Total Factor Productivity and Misallocation in the Agricultural Sector: A Text Analysis

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Abstract

Agricultural productivity growth has been central to food security efforts, yet productivity-driven intensification raises sustainability concerns by exacerbating environmental pressures and resource inefficiencies. Addressing these issues requires integrated insights on Total Factor Productivity (TFP) and resource misallocation, which are conceptually related but largely studied separately. This paper offers the first comprehensive bibliometric and text-mining analysis of research on TFP and misallocation in agriculture, examining them both jointly and independently. Using 688 peer-reviewed publications from the Scopus database through 2024, we apply Structural Topic Modeling (STM) and keyword co-occurrence networks to map thematic areas, trends, and gaps in the literature. Results reveal a fragmented research landscape with limited integration between productivity and misallocation studies, and underexplored dimensions including institutional contexts, regional disparities, and farm heterogeneity. We argue that bridging these themes is crucial for policy design, and propose a forward-looking research agenda to stimulate integrative, sustainability-oriented scholarship.

Keywords: Total Factor Productivity, Misallocation; Agricultural Sector; Text Analysis.

JEL Codes: Q12, O47, C88

1. Introduction

The agricultural sector faces growing pressures from population growth, environmental challenges, and evolving consumer demands. These dynamics have attracted sustained research interest in assessing their impacts on agriculture (Anderson, 2023; Latruffe and Le Mouël, 2009; Mustafa *et al.,* 2024; Spash, 1997). In both developed and emerging economies, sustainable productivity gains place Total Factor Productivity (TFP, henceforth) at the forefront of research and policy debates, as emphasized in major policy and analytical reports by international organizations (OECD, 2015; World Bank, 2008, 2011; FAO, 2022) as well as in the agricultural economics literature that documents the central role of productivity growth in explaining long-term developments in global agriculture (Fuglie, 2015). However, TFP growth is often hindered by the misallocation of key resources—land, labour, and capital. For example, land fragmentation or policy-induced distortions can lead to efficiency losses. Understanding how TFP relates to misallocation is crucial for unlocking productivity gains (Del Gatto *et al.,* 2011). Aggregate TFP depends on two dimensions: improvements in firm-level productivity and the efficient allocation of inputs. In an ideal market, inputs would flow from less productive to more productive firms. In practice, market imperfections often block this process, reducing aggregate TFP. Recent studies have linked cross-country differences in TFP to misallocation (Restuccia and Rogerson, 2008, 2013; Hsieh and Klenow, 2009; Bartelsman *et al.,* 2013; Asker *et al.,* 2014), showing that productivity heterogeneity often signals inefficient resource use rather than purely technological gaps. While a large body of applied economic research has investigated TFP and misallocation from multiple angles, these two strands have largely evolved in parallel. This separation represents a limitation for applied economic analysis and policy design, particularly in agriculture, where productivity outcomes critically depend on institutional settings, land markets, and farm structure. Productivity-enhancing policies may therefore yield limited or distorted effects if underlying misallocation mechanisms are not simultaneously considered. Bibliometric studies are recognized as a powerful analytical methodology to examine trends in past research output and map relationships among countries, keywords, and affiliations (Armenta-Medina *et al.,* 2020; Kryszak *et al.,* 2023). By allowing researchers to identify and visualize the main research themes under investigation, bibliometric studies also facilitate the development and planning of scientific policies. Building on bibliometric analysis, text-mining (T-M, henceforth) provides complementary capabilities for exploring academic literature. Unlike conventional search engines, which retrieve information in response to specific queries, T-M focuses on the discovery of novel insights that have not been explicitly documented (Gupta and Lehal, 2009). Against this background, the main contribution of this paper is meta-analytical rather than empirical. This paper combines bibliometric and T-M to investigate research on TFP, resource misallocation, and their intersections (that is, TFP and Misallocation). Building on the framework of Kryszak *et al.,* (2023), it explores not only trends in these fields but also the extent to which they are conceptually integrated or remain fragmented.

Based on this background, the study addresses the following key Research Questions (RQs):

RQ1: What are the main research themes and publication trends at the intersection of TFP and misallocation in agricultural research?

RQ2: How have these themes evolved over time, and to what extent are TFP and misallocation jointly analysed within the literature?

RQ3: What knowledge gaps and underexplored thematic linkages can be identified to inform future research and policy design?

To address RQ1, we first conducted a bibliometric analysis to trace the evolution of the literature over time and to identify the journals and outlets in which relevant contributions are published. To address RQ2 and RQ3, we apply text-mining (T-M) techniques—specifically keyword co-occurrence analysis and topic modelling—to the abstracts of the selected contributions. Rather than relying solely on predefined keywords supplied by authors, topic modeling allows themes to emerge directly from the data, providing a more objective lens through which to examine the literature.

Text-mining enables the identification of recurring patterns and latent thematic structures within the literature. Through co-occurrence analysis, we assess the extent to which keywords appear together in the same documents, with co-presence indicating joint analytical treatment of specific topics. Topic modeling further allows the discovery of underexplored or emerging themes, offering insights that go beyond similarity-based approaches adopted in previous works, such as Kryszak *et al.,* (2023). In this way, the joint bibliometric and text-mining approach sheds light on how productivity and misallocation are framed in applied agricultural economics and where important conceptual gaps remain. By addressing these questions, this paper provides a comprehensive mapping of the agricultural research landscape on TFP and misallocation. Given the important role of agriculture in driving sustainable development—particularly in developing economies—clarifying how productivity metrics and misallocation mechanisms are jointly addressed in the literature is essential for informing more coherent and effective policy interventions.

The paper proceeds as follows. Section 2 reviews TFP and Misallocation in the agricultural field and provides an overview of global productivity and misallocation patterns. Section 3 outlines the methodology. Sections 4 and 5 presents and discusses results. Section 6 concludes.

2. The background

This section provides a selective overview of the literature on TFP and Misallocation. The aim is not to be exhaustive, but rather to emphasize aspects that are central to our analysis. The last part of the background is focused on providing a look at the trends on agricultural productivity.

2.1 TFP: Definitions and measurement methodologies

In the economic literature, TFP is a central determinant of long-run growth, capturing how efficiently inputs such as labour and capital are transformed into output, including contributions from technological progress and innovation (for a review see Del Gatto *et al.,* 2011; Van Beveren, 2012). TFP has long been studied in contexts ranging from aggregate growth to specific sectors like agriculture.

The origins of the TFP concept. The concept's origins trace back to Tinbergen (1941), followed by Tintner (1944), Barton and Cooper (1948), and Kendrick (1956), who analysed input–output relationships. Abramovitz (1956) stressed that much growth cannot be explained solely by capital and labour accumulation. A decisive advance was marked by Robert Solow's contributions in the 1950s. In his pioneering articles (Solow, 1956; 1957), he introduced a neoclassical growth model in which TFP emerges as the "Solow residual", and so on that part of economic growth not explained by capital and labour accumulation. Using an aggregate production function and differential calculus, Solow showed that technological progress is an exogenous factor driving economic growth. However, the assumption of exogeneity of technological progress has been criticised. Endogenous growth theory, developed by Romer (1990) and Aghion and Howitt (1992), interprets technological progress as an endogenous phenomenon, driven by factors such as innovation, Research and Development (that is, R&D) and human capital accumulation. These studies broadened perspectives on TFP by integrating new elements into the production function. More recent studies, such as that of Kılınç (2014), have refined markup analysis using structural models of production, addressing the endogeneity of inputs and integrating the demand side. This distinction reflects the evolution of economic theory and the increasing focus on a more detailed analysis of production efficiency to include variables and dimensions beyond traditional tangible factors.

Methodological advances in TFP measurement. Since the 1990s, the measurement of TFP has benefited from important methodological advances (Van Beveren 2012). Early studies were based on traditional approaches, such as Ordinary Least Squares (OLS), but these suffered from problems of endogeneity and selection. The introduction of semiparametric methods, such as those of Olley and Pakes (OP, hereafter) (1996) and Levinsohn and Petrin (LP, henceforth) (2003), made it possible to address these limitations, improving the estimation of TFP at the micro level. Other significant contributions include the algorithm of Ackerberg *et al.* (2015), which further refined estimation techniques for panel data.

TFP in agriculture. Productivity growth in agriculture has been a particularly active field of study over the last fifty years. Agricultural TFP (or ATFP) is crucial to meet the growing demand for food and raw materials, especially in a context of demographic pressure. Pioneering studies, such as that of Hayami and Ruttan (1970), examined differences in agricultural productivity between countries, using Cobb-Douglas production technologies and cross-sectional data on about 40 nations. Subsequently, Kawagoe and Hayami (1983, 1985) and Lau and Yotopoulos (1989) explored the role of education, agricultural scale and research in influencing agricultural productivity. In the 1990s, Fulginiti and Perrin (1993, 1997, 1998) analysed agricultural productivity in developing countries, showing a decline in some cases, in contrast to convergence trends observed in other sectors. Blažková *et al.* (2020) highlighted an inverse U-shaped relationship between TFP and firms' age in post-communist economies. More recently, attention has focused on the impact of policies such as the European Common Agricultural Policy (CAP) and the Green Revolution on Agricultural TFP. The availability of new panel datasets and the development of advanced techniques have fostered an exponential growth of studies on this topic.

