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DECISION-MAKING IN AGRIBUSINESS, A MULTIVARIATE APPROACH AS A STRATEGY: CULTIVATED SOIL PRODUCTION, ANIMAL BREEDING, AND JOB OPPORTUNITIES

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ABSTRACT

Rapid population growth creates dynamics that demand efficiency and effectiveness in productive markets. In this context, assisted decision-making in agribusiness requires successful strategies that enable the needs of these markets to be met. To achieve these objectives, it is necessary to develop agricultural activities that generate information in key areas of production. Furthermore, with the emergence of big data and smart agriculture, a large amount of heterogeneous data with complex structures has been generated. This study seeks to provide a strategy that allows for sound decision-making to evaluate the feasibility of agribusiness by analyzing the factors of production of cultivated land, animal husbandry, and registered employment in Ecuador, through the application of a robust three-way multivariate analysis methodology, the KF-STATIS approach, with K -Fold (k=5) validation, in the Continuous Agricultural Area and Production Survey of Ecuador. The results found allowed us to identify common and differentiated structures in the agricultural production dynamics of Ecuadorian provinces. For the inter-structure, the first two principal components accumulated 69.91% of the total variance, showing a robust representation of the information. Contrasting production patterns were identified between regional quadrants, highlighting specialization in pastures, livestock, and poultry in the coastal area, and a silvopastoral and agroindustrial focus in the Andean and Amazonian regions. The validation of the model obtained an RV coefficient of 0.98, confirming its high stability and reliability. This knowledge strengthens agribusiness decision-making through integrated multivariate analysis of the area.

KEYWORDS: Agribusiness, Agricultural Intelligence, Multivariate Analysis, KF-STATIS.

1. INTRODUCTION

Today, farms believe that knowledge is very important for the growth of the agricultural market in a way that does not cause harm, through the combination of many types of data, new machinery, and the proper use of natural resources [1], [2]. The great complexity of methods for growing plants and raising animals requires approaches that combine factors such as plant varieties, animal productivity levels, and field work models in order to replicate situations of good use and resilience in the face of climate change challenges [3], [4]. Here, the emergence of artificial intelligence and machine learning tools has helped to better understand agricultural data and change the way decisions are made into something that is evidence-based [5].

Many recent studies say that switching to smart forms of agriculture requires not only new technologies but also a major change in the agricultural industry through models that predict and integrate data on space, climate, money, and labor [6], [7]. Multivariate analyses help to see connections between land use, the ability of animals to grow, and how easy it is to find workers, thereby improving effective plans in the food chain and green policy. [8]. These approaches make it possible to understand how changes in climate or money could affect ways of doing things, strengthening the capacity of rural communities to adapt.

The increase in multivariate models for farms and fields has proven necessary to find connections between productivity, new technology, and job creation. Recent research highlights the importance of big data in managing agricultural risks, improving water use, and detecting animal diseases. This provides new opportunities to integrate artificial intelligence in participatory ways for rural development [5], [8]. These changes are creating an increasingly connected agriculture where the quantity of products exceeds the ability to analyze and make good use of what is known.

This article is divided into five basic subtopics that illustrate the theoretical and methodological analysis of agricultural intelligence in the agricultural sector. To begin with, it discusses arable land and its study in smart agriculture as a basis for continuous production. Next, it looks at livestock and its effect on the agricultural sector, examining the biotechnological and economic factors of current livestock farming. Later, it reviews the option of working in the agricultural sector and how work goes hand in hand with agricultural growth. Multivariate analysis presents statistical tools for the integration of agricultural production variables. Finally, the KF-STATIS method is presented as a structure-linking model that allows for the comparison and linking of very different data sets in the field of agriculture.

1.1. *Search for soil used for planting plants and its use in smart agriculture*

New technologies have ushered in a new era in soil research thanks to the combination of sensors that work independently. The use of satellite photos and artificial intelligence algorithms. These tools can see how moist the soil is, as well as its condition and structure at a given moment, providing important information for taking good care of plants.

Between 2021 and 2023, knowing where the land used for planting, also called arable land, is located has become very important in the world of smart agriculture, as it is seen as important for maintaining a good cropping system [9], [10]. During this time, scientific writings have discussed at length the role of soil. Not only as a support for plants, but also as a complex living environment that, when managed correctly, leads to good production, food security, and the ability to withstand extreme climates [11].

In 2021, improvements in precision agriculture made a significant change by including sensors, remote sensing, and artificial intelligence to view different aspects of the land and make better choices about the field [12]. Subsequently, in 2022, research on the digitization of agriculture integrated Internet of Things (IoT) tools and multivariate predictive models, enabling real-time analysis of interactions between soil moisture, texture, and nutrient content. [13]. In 2023, trends toward conservation agriculture, which combines sustainable soil management with agroecological practices and reduced environmental impact, were consolidated [14]. These advances reflect a conceptual shift from intensive agriculture to intelligent management of arable land, based on accurate data and automated decision-making. Therefore, the period 2021-2023 represents a phase of scientific and technological maturity that redefines the role of soil as a dynamic and multifactorial system, making it crucial for the development of sustainable farms [11].

Currently, research on arable land for the period 2024-2025 reflects significant developments in smart agriculture focused on sustainability and adaptation to global climate variability [3]. In 2024, studies focused on the development of autonomous and accurate technologies for soil analysis, such as drones, remote sensors, and smart planting systems capable of recording soil moisture, compaction, and texture in real time [15], [16]. These developments have made it possible to optimize the use of agricultural inputs, improve irrigation efficiency, and strengthen resilience to extreme weather events by consolidating the integration of artificial intelligence into soil management [17].

