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The Innovation Lifecycle of AI-Driven Agriculture: Causal Dynamics in University-Industry-Research Collaboration

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Abstract

Considering the current prediction from the Food and Agriculture Organization, food production needs an increase of over 70 percent by 2050, agriculture sector requires a boost that is also obtained by integrating novelty technologies and methods of artificial intelligence (AI) field. The current research explores the innovation lifecycle of AI-driven agriculture field through a causal inference analysis within University-Industry-Research ecosystem, extracting four key pillars: scientific research papers, research projects, patents and startups. Using an extensive time-series database, Granger causality analysis is applied for uncovering prospective causal relationships that guide the interest in innovation within AI-driven agriculture. Our results indicate an overall increase in AI applied agriculture domain within all four pillars starting from the 2010 year for start-ups pillar and impacting in Granger point of view all the way to 2020 for patents perspective. The findings suggest a potential sequential innovation pathway where progress in one pillar propels advancements in the next, according this flow: startups, projects, scientific research and patents. The implications of this study are significant, providing insights that could guide strategic planning and investment in AI applications in agriculture. By understanding the potential causality and sequentially in innovation, policymakers, investors, and entrepreneurs can better align their efforts with the most impactful areas. This research not only advances in academic knowledge but also provides practical insights that influence real-world applications and practices in agricultural technology.

Keywords: innovation lifecycle; artificial intelligence; agriculture; granger causality; University-Industry-Research collaboration

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1. Introduction

The collaboration between universities and industry manifests in multiple directions, including research services, training in education and curiosity-led research, as [1] investigated. This collaboration is also present in the intersection of two major domains of worldwide interest in innovation and evolution, namely artificial intelligence and agriculture. As agriculture is the key component of economy, it also plays an important role in Sustainable Development Goals defined in [2] like: Zero Hunger, Sustainable Consumption and production, Life and Land, Clean Water and Sanitation objectives. Handling a wide variety of challenges such as the increase of human beings, the new trends in competitive markets, the climate change and the sustainability, traditional farming needed a twist in the perspective, leading to the smart farming context, thus transforming the traditional practices, in order to increase the productivity, quality, nutrition and security of crops, while reducing the impact on the environment, [3].

Innovation is seen at the intersection of industries, universities and research, as [4] also focused on the impact of innovation efficiency when it comes to industry-university-research cooperation. The study was done upon China between 2009-2015, having as main objective to determine the cause of the GDP decrease in 2010. They concluded with the affirmation that there is not a deep enough degree of cooperation between the industries and universities, mainly because of the fact that university research does not match the requirements of industries. The research also pointed that the government funding for innovation doesn't positively affect the innovation efficiency.

The core innovation subjects, also seen from [5] perspective, is given by enterprises, universities and scientific research institutions, playing different roles in innovation activities. The research [5] debate the fact that it is narrow to focus only on the innovation within the enterprises from the production level and overlook the basic of innovation. Also [6,7] pointed out that it is crucial to examine how each subject's impact, relationship and contribution affect the gap between the supply and demand side of production, education and research resources. But when it comes to food and agriculture production industry, [8,9] formed the conclusions that it is more seen as a lagging sector, not being the focal point of innovation policies. Similar vision is also highlighted in [10], pointing that innovative technologies developed in different field of science may bring interesting contributions to the sector of agriculture. The agriculture industry is seen in the traditional literature as a limited field of innovation generating forces, the innovation more likely to appear as a result from the knowledge transfer of other sectors, [11,12].

Current gaps in research and policy call for the need for an in-depth study of the particular domain of agriculture impacted by artificial intelligence technologies, [13]. This study investigates even deeper the sub-domains of agriculture along with AI technologies, focusing on innovation at the intersection of university, industry and research perspectives. The innovation impact is computed as a result of inference causality on time-series data collected from several databases that stores outputs of the four analyzed pillars: written academic work in scientific journals, projects as an intersection between universities along with companies, patents pilled by companies or as individuals within universities and also established startups. Another perspective was present in [14] a meta-analytical study of literature written in the field of agriculture, pointing the exponential increasement of interest in the field after 2011. The scope of the research was formed around the innovation purpose and type of innovation in agriculture. Nowadays artificial intelligence is similar to the term of innovation, as the study in [15] also emphasizes, multiple studies being conducted on this major correlation between artificial intelligence and its implementation in particular industries. Even though there is a massive interest in AI in general along with its impact in multiple industries, the literature lacks research focused on this proposed intersection of AI and agriculture along with the implications given by the innovation perspective transposed in the four major pillars. The scope of this study is not to determine the impact of AI in agriculture, but to characterize the evolution of a particular segment of agriculture, that in which AI was integrated.

1.1. Objective and Research Questions

In this paper, we incorporate the overall concept of innovation cycle seen from the university-industry-research collaboration perspective, leading to a framework used for integrating time-series evaluation of the four initial pillars derived from the innovation cycle. This perspective is demonstrated upon narrowing the industry as a whole and focusing on the direction of innovation within agriculture domain impacted by artificial intelligence technologies. For reaching the major objective of the paper, we have formulated a list of research questions that lead to the desired output.

The research questions presented in Table 1 derive from the overall causality network applied starting from the definition of innovation lifecycle of AI in agriculture field. Starting from the narrowing method solved by RQ1, the next research questions focuses of the time causality impact along the main actors of this scenario.

Table 1. Research Questions of innovation lifecycle of AI in agriculture.

RQ number	RQ description
RQ_1	What is the set of keywords defining the intersection between the domains of AI and Agriculture in research academic writing?

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RQ_2	Is there any sequential causality in the innovation lifecycle of AI in agriculture?
RQ_3	Does a shift in academic research activity drive subsequent changes in the number of projects developed?
RQ_4	Does the increase of research projects causing an increase in patents filing?
RQ_5	Does the increase of patent filing cause an increase in startup formation?
RQ_6	Is the overall evolution of the research domain similar to the evolution of the six particular sub-directions defined by the proposed classification?

The research follows a structured approach to address the previously formulated research questions. The initial step involves defining a theoretical model of the innovation lifecycle, drawing from both scientific literature and business practices. As the research horizon is defined by the two main areas, namely agriculture and artificial intelligence, clear borders had to be set for both to be able to reduce any biases to a minimum and ensure comparable datasets across pillars. As a result, the scope has been narrowed down to the most significant keywords. Multiple simulations are made and an objective function is desired to evaluate the relevance of the searching criteria. The research then progresses to refining the search query for optimal accuracy. Each key element will be incrementally added to test the results' relevance to the researched field. In the absence of a method that can include absolutely all the values to fully satisfy the applicability of AI in agriculture, a classification of the extracted data was considered based on the most comprehensive search query, which is, however, limited. Besides the general direction of AI-driven agriculture evaluated within the four pillars of innovation, a more detailed investigation is also taken into consideration by a more granulated classification on six sub-domains of agriculture where artificial intelligence is present. Using statistical methods, a comparison is made between the overall trend of AI in agriculture and the trend of AI for each of the six sub-domains proposed. Therefore, the next step involves comparing the means of the resulting series to determine if there are significant differences. If no significant differences are found, it indicates that the choice of search query does not substantially affect the temporal evolution of the analyzed dimensions, making it unnecessary to refine the query for greater accuracy.

In the continuation of the study, we focused on defining the data structure by selecting the dimensions necessary for creating time series, particularly the temporal dimension and the measure under analysis. This resulted in a series of frequencies representing the number of articles, projects, patents and startups that were extracted from four databases using a searching method that describes the intersection of the AI and agriculture domains. The resulting time series, corresponding to each stage of the innovation lifecycle, were smoothed and min max normalized to mitigate the cyclic effects caused by external events, or, in the case of projects, the ending of one program and the starting of another, as well as to make the series comparable. The next step involved determining the knee points, from which each series experiences a sudden change, to gain an initial understanding of the order of processes in the innovation cycle and whether it aligns with the formulated hypotheses. The second derivative approach was used to identify the points of maximum curvature. The knee point is where the curve changes from a gradual to a steep slope, indicating exponential growth.

To explore the causal relationships among the different stages of the innovation, Granger causality analysis was employed. This method was used to determine whether one time series could predict another, indicating potential causal influences among the stages. The analysis was conducted for each pairwise combination of the four variables. For instance, we tested whether the number of articles Granger-causes the number of projects, and vice versa, to understand the directional influence between research publications and the initiation of new projects. Similarly, the relationship between patents and startups was examined to identify whether patent activity precedes the emergence of new startups, suggesting a causal link between intellectual property development and entrepreneurial ventures. Each Granger causality test was conducted using lagged values appropriate for the temporal dynamics of the data, ensuring that the tests accounted for potential

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time delays between the stages. Alternatively, the cross-correlation analysis and other relevant tests have been used to understand the dynamic interactions between the stages.

1.2. Contribution and Research Paper Structure

The key findings of the current research can be summarized as follows:

- A methodology for automatically generating the most relevant search query for describing in an as narrow as possible method the intersection between AI and Agriculture domains of research;
- The evaluation on time axis between the general domain of AI in Agriculture and the specific sub-domains defined by the current classifier;
- A general evaluation of lifecycle innovation perspective for AI-driven Agriculture;
- Proposal framework for future planning of investment for AI in Agriculture increasing impact.

The research is structured as follows: Section 2 describes the main finding of the domain by conducting a literature review with the main topics of applications, methodologies and trends in the field of AI-driven agriculture. Section 3 introduces the methodology based on which the research is built upon, sequentially describing all the steps involved. In Section 4 we present the main results along with the discussions, while in Sector 5 we finish the research drawing the conclusions and taking further steps in future work to be added to this current research. Additional results along with all database used for this study will be made available on request.

2. Literature review

The intersection of artificial intelligence (AI) and agriculture has garnered significant research attention in recent years, reflecting the potential of AI to transform traditional farming practices. This review synthesizes findings from multiple studies to explore the applications, methodologies, and trends in this field.

