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## **Reduction of pesticide residues in quinoa through Lean Six Sigma and good agricultural practices: A process capability-based approach**

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**Abstract**---Pesticide residue variability is a persistent challenge in high-value agroexport supply chains, where upstream agricultural heterogeneity limits the effectiveness of industrial controls. This study develops an integrated Lean Six Sigma (LSS) and Good Agricultural Practices (GAP) framework to reduce chemical risk in quinoa production using a process capability-based approach. A dataset of 312 quinoa lots processed by AGRIPROCESS S.A.C. between July 2024 and July 2025 was analyzed following the DMAIC methodology. Chlorpyrifos was identified as the critical-to-quality parameter, accounting for most non-conformities relative to international maximum residue limits. Statistical analysis revealed significant process instability ( $C_p = 0.597$ ;  $C_{pk} = 0.560$ ), indicating an incapable and off-centered process. Upstream variability was strongly associated with low GAP compliance among specific suppliers, who contributed disproportionately to overall dispersion. Based on these findings, a comprehensive improvement model is proposed, integrating standardized agricultural practices, supplier segmentation, enhanced traceability, and real-time statistical process control. The proposed framework provides a replicable and data-driven strategy for reducing chemical variability, strengthening food safety, and improving regulatory compliance across agroexport supply chains in emerging economies.

**Keywords**---Lean Six Sigma, Good Agricultural Practices, Process capability, Pesticide residues, Chlorpyrifos, Agroexport supply chain,

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Statistical process control, DMAIC methodology, Food safety, Variability reduction.

## Introduction

Quinoa has gained significant global relevance as a high-value crop, yet pesticide residue levels continue to pose serious challenges for international market compliance and food safety assurance. Several studies highlight that residue variability in smallholder-based agricultural systems originates predominantly in upstream production stages, where heterogeneous farming practices, inconsistent pesticide application, and limited adherence to Good Agricultural Practices (GAP) generate fluctuations that are difficult to control at the industrial level. This pattern is particularly evident in export-oriented supply chains serving highly regulated markets such as the European Union, where maximum residue limits (MRLs) for pesticides are stringent and closely monitored.

The literature consistently emphasizes that chemical residue variability reflects systemic quality issues rather than isolated operational failures. In agroindustrial contexts, upstream variability is frequently amplified during postharvest processing, where industrial controls cannot compensate for degraded input quality. Despite this, most existing interventions rely on reactive measures—primarily laboratory testing and product rejection—rather than on preventive and data-driven approaches grounded in quality engineering principles.

Lean Six Sigma (LSS), particularly through the DMAIC (Define–Measure–Analyze–Improve–Control) framework, offers a robust methodology for identifying sources of variability, modeling process behavior, and implementing systematic improvements. Although LSS is widely applied in manufacturing, healthcare, and service industries, its integration into agricultural systems remains limited. Similarly, while GAP guidelines are recognized as essential for ensuring safe and sustainable production, their adoption is uneven across smallholder networks, underscoring the need to conceptualize agriculture as an extension of the industrial process.

However, a critical research gap persists: few studies have examined the combined application of LSS, GAP, and statistical process capability analysis to quantify and reduce pesticide residue variability in quinoa or other Andean crops. Previous research largely focuses on agronomic practices, toxicology, or descriptive evaluations, without connecting these perspectives to rigorous industrial engineering methodologies.

This study contributes to closing this gap by analyzing 312 quinoa lots processed between July 2024 and July 2025 and evaluating process capability indices (Cp, Cpk) for chlorpyrifos residues. The study provides three main contributions:

- (1) a rigorous statistical characterization of pesticide residue variability using capability analysis;
- (2) the integration of LSS and GAP as a unified framework for reducing upstream variability; and

(3) the proposal of a replicable, data-driven improvement model tailored to agroexport supply chains in emerging economies.

## Materials and Methods

### 6.1 Research Design and Methodological Framework

This research adopts a quantitative, descriptive–explanatory, and non-experimental design intended to characterize pesticide residue variability under real operational conditions. The methodological framework integrates **Lean Six Sigma (LSS)** and **Good Agricultural Practices (GAP)** using the **DMAIC** structure (Define–Measure–Analyze–Improve–Control), which enables systematic identification of variability sources and development of corrective actions based on statistical evidence.

The dataset consists of quinoa lots processed by AGRIPROCESS S.A.C. from **July 2024 to July 2025**, focusing on chlorpyrifos as the **critical-to-quality (CTQ)** parameter due to its regulatory relevance.

### 6.2 Data Collection and Inclusion Criteria

A total of **312 quinoa lots** were evaluated. Data sources included:

- ISO/IEC 17025-certified laboratory pesticide reports
- Reception and quality inspection records
- Supplier GAP audit results
- Traceability documentation
- Production and processing logs

Only lots with complete, validated chlorpyrifos results were included.

### 6.3 Variables

Primary CTQ Variable

- **Chlorpyrifos concentration (mg/kg)**  
Compared to the **European Union MRL (USL = 0.05 mg/kg)**.

Secondary Variables

- GAP compliance (%)
- Traceability level (0–3)
- Documentation completeness (%)
- Preharvest interval (PHI, days)
- Lot moisture (%)

These variables help evaluate upstream variability.

### 6.4 Application of the DMAIC Methodology

Define Phase

A SIPOC diagram was constructed to define suppliers, inputs, process stages, outputs, and regulation-driven customer requirements.