In 2025, research moved towards an environmental policy approach to soil, taking into account the important role of land in food security and reducing the effects of climate change [15], [18]. By applying multivariate models and computer-assisted simulations to soil dynamics, it was possible to anticipate cases of erosion, loss of organic matter, and access to nutrients, thus combining environmental protection with yield [19].

In this way, the 2024-2025 biennium shows great progress in the way we see soil as something alive and ready, and whose care using data helps to make better and more sustainable decisions in today's agricultural business [1], [7].

1.2. *Animal production and its impact on the agricultural industry*

Animal production has undergone major changes in agriculture, where environmentally friendly technologies, process automation, and the pursuit of energy efficiency are being introduced [20], [21]. In 2021, many studies showed the important role that livestock plays in the shift towards more balanced agri-food systems, where reducing emissions and managing food resources was very important [22], [23]. During this time, concerns also arose about animal welfare and product traceability, which directly affected the good standing of meat and dairy chains [24], [25].

In 2022, the combination of precision farming practices with smart animal husbandry systems made it possible to improve the use of food, water, and energy through sensors and algorithms that make [26], [27]. These innovations reduced production losses and improved health monitoring of species, particularly in pig and poultry farming, where models were used to predict growth and feed consumption [28].

In 2023, scientific literature consolidated a comprehensive view of livestock production as the backbone of the agro-industrial economy, linking profitability with environmental sustainability and rural job creation [21]. This multivariate approach emphasizes the interdependence between productivity, technological innovation, and environmental responsibility, and positions modern livestock farming as a vital component of a sustainable 21st-century agricultural economy.

Research today shows a clear shift in how animals are raised, driven by the use of smart technologies, environmental sustainability, and improvements in the agriculture and food chain [29], [30]. In 2024, studies focused on highlighting the negative effects of livestock systems and emphasized the need to reduce emissions from meat and dairy production through circular approaches and low-carbon economy methods [31], [32]. These studies say that it is very important to provide information on energy use, land use, and animal welfare to ensure that agricultural businesses are good in a place with high environmental standards [33], [34].

In 2025, the trend is moving toward Precision Livestock Farming (PLF), which combines sensors, computer vision, and artificial intelligence to monitor animals' physiological and behavioral parameters in real time [35], [36]. This approach helps prevent disease, improve nutrition, and optimize resources, thereby increasing the profitability and sustainability of livestock farms [30]. In addition, Industrial Internet of Things (IIoT) systems are being implemented to automate barn management, feeding, and environmental control, thereby improving traceability and transparency in production [37].

In general, current research consolidates livestock production as a strategic pillar of the agricultural industry in the 21st century, where digitization, production ethics, and sustainability come together to create more resilient, competitive, and responsible agro-industrial models [29].

1.3. *Employability in the agricultural sector*

Employability in the agricultural sector has become a strategic component of rural development and the economic sustainability of agricultural production chains. In a place that has automation, digitization, and major changes in the labor market, human talent plays a very important role. In innovation and competition within the field of agriculture [38], [39]. This new idea recognizes that technical knowledge, adaptability, and good digital skills are very important in helping workers enter increasingly advanced agricultural systems [40].

From 2021 to 2023, scientific literature highlighted the transition to an agro-smart employment model, where a mix of technologies and environmental care are making a difference for professionals [41]. During 2021, studies have discussed the impact of the use of machinery and online platforms on the new form of agricultural work, bringing opportunities and problems to rural workers. [39]. In 2022, the focus was on strengthening the digital and business skills needed to operate agro-industrial management and e-commerce systems with connections to the global market [38]. In 2023, the vision of employability as a process of social innovation was consolidated, in which technical training and the involvement of rural youth and women are essential factors in promoting a sustainable agricultural economy [42].

The results of recent research show a major shift in the idea of working in agriculture, due to digitization, automation, and the coming together of better ways to organize [43]. Changing technology in this field has led to increased demand for people who know how to use smart production systems, manage supply chains that help the planet, and are ready for mixed workplaces where data connection and analysis are very important [44].

In 2024, a study showed how important blockchain and digital traceability are as tools for ensuring clarity, fairness, and legality in rural work [43]. Technologies have made it easier to certify skills, better manage decentralized talent, and reduce the number of middlemen, thereby strengthening trust between producers, sellers, and buyers. In 2025, the focus was added to encompass strategic talent management in places where food is made, emphasizing how vital it is to constantly learn, work together as leaders, and let women and young people in on the action of doing new things to produce [45].

Nowadays, the ability to find work in the field is seen as a constantly changing process of recycling and digitization that is good for the environment. Technology does not take jobs away from people, but rather improves what they do with smart spaces where they work together. This new idea changes how labor relations are conducted in the area and helps to create a smarter and stronger workforce, in line with the Sustainable Development Goals [44].

1.4. Multivariate analysis

Multivariate analysis is a fundamental tool in modern agricultural research, as it allows for the simultaneous study of multiple variables that interact in complex agricultural systems. Methods such as principal component analysis (PCA), multivariate regression, and cluster analysis make it possible to identify patterns, optimize decisions, and improve the efficiency of natural and productive resource management [46], [47]. The application of multivariate analysis in agriculture helps to understand the interrelationships between ecological, economic, and technological factors, and to improve strategic planning in highly dynamic environments [48], [49].