2.1. Artificial Intelligence in Agriculture – Trends

Several studies have focused on systematic reviews to map the landscape of AI applications in agriculture. [16] provides a comprehensive analysis of AI methods utilized in agriculture, highlighting benefits and challenges associated with applications such as data collection using sensors, smart robots, and crop monitoring systems. Similarly, [17] examines 906 studies, narrowing the focus to 176 for bibliometric analysis, though it lacks detailed methodological justification for the chosen search terms. In the work of [18], a systematic literature review was conducted at the intersection of AI and IoT in the domain of agriculture, as the main components when it comes to Precision Agriculture.

The research [19] categorizes AI applications into 12 subdomains, including harvesting, precision farming, pest and disease management, and agricultural robotics. This taxonomy provides a structured framework for understanding the breadth of AI's role in agriculture. In parallel, [20] explores Agriculture 4.0, using digital repositories such as Web of Science and Scopus to identify emerging trends over the past decade.

Temporal trends in AI research are evident in studies such as [21], which notes a significant increase in interest around 2018. Using Scopus data from 2000 to 2021, this study reveals a growing focus on AI in agriculture. The paper [22] analyzes the Web of Things (WoT) domain, identifying trends and emphasizing solution proposals and experimental research. Although trends vary by year, 2016 stands out as an outlier for increased activity in this domain. Another perspective of analyzing the trends in AI-driven agriculture addresses the need for AI methods approach classification, such as the work [23], in which the authors reached the conclusions that 44% of the main AI technologies in agriculture are regarding robotics, 22% neural networks, while the rest of 34% representing deep learning, fuzzy logics, SVM, k-nearest, random forest. AI algorithms and methods are splitter into specific sub domains of agriculture in [24], such as: soil management, water

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management, livestock management and crop management. This classification is also an input of investigation in our current research when it comes to sub-domains of AI-driven agriculture.

The research [25] delves into the intersection of AI and geospatial analysis, noting an evolution toward machine learning and deep learning techniques, with agricultural robots and antennas emerging as prominent tools. Similarly, [26] investigates sustainability applications, employing PRISMA methodology to map trends over a 30-year period, highlighting a notable surge in publications post-2018.

The studies employ diverse methodologies, ranging from bibliometric analyses to systematic reviews. For example, [27] utilizes the Scopus database to identify 73 contributions focused on AI in agriculture, emphasizing applications such as precision farming, water optimization, and traceability systems. [28] adopts the PRISMA 2020 framework to examine factors influencing the adoption of AI in agriculture, livestock, and aquaculture, analyzing 38 studies, 55% of which are literature reviews.

In [29,30] there are provided some insights into specific subfields. [29] explores soil management, pest and weed control, and water-use optimization without detailing its query selection methodology. In contrast, [30] systematically reviews 25 years of research on the agricultural value chain, classifying 88 publications into empirical studies, case studies, and conceptual works.

Several studies focus on niche applications of AI in agriculture. [31] examines intelligent vertical agriculture, identifying machine learning models and algorithms used in studies from 2016 to 2022. This specialized focus aligns with broader trends in precision and smart farming. Additionally, [32] investigates AI's role in the business aspects of agriculture, using a targeted search query to extract relevant contributions. [33] focuses on a literature review using “Industry 4.0” key-term for investigating artificial intelligence technologies in Industry 4.0. Similar perspective of investigation is done within [34] for agricultural mapping, where a bibliographic data analysis and literature review establish the scientific contribution, collaboration, AI methods and trends in the field of agriculture mapping.

While these studies offer valuable insights, several limitations are evident. For instance, [17,30] lack robust methodologies for validating their search queries, potentially introducing biases. Similarly, [26] acknowledges limitations in its keyword-based selection criteria, which may restrict the scope of its findings. Similar situations of limited query for the research query within PRISMA methodology is present in [35], where the selection was done combining the keywords “Artificial intelligence” and “agri*”, this leading to this leading to unreliable initial set of elements to be analyzed.

The reviewed studies collectively highlight the transformative potential of AI in agriculture, encompassing diverse applications such as precision farming, sustainability, and geospatial analysis. However, methodological inconsistencies and limited query transparency in some studies underscore the need for standardized approaches. Although the use of AI models is solving a lot of the agriculture problems mentioned in the research [36], research in this topic is still in its initial stage. Future research should address these gaps while exploring emerging technologies and their implications for sustainable agricultural practices.

2.2. Classification Techniques and Challenges in Agriculture Field

Many researchers have used systematic reviews to explore how AI is applied in agriculture. For example, [37,38], offered a broad look at AI-based methods, discussing both the benefits and drawbacks of tools like sensors, smart robots, and crop monitoring systems. In a similar effort, [39] evaluated 906 studies and narrowed them down to 176 for a bibliometric analysis, but they provided limited details on how they chose their search terms. [40] grouped AI’s use in agriculture into 12 categories, such as harvesting, precision farming, pest and disease control, and robotics. This framework helps illustrate how widely AI can be used. Around the same time, [41] studied Agriculture 4.0 by gathering information from databases like Web of Science and Scopus to pinpoint new trends from the past decade. Temporal patterns in AI research also stand out, [44] noticed a spike in interest around 2018, based on Scopus data from 2000 to 2021. This reflects growing attention to

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AI applications in farming. Similarly, [42] studied the Web of Things (WoT) and noted a rise in solutions and experimental research. They found that 2016 was an unusual year with higher activity in this area. [43] looked at how AI and geospatial analysis have grown to include machine learning and deep learning approaches, noting a surge in agricultural robots and antennas.

Different methods have been used to study AI in agriculture such as [38,43] that focused more on specific topics. [43] looked at soil management, pest and weed control, and water usage but did not fully explain their search strategy. Certain reviews targeted niche areas. [44] examined vertical farming from 2016 to 2022 and listed the machine learning methods used. [45] looked at how AI influences the business side of agriculture, using a narrower search approach. Despite the useful findings, there are some gaps. For instance, [46,47] do not fully explain how they tested their search terms, which might introduce bias.

Overall, these studies highlight AI's transformative impact on agriculture, mentioning areas like precision farming, sustainability, and geospatial analysis. However, inconsistent methods and vague search term choices in some reviews indicate the need for more standardized approaches. Future work should address these issues and continue exploring new AI technologies for sustainable agricultural practices.

The literature shows a clear trajectory toward more intelligent, adaptive, and resource-efficient systems across domains. From pioneering zero-shot and generalized zero-shot techniques that expand recognition capabilities without exhaustive annotations, to agricultural innovations in marketing, quality control, robotics, machine learning applications, and digital twins, these advancements collectively underscore the transformative power of AI in addressing real-world challenges. As these methods continue to evolve, the convergence of zero-shot learning frameworks, robust model optimization, and agricultural domain adaptation promises a new era of innovation in both theoretical methodologies and practical applications.

3. Proposed Methodology

Starting from the innovation lifecycle steps defined by the existing literature, the present study focuses on the first four: academic world, projects started around innovation, possible patents resulting from the innovation and companies established around it. Table 2 describes the data sources used for each pillar, along with potential dimensions extracted.

Table 2. Source of databases for each involved pillar.

Pillar	Source	Dimensions
Academia	Web of Science, [48]	Years, Authors, Countries, Affiliation
Projects	Cordis (Horizon 2020 and Horizon Europe, FP1-FP7), (Cordis - EU research projects under HORIZON EUROPE, 2024), (Cordis – EU research projects under FP1-FP7, 2024), (Cordis – EU research projects under HORIZON 2020, 2024), [49–57]	Years, Authors, Countries, Affiliation
Patents	WIPO, [58]	Years, Authors, Countries, Affiliation
Companies	CrunchBase, [59]	Years, Countries, Companies, Investment plan

Web of Science is used for extracting relevant data referring to scientific articles written in the topics of artificial intelligence in agriculture. By using advanced search criteria, the data extracted includes publication dates, citation counts, journal impact factors, paper abstract, which are crucial for understanding the evolution and influence of scientific research in this domain. The robust indexing system of Web of Science ensures that only high-quality, peer-reviewed articles are included, providing a solid foundation for assessing academic progress and trends in AI applications in agriculture.

Cordis is added for gathering data across different calls and programs about projects written starting from the core of artificial intelligence in agriculture. Cordis is used to identify and analyze the progression and outcomes of projects that focus on AI in agriculture. This includes detailed project descriptions, funding amounts, project durations, consortium members, and final reports. The data from Cordis helps in understanding how EU policies and funding impact AI innovation cycles in the agricultural sector.

WIPO is the international database of patents used for extracting the number of patents filled with the main topic in AI-driven agriculture. By analyzing patent filings, one can gauge the technological advancements and the regions or entities that are leading in innovation. The database offers insights into the type of AI technologies being patented, the rate of patent filings over time, and the collaborative networks forming around these innovations.

CrunchBase is used for insight about companies that were formed under the main description of AI in agriculture. It provides information on company funding rounds, investor activities, mergers and acquisitions, and leadership changes. For this research, CrunchBase is used in tracking the emergence and growth of startups that are specifically categorized under AI applications in agriculture. This data helps in understanding market dynamics, investment trends, and the overall health and vibrancy of the entrepreneurial ecosystem in this field. Figure 1 summarizes the methodological steps undertaken to test the previously formulated hypotheses.

