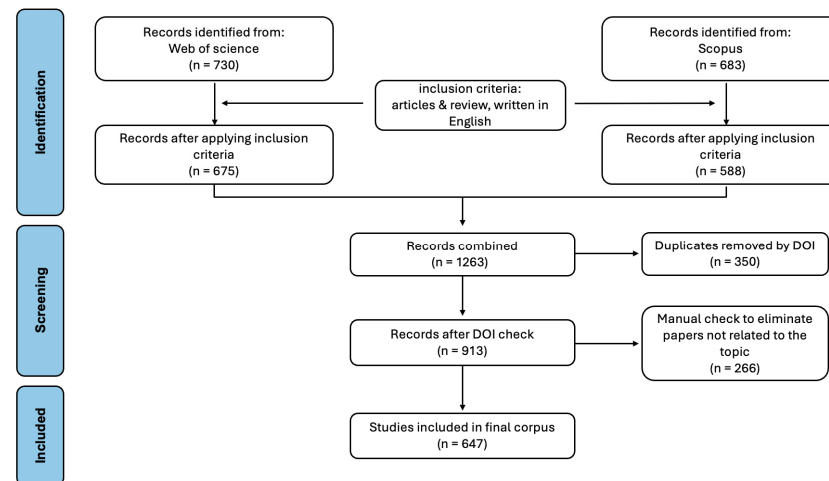


Figure 1. PRISMA flow diagram of the study-selection process for EEIO applications.

The final bibliometric corpus used for the analyses was constructed on the basis of predefined inclusion and exclusion criteria. Only records retrieved through the search strategies applied in Web of Science and Scopus were retained, provided they were written in English and classified as articles or reviews in the field of agricultural systems. This approach is consistent with the scope of the study, which maps EEIO-based research across the broader agricultural and agri-food domain, including trade- and policy-oriented contributions insofar as they operationally employ an input–output or EEIO framework. Furthermore, Records were excluded if they appeared in both databases, were published in a language other than English, or belonged to document types other than articles and reviews. Accordingly, relevance was determined at the bibliographic record level through search strings and database filters rather than through manual full-text screening. This approach is consistent with the bibliometric design of the study, although it may have allowed a small number of borderline records to remain in the dataset. Since the two databases are different, it was necessary to develop two separate search queries, as Web of Science and Scopus rely on different syntaxes for searches within their respective platforms. We begin with the analysis conducted in Web of Science. The query, based on the Topic Search (TS) field, was as follows:

TS = (((Environment*-Extended OR Environment* OR Extended) AND (Input-Output analysis OR Input-Output table* OR Input-Output matri* OR Input-Output model*)) OR (EEIO OR EE-IO OR EE-IOT OR EE-IOTs)) AND (agricultur*)).

This query returned 730 records. The results were then refined by applying inclusion criteria that limited the set to papers and review articles written in English, yielding a final sample of 675 English-language articles and reviews retrieved from Web of Science. Asterisks are used at the end of certain terms in the query to ensure that all words sharing the same root as the preceding string are captured. This device allows the query to be streamlined while at the same time avoiding the loss of potential synonyms, thereby enabling the selection of the largest possible number of relevant articles.

In Scopus, given its slightly different search system, the query had to be adapted. Instead of Topic Search, we used the field TITLE-ABS-KEY, which allows searching within titles, abstracts and keywords. The query used in Scopus was:

TITLE-ABS-KEY (((Environment*-Extended OR Environment* OR Extended) AND ("Input-Output analysis" OR "Input-Output table*" OR "Input-Output matri*" OR "Input-Output model*")) OR (EEIO OR "EE-IO" OR EE-IOT OR EE-IOTs)) AND (agricultur*)).

This search identified a total of 683 documents. The results were then refined by applying inclusion criteria that limited the set to papers and review articles written in

English, yielding a final sample of 588 English-language articles and reviews retrieved from Scopus.

Across the two database searches, a total of 1263 English-language articles and reviews were initially identified. Following the removal of duplicate records through a data-cleaning procedure conducted in R, based on identical DOI entries, 350 duplicates were excluded, resulting in a dataset of 913 unique publications. Subsequently, a manual screening was performed to remove papers not relevant to the research topic. After this selection process, the final corpus consisted of 647 English-language articles and reviews.

This search and screening strategy enabled the construction of a temporal and geographical overview of EEIO-based research in the agricultural domain, while also facilitating the identification of the most research-active countries, the authors exerting the greatest scholarly influence, and the journals most central to the dissemination of EEIO-related studies. In addition, keyword co-occurrence analysis combined with thematic clustering of the assembled literature revealed the principal domains in which EEIO methodologies are currently applied within agricultural contexts. These domains arise directly from the intersection of EEIO techniques and agriculture-specific terms. They encompass studies on emissions trading that examine the integration of agricultural sectors into carbon markets, offset schemes, and the economic consequences of emission permits under EEIO frameworks; research on water management that applies EEIO analysis to evaluate virtual water flows, water footprints, and scarcity effects linked to agricultural production and trade; investigations of energy-climate impacts that quantify energy consumption patterns and broader greenhouse gas emissions—extending beyond trading mechanisms—arising from agricultural activities and supply chains; and assessments of agri-food chain sustainability that explore the overall environmental performance of food systems, including multi-regional supply linkages, waste management practices, and circular economy indicators in the agricultural sector. In this way, the approach offers a structured portrayal of the field's evolution and underscores the key contributions that have shaped the use of EEIO models in analyzing agricultural systems across these critical areas.

3.3. Data Analysis and Visualization

All analyses were conducted in R (R Core Team, 2025) using R version 4.4.3 (28 February 2025), with the Bibliometrix package introduced by [53] in the R statistical computing environment. The final dataset covered the period 1978–2025, and the bibliometric analyses presented here therefore reflect the entire study period. Bibliometrix supports text mining and science-mapping procedures, enabling the systematic examination and visualization of complex bibliometric data.

In this study, we combined conceptual structure analysis based on co-occurrence with author-specified keywords to examine EEIO applications in the agricultural sector, identify the main thematic areas, and detect emerging research frontiers. Overall, this bibliometric approach provides a comprehensive and in-depth view of the research landscape on the use of EEIO methodology in agriculture and supports evidence-based strategic research planning and decision-making.

4. Results

4.1. Descriptive Features of the Extracted Data

This section summarizes the main descriptive indicators of the database under analysis. We first provide a concise overview of the dataset's composition, then examine the temporal dynamics of scholarly output to identify trends over time, and finally analyze the geographic distribution of publications to reveal the countries and regions that have contributed most substantially to this research field.

4.1.1. General Overview

Table 1 briefly presents the descriptive information on the dataset analyzed, thereby providing a general overview that serves to frame the present study and guide the subsequent discussion.

Table 1. Summary of studied dataset.

General Information	
Timespan	1978–2025
Sources (Journals, Books, etc.)	235
Documents	647
Annual Growth Rate %	8.94
Document Average Age	7.97
Average citations per doc	35.61
Annual average citations per document	4.136
References	24,351
Document Types	
article	609
article; bookschapter	1
article; early access	7
article; processing paper	6
review	24
Document Contents	
Keywords Plus (ID)	3800
Author's Keywords (DE)	1922
Authors	
Number of Authors	2374
Author appearances	3066
Authors of single-authored docs	40
Authors Collaboration	
Single-authored docs	40
Documents per Author	0.273
Co-Authors per Doc	4.74
International co-authorships %	25.66

The period under investigation extends from 1978 to 2025, during which a total of 647 scholarly publications were disseminated across 235 journals. The annual growth rate observed over these five decades is 8.94%, indicating sustained expansion in the field. The mean citation count of 35.68 per document and an average annual citation rate of 4.13 per document. These averages reflect a skewed citation profile in which a subset of publications accrues substantially more attention than the remainder of the sample. The mean document age is seven years, indicating that the dataset predominantly comprises work published within the last decade.

The collection is characterized by substantial topical diversity, reflected in 1922 authors' keywords and 3800 Keywords Plus entries, which together signal a broad and interdisciplinary research agenda. The selected documents list 2374 distinct authors contributing a total of 3066 authorships. Collaborative activity is pronounced: the mean number of authors per paper is 4.74, only 40 papers are single-authored, and 25.66% of publications involve international co-authorship, underscoring frequent cooperation among research teams across national boundaries.

4.1.2. Temporal and Geographical Trend

Figure 2 illustrates the evolution of publications and citations of the selected articles over the years. The output has followed a steady upward trajectory in this context. Applications of the EEIO model in agriculture have increased markedly over time. The highest growth rate occurred around the time of the Paris climate agreements; indeed, from 2015 onwards, there has been an exponential increase in publications, underscoring the importance of the topic and the attention it has attracted from the scientific community, likely supported by dedicated funding schemes from national governments.

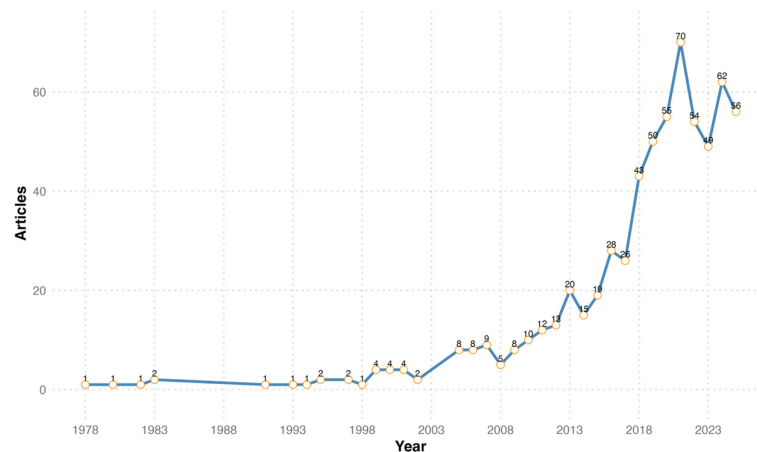


Figure 2. Trend article published over time (1978–2025).

Figure 3 indicates the top 20 countries that have contributed most to the application of the EEIO model to the agricultural system. China dominates the ranking, with a total of 270 published papers, and is therefore highlighted in red in the figure, followed by the United States with 47 papers and Spain with 29. Overall, the top 20 countries account for 82% of all contributions included in our dataset. One factor that may help explain China's predominance in this field is the significant role the country plays within global agri-food supply chains.

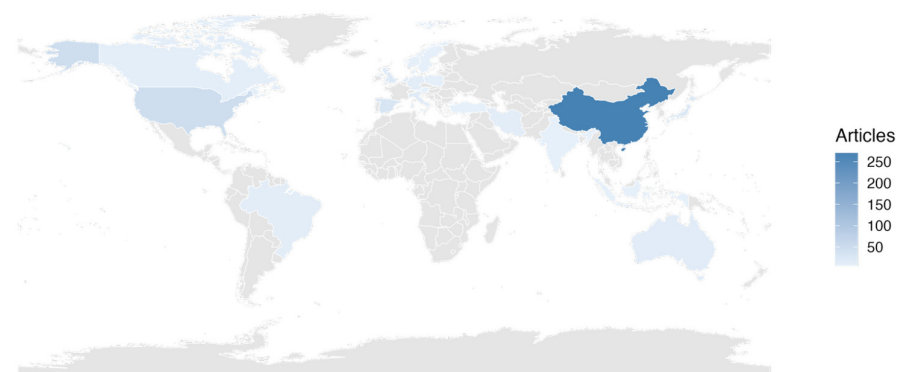


Figure 3. Publications by country (1978–2025). Note: Darker shades indicate higher publication output, while grey indicates countries outside the selected group.

To provide a more detailed picture of international collaboration, Figure 4 presents the collaboration network linking countries worldwide. The finding reveals distinct communities of cooperation among scholars from different countries. China, recognized as the leading contributor to the literature on the application of the EEIO model in agricultural systems, occupies a central position in the collaboration network, acting as a crucial node for many international partners and displaying a strong connection with the United

States. A prominent European collaborative cluster also emerges, involving Italy, Germany, the Netherlands, the United Kingdom, and Norway.

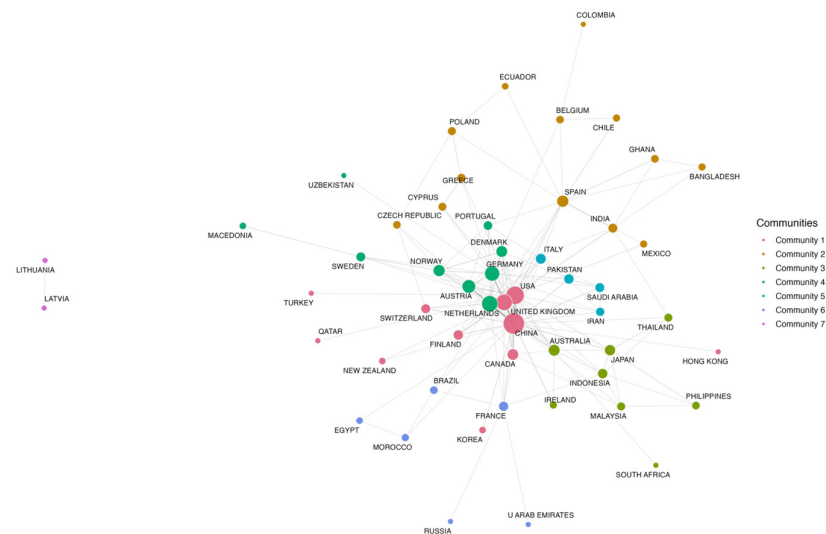


Figure 4. Countries' collaboration network (1978–2025). Note: Nodes represent countries, node size reflects their publication relevance in the dataset, links indicate collaboration ties, and colors identify different collaboration communities.

