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Quantitative Global Typologies of Rainbow Trout Production from FAO Statistics

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Abstract

Rainbow trout (*Oncorhynchus mykiss*) has become a cornerstone species in global freshwater aquaculture due to its adaptability, high nutritional value, and strong consumer demand. However, production levels differ substantially across countries, reflecting a variety of ecological, economic, and technological conditions. This study provides a quantitative, data-driven classification of worldwide rainbow trout production in order to identify common patterns and emerging trends. Using official FAO statistics covering the years 2016-2023 for 77 countries, we calculated three key indicators mean annual production, coefficient of variation (CV), and linear production trend and applied hierarchical cluster analysis based on Ward's method with Manhattan distance. Internal validation measures confirmed the robustness of the resulting clusters, while statistical significance was assessed using non-parametric Kruskal- Wallis tests followed by Dunn's pairwise comparisons. The analysis identified three distinct producer profiles. The first cluster, comprising 63 countries, is characterized by relatively low but stable production. The second cluster (11 countries) also represents low volume producers but exhibits high temporal variability, suggesting inconsistent or fragmented production systems. The third cluster includes only three countries Turkey, Iran, and Russia but shows markedly high production volumes with strong upward trends, positioning them as global growth leaders. By distinguishing stable, volatile and rapidly expanding producers, this study fills a gap in the literature and provides a framework for guiding aquaculture policy, investment and sustainability initiatives at the global scale.

Introduction

Aquaculture is rapidly evolving, now producing more seafood globally than wild-caught fisheries for the first time (FAO, 2024a). This shift makes it a crucial component of global food security, particularly in the context of a growing world population (Anonymous, 2022b). In recent years, the sector has shown significant development driven by advances in genetic research and feed technologies. This growth is further supported by the expansion of international trade, the accessibility of inland water resources, competitive pricing, rising income levels, and accelerating urbanization (D'Agaro et al., 2022). Globally, aquaculture production is increasing, with Asia remaining the dominant producer. Rainbow trout (*Oncorhynchus mykiss*), in particular, stands out as a commercially vital species due to its remarkable adaptability, rapid growth, and high consumer demand (Khammar et al., 2024; Yazman et al., 2025). Beyond its economic importance, it is highly valued for its nutritional profile, being rich in high-quality proteins, unsaturated fatty acids, and essential microelements. Notably, myofibrillar proteins constitute more than 55% of its total muscle protein, playing a critical role in maintaining the structural integrity and spatial stability of the muscle tissue (Zhou et al., 2020). Furthermore, rainbow trout is a key focus of the FAO's "Blue Transformation" strategy, which highlights its potential for sustainable development. However, the rapid expansion of the sector also presents environmental challenges, underscoring the necessity of sustainable practices and strategic initiatives like the 'Blue Transformation' to ensure long-term viability (Anonymous, 2024b).

For a successful rainbow trout farming operation, a deep understanding of production and yield is paramount. In the evolving aquaculture landscape, profitability and long-term sustainability depend on consistently maximizing output while maintaining quality. Unsupervised learning methods, particularly clustering (e.g., K-means), offer powerful tools for achieving this; studies report clustering efficiencies reaching 95–98% in aquaculture systems (Capetillo-Contreras et al., 2024). By analyzing historical production data, researchers can uncover hidden patterns, segment operations into clusters representing optimal yield conditions, identify bottlenecks, and reveal factor correlations. Such data-driven segmentation moves beyond traditional rule-based methods by offering automated pattern recognition built on unlabeled datasets, as demonstrated by the role of clustering in Predictive Health Management (PHM) systems for fish farming (Tan et al., 2024). The application of unsupervised learning in aquaculture is increasingly well-documented; comprehensive reviews of data mining and machine learning in fisheries illustrate its potential to significantly enhance production efficiency (Kaur et al., 2023).

Ward et al. (2013) assessed angler behavior and its impact on rainbow trout across 21 lakes in British Columbia, Canada. Through interviews with 1,956 anglers and fish population assessments, hierarchical cluster analysis identified four distinct angler groups based on spatial distribution, catchability, and harvest behavior. These groups varied across management regions, highlighting the need for tailored management strategies rather than a "one-size-fits-all" approach. Recognizing the diverse characteristics of anglers is crucial for optimizing fisheries management in spatially structured systems. Consequently, the authors emphasize that addressing the specific profiles of these distinct groups is essential for sustainable fishery management. Similarly, the development of rainbow trout production has been rapid in the highlands of central Mexico. Garcia-Mondragon et al. (2021) aimed to characterize these production systems using factor and cluster analysis. The identified groups, including small-scale artisan producers, represent the significant role of aquaculture in rural social development. Furthermore, public policies, government support schemes, market expansion, and increasing consumer demand for trout have collectively favored all four identified production clusters.

Ancco et al. (2023) characterized fish farming clusters and identified factors influencing the profitability of rainbow trout farming in the Abancay province, Peru. Analysis of data from all registered aquaculture farmers in the area revealed four distinct clusters: monoculture micro/small businesses, novice mixed farmers, consumption-oriented family mixed enterprises (utilizing unpaid labor), and extensive self-consumption farmers. Profitability was significantly associated with years of experience, water source, sales market, and primary farming activity. Similarly, Zabarburu et al. (2023) evaluated sustainability and efficiency in 39 Peruvian rainbow trout farms. Production units were grouped by output, and sustainability was assessed using a comprehensive index. Technical efficiency, measured by Data Envelopment Analysis (DEA), revealed that while most farms were technically inefficient, the Amazonas region showed higher efficiency levels. Underutilized resources, such as land, feed, and seed, present clear opportunities for improvement. The study concluded that Peruvian trout farming units differ significantly by production volume and operate at a medium sustainability level, with the majority exhibiting technical inefficiency.