Between 2021 and 2023, research on multivariate analysis will demonstrate its growing relevance for predictive modeling of agricultural performance, evaluation of sustainable production systems, and understanding of complex interactions between ecological, economic, and technological variables [50]. During this period, the multivariate approach became established as a key tool for integrating large amounts of information from heterogeneous sources, such as climate sensors, soil records, and market data. This enabled the identification of significant patterns that facilitate strategic decision-making in the agricultural sector [51].

In 2021, work focused heavily on improving the accuracy of statistical models used to make statements about agricultural variables under difficult conditions, with particular attention to important crops such as soybeans, corn, and tropical fruit [52]. There was talk of advances in ways of drawing lines between multiple variables and viewing principal components (PCA) that helped identify key aspects for productivity and resilience in the face of climate change.

Then, between 2022 and 2023, the market grew toward a mix of multi-variable analysis with artificial intelligence techniques and big data, creating hybrid models capable of jointly processing information on society, the economy, climate, and the market [51], [53]. This methodological synergy not only increased the accuracy of forecasts, but also provided a holistic view of the agricultural production system, linking ecological sustainability with economic profitability.

In recent years, multivariate analysis has been seen as a much-needed tool for predicting, finding, and improving agricultural production systems. Its combination with digital technologies and artificial intelligence models makes it clearer how difficult this reality is and what agricultural or monetary conditions are worth, while also looking at biological, economic, and climatic factors [54], [55]. This change in method has strengthened the ability of agricultural companies to predict how the work will go and make important decisions in situations where we do not know exactly what will happen [56], [57].

In 2024, research focused on creating predictive models to monitor crop yields and better understand agricultural environments, taking into account factors such as soil moisture, heat, genetic makeup, and food availability [55]. At the same time, the use of machine learning techniques and data mining increased. These complement typical statistical analysis and make it easier to understand large amounts of information generated by remote sensing sensors, drones, and digital spaces [58].

In 2025, the way things were done changed to combine aspects related to money and society. This allowed for the joint modeling of factors influencing profitability, access to credit, and the financial sustainability of agro-industrial companies. In addition, hybrid approaches emerged that combined neural networks and classical principal component analysis methods. This optimized the interpretation of nonlinear relationships between productivity, investment, and climate change [59], [60]. In summary, the 2024 and 2025 studies confirm that multivariate analysis has become an integral agricultural information tool, indispensable for planning, risk management, and the sustainability of agricultural businesses in the context of digital agriculture.

1.5. KF-STATIS

The KF-STATIS method [61], is an extension of the three-way STATIS method (Structuration des Tableaux A Trois Indices de la Statistique) [62], which allows the stable part between matrices measured over time to be analyzed. It also incorporates k-fold cross-validation to determine the STATIS model's ability to generalize in the processed data [63].

In the context of the data analyzed in this study, the KF-STATIS method enables the identification of the stable component of agricultural activities related to crop production, livestock, and employment. The robustness of the model's application is validated through five-fold cross-validation (k = 5).

Accordingly, this research seeks to answer the question: How does the use of multivariate methods particularly the KF-STATIS approach contribute to strengthening decision-making in agribusiness models through the integrated analysis of agricultural information? The corresponding hypothesis is as follows:

H1: The use of multivariate methods, specifically the KF-STATIS approach, strengthens decision-making in agribusiness models through the integrated analysis of agricultural information.

There is a growing need to use sophisticated modeling techniques to manage the complexity of the field and improve decision-making in the agricultural business. Multivariate methods allow us to look at many things at the same time —such as planted area, animal production, and off-farm work—by capturing how they are related in ways that other simple methods cannot show as well.

The KF-STATIS method, which is based on merging well-made tables and finding common ground, allows different sets of agricultural data to be compared at the same time. This property is very useful when dealing with different variables (agricultural, livestock, and labor), as the technique makes it possible to obtain a complete overview of the sector. The addition of K-fold cross-validation adds extra value by ensuring the robustness of the model in the face of overfitting, which provides more reliable estimates for cases of assumption and imitation.

In agriculture, this combination of methods not only helps to clearly see patterns of doing things and working, but also strengthens what is known about the field, such as turning official figures into good ideas for use in management. By combining accurate data according to FAO rules, the KF-STATIS method is a very good way to reduce uncertainty when planning, looking at different actions, and putting plans in place with a view to long-term sustainability..

Consequently, the proposed hypothesis is justified under the premise that multivariate methods and particularly the KF-STATIS approach not only describe the dynamics of the agricultural sector but also enhance strategic decision-making in the agribusiness industry, supporting a more resilient, sustainable, and evidence-based management model.

2. METHODOLOGY

2.1. Data source

The dataset corresponds to the Technical Bulletin of the Continuous Agricultural Production Statistics System (ESPAC) [64], published by the National Institute of Statistics and Census (INEC) of Ecuador in 2024. This dataset collects structured information on the country's agricultural and livestock production, broken down by province, canton, crop group, specific crop, and type of production system, with an emphasis on economic, technical, and social variables. Among the agricultural production activities to be studied in this paper are:

Table 1: Factors and study measures.