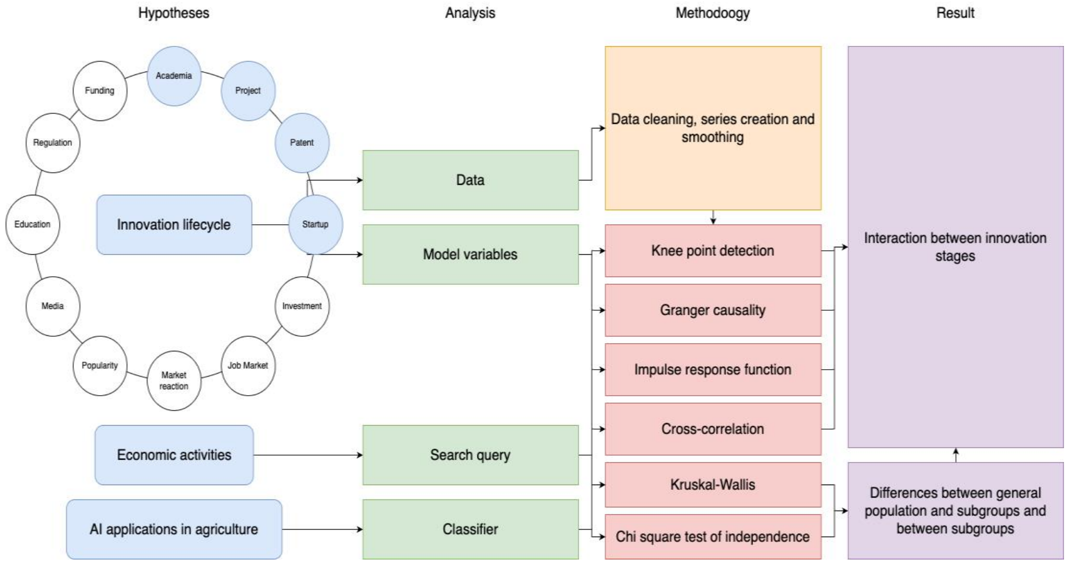

Figure 1. Overview of the main methodological steps.

The focal starting point of the methodology is represented by the innovation lifecycle formed as a circular flow of the key stages in the development and adoption of innovation. The cycle proposed as a continuous, interconnected process implies the following actors:

- Academia – as the ground of knowledge foundation;
- Project – the starting of development of ideas and directions extracted from the previous step, the academia;
- Patent – the protection of the intellectual property derived from the projects;
- Startup – the ideas patented and involved in new businesses;

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- Investment – rounds of investments in the startups;
- Job Market – Employment opportunities impacted by the new companies and investment appeared;
- Market reaction – The response of consumers and industries to the innovation on the market;
- Popularity – The recognition of innovation within the market;
- Media – Press and digital platforms presenting information around the innovation;
- Education – The training process for preparing students to handle the innovation into practice;
- Regulation – Government policies and legal frameworks;
- Funding – Financial support such as: grants for sustaining innovation, such as public or private investments.

The circularity is established by the funding last stage that lays the foundation for new innovation needs. The current research evaluates the evolution and impact in causality measures for the first four pillars.

3.1. Search Query Formulation

As the research horizon is defined by the two main areas, namely agriculture and artificial intelligence, clear borders had to be set for both to be able to reduce any biases to a minimum and ensure comparable datasets across pillars. As a result, the scope has been narrowed down to the most significant keywords. Many studies have taken into consideration the analysis of the literature review in the domain of intersection between artificial intelligence and agriculture. To address out first research question, RQ1, "What is the set of keywords defining the intersection between the domains of AI and Agriculture in research academic writing?", a methodology was created and followed.

Building the search query has started using the Boolean operator "AND" between the set of strings representing both artificial intelligence and agriculture. For each field of interest, a proper methodology was used for narrowing the string enough so that the result doesn't contain any objects that are not part of the desired dataset. The first query consisting of all fields that contain exactly the words "artificial intelligence" and "agri*" or "agro*", without the year 2024, has been tested on the Web of Science publications. The query has given 7499 results.

ALL = (artificial intelligence) AND (ALL = (agri*) OR ALL = (agro*))

For best describing the field of intersection between Agriculture and Artificial Intelligence, the key-terms used for describing the AI part are given by the set C = {"artificial intelligence", "machine learning", "IoT", "Robotics", "Object Detection"}. The key defining words for artificial intelligence have been determined from the intersections of multiple research works that used the PRISMA methodology for conducting systematic literature review, such as [16,17,19–21,25]. Therefore, artificial intelligence, machine learning, IoT and robotics have been highlighted as the factors that cover most of the information, reducing from the previous mentioned researches those terms that didn't determine disjoint sets.

In order to confirm that all relevant papers have been covered by the above query, the terms defining agriculture have been fetched from NACE -> A AGRICULTURE, FORESTRY AND FISHING -> 01 Crop and animal production, hunting and related service activities, [60].

All unique words have been extracted, resulting in a list of 50 relevant words, further narrowed down by using a text-based semantic grouping approach, leveraging natural language processing techniques and hierarchical clustering to group similar words. The most relevant groupings were obtained by applying a parameterization with 10 clusters, using the cosine similarity function to measure proximity between terms. Further, the clusters are analyzed and described using keywords that represent best each group of terms. The largest cluster (Cluster 0) includes general crop types and livestock categories, whereas other clusters focus on specific aspects of agriculture, such as oil seed processing (Cluster 4), post-harvest activities (Cluster 1), and hunting/trapping activities (Clusters 3 and 5). Additionally, livestock-related clusters were formed for poultry (Cluster 8) and pig farming (Cluster 9), while agricultural production terms were grouped separately in Cluster 2.

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This classification provides a structured way to analyze agricultural concepts in relation to AI applications.

Considering the formalization query given by the initial $Q_1 = (C_1$ OR C_2 OR … $C_n)$ AND $(CC_1$ OR CC_2 OR … $CC_m)$, we conducted an isolation methodology for determining the impact of each unique term, let it be called X, where X is extracted from the initial set of 50 relevant words from agriculture domain. The set C_i is represented by the elements from the keywords from AI domain, while CC_j is represented by the 50 unique words extracted from NACE taxonomy that are relevant to the desired selection. The objective is to gradually build upon an initial query and determine, at each step, the keywords relevant to the field of Agriculture. The methodology conducted accepted the premise that the CC_i keywords are independent and only analyzed in single use impact. Considering the query $Q_2 = (C_1$ OR C_2 OR … $C_n)$ AND $(CC_1$ OR CC_2 OR … CC_m OR X), for each X keyword from the set M, Card(Q_2/Q_1) is computed, where $Q_2/Q_1 = (C_1$ OR C_2 OR … $C_n)$ AND (NOT(CC_1) AND NOT(CC_2) AND … NOT(CC_m)) AND X. The cardinality of the set resulting from the query Q_2/Q_1 represents the total number of new publications extracted only if term X is considered. Using the notation n = Card(Q_2/Q_1), a quality metric is introduced in the methodology.

$$relevance_X = \frac{m}{n} \quad (1)$$

where m is the number of relevant publications classified using Web of Science categories in the intersection of AI and Agriculture domains.

A threshold of 0.9 is deciding whether the X term to be used in the final search query or not. The testing of the search methodology was conducted using Web of Science database. The starting query was defined by TS = (("artificial intelligence" OR "machine learning" OR "IoT" OR "Robotics" OR "Object Detection") AND (agri*)), resulting in 17895 elements. After that, each term from the set {tree, pig, crop, seed, oil, animal, farming, crop, production, harvest, hunting, trapping, land} is added to the equation. For example, in the case of X =" tree" term, the cardinality of the result reached 51834. This is a good example of the situation of words that are polysemous, tree having multiple meanings depending on the context, a biological meaning and a computer science data structure. For that, isolating only the new results for "tree" term it resulted in a number of 33966 elements. The small difference is given by the fact that the wild card * cannot be used in the NOT Boolean operator, the query being adjusted to TS = (("artificial intelligence" OR "machine learning" OR "IoT" OR "Robotics" OR "Object Detection") AND "tree") NOT TS = ("agriculture" OR "agribusiness" OR "agricultural" OR "agrifood" OR "agronomy"). Only 2148 elements are classified within the environment sciences, the rest integrated in multiple fields referring to computer science fields. Figure 2 illustrates the web of science categories.

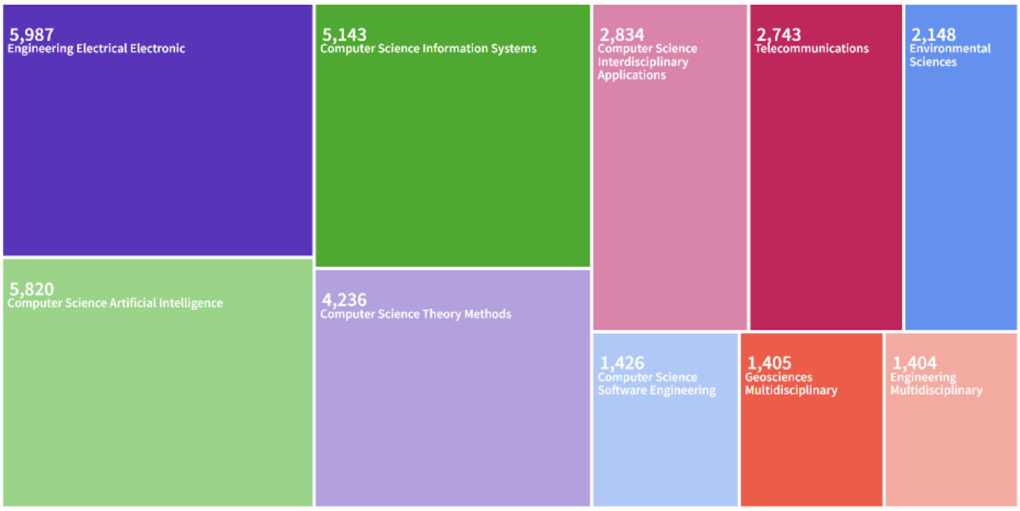

Figure 2. Web of Science categories for "tree" term for agriculture related works.

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Each key term is iterated and the final query obtained is TS = (("artificial intelligence" OR "machine learning" OR "IoT" OR "Robotics" OR "Object Detection") AND (agri* OR farm* OR crop OR "AgTech" OR animal OR land)).

The obtained query is run for each pillar, Table 3 containing the results and specific selection method depending on the database used. For companies' pillar, the industries declared by the company should be found both in Agriculture and Artificial Intelligence sets. For Patents pillar, the selection method is similar to web of science query, where the search is done upon the front page of the patent. In the case of Projects pillar, using Cordis database, the excels for all the calls that are referred in this research, FP1-FP7, Horizon Europe, Horizon 2020, were concatenated based on the common fields that are present in each call. A number of 124.607 projects are filtered based on a python script, resulting in 1147 projects that contain in the title or abstract at least one key-term from {"artificial intelligence", "machine learning", "IoT", "Robotics", "Object Detection"} and a least one from {agri*, farm*, crop, "AgTech", animal, land}.