An emerging area is Total Green Factor Productivity (GTFP or AGTFP), which incorporates environmental considerations such as undesirable outputs (that is, emissions and waste). TFP remains a central concept for understanding economic growth and productivity across various sectors, including agriculture, where it is critical for addressing challenges related to food security and environmental sustainability.

2.2 Misallocation: Definitions and measurement methodologies

Misallocation**,** defined as the inefficient allocation of productive resources such as labour, capital, and land, has emerged as a critical concept in understanding economic inefficiencies, particularly in sectors such as agriculture. This inefficiency is assessed relative to an idealized scenario where markets operate without frictions, and factors of production flow freely to their most productive uses. These phenomena are often linked to informational asymmetries that affect productivity and resource allocation (Stiglitz, 1988).

The recent literature on misallocation and productivity has raised important questions regarding the underlying models used to estimate distortions. A key issue is whether the distortions measured in these studies are truly due to misallocation or whether they are the result of model misspecification. For example, Hsieh and Klenow (2009, hereafter HK) provide a foundational framework for measuring misallocation, where deviations in the marginal revenue products (MRPs) of inputs across firms indicate inefficiencies. They propose a measure called TFP revenue, which combines labour and capital MRPs to quantify distortions. Using this approach, they demonstrated that eliminating misallocation in developing economies like China and India could lead to significant gains in terms of productivity measures. This model assumes homogeneous production technologies, constant returns to scale, and uniform markups. However, Ruzic and Ho (2021) found that, based on this assumption, misallocation in the U.S. increased over time. When they extended the model to account for heterogeneous technologies, they observed a declining trend in misallocation, indicating that the assumptions in HK's framework may need refinement. As another example, Bun and de Winter (2022) show that allowing for differences in production technologies across firms, as well as allowing for non-unitary substitution between labour and capital, did not affect the measured distortions significantly. This suggests that model assumptions are critical when interpreting misallocation and productivity estimates. The HK framework has inspired extensions to measure the impacts of specific distortions. For instance, OP (1996) decomposes industry-level productivity into average firm productivity and the covariance between firm size and productivity, while Bartelsman *et al.* (2013) connect firm-level heterogeneity to broader productivity distributions. In agriculture, misallocation takes on a unique significance due to sector-specific market frictions in land, labour, credit, and insurance (Stiglitz 1988). These inefficiencies limit productivity and highlight the sector's vulnerability to institutional and structural barriers. Misallocation arises from both structural and market-specific distortions, including: *(i)* Market frictions such as inadequate credit access, rigid labour regulations, and imperfect information, which restrict efficient factor allocation; *(ii)* Idiosyncratic shocks, where differences in firm-level TFP can widen MRPs across firms, reflecting distortions; and *(iii)* Sectoral and regional rigidities, as seen in countries like Italy (Calligaris *et al.,* 2016), where credit constraints and regulatory inefficiencies exacerbate misallocation, contributing to economic slowdowns. Shocks influencing firm-level TFP may result in higher dispersion (greater misallocation) but do not uniformly affect aggregate TFP. For instance, productivity gains by highly efficient firms may increase both dispersion and average TFP, whereas inefficiencies among less productive firms may reduce both dispersion and average TFP.

An ongoing debate in the literature concerns whether measured distortions truly reflect misallocation or are artifacts of model misspecification. For example, HK's assumption of constant markups has been critiqued for oversimplifying firm heterogeneity. Ruzic and Ho (2021) demonstrate that accounting for varying technologies alters misallocation trends. Thus, robust methodologies that address potential biases are essential for accurately quantifying the role of misallocation in productivity gaps.

Misallocation plays a critical role in explaining productivity differences across sectors, regions, and countries. In sectors such as agriculture, where market frictions are particularly pronounced, mitigating misallocation can have significant implications for economic development and policy design.

2.3 Productivity and misallocation in Agriculture: a look at the data

Measuring agricultural productivity has long been central to policy and research debates, as accurate estimates are essential for effective interventions. Rising global populations, coupled with slowing yield growth, intensify the need for improved measurement and sustainability in agriculture (FAO 2017a). Agricultural productivity is also at the center of growth in countries like Africa, as stated in the Malabo Declaration of 2014 (African Union Commission, 2014) to jointly achieve targets of growth, nutrition and food security. Figure 1 provides an overview of the trends in productivity in the agricultural sectors for macro-regions in the world.

As shown in Figure 1 agricultural productivity has increased over the decades for all the regions. There is also a converging pattern for all the regions towards relatively higher levels of productivity starting from the end of the 20th century. This suggests that, alongside other factors, agriculture-led growth policies—notably in Africa—have contributed to these gains.

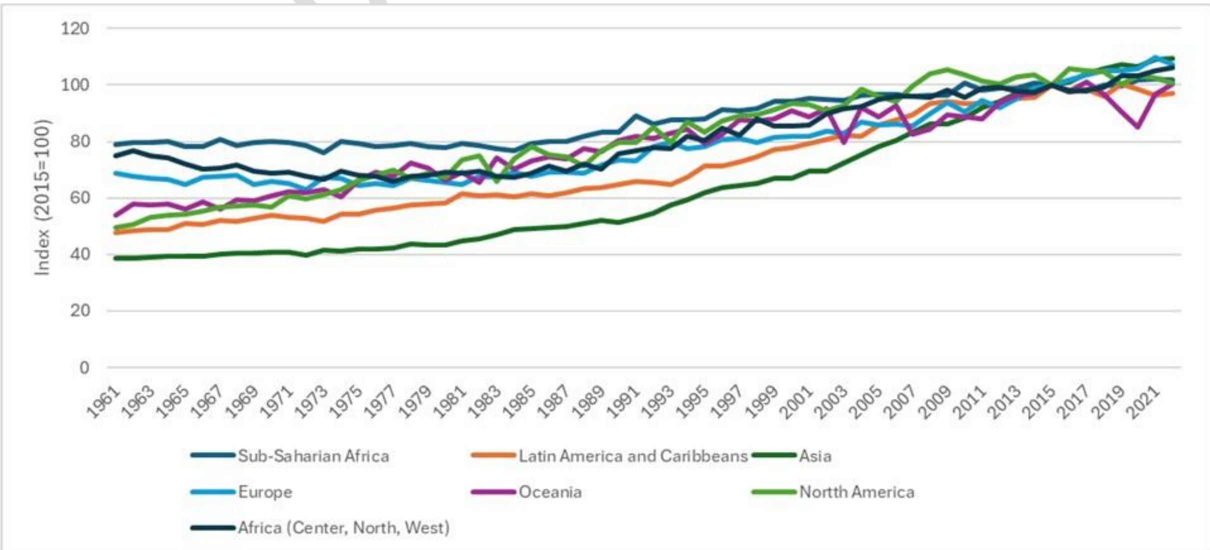

Figure 1. Trends of TFP in Agriculture for Macro-regions

Source: Authors' elaboration on data from the USDA

Figure 2 further illustrates global differences in agricultural productivity through a country-level map. Relatively higher levels of productivity are shown in some African countries and the Middle East. This highlights the importance of agriculture in the economic structure of those states. In some countries, agriculture represents a pivotal sector to promote sustainable development. Furthermore, more refined methods might be also able to spot inefficiency in allocation of production factors when dealing with agricultural outcomes.