Measure Phase

Descriptive statistics were computed, and measurement validity was ensured through ISO/IEC 17025 accreditation.

Analyze Phase

Root causes were identified using Pareto charts, Ishikawa diagrams, FMEA, correlation matrices, and supplier segmentation.

### Improve Phase

An integrated improvement model was developed, incorporating standardized pesticide management, supplier differentiation, and enhanced traceability protocols.

### Control Phase

Control charts ( $\bar{X}$ -R) and documentation controls were designed to maintain improvements.

## 6.5 Statistical Analysis

### 6.5.1 Normality Assessment

Normality of the chlorpyrifos data was evaluated using the **Shapiro-Wilk test**:

$$W = \frac{(\sum_{i=1}^n a_i x_{(i)})^2}{\sum_{i=1}^n (x_i - \bar{x})^2}$$

Where:

- $x_{(i)}$  = ordered values
- $a_i$  = expected normal coefficients
- $n=312$

A significance level of  $\alpha = 0.05$  was used.

### 6.5.2 Estimation of Process Standard Deviation

The standard deviation ( $\sigma$ ) was computed as:

$$\sigma = \sqrt{\frac{1}{n-1} \sum_{i=1}^n (x_i - \bar{x})^2}$$

Both within-subgroup and overall standard deviations were evaluated.

### 6.5.3 Process Capability Indices

The European MRL acts as a **unilateral upper specification limit (USL = 0.05 mg/kg)**.

#### Process Capability (Cp)

Because pesticide residues have no lower specification:

$$Cp = \frac{USL}{6\sigma}$$

#### Process Capability Index (Cpk)

$$Cpk = \frac{USL - \bar{x}}{3\sigma}$$

### 6.5.4 Performance Indices (Long-Term Capability)

To capture long-term variability, performance indices were calculated:

$$Pp = \frac{USL}{6s}$$

$$Ppk = \frac{USL - \bar{x}}{3s}$$

Where s is the overall standard deviation including drift.

### 6.5.5 Statistical Process Control (SPC)

Control limits for the  **$\bar{X}$  chart**:

$$UCL_{\bar{X}} = \bar{\bar{X}} + A_2 \bar{R}$$

$$LCL_{\bar{X}} = \bar{\bar{X}} - A_2\bar{R}$$

Control limits for the **R chart**:

$$UCL_R = D_4\bar{R}$$

$$LCL_R = D_3\bar{R}$$

SPC patterns (runs, trends, shifts) were analyzed following Western Electric rules.

### 6.6 Ethical and Regulatory Considerations

All pesticide analyses complied with ISO/IEC 17025 standards. Data were operational, anonymized, and non-sensitive. No human or animal subjects were involved. Peruvian agricultural regulations (SENASA) were followed throughout.

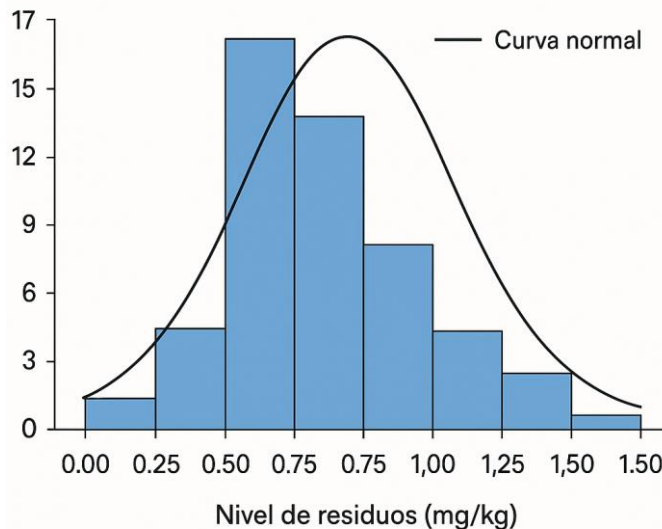
## Results

### 7.1 Descriptive Analysis of Chlorpyrifos Residues

A total of **312 quinoa lots** were evaluated, showing substantial dispersion in chlorpyrifos concentrations. The mean value was **0.0265 mg/kg**, with a standard deviation of **0.0139 mg/kg**, a minimum of **0.004 mg/kg**, and a maximum of **0.089 mg/kg**. Approximately **17%** of the lots exceeded the European Union Maximum Residue Limit (EU-MRL) of **0.05 mg/kg**, indicating consistent non-compliance risks.

The coefficient of variation (**CV = 52.45%**) reveals high process variability, indicating a lack of upstream process stability. Distribution analysis showed moderate normality, but with noticeable right skewness due to extreme values associated with specific suppliers and seasonal peaks.

histograma y curva normal del nivel de residuos (mg)