Additionally, unsupervised machine learning methods are extensively applied to diverse fields such as genomics (Blankenship et al., 2011; Palombo et al., 2021), environmental studies (Varol, 2020), and health management (Karadas et al., 2025). These methods excel at uncovering hidden patterns and structures within complex biological datasets, making them particularly valuable when pre-existing labels or prior hypotheses are limited. However, existing studies typically adopt a narrow focus, concentrating on local contexts or specific technical domains. Furthermore, these analyses frequently rely on qualitative methods—such as interviews and case studies—which, while insightful, may fail to provide a comprehensive global perspective. This methodological and contextual confinement leaves a critical gap in the literature, which the present study aims to fill by providing a data-driven, worldwide classification of rainbow trout production.

The present study directly addresses this gap by presenting a worldwide classification of rainbow trout production through a comprehensive, data-driven approach. Moving beyond localized or qualitative perspectives, our methodology identifies and analyzes global production clusters based on quantitative metrics, specifically examining production averages, temporal variations, and short-term trends. This approach provides a broad, empirical understanding of the sector's global dynamics—a perspective that has previously been absent from academic discourse. The primary objective of this study is to develop a robust framework for classifying global production to reveal underlying patterns and growth dynamics. To achieve this, we address the following research question: "What are the dominant global clusters of rainbow trout production, and what characteristics define these clusters in terms of production volume, stability, and growth trends?"

This research has significant implications across several domains. From an academic standpoint, it offers a novel classification system, providing valuable insights for researchers in aquaculture economics, ecology, and management. Economically, the findings can inform policy decisions and investment strategies by highlighting areas of high growth potential and identifying opportunities for targeted interventions. Socially, understanding these production dynamics is essential for promoting equitable resource distribution, ensuring sustainable practices, and supporting the livelihoods of communities dependent on the sector. Unlike conventional production-based classifications that rely primarily on descriptive statistics, this study employs a multi-index validation framework combined with hierarchical clustering to construct statistically robust and globally comparable production profiles. By integrating trend, variability, and mean production indicators, the proposed approach moves beyond static categorizations to offer a dynamic perspective on aquaculture production trajectories across countries.

Rainbow Trout Production Worldwide

Rainbow trout is one of the most widely distributed and commercially significant freshwater cultured fish species globally. Its aquaculture originated from successful farming practices in California, USA, in the late 19th century. Following the first exports of rainbow trout eggs to international markets in 1877, most of the cultured strains currently farmed worldwide are believed to be derived from these California-origin genetic lines. This includes both freshwater-reared rainbow trout and seawater-grown steelhead trout (Hardy et al., 2000). In Europe, trout aquaculture has historically been prominent in countries such as the United Kingdom, Denmark, and Germany, with the first egg shipments to the UK occurring in 1885 (Hinshaw et al., 2004).

The rainbow trout sector experienced substantial expansion during the 1980s (Shaw & Gabbott, 1992). Originally focused on augmenting wild populations, trout farming transitioned toward large-scale commercial food production in the mid-20th century, a shift facilitated by the establishment of specialized processing facilities (Brannon & Klontz, 1989). This period witnessed a significant surge in production volumes, driven primarily by the development of economically viable pelleted feeds, which enabled the global expansion of trout aquaculture (Hinshaw et al., 2004). The global rainbow trout market has maintained a consistent growth trajectory in recent years. Valued at approximately USD 4.5 billion in 2023, the market is projected to reach USD 7.3 billion by 2032, representing a compound annual growth rate (CAGR) of 5.5%. This growth is underpinned by the increasing demand for healthy and sustainable protein sources, technological advancements in aquaculture practices, and a heightened emphasis on environmental stewardship. Growing consumer awareness regarding the health benefits of omega-3-rich fish has significantly stimulated market interest. Furthermore, the rising prevalence of pescatarian and flexitarian dietary patterns has emerged as a key driver fueling market expansion (Dataintelo, 2024).

According to the 2023 aquaculture production data reported by the Food and Agriculture Organization (FAO, 2023), production remains concentrated within a limited number of key nations, as illustrated in Figure 1.

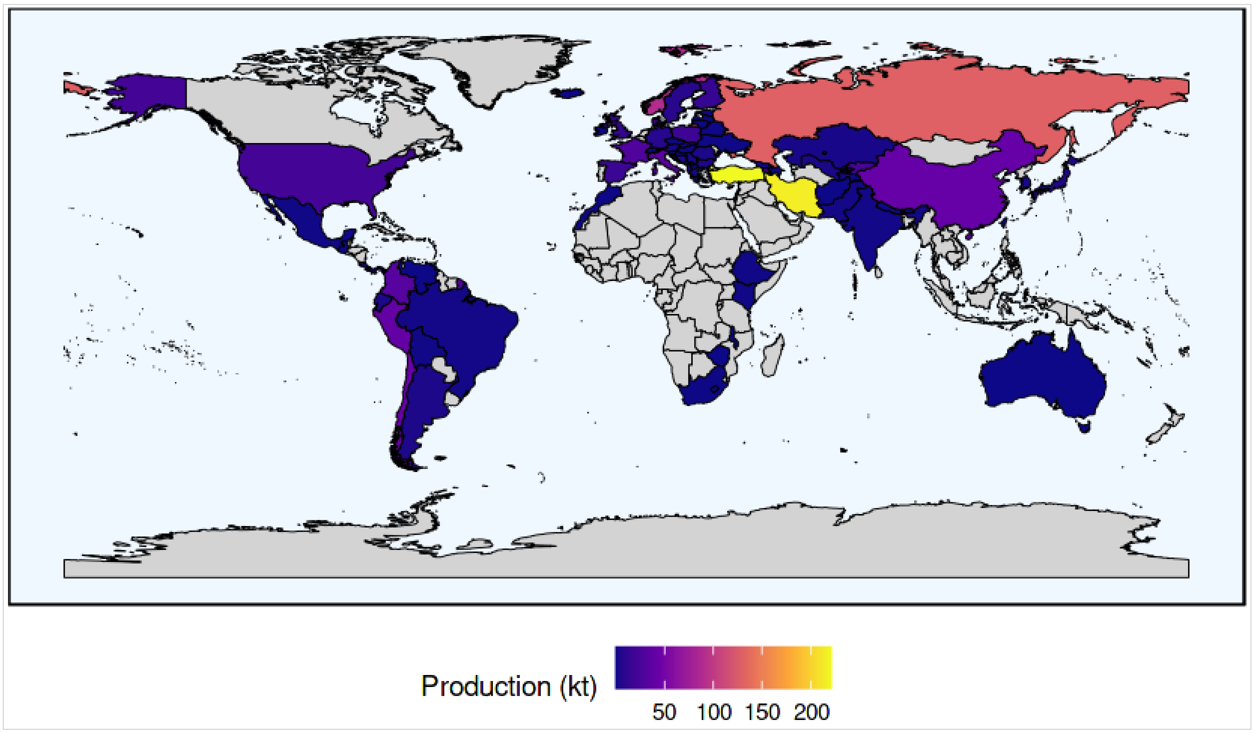

Figure 1. Map of rainbow trout production in 2023.