Factor	Measurements / Variables
T1 Area by Land Use Category, by Region and Province	• Permanent Crops • Temporary Crops and Fallow Land • Cultivated Pastures • Natural Pastures • Moorlands (Páramos) • Forests and Woodlands • Other Land Uses

T10 Number of Livestock Heads by Species, by Region and Province	• Cattle • Swine • Sheep • Donkey • Horse • Mule • Goat
T61 Number of Heads of Other Livestock Species, by Region and Province	• Donkey • Horse • Mule • Goat
T62 Number of Poultry Raised in the Field by Species, by Region and Province	• Roosters and Hens • Chicks and Pullets • Ducks • Turkeys
T69 Number of Paid and Unpaid Workers by Sex, by Region and Province	• Unpaid Male Workers • Unpaid Female Workers • Permanent Male Workers • Permanent Female Workers • Occasional Male Workers • Occasional Female Workers
T70 Area Planted with Cultivated Pastures, by Region and Province	• *Brachiaria* • *Gramalote* • Honey Grass (*Pasto Miel*) • *Saboya* Grass • Mixed Pastures • Other Cultivated Pastures

Note: The factors were selected from the Technical Bulletin of the Continuous Agricultural Production Statistics System (ESPAC).

2.2. *Data structure for the analysis format*

According to the structure defined in [61], in Figure 1, the dimensions of the model are adapted to the data set that is the subject of our study. First, the matrix is defined, where the columns correspond to factors related to land use. The columns relate to the provinces, and the rows correspond to the measurements taken by province. Dimension k seeks to measure how the matrices relate to the factors of agricultural production.

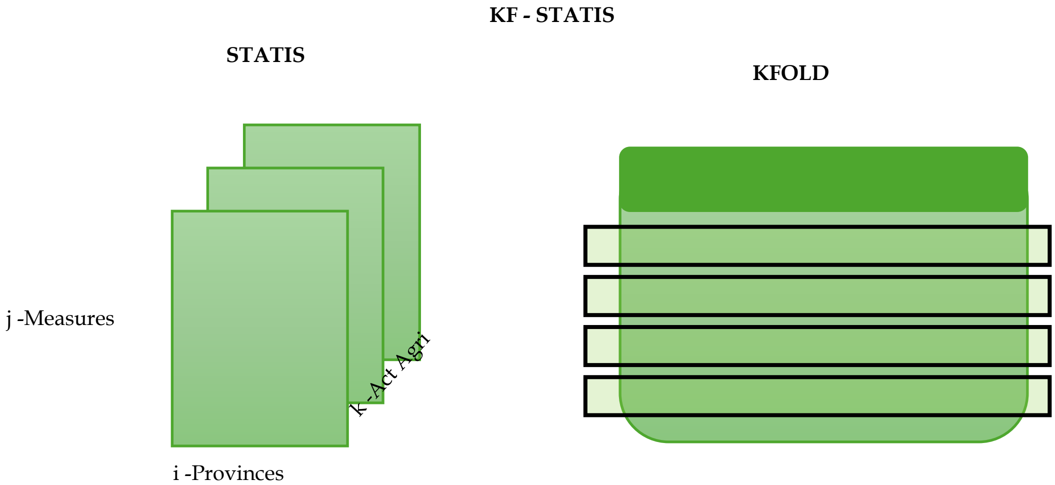

Figure 1: Structure of the adapted model.
Note: Structure adapted to the study context

Table 2: Definition of the dataset structure.

Variable	Description
Table	Represents the type of agri-productive activity analyzed.
Means	Corresponds to the provinces of Ecuador, used as the units for calculating average values.
Provinces	Refers to the 24 administrative provinces of Ecuador included in the analysis.

Note: Structure of the dataset required for the KF-STATIS model

3. RESULTS

3.1. *Analysis of the Interstructure*

For the definition of the Inter-Structure, six principal components were extracted. The first two components, which account for the largest proportion of explained variance, together captured 69.91% of the total variance (see Table 2). This value is considered adequate and supports the following interpretation.

In Figure 2A, the table T10 (Number of Livestock Heads by Species, by Region and Province) best represents the overall trend and characteristics of the agricultural activities analyzed in this study. Additionally, Figure 2B reveals a strong similarity between T1 (Area by Land Use Category, by Region and Province) and T70 (Area Planted with Cultivated Pastures, by Region and Province), attributable to their weighted nature across matrices. Furthermore, a sequential relationship was identified between T61 (Number of Heads of Other Livestock Species, by Region and Province) and T10 (Number of Livestock Heads by Species, by Region and Province), as well as between these and T69 (Number of Paid and Unpaid Workers by Sex, by Region and Province) and T62 (Number of Poultry Raised in the Field by Species, by Region and Province). Together, these interconnected activities define a productive and agro-industrial niche that contributes to the generation of employment opportunities.

Table 3: Intra Structure Cumulative Variance.