Based on the aforementioned findings, the contributing countries may be classified according to two complementary dimensions—shared regulatory frameworks and levels of economic development—to enhance interpretability within a policy-relevant analytical framework. This classification reveals distinct clusters that align research agendas with institutional contexts and national priorities. A prominent European collaborative cluster emerges, encompassing Italy, Germany, the Netherlands, the United Kingdom, and Norway. These nations operate under harmonized regulatory architectures, most notably the European Union's Common Agricultural Policy (CAP), the Green Deal, and associated environmental directives. Such frameworks promote standardized application of environmentally extended input–output (EEIO) models and facilitate cross-border data sharing, thereby enabling coordinated research on sustainable agriculture and resource management. The data further exhibit a clear dichotomy between emerging and developed economies. China, as a leading emerging economy, directs its research output toward strengthening global agri-food supply-chain resilience and safeguarding domestic food security. In contrast, the United States—alongside the European cluster—represents developed economies characterized by mature environmental accounting standards and an emphasis on technological innovation in sustainable agriculture. This grouping underscores how regulatory cohesion and developmental stage jointly shape the orientation and applicability of scholarly contributions in the field.

While this review provides a comprehensive overview of EEIO applications in agriculture, several limitations must be acknowledged. First, the geographical distribution of publications is heavily skewed, with China accounting for a disproportionate volume of the literature (270 papers vs. 47 for the US). This dominance may reflect specific national funding priorities rather than a global consensus, potentially limiting the generalizability of the findings to regions with lower research output. Second, the reliance on English-language databases may exclude significant local policy studies published in native languages, particularly within the European and South American contexts. Finally, the correlation between publication spikes and policy events (e.g., the 2015 Paris Agreement) is observational; while

funding schemes likely supported this growth, direct causal links between specific national policies and publication output require further granular analysis.

4.2. Keywords Analysis

An analysis of the keywords provides insight into the conceptual structure of the field and helps delineate the principal thematic domains that have shaped scholarly developments in the application of EEIO models to the agricultural sector. The analysis was conducted by considering both Keywords Plus (ID) and Author Keywords (DE), and then performing a cluster analysis on the 100 most frequently used keywords in order to identify the main thematic areas. The analysis concludes with an examination of temporal trends over the last ten years, with the aim of understanding the directions in which research is currently evolving.

4.2.1. Most Frequent Keywords

Tables 2 and 3, respectively, indicate the top twenty DE keywords, i.e., those provided directly by the authors, and the top twenty ID keywords, which are automatically assigned by the databases in which the articles are indexed.

A comparative analysis of the two tables reveals no substantial differences in the dominant themes identified by author-supplied keywords (DE) and database-assigned keywords (ID). The primary distinction lies in the absolute frequency of term occurrence. In both cases, the core vocabulary centers squarely on the Input–Output framework, with terms such as “input-output analysis,” “input-output model,” and “input-output” among the most frequently cited. A meaningful point of comparison between DE and ID concerns the main application topics: both tables consistently feature keywords related to climate change and resource use, including “carbon/carbon footprint”, “land use”, “water supply/water footprint”, and “energy”. This pattern indicates that the EEIO approach is primarily employed in the literature to quantify environmental pressures along agricultural supply chains. Likewise, the presence of terms such as “virtual water” and “water footprint” in Table 2 suggests a specific author-driven focus on water resources and on the pressures that agricultural production systems exert on them.

A further comparison concerns analytical approaches. The DE keywords (Table 2) explicitly highlight specific methodological techniques, as reflected in the recurrent use of terms such as “multi-regional input-output analysis/model”, “structural decomposition analysis”, “Structural path analysis” and “life cycle assessment”. These keywords indicate that authors frequently frame their contributions through emphasis on the analytical methods employed. In contrast, the ID keywords (Table 3) place greater emphasis on broader thematic categories—such as “environmental impact”, “economic analysis”, “trade”, and “consumption”—which is consistent with the logic of automated indexing adopted by the bibliographic databases in which these contributions are recorded. Finally, based on geographical analysis, the prominence of the term “China” reinforces the centrality of the Chinese context within scientific output in this research domain. Overall, the comparison between DE and ID keywords provides a concise overview of the field: it confirms a strong focus on key environmental dimensions of agricultural-system analysis (carbon, water, land, and energy), while also highlighting the diversity of analytical approaches employed, including multi-regional input-output analysis (MRIO), structural decomposition analysis (SDA), spatial analysis (SPA), and integrated input-output–life cycle assessment (IO–LCA) frameworks.

Table 2. Top 20 selected keywords by Authors.

Keyword	Frequency	Percentage
input output analysis	89	2.85
input output model	41	1.31
China	38	1.22
Water footprint	34	1.09
Agriculture	32	1.02
Input-output	30	0.960
Industrial ecology	24	0.768
Structural decomposition analysis	23	0.736
Carbon footprint	19	0.608
Input-Output analysis	19	0.608
Multi-regional input-output	19	0.608
Structural path analysis	17	0.544
Sustainability	17	0.544
land use	16	0.512
Sustainable development	16	0.512
virtual water	15	0.480
Life cycle assessment	14	0.448
Greenhouse gas emissions	13	0.416
Trade	12	0.384
energy	11	0.352

Table 3. Top 20 selected keywords in the literature.

Keyword	Frequency	Percentage
Input-output analysis	247	1.96
China	211	1.67
agriculture	182	1.44
consumption	123	0.974
article	110	0.871
sustainable development	96	0.760
trade	79	0.626
Environmental economics	78	0.618
Environmental impact	76	0.602
Water supply	71	0.562
Energy	68	0.539
Carbon	65	0.515
Footprint	58	0.459
Impact	58	0.459
Input-Output analysis	57	0.452
sustainability	56	0.444
Input-output	55	0.436
Input/output analysis	55	0.436
Economic analysis	54	0.428
Carbon emission	53	0.420

4.2.2. Cluster Analysis

To obtain a more detailed description of the topics addressed and of the application of the EEIO model to agriculture, we performed a co-occurrence analysis of keywords, focusing on the 100 most frequent terms in the corpus under study. The keyword map, shown in Figure 5, was generated using the Bibliometrix library, which enabled us to construct semantic networks based on the frequency with which terms co-occur within the documents analyzed. Partitioning the keyword map into clusters enabled the identification

of coherent thematic groupings, which in turn elucidate the principal lines of inquiry in studies applying the model to the agricultural sector.

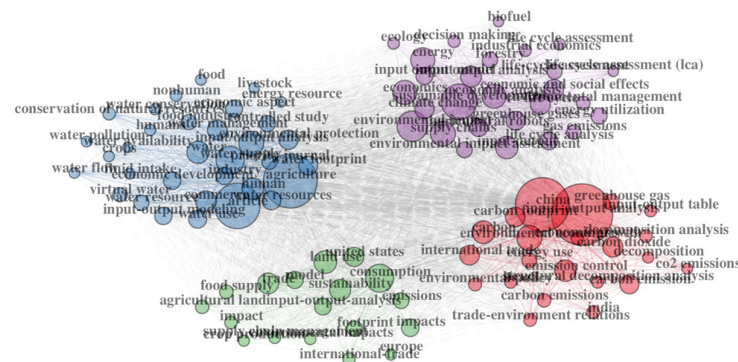


Figure 5. Cluster Map of the Top 100 Keywords in the EEIO–Agriculture Literature. Note: Nodes represent keywords, node size reflects their frequency of occurrence, links indicate co-occurrence relationships, and colors identify thematic clusters.

The effort to identify the principal thematic cores within the literature on Environmentally Extended Input–Output (EEIO) applications in agriculture led to the delineation of four distinct thematic clusters. Each cluster captures a coherent set of research orientations and recurring concepts within the field. These clusters are outlined below:

- **Cluster 1—Carbon, trade, and environmental policy (red):** This cluster encompasses keywords pertaining to emissions estimation, the design of environmental policies, and the reconstruction of international flows associated with the production and consumption of agricultural goods. The thematic core centers on analyzing emissions embodied in trade by tracing flows along the entire agrifood value chain. This underscores the ability of EEIO analysis to assign environmental pressures not only to the geographic sites of production but also to the demand- and trade-driven systems that induce agricultural activity. In this regard, agriculture emerges as a pivotal component of the global carbon budget and of related mitigation efforts, because its climate footprint is determined by intersectoral linkages and cross-border exchanges generated by the international fragmentation of production.
- **Cluster 2—Agriculture and water resources (blue):** This cluster encompasses terms associated with agricultural systems and water-resource management, thereby underscoring the relevance of the EEIO framework in this domain. In particular, EEIO enables water use to be traced across the entire supply chain, supporting the identification of hotspots and the assessment of inefficiencies within agrifood production. Beyond conventional water-footprint accounting, this cluster also reflects broader perspectives in which water is examined as a fundamental component of the WEF nexus. In this case, EEIO has been widely applied to link demand for agricultural products not only to direct water withdrawals, but also to the energy use and chemical inputs required for production, thus providing an integrated view of intersectoral interdependencies.
- **Cluster 3—Energy and environmental/climate impacts (purple):** This cluster includes keywords that relate to analyses of the energy and climate impacts of agricultural systems, often referencing integrated methodological approaches, such as the combined use of EEIO and Life Cycle Assessment. The cluster indicates that emissions and energy use extend beyond agriculture’s sectoral boundaries and must be assessed across entire supply chains to accurately capture their magnitude and distribution. This perspective underscores the importance of EEIO analysis for quantifying climate-related environmental pressures and for clarifying trade-offs between productivity, energy efficiency, and reductions in greenhouse gas emissions.

- Cluster 4—Sustainability of agrifood supply chains (green): The principal focus of this cluster is the sustainability of agrifood supply and value chains, signaling a body of research devoted to holistic assessments of sustainability performance—encompassing management practices, traceability mechanisms, and governance of the transition. Within this framework, EEIO analysis contributes to these evaluations by mapping the relationships among intermediate inputs, production activities, and final consumption, and by supplying comparable indicators that can guide policy and strategic decisions to reshape agrifood systems.

4.2.3. Trend Topics

Regarding the keywords, Figure 6 depicts the trend topics by tracing the temporal evolution of the most relevant terms over the last decade, thereby identifying the most recent research frontiers that have emerged in the application of the EEIO model to the agricultural system.

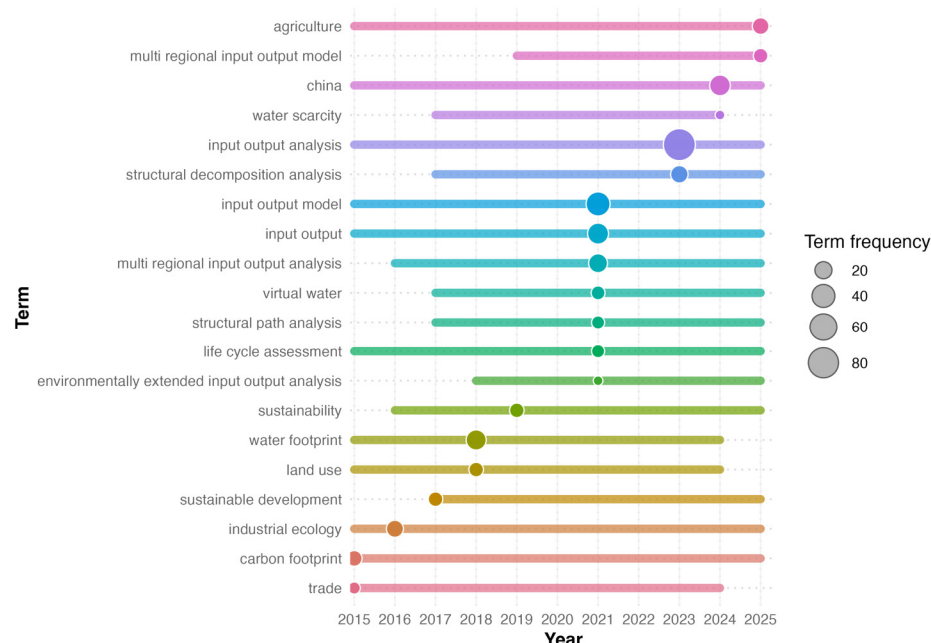


Figure 6. Trends of the Top 20 Topics Over the Last Decade in the EEIO–Agriculture Literature.

Several terms have remained stable over the periods, including “agriculture”, “input–output analysis”, “input–output model”, and its variants such as “multi-regional input–output model”. The sustained prominence of these keywords corroborates the robustness of the search strategy and affirms that the analysis remains tightly focused on applications of the input–output framework to the agricultural sector. At the same time, recurrent references to life cycle assessment, sustainability, and land use indicate an ongoing convergence between EEIO methodologies, life cycle analysis, and empirical assessments of the environmental impacts of agricultural systems. In addition, a number of topics have gained prominence in recent years, giving rise to new research lines in the analysis of agricultural systems. Among these are structural decomposition analysis and structural path analysis—two analytical techniques that, when integrated with the EEIO framework, enable the decomposition of environmental impacts and the identification of the underlying drivers of emissions or resource use. The growing global attention to water resource management and the increasing awareness of water scarcity are likewise reflected in the scientific literature, as shown by the expanding body of research on water footprint and virtual water. Similarly, terms related to the environmental impacts of agricultural systems

continue to consolidate, with research strands devoted to the estimation of carbon footprint, sustainability and sustainable development which are themselves linked to the efforts that have characterized international climate policies in recent years, increasingly aimed at the environmental impact of production systems.