Türkiye led global production with approximately 221 kt (metric kilotons), followed closely by Iran at 215 kt. Other significant contributors included Russia (130.3 kt), Norway (90.0 kt), Chile (44.3 kt), and China (41.1 kt). Notable production levels were also recorded in Peru (39.86 kt), Italy (34.15 kt), Colombia (31.7 kt), and France (28.6 kt). Analysis of relative market shares reveals that Türkiye accounted for approximately 20% of global production, followed by Iran (19.5%), Russia (11.8%), and Norway (8.15%). The remaining shares were distributed among Chile (4%), China (3.72%), Peru (3.61%), Italy (3.09%), Colombia (2.87%), and France (2.59%). These figures underscore a high degree of consolidation in rainbow trout aquaculture, with the top three producers alone representing more than half of the global output.

Materials and Methods

This analysis utilizes rainbow trout production data sourced from the FAO Fisheries Database (FAO, 2023). A period of eight years, from 2016 to 2023, was selected to identify both short-term fluctuations and emergent trends in production patterns. Data for 77 countries that maintained a complete record over this eight-year timeframe were included, while countries with missing data points were excluded to ensure longitudinal consistency. Prior to clustering, the production data underwent rigorous pre-processing and descriptive statistical analysis. Specifically, for each country, we computed the mean annual production, the coefficient of variation (CV) to quantify production volatility, and a linear trend indicator. The CV, representing the standard deviation relative to the mean, serves as a measure of production stability. Trend analysis was performed using linear regression; the trend indicator was assigned a value of 0 if the calculated slope was not statistically significant. These calculated indicators were subsequently utilized as the primary variables for the hierarchical clustering analysis.

Prior to clustering, all variables were standardized to a [0, 1] scale using min-max normalization to ensure comparability and mitigate the influence of differing measurement units. The dataset was also screened for missing values and potential multicollinearity to ensure analytical integrity. To guarantee robustness, the analysis avoided reliance on a single algorithmic assumption. Instead, a comprehensive suite of clustering approaches representing distinct statistical strategies was evaluated: partitioning methods (K-means, PAM, CLARA), hierarchical procedures (AGNES, DIANA), and model-based clustering (Xu & Wunsch, 2008; Kassambara, 2017; Scrucca et al., 2016). The optimal method and the number of clusters were determined objectively through a dual-validation framework. This involved seven internal validation indices—including connectivity, silhouette width, and the Dunn index—and four stability measures (APN, AD, ADM, FOM) (Brock et al., 2008). This comparative approach identified Ward's method (AGNES) with Manhattan distance as the superior framework, effectively minimizing within-cluster heterogeneity while optimizing both stability and cluster separation (Xu & Wunsch, 2008; Shathya, 2015).

The Agglomerative Nesting (AGNES) algorithm with Ward's linkage operates as a bottom-up hierarchical approach that iteratively merges clusters to minimize total within-cluster variance at each step (Xu & Wunsch, 2008). This method was selected for its efficacy in producing compact, spherical clusters with high internal homogeneity. For the dissimilarity matrix, Manhattan distance was prioritized over Euclidean distance. This choice was necessitated by the non-Gaussian distribution and the presence of significant outliers in the production data. Unlike Euclidean distance, which squares differences, Manhattan distance is less sensitive to extreme values, thereby providing a more robust and stable assessment of dissimilarity in skewed datasets (Shathya, 2015).

Subsequently, we assessed whether the identified clusters differed significantly regarding production, trend, and variation metrics. Since initial exploratory analyses (Q–Q plots and Shapiro–Wilk tests; Shapiro & Wilk, 1965) indicated violations of normality for both raw data and model residuals, a non-parametric approach was adopted. Specifically, the Kruskal–Wallis one-way analysis of variance (Kruskal & Wallis, 1952) was applied ($\alpha = 0.05$). When the overall test statistic was significant, Dunn's pairwise comparisons (Dunn, 1964) were conducted, with p-values adjusted via the Holm method (Holm, 1979) to control the family-wise error rate.

All statistical analyses were carried out in R (v. 4.2.2). Clustering procedures utilized the *mclust* (v. 6.0.0), *clValid* (v. 0.7), *NbClust* (v. 3.0.1), *hopkins* (v. 1.1), and *factoextra* (v. 1.0.7) packages. Data wrangling, cleaning, and general visualization were performed with the *tidyverse* suite (v. 1.3.2). Geospatial mapping was implemented using *sp* (v. 1.6.0), *sf* (v. 1.0.9), and the *rnaturalearth* ecosystem. Post-hoc comparisons were facilitated by the *FSA* package (v. 0.10.0).

Results

The preliminary analysis of the 77-country dataset reveals a highly heterogeneous landscape of global rainbow trout production. Beyond the vast range in output (0.015 to 189.95 kt), the distribution is markedly skewed; a small number of high-volume producers stand in stark contrast to the vast majority of low-volume or nascent production systems. This imbalance, coupled with high volatility in production stability (CV values reaching 1.96), indicates that global averages obscure more than they reveal. As visualized in Figure 2, the prevalence of outliers and non-Gaussian distribution patterns confirms that production behaviors are too diverse for simple linear interpretations. This complexity necessitates the robust, multi-method clustering approach employed in this study to identify meaningful global production dynamics.