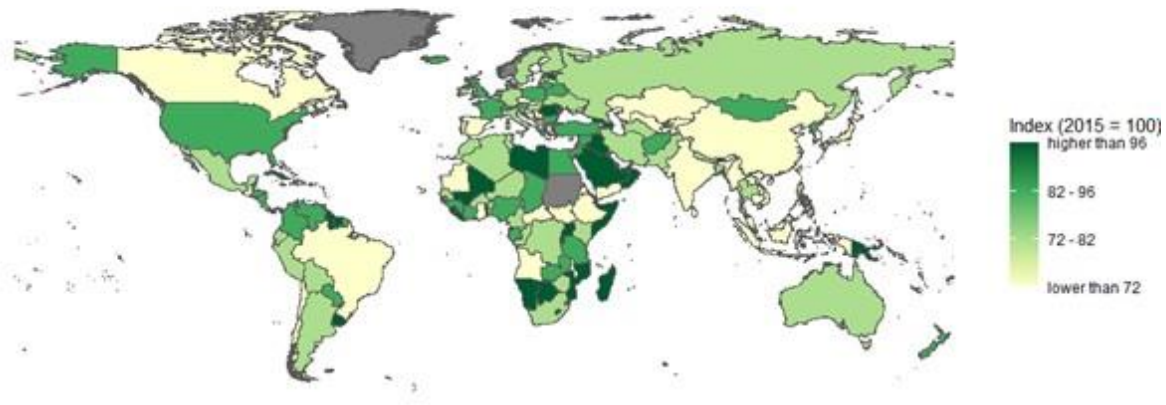

Figure 2. Map of Productivity in Agriculture: average 1961-2022

Source: Authors' elaboration on data from the USDA

With regards to Misallocation in the agricultural sector, Adamopoulos and Restuccia (2014), provided an estimate of output efficiency gains related to the reallocation of aggregate productivity factor for both developed and developing countries. The authors estimated that aggregated productivity factors can explain more than 60% of differences in agricultural productivity among developed economies. For developing economies there are farm-size distortions that create misallocation of resources from productive farms to non-productive ones. More recent country-based studies, for instance in Uganda, highlighted that output gains from reallocation of production factors would increase national agricultural output of 2.268% (Aragón *et al.,* 2024). In India, a more efficient land reallocation would lead to 65% of increase in productivity reaching more than 100% in some states (Bolhuis *et al.,* 2021). More than half of those lost gains are related to state-level rental barriers (Bolhuis *et al.,* 2021). In Malawi, a more efficient allocation of production between farmers would increase production between 1.7 and 2.8 times the current level (Chen *et al.,* 2023). Factors such as the legal framework for transactions, land security, credit constraints, direct or indirect restrictions on farm size (that is, taxes to large farms) are among the barriers to efficient allocation of land in developing countries (Adamopoulos and Restuccia, 2014). For instance, when allowing for reallocation across villages and land, output gains increase from 54% to 83% in China (Adamopoulos *et al.,* 2022).

3. Empirical analysis

Bibliometric analysis, as defined by Pritchard (1969), involves the use of statistical and mathematical methods to examine written communication processes and the development of scientific disciplines. Through quantitative techniques, bibliometric analyses aim to study academic knowledge within a specific field and map its evolution over time (Hall, 2011; Khaldi and Prado-Gascó, 2021). The goal is to identify significant contributions, both in terms of quantity and quality, made by key authors to the literature in a particular domain. This process helps to uncover potential future research directions and paradigm shifts within the field (Kumar *et al.,* 2020; Ho, 2021; Lindsey, 1980). Topic modeling has emerged as a vital statistical tool for analysing large collections of text. Rooted in probabilistic latent semantic analysis (pLSA) and extended through Latent Dirichlet Allocation (LDA) (Blei *et al.,* 2003), topic modeling identifies latent semantic structures within text corpora. However, it faces several challenges: quantitative metrics to select the optimal number of topics might not deliver meaningful results. In addition, topic modeling might fail to uncover specific subtopics when carrying out domain-specific studies.

This work will employ Structural Topic Model (STM or *stm*, henceforth), an advanced framework that incorporates document-level metadata to uncover the relationships between topics and associated covariates, such as time, location and demographic features. Unlike traditional methods such as Latent Dirichlet Allocation (LDA), which assumes uniform topic distributions across all documents, STM allows for the incorporation of document-level covariates, such as time, region, or industry, facilitating a more nuanced understanding of how topics evolve across different contexts. This feature is particularly important for analyzing economic topics like TFP and misallocation, which are likely to vary with external factors such as technological progress, policy changes, and economic conditions (Roberts *et al.*, 2016). Furthermore, STM's ability to separately model topic prevalence and content provides a richer, more interpretable representation of the data compared to LDA's joint modeling approach, enhancing the accuracy of the topic extraction process. In LDA, our topic prevalence and content came from Dirichlet distributions with hyperparameters we set in advance — sometimes referred to as a and b. With STM, our topic prevalence and content come from document metadata. On the other hand, with respect to Correlated Topic Models (CTM) offer insights into topic correlations, STM's integration of covariates provides a more flexible framework for capturing dynamic relationships between topics. Thus, STM is a better fit for our research question which tries to investigate the relationship among studies on TFP and Misallocation studies. Furthermore, when comparing model performances, STM appears to perform better with respect to competing algorithms (Roberts *et al*., 2016).

The semi-collapsed variational Expectation-Maximisation (EM) algorithm is used for efficient inference in STM, optimizing over both latent variables and parameters by partially marginalizing some variables while approximating others. The algorithm is divided into two steps. In the E- step the inference consists in optimizing the variational posterior for each document's topic proportions. In the M-step, the algorithm estimates the topical prevalence and content coefficient. For the non-conjugate component arising from the logistic distribution, a Laplace approximation is used (Roberts *et al.,* 2016). This approach builds on the Dirichlet-Multinomial regression and he Sparse Additive Generative Model, extending both frameworks by allowing for covariance among topics and the possibility to capture changes in topical content (Roberts *et al.,* 2016). The semi-collapsed variational EM algorithm balances computational efficiency and modeling flexibility, allowing to the possibility to include more covariates and dealing with large and complex datasets (Roberts *et al.,* 2014).

3.1 Data

Data have been retrieved from the *Scopus* one of the main academic and publicly available[1] databases for citation and abstract analysis. From Scopus we extracted data on Authors, Journal, Keywords and the Abstracts. We retrieved from Scopus three different datasets that were the basis for the bibliometric analysis and topic modelling. Our research encompasses TFP, misallocation and the intersection between the two. We thus designed separate research algorithms for the three topics. The algorithms were the following:

- **TFP:** [(farm*) OR ("agricultur*") AND ("total factor* product*") AND ("tfp*")] based on "TITLE-ABS-KEY". Number of contributions selected: **523**

[1] Meta-data of publications can be accessed free of charge upon subscription.

- **Misallocation:** [("farm*") OR ("agricultur*") AND ("misallocat*")] based on "TITLE-ABS-KEY". Number of contributions selected: **146**
- **TFP and Misallocation:** [("farm*") OR ("agricultur*") AND ("total factor* product*") OR ("tfp*") AND ("misallocat*")] based on "TITLE-ABS-KEY". Number of contributions selected: **19**

The use of the AND operator between "total factor* product*" and "tfp*" in the TFP dataset was intended to ensure a high degree of conceptual precision, capturing contributions that explicitly engage with TFP both in full and abbreviated form. By contrast, the use of the OR operator in the TFP and Misallocation dataset reflects a more inclusive strategy aimed at capturing the broadest possible intersection between the two literatures. Furthermore, the use of parentheses allowed us to group terms in a logical way considering our research question.

We conducted our search using titles, abstracts, and keywords. We also verified the dataset manually by sampling the first 100 records to ensure that the corpus reflects the intended focus.

Appendices 1 and 2 in the Supplementary material explains the selection process of the final set of records. As this study has been carried out with bibliographic data, no ethical concerns are raised in the process of collection of the data.

3.2 Methods

We first collected key bibliographic information, including the number of publications per year registered in Scopus and the top 15 journals in which these papers were published. Subsequently, we performed a text analysis on the *Abstract* assessing the co-occurrence of the keywords of interests for the sake of this work: "Misallocation", "TFP", "Agriculture" and "Productivity". First, we performed the co-occurrence network including all the terms for the three corpora with frequency higher than 50%. This provides us with the network of association of our core terms with other key terms in the corpora. As a second step we focused on those three words, computing the co-occurrence matrix. This matrix highlights the extent to which "Misallocation" and "Productivity" have been addressed together within the same studies. The final step of the analysis involved topic modelling with the *stm* package in R with default priors, 500 EM iterations, and convergence monitored through log-likelihood stabilization (Roberts *et al.* 2019). We extracted the main topics that emerged from the analysis of the single tokens. Appendix 2 of the supplementary material explains the process of creating the dataset for the text-mining.

4. Results

4.1 Bibliometric results: TFP corpus

A bibliometric analysis was conducted on the corpus comprising 523 research articles from 1989 to 2024. As can be seen from Fig. 3, there was a period of consolidation until 2006, then the trend increased until 2013-2014. From 2015 there was another increasing trend which has not stopped until the end of the period we consider.

