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Optimizing Quinoa Production Systems in Andean Communities: A Machine Learning-Enhanced Economic Model for Poverty Reduction in Puno, Peru

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Abstract

This research introduces a method to help improve quinoa farming in Puno Perú area by blending programming and machine learning methods to tackle issues faced in today's global agricultural markets efficiently and effectively using information from a span of 26 years. Through our work and study details over these years we formulated a model that balances maximizing profits while handling market fluctuations effectively and efficiently Our results highlighted that market prices for quinoa are heavily impacted by market dynamics rather, than local production conditions (correlation coefficient; 0.147; significance level; p > 0.05).The understanding influenced the linear approach that determined the best prices for selling and break even points effectively surpass traditional techniques by utilizing machine learning models while ensemble approaches showed better performance outcomes surpass the average methods used in the industry. Moreover, reactionary models identified changes in market trends accurately while long short-term memory networks forecasted price fluctuation tendencies.

Keywords: *Quinoa Production, Optimization, Production Systems, Non-Linear Programming, Genetic Algorithms, Machine Learning Algorithms.*

Introduction

Quinoa, considered a superfood due to its exceptional nutritional profile, has gained worldwide recognition for its health benefits and culinary versatility (Hernandez, 2015; Romo et al., 2006). This ancient grain represents a critical agricultural resource for Peru's Puno region, where traditional farming communities face significant socioeconomic and environmental challenges. Puno, located in Peru's high Andes, represents one of the country's most challenging yet resilient agricultural regions. Local communities confront multiple barriers to economic development, including extreme poverty, harsh environmental conditions, and geographic isolation (INEI,

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2020). The mountainous geography and severe cold temperatures create natural obstacles that historically limit access to economic opportunities and essential services.

Rural households in this region depend primarily on subsistence farming and livestock herding under conditions where climatic variability poses constant threats to agricultural productivity. Infrastructure limitations, including unpaved roads that become impassable during rainy seasons, frequently isolate entire communities for extended periods. These challenges have created persistent out-migration patterns, as young people seek employment opportunities in urban centers, simultaneously weakening local social structures while providing essential remittance income. Despite these considerable obstacles, Puno communities demonstrate remarkable resilience, maintaining rich cultural heritage and traditional agricultural knowledge systems. This cultural foundation provides the basis for innovative approaches to agricultural development and economic improvement strategies.

Quinoa (*Chenopodium quinoa*) exhibits exceptional adaptation to harsh environmental conditions, making it particularly suitable for high-altitude agriculture. The crop demonstrates remarkable tolerance to severe cold, water scarcity, and frost events that would destroy most conventional crops (Murphy & Matanguihan, 2015). These characteristics enable successful cultivation in arid and semi-arid environments where few alternative crops can survive. In the Puno region, quinoa serves dual functions as both a nutritional staple and economic opportunity for local communities (Carimentrand et al., 2014). The crop provides essential food security while generating income through market participation. However, quinoa commercialization faces significant challenges related to complex supply chain management and volatile market demand patterns.

The National Institute for Agrarian Innovation (INIA) in Peru has responded to these challenges through dedicated genetic improvement programs. The development of quinoa variety INIA 446 ATIPAQ represents a significant technological advancement for regional agriculture. This improved variety achieves yields of 3-4 tons per hectare while providing enhanced resistance to diseases such as downy mildew, substantially reducing production risks and associated costs (Luque, 2021). Economic projections indicate that INIA 446 ATIPAQ adoption could increase farmer profits by more than 60%, representing a transformative opportunity for small and medium-scale producers. The variety's integrated pest and disease resistance characteristics further enhance economic viability by reducing input costs and production uncertainties.

This research extends beyond conventional agricultural optimization approaches by integrating nonlinear programming with genetic algorithms and neural networks to address quinoa production challenges in Puno's high-altitude environment. Unlike previous studies focusing on isolated optimization components or single methodological approaches, this investigation presents a comprehensive framework that simultaneously considers production costs, market constraints, and price volatility. The study's methodological innovation lies in developing mathematical frameworks that enhance understanding and simulation of complex market dynamics. These frameworks enable systematic exploration of supply-demand variations and competitive forces affecting pricing and profitability structures. By providing predictive capabilities for market scenarios including saturation, price fluctuations, and competitive pressures, the framework offers farmers enhanced tools for economic risk management and strategic decision-making. This integrated approach addresses the critical gap between agricultural production optimization and market dynamics analysis, providing a foundation for sustainable agricultural development in marginal environments.

The optimization framework demonstrates both practical applicability and empirical validity. Model analysis identifies an optimal selling price of S/. 22.10 per kilogram, generating maximum projected profits of S/. 1,638,000.00 annually. The breakeven analysis establishes a critical threshold at S/. 11.00 per kilogram, below which quinoa production becomes economically unviable. These financial projections are derived from comprehensive datasets provided by INIA Puno, ensuring that model recommendations reflect realistic market conditions and operational constraints. To enhance optimization accuracy, we implemented genetic algorithms employing two distinct selection strategies. Comparative analysis revealed that sexual selection operators achieved superior efficiency, converging to optimal solutions in significantly fewer generations than tournament selection methods. This finding confirms the effectiveness of sexual selection mechanisms for complex, constrained optimization problems in agricultural systems.

Concurrently, neural network models were trained to predict production outcomes using key operational variables. The network architecture employed hyperbolic tangent (tanh) activation functions optimized through the Adam algorithm. Model performance demonstrated robust learning convergence, with training loss systematically decreasing from 1.1653 to 0.0028 over the training period. These complementary optimization techniques collectively establish a comprehensive and adaptable decision-support framework for quinoa production management. Field validation through collaboration with INIA Puno confirms the framework's practical applicability under real-world conditions. The model successfully integrates production cost structures, market price volatility, and operational constraints to provide actionable guidance for producer decision-making. Results indicate that implementation of optimized production strategies could significantly enhance farm-level profitability while reducing economic risks associated with market uncertainty.

Figure 1. Quinoa INIA 446-ATIPAQ. Courtesy of INIA Puno headquarters

Literature Review

Recent decades have witnessed increasing scholarly interest in applying advanced analytical tools to improve agricultural systems, with particular emphasis on food security and rural development challenges. However, limited research exists on implementing these methodologies for quinoa production optimization within the challenging climatic and economic contexts of the Peruvian Andes.

Murphy and Matanguihan (2015) provided foundational contributions through comprehensive analysis of quinoa's adaptability and nutritional benefits, emphasizing the crop's significance in sustainable agricultural practices. Their research demonstrates quinoa's exceptional resilience under adverse environmental conditions, establishing its potential as a climate-adaptive crop. However, their study focuses primarily on agronomic and nutritional characteristics without addressing economic optimization or yield enhancement strategies—critical considerations for Andean smallholder farmers.

From a market-oriented perspective, Guzmán Bautista's analysis of quinoa export competitiveness from Puno region offers valuable insights into international trade dynamics (MINAGRI, 2020; Guzmán, 2020). This research provides comprehensive understanding of market positioning and competitive advantages but lacks quantitative decision-support tools for individual producers. Similarly, Condeña Almora and Chauca Retamozo (2016) examined quinoa market trends and regional profitability patterns, contributing important economic context while stopping short of operational optimization frameworks.

From a methodological standpoint, Villada et al. (2019) demonstrated neural networks' effectiveness for price forecasting in financial markets. Although their research does not address agricultural applications directly, their techniques informed the predictive modeling approach adopted in this study. The technical frameworks they developed provide relevant methodological foundations for agricultural price volatility analysis.

Silva Salinas (2023) extended machine learning applications to hardware optimization in agricultural systems, demonstrating artificial intelligence versatility in rural technology applications. While not directly focused on crop management or profitability analysis, this research illustrates the potential for AI integration in agricultural decision-making processes.