Overall, the descriptive findings reveal substantial variation in rainbow trout production across 77 countries over the eight-year period. While many countries exhibit stable or moderately increasing production trends, the presence of extreme values particularly in the early and final years points to possible structural shifts, external disruptions, or inconsistencies in reporting practices. These fluctuations underscore the heterogeneity of production dynamics among countries.

Before proceeding with the clustering, the relationships between the predictor variables were examined. Pearson correlation coefficients indicated no substantial multicollinearity (Table 1), confirming that each variable contributes unique, non-redundant information to the model.

The clustering tendency of the data structure was assessed using the Hopkins statistic. The results indicated a strong clustering tendency (H = 0.961, n = 500; p < 0.00), confirming that the dataset is highly suitable for clustering analysis rather than being a product of random distribution. A visual inspection through a Visual Assessment of Cluster Tendency (VAT) plot (Figure 3) further supported the appropriateness of the data structure for the subsequent hierarchical analysis.

In order to determine the optimal number of clusters, 22 different clustering validity indices were calculated using the Ward.D2 linkage method combined with Manhattan distance. According to the majority rule approach, the number of clusters recommended by the highest number of indices was selected. Specifically, 10 out of 22 indices suggested that the most appropriate number of clusters was three.

Furthermore, the most suitable clustering algorithm was identified based on the recommendation of seven different internal validation measures. Among these, four measures favored the "AGNES" (Agglomerative Nesting) method, which was therefore adopted as the preferred hierarchical clustering approach. The silhouette plot generated for the resulting clusters (Figure 4) indicated a high degree of internal consistency, validating the robustness and coherence of the formed clusters.

Following the criteria established by Hennig (2019), the structural validity of the three-cluster solution was evaluated using standardized internal validation metrics. The results confirm the presence of statistically robust clusters, characterized by strong cohesion (average within-cluster distance: 0.888) and low internal variance. While inter-cluster separation was moderate (overall separation index: 0.115), the average silhouette width of 0.684 and a Pearson gamma coefficient of 0.883 collectively indicate a stable structure with a satisfactory balance between internal

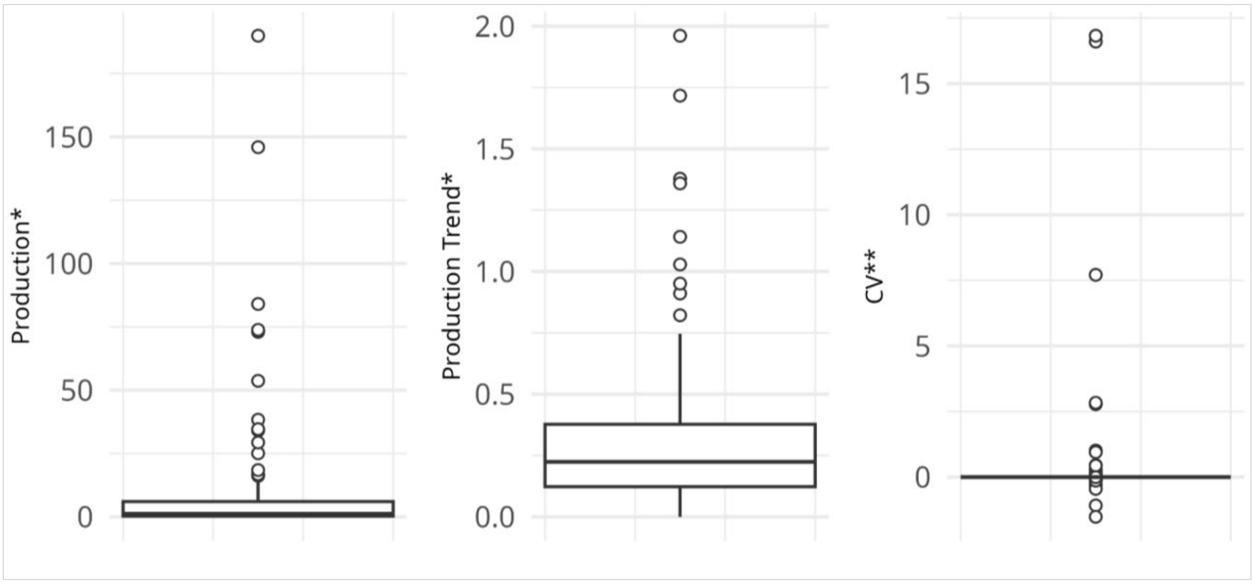

Figure 2. Distribution of mean annual production, linear production trends, and the coefficient of variation (CV) among global rainbow trout producers (N = 77).

Table 1. Pearson correlation matrix of the variables utilized in the hierarchical clustering analysis (N = 77)

	Mean	CV*	Trend
Mean	1.000	-0.148	0.693
CV*	-0.148	1.000	0.038
Trend	0.693	0.038	1.000

* coefficient of variation.

consistency and external separation. Furthermore, the high density measures (0.962) and a moderate entropy level (0.518) suggest that the clusters possess well-defined cores and a suitably balanced distribution of observations.

In summary, these metrics collectively confirm that the three-cluster solution produced by the AGNES method is robust, consistent, and well suited to the data, achieving a balanced trade-off between compactness, separation, and interpretability (Figure 5).

Descriptive statistics revealed notable differences in production levels, trends, and coefficients of variation (CV) across the three clusters (Table 2). Cluster 1 (n = 63) was characterized by relatively low mean production and a stable trend, reflecting high consistency among small-scale producers. Cluster 2 (n = 11) displayed the lowest production volumes coupled with the highest CV values, suggesting significant temporal fluctuations and internal heterogeneity. In contrast, Cluster 3 (n = 3) comprising the market leaders exhibited distinctly high production levels and a steeply increasing growth trend. With a moderate CV, this cluster demonstrates rapid yet remarkably consistent expansion in global output.