Table 3. Selection criteria for all pillars involved in the research.

Pillar	Download method	Selection restrictions	Results dimension
Academia	Advanced search within web of science website	TS = (("artificial intelligence" OR "machine learning" OR "IoT" OR "Robotics" OR "Object Detection") AND (agri* OR farm* OR crop OR "AgTech" OR animal OR land))	33473
Projects	All excel documents referring to all projects between 1984-2027	A python script that extracts only those projects containing within the title or abstract key terms from the two sets: (("artificial intelligence" OR "machine learning" OR "IoT" OR "Robotics" OR "Object Detection") AND (agri* OR farm* OR crop OR "AgTech" OR animal OR land))	1147
Patents	Advanced search within Patentscope WIPO website	FP: ((artificial intelligence OR machine learning OR IoT OR Robotics OR Object Detection) and (agri* OR farm* OR crop OR AgTech OR animal OR land))	955
Startups	Crunchbase website	Industries = {“IoT”, “Robotics”, “Machine learning”, “AI”} and Industries = {“Animal feed”, “Agriculture”, “Farming”, “AgTech”}	825

3.2. AI applications in Agriculture – Classification

Going further to the classification, among the general evaluation of the intersection of AI and Agriculture fields, a subcategory evaluation is conducted. For that, a taxonomy is needed for classifying each element of the current analysis in one subcategory of agriculture in AI field. Several studies were conducted based on a classification of AI-driven agriculture topics. In the work [61], the authors identified 13 main applications of AI in agriculture. The starting point has been the study of [62], as it documents a clear hierarchical structure of farm systems, starting from a regional overview and going towards the agricultural sector and cropping system management. In connection to AI, [17,20] have defined the most important applications for those systems that cover most of the sector. We have chosen to focus on the cropping systems, and keep livestock, climate, vegetation, secondary and tertiary systems out of scope. Therefore, Table 4 contains the resulted domains of agriculture - AI relation.

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Table 4. Domains of agriculture – AI relation.

L0	L1	L2	L3	L4	L5	L6	CODE
Regional system	Agricultural sector	Farm system	Cropping system	Pre-harvesting	Crop system	Nutrients management	NM
Regional system	Agricultural sector	Farm system	Cropping system	Pre-harvesting	Crop system	Water management	WM
Regional system	Agricultural sector	Farm system	Cropping system	Pre-harvesting	Crop system	Crop management	CM
Regional system	Agricultural sector	Farm system	Cropping system	Pre-harvesting	Weeds, pathogens and insects	Disease control	DI
Regional system	Agricultural sector	Farm system	Cropping system	Pre-harvesting	Soil	Soil monitoring	SM
Regional system	Agricultural sector	Farm system	Cropping system	Pre-harvesting	Soil	Irrigation management	IM
Regional system	Agricultural sector	Farm system	Cropping system	Pre-harvesting	Soil	Fertilization management	FM
Regional system	Agricultural sector	Farm system	Cropping system	Pre-harvesting	Soil	Weather prediction	WP
Regional system	Agricultural sector	Farm system	Cropping system	Harvesting	Harvesting		HM
Regional system	Agricultural sector	Farm system	Cropping system	Harvesting	Biomass		BM
Regional system	Agricultural sector	Farm system	Cropping system	Performance management			PM
Regional system	Agricultural sector	Farm system	Cropping system	Sustainability monitoring			SU

Note: L0, L1, L2, L3, L4, L5, L6 represent the levels of the agriculture domains hierarchy. All leaf categories have been initially considered for the study.

These categories have been reduced to six for more reliability, based on their coverage area. Therefore, crop management includes land preparation, seeding, planting and crop rotation. Disease control integrates biological control, cultural practices, and chemical applications to minimize environmental impact. Soil monitoring assesses soil properties to detect changes and manage threats like erosion and contamination. Irrigation and fertilization management ensures optimal water and nutrient application for crop growth and includes, by extension, the horizon defined by nutrient and water management. Weather prediction applies scientific methods to forecast atmospheric conditions. Performance management and sustainability monitoring leverage AI to enhance productivity, efficiency, and environmental sustainability. As a result, the final set of subcategories used for the next step of the classification is given by S = {crop management, disease & pest, fertilization & irrigation, soil, sustainable farming, weather forecasting}.

These categories are useful to describe data, determine more homogenous series and diagnose the slope. In addition, correctly classified values can be further matched across all innovation cycle steps, leading towards representative and accurate causality methods application.

3.3. Classifier of AI in Agriculture Sub-Domains

Recent advancements in Natural Language Processing (NLP) have led to significant improvements in zero-shot classification, where models assign labels to text without prior training on labeled data for that specific task [63], particularly for domains where labeled datasets are scarce or continuously evolving. Traditional text classification approaches rely on supervised learning with annotated datasets, but these methods require significant manual effort. Zero-shot ranking methods, such as those explored by [64] utilize transformer models to assess entailment probabilities between input text and predefined category labels.

For this study, a Python-based workflow has been developed to perform zero-shot classification on a collection of objects described by titles and abstracts. Our first classifications were done using two models: "facebook/bart-large-mnli", a variant of the BART (Bidirectional and Auto-Regressive Transformer) architecture fine-tuned on the Multi-Genre Natural Language Inference (MNLI) dataset and "MoritzLaurer/deberta-v3-large-zeroshot-v2.0", a variant of the DeBERTa v3 (Decoding-enhanced BERT with Disentangled Attention) architecture, fine-tuned for zero-shot classification using a hypothesis-based approach. Both of those models were initially used for classification tasks, making use of their pre-trained language understanding to assign relevant categories without the need for labeled training data.

Our scripts first normalize and clean each text entry, then leverage the BART-based and DeBERTa classifiers via the HuggingFace pipeline API to assign one of several predefined, agriculture-related categories and then the resulting classifications, along with their confidence scores, are compiled into a structured spreadsheet. Upon comparing the results of those two models, we chose to continue with the BART-based classifier because it consistently provided higher-confidence scores and more accurate classifications within the agricultural domain. Its performance was more stable, with fewer ambiguous or overlapping assignments, making it a more reliable choice for categorizing AI-related agricultural texts in a zero-shot setting. Several researches such as [65,66] highlight the classification techniques using AI and their misinterpretations with inconsistent labeling and performance variations across classifiers when considering very niche topics which is very similar to our case. A quick result classification can be seen in Table 5 where the BART model outperformed the Mortiz model. While the abstracts are not included in the visual representation, they were an important part of the classification process.

Table 5. Zero-Shot Classification of AI in Agriculture: BART vs. MoritzLaurer.

Title	BART Label	BART Score	MoritzLaurer Label	MoritzLaurer Score	Actual label
AI & ML-Based Crop Surveillance	Crop management	0.9439	Crop management	0.7439	Crop management
Agricultural intelligent irrigation system based on artificial intelligence and big data	Crop management	0.8885	Disease & pest	0.5385	Crop management
Artificial-intelligence agricultural crop detection method, mobile terminal and computer readable medium	Crop management	0.7008	Fertilization & irrigation	0.4784	Crop management
A Field Crop Efficiency Detection Method	Crop management	0.9760	Sustainable farming	0.7994	Crop management
Agricultural vegetable growth detection method and system based on artificial intelligence disease and pest	Disease & pest	0.6548	Disease & pest	0.3356	Disease & pest

Although DeBERTa v3 has a strong performance for most NLP general tasks, according to https://arxiv.org/pdf/2111.09543, our empirical observations among with the results showed that BART provided more consistent and domain-relevant classifications for AI applications in agriculture. By following the above steps, we are able to create a procedure that provides a streamlined, data-driven approach of interpreting and organizing textual inputs without having the need to do any kind of manual annotations, thanks to the advanced language processing capabilities of the BART model.

3.4. Series Smoothing

Various time series smoothing techniques were applied to normalize and smooth the data series, as they have been proven particularly helpful in studies focusing on agriculture topics, such as [67–69], thereby allowing for a clearer understanding of the underlying dynamics. The four categories - articles, patents, projects and startups, spanning from 1982 to 2023 - were considered. Each dataset was processed using several smoothing techniques.

Simple Moving Average (SMA) calculates the average of a defined number of data points. For this study, a 3-point window was used, meaning each data point was replaced by the mean of itself and the two surrounding points. This method helps to smooth out short-term fluctuations and highlight longer-term trends. The formula for SMA is:

$$SMA_t = \frac{1}{N}\sum_{i=t-(N-1)}^{t} x_i \quad (2)$$

where N is the window size, t is the current time step, and x_i represents the values in the time series.

The Exponential Moving Average (EMA) assigns more weight to recent data points, making it more responsive to recent changes compared to the SMA. In this analysis, a span of 12 was chosen, balancing the sensitivity to new trends while smoothing out the noise. EMA is defined as:

$$EMA_t = \alpha \cdot x_t + (1-\alpha) \cdot EMA_{t-1} \quad (3)$$

where α is the smoothing factor equal to 2/(span+1), and x_t is the value at time t. The first term x1 was initialized with the first value of the normalized dataset for each pillar. This recursive method is especially useful for datasets with recent variability.

In addition, [70] have mentioned the Lowess method as an alternative to the above-mentioned techniques for increased robustness, as it accounts for non-normal distributions. It effectively smooths the series by allowing a flexible fitting, which can capture local variations. For this study, a fraction parameter equal to 0.1 was used, indicating that 10% of the data points were used to fit each local regression. This method is suitable for identifying underlying patterns that might not be visible through more rigid smoothing techniques. Lowess is particularly beneficial for data exhibiting non-linear trends.