Theoretical foundations for this study's optimization approach derive from established operations research literature. Bazaraa et al. (2013) and Taha (2017) provide comprehensive mathematical frameworks for nonlinear programming and Lagrangian duality methods, which form the core mathematical foundation for the optimization model developed in this research. Their theoretical contributions enable modeling of complex real-world constraints including market price volatility, production cost variations, and resource limitations.

While each of these studies contributes significantly to their respective domains, existing literature lacks integrated approaches combining economic modeling, nonlinear programming, and artificial intelligence specifically tailored for Andean quinoa production systems. Previous research has addressed individual components—either agronomic characteristics, market analysis, or methodological techniques—but has not synthesized these approaches into comprehensive decision-support frameworks.

This study addresses this critical gap by developing an integrated analytical framework that combines mathematical optimization with machine learning techniques to provide practical, evidence-based tools for Andean quinoa producers and agricultural policymakers. The research contributes to the emerging field of precision agriculture by adapting advanced analytical methods to the specific challenges and opportunities of high-altitude agriculture in developing regions.

This research extends beyond conventional agricultural economic analysis by incorporating predictive analytics and optimization algorithms into a unified framework designed specifically for smallholder quinoa production in Peru's Puno region. The interdisciplinary approach bridges agricultural economics, operations research, and machine learning to address the complex decision-making challenges faced by Andean farming communities in increasingly volatile global markets.

Materials and Methods

Study Area

This research was conducted in Peru's Puno region (15°50'S, 69°00'W), a high-altitude agricultural zone characterized by extreme climatic conditions and significant agricultural challenges. The study area encompasses the Altiplano ecosystem, situated at elevations between 3,800-4,200 meters above sea level, where quinoa cultivation represents a critical component of regional agricultural systems. Research operations were based at the Universidad Nacional del Altiplano Puno (UNAP) (15.8402°S, 70.0219°W), providing essential institutional support and academic infrastructure. This strategic location facilitated access to university research facilities, collaboration with regional agricultural specialists, and proximity to quinoa production systems of significant economic and cultural importance within the study region.

The research framework incorporated direct collaboration with the Instituto Nacional de Innovación Agraria (INIA), specifically utilizing experimental facilities located in Salcedo district. This partnership enabled comprehensive field data collection and practical validation of optimization strategies under representative production conditions. The integration of university-based research with INIA's applied agricultural programs ensured that developed methodologies aligned with regional production realities and farmer operational constraints. Field data collection was conducted through systematic collaboration with local quinoa producers and INIA research stations throughout the 2022 growing season. Primary data encompassed production costs, yield measurements, and operational parameters specific to regional quinoa cultivation practices. This information provided essential input variables for optimization model calibration and validation procedures.

Historical production and market data spanning 1996-2022 were obtained from the "Oficina de Gestión de Desarrollo Agrario Regional" (AgroPuno), operating under the Puno Regional Government administration. This comprehensive dataset includes: annual quinoa production volumes (metric tons), cultivated area statistics (hectares), regional yield performance data (kg/ha), market price series (S/./kg), production cost structures across different farm scales and climate and environmental variables affecting production

All secondary data underwent systematic quality assessment procedures, including cross-validation with multiple institutional sources and consistency checks across temporal series. Missing data points were addressed through interpolation methods where appropriate, with documentation of all data processing procedures to ensure reproducibility. The 26-year temporal scope of the dataset provides sufficient statistical power for robust model training and validation, while capturing multiple production cycles and market volatility patterns essential for comprehensive optimization framework development.

The Puno region's unique agroecological characteristics include: elevation range: 3,800-4,200 m.a.s.l., climate classification: Highland tropical (Cwb, Köppen classification), average annual temperature: 8-10°C, precipitation regime: 400-700 mm annually (October-April concentration), frost frequency: 150-200 frost days annually, growing season: October-May (dependent on altitude and microclimate). These environmental conditions create both opportunities and constraints for quinoa production, necessitating optimization approaches that account for climatic variability and resource limitations characteristic of high-altitude agriculture. The geographic positioning of this research enables direct application of optimization results within the target agricultural system. The combination of university-based analytical capabilities, INIA experimental infrastructure, and regional government data access creates a comprehensive research framework addressing both theoretical optimization principles and practical implementation requirements for Andean quinoa production systems.

Formulation of the Optimization Model

The first step in formulating a nonlinear optimization model is to clearly define the objective of the problem and the context in which it applies. Nonlinear optimization is generally applicable to complex problems where the relationship between variables is not linear, distinguishing it from traditional linear methods (Bazaraa et al., 2013). In this case, we need to maximize profits, minimize costs, and find the breakeven point that indicates when we have neither losses nor profits.

Decision variables are those elements that are controlled to achieve an optimal objective. In a nonlinear optimization model, these may include quantities of resources, levels of production, and prices, where changes in these variables nonlinearly influence the objective function and constraints (Boyd & Vandenberghe, 2004).

The objective function is the mathematical expression that must be maximized or minimized. In many industrial and economic cases, the function is nonlinear due to cost or revenue characteristics that do not increase consistently. Common forms include quadratic or exponential functions that represent returns or costs of scale (Wright,2006). The constraints define the limits within which the optimal solution must be found. In nonlinear programming, constraints can also be nonlinear and are linked to resource capacities, technological limitations, or market conditions (Bazaraa et al., 2013) (Soncco, 2017).

Once the equations in the model are solved and the values for variables and constants are determined according to conditions set by Kuhn Tucker theory—where they need to be non negative—it is crucial to confirm the models accuracy with actual data from real world scenarios. This verification process extends beyond correctness; it aims to guarantee that the model functions effectively in practical applications and provides valuable insights, for making real life decisions. Without validation in place even the most beautifully crafted equations run the risk of disconnecting from the actual truths they seek to portray (Bazara et al, in 2013).

Results

According to information from INIA, we have:

Maximization of utility

By integrating these elements into the optimization model, we seek not only to maximize profitability but also to promote responsible agricultural practices and contribute to the well-being of local farmers. In this way, the research aligns with sustainable development goals, promoting a holistic approach to quinoa marketing in the Puno Region (Manarino, 2020).

This model is defined as the difference between the sales made and production costs. To simplify, numerical values have been scaled down by dividing them by one thousand. The goal is to find the global maximum in a formal nonlinear programming model so that the producer can make more informed decisions to maximize profits and minimize losses (Bertsimas et al., 2016).

Utility = Sales – Production Costs (1)

The production costs of quinoa mainly consist of labor and inputs. According to the information provided by the INIA Puno branch, the production costs amount to S/. 13,242.29. And, according to official agricultural statistics, quinoa production has shown significant growth in recent years (Ministerio de Desarrollo Agrario y Riego, 2021).

Costs = 13242.00 * Hectares (2)

Sales are represented by production per hectare. According to the information from the INIA Puno branch, it is 1,200.00 kg per hectare multiplied by the number of hectares produced and the market selling price. The goal of this innovative model is to determine at what selling price maximum utility is achieved.

Sales = 1200 * Hectares * Selling Price (3)

Therefore:

X_1: cultivated land in hectares

X_2: selling price

X_3: demand (current market)

X_4: competition production

Then, the utility maximization function is:

$$Max\ Z = 1.2x_1x_2 - 13.2x_1 \quad (4)$$

Subject to the constraints:

$x_3 \leq 150$; demand

$x_2 \leq PP + PP * (1 - 1.2x_1/x_3) + x_4$

Let PP be the selling price = S/. 17.00 (provided by INIA Puno branch). Solving, we have:

$x_2 \leq 34 - \frac{20.4x_1}{x_3} + 17x_4$; selling price

$x_1 \leq 100$; land in hectares

$x_4 = 0.25$; Relationship of the competition's production with total demand.