Statisticians	CP1	CP2	CP3	CP4	CP5	CP6
Eig	3,312	0,883	0,7	0,581	0,351	0,174
% variance	55,20%	14,72%	11,66%	9,68%	5,85%	2,90%
% Variance Cumulative	55,20%	69,91%	81,57%	91,26%	97,10%	100,00%

Note: Components 1 and 2 account for 69.91% of the explained variance

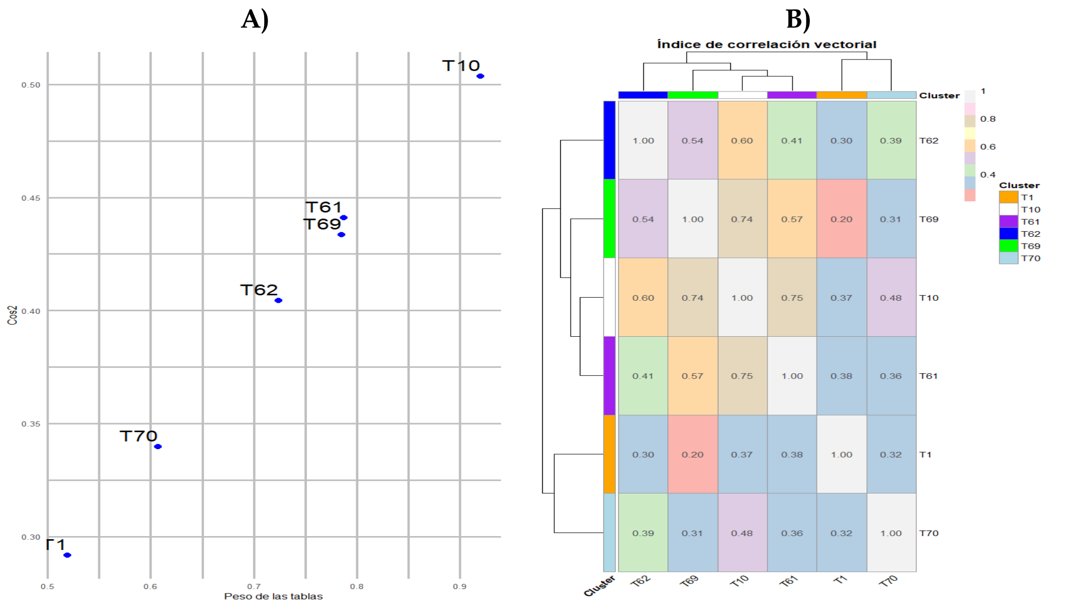

Figure 2: Correlation tables.

3.2. *Compromise Structure*

For the definition of the compromise, twenty-four principal components were extracted. For the corresponding analysis, the first two components accounting for 68.46% of the cumulative variance were selected (see Table 3). This value is considered adequate and supports the following interpretation.

In Figure 3, two relevant clusters are observed. The first cluster, located in Quadrant II, includes five coastal provinces, four highland provinces, and three from the Amazon region: Manabí, Esmeraldas, Los Ríos, Santo Domingo de los Tsáchilas, Guayas, Carchi, Bolívar, Riobamba, Napo, Pastaza, Santa Elena, and Sucumbíos. The second cluster, located in Quadrant III, comprises one coastal province, eight from the highlands, and three from the Amazon region: Azuay, Cañar, Cotopaxi, Chimborazo, Imbabura, Loja, Pichincha, Tungurahua, El Oro, Morona Santiago, Orellana, and Zamora Chinchipe.

Based on the clustering patterns, it is noteworthy that the provinces grouped in Quadrant II are predominantly from the highland and Amazon regions, whereas those in Quadrant III show a more balanced distribution between coastal and highland provinces, with a comparable number of provinces from the Amazon.

Table 4: Commitment Cumulative variance.

Main component	Eig	Variance	Variance Cumulative
CP1	1,763	0,594	59,40%
CP2	0,269	0,091	68,46%
CP3	0,251	0,084	76,90%
CP4	0,170	0,057	82,64%
CP5	0,128	0,043	86,95%
CP6	0,086	0,029	89,84%
CP7	0,081	0,027	92,57%
CP8	0,064	0,021	94,71%
CP9	0,048	0,016	96,31%
CP10	0,032	0,011	97,38%
CP11	0,024	0,008	98,20%
CP12	0,018	0,006	98,80%
CP13	0,014	0,005	99,25%
CP14	0,009	0,003	99,55%
CP15	0,006	0,002	99,77%
CP16	0,003	0,001	99,86%
CP17	0,002	0,001	99,93%
CP18	0,001	0,000	99,96%
CP19	0,001	0,000	99,98%
CP20	0,000	0,000	99,99%
CP21	0,000	0,000	99,99%
CP22	0,000	0,000	100,00%
CP23	0,000	0,000	100,00%
CP24	0,000	0,000	100,00%