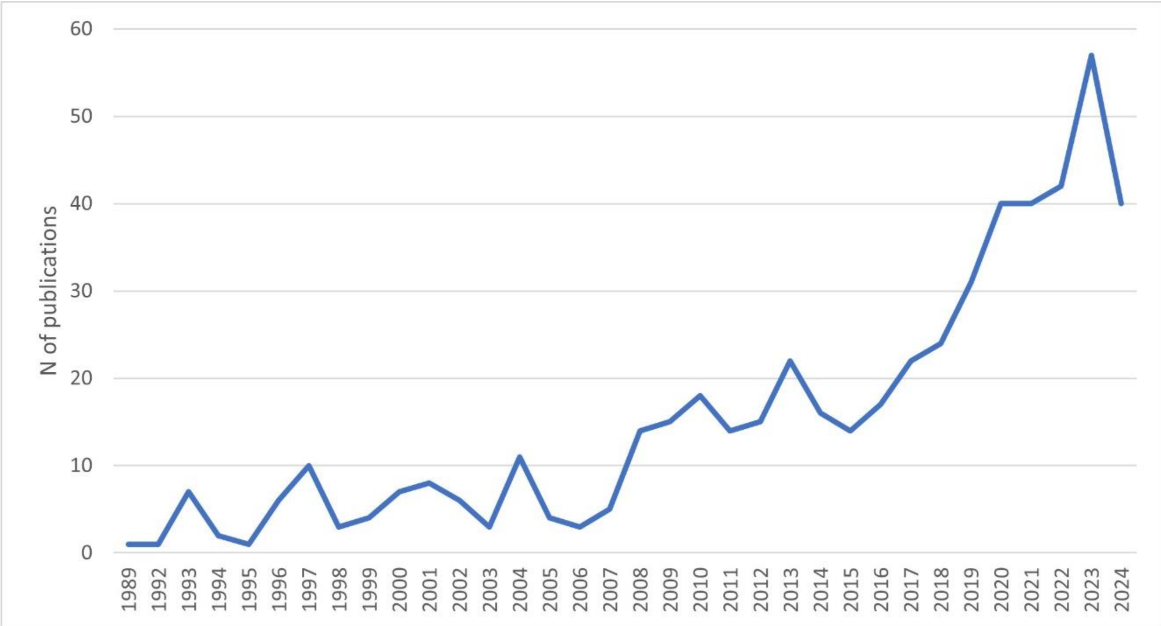

Figure 3. Evolution of the Publications over the years: TFP

Source: Authors' elaboration on data from Scopus

Table 1 reports the Top 15 journals in which this topic has been published. Overall, works on TFP have been published in 22 different journals. 4% of those papers are published in *Journal of Agricultural Economics*. Most of the journals within the top 15 deal with topics of agricultural economics, productivity and sustainability in general.

Table 1. Top 15 journals in which the papers have been published: TFP

Journal	N. Publications	Frequency
Journal of Agricultural Economics	22	4%
Agricultural Economics	19	4%
Agriculture (Switzerland)	17	3%
American Journal of Agricultural Economics	17	3%
Sustainability (Switzerland)	17	3%
Journal of Productivity Analysis	15	3%
Applied Economics	14	3%
Australian Journal of Agricultural and Resource Economics	11	2%
Food Policy	11	2%
Agricultural Economics (Czech Republic)	9	2%
Agrekon	8	2%
Agricultural Economics (United Kingdom)	7	1%
China Agricultural Economic Review	7	1%
New Medit	5	1%

Source: Authors' elaboration

4.2 T-M Results: TFP corpus

Figure 4 shows the co-occurrence network of the top 20 words with a frequency higher than 50%. The thicker the line, the higher is the co-occurrence of those terms in one document. At the center of the network, we find the words Productivity, Growth, Agricultural, and TFP.

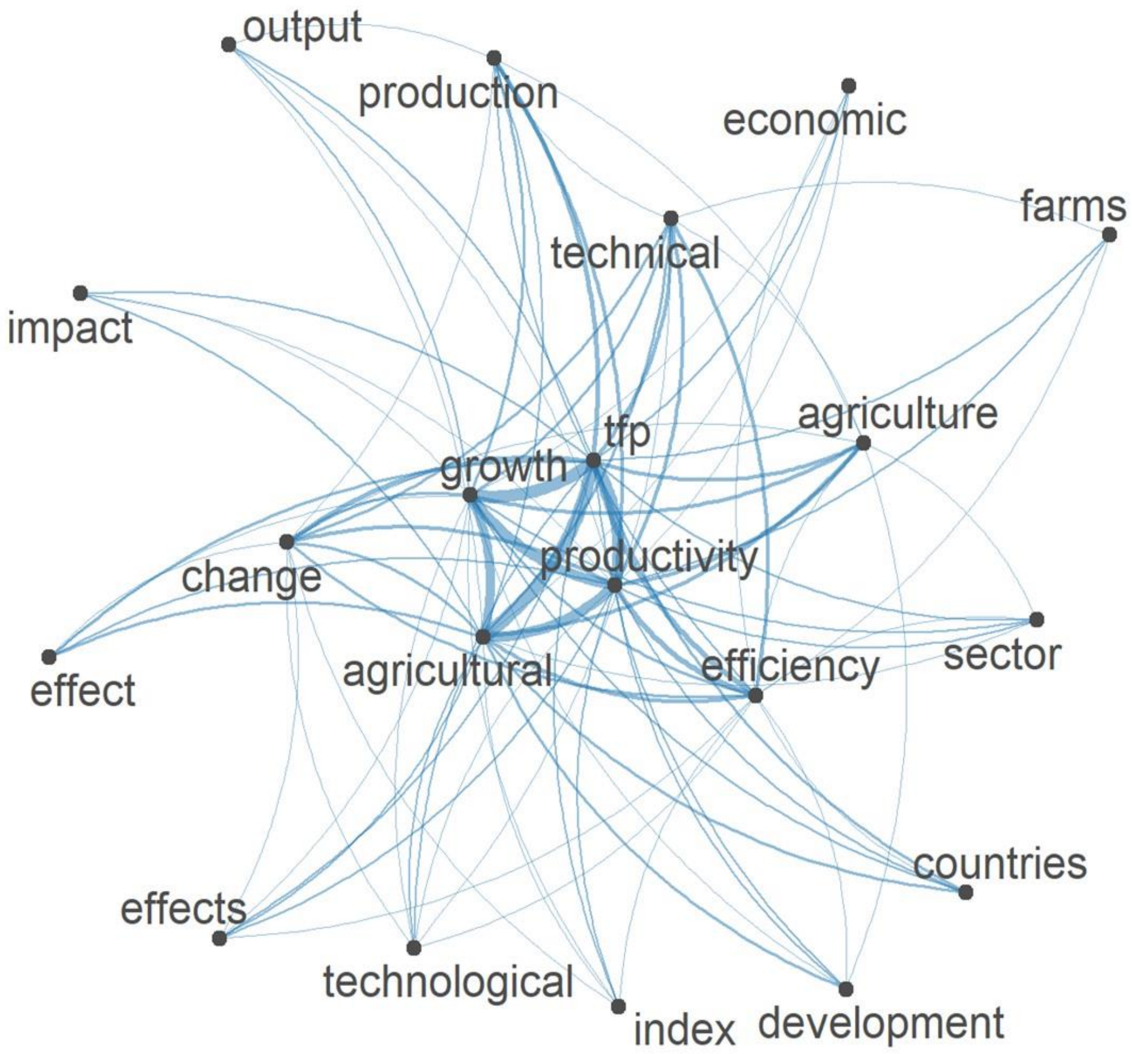

Figure 4. Network of Co-occurrences: TFP

Source: Authors' elaboration on data from Scopus

Table 2 reports the results of the *stm* algorithm applied to the abstracts of the selected contributions. The keywords extracted by the *stm* algorithm indicate that Topic 1 Green Urban Industrial Productivity is primarily related to Urban, Export, and G20. Relevant keywords in Topic 2 Technical Measurement of Productivity are Mix, Component, Data Envelopment Analysis (DEA), Malmquist. For Topic 3 EU Farms and Productivity, Milk, EU, and Farms whereas in Topic 4 Technological Development we find India, Research and Development (R&D), Convergence, and Aggregate.

Table 2. Topics resulted from the STM algorithm: TFP

Green Urban Industrial Productivity	Technical Measurement of Productivity	EU Farms and Productivity	Technological Development	Climate-related Productivity
urban	mix	milk	India	climate
export	components	EU	Indian	water
rural	technical	farms	R&D	temperature
g20	P.A.	size		cultivated
promoting	malmquist	payments	public	rice
carbon	distance	old	growth	variability
industrial	scale	farm	rates	grain
green	efficiency	dairy	cent	Japan
industries	envelopment	firms	convergence	fertilizer
enterprises	DEA	maize	aggregate	security

Source: Authors' elaboration

Notes:

P.A.: Precision Agriculture

g20: Group 20

DEA: Data Evelopment Analysis

R&D: Research and Development

EU: European Union

Finally, Topic 5 Climate-related Productivity focuses on Water, Temperature and Variability. Once the topics were defined, we analysed their prevalence over time across the various contributions (Figure 5). Topics 2 and 4 show a decreasing trend in their proportion from 1989 to 2024. On the other hand, Topics 1-3-5 show an opposite trend from a negative proportion to a positive one in recent years.