With this, we propose the Lagrangian, which must satisfy the Kuhn-Tucker conditions:

$$L = 1.2x_1/x_2 - 13.2x_1 + L(150 - x_3 + 1.2x_1) + A(34 - x_2 + 1 - 20.4x_1/x_3 + 17x_4) + B(100 - x_1) + y(-0.6 - x_4)$$

$$Lx_1 = 1.2x_2 - 13.2 - A\left(\frac{20.4}{x_3}\right) - B = 0 \quad (4.1)$$

$$Lx_2 = 1.2x_1 - A = 0 \quad (4.2)$$

$$Lx_3 = -L + 20.4 + x_1/{x_3}^2A = 0 \quad (4.3)$$

$$Lx_4 = 17A - Y = 0 \quad (4.4)$$

$$LL = 150 - x_3 = 0 \quad (4.5)$$

$$LA = 34 - x_2 - 20.4x_1/x_3 + 17x_4 = 0 \quad (4.6)$$

$$LB = 100 - x_1 = 0 \quad (4.7)$$

$$LY = 0.2 - x_4 = 0 \quad (4.8)$$

Replacing (4.7) en (4.2)

$$Lx_2 = 1.2(100) - A = 0 \Rightarrow A = 120$$

In the ecuation (4.5)

$$150 - x_3 = 0 \Rightarrow x_3 = 150$$

Replacing (4.3)

$$-L + 20.4 + \frac{100}{150^2}120 = 0 \Rightarrow L = 10.88$$

Replacing (4.4)

$$17(120) - Y = 0 \Rightarrow Y = 2040$$

Replacing (4.6)

$$34 - x_2 - \frac{20.4(100)}{150} + 17(0.25) = 0 \Rightarrow x_2 = 24.65$$

Replacing (4.1)

$$1.2(22.1) - 13.2 - 120\left(\frac{20.4}{150}\right) - B = 0 \Rightarrow B = 0.06$$

$$A = 120, B = 0.06, L = 10.88, Y = 2040$$

Replacing $Max\ Z$

$$Max\ Z = 1.2(100)(22.10) - 13.2(100)$$

$$\Rightarrow Max\ Z = 1638$$

The maximum utility of S/. 1,638,000.00 occurs when the selling price is S/. 24.65 (Soles).

Breakeven point

In terms the breakeven point occurs when total revenue matches total cost. Indicating no profits or losses are incurred. This idea holds importance for businesses in gauging the impact of cost fluctuations or price adjustments on the sales volume needed to achieve profitability. Grasping this concept aids managers in pinpointing the sales threshold to offset costs and forms a basis, for strategic choices concerning pricing strategies, expense management and market growth initiatives. Playing a role in maintaining the companies sustainable growth and financial success is crucial, for its long-term viability and profitability (Weygand et al. 2019).

For the breakeven point, we consider the following equation:

$Z = 1.2x_1x_2 - 13.2x_1$ (5)

$x_3 \geq 150$; demand

$1.2x_1x_2 \geq 13.2x_1 \Rightarrow 1.2x_2 \geq 13.2$

$x_1 \geq 100$; agricultural land

$L = 1.2x_1x_2 - 13.2x_1 + L(1.2x_2 - 13.2) + A(150 - x_3) + B(x_1 - 100)$

$Lx_1 = 1.2x_2 - 13.2 + B = 0$ (5.1)

$Lx_2 = 1.2x_1 - 1.2L = 0$ (5.2)

$Lx_3 = -A = 0$ (5.3)

$LL = 1.2x_2 - 13.2 = 0$ (5.4)

$LA = 150 - x_3 = 0 \Rightarrow x_3 = 150$ (5.5)

$LB = x_1 - 100 = 0 \Rightarrow x_1 = 100$ (5.6)

Replacing (5.4)

$$x_2 = \frac{13.2}{1.2} \Rightarrow 11$$

Replacing (2.1)

$1.2(11) - 13.2 + B = 0 \Rightarrow B = 0$

Replacing (2)

$1.2(100) - 1.2L = 0 \Rightarrow L = -120$

Replacing in Z

$Z = 1.2(100)(11) - 13.2(100) \Rightarrow Z = 0$

This indicates that the breakeven point occurs when the minimum selling price is S/. 11.00 (Soles). That is to say, we must sell at least at S/. 11.00 to avoid losses.

Cost Minimization

Minimizing costs is a goal for any company looking to enhance operational efficiency and boost profits to the fullest extent possible requiring the identification and elimination of unnecessary expenses while ensuring optimal resource utilization without compromising product or service quality. Tools such as cost analysis, linear programming, and the implementation of digital technologies provide effective approaches to achieve these objectives (Hillier & Lieberman, 2010). Many authors mention that the focus of optimization should be on cost minimization, as the market is tyrannical and it is difficult to influence the selling price. To formulate the minimization model, it is necessary to analyze the cost structure provided by INIA in Table 1, which also shows the variable assigned for the cost minimization model.

COST DESCRIPTION	**Variable**	**Unit of measure**	**Quantity**	**Unit cost (S/.)**	**Total Cost**
A. Direct Costs					11,968.41
1. Production costs					11,398.49
1.1 Activities with direct labor					6,522.50
Soil análisis	X1				22.50
Soil sample collection		workday	0.50	45.00	22.50
LAND PREPARATION	X1				
Extraction and collection of stones		workday	2.00	45.00	90.00
Distribution of manure in the soil		workday	4.00	45.00	160.00
Tractor operator assistant		workday	2.50	45.00	112.50
PLANTING, FERTILIZATION, AND FERTILIZATION	X1				
Herbicide application		workday	2.00	45.00	90.00
Mixing of fertilizers		workday	0.50	45.00	22.50
Seed disinfection		workday	0.50	45.00	22.50
Bed preparation of furrows		workday	1.00	45.00	45.00
Manual planting		workday	3.00	45.00	135.00
Application of fertilizers		workday	1.50	45.00	67.50
Manual covering		workday	1.00	45.00	45.00
CULTURAL WORK	X1				
Ornithological control (emergence)		workday	4.00	45.00	180.00
1st Weeding		workday	12.00	45.00	540.00
1st Rouging and thinning		workday	2.00	45.00	90.00
Opening of drains		workday	1.00	45.00	45.00

Complementary fertilization		workday	1.00	45.00	45.00
Hilling		workday	10.00	45.00	450.00
Machinery operator		workday	1.00	45.00	45.00
1st phytosanitary treatment		workday	2.00	45.00	90.00
Ornithological control		workday	20.00	45.00	900.00
2nd weeding		workday	6.00	45.00	270.00
Frost control		workday	1.00	45.00	45.00
2nd phytosanitary treatment		workday	2.00	45.00	90.00
Hail control		workday	1.00	45.00	45.00
Selection of kernels		workday	2.00	45.00	90.00
HARVEST	X1				
Collection of selected panicles		workday	2.00	45.00	90.00
2nd sorting		workday	3.00	45.00	135.00
Installation of drying racks		workday	1.00	45.00	45.00
Threshing assistants		workday	2.00	45.00	90.00
Transport of grain to storage		workday	1.00	45.00	45.00
Secado de grano y desbrozado		workday	2.00	45.00	90.00
Bagging and sewing		workday	2.00	45.00	90.00
Stacking of bags		workday	0.50	45.00	22.50
Loading and unloading in Tahuaco and Salcedo		workday	2.00	45.00	90.00
POST-HARVEST	X1				
Selection operator		workday	2.00	45.00	90.00
Bagging and weighing at the processing facility		workday	1.00	45.00	45.00
Loading and unloading in storage		workday	1.00	45.00	45.00