Given the substantial contribution of agricultural production to global climate change, the sector is increasingly examined through the lens of EEIO modelling. This framework supports intersectoral analyses capable of capturing the complexity of interconnected economic activities and their associated environmental impacts.

4.3. Journal Analysis

Examining the journals that have published a significant body of research on the use of EEIO models in agricultural system analysis over time allows for the identification of the outlets that serve as key platforms for disseminating findings in this domain. Such an examination helps researchers recognize the central venues within the field and can guide informed decisions about suitable journals for submitting their work.

4.3.1. Top 20 Journals

Figure 7 presents a ranking of the 20 journals according to the number of articles on the topic published over the years. As can be seen, the top positions are occupied by journals oriented towards environmental issues and sustainability.

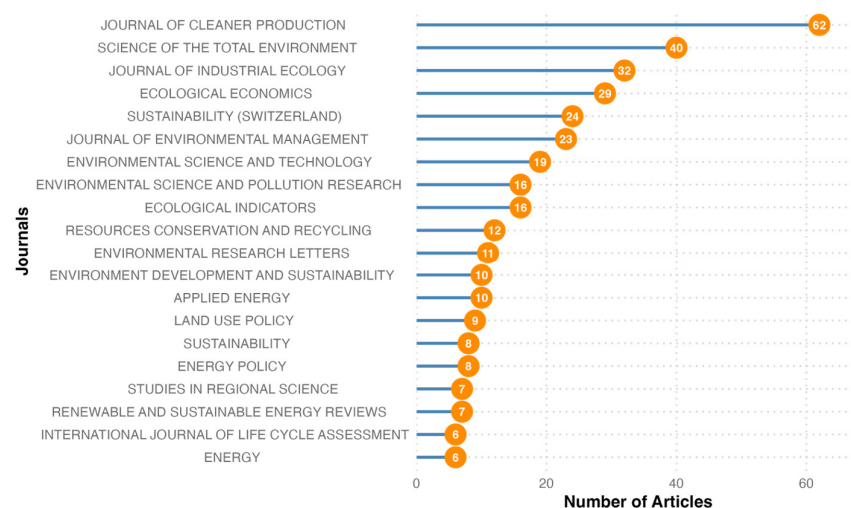


Figure 7. Top 20 Journals in the EEIO–Agriculture Literature (1978–2025).

The Journal of Cleaner Production emerges as the leading publication outlet, with 62 articles on the application of EEIO models to agricultural systems, substantially surpassing all other journals. It is followed by Science of the Total Environment with 40 articles and the Journal of Industrial Ecology with 32. A second group of prominent journals includes Ecological Economics with 29 articles, Sustainability (Switzerland) with 24, and the Journal of Environmental Management with 23. Other relevant contributions come from Environmental Science and Technology with 19 articles, as well as Environmental Science and Pollution Research and Ecological Indicators, each with 16, which contribute meaningfully to the development of the literature on EEIO applications in the agricultural domain.

Journals with a narrower focus on agri-food systems or land and energy policy occupy the lower portion of the publication ranking; examples include Land Use Policy; Energy Policy; and Renewable and Sustainable Energy Review. Because rankings based solely on publication counts provide only a partial picture of a journal’s influence, we also constructed an alternative ranking based on impact indicators, presented in Table 4.

Table 4. Top 20 journals based on H-Index.

Rank	Journal Name	H Index	G Index	M Index	Total Citation	No. Papers	Publication Year
1	Journal of Cleaner Production	27	45	1.68	2199	62	2011
2	Science of the Total Environment	24	40	1.71	2071	40	2013
3	Ecological Economics	20	29	0.62	1501	29	1995
4	Journal of Industrial Ecology	20	32	0.90	1946	32	2005
5	Environmental Science and Technology	16	19	0.80	1231	19	2007
6	Ecological Indicators	13	16	1	389	16	2014
7	Journal of Environmental Management	13	23	0.52	623	23	2002
8	Applied Energy	9	10	0.50	1068	10	2009
9	Sustainability (Switzerland)	9	14	0.90	241	24	2017
10	Environmental Research Letters	8	11	0.80	469	11	2017
11	Environmental Science and Pollution Research	8	12	0.67	167	16	2015
12	Land Use Policy	8	9	0.67	335	9	2015
13	Energy Policy	7	8	0.35	723	8	2007
14	Renewable and Sustainable Energy Reviews	6	7	0.4	327	7	2012
15	Sustainability	6	8	0.6	132	8	2017
16	Energy	5	6	0.33	113	6	2012
17	International Journal of Life Cycle Assessment	5	6	0.29	138	6	2010
18	Environment Development and Sustainability	2	2	0.50	15	2	2023
19	Resources Conservation and Recycling	1	1	0.12	18	1	2019
20	Studies in Regional Science	1	2	0.04	8	7	2006

Note: H-Index: measures productivity and scientific impact; G-Index: measure of an author's citation performance; M-Index: H-index normalized by academic career length.

The prominence of the Journal of Cleaner Production and Science of the Total Environment is reinforced when impact metrics are considered: the two journals exhibit the highest h-indices in the set (27 and 24, respectively) and have accumulated the largest totals of citations (2199 and 2071). Their m-index values exceed 1.5, signaling sustained citation growth over time. Accounting for these impact indicators alters the ordering of the remaining titles, producing a noticeable rearrangement of the mid- and lower-tier positions in the ranking. The Journal of Applied Energy is a remarkable example of the limitations of a purely quantitative assessment based on publication numbers: it had only 10 articles in the previous ranking and placed 13th. However, when the impact metrics are considered—it exhibits a highly influential profile with a total of 1068 citations and an h-index of 9—indicating that articles published in this journal tend, on average, to be highly cited. Furthermore, journals such as Energy Policy and Land Use Policy rise in the ranking when impact metrics are considered. These outlets pair strong h-index values with substantial overall citation counts, positioning them as especially suitable venues for work aimed at achieving high scientific visibility.

It is also worth noting that more recent journals such as Sustainability (Switzerland) and Sustainability have relatively high m-index values given the year in which they began publishing on the topic, suggesting a rapid growth of interest in EEIO applications to agriculture, including in open-access or more general sustainability-oriented journals.

4.3.2. Bradford's Law

To deepen the bibliometric assessment and pinpoint the field's most authoritative outlets, we applied Bradford's law [54,55]. This bibliometric principle holds that publications

on a given topic concentrate in a relatively small core of journals, while the remaining literature is progressively dispersed across an expanding number of more peripheral outlets. By partitioning our dataset into Bradford zones, we were able to identify the compact set of journals that generate the bulk of EEIO–agriculture research and to characterize the distribution of the remaining contributions across less central venues.

Figure 8 shows the application of Bradford’s law to the journals included in the studied dataset. The downward-sloping curve highlights an initial zone in which the highest number of publications is concentrated relative to the number of journals involved, marked by a grey box that denotes the segment of “core sources”. Beyond this initial area, the curve gradually flattens, delineating intermediate and peripheral zones characterized by a growing number of sources but a decreasing number of publications.

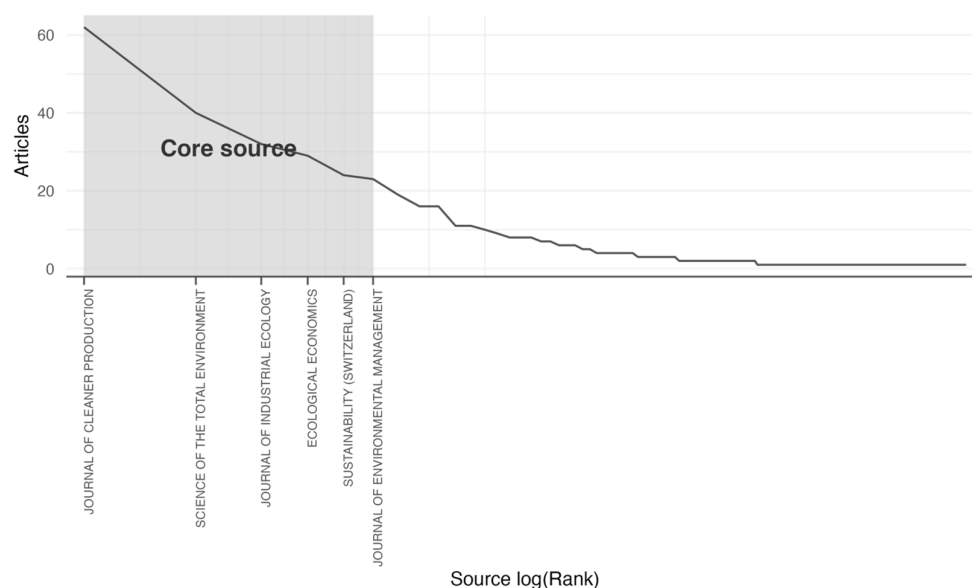


Figure 8. Core sources by Bradford’s Law. Note: The grey box marks the core-source area across Bradford zones.

Table 5: Summarized results of the application of Bradford’s law.

Table 5. Summary of Bradford’s law.

Zone	Number of Cumulative Articles	Number of Sources
Zone 1	210	6
Zone 2	431	37
Zone 3	646	194
Total	646	237

Zone 1, which corresponds to the “core source” area, comprises only 6 journals that together account for 210 articles, i.e., 32.5% of the entire corpus analyzed. This zone represents the core of the scientific literature on the application of the EEIO model to agriculture, and the journals it contains constitute an essential reference base for those engaged in methodological or applied research in this field. As shown in the table, the remaining published papers are distributed across an increasingly large number of scientific journals.

The application of Bradford’s law thus makes it possible to identify a central nucleus of journals in which publications on the topic under analysis are concentrated.

4.4. Paper Analysis

Analysing the documents in the corpus by identifying those most frequently cited in reference lists, those most cited globally and those most cited locally makes it possible to sketch an overall picture of the theoretical and applied evolution of research on agricultural systems using the EEIO model.

4.4.1. Milestones of the Basic Theory

Tracing the manuscripts most frequently cited within the reference lists of our corpus permits the identification of the foundational works that underpin the theoretical framework under study and, in doing so, delineates the principal milestones in the field's intellectual development. Table 6 reports the twenty manuscripts that occur most often across the bibliographies of the corpus.

Table 6. Top 20 most cited manuscripts.

Rank	Author	Year	DOI	Citation
1	[22]	2009	10.1017/CBO9780511626982	87
2	[38]	1970	10.2307/1926294	67
3	[29]	1936	10.2307/1927837	53
4	[56]	2013	10.1080/09535314.2013.769938	46
5	[57]	2018	10.1111/JIEC.12715	38
6	[58]	2009	10.1016/j.ecolecon.2009.08.026	38
7	[59]	2013	10.1016/J.ECOLECON.2013.06.018	33
8	[60]	2012	10.1038/NATURE11145	32
9	[7]	2013	10.1016/J.GLOENVCHA.2012.12.010	32
10	[61]	2013	10.1016/J.GLOENVCHA.2013.04.006	32
11	[62]	2012	10.1073/PNAS.1109936109	31
12	[63]	2012	10.1021/ES301949T	31
13	[64]	2012	10.1021/ES300171X	30
14	[65]	2007	10.1016/J.ECOLECON.2006.12.003	29
15	[66]	2014	10.3390/SU7010138	28
16	[67]	2014	10.1016/J.ECOLECON.2014.02.006	28
17	[11]	2008	10.1021/ES072023K	27
18	[68]	2018	10.1038/S41561-018-0113-9	27
19	[25]	2009	10.1021/ES803496A	25
20	[69]	2015	10.1073/PNAS.1404130112	25

The finding indicates that the core reference literature in the field largely consists of the classic contributions to input–output analysis. The handbook of [22] occupies the foremost position, offering an authoritative and wide-ranging treatment of input–output methods and their extensions. It is followed by the foundational contributions of [29,38], whose work constitutes the conceptual core of both input–output analysis and its environmental adaptations. Alongside these theoretical cornerstones, we find authors who have shaped the recent evolution of the Input–Output framework, such as [57,68,69]. Through their work, they have introduced multi-regional databases, new environmental indicators and increasingly sophisticated methods for tracing environmental footprints, thereby contributing to the advancement of the theoretical framework.

4.4.2. Most Cited Papers

Table 7 summarizes the 20 papers in the corpus that have received the highest number of citations over time, highlighting their substantial relevance and scientific visibility.

Table 7. Top 20 cited papers.