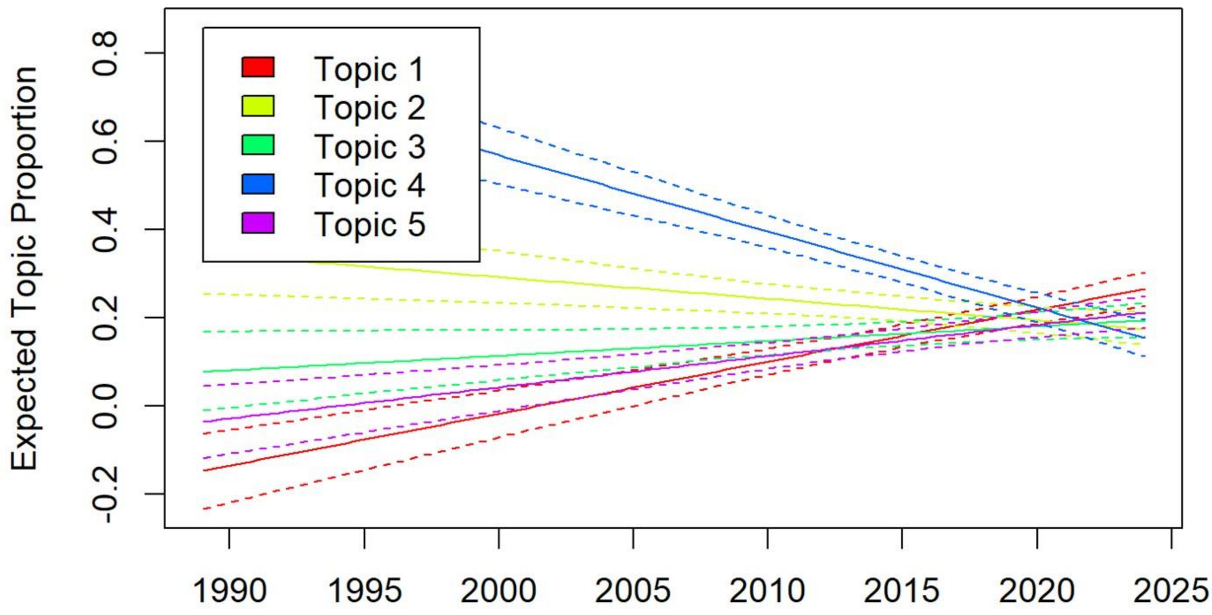

Figure 5. Prevalence of Topics over the years: TFP

Source: Authors' elaboration on data from Scopus

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360 ### 4.3 Bibliometric results: Misallocation corpus

361 A bibliometric analysis was conducted on the corpus, which includes research articles published 362 between 1968 and 2024. As illustrated in Figure 6, studies on misallocation in agriculture were 363 relatively rare until 2021. However, from 2022 onward, there has been a marked increase in the 364 number of articles addressing this topic.

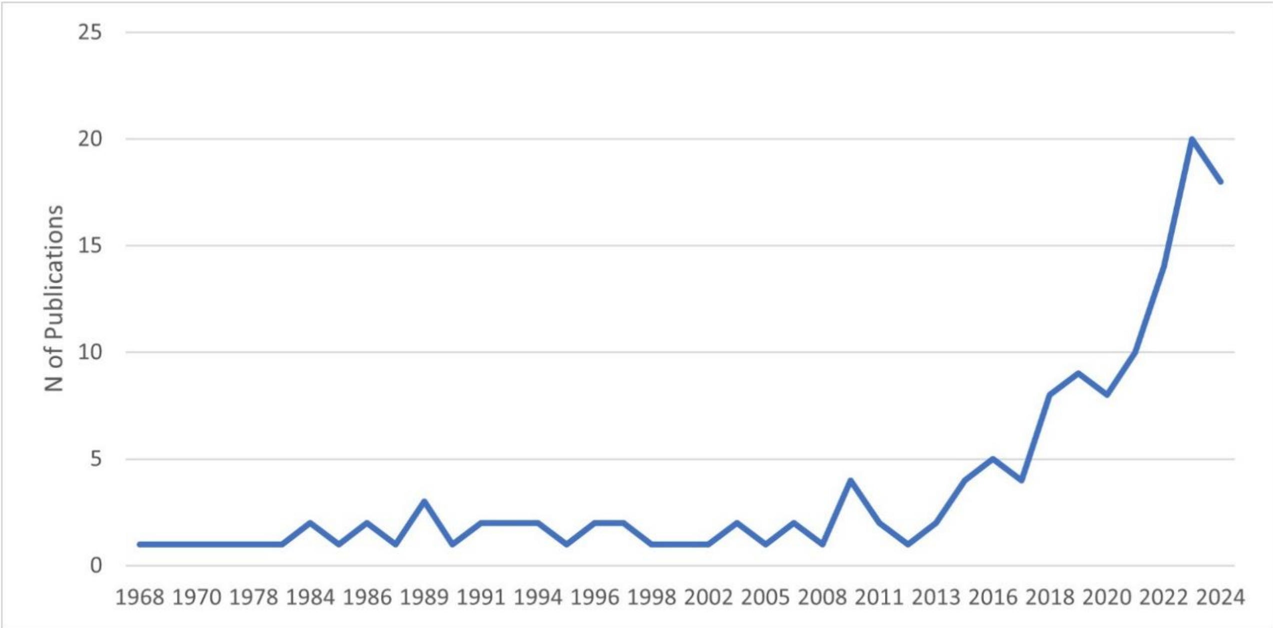

Figure 6. Evolution of publications over the years: Misallocation

Source: Authors' elaboration on data from Scopus

Table 3 shows the top 15 journals in which contributions on Misallocation in Agriculture have been published. The research algorithm extracted 113 journals in which this topic has been published. The higher share is accounted to the *Journal of Development Economics* with 7% of the sample (10 papers). The top 3 journals deal with Development Economics and Agricultural Economics.

Table 3. Top 15 journals in which the papers have been published: Misallocation

Journal	N. Publications	Frequency
Journal of Development Economics	10	7%
Food Policy	6	4%
Agriculture (Switzerland)	4	3%
American Journal of Agricultural Economics	4	3%
Applied Economics	4	3%
Canadian Journal of Agricultural Economics/Revue canadienne d'agroeconomie	4	3%
Sustainability (Switzerland)	4	3%
American Economic Journal: Macroeconomics	3	2%
Economic Modelling	3	2%
International Journal of Environmental Research and Public Health	3	2%
Journal of Cleaner Production	3	2%
World Development	3	2%
Agricultural Economics (United Kingdom)	2	1%
Asian Development Review	2	1%

Source: Authors' elaboration

4.4 T-M Results: Misallocation corpus

Figure 7 shows the co-occurrence network of the 20 most frequent words with frequency higher than 80%. Beyond Misallocation, the terms most central in the word network are *Agricultural* and *Land*. A focused analysis was also conducted on the co-occurrence of key terms closely related to our research questions. More specific analyses on the co-occurrences can be found in Appendix 3 in the Supplementary material.