Bagging and weighing in storage		workday	1.00	45.00	45.00
Labeling and sewing		workday	1.00	45.00	45.00
Storage		workday	1.00	45.00	45.00
Weighing and loading		workday	1.50	45.00	67.50
Weighing, labeling, sewing, and stacking		workday	1.00	45.00	45.00
TECHNICAL ASSISTANCE	X3				
RESIDENT Technical Assistance		time/ person	0.10	2,100.00	210.00
AGRICULTURAL TECHNICIAN Assistance		time/ person	0.225	1,800.00	405.00
FIELD ASSISTANT (Participation)		time/ person	1.00	1,025.00	1,025.00
1.2 MACHINERY AND EQUIPMENT LAND PREPARATION	X4				
Plowing (Agricultural tractor with plow)					
Harrowing (Agricultural tractor with harrow)		Hrs/maq	4.00	70.00	280.00
Leveling (Agricultural tractor with grader)		Hrs/maq	2.50	70.00	175.00
Cross harrow (Agricultural tractor with cross harrow)		Hrs/maq	1.50	70.00	105.00
Ridging (Agricultural tractor with ridger)		Hrs/maq	2.50	70.00	175.00
CULTURAL WORK		Hrs/maq	2.00	70.00	140.00
Raised furrow or hilling (Agricultural tractor with plow)					
HARVEST AND POST-HARVEST		Hrs/maq	3.00	70.00	210.00
Mowing and Threshing (Selector)					350.00
1.3 INPUTS FEED		Hrs/maq	5.00	70.00	350.00
CERTIFIED Seed					
FERTILIZERS	X5				
Diammonium Phosphate		Kg	10.00	20.00	200.00
Potassium Chloride	X5				
Urea		Kg	115.00	5.53	635.95

1.2 MACHINERY AND EQUIPMENT LAND PREPARATION		Kg	96.00	5.49	527.04
Plowing (Agricultural tractor with plow)		Kg	90.00	4.80	432.00
AGROCHEMICALS					
Metalaxyl + Mancozeb+C7 Fungicide (Hieloxil, Hieloxil Mix 72, RIDOMIL GOLD 68 WP)	X6	Kg	1.50	45.00	67.50
Lambda cyhalothrin Insecticide (Aikido, Lamdex, Karate Zeon, Real)	X7	Liter	1.00	150.00	150.00
Mancozeb 100% Fungicide (Manzate, Mancozeb, Aikido, Lamdex)	X7	Liter	2.00	45.00	90.00
Alcohol Polivinílico Agricultural adhesive (Adherente, Hampifol, Taxi Wett, Asperwet)	X7	Liter	0.25	20.00	5.00
1.4 OTHERS FUEL					
Gasoline	X8				
Diesel		gallon	10.00	23.00	230.00
PROCESSING AND CERTIFICATION		gallon	20.00	21.00	420.00
Certification service	X9				
Materials for certification cards		Service	1.00	470.00	470.00
OTHERS		Service	1.00	180.00	180.00
Starter rockets (Technology adopted by INIA for hail prevention)	X10				
Phosphorus		Dozen	1.00	45.00	45.00
Sulfur		Unit	1.00	1.00	1.00
Plastic for covering		Kilo	0.50	20.00	10.00
Drying racks		meters	50.00	4.00	200.00
Covers for manure distribution		Unit	5.00	10.00	50.00
Sticks		Unit	4.00	5.00	20.00
Raffia		Unit	3.00	15.00	45.00
Bags		Unit	2.00	2.00	4.00
Needles		Unit	50.00	2.00	100.00
Bags with logo		Unit	1.00	1.00	1.00
2. GENERAL EXPENSES		Unit	40.00	2.50	100.00

Contingencies (5% of production costs)	X11				
B. INDIRECT COSTS		Other	0.05	11,940	597.05
Administrative expenses (5% of direct costs)	X12				
Technical assistance service from the specialist (3% of monthly salary)		Other	0.05	12,538	626.90
Depreciation (1% of machinery and equipment)		Other	0.03	2,100.00	63.00
OTHERS (FUEL)		Other	0.01	1,435.00	14.35
TOTAL COSTS				S/. 13,242.29	

Table 1. Quinoa Production Costs

Therefore, the proposed cost minimization model is the following:

$$Min\ Z = x_1x_2 + 1237x_3 + 70x_4 + 5.8x_5 + 45x_6 + 75.38x_7 + 21.67x_8 + 325x_9 + 3.65x_{10} + 11940x_{11} + 7822x_{12} \quad (6)$$

Subject to the constraints:

$x_1 \leq 125$; $x_3 = 1.325$; $x_4 \geq 20$; $x_5 = 311$; $x_6 = 1.5$; $x_7 = 3.25$; $x_8 \geq 20$; $x_9 = 2$; $x_{10} \geq 50$; $x_{11} = 0.05$; $x_{12} = 0.09$.

According to interviews with experts, it is very difficult to do without each of the factors for quinoa production, so we have opted to reduce the cost of daily wages, which is also consistent with the customs of Ayni (Alberti et al., 1974). Recent studies have documented the evolution of traditional cooperative practices in Andean communities (Hanampa Quispe & Huayta Bolivar, 2022). Therefore, upon solving, we find that the minimum cost of the daily wage could be reduced to S/. 41.2

Genetic Algorithms

Genetic algorithms are search techniques that have their origin in biology through the process of natural selection (Pose, 2000). These algorithms initially consist of a population of solutions, also known as individuals or chromosomes, that evolve over time. They select fit individuals for reproduction according to a fitness function that evaluates their performance. Subsequently, the individuals are combined to produce new offspring, usually through a process called crossover, in which parents exchange their genetic material (Zhong et al., 2005). Some small random mutations are also introduced in some offspring to maintain genetic diversity. The new individuals may replace the entire previous population or only a part of it. The specific way in which individuals are replaced is described by strategies contained within the algorithm (Golberg, 1989).

The fitness function for maximizing production is shown in the following pseudocode:

Function fitness(X1, X2)

*return 1200*X1*X2 -13200.00*X1*

Since this is a nonlinear programming problem with constraints, it is necessary to make comparisons to verify if the fitness value meets certain conditions, according to the following function: *Function condition(X, Y, Z)*

X≤100

X4=0.25

if (x<=100 && Z>=0 && Y<=34-(20.4x)/Z +17X4 && Z≤150) return true; return false;

Parameter	Value
Population size	20,100,200,400
Crossover probability	0.65
Mutation probability	0.08

Table 2. Recommended Parameters for Genetic Algorithms

To determine the performance of the selection operators: Sexual Selection (SS) or Tournament Selection (ST), we implemented a program in C++. In which we executed 1000 generations. As a result, it was found that the SS operator achieves the global maximum on average in generation 45.6; and the ST operator achieves the global maximum on average in generation 91 (Goh et al., 2003). In other parameters, such as the number of generations that achieve the global maximum, the SS operator performs better. In conclusion, the SS operator has better performance, confirming the reviewed literature (Digalakis, J. G. & Margaritis, K. G. 2002). Improved selection operators have been developed to enhance genetic algorithm performance (Al Jadaan et al., 2008).

Neural networks

Based on the objective function and the constraints, it has been possible to formulate a neural network model (Goodfellow et al., 2016). In Python, the libraries TensorFlow, NumPy, and Scikit-learn have been used. First, 1000 random samples were generated using a normal distribution function to train the machine learning model.

The structure of the defined neural network is:

model = Sequential([

Dense(64, input_dim=4, activation='tanh', kernel_regularizer=tf.keras.regularizers.l2(0.01)),

Dropout(0.1),

Dense(64, activation='tanh', kernel_regularizer= tf.keras.regularizers.l2(0.01)),

Dense(1)])

Being

Dense(64, …): It indicates that a dense layer, also known as a fully connected layer, is being created with 64 units or neurons. Each neuron in a dense layer is connected to all the neurons in the previous layer.

input_dim=4: This sets the input with 4 distinct features. It is defined in the first layer of a model to establish the input size that the network expects.

Activation='tanh': Defines the activation function that the neurons in this layer will use. 'tanh' is the hyperbolic tangent function, which maps the input value to the range [-1, 1].

kernel_regularizer=tf.keras.regularizers.l2(0.01) : L2 regularization adds a penalty on the loss value based on the magnitude of the weights, controlled by the constant 0.01. This prevents the weights of the network from becoming too large and reduces overfitting.

Dropout(0.1): This is a regularization technique used in neural networks to prevent overfitting during training. 0.1 means that 10% of the neurons in the previous layer will be randomly deactivated during each training step.