Rank	Author	Journal	Year	DOI	TC
1	[70]	Environmental Chemistry Letters	2022	10.1007/s10311-022-01435-8	921
2	[57]	Journal of Industrial Ecology	2018	10.1111/jiec.12715	701
3	[71]	Field Crops Research	1997	10.1016/S0378-4290(97)00037-3	492
4	[72]	Nature Ecology & Evolution	2019	10.1038/s41559-019-0824-3	364
5	[61]	Global Environmental Change	2013	10.1016/j.gloenvcha.2013.04.006	320
6	[73]	Waste Management	2009	10.1016/j.wasman.2008.08.031	312
7	[74]	Energy Policy	2010	10.1016/j.enpol.2010.06.004	304
8	[75]	Applied Energy	2009	10.1016/j.apenergy.2008.07.009	292
10	[28]	Science of the Total Environment	2018	10.1016/j.scitotenv.2017.09.138	273
11	[76]	Environmental Science and Technology	2019	10.1021/acs.est.9b03413	233
12	[77]	Ecological Economics	2002	10.1016/S0921-8009(02)00183-0	229
13	[78]	Applied Energy	2017	10.1016/j.apenergy.2016.04.020	226
14	[79]	Energy Conversion and Management	2007	10.1016/j.enconman.2006.06.006	222
15	[80]	Environmental Research Letters	2018	10.1088/1748-9326/aae19a	219
16	[81]	Ecological Economics	2010	10.1016/j.ecolecon.2009.12.008	213
17	[82]	Environmental Science and Technology	2010	10.1021/es100886r	212
18	[83]	Journal of Cleaner Production	2013	10.1016/j.jclepro.2012.11.007	193
19	[84]	Science of the Total Environment	2019	10.1016/j.scitotenv.2019.01.197	181
19	[85]	Science of the Total Environment	2020	10.1016/j.scitotenv.2019.136255	178
20	[86]	Applied Energy	2020	10.1016/j.apenergy.2019.114431	177

The most highly cited document is a review study done by [70], which addresses strategies for achieving carbon neutrality in production systems and has accumulated 921 citations. Although it does not focus exclusively on the agricultural sector, this work helps define the broader context in which applications of the EEIO model are becoming increasingly relevant. It is followed by the contribution of [57], with 701 citations, which examines the structure and construction method of EXIOBASE, one of the most important multiregional databases for analyzing global agricultural flows, material consumption footprints, and environmental interdependencies.

The other highly cited studies in this context underscore the central role of environmentally extended Input–Output approaches in three main areas: (i) land use and its close links with biodiversity and economic growth [72]; (ii) the water–land–agriculture nexus, explored in the works [28,61,77]; and (iii) the analysis of energy flows in the production of agricultural goods in studies such as [75,79]. Taken together, these findings show that the papers attracting the greatest attention within the scientific community are those dealing with the sustainability of resource use, environmental accounting, and the tracing and impact of agri-food flows along global value chains.

4.4.3. Local Cited Papers

An indicator that helps to complete the analytical picture is the Local Citation Score (LCS), which identifies the papers within the corpus that have received the highest number of citations from other studies in the same corpus. Table 8 summarizes the 20 papers with the highest local citation scores.

Table 8. Top 20 local cited papers.

Author	DOI	Year	LCS	GCS
[28]	10.1016/j.scitotenv.2017.09.138	2018	16	273
[79]	10.1016/j.enconman.2006.06.006	2007	14	222
[87]	10.1016/j.ecolecon.2015.03.008	2015	11	152
[88]	10.1016/j.ecolind.2014.05.019	2014	8	52
[89]	10.1111/jiec.12258	2015	8	53
[90]	10.1016/j.jclepro.2015.07.113	2016	6	48
[17]	10.1111/jiec.12392	2016	6	58
[91]	10.1016/S0167-8809(99)00097-3	2000	5	65
[92]	10.1016/j.jclepro.2011.07.001	2011	5	140
[93]	10.1016/j.energy.2017.01.069	2017	5	61
[1]	10.1016/j.jclepro.2019.04.091	2019	5	69
[49]	10.1016/j.ecolind.2023.109981	2023	5	18
[94]	10.1002/2016EF000371	2016	4	26
[2]	10.1016/j.jclepro.2017.04.118	2017	4	41
[95]	10.1016/j.jclepro.2017.06.071	2017	4	106
[96]	10.1016/j.jclepro.2018.06.173	2018	4	85
[72]	10.1038/s41559-019-0824-3	2019	4	364
[97]	10.1088/1748-9326/ab07f5	2019	4	61
[98]	10.1016/j.chieco.2016.06.007	2020	4	42
[8]	10.1029/2019WR026190	2020	4	34

Note: GCS: Global Cited Score.

The article by [28], which examines the global land–water nexus, records the highest local citation count and is widely cited both within the corpus and in the broader scholarly literature. It is followed by contributions centered on the energy analysis of agricultural production systems [79], the development and application of environmental indicators [87,88], and research on water footprints and virtual water trade [17,82].

A noteworthy pattern emerges when comparing global and local citation metrics: certain studies—such as [72]—exhibit high global citation counts but relatively modest local citations. This indicates that, although these works hold considerable influence across the wider scientific community, they are less deeply embedded within the specific citation network of publications applying the EEIO framework to agricultural systems.

4.5. Authors' Analysis

Analyzing the authors represented in our corpus allows us to identify the principal contributors to the literature and to characterize the scholarly community advancing the application of the Environmentally Extended Input–Output model to agricultural systems. This author-level analysis reveals patterns of productivity, influence and collaboration, highlighting core researchers, emerging voices and collaborative clusters that have shaped the field's intellectual trajectory and guided its methodological development.

4.5.1. Author Productivity and Their Ranking

Table 9 reports the ranking of authors in the corpus based on their total number of publications.

As can be tracked, the top positions are occupied by a small group of authors with very high scientific productivity. At the top of the list is Sai Liang with 15 articles, followed by Richard Wood with 13 papers, Rosa Duarte with 10, and Kuishuang Feng with 10 documents, as well as two authors with 9 contributions each: Bo Zhang and Martin Bruckner. This group of researchers forms the backbone of the field that is advancing the application of environmentally extended input–output modelling to the agri-food sector

Table 9. Top 20 Authors.

Rank	Authors	Articles
1	Liang, Sai	15
2	Wood, Richard	13
3	Duarte, Rosa	10
4	Feng, Kuishuang	10
5	Cazcarro, Ignacio	9
6	Zhang, Bo	9
7	Bruckner, Martin	8
8	Chen, Bin	8
9	Hubacek, Klaus	8
10	Lenzen, Manfred	8
11	Sánchez-Chóliz, Julio	8
12	Tukker, Arnold	8
13	Yang, Zhifeng	8
14	Liu, Yu	7
15	Sun, Laixiang	7
16	Wang, Zhen	7
17	Zhang, Zhenjun He	7
18	Bai, Yuping	6
19	Duchin, Faye	6
20	Hu, Yuanchao	6

To provide a more comprehensive and nuanced understanding of the most prolific authors, we analyzed, for each individual, their publications within our corpus over time, along with the corresponding annual citation counts. The detailed results are presented in Figure 9.

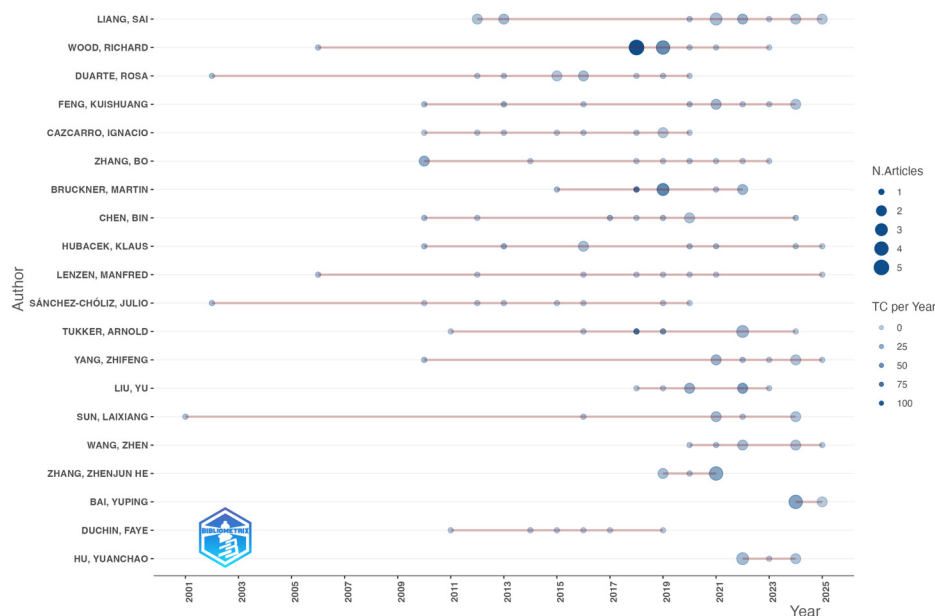


Figure 9. Top 20 author productivity over time in the EEIO–agriculture literature. Note: Each circle represents an article in a given year; circle size indicates the number of articles, and darker blue indicates higher citations per year.

Results indicate that some authors not only maintain a high level of continuity in their scientific output, but also record pronounced peaks in the number of citations received in specific years. Authors such as Wood, Bruckner, Feng and Chen display the highest annual citation counts, indicating the substantial impact of their work on the topic under

examination. At a more aggregate level, this figure also reveals an expansionary phase in publications beginning around 2015, coinciding with intensified efforts by national governments to reduce their environmental impact and to combat climate change.

4.5.2. Lotka's Law

Building on Lotka's law, introduced in 1926 by Alfred J. Lotka [99], we investigated the productivity patterns of the authors within our dataset. This law enables the characterization of author productivity by analyzing the distribution of published articles in the corpus under study [100]. The results, reported in Table 10, show that 84% of the authors in our corpus have published only one article on the topic, a value substantially higher than the theoretical prediction of 64%. This indicates a broad participation by occasional authors or by scholars approaching this research area for the first time. A small minority of authors, just 10%, have produced two articles, and the share of those with three or more publications declines steadily thereafter. This configuration points to an expanding field of research, in which a small, established core of authors with a sustained focus on the topic coexists with a long tail of contributors who sporadically add to the literature on the application of the EEIO model to the study of agricultural systems.

Table 10. Output of Lotka's law.

Documents Written	N. of Authors	Proportion of Authors	Theoretical Estimates
1	2001	84%	64%
2	234	10%	16%
3	71	3%	7%
4	31	1%	4%
5	16	1%	3%
6	5	0%	2%
7	4	0%	1%
8	7	0%	1%
9	2	0%	1%
10	2	0%	1%
13	1	0%	0%
15	1	0%	0%

4.5.3. Authors Network

To conclude the authorship analysis, attention turns to co-authorship networks to characterize inter-author linkages. Figure 10 maps the authors in the corpus, offering a visual account of the collaboration structure.

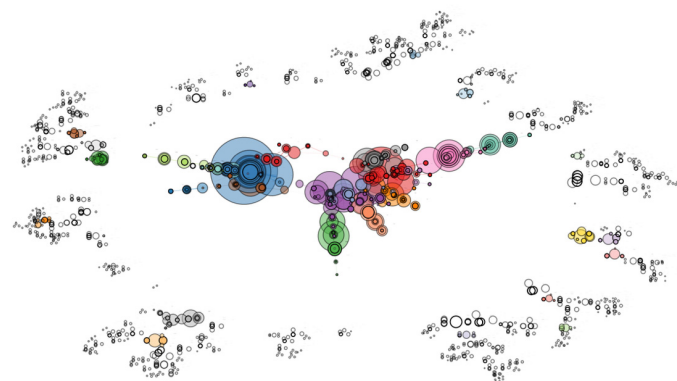


Figure 10. Distribution of Authors Across the Study Dataset in the EEIO-agriculture literature. Note: nodes represent authors, links indicate co-authorship relationships, and colors identify collaboration communities.

It can be observed that the peripheral areas of the authorship network exhibit a high degree of fragmentation, characterized by small and weakly connected clusters. In contrast, progressively more cohesive and highly interconnected groups emerge toward the center, corresponding to the core of the corpus.

To obtain a clearer level of detail, Figures 11–13 show the progression of the cumulative citation impact of the top 1000 authors by number of citations, corresponding to the central group in Figure 9. This progressive view of 25–50–75% of total impact makes it possible to identify the author communities that exert the greatest influence on the research topic, moving from an overall picture to a more fine-grained analysis. This is complemented by Table 11, which reports, for each identified community, the top 10 authors by number of citations, together with additional useful information such as the total number of authors in the community and the overall citation count of the community.