Nevertheless, [71] have applied a Gaussian filter to the data series, which weights each data point according to a Gaussian (bell-shaped) curve. A window size of k=5 was therefore used in the present study, where each value was replaced by a weighted average of itself and its four surrounding points. This approach is effective at smoothing while retaining the general shape of the data trends, and is defined as:

$$y_t = \sum_{i=-k}^{k} G(i) \cdot x_{t+1} \quad (4)$$

where G(i) represents the Gaussian weights, and k is the size of the window. The Gaussian filter helps in minimizing the effect of outliers while preserving the overall trend.

Each dataset was subject to all the aforementioned smoothing methods. The original and smoothed values were plotted for comparison to assess how effectively each method captured trends and minimized noise. The SMA and EMA methods are simple yet effective for steady trends, whereas Lowess and Gaussian smoothing are more versatile in handling non-linear patterns and variable data. The choice of method has been made according to the specific characteristics of each series, allowing for a flexible and more accurate result.

3.5. Knee Point Detection

Knee points represent moments in time where a significant shift occurs, marking a point of maximum curvature in the data trend. This type of investigation within a time series gave multiple positive responses in research such as [72], where they redesigned the Bayesian Information Criterion (BIC) method for partitioning-based clustering algorithms by proposing a new knee point finding method based on it. The concept of maximum curvature is used in scientific research for capturing the point where the rate of change reaches the maximum value, meaning that the curve bends the most at this value of x-axis. The formula used for detecting this point is defined by:

$$curvature = \frac{f''(x)}{\sqrt{(1+f'(x)^2)^3}} \quad (5)$$

where f(x) is the function associated with the time series data, and x represents the time variable.

In this current methodology, we evaluate the differences between the maximum curvature applied to the same datasets representing articles, patents, projects and startups, spanning the years from 1982 to 2023 and the value of maximum second derivate. The detection technique leverages the concept of curvature analysis. Specifically, the approach involves calculating the first and second derivatives of the time series data to identify points where the curvature is maximized. The knee point is the point where the rate of change shifts most noticeably, highlighting a critical transition period in the dataset. The first derivative provides the rate of change of the data with respect to time. It measures how fast the data values are increasing or decreasing, while the second derivative indicates the change in the rate of the first derivative. By analyzing the second derivative, it is possible to identify points of maximum curvature where the rate of change undergoes a significant shift. The formula for calculating the second derivative is:

$$f''(x) = \frac{d}{dx}\left(\frac{df(x)}{dx}\right) \quad (6)$$

where f(x) is the function associated with the time series data, and x represents the time variable.

The method implemented in this study involves several steps. The time series data for each category is extracted, with the years serving as the time axis. Using numerical differentiation, the first and second derivatives of each dataset are calculated. The knee point is identified as the position where the second derivative reaches its maximum value, indicating a point of highest curvature. This approach assumes that a significant change in trend or growth rate is marked by an inflection point that can be detected via curvature analysis. The formula used to identify the knee point is as follows:

$$Knee\ index = argmax\left(f''(x)\right) \quad (7)$$

where argmax identifies the index at which the second derivative is maximized.

3.6. Causal Inference

To investigate the dynamic relationships between research outputs, technological innovation, practical implementation activities, and entrepreneurial activity, we employed a three-step approach combining Granger causality analysis, impulse response function analysis, and cross-correlation analysis. This perspective was chosen to identify causal links, quantify the temporal dynamics between variables, and explore their lead-lag relationships, as indicated by [73], and reiterated by [74,75]. Granger causality analysis was employed to assess whether one time series could predict another, based on past values. The analysis was conducted for all variable pairs using lag selection through the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), hypothesis testing, with the null hypothesis defined as "variable x does not Granger-cause variable y", and causality network assessment, where nodes represent variables and directed edges indicate Granger causality. To further explore the dynamic interactions between variables, impulse response functions (IRFs) were derived using a Vector Autoregressive (VAR) model. The model in cause was fitted using the preprocessed time-series data, ensuring optimal lag length as determined in the Granger causality step and was used to estimate how a unit shock to one variable influences other

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variables over time. The results were visualized in impulse response plots, illustrating the magnitude and duration of the responses.

To complement the findings from the Granger causality and IRF analyses, cross-correlation analysis was performed to examine lead-lag relationships between variable pairs at different lags. The cross-correlation function (CCF) was computed for each pair, with specific attention to lag structure, where positive and negative lags were analysed to identify whether changes in one variable precede or follow changes in another. The statistical significance of cross-correlation coefficients was evaluated to ensure robust conclusions. Nevertheless, cross-correlation plots were generated to identify peaks and troughs, highlighting significant relationships and their temporal dynamics.

4. Results and Discussions

4.1. General to Sub-Domain Classification Data Along All Pillars

To evaluate the research questions regarding the sequential progression of innovation from articles to projects, patents, and start-ups, we analyzed the yearly distribution of data across six categories: *{crop management, disease & pest, fertilization & irrigation, soil, sustainable farming, weather forecasting}*. For the articles dimension, 33473 publications were considered, based on the criteria established in the previous stage. This resulted in a positive trend and an exponential increase in the number of articles, with a turning point after 2017, as presented in Figure 3. Among subcategories, soil management showed stabilization around 2022, possibly reflecting research maturity in this area. In contrast, other subcategories, such as disease and pest management and sustainable farming, displayed steady growth but without distinct inflection points.

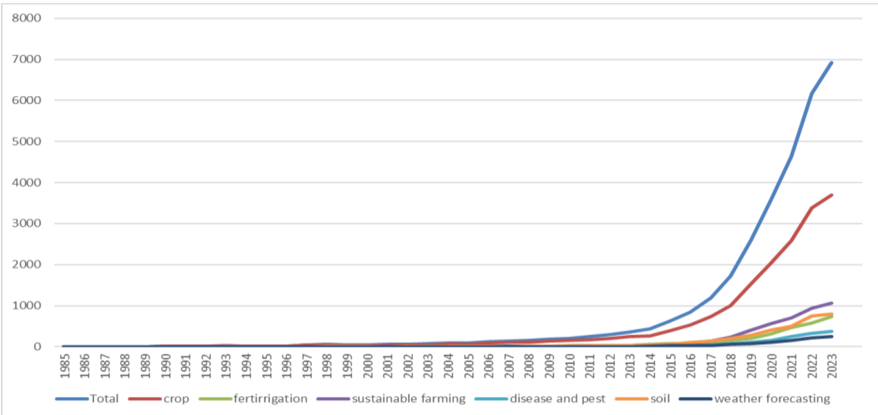

Figure 3. The evolution of publications per classes (Source: Authors' computation).

Project data was retrieved from the Cordis database for Horizon Europe, Horizon 2020, FP1 to FP7, yielding a dataset of 124,607 records. After filtering, 1,147 projects were identified for the 1985–2023 period. To mitigate cyclic patterns caused by program cycles, the analysis counted projects active in each year rather than their start years.

Figure 4 demonstrates a consistent increase since 1985, with dips in 1998, 2002, and 2019 corresponding to program transitions or the COVID-19 pandemic. An exponential growth phase began in 2014 with the launch of Horizon 2020.

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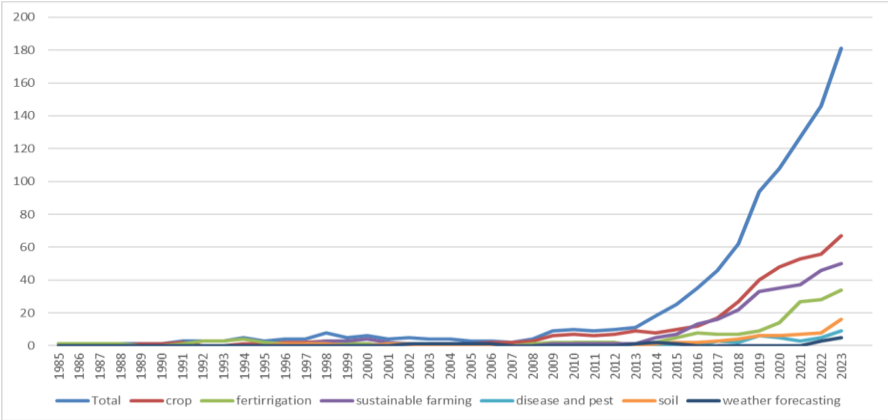

Figure 4. The evolution of projects per categories (Source: Authors' computation).

Patent data analysis identified 955 records for the period. A significant increase occurred after 2015, peaking before 2020, followed by a decline, as in Figure 5. This suggests a burst of innovation activity, possibly linked to agricultural technological advancements, with a recent decline that could signal market saturation or reduced patent filings.

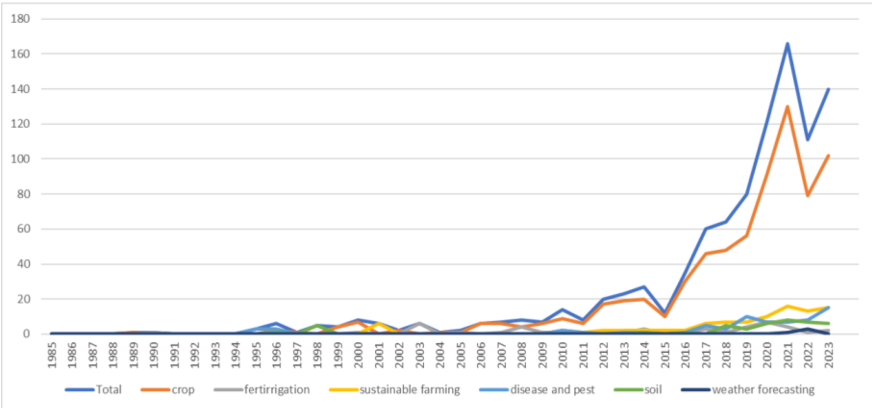

Figure 5. The evolution of patents per categories (Source: Authors' computation).