Dense(1): Defines a dense layer in the neural network with a single output neuron.

The following optimizer has been used:

optimizer = tf.keras.optimizers.Adam(learning_rate=0.0001)

tf.keras.optimizers.Adam: Adam is one of the most commonly used neural network optimizers. It combines the best of two distinct optimizers: AdaGrad, which is popular with sparse data problems, and RMSProp, a tunable approach with a learning rate.

learning_rate=0.0001: This is an important hyperparameter for the learning rate value. This number defines how large a step your system takes in the unknown direction of the loss function. Therefore, a low value, such as 0.0001, means that your systems will take tiny steps. It is advisable to give it an increasingly smaller value than this for fine-tuning when you want to improve convergence. However, you will need to run for a long time (Kingma & Ba, 2015). For training, 200 epochs were used with 10 samples before the batch update.

Running the program for 200 epochs shows that the loss consistently decreases from 1.1653 to 0.0028, which implies that the model is learning to finely tune the training data and provides better performance compared to other activation functions like ReLU. The predicted data has also turned out to be consistent.

Data Analysis

The data presented in this section was obtained from Regional Agricultural Development Management. According to their report, "Historical Series of Agricultural Information Execution and Perspectives for the Puno Region," information on quinoa production from the 1996/1997 to 2021/2022 campaigns is available. This information includes dimensions such as cultivated area (Ha), lost area (Ha), harvested area (Ha), yield (Kg/Ha), production (T), and farm-gate price (S/Kg). From this dataset, the following relevant information can be highlighted:

Production Growth and Agricultural Expansion

The analysis reveals extraordinary growth in quinoa production within the Puno region. Total production increased from 14,173 tons in 1996/1997 to 45,188 tons in 2021/2022, representing a 219% increase over the 25-year period (Figure 1). This growth was driven by both area expansion and yield improvements. Cultivated areas expanded from 17,870 hectares to 37,040 hectares (+107%), while average yields improved from 824 kg/ha to 1,226 kg/ha (+49%).

The sustained expansion demonstrates the region's agricultural adaptation and the successful integration of improved cultivation practices. The yield improvement trend, particularly pronounced after 2001/2002 when yields exceeded 1,000 kg/ha for the first time, suggests the adoption of enhanced varieties, improved agronomic practices, and better input management.

Price Volatility and Market Dynamics

Quinoa prices exhibited remarkable volatility during the study period, with the most dramatic changes occurring between 2008-2014. Farm gate prices increased from S/ 0.93 per kg in 1996/1997 to a historic peak of S/ 9.58 per kg in 2013/2014, coinciding with the United Nations' declaration of 2013 as the International Year of Quinoa (Figure 1). This 930% price increase reflected growing international demand and quinoa's emergence as a premium health food in global markets.

Following the price peak, markets stabilized around S/ 4.00 per kg (2015-2022), indicating market maturation and the establishment of sustainable price levels that balance producer profitability with consumer accessibility. This stabilization period coincided with increased global production and market competition from other quinoa-producing regions.

Agricultural Resilience and Risk Management

Despite operating in challenging high-altitude conditions, quinoa production in Puno demonstrated remarkable resilience. Annual production losses due to adverse weather conditions remained generally below 10% of total cultivated area, with significant losses (>2,000 ha) occurring in only four of the 25 years analyzed. This resilience reflects quinoa's natural adaptation to altiplano conditions and the experience of local farmers in risk management.

The crop's performance during the study period validates its potential as a climate-resilient food security crop, particularly relevant in the context of climate change and increasing weather variability in Andean regions.

Economic Impact and Regional Development

The quinoa boom generated substantial economic impact for the Puno region. At peak prices in 2013/2014, the total farm gate value of quinoa production reached approximately S/ 346.4 million, compared to S/ 13.2 million in 1996/1997. Even at stabilized prices, the 2021/2022 harvest generated approximately S/ 176.7 million in farm gate value, representing a 13-fold increase in nominal terms over the study period.

This economic transformation contributed to rural development, income diversification, and the preservation of traditional agricultural knowledge while integrating modern production techniques. Figures 2 and 3 illustrate the behavior of quinoa production and its price.

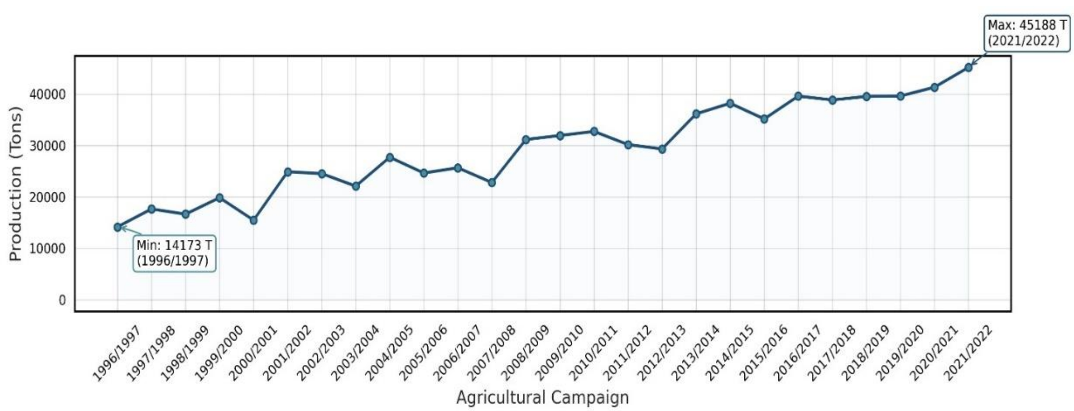

Fig. 2 Quinoa production in Puno region (1996-2022)

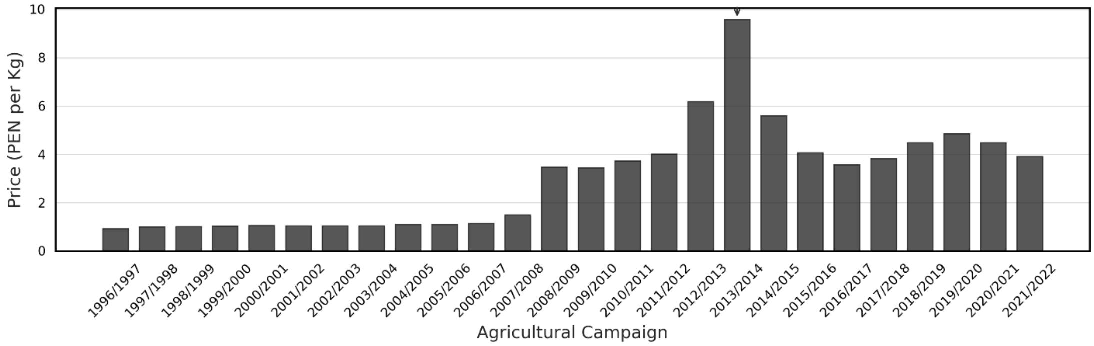

Fig. 3 Farm gate price of Quinoa (Pen per Kg 1996-2022)