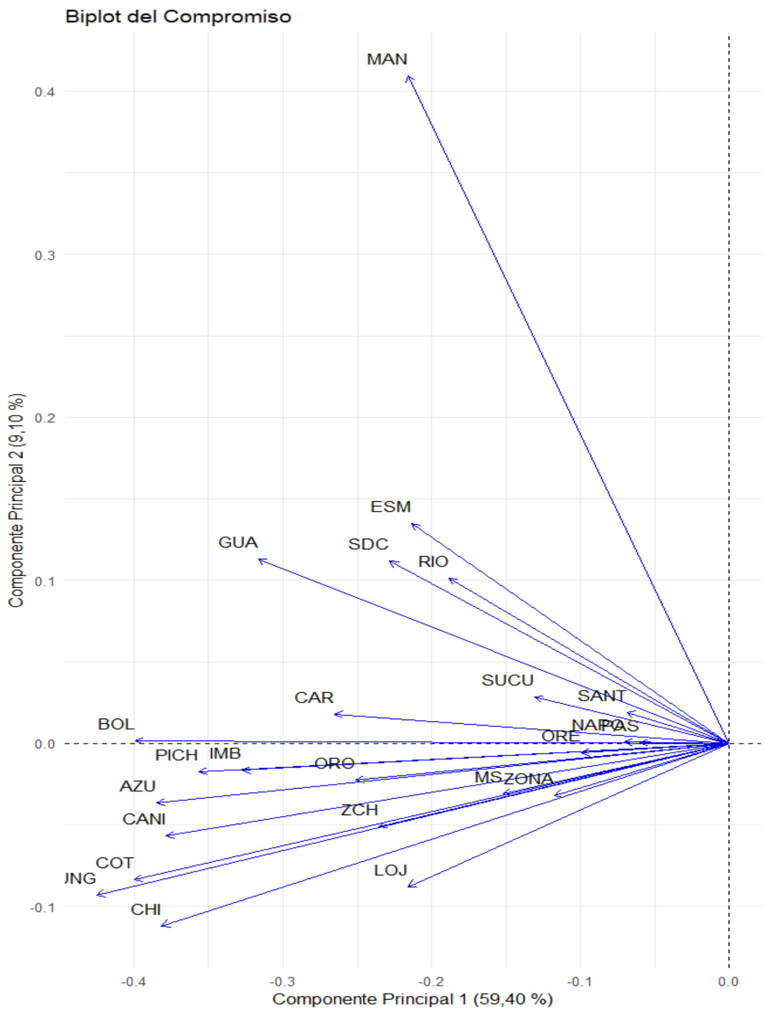

Figure 3: Compromise.

3.3. *Intra structure*

Based on the intra-structure projections and the measurements for each agricultural activity in quadrants II and III (see Figure 4), the following interpretation is provided:

3.3.1. Quadrant II

According to data from the ESPAC 2024 Technical Bulletin, the provinces of Manabí, Esmeraldas, Los Ríos, Santo Domingo de los Tsáchilas, Guayas, Carchi, Bolívar, Riobamba, Napo, Pastaza, Santa Elena, and Sucumbíos report high levels of agricultural and livestock activity. This trend is particularly evident in the extensive use of land for Cultivated Pastures (T1) (see Figure 4A) and in the large numbers of cattle and swine heads (T10) (see Figure 4B), especially in the province of Manabí.

However, the intra-structure analysis reveals deeper and more complex patterns. Within this quadrant, latent relationships emerge between specific provinces and productive activities. Manabí exhibits a strong structural correlation not only with the area of cultivated pastures but also with horse breeding (T61) (see Figure 4C) and chicken and poultry rearing (T62) (see Figure 4D). This pattern suggests the presence of an intensive and diversified agro-livestock system that is not immediately observable through surface-level data. Esmeraldas, in turn, appears as a key node in the rearing of young poultry, potentially indicating a capital rotation strategy within its poultry production systems.