For start-ups, 825 entries were analyzed. The frequency distribution, Figure 6, showed a gradual increase until the mid-2000s, followed by a sharp rise after 2010, peaking between 2014 and 2018. A decline is evident after 2020. Among categories, crop-related start-ups dominated, with the highest activity during 2016–2018, sustainable farming and disease and pest management also showed strong contributions, peaking during the same period, fertilization and irrigation, soil management, and weather forecasting showed lower but steady activity throughout the period.

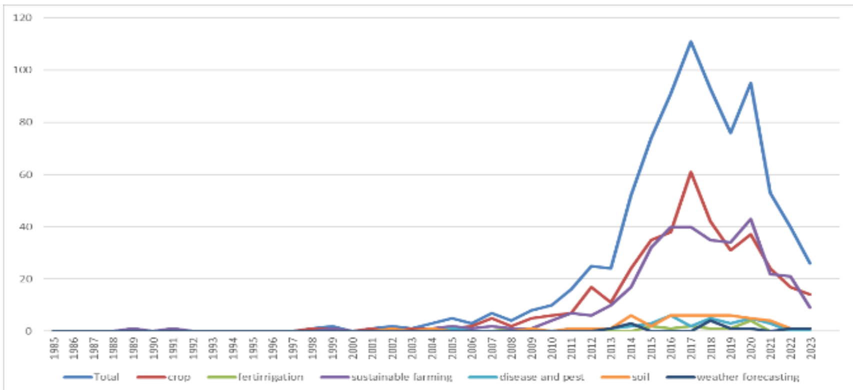

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Figure 6. The evolution of start-ups per categories (Source: Authors' computation).

This distribution highlights a concentration of start-up activity during 2010–2016, likely driven by advancements in agricultural technology, policy incentives, and increased investment in Agritech. The subsequent decline may reflect market consolidation or a shift in funding priorities.

In response to our research question, RQ_6, Is the overall evolution of the research domain similar to the evolution of the six particular sub-directions defined by the proposed classification?, statistical analyses were conducted using the Kruskal-Wallis test to determine whether there are significant differences between the six categories and the Chi-square test to evaluate deviations from the total frequency distribution per year. The results of the first method are summarized in Table 6.

Table 6. Differences between the innovation phases (Source: Authors' computation using Python).

Innovation phase	Degrees of freedom	H	Validation
Articles	5	4353.98	H1: Significant differences
Projects	5	68.9	H1: Significant differences
Patents	5	88.59	H1: Significant differences
Start-ups	5	40.02	H1: Significant differences

Kruskal-Wallis results for articles indicated statistically significant differences among the six categories, suggesting that certain categories show a stronger presence in the academic literature.

The Chi-square test also validated H_1, confirming that the observed frequencies of articles significantly deviate from the expected yearly totals, highlighting temporal dynamics and potential shifts in research focus. For projects, the Kruskal-Wallis test similarly validated H_1, demonstrating that the distribution of projects across categories is non-uniform and likely influenced by varying levels of practical applicability or funding priorities. However, the Chi-square test validated H_0, indicating no significant deviation from the expected total yearly frequencies. This suggests that while project distributions differ by category, their overall yearly volume remains consistent with general trends. patents showed significant differences across categories, as evidenced by the same test. These differences point to varying innovation intensities, likely driven by technological advancements or market demand in specific areas. The Chi-square test also validated H_1, indicating that patent filings deviate significantly from the total yearly frequencies, reflecting the uneven pace of innovation across time. Start-ups showed significant differences across categories, suggesting that entrepreneurial activity is influenced by category-specific situations. The Chi-square test results further revealed significant deviations from total yearly frequencies, aligning with the findings for patents and indicating that start-up formation is closely tied to temporal and categorical variations.

The analyses indicate that the hypothesized sequential progression of innovation is partially validated. Articles, patents, and start-ups all show significant categorical and temporal variations, as evidenced by both Kruskal-Wallis and Chi-square tests. However, projects demonstrate a divergence in this trend, with significant categorical differences but no deviation from yearly frequencies.

4.2. Results in Smoothing Techniques

To investigate the temporal relationships among the four innovation phases, we analyzed normalized annual data spanning from 1985 to 2023. Due to inherent fluctuations and noise in the raw time series data, smoothing techniques were applied to highlight underlying trends and facilitate clearer visual interpretation, including Simple Moving Average (SMA), Simple Exponential Smoothing (SES), and Gaussian smoothing. Therefore, the following methods were selected, based on the visual representation: original data for articles, SMA for projects, patents and startups.

Figure 7 illustrates the smoothed and original time series for each innovation phase. The visual representations suggest a sequential pattern where peaks in the number of projects are followed by increases in articles, which are then succeeded by rises in patents. Startups seem to evolve rapidly

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compared to the other dimensions involved in the innovation. This observation preliminarily supports the hypothesized progression in the innovation cycle.

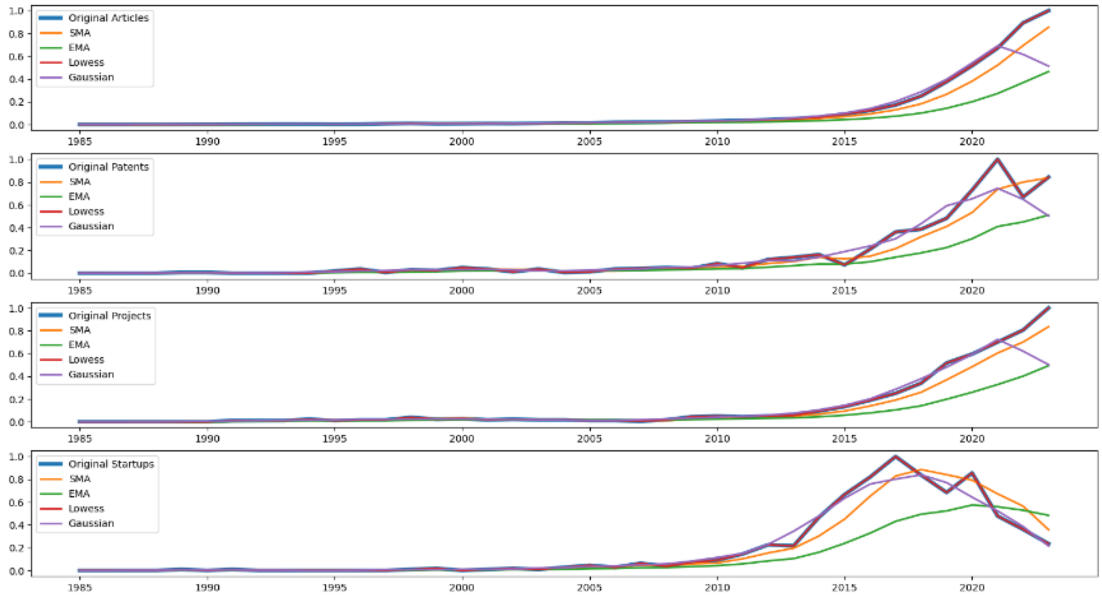

Figure 7. Original series compared to the different methods of smoothing (Source: Authors' computation using Python).

4.3. Chronology in Knee Points

To further quantify the onset and intensification of activity in each phase, knee point analysis was conducted using the second derivative method and maximum curvature. As stated previously in the methodology, knee point was used to detect a significant acceleration in the trend, highlighting critical years of innovation surges for each phase. The second derivate method results are compared to those generated by the maximum curvature. Figure 8 contains the resulted knee points for each time series associated to each pillar, while Figure 9 contains the same type of outputs but computed with the maximum curvature knee point method detection.

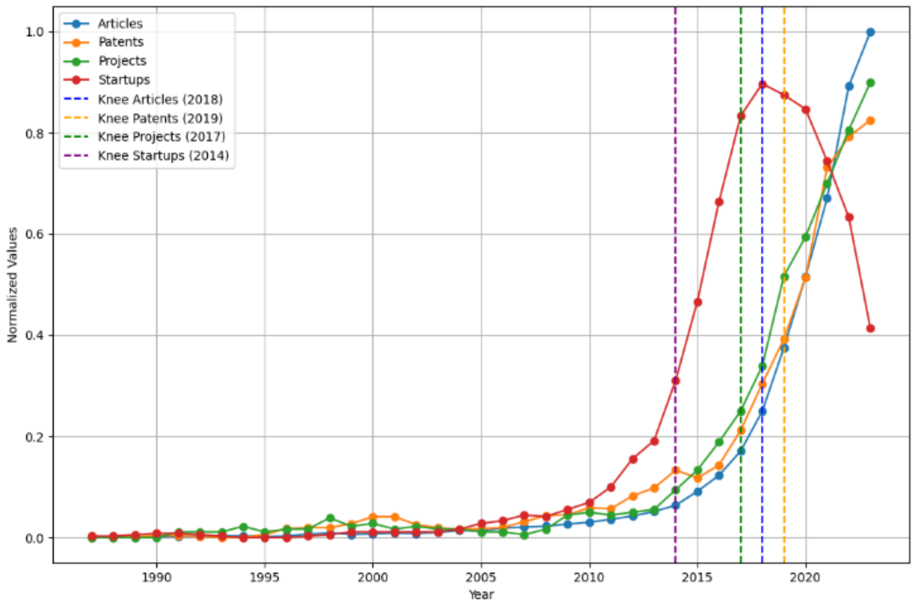

Figure 8. Knee point detection using maximum second derivate (Source: Authors' computation using Python).

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The detected knee points were 2014 for start-ups, 2017 for projects, 2018 for articles and 2019 for patents. These results indicate a chronological progression, with start-ups preceding other phases, followed by projects, articles, and finally patents, as shown in Figure 8. The early knee point for start-ups relative to projects suggests a potential decoupling between entrepreneurial activity and structured project initiatives, potentially due to independent funding or market-driven ventures. Moreover, the appearance of projects before articles and patents suggests a natural progression toward tangible outcomes, indicating that the latter may be considered results or derivatives of the former.