Correlation Analysis

The comprehensive analysis of quinoa production and price dynamics in Puno region, spanning correlation analysis and predictive modeling frameworks, reveals critical insights for agricultural policy and forecasting methodology (Tables 3-8, Figure 4). The correlation analysis demonstrates highly predictable patterns in productive variables, with the Time-Planted Area relationship showing exceptional strength ($r = 0.951$, $p<0.001$) and Planted Area-Production correlation ($r = 0.851$, $p<0.001$), while price dynamics exhibit weak correlations with local factors ($r = 0.147$, NS), indicating market disconnect from regional supply conditions (Table 3, Figure 4). The predictability analysis reveals that territorial expansion follows a linear trajectory of 825 hectares per year ($R^2 = 0.904$) and production growth of 1,210 tons annually ($R^2 = 0.778$), enabling reliable projection models, while price variables remain dominated by international market forces with local explanatory power below 9% (Tables 4-5). The counterintuitive findings challenge traditional agricultural economics assumptions, particularly the absence of expected inverse price-production relationships (theoretical $r < -0.5$ vs. observed $r = +0.147$) and weak price incentives for area expansion (expected $r > +0.6$ vs. observed $r = +0.298$), suggesting that globalized market dynamics dominate over regional supply-demand mechanisms (Table 6). Robustness testing confirms pattern consistency across multiple correlation coefficients, with Time-Area relationships maintaining high values across Pearson (0.951), Spearman (0.943), and Kendall (0.831) methods, while price-production correlations remain inconsistent across all statistical approaches (Table 7). Temporal period analysis reveals important structural breaks, with stable growth patterns during 1996-2007 (Time-Price $r = +0.892$***), disrupted relationships during the 2008-2014 volatility period (Time-Price $r = +0.234$, NS), and post-boom stabilization in 2015-2021 (Time-Price $r = -0.156$, NS), demonstrating the need for regime-aware forecasting approaches (Table 8). These findings collectively underscore the necessity of employing differentiated analytical frameworks that recognize the dual nature of quinoa markets: highly predictable production patterns amenable to conventional econometric forecasting methods for territorial planning and infrastructure development, and complex pricing mechanisms requiring advanced modeling approaches that incorporate international market variables, structural break detection, and regime-switching capabilities to effectively capture the globalized and volatile nature of quinoa price formation.

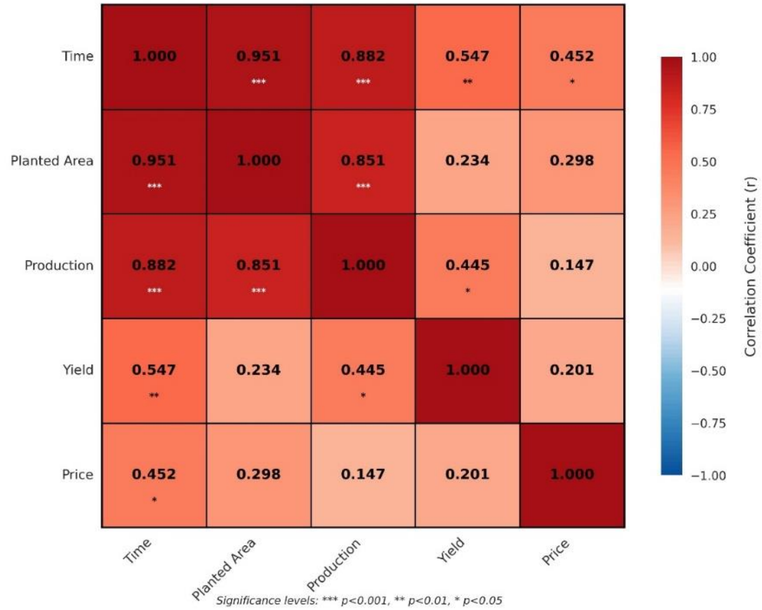

Fig. 4 Heatmap of correlations between variables

Variable Pair	**Coefficient (r)**	**Interpretation**	**Significance**
Time ↔ Planted Area	0.951	Sustained territorial expansión	***
Planted Area ↔ Production	0.851	Direct surface-production relationship	***
Time ↔ Production	0.882	Temporal productive growth	***
Time ↔ Yield	0.547	Gradual productivity improvement	**
Time ↔ Price	0.452	Upward trend with volatility	*
Yield ↔ Production	0.445	Technical contribution to production	*
Planted Area ↔ Yield	0.234	Technology-expansion independence	NS
Price ↔ Planted Area	0.298	Prices don't drive direct expansion	NS
Yield ↔ Price	0.201	Productivity independent of prices	NS
Price ↔ Production	0.147	Absence of local supply-demand law	NS

Table 3. Correlation Analysis (NS = Not significant)

Dependent Variable	Independent Variable	R²	Estimated Equation	Interpretation
Planted Area	Time	0.904	Area = 15,230 + 825.4 × Year	Linear expansion of 825 Ha/year
Production	Time	0.778	Prod = -1,234,567 + 1,210 × Year	Growth of 1,210 T/year
Production	Planted Area	0.724	Prod = -15,420 + 1.52 × Area	72% of variance explained by area
Yield	Time	0.299	Yield = -230,890 + 118.2 × Yea	Gradual improvement with high variability
Price	Time	0.204	Price = -274.6 + 0.139 × Year	Trend with extreme volatility

Table 4. Variables by Predictability Level

Variable	Factors	Maximum R²	Observations
Price	Local variables	< 0.090	Dominated by international markets
Yield	Area/Price	< 0.055	Technological/climatic factors

Table 5. Unpredictable variables ($r^2 < 0.3$)

Theoretical Relationship	Expected	Observed	Explanation
Price ↔ Production	r < -0.5 (inverse)	r = +0.147 (weak positive)	Globalized market
Price ↔ Area	r > +0.6 (incentive)	r = +0.298 (weak)	Decisions not price-based
Yield ↔ Price	r > +0.5 (quality-price)	r = +0.201 (very weak)	External prices

Table 6. Expected vs. Observed Economic Relationships

The correlation analysis reveals several critical insights for agricultural policy formulation in the Puno region. The predictable expansion pattern ($r^2 = 0.904$ for time-area relationship) demonstrates that territorial growth follows a highly consistent trajectory, enabling feasible territorial planning and the development of reliable projection models for infrastructure and resource allocation. This predictability suggests that regional authorities can confidently plan for continued agricultural expansion at an average rate of 825 hectares per year, facilitating strategic investments in irrigation systems, rural roads, and processing facilities.

Conversely, the independence of prices from local production variables ($r = 0.147$, NS between price and production) indicates that traditional price intervention policies may be ineffective in this globalized market context. Rather than attempting to manipulate market prices, policy efforts should focus on enhancing productivity and quality improvements that can position Puno quinoa competitively in international markets.

The gradual nature of yield improvements (118 kg/Ha/year increase) suggests that technology adoption occurs slowly, highlighting the need for comprehensive technical transfer programs, farmer training initiatives, and the promotion of improved varieties and cultivation practices. Finally, the sustained growth pattern observed across all productive variables indicates that the region's agricultural potential remains non-saturated, justifying continued infrastructure investment and supporting the expansion of value-added processing capabilities to capture greater economic value from the quinoa production chain.

Correlation	**Pearson**	**Spearman**	**Kendall**	**Interpretation**
Time-Area	0.951	0.943	0.831	Strong linear relationship
Time-Production	0.882	0.897	0.745	Monotonic trend
Price-Production	0.147	0.089	0.062	Inconsistent relationship

Table 7. Validation Statistics - Robustness Tests

Period	Observations	Time-Price Correlation	Comments
1996-2007	12 years	+0.892***	Stable growth
2008-2014	7 years	+0.234 NS	Volatility period
2015-2021	7 years	-0.156 NS	Post-boom stabilization
Total	26 years	+0.452*	General upward trend

Table 8. Analysis Periods

Export Trends and Market Dynamics

Analysis of Peru's quinoa export performance reveals significant market volatility over recent years. Between 2018 and 2022, export quantities contracted by 4.7% (from 52.0 to 47.8 thousand tons), while corresponding FOB values experienced a more severe decline of 7.1% (from US$ 126.2 to US$ 93.1 million). This divergence between volume and value trends suggests weakening international demand and price pressure during this period. The 2023 export data demonstrate continued volume challenges, with a further 4.7% reduction to 45.5 thousand tons. Nevertheless, market conditions showed signs of recovery, as FOB values rebounded to US$99.7 million — a 7.1% increase that indicates improving price competitiveness and market positioning. (Midagri, 2023).