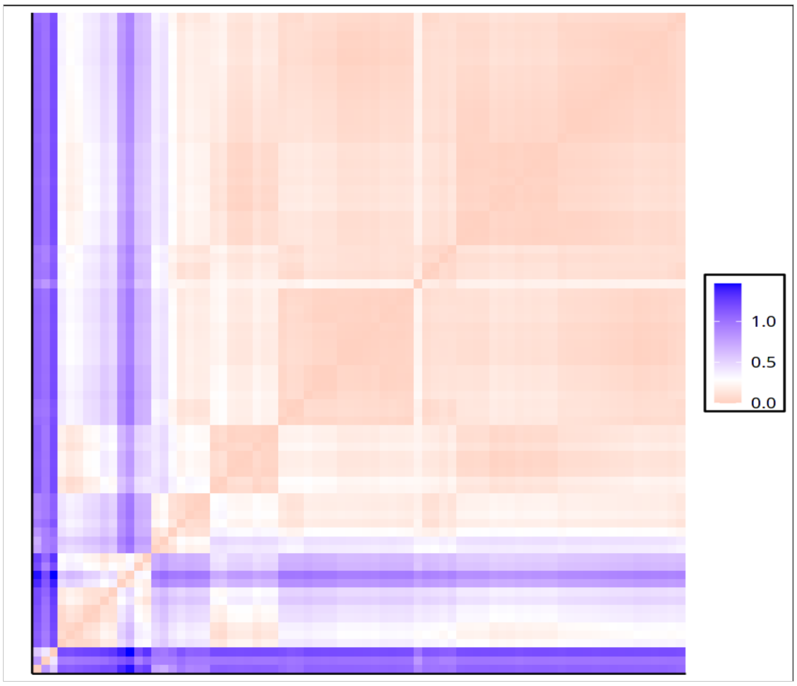

Figure 3. Clustering tendency of the rainbow trout dataset.

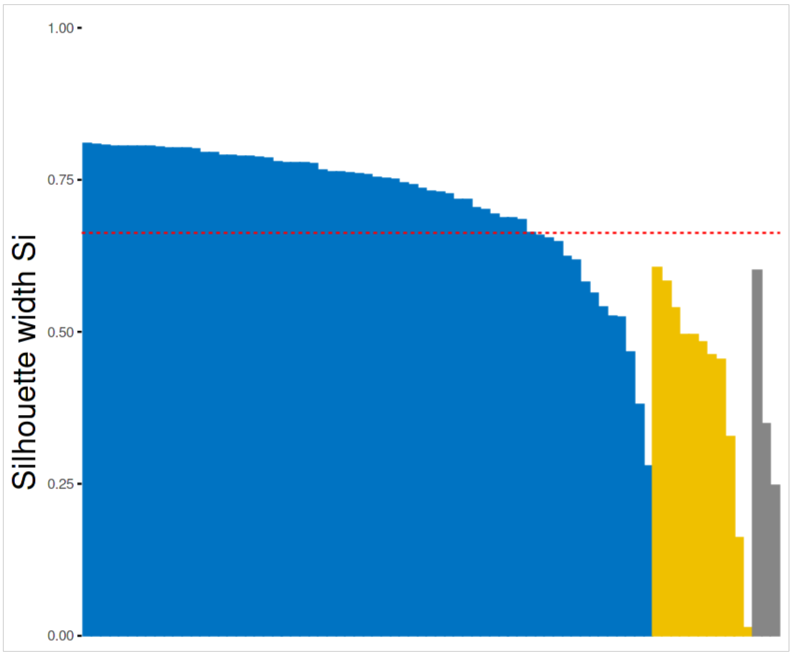

Figure 4. Silhouette plot of the rainbow trout clusters.

To assess whether these observed differences were statistically significant, non-parametric Kruskal-Wallis tests were conducted for each variable, followed by Dunn's post hoc tests with Holm adjustment for multiple comparisons. For the mean variable, the Kruskal-Wallis test indicated a statistically significant difference among at least two clusters (χ^2 = 9.88, df = 2, P<0.01). Pairwise comparisons showed no significant difference between Clusters 1 and 2 (Z = -0.806, P= 0.221), whereas significant differences were observed between Clusters 1 and 3 (Z = -2.7855, P= 0.0107) and Clusters 2 and 3 (Z = -3.1402, P= 0.0051).

Similarly, for the trend variable, the Kruskal-Wallis test also revealed significant differences (χ^2 = 11.5, df = 2, P<0.01). No statistically significant difference was found between Clusters 1 and 2 (Z = -0.806, P= 0.420), while significant differences emerged between Clusters 1 and 3 (Z = -3.3493, P= 0.0024) and Clusters 2 and 3 (Z = -2.6339, P= 0.0169). In contrast, the CV (coefficient of variation) showed a highly significant overall difference across clusters (χ^2 = 28.5, df = 2, P<0.001). Post hoc analysis revealed a significant difference between Clusters 1 and 2 (Z = -5.3304, P<0.001), while differences between Clusters 1 and 3 (Z = -0.7792, p = 0.436) and Clusters 2 and 3 (Z = 1.9673, P= 0.0983) were not statistically significant.

These results statistically reinforce the descriptive distinctions between the clusters. Specifically, the variables mean and trend significantly differentiate high-production and growth-oriented countries (Cluster 3) from the other two clusters, while CV highlights the high internal variability in Cluster 2 compared to Cluster 1. Overall, the clustering structure captures meaningful heterogeneity in production dynamics across countries.