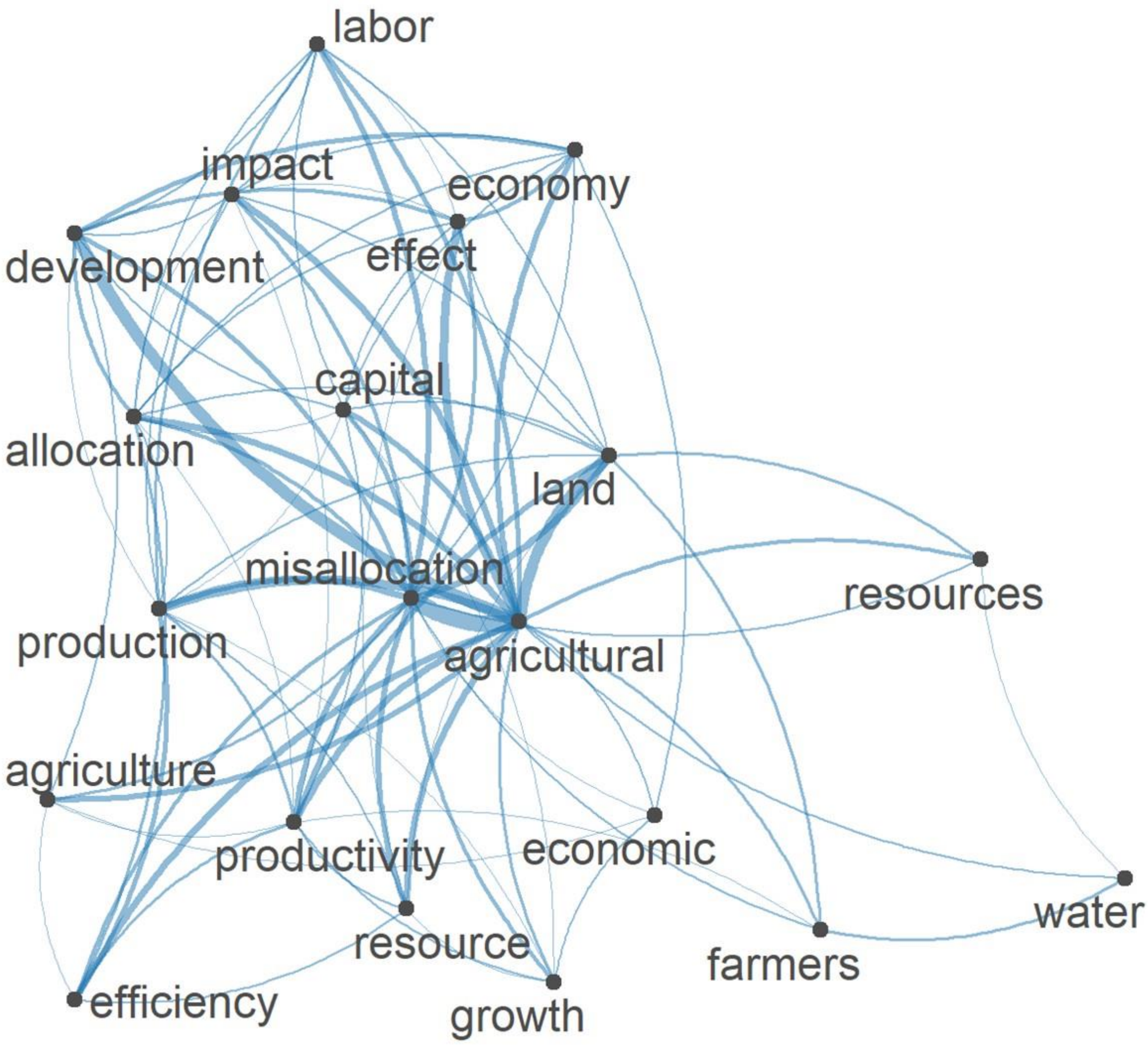

Figure 7. Network of Co-occurrences: Misallocation

Source: Authors' elaboration on data from Scopus

Table 4 shows the results of the *stm* algorithm for the Abstract of contributions on Misallocation in Agriculture. Topic 1 Green Misallocation includes terms related to environment, particularly Emission, Certification and Intensity. Topic 2 Impact of deforestation features terms related to Farms, Deforestation and Inefficiency. Topic 3 Farmers and Energy is associated with Wind, Utilities and Policies. Topic 4 contains terms related to Adaptation, Disease, Aid and Unemployment. Topic 5 Abandonment of farms centers around abandonment, employment and off-farm.

Table 4. Topics resulted from the STM algorithm: Misallocation

Green Misallocation	Impact of deforestation	Farmers and Energy	Climate and Health Adaptation	Abandonment of farms
mismatch	ir	wind	adaptation	off-farm
titling	fluxes	farmer	disease	abandonment
green	loans	organisations	cycle	farmland
agricultural	long-term	states	aid	employment
security	profitability	service	livestock	agriculture-related
aces	tenure	utilities	poverty	cropland
certification	inefficiency	wlf	food	rent
emission	farms	sectors	dts	transfers
futures	deforestation	policies	pandemic	cap
intensity	fictitious	sectoral	unemployment	significantly

Source: Authors' elaboration

Notes:

wlf: Water Land Food

ir: Impulse-Response

dts: Digital Traceability Systems

Figure 8 illustrates the prevalence of these five topics over time, based on publication year. Topic 1 has shown a steady increase since 1970, whereas Topic 2 has experienced a marked decline. The proportion of Topic 3 has remained relatively stable.

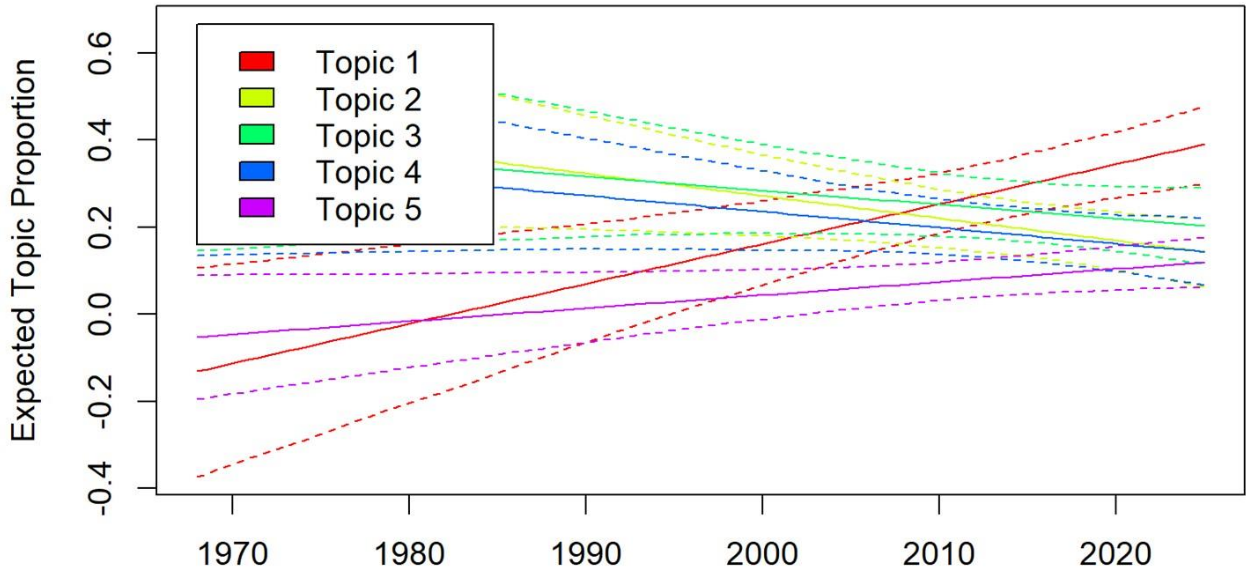

Figure 8. Prevalence of the Topics over the years: Misallocation

Source: Authors' elaboration on data from Scopus

5.1 Bibliometric results: TFP and Misallocation corpus

To trace the evolution of the topic and identify the main research streams, we focused on the intersection of the two terms in our analysis. Between 1995 and 2021, only one or two articles appeared annually (Figure 9). The highest number of publications was 2023, with 8 articles. As of December 2024, two articles have been published on the topics of TFP and Misallocation.

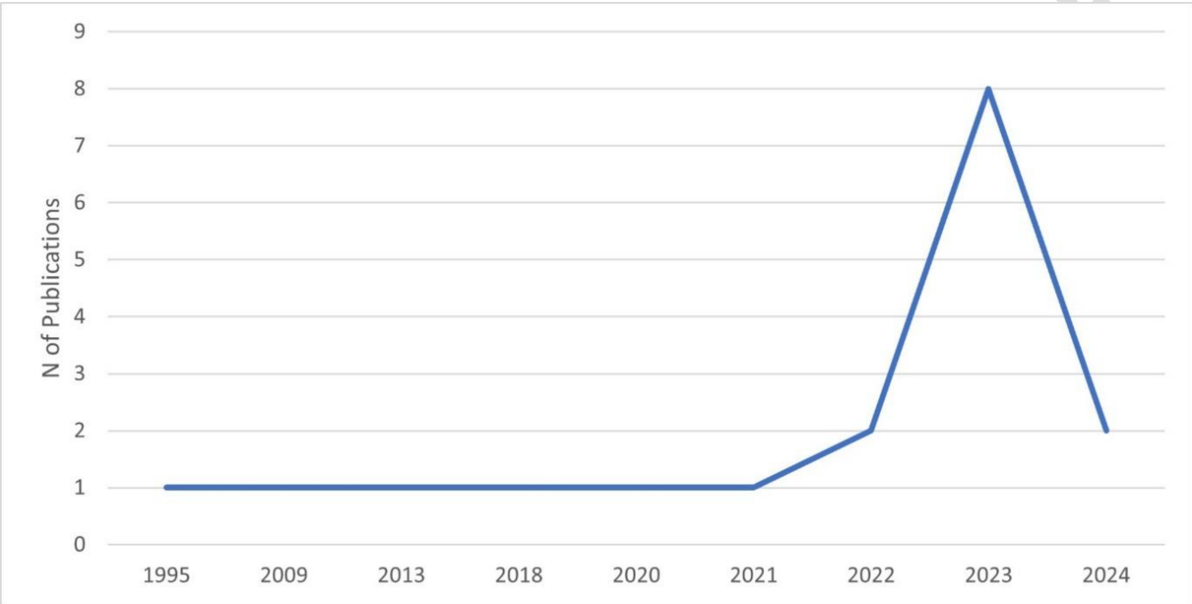

Figure 9. Evolution of the publications over the years: TFP and Misallocation
Source: Authors' elaboration on data from Scopus

Table 5 reports the distribution of the publications in the Top 15 journals. The 19 contributions selected by the algorithm were published in 16 different journals. In this case, the Top 5 include a mix of broader-scope journals—some focused on economic modelling, food policy, and sustainability—and three journals specifically dedicated to agricultural economics.