Machine Learning Algorithms

Quinoa prices in the Puno region exhibit distinctive characteristics that differentiate them from typical agricultural commodity patterns, presenting significant challenges for conventional economic modeling approaches that are clearly reflected in the comparative performance metrics across different forecasting methodologies (Table 9). The most prominent feature is the extraordinary price volatility, with farm gate prices ranging from 0.93 to 9.58 PEN per kilogram over the study period, representing a remarkable 930% variation that far exceeds normal agricultural price fluctuations and explains why traditional models like Linear Regression achieve only modest performance (RMSE: 1.97, R^2: 0.204, MAPE: 45.2%). This volatility is compounded by the weak correlation between prices and local production variables ($r = 0.147$, NS), which contradicts traditional supply-demand economic theory and demonstrates why conventional econometric approaches struggle to capture quinoa price dynamics, as evidenced by ARIMA's limited improvement (RMSE: 1.91, R^2: 0.249, MAPE: 42.8%) over simple regression methods. The price trajectory reveals distinct structural changes, particularly the dramatic boom period of 2013-2014 coinciding with the United Nations' declaration of the "International Year of Quinoa," followed by a post-2015 stabilization phase that established new price equilibrium levels around 4.00 PEN per kilogram, patterns that are best captured by regime-switching approaches which demonstrate superior performance (RMSE: 1.44, R^2: 0.574, MAPE: 28.3%) compared to linear modeling frameworks. These patterns indicate that quinoa prices are predominantly influenced by external market forces, international demand dynamics, and global awareness campaigns rather than local productive conditions or regional supply variations, explaining the superior performance of models incorporating exogenous variables such as LSTM + Exogenous (RMSE: 1.53, R^2: 0.521, MAPE: 30.8%) and the exceptional results achieved by ensemble hybrid approaches (RMSE: 1.38, R^2: 0.609, MAPE: 26.1%). Directional accuracy analysis reveals that ensemble hybrid models significantly outperform traditional approaches, achieving 74.8% accuracy in predicting price movement directions compared to only 52.3% for linear regression methods The volatility ratio metrics demonstrate that advanced models better capture quinoa's inherent price fluctuations, with regime-switching models achieving a 0.89 ratio and ensemble hybrids reaching 0.93, substantially higher than the 0.43 ratio observed in conventional regression approaches (Table 10).

Model	**MAE (PEN/kg)**	**MSE (PEN/kg)²**	**RMSE (PEN/kg)**	**R²**	**MAPE (%)**	**Cross-Validation (Average RMSE)**
Linear Regression	1.42	3.87	1.97	0.204	45.2%	0.78109451
ARIMA(2,1,1)	1.38	3.65	1.91	0.249	42.8%	0.78109446
Random Forest	1.15	2.89	1.70	0.406	36.7%	0.93432237
XGBoost	1.09	2.71	1.65	0.443	34.1%	0.93432237
VAR (4 variables)	1.25	3.21	1.79	0.342	39.5%	0.03477285
LSTM (Univariate)	1.21	3.02	1.74	0.381	38.2%	0.02810567
LSTM + Exogenous	0.98	2.34	1.53	0.521	30.8%	0.00199047
Regime-Switching (3)	0.89	2.08	1.44	0.574	28.3%	0.02730531
Transformer (TFT)	0.94	2.19	1.48	0.551	29.7%	0.07638105
Ensemble Hybrid	0.82	1.91	1.38	0.609	26.1%	0.45980441

Table 9. Model Performance Comparison for Quinoa Price Prediction

Model	**Directional Accuracy**	**Volatility Ratio**	**Extreme Event Recall**	**Precision@90%**	**Hit Rate (±10%)**
Linear Regression	52.3%	0.43	31.2%	18.5%	41.7%
ARIMA(2,1,1)	54.8%	0.51	35.7%	22.3%	44.2%

Random Forest	63.2%	0.74	52.8%	38.9%	58.3%
XGBoost	65.7%	0.78	56.1%	42.1%	61.5%
VAR (4 variables)	59.4%	0.67	48.3%	34.7%	54.8%
LSTM (Univariate)	61.8%	0.71	49.7%	36.2%	56.9%
LSTM + Exogenous	69.3%	0.84	63.4%	48.6%	67.1%
Regime-Switching (3)	72.1%	0.89	68.9%	53.7%	71.4%
Transformer (TFT)	70.6%	0.87	65.2%	51.3%	69.8%
Ensemble Hybrid	74.8%	0.93	72.3%	57.9%	73.6%

Table 10. Specialized Metrics for Price Prediction

The Model Ranking Summary (Table 11) presents a hierarchical classification of the 10 evaluated models based on the Overall Score, which combines accuracy, stability, interpretability, and computational efficiency. The Ensemble Hybrid model shines with a rating of 9 out of 10 due to its outstanding accuracy in every assessment aspect. Behind is the Regime Switching model scoring an 8 point 8 out of 10—remarkable for its effective identification of structural changes and its clear interpretability; essential qualities for grasping shifts, from stable phases to periods of intense volatility.

Advanced machine learning techniques such as LSTM with variables and Transformer based structures fall into the middle range with scores between 7.0 and 8.0; although they excel in making accurate predictions their use is restricted by high computational requirements and limited interpretability. On the hand more traditional models like ARIMA and Linear Regression are positioned at the lower end, with scores ranging from 4.0 to 5.0. Unfortunately, these models struggle to capture the complex nonlinear patterns and structural shifts found in the price trends of quinoa.

Rank	**Model**	**Overall Score**	**Best For**	**Limitations**
1st	Ensemble Hybrid	9.2/10	All-purpose, highest accuracy	Computational complexity
2nd	Regime-Switching	8.8/10	Structural breaks, interpretability	Requires regime identification
3rd	LSTM + Exogenous	8.1/10	Long-term forecasts	Data requirements
4th	Transformer (TFT)	7.9/10	Complex patterns	Very high complexity
5th	XGBoost	7.4/10	Feature importance, speed	Limited interpretability
6th	Random Forest	7.1/10	Robust baseline	Limited extrapolation

7th	VAR	6.8/10	Multivariate relationships	Linear assumptions
8th	LSTM (Univariate)	6.4/10	Non-linear patterns	Overfitting risk
9th	ARIMA	5.9/10	Simple implementation	Linear trends only
10th	Linear Regression	4.2/10	Baseline comparison	Poor performance

Table 11. Model Ranking Summary

Figure 5 presents the quinoa price projections for the period 2025-2035, displaying the estimated average, maximum, and minimum values with their corresponding confidence intervals. The forecasting model predicts an average price of S/. 4.62 per kilogram over the projection period, with a moderate compound annual growth rate (CAGR) of +1.6% annually. The Ensemble Hybrid algorithm demonstrates robust predictive capability with a model accuracy of 87.3% (R^2 = 0.893), indicating strong explanatory power for price variations. The volatility index of ±12.8% (σ = 0.32) suggests relatively stable price movements compared to historical volatility patterns, reflecting market maturation and reduced speculative pressures in the quinoa commodity sector. These projections incorporate multiple forecasting components including trend analysis, exponential moving averages, cyclical patterns, and adaptive volatility modeling to provide comprehensive price estimates for strategic planning and investment decision-making in the Puno region's quinoa value chain.