These results indicate that the three clusters correspond to distinctly different country profiles with respect to their production dynamics. The first cluster comprises countries with relatively low average production, minimal year to year fluctuation, and low relative variability, suggesting mature, stable production systems. In contrast, the second cluster despite similarly low mean production exhibits pronounced internal variability and temporal swings, characteristic of inconsistent or intermittently influenced production environments. Finally, the third cluster, though small in membership, displays markedly higher production values alongside steep upward trends and moderate variability, marking these nations as emerging or rapidly expanding producers with robust growth trajectories. Notably, Turkey, Iran, and Russia are positioned within this high-volume growth leader cluster, underscoring their central role in shaping future rainbow trout

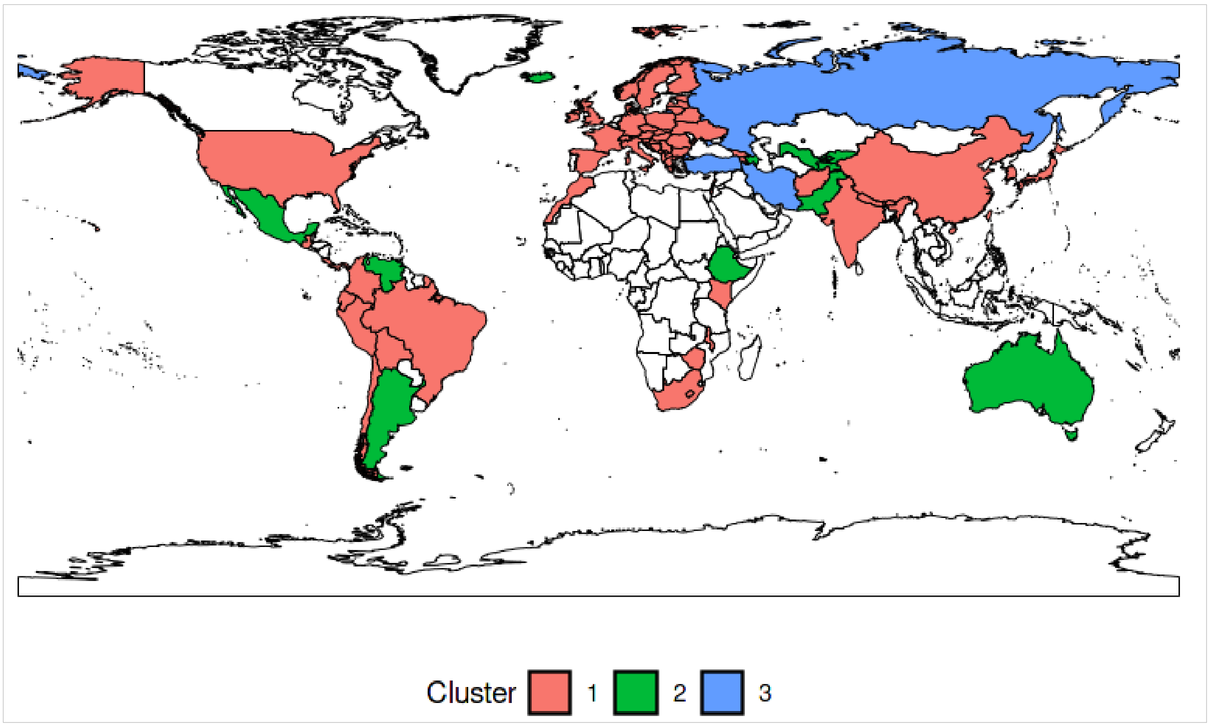

Figure 5. Spatial distribution of the resulting clusters.

Table 2. Summary statistics of clusters (mean±SD)

Cluster	Mean*	Trend*	CV*	n**
1	8.39±16.95	0.05±0.42	0.21±0.13	63
2	1.45±1.99	0.21±1.01	1.16±0.41	11
3	136.57±58.62	13.71±5.20	0.32±0.24	3

* ±SD (Standart Deviation); ** Number of countries included in each cluster.

production trends. Collectively, this segmentation delineates stable low-volume producers, volatile low-volume producers, and high-volume growth leaders, thereby offering a meaningful clustering based on both production scale and dynamic behavior.

Discussion

The study identified three distinct clusters among countries engaged in rainbow trout aquaculture, reflecting differentiated production dynamics at the country level. These findings both align with and extend beyond prior research, offering a more nuanced understanding of global production dynamics.

Cluster 1: Mature, Stable Production Systems

This cluster represents countries with established trout farming traditions and relatively stable production volumes. Such systems are characterized by low inter-annual variability and robust institutional frameworks. Examples include Italy (D'Agaro et al., 2022) and Germany (Risius et al., 2017), where long-standing infrastructure and regulatory stability support consistent output. While earlier studies (e.g., Shaw & Gabbott, 1992) highlighted similar trends, our results indicate that stability often occurs in countries where trout farming remains modest compared to other finfish sectors such as seabass or seabream.

Cluster 2: Fragmented Production with High Variability

The second cluster includes countries with pronounced fluctuations and limited organizational coherence in production systems. Cases such as Australia, Argentina, and Mexico exhibit temporal swings that resemble patterns previously noted in the United States, where regulatory and market barriers constrained sectoral growth (Engle et al., 2005; Engle et al., 2019; Engle et al., 2021). These dynamics may reflect structural inefficiencies, inconsistent management practices, or economic pressures, distinguishing them from more coordinated examples observed in France, Japan and many other countries (Sone & Nortvedt, 2009). This highlights regional heterogeneity in production stability and organization.

Cluster 3: Rapidly Expanding Producers

The third cluster captures countries experiencing rapid growth in production volumes, notably Turkey, Iran, and Russia. These systems appear to be scaling up in response to rising domestic demand and favorable production conditions, echoing—but also diverging from—earlier accounts of expansion in China. While such growth may contribute to global supply, it also raises questions regarding sustainability and resource management, as intensification could increase pressures on water resources, feed inputs, and regulatory oversight.

In summary, the three-cluster structure highlights both continuity with established models and the emergence of new regional production dynamics. Mature and stable systems (Cluster 1) confirm previous observations, while fragmented and variable producers (Cluster 2) illustrate the persistent influence of structural and regulatory challenges. More importantly, the rapid expansion of emerging producers (Cluster 3) signals a shift in the global geography of rainbow trout aquaculture beyond the traditional Euro-American and Japanese contexts. These findings underscore the need to consider regulatory environments, market demand stability, and sustainability concerns when interpreting the trajectory of national aquaculture systems.