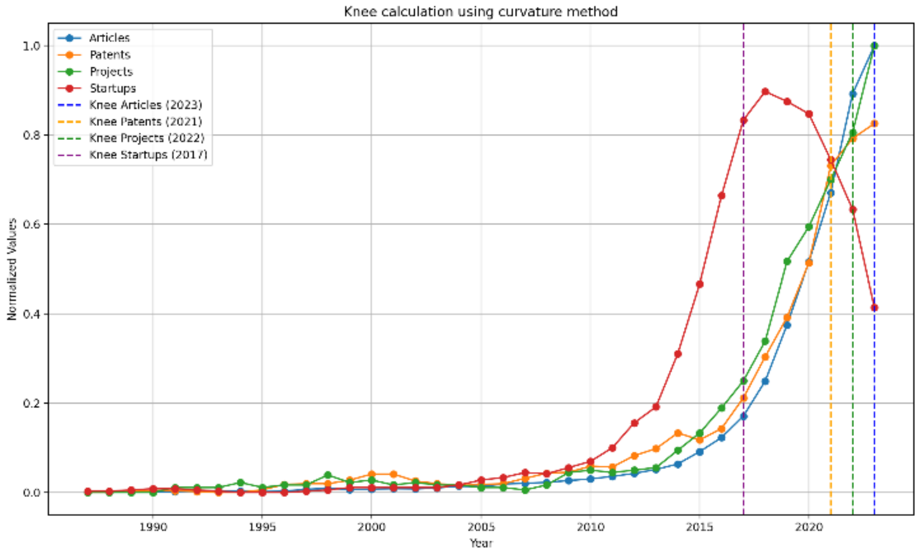

Figure 9. Knee point detection using maximum curvature (Source: Authors' computation using Python).

For the maximum curvature, the values obtained within Figure 9 indicate as knee points the years 2017 for start-ups, 2022 for projects, 2023 for articles and 2021 for patents. The results obtained indicate for this evaluation the maximum point that describes an intensive interest in each of the analyzed pillars. A particular value that has a different evaluation is given by the maximum curvature of the articles time series, the value being equal to the upper limit of the series, indicating the fact that there is still an increase in interest in publishing in scientific journals the results obtained by the research done within the intersection of AI and agriculture. Summarizing the results from Figures 9 and 10, Table 7 contains the starting and ending point of intensive increase of interest in each of the four pillars.

Table 7. Interval of intensive interest in dissemination (Source: Authors' computation using Python).

Pillar	Start year of intensive interest (knee index)	End year of intensive interest (max curvature)
Academia	2018	2023
Projects	2017	2022
Patents	2019	2021
Startups	2014	2017

Based on the interval defined within Table 7, Figure 10 highlights for each time series the years within the lower and upper limit of the two indicators.

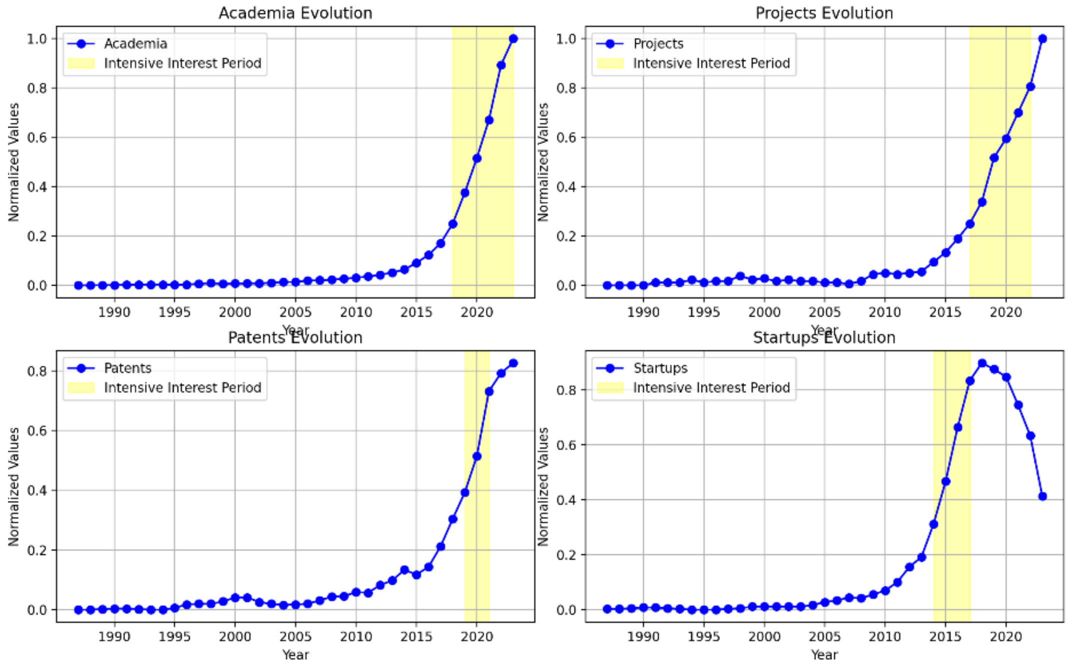

Figure 10. Golden period of innovation in all four pillars (Source: Authors' computation using Python).

The publications in the academia environment show a stable growth between 2010-2017, after that detecting that sharp increase. The highlighted period between 2018-2023 suggests a significant interest in research activity. The reasons behind the evolution are given by possible polity incentives, emerging scientific interest along with technological advancements. The upper limit of the highlighted period is generated solely on the reason of time series ending, but not the potential increasement. For the projects time series, we deduce a similar trajectory to the academia environment, following a slowly evolution since 2010, with a strong increase in 2017. The period determined by an accelerated rate of investments in projects, 2017-2022, indicate period of similar implications in the Cordis programs.

The filing of patents shows more of a stable evolution until 2014, with a higher slope starting from 2019. The peak period 2019-2021 refer to the window where an intense transition from research to commercialization was done. The golden period of startups foundation was between 2014-2017, but with a visible saturation reached around 2018, leading to a decrease of interest. This can be explained by possible changes in regulations, funding or even market limitations. This decline can also suggest other sources such as a shifting in the investors interest, the competition or even consolidation.

The overall compared evolution given by the academia and projects dragging the patent series indicate the outcomes of research being translated into more tangible advancements in technology. For academia and projects series are seen as leading indicators when it comes to innovation, the early growth showing a steady projection before the immersive rise in the recent years.

4.4. Causality in Innovation Lifecycle

To examine the dynamic relationships between research outputs, technological innovation, and implementation activities, we applied Granger causality tests for all possible combinations of the series, thereby addressing our research questions on causality, RQ_2, *Is there any sequential causality in the innovation lifecycle of AI in agriculture?* The tests were conducted using lags ranging from 1 to 5 years to assess whether past values of one time series can predict the future values of another. The results, visualized in Figure 11 as a causality network, reveal several significant relationships between the variables. The intensity of the relationship has been considered strong or weak based on the number of significant consecutive lags.

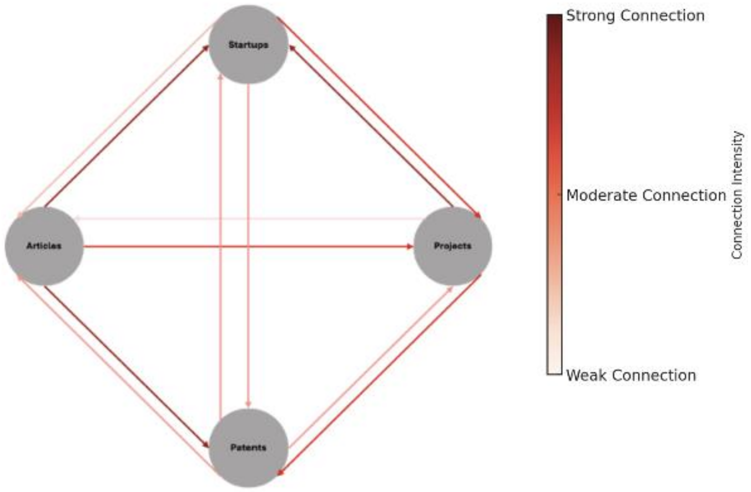

Figure 11. Causality Network (Source: Authors' computation) .

The results demonstrate that articles strongly predict patents and start-ups across most of the lags. This suggests that increases in research activity act as a significant driver for subsequent technological innovations. Conversely, patents and start-ups also influence articles, though to a lesser extent and primarily at lower lags. These bidirectional relationships suggest a feedback loop where technological advancements inspire further research activity, creating a reinforcing cycle between innovation and research output. When looking at the start-ups, the analysis indicates strong influence by articles and projects, and a weaker one by patents, suggesting that research activity and technological innovations drive the establishment of new entrepreneurial initiatives. However, the influence of start-ups on other variables, particularly articles and patents, appears limited. This asymmetry suggests that while research and innovation stimulate the creation of start-ups, these entrepreneurial activities contribute less to upstream research or further innovation. Similarly, articles were found to Granger-cause projects at lower lags, indicating that research outputs can lead to practical applications, particularly in the short term. However, the reverse relationship was weaker and inconsistent, suggesting that while practical implementations might inspire research, the effect is neither robust nor sustained. The relationship between patents and projects highlights another interesting connection, where patents appear to have only a limited and inconsistent influence on projects. This asymmetry suggests that implementation fosters new technological developments, as real-world use cases also demonstrate.

To further explore the dynamic interactions among the series, impulse response analysis was conducted and is presented in Figure 12.