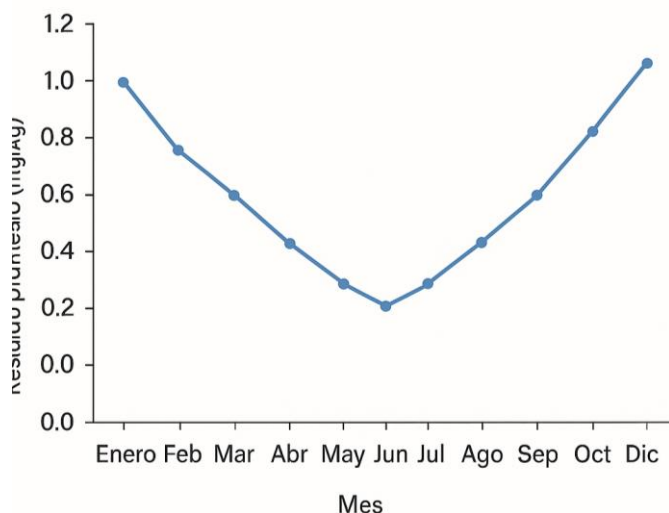


**Figure 1:** Histogram with overlaid normal curve showing right-skewed distribution

### 7.2 Monthly Variability and Seasonality Patterns

Monthly mean values indicated clear seasonality. The highest concentrations occurred during **May and June**, when pest pressure in high-Andean production zones tends to intensify and pesticide use increases. During these months, non-conformity rates rose to **26%**, nearly double the annual average.

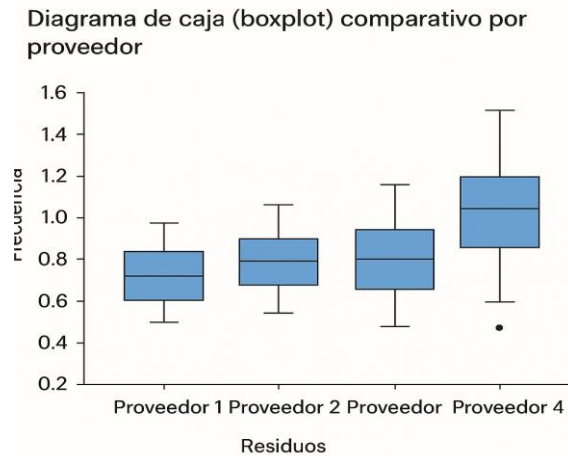
Conversely, the period from **November to February** exhibited lower averages and reduced variability, corresponding to periods of decreased pesticide use.



**Figure 2:** Line plot of monthly mean chlorpyrifos concentrations with 95% confidence intervals.

### 7.3 Outlier Detection and Supplier Dispersion

Boxplots grouped by supplier revealed non-random patterns of outliers. Specific suppliers consistently produced higher-residue lots, suggesting structural rather than incidental causes. Outliers predominantly originated from suppliers with **low GAP compliance**, reinforcing the conclusion that agricultural practices are a major determinant of residue variability.



**Figure 3:** Boxplots comparing residue distributions for each supplier (P1–P5).

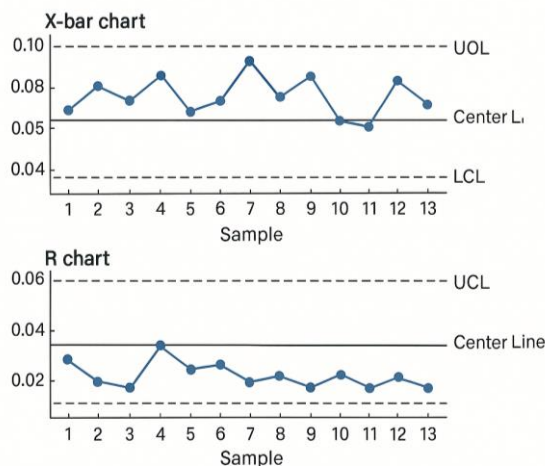
#### 7.4 Process Capability Analysis

Capability indices were computed using the upper specification limit (**USL = 0.05 mg/kg**). The results were:

- **C<sub>p</sub> = 0.597**
- **C<sub>pk</sub> = 0.560**
- **P<sub>p</sub> = 0.521**
- **P<sub>pk</sub> = 0.488**

These values confirm that the process is **incapable** of consistently meeting the specification and operates off-centered relative to the USL. The gap between C<sub>p</sub> and C<sub>pk</sub> shows that even if variability were reduced, mean performance remains too close to the limit.

From a Six Sigma perspective, the estimated sigma level is **below 2**, far from the 4.5–6 sigma required for high-risk food safety processes.



**Figure 4:** Capability analysis plot showing distribution vs. USL with C<sub>p</sub> and C<sub>pk</sub> lines.

### 7.5 Supplier Performance and GAP Compliance

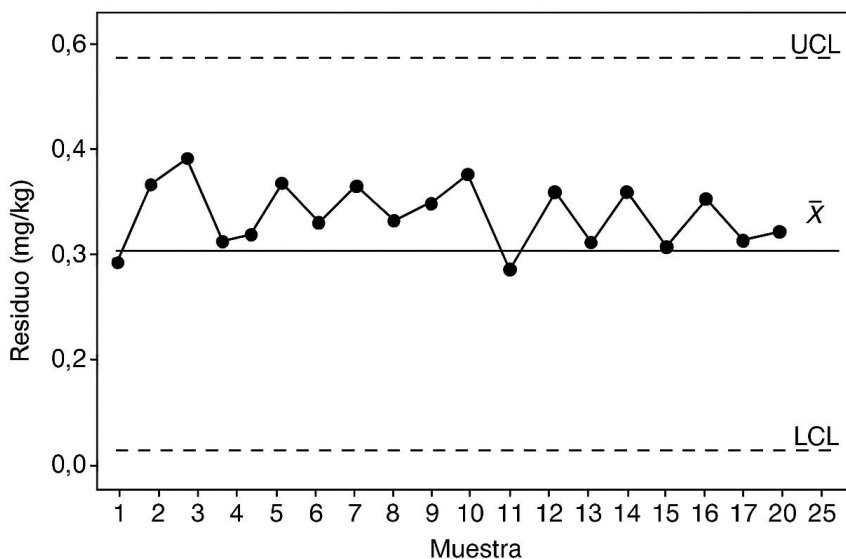
Suppliers were classified according to GAP compliance levels. Results were:

GAP Category	Share of Lots	Non-Conformity Rate
High compliance	39%	3%
Medium compliance	44%	12%
Low compliance	17%	38%

Correlation analysis showed strong, statistically significant associations:

- GAP compliance vs. residue levels:  $r = -0.71$ ,  $p < 0.001$
- Documentation completeness vs. residue levels:  $r = -0.64$ ,  $p < 0.001$

Suppliers with low GAP compliance contributed **over 70% of overall variability**, identifying them as the primary improvement targets.



**Figure 5:** Scatterplot of GAP compliance vs. residue concentration with regression line.

### 7.6 Root Cause Identification

The Analyze phase of DMAIC revealed the following dominant sources of variation:

Materials

- Irregular pesticide mixing
- Use of unauthorized agrochemicals

Methods

- Inconsistent preharvest interval (PHI) monitoring
- Non-standardized spraying practices

Manpower

- Insufficient training among smallholder farmers

### Machines

- Poor calibration of spraying equipment

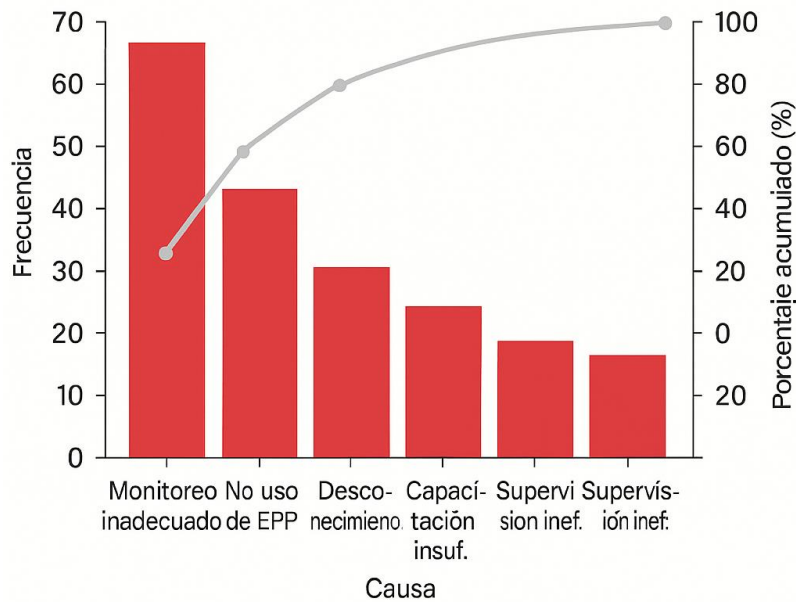
### Measurement

- Incomplete or inconsistent field documentation

### Environment

- Climate effects (temperature and humidity) affecting degradation dynamics

Pareto analysis confirmed that **four suppliers** accounted for **80% of total deviations**.



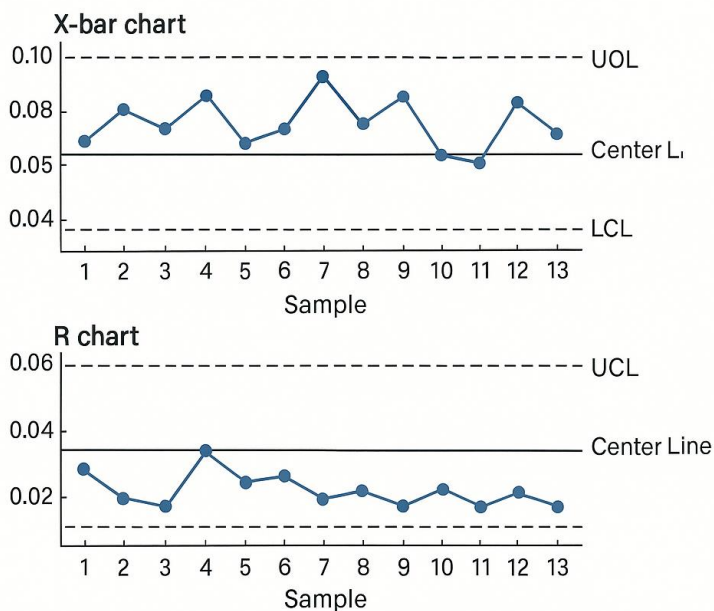
**Figure 6:** Pareto chart of root causes.

### 7.7 Statistical Process Control (SPC) Analysis

X-R charts revealed multiple violations of control limits, including:

- Points above UCL
- Long runs above the mean
- Upward trends during pesticide-intensive months

These patterns confirm the presence of **special-cause variation**, primarily linked to supplier behavior and seasonal agricultural conditions.