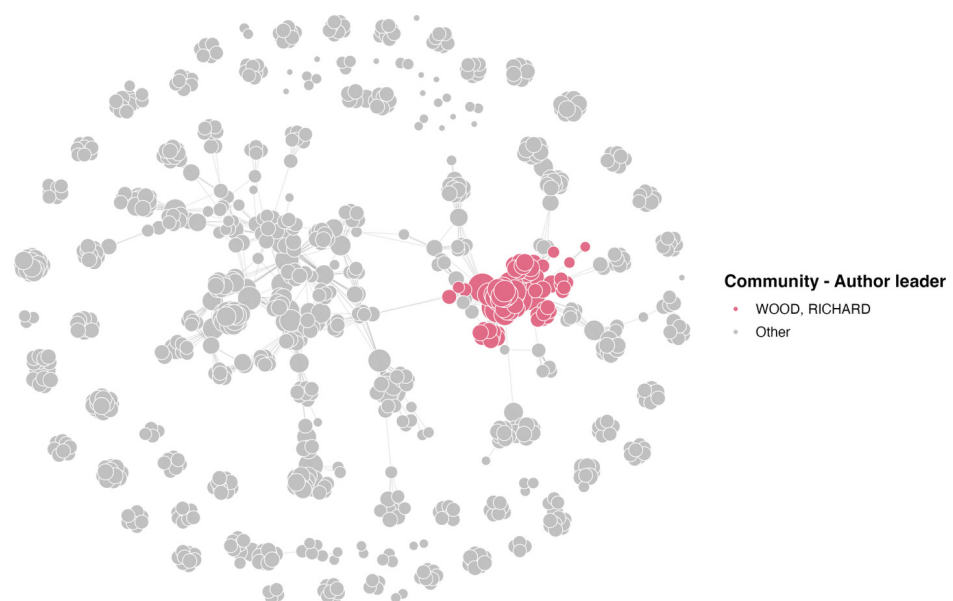


Figure 11. Citation-Filtered Author Collaboration Network (Top 25% of 1000 samples). Note: Nodes represent authors, links indicate collaboration ties, and colors identify the main author communities.

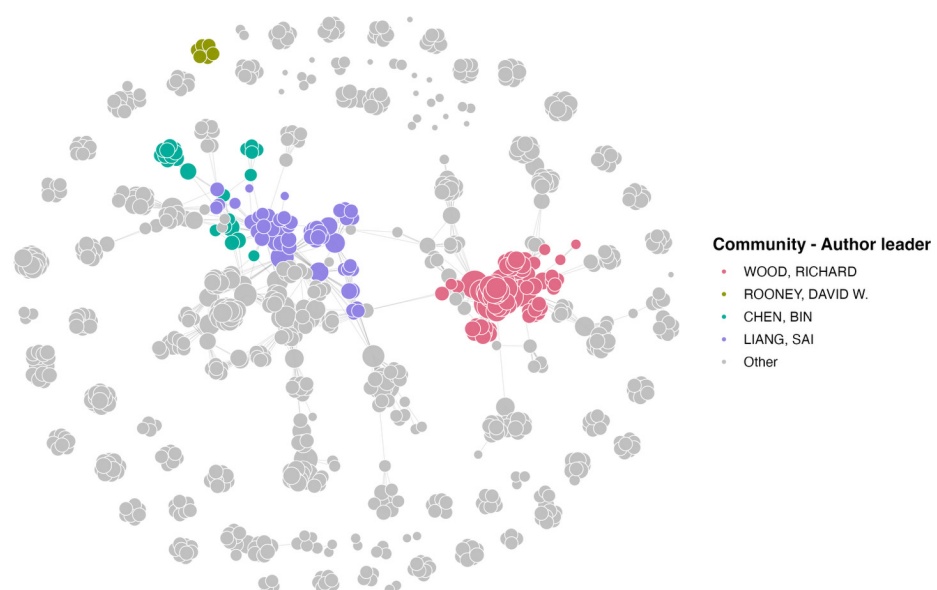


Figure 12. Citation-Filtered Author Collaboration Network (Top 50% of 1000 samples). Note: Nodes represent authors, links indicate collaboration ties, and colors identify the main author communities.

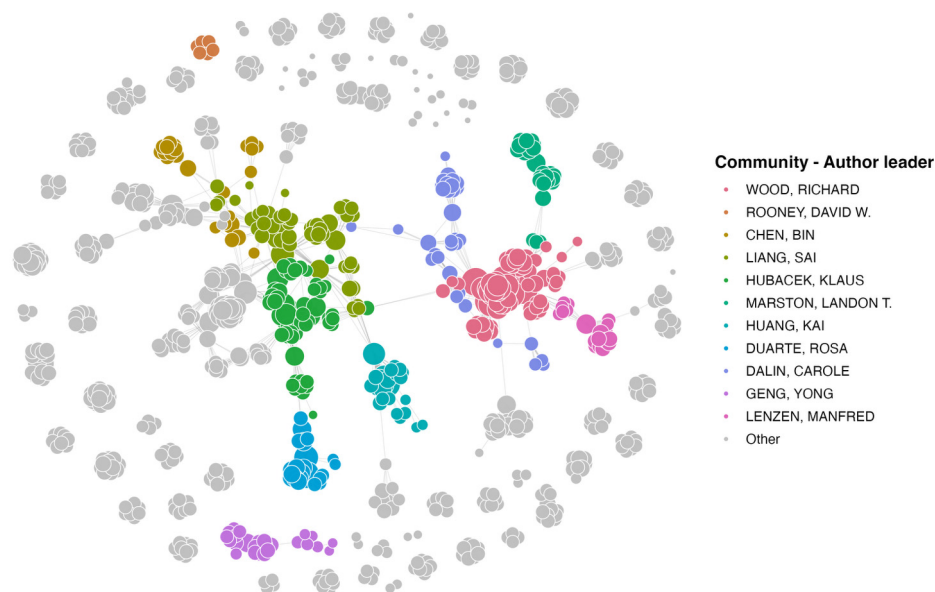


Figure 13. Citation-Filtered Author Collaboration Network (Top 75% of 1000 samples). Note: Nodes represent authors, links indicate collaboration ties, and colors identify the main author communities.

Table 11. Top 10 authors among all studied communities.

Community	Author	Total Citation Single Author	No. Author Inside Community	Total Citation of Community
WOOD, RICHARD	Wood, Richard	1647	86	28,368
	Bruckner, Martin	1427		
	Tukker, Arnold	1233		
	Kastner, Thomas	1154		
	Eisenmenger, Nina	1118		
	Stadler, Konstantin	1103		
	Plutzer, Christoph	1065		
	Theurl, Michaela C.	1065		
	Giljum, Stefan	914		
	De Koning, Arjan	820		
ROONEY, DAVID	Rooney, David W.	921	8	7368
	Chen, Lin	921		
	Fawzy, Samer	921		
	Msigwa, Goodluck	921		
	Osman, Ahmed I.	921		
	Yang, Mingyu	921		
	Yap, Pow Seng	921		
	Yap, Pow-Seng	921		
CHEN, BIN	Chen, Bin	725	26	6438
	Chen, G. Q.	616		
	Chen, Guoqian	596		
	Zhang, Bo	587		
	Han, M. Y.	417		
	Fang, Delin	283		
	Chen, B.	273		
	Li, J. S.	273		
	Li, Z.	273		
	Liu, S. Y.	273		

Table 11. Cont.

Community	Author	Total Citation Single Author	No. Author Inside Community	Total Citation of Community
LIANG, SAI	Liang, Sai	516	58	5580
	Liu, Yu	401		
	Yang, Zhifeng	397		
	Xu, Ming	296		
	Zhang, Tianzhu	250		
	Xie, Yulei	230		
	Ji, Ling	193		
	Xu, Wenhao	193		
	Zhao, Hongyan	148		
	Zhang, Qiang	148		
HUBACEK, KLAUS	Hubacek, Klaus	816	57	5483
	Feng, Kuishuang	812		
	Yu, Yang	598		
	Guan, Dabo	409		
	Sun, Laixiang	342		
	Zhao, Xu	277		
	Zhao, Dandan	193		
	Liu, Junguo	188		
	Tillotson, Martin	173		
	Wang, Saige	143		
MARSTON, LANDON	Marston, Landon T.	236	27	2980
	Read, Quentin D.	194		
	Brown, Samuel	178		
	Brown, Samuel P.	178		
	Cuellar, Amanda D.	178		
	Finn, Steven M.	178		
	Gephart, Jessica A.	178		
	Gephart, Jessica A. . .	178		
	Meyer, Ellen	178		
	Muth, Mary K.	178		
HUANG, KAI	Huang, Kai	215	27	1730
	Yu, Yajuan	215		
	Wang, Zhen	149		
	Li, Cai	138		
	Shi, Zhihua	107		
	Wang, Ling	107		
	Yu, Shuxia	107		
	Yan, Hua	98		
	Liu, Gang	90		
	Hu, Yuanchao	83		
DUARTE, ROSA	Duarte, Rosa	562	28	1727
	Cazcarro, Ignacio	263		
	Duchin, Faye	188		
	Sanchez-Choliz, Ju. . .	148		
	Serrano, Ana	127		
	Sarasa, Cristina	31		
	Amponsah, Samuel K.	26		
	Arto, Inaki	26		
	Asenso, Joseph K.	26		
	Ofori-Danson, Patr. . .	26		

Table 11. Cont.

Community	Author	Total Citation Single Author	No. Author Inside Community	Total Citation of Community
DALIN, CAROLE	Dalin, Carole	215	33	1702
	Newbold, Tim	201		
	Weinzettel, Jan	139		
	Pfister, Stephan	136		
	Scherer, Laura	103		
	Ye, Quanliang	99		
	Sun, Zhongxiao	75		
	Behrens, Paul	70		
	Zhuo, La	56		
	Scherer, Laura A.	47		
GENG, YONG	Geng, Yong	341	26	1607
	Dong, Huijuan	339		
	Tsuyoshi, Fujita	280		
	Kang, Jianing	104		
	Chen, Yihui	59		
	Moss, Dana Avery	59		
	Qian, Yiying	59		
	Tian, Xu	59		
	Yu, Yanhong	59		
	Zhong, Shaozhuo	59		
LENZEN, MANFRED	Lenzen, Manfred	292	20	1571
	Dey, C	172		
	Dey, Christopher J.	172		
	Lenzen, M	172		
	Lundie, S	172		
	Lundie, Sven	172		
	Wood, R	172		
	Malik, Arunima	111		
	Geschke, Arne	66		
	Singh, Shweta	34		

Figure 11 presents the top 25% of citations among the 1000 most-cited authors. The results reveal a single dominant community, which is labelled after Richard Wood, as he emerges as the most influential author within this group, with 1647 citations related to the topic under examination. Overall, this community comprises 86 authors and a total of 28,368 citations. Among its most prominent members are Martin Bruckner, Arnold Tukker, Thomas Kastner, Nina Eisenmenger and Konstantin Stadler, whose work has contributed to the construction and evolution of the current research framework on sustainability, environmental footprints and material flows through applications of the EEIO model to agricultural systems. This community represents the main theoretical reference point for EEIO-based research.

Figure 12 illustrates the expansion of the citation threshold to 50%, revealing three additional author communities, namely the “Ronney David”, “Chen Bin” and “Linag Sai” communities. Together, these groups account for an additional 25% of total citations.

The Ronney David community, led by the eponymous author with 921 individual citations, is composed of 8 author and comprises a total of 7368; it is characterized by a focus on energy analysis of agricultural system bio-energy domain. The Chen Bin community, led by the eponymous author with 725 individual citations, is composed of 26 authors and comprises a total of 6438 citations; it is characterized by a strong focus on the water–energy–land nexus and on the accounting of environmental impacts. The Linag Sai community,

headed by the author of the same name with 516 individual citations, includes 58 authors and totals 5580 citations, and is mainly centered on climate change and environmental impact assessment.

The thematic and methodological affinity between these areas is evident in the figure, which shows the two communities clustered closely and densely interconnected. Raising the inclusion threshold brings additional research themes into view, thereby clarifying the domains of application and the specific specializations represented by authors in the corpus.

Finally, Figure 13 shows the expansion to 75% of total citations among the top 1000 authors in the corpus. The network becomes progressively more diversified, with communities of smaller size, as also indicated in Table 11. It is nonetheless apparent that many of the identified communities remain centered on the “Wood Richard” core, indicating a close alignment in the themes addressed. By contrast, communities such as the “Hubacek Klaus” cluster—comprising 57 authors and accounting for 5483 total citations—point to complementary lines of inquiry, including research focused on the climate change and environmental impact assessment.

5. Discussions

This study systematically reconstructs the evolution of the EEIO framework as applied to the agricultural sector and moves beyond a mere bibliometric account. Over the past decade the literature shows a marked increase in EEIO adoption, reflecting a clear demand for methods that represent the economy as an integrated system rather than as a collection of isolated sectors. By explicitly modelling intersectoral linkages and environmental flows across full supply chains [101], EEIO approaches provide policymakers with robust quantitative instruments to design and assess sustainability strategies for agrifood systems. This methodological expansion has occurred in tandem with intensified global concern for environmental degradation, climate-change mitigation, the Sustainable Development Goals (SDGs), and the stewardship of increasingly scarce natural resources.