Table 5. Top 15 journals in which the papers have been published: TFP and Misallocation

Journal	N. Publications	Frequency
Economic Modelling	2	11%
Food Policy	2	11%
Sustainability (Switzerland)	2	11%
Agriculture (Switzerland)	1	5%
American Economic Journal: Macroeconomics	1	5%
Applied Economics	1	5%
Australian Journal of Agricultural and Resource Economics	1	5%
China and World Economy	1	5%
Economics of Transition and Institutional Change	1	5%
International Journal of Environmental Research and Public Health	1	5%
Journal of Cleaner Production	1	5%
Journal of Development Economics	1	5%
Journal of Environmental Planning and Management	1	5%
Review of Economic Dynamics	1	5%
Review of Economic Studies	1	5%
Science of the Total Environment	1	5%

Source: Authors' elaboration

5.2 T-M Results: TFP and Misallocation corpus

Figure 10 illustrates the co-occurrence network of the top 20 most frequent terms (with a frequency above 80%) across documents. Besides, Productivity, Agricultural, and Production, central terms in the network include Green, Resource, and Impact.

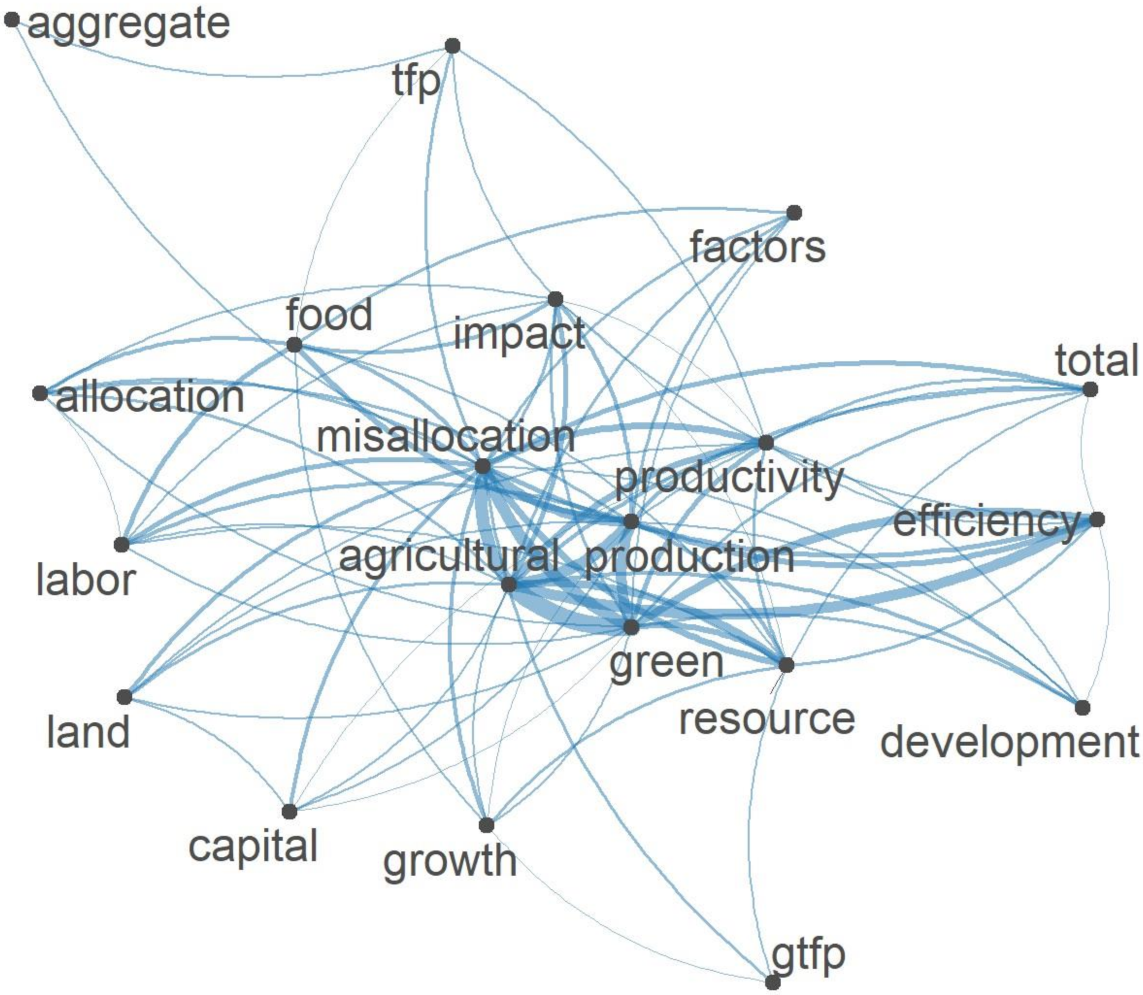

Figure 10. Network of Co-occurrences: TFP and Misallocation

Source: Authors' elaboration on data from Scopus

Table 6 displays the main topics identified by the *stm* algorithm. Keywords of Topic 1 Environmental and Green Productivity are Green, Sustainable, Efficiency. Topic 2 Factor Distortions and Productivity Variation: Variations, Distortions, Non- state whereas in Topic 3 Firm Performance and Structural Change there are CAP, Subsidies, Reduction. Topic 4 Farm Structure and Policy Context: Debt, Firm, Farm. Topic 5 Food Security and Global Shocks: Food, Pandemic, Security, Resource.

Table 6. Topics resulted from the STM algorithm: TFP and Misallocation dataset

Topics 1	Topics 2	Topics 3	Topics 4	Topics 5
Environmental and Green Productivity	**Factor Distortions and Productivity Variation**	**Firm Performance and Structural Change**	**Farm Structure and Policy Context**	**Food Security and Global Shocks**
green	variation	agriculture-related	debt	food
sustainable	within	enterprises	firm	pandemic
aggtfp	provinces	reform	governments	growth
cycle	distortions	cap	small	gtfp
life	capital	tfp	Australian	covid-19
efficiency	sectors	leasing	farms	security
agricultural	accounting	profitability	farm	year
production	losses	subsidies	local	resource
environmental–economic	non-state	reduction	markets	mainly
grain	economy	significant	farm-level	China

Source: Authors' elaboration

Note:

aggtfp: Aggregate Total Factor Productivity

gtfp: Green Total Factor Productivity

tfp: Total Factor Productivity

cap: Common Agricultural Policy

Figure 11 shows the prevalence of the topics resulted from the T-M algorithm over time. Overall, the proportion of these topics has declined. However, after 2020, the presence of Topic 1 began to increase, along with Topic 5. The other topics seem to have decreased from the first years of publications.

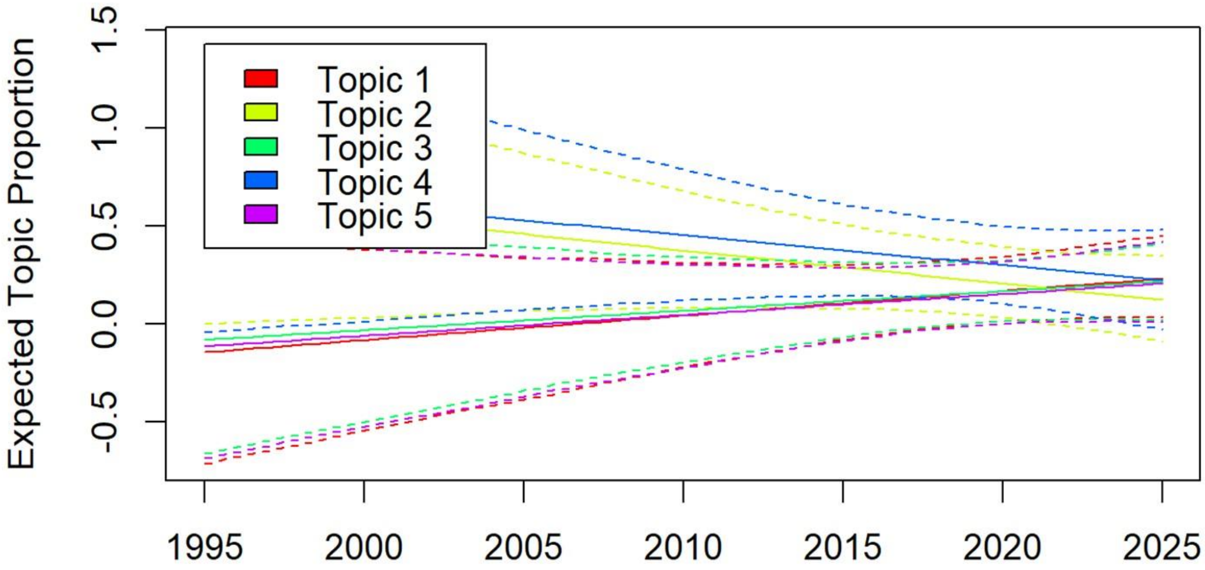

Figure 11. Topic prevalence over the years: TFP and Misallocation
Source: Authors' elaboration on data from Scopus

Tables 7 and 8 in Appendix 3 of the Supplementary material show the co-occurrence matrix for the terms "Misallocation", "Agriculture" and "TFP".