**Figure 7:** X-R chart highlighting instability and special-cause signals.

### 7.8 Summary of Key Findings

1. Chlorpyrifos levels exhibit **high dispersion** with significant right skewness.
2. Residues show **seasonal patterns** associated with pest cycles.
3. The process is **statistically incapable** ( $C_p < 1$ ;  $C_{pk} < 1$ ).
4. **Upstream variability** is the dominant source of deviation.
5. Low GAP-compliance suppliers generate the majority of failures.
6. SPC confirms structural instability and recurring special causes.

### Discussion

The results of this study demonstrate that pesticide residue variability in quinoa is not primarily the consequence of industrial processing deficiencies but rather a manifestation of **systemic upstream variation**, consistent with foundational principles in quality engineering and total quality management. The high dispersion observed in chlorpyrifos levels and the significant proportion of non-conforming lots support Deming's assertion that the majority of quality problems originate from the system itself rather than from individual operators. This aligns with modern interpretations of supply chain quality, where agricultural activities function as **extended process parameters** influencing final product outcomes.

The discrepancy between the process capability indices ( $C_p = 0.597$  and  $C_{pk} = 0.560$ ) reinforces the theoretical challenges associated with **unilateral specification processes**. As highlighted in the statistical capability literature, processes governed by a single upper specification limit tend to exhibit mean shifts toward the boundary of acceptability when upstream variability is not

tightly regulated. The right-skewed distribution observed in this study confirms this behavior and indicates the presence of **persistent special-cause variation**, which renders classical process stability assumptions invalid.

The strong negative correlations between GAP compliance and pesticide residues provide empirical support for the theoretical argument that quality in agroexport systems must be conceptualized as a multi-level construct. In particular, the findings substantiate the view that **documentation fidelity, traceability, and standardized agricultural practices** play a role analogous to supplier quality systems in manufacturing. This strengthens the argument proposed by TQM scholars that upstream governance mechanisms are essential for achieving sustainable improvements in overall process capability.

Seasonal patterns identified in this research also contribute to the emerging academic debate on integrating environmental and ecological factors into industrial engineering models. Traditional LSS applications assume relatively stable process conditions; however, agroecosystems introduce **dual-source variability**—both human-driven and environmental. This underscores the need for extending classical Six Sigma frameworks to incorporate climate-related uncertainty and environmental process drivers, potentially informing the development of **eco-capability models**.

Furthermore, the study demonstrates that the DMAIC methodology remains a robust and adaptable metaframework even in domains where process control is structurally limited. Despite criticisms that agricultural systems offer insufficient controllability for rigorous LSS implementation, the results show that DMAIC enables the identification of high-leverage intervention points, such as supplier segmentation, GAP standardization, and real-time SPC integration. This reinforces the compatibility between LSS and sustainability-oriented agricultural governance models.

Another theoretical implication relates to the persistence of chlorpyrifos in high-altitude agricultural systems. The inability of industrial postharvest processes to reduce pesticide residues validates findings in food safety literature emphasizing that **chemical risk must be mitigated at the source**, rather than through downstream remediation efforts. The results therefore support a preventive, system-focused paradigm consistent with risk-based quality management frameworks.

Finally, the identification of a small subset of suppliers responsible for the majority of deviations aligns with Pareto-based theories of variation concentration and supplier-driven quality. This highlights the importance of strategic resource allocation and targeted improvement programs, especially within smallholder-dominated supply networks.

In summary, the findings extend theoretical discussions in quality engineering, supply chain management, and agricultural systems by demonstrating that reducing pesticide residue variability requires integrating LSS principles with GAP governance, environmental considerations, and supplier performance systems.

The study thereby advances a multi-dimensional perspective on process capability within agroexport contexts.

## Conclusions

This study demonstrates that pesticide residue variability in quinoa agroexport chains arises primarily from systemic upstream factors rather than from industrial processing limitations. The integration of Lean Six Sigma (LSS) and Good Agricultural Practices (GAP) provided a robust analytical framework for identifying and quantifying these sources of variation. The process capability indices obtained (**C<sub>p</sub> = 0.597**, **C<sub>pk</sub> = 0.560**) confirm that the current production system is statistically incapable of consistently meeting the chlorpyrifos Maximum Residue Limit (MRL) required by international markets. This incapability reflects both high intrinsic variability and inadequate centering of the process relative to regulatory thresholds.

A key conclusion of this research is that agricultural practices must be conceptualized as **extended process parameters**, whose instability directly constrains achievable sigma performance. The strong associations between low GAP compliance and elevated residue levels highlight the need to strengthen upstream governance, particularly through standardized pesticide management, documentation fidelity, and continuous supplier training. The seasonal patterns identified further indicate that environmental and agronomic factors significantly affect chemical degradation dynamics, reinforcing the importance of adaptive management strategies.

The DMAIC-based model proposed in this study offers a replicable improvement framework that integrates statistical analysis, supplier segmentation, and preventive traceability mechanisms. Its applicability extends beyond quinoa to other high-value agroexport commodities facing similar residue compliance pressures. From a theoretical standpoint, the study contributes to ongoing debates on how to adapt industrial engineering tools to agricultural systems characterized by ecological variability and fragmented supply structures.

Overall, reducing pesticide residue variability requires a shift from reactive inspection-based models to preventive, data-driven, and system-oriented approaches. By combining LSS principles with GAP governance, agroexport chains can improve regulatory compliance, strengthen food safety outcomes, and enhance competitiveness in highly regulated markets.