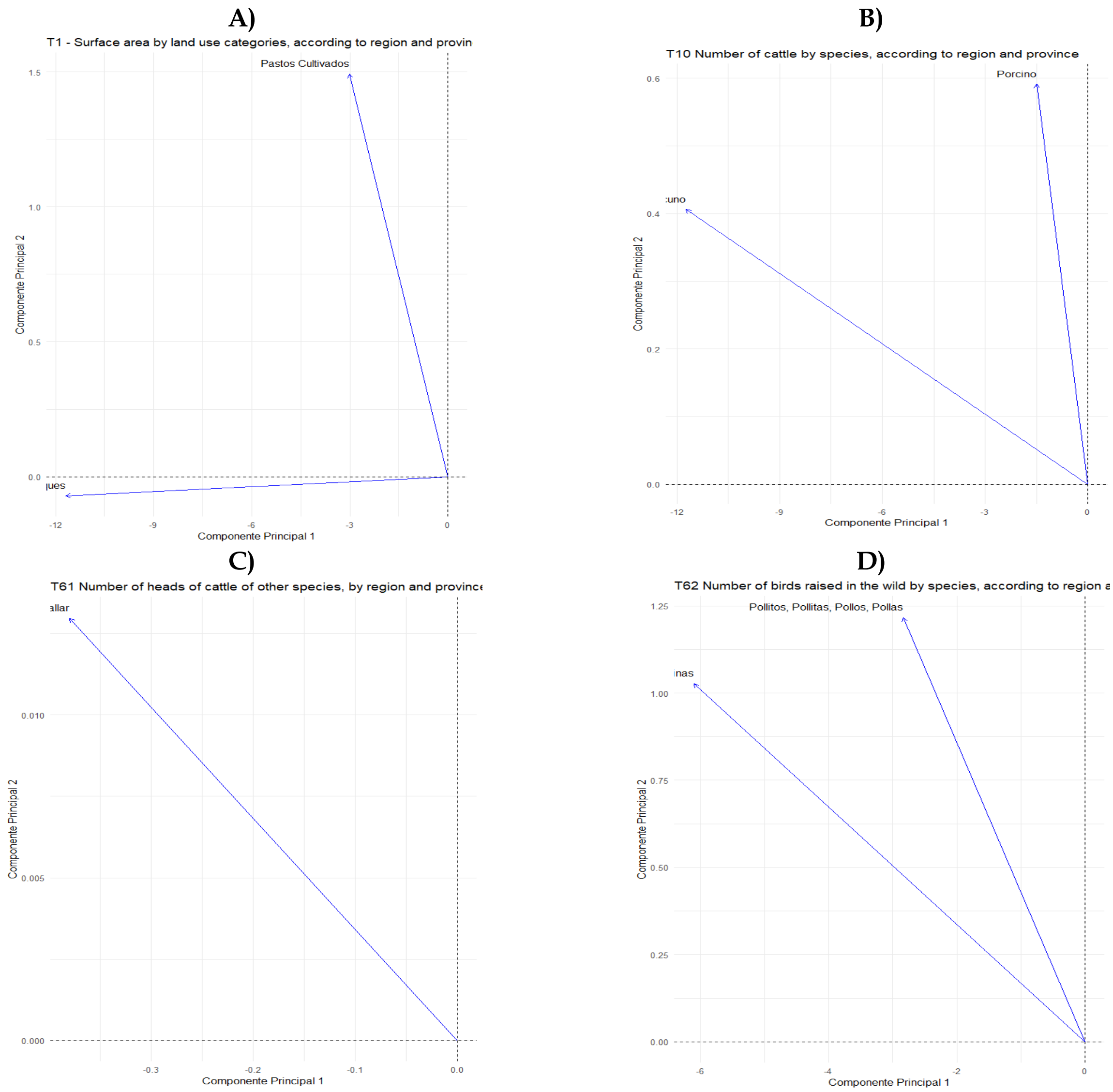

Figure 3: Intra structure.

Note: A) T1 Surface area by land use categories, according to region and province. B) T10 Number of cattle by species, according to region and province. C) T61 Number of heads of cattle of other species, by region and province. D) Number of birds raised in the wild by species, according to region and province.

3.3.2. Quadrant III

The ESPAC 2024 Technical Bulletin reports that provinces such as Azuay, Cañar, Cotopaxi, Chimborazo, Imbabura, Loja, Pichincha, Tungurahua, El Oro, Morona Santiago, Orellana, and Zamora Chinchipe concentrate their activities on forest land use (Forests and Woodlands) (T1) (see Figure 5A), emphasizing environmental conservation and silvopastoral management. Likewise, Activity T69 (see Figure 5B) shows a significant share of the agro-industrial labor force, indicating the predominance of family-based and collective labor within the Andean–Amazonian region.

From the perspective of the intra-structure, these patterns become more clearly defined. Distinct groups of provinces display structural affinities in the use of mixed pastures and other cultivated forage types (T70) (see Figure 5C), reflecting a productive specialization that integrates traditional and agroecological practices. For instance, Loja, Chimborazo, and Zamora Chinchipe share a similar land-use structure that would not be apparent from isolated data alone.

This structural analysis reveals that the agricultural dynamics within Quadrant III follow a complex regional logic, in which land-use strategies, employment patterns, and diversification processes are interwoven beyond the totals reported in descriptive tables.

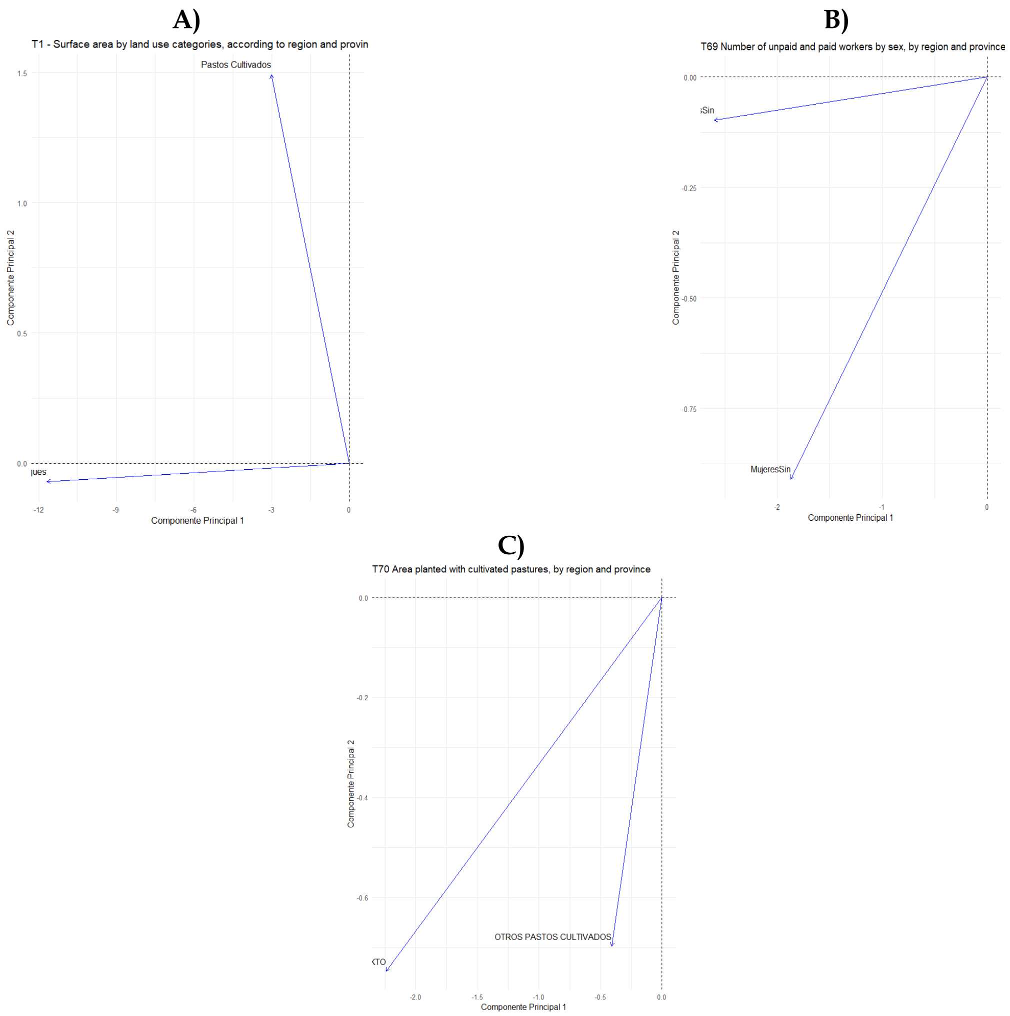

Figure 4: Intra-structure for each k-table.