A review of keyword clusters and prevailing themes in EEIO studies applied to agricultural systems points to several research directions that currently guide the field. One prominent direction relates to climate change and is increasingly reinforced by public investment, particularly within Europe, aimed at developing analytical frameworks capable of assigning responsibility along complete production chains [97]. A critical interpretation of these clusters reveals significant implications for the future development of EEIO research in agriculture. The prominence of Cluster 1 (Carbon, trade, and environmental policy) and Cluster 3 (Energy and climate impacts) suggests that the field is transitioning from static environmental accounting toward dynamic driver analysis. The increasing frequency of keywords such as “structural decomposition analysis” and “structural path analysis” indicates that future research must prioritize identifying the specific socio-economic drivers of environmental pressure rather than merely quantifying footprints. This has encouraged a growing body of work on emissions embodied in intermediate inputs and on the distinction between production- and consumption-based impact accounting, which is central to the formulation of effective mitigation policies for agriculture [102]. Similarly, the convergence of EEIO with LCA observed in the keyword trends points to a necessary methodological evolution: hybrid modeling. Future research should aim to reconcile the sectoral breadth of EEIO with the process-level detail of LCA to address the limitations of sectoral aggregation, particularly in heterogeneous agricultural systems. A second direction reflects the consolidation of the Water–Energy–Food nexus as both an analytical lens and a policy-oriented framework [49]. From this perspective, EEIO models are especially valuable because they allow interconnections among resources and sectors to be examined within a single, coherent structure [63,103]. A third direction is linked to the expanding

attention given to global value chains, which necessitates multi-country assessments of agricultural impacts. Recognition that a considerable share of environmental pressures is embedded in intersectoral and international exchanges highlights the relevance of EEIO for capturing cross-border effects and for framing agrifood sustainability within an increasingly globalized economy characterized by fragmented production processes [80,104]. The bibliometric findings also offer explicit insights into how EEIO trends relate to sustainability policies and agri-food system transformation. The observed exponential increase in publications post-2015 correlates strongly with the Paris Agreement and the adoption of the SDGs, suggesting that EEIO is increasingly utilized as a monitoring tool for Nationally Determined Contributions (NDCs) and international climate commitments. Furthermore, the strong association between “international trade” and “carbon footprint” keywords reflects the growing policy relevance of consumption-based accounting in the context of emerging regulations such as Carbon Border Adjustment Mechanisms (CBAM). The geographical analysis further elucidates divergent policy priorities: the European cluster’s focus aligns with the EU Green Deal and CAP, emphasizing regulatory harmonization and cross-border data sharing. In contrast, China’s dominance in the literature reflects policy priorities centered on domestic food security and supply-chain resilience. This dichotomy suggests that future EEIO applications must be context-sensitive, tailored to either support regulatory compliance in developed economies or enhance supply-chain stability in emerging economies. Within this context, the main application areas that emerge—such as emissions embodied in trade, water-resource use, energy and climate-related impacts, and the sustainability of agrifood supply chains—can be understood as methodological responses to these broader strategic demands [94,105]. Assessments of embodied emissions, for instance, are closely linked to evaluating climate-policy outcomes and to identifying situations in which apparent reductions in one region are offset by increased pressures elsewhere. Similarly, the strong emphasis on water-related analyses reflects the central role of agriculture in water security and system resilience, while illustrating the capacity of EEIO approaches to operationalize concepts such as water footprints in a manner that remains consistent with underlying economic structures and international trade relations.

With respect to energy and broader environmental impacts, energy is a fundamental determinant of agricultural performance and supply-chain outcomes: shifts in energy use, efficiency, or sourcing can substantially alter environmental results across production stages [106,107]. The literature increasingly documents trade-offs whereby productivity gains that lower impacts in one segment may amplify pressures elsewhere through greater fertilizer inputs, higher overall energy demand, and increased emissions from transport and logistics. Environmentally extended input–output analysis is well-suited to reveal these dynamics because it explicitly represents indirect and upstream linkages that single-sector methods typically overlook. By quantifying both direct and indirect flows, EEIO enables more reliable assessments of whether proposed interventions produce genuine net improvements or simply relocate environmental burdens across sectors or regions [108].

The analysis of scientific-community structure and collaboration patterns indicates that the EEIO analysis in agricultural research is entering a phase of consolidation. A small set of well-established hubs coexists with a widening periphery of emerging contributors, a pattern that reflects both the recognition of EEIO as a standard analytical tool and the entry of new research groups responding to novel policy questions and increasingly detailed datasets. This diversification of contributors—drawn from a range of disciplinary backgrounds—underscores the cross-cutting nature and growing relevance of the framework. Nonetheless, the application of EEIO to agricultural systems encounters several important methodological limitations that must be acknowledged when interpreting results for policy use [45]. First, core modelling assumptions—fixed technical coefficients, linear

relationships, and homogeneous sectoral technologies—constrain the capacity of EEIO to capture intra-sectoral heterogeneity, structural change, and adaptive responses to external shocks [109,110]. Second, the sectoral aggregation embedded in conventional IO tables tends to mask variation among the disparate activities included within the agricultural sector [111]. Third, environmental extensions are vulnerable to uncertainty, data inconsistencies, and researcher choices in accounting methods, all of which reduce comparability across studies [112,113]. However, a transparent assessment requires acknowledging limitations inherent to both the EEIO framework and this bibliometric study. Regarding the bibliometric methodology, the geographical distribution of publications is heavily skewed, with China accounting for a disproportionate volume of the literature, which may reflect specific national funding priorities rather than a global consensus. Additionally, the reliance on English-language databases may exclude significant local policy studies, and the correlation between publication spikes and policy events remains observational rather than causal. These constraints do not negate the value of EEIO; rather, they indicate where careful qualification and transparent reporting are required when using EEIO outputs to inform policy [114].

These limitations also delineate a targeted research agenda that is closely aligned with the main themes identified in this review. Future studies should first use structural decomposition and structural path analysis to isolate the socioeconomic drivers behind embodied emissions, water use, and energy demand, rather than only reporting aggregate footprints. They should also develop hybrid EEIO–LCA frameworks, ideally tested on specific agrifood commodities or supply chains, to combine EEIO’s sector-wide coverage with the process-level detail needed to reduce aggregation bias. In parallel, multi-regional EEIO tables with higher sectoral and spatial resolution are needed to better represent international trade, supply-chain fragmentation, and regional heterogeneity, particularly in the context of climate policy and carbon border measures. Because environmental extensions and accounting choices can materially affect results, future work should apply formal uncertainty analysis, including stochastic simulation and sensitivity testing, to identify which assumptions most influence outcomes. Another priority is to extend EEIO into dynamic formulations that can capture technological change, substitution effects, and policy scenarios over time. Finally, EEIO should be coupled more systematically with land-use, ecological, and socio-economic models to examine feedbacks, trade-offs, and distributional effects across the water–energy–food nexus, while greater use of open data, harmonized indicators, and transparent reporting standards would improve reproducibility and cross-study comparability. Advancing these directions would make EEIO applications in agrifood systems more robust, policy-relevant, and actionable.

6. Conclusions

This study synthesizes how EEIO models have been deployed to study agricultural systems, based on a systematic corpus of 647 publications retrieved from Scopus and Web of Science covering 1978–2025. The bibliometric and keyword analyses show a clear acceleration of research since 2015, reflecting broader uptake of EEIO as a method for tracing economy-wide interdependencies and their environmental consequences. Four principal application domains emerge from the literature: emissions embodied in trade, water resource management, energy and climate-related impacts, and the sustainability of agri-food supply chains. At the country level, China is both the most prolific contributor and a central node in international collaboration networks.

These results confirm the practical value of EEIO for framing system-level questions in agriculture, while also underscoring well-documented methodological constraints. Fixed technical coefficients, coarse sectoral aggregation, and uncertainty in environmental ex-

tensions limit the capacity of standard EEIO results to resolve farm-scale or crop-specific processes. Consequently, findings based on EEIO demand careful interpretation when used to inform strategic decision making or policy design. To strengthen the evidence base and policy relevance of future work, we recommend three complementary directions. First, improve data resolution and harmonization by developing higher spatial and sectoral disaggregation and by standardizing environmental extension methods across databases. Second, integrate EEIO with higher resolution approaches, such as process-based life cycle assessment, farm-level surveys, remote sensing and agent-based models, to reconcile economy-wide accounting with production system detail. Third, adopt robust uncertainty and sensitivity analyses together with scenario exploration to make policy inferences more transparent and defensible. Additional priorities include expanding multi-regional EEIO frameworks to better capture trade-mediated impacts, and enhancing engagement with stakeholders and policymakers so that model outputs are interpretable and actionable.

In sum, EEIO remains a powerful framework for analyzing the complex interactions between agricultural production, intermediate demands and environmental pressures. Its capacity to inform a sustainable transition of agrifood systems will be greatest where improved data, methodological pluralism and explicit treatment of uncertainty are used to link economy-wide insights to the realities of specific crops, supply chains and governance contexts.

Author Contributions: Conceptualization, G.G., M.Z., M.C., S.R. and M.V.; methodology, G.G., M.Z. and M.V.; formal analysis, G.G. and M.Z.; investigation, G.G. and M.Z.; data curation, G.G. and M.Z.; writing—original draft preparation, G.G. and M.Z.; writing—review and editing, G.G., M.Z. and M.V.; visualization, M.C.; supervision, M.V. and S.R. project administration, M.V.; funding acquisition, M.V. All authors have read and agreed to the published version of the manuscript.

Funding: We acknowledge financial support under the National Recovery and Resilience Plan (NRRP), Mission 4, Component 2, Investment 1.1, Call for tender No. 104 published on 2 February 2022 by the Italian Ministry of University and Research (MUR), funded by the European Union—NextGenerationEU—A environmentally extended Rural-Urban model to study the Ecosystems-Economy-Society nexus (RUEESnexus)—n. 2022Z879W3—Grant Assignment Decree No. 967 adopted on 30 June 2023 by the Italian Ministry of Ministry of University and Research (MUR). This work reflects only the authors' views and opinions, and neither the Ministry for University and Research nor the European Commission can be considered responsible for them.

Data Availability Statement: Publicly available datasets were analyzed in this study. These data can be found at the following: <https://www.scopus.com/pages/home#researcher-discovery> (accessed on 15 November 2025) and <https://www.webofscience.com/wos/woscc/advanced-search> (accessed on 15 November 2025).

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Amiri, Z.; Asgharipour, M.R.; Campbell, D.E.; Armin, M. A Sustainability Analysis of Two Rapeseed Farming Ecosystems in Khorramabad, Iran, Based on Emergy and Economic Analyses. *J. Clean. Prod.* **2019**, *226*, 1051–1066. [[CrossRef](#)]
2. Camanzi, L.; Alikadic, A.; Compagnoni, L.; Merloni, E. The Impact of Greenhouse Gas Emissions in the EU Food Chain: A Quantitative and Economic Assessment Using an Environmentally Extended Input-Output Approach. *J. Clean. Prod.* **2017**, *157*, 168–176. [[CrossRef](#)]
3. Kanianska, R. Agriculture and Its Impact on Land-Use, Environment, and Ecosystem Services. In *Landscape Ecology—The Influences of Land Use and Anthropogenic Impacts of Landscape Creation*; InTech: Nappanee, Indiana, 2016.
4. Mahmood, H.; Hassan, M.S.; Meraj, G.; Furqan, M. Agriculture's Role in Environmental Sustainability: A Comprehensive Review of Challenges and Solutions. *Chall. Sustain.* **2024**, *12*, 178–189. [[CrossRef](#)]
5. Engström, R.; Wadeskog, A.; Finnveden, G. Environmental Assessment of Swedish Agriculture. *Ecol. Econ.* **2007**, *60*, 550–563. [[CrossRef](#)]