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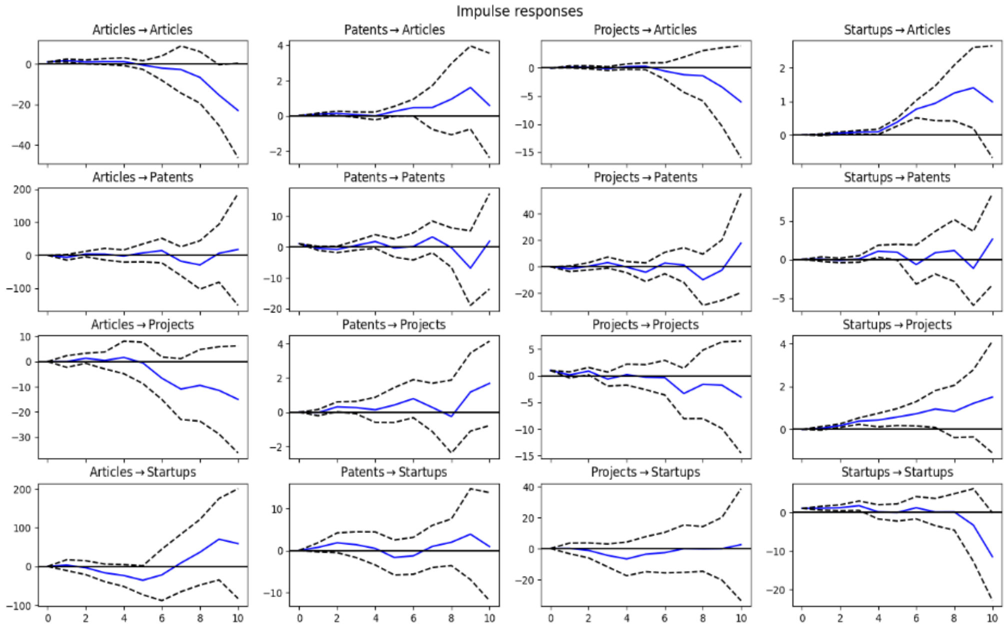

Figure 12. Impulse Response Functions (Source: Authors' computation using Python).

A shock to patents leads to a positive response in articles, reaffirming the earlier causality findings and suggesting that technological advancements can stimulate new research publications. Contrariwise, a shock to articles has a negative effect on patents, stating that research activity may inhibit patent filings. The analysis further reveals that articles influence projects with a fluctuating but generally negative response, highlighting that the translation of research into practical applications is subject to variability and additional influencing factors. The influence of projects over articles is rather a temporary adjustment and does not have a strong effect long term. On the other hand, patents have a positive effect on projects with a higher intensity on the long run, suggesting a longer buffer between transforming a prototype into a ready-to-market product. Start-ups demonstrate an interesting behavior. Shocks to start-ups show limited but positive effects on both articles and patents, indicating that entrepreneurial activity has some influence on new research outputs and applied implementations and innovation, although the effect is weaker compared to the role of patents. On the other hand, start-ups demonstrate strong persistence to projects, as demonstrated by the autocorrelated response, showing that they represent a powerful driver towards continuous development.

To complement these findings, we performed cross-correlation analysis to identify the lag structure and temporal relationships between the series. The cross-correlation plots presented in Figure 13 provide insights into the lead-lag dynamics. The relationship between articles and patents shows no significant cross-correlation at any lag, suggesting that changes in the number of published articles do not directly lead to or follow changes in patent filings. However, patents show a significant cross-correlation with articles, particularly at lag 0 and negative lags, implying that an increase in patents precedes an increase in research publications. This further supports the notion that technological advancements foster additional research activity. The relationship between patents and projects is similarly robust, with a significant peak around lag 0 and positive lags, indicating that increases in patents are followed by increases in projects. This suggests that patent activity serves as a leading indicator for the initiation of practical implementation activities. In contrast, no significant cross-correlation was observed between articles and projects, nor between projects and articles, implying that research outputs do not directly influence project initiation, and project activities have limited feedback effects on academic research. Start-ups show dynamics in the cross-correlation analysis. The results reveal that start-ups are significantly influenced by patents, with positive correlations at lag 0 and subsequent lags. This suggests that technological innovations act as a foundation for entrepreneurial activity, encouraging the creation of new start-ups. However, the influence of start-ups on other series remains marginal, as no significant cross-correlation was observed between start-ups and articles or projects. This further reinforces the earlier conclusion that start-ups are primarily downstream processes influenced by innovation, with limited feedback effects on upstream research or implementation activities.

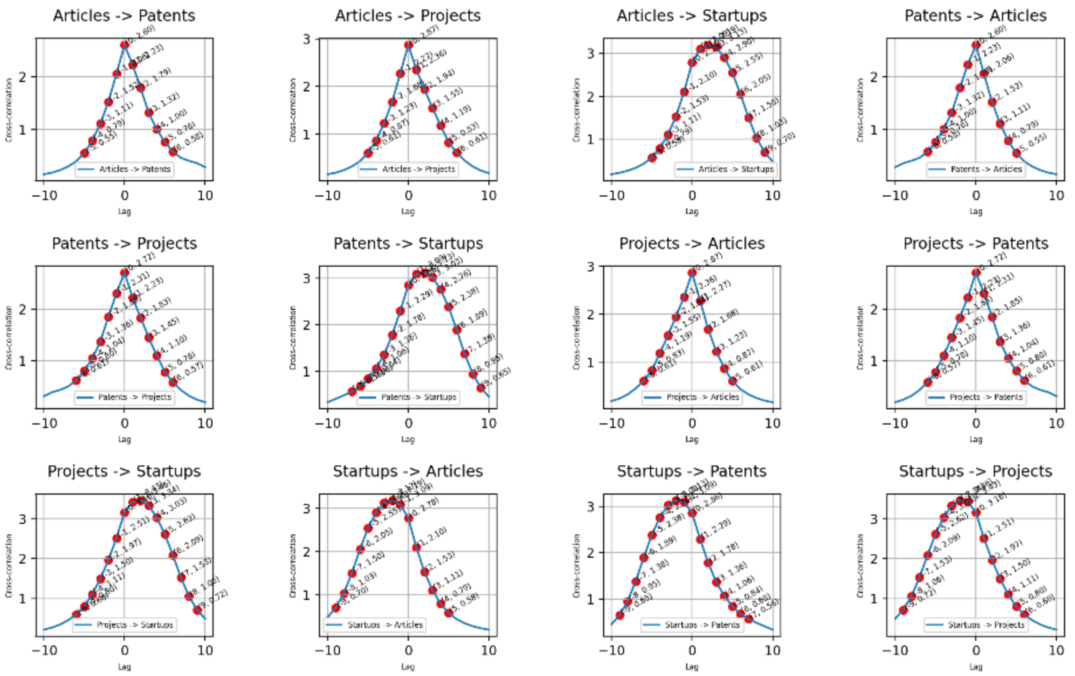

Figure 13. Cross-Correlation Plots (Source: Authors' computation using Python).

Overall, these results highlight the significant role of patents as a leading indicator of both research outputs and implementation activities, while also emphasizing the emergence of start-ups as a key downstream outcome of innovation processes. The observed bidirectional relationships between articles and patents suggest a feedback loop between research and innovation, while the strong influence of patents on projects underscores the importance of technological advancements in driving applied activities. However, the lack of significant relationships between articles and projects suggests that practical applications may rely more on innovation outputs than on direct academic research. Finally, the limited influence of start-ups on upstream processes suggests that entrepreneurial activities are primarily influenced by, rather than influencing, broader innovation and research systems.

4.5. Limitations and Future Improvements

The current research reached to answer the proposed research questions but some limitations need to be drawn for a proper interpretation of the results. While the three pillars defined by research academic work in articles, patents filling and companies established with the fields of interest AI along with agriculture are transposed in time series extracted from worldwide sources, thus describing the overall evolution and interest in this domain, the projects pillar was formed only out of Cordis projects. This database is representing the image of research and investment in research in the European union. Further investigations can be taken in consideration for extension with other such programs.

Another aspect crucial to be mentioned in this section in the method that involves the criteria of selection when it comes to all analyzed pillars. The presented implementation of the methodology within section 3 was conducted starting from the premises that it is nearly impossible to compare using LLM techniques all materials available within WOS database in order to determine those that are of great importance of the intersection of fields agriculture and AI. For that, our approach used the set of key-words for field description. Seen as an initial limitation, it then transformed into a generical method for transposing the set of key-words in other databases, such as: Cordis, Crunchbase and WIPO.

Further development of the study could involve incorporating additional phases of the innovation lifecycle and extending the analysis to other industries to assess the general character of the findings.

5. Conclusions

In the present work we have investigated the intersection between two domains of maximum impact in nowadays evolution, namely artificial intelligence and agriculture. The objective of extending current research done upon this intersection of domains with a more in deep evaluation of the major pillars that are describing the innovation lifecycle was reached using time-series investigations, statistical methods for smoothing the series and for causal analysis, along with additional approach combining sub-domain classification for particular evaluation of the evolution of this domain in sub-categories.

The overall compared evolution given by the academia and projects dragging the patent series indicate the outcomes of research being translated into more tangible advancements in technology. For academia and projects series are seen as leading indicators when it comes to innovation, the early growth showing a steady projection before the immersive rise in the recent years. Some implications between the analysis of academia and project evolution may suggest more investments that need to be done in research and innovation projects, thus supporting the surge in the academic research. For the patents' direction, the innovation environment more likely shifted towards protecting the intellectual property, leading to a maturity in the advancements within the technological field. The only pillar that faced a decrease of interest is represented by the startups, this decline suggesting more of a consolidation within the domain or a shifting in the investors' interests.

The results of the statistical analysis confirm a sequential progression, answering research question RQ_2, with start-ups emerging first, followed by projects, articles, and finally patents, highlighting a structured but non-linear innovation pathway. The Granger causality supports the hypothesis that academic research drives patents and start-ups, while also indicating weak feedback effects, from patents and start-ups back to research. However, the influence of articles on projects and vice-versa is less pronounced, suggesting that research activity does not directly lead to implementation efforts, answering to RQ_3. These findings are further reinforced by impulse response analysis, where a shock to patents positively influences research output, while a shock to articles demonstrates a negative effect on patents, implying that increased research activity does not necessarily translate into the same outcome for technological filings. Cross-correlation results further validate the role of patents as a leading indicator for both research and implementation activities, as well as the role of start-ups as a downstream outcome with limited feedback effects. In relation to the research questions, there is evidence of sequential causality in the innovation lifecycle, with patents acting as a driver of both research and application, RQ_5. However, the expected influence of projects on patents remains weak, and the link between academic research and project initiation appears inconsistent.

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