The first documented practices of commercially successful trout farming were carried out between 1870 and 1873 in the state of California, United States (Needham & Behnke, 1962; Behnke, 1992). Following the production successes achieved during this period, the international export of rainbow trout (*Oncorhynchus mykiss*) eggs from the U.S. began in 1877 (Hardy et al., 2000). As a result of this dissemination, it is believed that most of the cultured rainbow trout strains currently farmed worldwide both freshwater-reared rainbow trout and seawater-grown steelhead trout are derived from California-origin genetic lines. Trout farming in Europe is thought to have started with the shipment of rainbow trout eggs to the United Kingdom in 1885, with broodstock from these eggs later being used in the first trout farms established in Denmark (Hinshaw et al., 2004). Early trout farming practices in both the U.S. and Europe primarily focused on stocking programs to support wild populations. However, a turning point occurred in the mid-1950s with the establishment of a large-scale processing facility in Idaho (Brannon & Klontz, 1989), marking the transition of trout farming into commercial food production. In this period, the increase in processing capacity and the development of economically viable pelleted feeds laid the foundation for industrial trout aquaculture not only in the U.S. but also globally. Historically, rainbow trout aquaculture in Europe has been particularly prominent in countries such as the United Kingdom, Denmark, and Germany (Statista, 2015). The sector experienced significant growth during the 1980s, with a rapid increase in production volume (Shaw & Gabbott, 1992). Over time, trout became the most commonly cultured fish species in Italy (D'Agaro et al., 2022), and in Germany, it gained recognition as a valuable source of nutrition (Risius et al., 2017). Similarly, rainbow trout has become an important species in commercial aquaculture in France (Bazoche & Poret, 2021), Japan (Sone & Nortvedt, 2009), and many other countries.

Salmonid species naturally inhabit the cold waters of high latitudes in the Northern Hemisphere. However, their high economic value as a food source and popularity in recreational fisheries have led to their translocation to aquatic systems outside their native habitats for decades (Fausch, 1988). The invasive potential of a species defined as its ability to establish self-sustaining populations in new environments (Rejmánek, 2011) varies depending on the compatibility of its biological characteristics with the target ecosystem. For instance, the coho salmon (Oncorhynchus kisutch, Walbaum, 1792) has successfully established populations in the Great Lakes Basin of North America (Fausch & White, 1986) and parts of Patagonia (Górski et al., 2017), whereas it has failed to form self-sustaining populations in northern Japan, despite repeated stocking attempts for fisheries purposes (Koseki, 2013). Both biotic factors (e.g., ecological interactions with native species) and abiotic conditions (e.g., water temperature, geographical structure) influence the species' invasive success.

The rainbow trout (*Oncorhynchus mykiss*, Walbaum, 1792) is one of the most widely distributed invasive salmonids globally. Although its natural range is limited to the Pacific coastal regions between North America and the Kamchatka Peninsula, it has been introduced to various cold-water sources worldwide due to its economic value (Myers, 2018). Today, it can be found not only in the Northern Hemisphere but also in the Southern Hemisphere and high altitude regions at lower latitudes (Jonsson & Jonsson, 2011; MacCrimmon, 1971). The invasive potential of rainbow trout lies in its ability to reproduce naturally and establish permanent populations in new habitats. This species negatively affects native fish populations through competition and predation, contributing to the decline of endemic species such as the cutthroat trout (*O. clarkii*) and brook trout (*Salvelinus fontinalis*) in North America (Budy & Gaeta, 20178; Krueger & May, 1991). Additionally, hybridization between rainbow trout and cutthroat trout poses a significant threat to the genetic integrity of the latter (Boyer, Muhlfeld & Allendorf, 2008). Rainbow trout has also severely impacted non-salmonid species; for example, several endemic freshwater fish from the Galaxiidae family in New Zealand became extinct following rainbow trout invasion (Lintermans, 2000; Townsend, 1996). In this context, the International Union for Conservation of Nature (IUCN) has listed rainbow trout among the world's top 100 worst invasive alien species (Lowe, Browne, Boudjelas & Pooter, 2000).

As of 2023, aquaculture production in the European Union (EU) has been predominantly composed of finfish especially rainbow trout, gilthead seabream, European seabass, carp, tuna, and salmon and mollusks, particularly mussels and oysters. During this period, rainbow trout (*Oncorhynchus mykiss*) emerged as the most economically valuable species in EU aquaculture, accounting for 17.7% of total production. The farming of seabass, seabream, and oysters followed in economic importance (Eurostat, 2025).

Despite the long-standing history of trout in aquaculture, market-based research on this species remains limited. There is a lack of comprehensive literature on topics such as demand dynamics, supply chain structures, price formation, production volumes, and marketing strategies. Early marketing studies from the 1990 s revealed that trout fillets in Italy were sold at price levels comparable to beef tenderloin (Shaw & Gabbott, 1992). A concurrent study in Canada found that both brown and rainbow trout were generally accepted by consumers, although acceptance levels varied depending on the aquatic environment in which the fish were raised (Rounds et al., 1992). More recent studies have investigated the product attributes influencing consumer preferences for trout. Research conducted in Germany identified key factors in purchasing decisions as the production method, organic labeling, visual quality, processing form, branding, certification status, and taste (Risius et al., 2017). Ankamah-Yeboah et al. (2019) demonstrated that German consumers were willing to pay a premium for organically labeled trout products.