## Limitations

This study presents several limitations that should be considered when interpreting its findings. From a methodological perspective, the analysis relies exclusively on historical operational data collected under real production conditions, which restricts the ability to control for confounding variables inherent to agricultural systems. The use of non-probabilistic sampling, although appropriate for industrial datasets, may limit the statistical generalizability of the findings. Additionally, the absence of experimental manipulation precludes causal inference, constraining the conclusions to associative and explanatory patterns.

rather than definitive causal relationships. The calculation of capability indices also assumes short-term stability within subgroups, an assumption challenged by the presence of environmental-driven variability.

From an operational and supply chain perspective, variability in documentation quality across smallholder suppliers limits the depth of traceability and reduces the granularity of agronomic information captured in the dataset. Inconsistent record-keeping affects the ability to model factors such as precise pesticide dosage, application timing, and environmental conditions. Furthermore, the study covers a one-year period; however, pesticide degradation and usage patterns may follow multi-year climatic cycles, suggesting the need for extended longitudinal analyses in future research. The lack of access to external regulatory or national monitoring databases also restricted broader triangulation of results.

Despite these limitations, the study provides a rigorous statistical foundation and a replicable methodological framework that can guide future investigations and operational improvement initiatives, particularly when supplemented with more granular, multi-year, and digitally captured agricultural data.

### **Future Work**

Future research should advance toward the development of **integrated quality governance frameworks** capable of addressing the multi-layered variability documented in agroexport production systems. Given the influence of both anthropogenic and environmental factors on pesticide residue behavior, future studies should incorporate **longitudinal and multi-regional datasets** to capture inter-annual climate cycles, changing pest dynamics, and evolving producer practices. Expanding the analytical scope beyond a single enterprise will also improve generalizability and enable comparative evaluations across diverse production systems.

Methodologically, there is substantial potential for incorporating **advanced statistical and computational models**, such as multilevel regression, Bayesian inference, Monte Carlo simulation, and machine learning algorithms (e.g., Random Forest, XGBoost, LSTM networks). These tools could support the development of **predictive capability indices** that dynamically capture variability under fluctuating agronomic and environmental conditions, extending the classical Cp/Cpk framework.

From an operational standpoint, future work should explore the integration of **digital traceability technologies**, including blockchain-based verification systems, IoT sensors for real-time pesticide monitoring, and mobile platforms for GAP compliance assessment. These technologies can enhance data integrity and enable early identification of high-risk lots. Additionally, research on **behavioral and incentive-based interventions** may provide insights into improving GAP adoption among smallholder farmers, particularly in geographically dispersed and resource-constrained contexts.

At a strategic level, future studies should examine hybrid governance structures that combine LSS methodologies, sustainability-oriented agricultural frameworks,

and supply chain risk management principles. Such approaches could promote the transition from reactive inspection systems toward **preventive, data-driven, and resilience-oriented agroexport models** capable of meeting stringent international regulatory standards.

## **Declarations**

### *12.1 Ethics Statement*

This study is based solely on historical, anonymized, and non-sensitive operational data provided by AGRIPROCESS S.A.C. No experiments involving human participants or animals were conducted; therefore, ethical approval was not required.

### *12.2 Funding Statement*

This research received no specific grant from public, commercial, or not-for-profit funding agencies. The study was conducted with institutional and academic support from the authors.

### *12.3 Conflict of Interest Statement*

The authors declare that there are **no conflicts of interest**—financial, personal, or institutional—that could have influenced the outcomes of this study.

### *12.4 Data Availability Statement*

The datasets generated and analyzed during the current study contain confidential operational information belonging to AGRIPROCESS S.A.C. As such, they are not publicly available. However, anonymized data may be made available upon **reasonable request** to the corresponding author.

### *12.5 Author Contributions (CRediT Taxonomy)*

**Julio César Carrasco Bocangel:** Supervision, Methodology, Statistical analysis, Validation, Writing – review and editing, Visualization, Project administration.

**Fiorella del Carmen Valdivia Rosas:** Conceptualization, Literature review, Methodology, Data curation, Formal analysis, Writing – original draft. Both authors reviewed and approved the final manuscript.

### *12.6 AI Use Statement*

Artificial intelligence tools were used exclusively for editorial assistance, including language refinement, formatting, structural organization, and clarity enhancement.

All scientific ideas, interpretations, analyses, and conclusions were conceived, produced, and validated by the authors.