6. Tilman, D.; Fargione, J.; Wolff, B.; D'Antonio, C.; Dobson, A.; Howarth, R.; Schindler, D.; Schlesinger, W.H.; Simberloff, D.; Swackhamer, D. Forecasting Agriculturally Driven Global Environmental Change. *Science* **2001**, *292*, 281–284. [[CrossRef](#)]
7. Weinzettel, J.; Hertwich, E.G.; Peters, G.P.; Steen-Olsen, K.; Galli, A. Affluence Drives the Global Displacement of Land Use. *Glob. Environ. Change* **2013**, *23*, 433–438. [[CrossRef](#)]
8. Garcia, S.; Rushforth, R.; Ruddell, B.L.; Mejia, A. Full Domestic Supply Chains of Blue Virtual Water Flows Estimated for Major U.S. Cities. *Water Resour. Res.* **2020**, *56*, e2019WR026190. [[CrossRef](#)]
9. Lenzen, M. Errors in Conventional and Input-Output—Based Life—Cycle Inventories. *J. Ind. Ecol.* **2000**, *4*, 127–148. [[CrossRef](#)]
10. Matthews, H.S.; Hendrickson, C.T.; Weber, C.L. The Importance of Carbon Footprint Estimation Boundaries. *Environ. Sci. Technol.* **2008**, *42*, 5839–5842. [[CrossRef](#)] [[PubMed](#)]
11. Peters, G.P.; Hertwich, E.G. CO₂ Embodied in International Trade with Implications for Global Climate Policy. *Environ. Sci. Technol.* **2008**, *42*, 1401–1407. [[CrossRef](#)]
12. Hoekstra, A.Y.; Chapagain, A.K. Water Footprints of Nations: Water Use by People as a Function of Their Consumption Pattern. *Water Resour. Manag.* **2006**, *21*, 35–48. [[CrossRef](#)]
13. Aldaya, M.M.; Chapagain, A.K.; Hoekstra, A.Y.; Mekonnen, M.M. *The Water Footprint Assessment Manual*; Routledge: London, UK, 2012; ISBN 9781136538520.
14. Dong, H.; Geng, Y.; Sarkis, J.; Fujita, T.; Okadera, T.; Xue, B. Regional Water Footprint Evaluation in China: A Case of Liaoning. *Sci. Total Environ.* **2013**, *442*, 215–224. [[CrossRef](#)]
15. Braungart, M.; McDonough, W.; Bollinger, A. Cradle-to-Cradle Design: Creating Healthy Emissions—A Strategy for Eco-Effective Product and System Design. *J. Clean. Prod.* **2007**, *15*, 1337–1348. [[CrossRef](#)]
16. Dong, G.; Mao, X.; Zhou, J.; Zeng, A. Carbon Footprint Accounting and Dynamics and the Driving Forces of Agricultural Production in Zhejiang Province, China. *Ecol. Econ.* **2013**, *91*, 38–47. [[CrossRef](#)]
17. Yu, Y.; Feng, K.; Hubacek, K.; Sun, L. Global Implications of China's Future Food Consumption. *J. Ind. Ecol.* **2016**, *20*, 593–602. [[CrossRef](#)]
18. Strassner, C.; Kahl, J. Understanding a Food Systems Approach. In *Organic Food Systems: Meeting the Needs of Southern Africa*; CABI: Wallingford, UK, 2020; pp. 51–59.
19. De Matteis, L.; Mattioni, D.; Garcia Campos, P.; Ilie, E.T.; Wieggers, E.; Hawkes, C. International Experiences of Systems Approaches: Re-Thinking Policies and Governance to Transform Agrifood Systems. *Philos. Trans. R. Soc. B Biol. Sci.* **2025**, *380*, 20240159. [[CrossRef](#)]
20. FAO. *Transforming Food and Agriculture Through a Systems Approach*; FAO: Rome, Italy, 2025; ISBN 978-92-5-139963-7.
21. Pang, Q.; Lv, X.; Zhang, L. Industrial Trade and Embodied Energy Transfer Patterns Analysis in China: A Perspective of Multilayer Complex Networks. *Energy* **2025**, *332*, 137264. [[CrossRef](#)]
22. Miller, R.E.; Blair, P.D. *Input-Output Analysis*; Cambridge University Press: Cambridge, UK, 2009; ISBN 9780521739023.
23. Shmelev, S.E. A Key Sector Approach to the Environmentally Extended Input-Output Analysis of the UK Economy. In *Sustainability Analysis*; Palgrave Macmillan: London, UK, 2012; pp. 69–99.
24. Minx, J.C.; Wiedmann, T.; Wood, R.; Peters, G.P.; Lenzen, M.; Owen, A.; Scott, K.; Barrett, J.; Hubacek, K.; Baiocchi, G.; et al. Input-output analysis and carbon footprinting: An overview of applications. *Econ. Syst. Res.* **2009**, *21*, 187–216. [[CrossRef](#)]
25. Hertwich, E.G.; Peters, G.P. Carbon Footprint of Nations: A Global, Trade-Linked Analysis. *Environ. Sci. Technol.* **2009**, *43*, 6414–6420. [[CrossRef](#)] [[PubMed](#)]
26. Guan, S.; Han, M.; Wu, X.; Guan, C.; Zhang, B. Exploring Energy-Water-Land Nexus in National Supply Chains: China 2012. *Energy* **2019**, *185*, 1225–1234. [[CrossRef](#)]
27. Cao, Q.; Song, J.; Liu, C.; Yang, W. Evolving Water, Energy and Carbon Footprints in China's Food Supply Chain. *J. Clean. Prod.* **2023**, *423*, 138716. [[CrossRef](#)]
28. Chen, B.; Han, M.Y.; Peng, K.; Zhou, S.L.; Shao, L.; Wu, X.F.; Wei, W.D.; Liu, S.Y.; Li, Z.; Li, J.S.; et al. Global Land-Water Nexus: Agricultural Land and Freshwater Use Embodied in Worldwide Supply Chains. *Sci. Total Environ.* **2018**, *613–614*, 931–943. [[CrossRef](#)]
29. Leontief, W.W. Quantitative Input and Output Relations in the Economic Systems of the United States. *Rev. Econ. Stat.* **1936**, *18*, 105. [[CrossRef](#)]
30. Georgescu-Roegen, N.; Leontief, W.W. The Structure of the American Economy, 1919–1939: An Empirical Application of Equilibrium Analysis. *Econometrica* **1951**, *19*, 351. [[CrossRef](#)]
31. Du, Q.; Liao, C.-Y.; Mao, Y.-H. Quantitative Analysis on L.-K. Hua's Input-Output Model. *Discret. Contin. Dyn. Syst.-S* **2025**, *18*, 2912–2923. [[CrossRef](#)]
32. Tran, T.K.; Sato, H.; Namatame, A. Key Economic Sectors and Their Transitions: Analysis of World Input-Output Network. In *Robustness in Econometrics*; Springer International Publishing: Cham, Switzerland, 2017; pp. 381–399.
33. Gymnopoulos, A.; Tsaliki, P. Production, Nonproduction Sectors, and Economic Growth: An Input-Output Analysis of the US Economy, 1995–2018. *Rev. Radic. Political Econ.* **2026**, *58*, 157–171. [[CrossRef](#)]

34. Vltavska, K.; Fischer, J. Macroeconomic impact of expenditures on higher education: Regional input-output analysis. *J. Effic. Responsib. Educ. Sci.* **2017**, *10*, 116–120. [[CrossRef](#)]
35. Gürkan, Y.; Keçeli, S. The Intersectoral Linkage Effects in Turkish Economy: An Application of Static Leontief Model. *Panoeconomicus* **2009**, *56*, 301–326. [[CrossRef](#)]
36. Tounsi, S.; Ezzahid, E.H.; El Alaoui, A.; Nihou, A. Key Sectors in the Moroccan Economy: An Application of Input-Output Analysis. *Economics* **2013**, *7*, 1–19. [[CrossRef](#)]
37. Ayres, R.U.; Kneese, A.V. Production, Consumption, and Externalities. In *The Roots of Logistics*; Springer: Berlin/Heidelberg, Germany, 2012; pp. 363–388.
38. Leontief, W. Environmental Repercussions and the Economic Structure: An Input-Output Approach. *Rev. Econ. Stat.* **1970**, *52*, 262. [[CrossRef](#)]
39. Yokoi, R.; Kanemoto, K.; Itsubo, N.; Motoshita, M. Potential Impact of Abiotic Resource Use Considering Country-Specific Supply Chain: Consumption-Based Characterization and Normalization Utilizing a Multi-Regional Input-Output Model. *Int. J. Life Cycle Assess.* **2025**, *30*, 2003–2019. [[CrossRef](#)]
40. Yu, H.; Zhang, S.; Sun, M.; Xu, C. Environmental Extended Multiregional Input-Output Model Unveiling the Microfiber Footprint Embodied in the Textile Interprovincial Trade in China. *Environ. Sci. Technol. Lett.* **2025**, *12*, 1567–1574. [[CrossRef](#)]
41. Fotova Čiković, K.; Keček, D.; Mikulić, D. An Application of an Environmentally Extended Input-Output Model to the Assessment of CO₂ Emissions of Croatian Economic Sectors. *Croat. Oper. Res. Rev.* **2025**, *16*, 137–150. [[CrossRef](#)]
42. Sun, Y.-Y.; Cadarso, M.A.; Driml, S. Tourism Carbon Footprint Inventories: A Review of the Environmentally Extended Input-Output Approach. *Ann. Tour. Res.* **2020**, *82*, 102928. [[CrossRef](#)]
43. Schepelmann, P.; Vercauteren, A.; Acosta-Fernandez, J.; Saurat, M.; Boonen, K.; Christis, M.; Marin, G.; Zoboli, R.; Maguire, C. Driving Forces of Changing Environmental Pressures from Consumption in the European Food System. *Sustainability* **2020**, *12*, 8265. [[CrossRef](#)]
44. Horvath, A.; Qin, Y. An Integrated Food-Energy-Water Systems Model for Tackling Questions Related to Agricultural Produce and Food Supply Chains. In Proceedings of the 22nd EGU General Assembly, Online, 4–8 May 2020.
45. Canning, P.; Rehkamp, S.; Yi, J. Environmental Input-Output (EIO) Models for Food Systems Research: Application and Extensions. In *Food Systems Modelling*; Elsevier: Amsterdam, The Netherlands, 2022; pp. 179–212.
46. Reutter, B.; Lant, P.; Reynolds, C.; Lane, J. Food Waste Consequences: Environmentally Extended Input-Output as a Framework for Analysis. *J. Clean. Prod.* **2017**, *153*, 506–514. [[CrossRef](#)]
47. Xu, C.-G.; Cai, J.; Yu, Y.-S.; Yan, K.-F.; Li, X.-S. Effect of Pressure on Methane Recovery from Natural Gas Hydrates by Methane-Carbon Dioxide Replacement. *Appl. Energy* **2018**, *217*, 527–536. [[CrossRef](#)]
48. Lu, Y.; Chen, B. Energy-Water Nexus in Urban Industrial System. *Energy Procedia* **2016**, *88*, 212–217. [[CrossRef](#)]
49. Sturla, G.; Ciulla, L.; Rocchi, B. Natural and Social Scarcity in Water Footprint: A Multiregional Input-Output Analysis for Italy. *Ecol. Indic.* **2023**, *147*, 109981. [[CrossRef](#)]
50. Tennakoon, S.M.A.V.S. Multi-Regional Input-Output Analysis (MRIO): Exploring Trends and Gaining Key Insights Through Bibliometric Analysis. *Manag. Dyn. Knowl. Econ.* **2024**, *12*, 321–341. [[CrossRef](#)]
51. Alharbi, F.; Gufran, K.; Alqerban, A.; Alqahtani, A.S.; Asiri, S.N.; Almutairi, A. Evaluation of Compliance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) Guidelines for Conducting and Reporting Systematic Reviews in Three Major Periodontology Journals. *Open Dent. J.* **2024**, *18*, 1–10. [[CrossRef](#)]
52. Moher, D.; Liberati, A.; Tetzlaff, J.; Altman, D.G. Preferred Reporting Items for Systematic Reviews and Meta-Analyses: The PRISMA Statement. *BMJ* **2009**, *339*, b2535. [[CrossRef](#)] [[PubMed](#)]
53. Aria, M.; Cuccurullo, C. Bibliometrix: An R-Tool for Comprehensive Science Mapping Analysis. *J. Informetr.* **2017**, *11*, 959–975. [[CrossRef](#)]
54. Bradford, S.C. Sources of Information on Specific Subjects. *Eng. Illus. Wkly. J.* **1934**, *137*, 85–86.
55. Desai, N.; Veras, L.; Gosain, A. Using Bradford's Law of Scattering to Identify the Core Journals of Pediatric Surgery. *J. Surg. Res.* **2018**, *229*, 90–95. [[CrossRef](#)]
56. Lenzen, M.; Moran, D.; Kanemoto, K.; Geschke, A. Building Eora: A global multi-region input-output database at high country and sector resolution. *Econ. Syst. Res.* **2013**, *25*, 20–49. [[CrossRef](#)]
57. Stadler, K.; Wood, R.; Bulavskaya, T.; Södersten, C.; Simas, M.; Schmidt, S.; Usubiaga, A.; Acosta-Fernández, J.; Kuenen, J.; Bruckner, M.; et al. EXIOBASE 3: Developing a Time Series of Detailed Environmentally Extended Multi-Regional Input-Output Tables. *J. Ind. Ecol.* **2018**, *22*, 502–515. [[CrossRef](#)]
58. Wiedmann, T. A Review of Recent Multi-Region Input-Output Models Used for Consumption-Based Emission and Resource Accounting. *Ecol. Econ.* **2009**, *69*, 211–222. [[CrossRef](#)]
59. Lenzen, M.; Moran, D.; Bhaduri, A.; Kanemoto, K.; Bekchanov, M.; Geschke, A.; Foran, B. International Trade of Scarce Water. *Ecol. Econ.* **2013**, *94*, 78–85. [[CrossRef](#)]