Note: A) T1 Surface area by land use categories, according to region and province. B) T69 Number of unpaid and paid workers by sex, by region and province. C) T70 Area planted with cultivated pastures, by region and province.

3.4. Kfold

To evaluate the structural stability of the multivariate model, a K-Fold Cross-Validation procedure with k = 5 partitions was applied. This technique allowed for the estimation of the consistency of the relationships projected within the factorial space, minimizing the risk of overfitting and ensuring the robustness of the extracted patterns.

The analysis yielded an RV coefficient of 0.98, indicating an exceptionally high degree of similarity among the factorial configurations obtained from the different data partitions. This value confirms that the latent structure identified is highly stable and that the observed relationships between variables and individuals (provinces and activities) are not the result of random variation or a particular data configuration, but rather represent reproducible patterns under varying partition conditions.

This finding supports the internal validity of the model and reinforces confidence in the interpretations derived from the intra-structure analysis, enabling a reliable projection of results to comparable or extrapolated contexts.

4. DISCUSSION

Multivariate analysis using the KF-STATIS framework, combined with five-fold cross-validation, revealed a robust and consistent structural configuration in the representation of agricultural data across Ecuadorian provinces. The cross-validation procedure confirmed that the first two principal components explained 69.91% of the total variance, a proportion sufficient to provide a statistically robust basis for identifying underlying patterns. The correlation figures also confirm significant structural relationships between variables such as livestock (T10), pasture management (T70), poultry farming (T62), and the agricultural labor force (T69). These reflect an agro-productive network that integrates natural resources, territorial distribution, and employment structures.

The analysis also revealed a clear segmentation between provinces and regions, grouped according to different agro-industrial dynamics. The intrastructural projections of quadrants II and III confirm that productive diversification and land-use strategies are not homogeneous, but are determined by historical, geographic, and organizational factors. The coastal provinces are characterized by diversified agricultural systems, while the Andean-Amazonian provinces combine silvopastoral approaches with intensive family labor models, highlighting the regional differentiation of production systems.

The k-fold validation ($k = 5$) yielded an RV coefficient of 0.98, confirming the robustness and reproducibility of the proposed model. This result demonstrates that the observed patterns are not random or the result of overfitting, but rather reflect stable structural relationships across multiple data partitions within the same analytical universe. The robustness of this validation supports the internal consistency of the model and allows its results to be projected to similar agroindustrial contexts. Furthermore, the results support the hypothesis that the use of multivariate analysis frameworks, particularly KF-STATIS, improves strategic decision-making in agricultural economic models through the integrated analysis of agricultural datasets.

The method effectively combines multiple agricultural data tables (k-tables), revealing configurations that would not be evident through simpler or isolated analyses. Supported by robust principal components, this integration allows for a clearer understanding of land use, production processes, and labor distribution, thus providing decision-makers with valuable insights into the structural dynamics of regional agricultural systems.

Furthermore, the inclusion of the k-fold cross-validation technique provided empirical evidence of the model's stability and predictive potential. The high agreement between factor configurations across partitions underscores the method's ability to produce reliable and transferable results when applied to new or comparable datasets. This methodological synergy not only improves the analytical quality and explanatory depth of the study, but also strengthens the strategic capacity for agricultural policy design and facilitates the allocation of resources and interventions in areas with complex structural patterns.

5. CONCLUSIONS

This study shows that intelligence on how to manage land is supported by new methods such as multiple analyses and the KF-STATIS method, which is key to organizing and making agriculture more sustainable. The different parts of the analysis showed that the digital transformation of agriculture, the modernization of livestock systems, the emergence of smart working options, and the combination of comprehensive statistical models are creating a place where technology and people are constantly changing.

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The data shows that combining information on agriculture, livestock, and labor reveals patterns hidden in normal studies, thus providing a comprehensive view of how the land works and produces. The use of the KF-STATIS model, tested with various tests, showed that there is stability and strength in the complex relationships, reaching an RV number of 0.98; this shows how solid and repeatable the results are. Furthermore, the use of digital technologies, artificial intelligence, and modern statistical techniques is shifting towards a data-driven agricultural management model that can prevent bad weather, improve resource use, and help make important decisions based on evidence. The study in different areas showed that there is great inequality between provinces and highlighted Ecuador's productive diversity, as well as the need for different policies that are well-suited in terms of sustainability. New work.

In summary, the hypothesis is confirmed: the use of multivariate methods, particularly the KF-STATIS approach, enhances the ability of agribusinesses to transform agricultural information into strategic knowledge, thereby strengthening their resilience, competitiveness, and commitment to sustainable development. This research establishes a foundation for future studies in predictive agricultural intelligence, where data become the central axis of innovation and rural governance.

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