## **Supplementary Material**

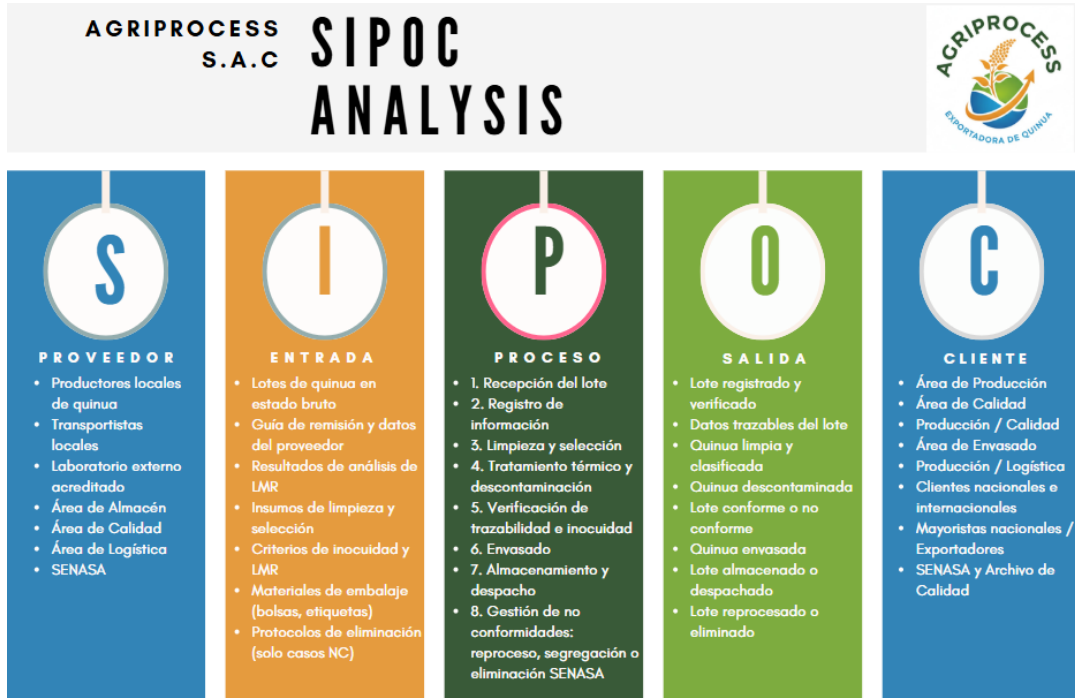
The following supplementary materials provide additional methodological detail, statistical outputs, and visual analyses that support the findings of the main manuscript. All items contribute to transparency, reproducibility, and methodological rigor.

*S1. SIPOC Diagram of the Quinoa Supply Chain*

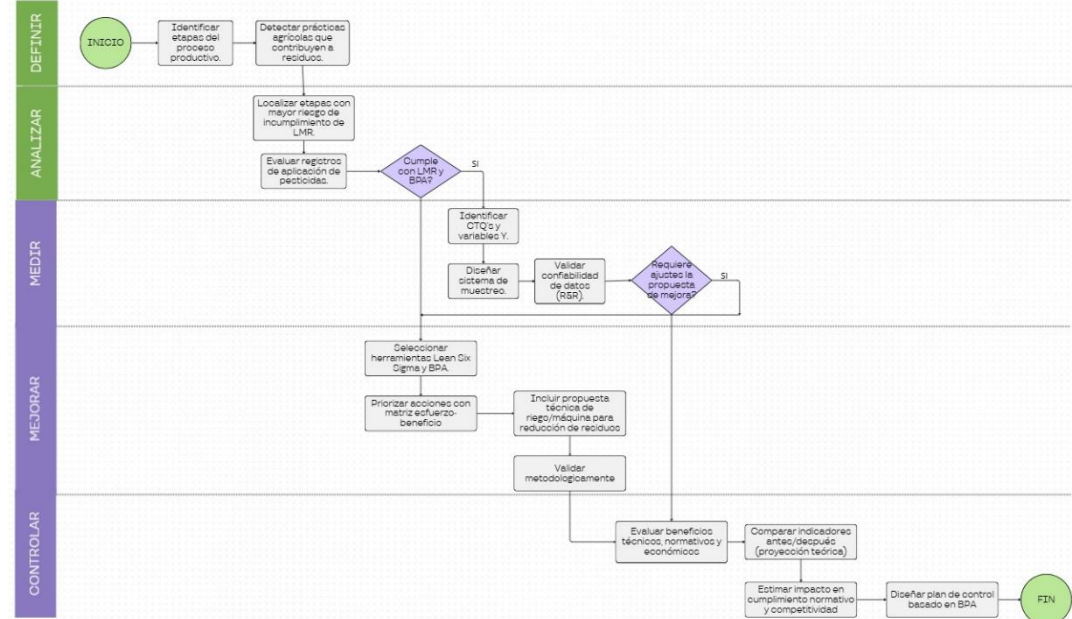
**Description:**

A high-level SIPOC (Suppliers–Inputs–Process–Outputs–Customers) diagram mapping agricultural suppliers, critical inputs (pesticides, documentation), industrial subprocesses, and regulatory-driven customers.

**Purpose:** Defines process boundaries and critical inputs for the DMAIC Define phase.



S2. BPMN Process Flowchart (End-to-End Agroindustrial Process)

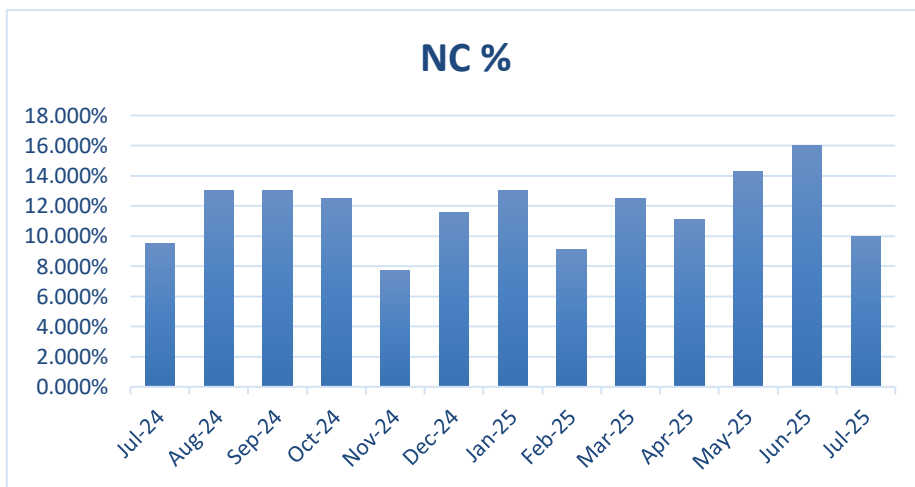


**Description:**

A BPMN 2.0 flowchart depicting the complete production flow from field operations to industrial processing, laboratory testing, and lot release.