A study conducted in Japan evaluated consumer preferences for raw rainbow trout, finding that the anatomical origin of the fillet (e.g., dorsal or ventral) was the most decisive factor in consumer choice (Sone & Nortvedt, 2009). Meanwhile, consumer perceptions of novel feeding strategies, such as the use of insect meal in trout diets, have been explored in France (Bazoche & Poret, 2021) and Spain (Llagostera et al., 2019). Environmental sustainability practices in Europe have also gained attention. According to D'Agaro et al. (2022), 57% of salmon and trout farms operating across Europe are involved in at least one environmental certification program. Norway has surpassed early producers like the UK and Denmark to become a global leader in trout production, primarily due to seawater cage farming of rainbow trout (steelhead trout). However, the fact that steelhead and Atlantic salmon prices move in parallel (Landazuria et al., 2020) does not fully explain the motivations behind production diversification. In the U.S., steelhead trout is classified as a distinct product due to its different life cycle and larger harvest size (Crouse et al., 2018; National Wildlife Foundation, 2022). In the 1980s, trout was not among the most preferred fish species across the U.S., although it was a favorite in certain regions (Engle et al., 1990). In subsequent years, rainbow trout achieved a high market share, particularly in the North-Central U.S., and became one of the top-selling species in grocery stores (Hushak et al., 1993; Riepe, 1999a, 1999b). Consumer preference studies in cities like Chicago and Los Angeles have highlighted the importance of product form in purchasing decisions (Foltz et al., 1999; Dasgupta et al., 2000). A 2020 survey revealed that rainbow trout was the most preferred species when available, indicating that demand is not confined to specific regions (Valle de Souza et al., 2021; Athnos et al., 2022). Supermarket data also show that product form, packaging, and promotional strategies influence sales (Capps & Lambregts, 1991; Wessells & Wallström, 1999), although trout is often positioned among lower-priced items (Dey et al., 2014, 2017). During the COVID-19 pandemic, fish consumption was expected to increase, but high prices and declining incomes resulted in decreased demand (Engle et al., 2023a).

Despite being one of the longest-standing aquaculture sectors in the United States, trout farming has experienced relatively limited growth due to persistent regulatory and structural barriers (Fornshell, 2002). Although there is significant domestic demand for rainbow trout, producers frequently highlight that strict regulatory frameworks continue to hinder sectoral expansion (Engle et al., 2005; Engle et al., 2019; Engle et al., 2021). The increasing import volumes of steelhead and rainbow trout from countries such as Norway, Chile, and Peru suggest that this domestic demand remains insufficiently met. In particular, the growing market share of imported steelhead trout especially due to its visual and sensory similarity to salmon further emphasizes the gap in domestic production (Sun et al., 2022a; Landazuria et al., 2020).

Interestingly, although seafood consumption generally increased during the COVID-19 pandemic, trout sales and prices showed a more pronounced decline when compared to species such as catfish (van Senten et al., 2020; van Senten et al., 2021). Moreover, consumer preferences for trout vary regionally within the U.S., with the Pacific region showing notably higher levels of acceptance and demand (Sun et al., 2022a). However, the U.S. trout farming industry continues to maintain strong comparative advantages in terms of environmental sustainability and production efficiency (Engle et al., 2020; Engle et al., 2021).

Nevertheless, regulatory compliance imposes considerable financial burdens, with adaptation-related costs accounting for approximately 12% of total production expenditures (Engle et al., 2019). Similar cost burdens are reported in other aquaculture species such as tilapia, catfish, and hybrid striped bass (Hegde et al., 2023; Engle & van Senten, in press). These pressures are particularly pronounced for small- and medium-scale producers, for whom high compliance costs and complex permitting procedures represent major barriers to growth (van Senten & Engle, 2017; Boldt et al., 2022). Estimates suggest that producers incur multi-million-dollar annual losses in potential production and sales due to inflexible regulatory systems (Engle et al., 2005). Some of these burdens could be alleviated by adopting risk-based regulatory approaches, such as adjusting inspection frequencies and testing requirements based on historical performance (van Senten et al., 2018; Engle et al., 2021). If policy reforms are implemented to support sustainable trout farming in the U.S. the sector could not only meet growing consumer demand but also contribute to rural economic development, job creation, and improved national food security (Kaliba & Engle, 2004; Hegde et al., 2022; Engle & van Senten, 2022).

Conclusions

This study's cluster analysis provides a useful framework for understanding the economic drivers and production systems shaping global rainbow trout aquaculture output, particularly in the context of meeting growing protein demand through aquaculture. Three distinct producer profiles were identified stable low-volume, volatile low-volume, and high-volume growth leaders which reflect differences in market development, investment capacity, economies of scale, and resource use across countries. The inclusion of Turkey, Iran, and Russia within the high-volume cluster indicates their notable contributions to recent global production increases. This profile often aligns with larger domestic markets, export potential, or substantial investments in infrastructure such as feed mills and processing facilities. By contrast, the volatility observed among low-volume producers points to challenges potentially linked to climate sensitivity, market access constraints, limited capital, or slower technological adoption that may require targeted support to foster resilience and sustainable growth.

The findings also have implications for international trade patterns (e.g., identifying major supply hubs such as Turkey and Russia) and investment strategies. High-volume producers may emerge as key future suppliers, while stable low-volume operations could represent more sustainable or niche-oriented models deserving closer examination. From a food security perspective, recognizing the characteristics of different production profiles can help shape strategies to enhance both the availability and reliability of farmed trout as a protein source.

In conclusion, the clustering approach underscores both opportunities such as leveraging high volume growth and challenges, including volatility in smaller-scale operations, within the rainbow trout aquaculture sector. By providing distinct clusters based on production dynamics, it lays a foundation for further academic research and can inform sectoral development policies aimed at promoting sustainability and productivity across diverse contexts.

Future research should integrate environmental variables such as water temperature fluctuations, water availability, and climate change projections alongside trade policies to refine these production clusters and predict long-term sustainability. Although the present analysis focuses on rainbow trout aquaculture, the clustering framework developed in this study is highly transferable to other aquaculture species and broader global production systems. This methodological structure provides a scalable analytical model for evaluating production dynamics in diverse aquaculture contexts, facilitating more informed decision-making for global food security.

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Author Contribution

First Author: Conceptualization, Writing -review and editing; Second Author: Data Curation, Formal Analysis, Investigation, Methodology, Visualization and Writing -original draft; First and Second Author: Funding Acquisition, Project Administration, Resources, Writing - review and editing; and First and Second Author: Supervision, Writing - review and editing.

Conflict of Interest

The authors declare that they have no known competing financial or non-financial, professional, or personal conflicts that could have appeared to influence the work reported in this paper.

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