6. Findings and discussion of content analysis

The analysis has been carried out on three separate corpora (see Appendix 1, 135 records on Misallocation, 19 on Misallocation and TFP, 473 on TFP) The observed publication patterns point to distinct yet partially overlapping trajectories in research on TFP, Misallocation, and their intersection (that is, TFP and Misallocation) within agricultural and economic studies. TFP-related publications are more frequently associated with journals in agricultural economics and sustainability, whereas Misallocation-related contributions appear more often in development and agricultural economics outlets (Table 3). Topic modeling highlights recurring associations across the three corpora, particularly around land use, environmental sustainability, and resource efficiency.

The co-occurrence network (Figure 7) shows that terms such as *Production*, *Land*, *Efficiency*, and *Resource* feature prominently, indicating the centrality of resource use in discussions of agricultural productivity. At the same time, differences in thematic orientation emerge across datasets. TFP-related studies are more frequently associated with environmental and climate-related terms, whereas

Misallocation-related studies tend to be discussed alongside institutional and structural dimensions of inefficiency.

Publications combining both themes appear in outlets that balance development economics and agricultural productivity, often addressing issues of economic growth and structural transformation. However, content analysis shows a limited co-occurrence of TFP and Misallocation within the same documents, indicating that, while Misallocation studies represent a subset of the broader TFP literature, the two topics have largely evolved in parallel. Within the TFP corpus, the analysis frequently associates productivity with environmental and sector-specific dimensions. For instance, some topics are characterized by terms related to livestock and crop productivity (Topic 3 EU Farms and Productivity: Milk, Dairy, Maize) (Sarma *et al.,* 2024; Temoso *et al.,* 2023) while others link productivity to climatic and ecological conditions (Topic 5 Climate-related Productivity: Climate, Temperatures) (Das, 2023; Míša and Křen, 2001). Related contributions in the applied agricultural economics literature have also explored the link between productivity performance and environmental outcomes at the farm level, for instance through the analysis of carbon footprints and environmental indicators (Baldoni *et al.,* 2017). These associations point to a stronger emphasis on microeconomic and sectoral aspects of agricultural productivity. By contrast, Misallocation corpus is more often associated with institutional and structural inefficiencies (Brandt *et al.,* 2013; Du *et al.,* 2019; Song *et al.,* 2024), including income distortion, farmland abandonment, and institutional inefficiencies (Topic 5 Abandonment of farms: Abandonment, Distortion, Transfer). These studies frequently examine how structural reforms and institutional contexts influence resource allocation and productivity disparities. Although integrative studies linking TFP and misallocation remain limited, they provide valuable insights into how resource misallocation can undermine productivity growth. Emerging themes include the role of misallocation in structural transformation and responses to global shocks, such as the COVID-19 pandemic's effects on agricultural systems (Topic 3 Food Security and Global Shocks: Pandemic, Food, Growth) (Sun *et al.,* 2023). Shared interests in efficiency, sustainability, and resource management suggest a strong potential for interdisciplinary integration (Lei *et al.,* 2023). Keywords like Land and Production underline the commonality in addressing agricultural productivity and economic efficiency. Nevertheless, the relatively small number of publications explicitly linking TFP and Misallocation suggests that integrative approaches remain underexplored and warrant further investigation.

7. Conclusions and future research agenda

From the end of the 20th century, productivity in agriculture has increased in every region of the world, converging to higher levels in more recent years (Figure 1). Among other factors, this pattern highlights the role of policies aimed at promoting agriculture-led growth, especially in developing nations. Thus, more accurate estimation of productivity may support more informed policymaking and more effective policy design. In this framework, this paper has surveyed the literature on two core topics in agricultural economics: *TFP* and *misallocation*. The objective was to uncover hidden topics, divergences and common patterns in these research domains. By systematically examining the existing body of literature, we have identified key components and trends in TFP and misallocation studies, as well as documented how past and current research themes have evolved over time. Across the three datasets considered—TFP, Misallocation, and their intersection (that is, TFP and Misallocation)—the analysis highlights both commonalities and divergences in thematic focus, publication outlets, and temporal dynamics. While the two fields exhibit some shared trends in their evolution, they also display distinct patterns in terms of disciplinary orientation and research emphasis.

Research on TFP in agriculture has a long history, with a notable acceleration during the late 1990s and early 2000s (RQ1). This phase coincided with major advances in computing capacity and data availability, which enabled more sophisticated productivity analyses. In addition, growing global attention to food security and the role of technological innovations, such as genetically modified crops and precision farming techniques, features prominently in this strand of the literature. Policies aimed at liberalizing agricultural markets also appear frequently in studies examining productivity trends during this period (FAO, 2017a; 2017b; OECD, 2019). In contrast, misallocation literature expanded rapidly after 2015 (RQ1). This later surge is frequently associated with improved access to micro-level data and the influence of seminal contributions by Restuccia and Rogerson (2008) and Hsieh and Klenow (2009), which highlighted misallocation as a key factor in explaining productivity differences across countries and sectors. Some publication outlets, such as Economic Modelling, Applied Economics, and Food Policy, are common to both corpora (RQ3). However, TFP studies are more broadly distributed across journals in environmental economics, agricultural sciences, and climate-related fields, whereas misallocation research is more concentrated in development and applied economics journals. Studies addressing both TFP and misallocation, tend to appear in outlets at the intersection of these domains, suggesting potential synergies even though explicit integration remains limited (RQ3).

Using a text-driven topic modeling approach, the analysis identifies several common and distinct themes across the corpora. Both TFP and misallocation studies are frequently associated with land use and resource allocation, reflecting a shared concern with agricultural efficiency (RQ1). TFP-related research is often linked to climate change and technological innovation, whereas misallocation studies tend to focus on institutional inefficiencies and market distortions, offering a more structural perspective on barriers to productivity growth. The COVID-19 pandemic emerges as a cross-cutting theme in both strands, with studies examining how systemic inefficiencies and external shocks affect agricultural productivity and resource allocation (Chaoran *et al.,* 2023). These findings indicate overlapping interests in land use, efficiency, and environmental impacts, alongside clear thematic differentiation between the two literatures (RQ2).

The identification of these themes suggest scope for integrating misallocation perspectives into broader TFP analyses, particularly in areas related to resource optimization and environmental sustainability (RQ3). While productivity metrics provide insights into aggregate performance, misallocation analysis offers a more granular view of inefficiencies in resource use. Bridging these approaches may help generate new perspectives on agricultural systems, especially in the context of climate change, food security, and sustainable resource management.

Future research could build on these findings by: *(i) linking micro-level heterogeneity to aggregate outcomes,* examining how as farm size, tenure, location, and asset endowments shape the relationship between productivity and misallocation; *(ii) integration institutional and political economy dimensions* into empirical analyses, with attention to governance and policy frameworks; *(iii) developing dynamic models* to study how misallocation evolves during structural transformations such as mechanization, urbanization, and demographic change; (iv) *investigating the role of technological change and green productivity*, including digital tools, biotechnology, and climate resilience strategies; *(v) bridging bibliometric insights and policy-relevant quantitative models*, such as CGE models or structural models, to assess policy impacts; *(vi) expanding data sources and journal scope,* incorporating grey literature, policy reports, and non-Scopus indexed journals to ensure a more comprehensive understanding of the field. The analysis of this work is limited to the bibliography retrieved from the Scopus database, but it could be replicated merging other sources (such as Web of Science) to enhance comprehensiveness. Another limitation concerns the nature of the analytical strategy. Topic modelling delivers fully data-driven results, and its computation is based on both a qualitative and quantitative assessment. Given the exploratory nature of our analysis, future research should enhance robustness of these findings through comparing results with other well-established approaches in the literature. A further limitation relates to the retention of lexical and morphological variants (e.g., singular/plural forms, adjectival variants, and related productivity terms). Although we explain the motivation behind not applying lemmatization in the preprocessing stage, this choice may still affect topic coherence and semantic consolidation. In particular, retaining such variants may introduce a degree of fragmentation in the term–document representation, potentially influencing topic stability and interpretability.

Given the exploratory and descriptive nature of the study, this limitation does not invalidate the results; however, it represents a methodological trade-off that should be acknowledged. Applying lemmatization or alternative normalization procedures could lead to different topic configurations and potentially more consolidated semantic structures. Future works should therefore pay greater attention to text preprocessing strategies in order to further improve the robustness of bibliometric and topic-modeling analyses. Despite their conceptual complementarity, TFP and misallocation are still frequently examined in isolation. Strengthening connections between these research areas may enhance the policy relevance of future studies and support more comprehensive strategies for the sustainable development of global agricultural systems.

Endnotes

1. BRICS is an interstate association comprised of the Federative Republic of Brazil, the Russian Federation, the Republic of India, the People's Republic of China, and the Republic of South Africa. On January 2024, Egypt, Iran, the United Arab Emirates, Saudi Arabia, and Ethiopia joined BRICS.
2. The analysis has been carried out using R Studio software R version 4.4.0 (2024-04-24 ucrt) -- "Puppy Cup".

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