60. Lenzen, M.; Moran, D.; Kanemoto, K.; Foran, B.; Lobefaro, L.; Geschke, A. International Trade Drives Biodiversity Threats in Developing Nations. *Nature* **2012**, *486*, 109–112. [[CrossRef](#)]
61. Yu, Y.; Feng, K.; Hubacek, K. Tele-Connecting Local Consumption to Global Land Use. *Glob. Environ. Change* **2013**, *23*, 1178–1186. [[CrossRef](#)]
62. Hoekstra, A.Y.; Mekonnen, M.M. The Water Footprint of Humanity. *Proc. Natl. Acad. Sci. USA* **2012**, *109*, 3232–3237. [[CrossRef](#)] [[PubMed](#)]
63. Steen-Olsen, K.; Weinzettel, J.; Cranston, G.; Ercin, A.E.; Hertwich, E.G. Carbon, Land, and Water Footprint Accounts for the European Union: Consumption, Production, and Displacements through International Trade. *Environ. Sci. Technol.* **2012**, *46*, 10883–10891. [[CrossRef](#)] [[PubMed](#)]
64. Lenzen, M.; Kanemoto, K.; Moran, D.; Geschke, A. Mapping the Structure of the World Economy. *Environ. Sci. Technol.* **2012**, *46*, 8374–8381. [[CrossRef](#)] [[PubMed](#)]
65. Wiedmann, T.; Lenzen, M.; Turner, K.; Barrett, J. Examining the Global Environmental Impact of Regional Consumption Activities—Part 2: Review of Input–Output Models for the Assessment of Environmental Impacts Embodied in Trade. *Ecol. Econ.* **2007**, *61*, 15–26. [[CrossRef](#)]
66. Wood, R.; Stadler, K.; Bulavskaya, T.; Lutter, S.; Giljum, S.; De Koning, A.; Kuenen, J.; Schütz, H.; Acosta-Fernández, J.; Usubiaga, A.; et al. Global Sustainability Accounting—Developing EXIOBASE for Multi-Regional Footprint Analysis. *Sustainability* **2014**, *7*, 138–163. [[CrossRef](#)]
67. Zhang, C.; Anadon, L.D. A Multi-Regional Input–Output Analysis of Domestic Virtual Water Trade and Provincial Water Footprint in China. *Ecol. Econ.* **2014**, *100*, 159–172. [[CrossRef](#)]
68. Wiedmann, T.; Lenzen, M. Environmental and Social Footprints of International Trade. *Nat. Geosci.* **2018**, *11*, 314–321. [[CrossRef](#)]
69. Zhao, X.; Liu, J.; Liu, Q.; Tillotson, M.R.; Guan, D.; Hubacek, K. Physical and Virtual Water Transfers for Regional Water Stress Alleviation in China. *Proc. Natl. Acad. Sci. USA* **2015**, *112*, 1031–1035. [[CrossRef](#)]
70. Chen, L.; Msigwa, G.; Yang, M.; Osman, A.I.; Fawzy, S.; Rooney, D.W.; Yap, P.-S. Strategies to Achieve a Carbon Neutral Society: A Review. *Environ. Chem. Lett.* **2022**, *20*, 2277–2310. [[CrossRef](#)]
71. van Ittersum, M.K.; Rabbinge, R. Concepts in Production Ecology for Analysis and Quantification of Agricultural Input–Output Combinations. *Field Crops Res.* **1997**, *52*, 197–208. [[CrossRef](#)]
72. Marques, A.; Martins, I.S.; Kastner, T.; Plutzer, C.; Theurl, M.C.; Eisenmenger, N.; Huijbregts, M.A.J.; Wood, R.; Stadler, K.; Bruckner, M.; et al. Increasing Impacts of Land Use on Biodiversity and Carbon Sequestration Driven by Population and Economic Growth. *Nat. Ecol. Evol.* **2019**, *3*, 628–637. [[CrossRef](#)]
73. Ngoc, U.N.; Schnitzer, H. Sustainable Solutions for Solid Waste Management in Southeast Asian Countries. *Waste Manag.* **2009**, *29*, 1982–1995. [[CrossRef](#)] [[PubMed](#)]
74. Chen, G.Q.; Zhang, B. Greenhouse Gas Emissions in China 2007: Inventory and Input–Output Analysis. *Energy Policy* **2010**, *38*, 6180–6193. [[CrossRef](#)]
75. Kizilaslan, H. Input–Output Energy Analysis of Cherries Production in Tokat Province of Turkey. *Appl. Energy* **2009**, *86*, 1354–1358. [[CrossRef](#)]
76. Graedel, T.E. Material Flow Analysis from Origin to Evolution. *Environ. Sci. Technol.* **2019**, *53*, 12188–12196. [[CrossRef](#)]
77. Duarte, R.; Sánchez-Chóliz, J.; Bielsa, J. Water Use in the Spanish Economy: An Input–Output Approach. *Ecol. Econ.* **2002**, *43*, 71–85. [[CrossRef](#)]
78. Fang, D.; Chen, B. Linkage Analysis for the Water–Energy Nexus of City. *Appl. Energy* **2017**, *189*, 770–779. [[CrossRef](#)]
79. Esengun, K.; Gündüz, O.; Erdal, G. Input–Output Energy Analysis in Dry Apricot Production of Turkey. *Energy Convers. Manag.* **2007**, *48*, 592–598. [[CrossRef](#)]
80. Hertwich, E.G.; Wood, R. The Growing Importance of Scope 3 Greenhouse Gas Emissions from Industry. *Environ. Res. Lett.* **2018**, *13*, 104013. [[CrossRef](#)]
81. Yu, Y.; Hubacek, K.; Feng, K.; Guan, D. Assessing Regional and Global Water Footprints for the UK. *Ecol. Econ.* **2010**, *69*, 1140–1147. [[CrossRef](#)]
82. Zhao, X.; Yang, H.; Yang, Z.; Chen, B.; Qin, Y. Applying the Input–Output Method to Account for Water Footprint and Virtual Water Trade in the Haihe River Basin in China. *Environ. Sci. Technol.* **2010**, *44*, 9150–9156. [[CrossRef](#)]
83. Wang, Z.; Huang, K.; Yang, S.; Yu, Y. An Input–Output Approach to Evaluate the Water Footprint and Virtual Water Trade of Beijing, China. *J. Clean. Prod.* **2013**, *42*, 172–179. [[CrossRef](#)]
84. Liu, D.; Guo, X.; Xiao, B. What Causes Growth of Global Greenhouse Gas Emissions? Evidence from 40 Countries. *Sci. Total Environ.* **2019**, *661*, 750–766. [[CrossRef](#)]
85. Read, Q.D.; Brown, S.; Cuéllar, A.D.; Finn, S.M.; Gephart, J.A.; Marston, L.T.; Meyer, E.; Weitz, K.A.; Muth, M.K. Assessing the Environmental Impacts of Halving Food Loss and Waste along the Food Supply Chain. *Sci. Total Environ.* **2020**, *712*, 136255. [[CrossRef](#)] [[PubMed](#)]

86. Wang, X.-C.; Klemeš, J.J.; Wang, Y.; Dong, X.; Wei, H.; Xu, Z.; Varbanov, P.S. Water-Energy-Carbon Emissions Nexus Analysis of China: An Environmental Input-Output Model-Based Approach. *Appl. Energy* **2020**, *261*, 114431. [[CrossRef](#)]
87. Bruckner, M.; Fischer, G.; Tramberend, S.; Giljum, S. Measuring Telecouplings in the Global Land System: A Review and Comparative Evaluation of Land Footprint Accounting Methods. *Ecol. Econ.* **2015**, *114*, 11–21. [[CrossRef](#)]
88. Guo, S.; Shen, G.Q.; Chen, Z.-M.; Yu, R. Embodied Cultivated Land Use in China 1987–2007. *Ecol. Indic.* **2014**, *47*, 198–209. [[CrossRef](#)]
89. Schaffartzik, A.; Haberl, H.; Kastner, T.; Wiedenhofer, D.; Eisenmenger, N.; Erb, K. Trading Land: A Review of Approaches to Accounting for Upstream Land Requirements of Traded Products. *J. Ind. Ecol.* **2015**, *19*, 703–714. [[CrossRef](#)]
90. Cazcarro, I.; Duarte, R.; Sánchez-Chóliz, J. Downscaling the Grey Water Footprints of Production and Consumption. *J. Clean. Prod.* **2016**, *132*, 171–183. [[CrossRef](#)]
91. Tellarini, V.; Caporali, F. An Input/Output Methodology to Evaluate Farms as Sustainable Agroecosystems: An Application of Indicators to Farms in Central Italy. *Agric. Ecosyst. Environ.* **2000**, *77*, 111–123. [[CrossRef](#)]
92. Virtanen, Y.; Kurppa, S.; Saarinen, M.; Katajajuuri, J.-M.; Usva, K.; Mäenpää, I.; Mäkelä, J.; Grönroos, J.; Nissinen, A. Carbon Footprint of Food—Approaches from National Input-Output Statistics and a LCA of a Food Portion. *J. Clean. Prod.* **2011**, *19*, 1849–1856. [[CrossRef](#)]
93. Houshyar, E.; Grundmann, P. Environmental Impacts of Energy Use in Wheat Tillage Systems: A Comparative Life Cycle Assessment (LCA) Study in Iran. *Energy* **2017**, *122*, 11–24. [[CrossRef](#)]
94. Mayer, A.; Mubako, S.; Ruddell, B.L. Developing the Greatest Blue Economy: Water Productivity, Fresh Water Depletion, and Virtual Water Trade in the Great Lakes Basin. *Earths Future* **2016**, *4*, 282–297. [[CrossRef](#)]
95. Nabavi-Pelesaraei, A.; Rafiee, S.; Mohtasebi, S.S.; Hosseinzadeh-Bandbafha, H.; Chau, K. Energy Consumption Enhancement and Environmental Life Cycle Assessment in Paddy Production Using Optimization Techniques. *J. Clean. Prod.* **2017**, *162*, 571–586. [[CrossRef](#)]
96. Taki, M.; Soheili-Fard, F.; Rohani, A.; Chen, G.; Yildizhan, H. Life Cycle Assessment to Compare the Environmental Impacts of Different Wheat Production Systems. *J. Clean. Prod.* **2018**, *197*, 195–207. [[CrossRef](#)]
97. Bruckner, M.; Häyhä, T.; Giljum, S.; Maus, V.; Fischer, G.; Tramberend, S.; Börner, J. Quantifying the Global Cropland Footprint of the European Union’s Non-Food Bioeconomy. *Environ. Res. Lett.* **2019**, *14*, 045011. [[CrossRef](#)]
98. Feng, W.; Cai, B.; Zhang, B. A Bite of China: Food Consumption and Carbon Emission from 1992 to 2007. *China Econ. Rev.* **2020**, *59*, 100949. [[CrossRef](#)]
99. Lotka, A.J. The Frequency Distribution of Scientific Productivity. *J. Wash. Acad. Sci.* **1926**, *16*, 317–323.
100. Kawamura, M.; Thomas, C.D.L.; Tsurumoto, A.; Sasahara, H.; Kawaguchi, Y. Lotka’s Law and Productivity Index of Authors in a Scientific Journal. *J. Oral Sci.* **2000**, *42*, 75–78. [[CrossRef](#)]
101. Cahyadi, E.R.; Hidayati, N.; Zahra, N.; Arif, C. Integrating Circular Economy Principles into Agri-Food Supply Chain Management: A Systematic Literature Review. *Sustainability* **2024**, *16*, 7165. [[CrossRef](#)]
102. Zhao, L.; Lv, Y.; Wang, C.; Xue, J.; Yang, Y.; Li, D. Embodied Greenhouse Gas Emissions in the International Agricultural Trade. *Sustain. Prod. Consum.* **2023**, *35*, 250–259. [[CrossRef](#)]
103. Vallejos, X.; Hidalgo, S.; González, B.; Neumann, P. Estimation of the Water Footprint of Wood Construction in Chile Using a Streamlined Input-Output-Based Model. *Sustainability* **2025**, *17*, 1061. [[CrossRef](#)]
104. Attinasi, M.-G.; Boeckelmann, L.; de Castro Martins, B.; Meunier, B.; Borin, A.; Conteduca, F.P.; Mancini, M. Supply Chain Decoupling in Green Products: A Granular Input-Output Analysis. *Energy Econ.* **2025**, *149*, 108773. [[CrossRef](#)]
105. Liu, X.; Cifuentes-Faura, J.; Shi, W.; Tian, C. Exploring the Carbon Emission Transfers Pathway to Address the Issue of Sustainable Development: A Multi-Regional Input-Output Perspective. *Sustain. Dev.* **2025**, *33*, 5676–5703. [[CrossRef](#)]
106. Corigliano, O.; Morrone, P.; Algieri, A. Navigating the Challenges of Sustainability in the Food Processing Chain: Insights into Energy Interventions to Reduce Footprint. *Energies* **2025**, *18*, 296. [[CrossRef](#)]
107. Sampedro, J.; Kyle, P.; Ramig, C.W.; Tanner, D.; Huster, J.E.; Wise, M.A. Dynamic Linking of Upstream Energy and Freight Demands for Bio and Fossil Energy Pathways in the Global Change Analysis Model. *Appl. Energy* **2021**, *302*, 117580. [[CrossRef](#)]
108. Vercauteren, A.; Christis, M.; Geerken, T.; Van der Linden, A. Policy Needs (to Be) Covered by Static Environmentally Extended Input-Output Analyses. *Econ. Syst. Res.* **2020**, *32*, 121–144. [[CrossRef](#)]
109. Avelino, A.F.T. Disaggregating Input-Output Tables in Time: The Temporal Input-Output Framework. *Econ. Syst. Res.* **2017**, *29*, 313–334. [[CrossRef](#)]
110. Altimiras-Martin, A. A Supply-Driven Model Consuming Simultaneously All Primary Inputs: Unfolding Analytical Potential beyond the Ghosh Model. *Econ. Syst. Res.* **2024**, *36*, 249–264. [[CrossRef](#)]
111. Steen-Olsen, K.; Owen, A.; Hertwich, E.G.; Lenzen, M. Effects of sector aggregation on CO₂ multipliers in multiregional input-output analyses. *Econ. Syst. Res.* **2014**, *26*, 284–302. [[CrossRef](#)]
112. Chircop, J.; Tarsalewska, M.; Trzeciakiewicz, A. Learning to Be Green: Accounting Comparability and Environmental Violations. *Br. Account. Rev.* **2025**, *57*, 101240. [[CrossRef](#)]

113. Nadiminti, V.; Nerius, E. A Systematic Review of Environmental Accounting. *Interdiscip. J. Papua New Guin. Univ. Technol.* **2025**, *27*, 1–13. [[CrossRef](#)]
114. Zhao, Y.; Zhang, J.; Li, S.; Yu, M. Greenhouse Gas Accounting and Emission Reduction in Prefabricated Construction: Insights from Extended Input-Output Analysis. *Constr. Innov.* **2025**, *26*, 1252–1277. [[CrossRef](#)]

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.