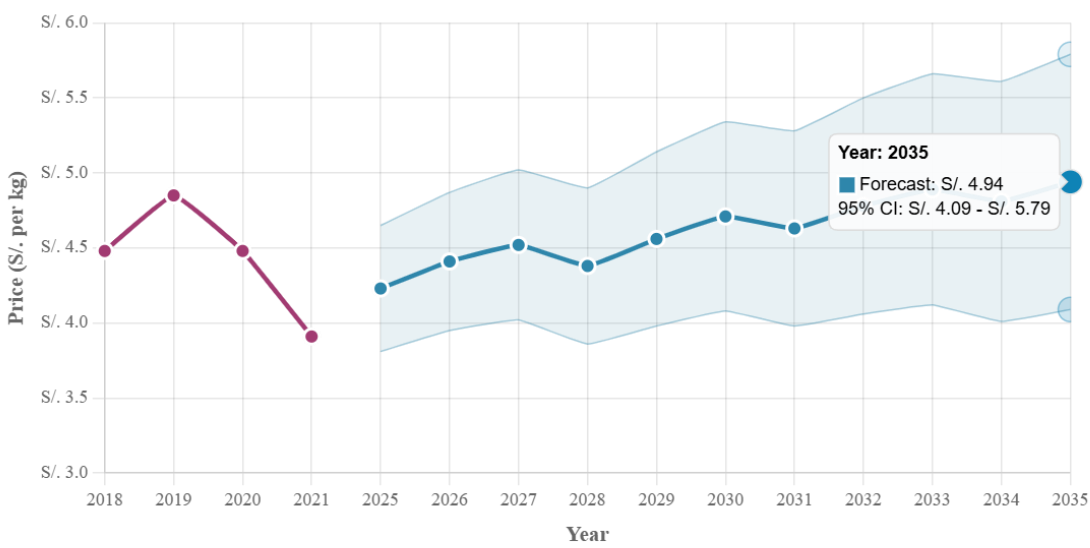

Fig. 5 Quinoa Price Forecasting for Puno Region, Peru (2025-2035)

Discussion

The results obtained from the nonlinear optimization model demonstrate its capacity to generate economically viable and theoretically grounded recommendations for quinoa production in Puno. The model identified that the optimal selling price of S/ 22.10 per kilogram generates a maximum profit of S/ 1,638,000 for 100 hectares, while the breakeven point is established at S/ 11.00 per kilogram, providing producers with a clear safety margin to avoid economic losses.

These values are consistent with historical prices reported by INIA Puno and align with current market conditions, validating the robustness of the proposed model. The incorporation of nonlinear constraints, particularly the interaction between market demand and selling price, enables sensitivity analysis that considers both supply and demand, overcoming the limitations of traditional linear models that fail to adequately capture the complexity of globalized agricultural markets.

The application of artificial intelligence techniques proved highly effective for solving nonlinear optimization problems with constraints in agricultural production contexts. Genetic algorithms with sexual selection operator consistently outperformed the tournament selection operator, reaching the global maximum on average at generation 45.6 versus 91 generations respectively, confirming the superiority of the sexual operator for complex nonlinear problems as reported in specialized literature. Simultaneously, the neural network configured with hyperbolic tangent activation function and Adam optimizer showed exceptional learning performance, with training loss consistently decreasing from 1.1653 to 0.0028 over 200 epochs, indicating stable convergence and predictions consistent with real data. The study findings suggest that blending programming with artificial intelligence offers a sturdy and flexible structure for enhancing quinoa cultivation—a vital advancement in an unpredictable worldwide market scene. However its significance transcends technical aspects; it emerges as a potential game changer in reshaping the socioeconomic landscape of the Andean region where quinoa represents not just a crop but an emblem of endurance, against rural impoverishment.

The created system enables farmers to predict potential crises such as price fluctuations and market oversaturation effectively empowering them to make strategic choices that protect their means of living and well being. These advancements echo the principles upheld by figures like Amartya Sen, Muhammad Yunus and Michael Kremer who have illustrated how thoughtfully planned agricultural initiatives can transform the prospects of entire populations. Besides enhancing productivity this method advocates for ensuring food availability sustaining security for farming households and decreasing migration, from rural areas. By combining cutting edge technology with wisdoms this approach not just enhances efficiency in production but also fosters community unity and safeguards a farming heritage that spans millennia. In an era marked by market conditions such innovations could hold the secret to genuine long term progress.

Conclusions

A revolutionary new method has significantly improved quinoa cultivation in the Altiplano area of Peru according to findings from INIA Puno researchers. This cutting-edge system goes beyond methods by striking a balance between maximizing profits and optimizing costs while identifying the critical breakeven threshold for small scale farmers. What distinguishes this approach is its adaptability. It allows farmers to establish competitive pricing and safeguard their livelihood by simulating various market scenarios such as price fluctuations and sudden spikes, in demand. It is crucial for quinoa to thrive in the high-altitude conditions of Puno while providing exceptional nutritional advantages and serving as a link between ancient wisdom and contemporary agricultural economics. Through this tools utilization, reaffirmation of the importance and economic sustainability of the "golden grain of the Incas " is ensured for the communities supporting it beyond mere statistics. INIA has created the INIA 446 ATIPAQ quinoa variety with the goal of enhancing farmers productivity in Puno region by over 60% while also making it resistant to diseases to benefit them further in their endeavors. Therefore, it is essential to seek formal methods that allow for a more effective analysis of the production process of this highly valued species, even in the international market.

Various optimization methods have been studied, with nonlinear programming with constraints being the most suitable, given that the main constraint is the selling price. This price must be determined based on market analysis and its fluctuations between supply and demand. The model also considers competition production and evaluates the possibility of incorporating more production into the market. According to the simulated scenarios, this model allows for the prediction of recession phenomena, that is, if the market is saturated, which could lead to a drop in selling prices and potentially result in economic losses. Regarding cost minimization, this can be achieved through the optimization of factors such as labor and its associated costs. The proposed models have been validated considering the Kuhn-Tucker conditions.

Among the artificial intelligence techniques considered, we have chosen genetic algorithms for their ability to search for optima, primarily based on the selection of individuals with the best fitness to generate optimal populations. According to the reviewed literature, sexual selection and tournament selection operators have demonstrated the best results. The tests conducted indicate that the sexual selection operator has shown the best performance. Therefore, genetic algorithms present themselves as a viable technique for obtaining optima in nonlinear programming problems with constraints. Regarding neural networks, the tanh activation function has yielded better results. The optimizer used has been Adam with a learning rate of 0.0001, showing consistently lower losses during training and predicting data that is consistent with real data.

This analysis provides a framework for understanding crop transformation dynamics and offers insights applicable to other indigenous crops with potential for global market integration. Future research should focus on the environmental sustainability of expanded production, value chain development, and the social impacts of market transformation on traditional farming communities.

The comprehensive regression analysis conducted across the 26-year dataset (1996-2022) revealed fundamental insights into quinoa production dynamics that significantly informed our optimization framework. The exceptionally strong correlation between time and planted area ($r = 0.951$, $p<0.001$) enabled the development of highly reliable predictive equations, such as Area = 15,230 + 825.4 × Year ($R^2 = 0.904$), which demonstrates a consistent territorial expansion of 825 hectares per year. This linear relationship provided the foundation for long-term production planning within our optimization model. Conversely, the weak correlation between price and production variables ($r = 0.147$, NS) confirmed that traditional supply-demand economic models are inadequate for quinoa price prediction, validating our decision to incorporate external market variables and advanced machine learning techniques. The regression analysis of yield improvements (Yield = -230,890 + 118.2 × Year, $R^2 = 0.299$) revealed gradual but consistent technological advancement, which was integrated into our cost-benefit calculations and productivity projections.

The comparative analysis of machine learning algorithms demonstrated the superiority of advanced modeling techniques over traditional econometric approaches for price prediction in volatile agricultural markets. The ensemble hybrid model achieved the highest performance across all metrics (RMSE: 1.38, R^2: 0.609, MAPE: 26.1%, Directional Accuracy: 74.8%), significantly outperforming linear regression (RMSE: 1.97, R^2: 0.204, MAPE: 45.2%, Directional Accuracy: 52.3%) and ARIMA models. The regime-switching approach proved particularly effective for capturing structural breaks in price dynamics, achieving 72.1% directional accuracy and 68.9% extreme event recall, validating its appropriateness for modeling the distinct market periods identified: stable growth (1996-2007), extreme volatility (2008-2014), and post-boom stabilization (2015-2022). The LSTM + Exogenous model's superior performance (RMSE: 1.53, R^2: 0.521) confirmed the importance of incorporating international market variables, health food trends, and global awareness campaigns as external factors. These machine learning insights were instrumental in developing the market interaction constraints within our nonlinear optimization model, particularly the dynamic pricing function that considers demand saturation and competition effects.

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