**Purpose:** Identifies variability nodes and non-standardized practices within the chain.

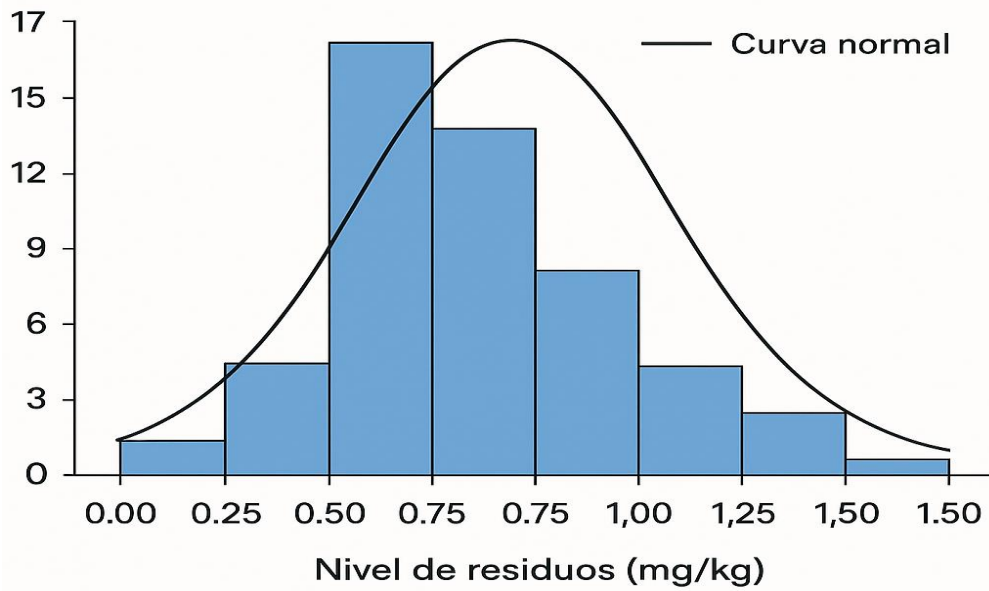
S3. Extended Descriptive Statistics for Chlorpyrifos Residues



**Description:**

Comprehensive statistical table including percentiles (P5–P95), skewness, kurtosis, interquartile ranges, and seasonal breakdown.

**Purpose:** Supports distributional analysis and complements normality testing.

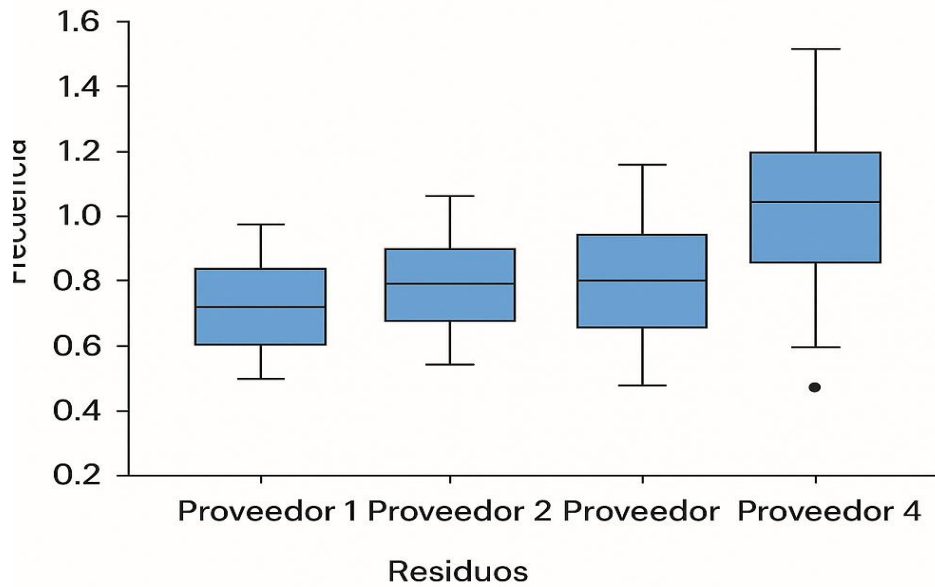
*S4. Histogram and Kernel Density Plot of Residue Levels***histograma y curva normal del nivel de residuos (mg****Description:**

Histogram with overlaid normal and kernel density curves, illustrating right skewness and tail behavior.

**Purpose:** Visualizes distribution characteristics relevant to capability analysis.

S5. Monthly Boxplots Showing Seasonal Variability

### Diagrama de caja (boxplot) comparativo por proveedor

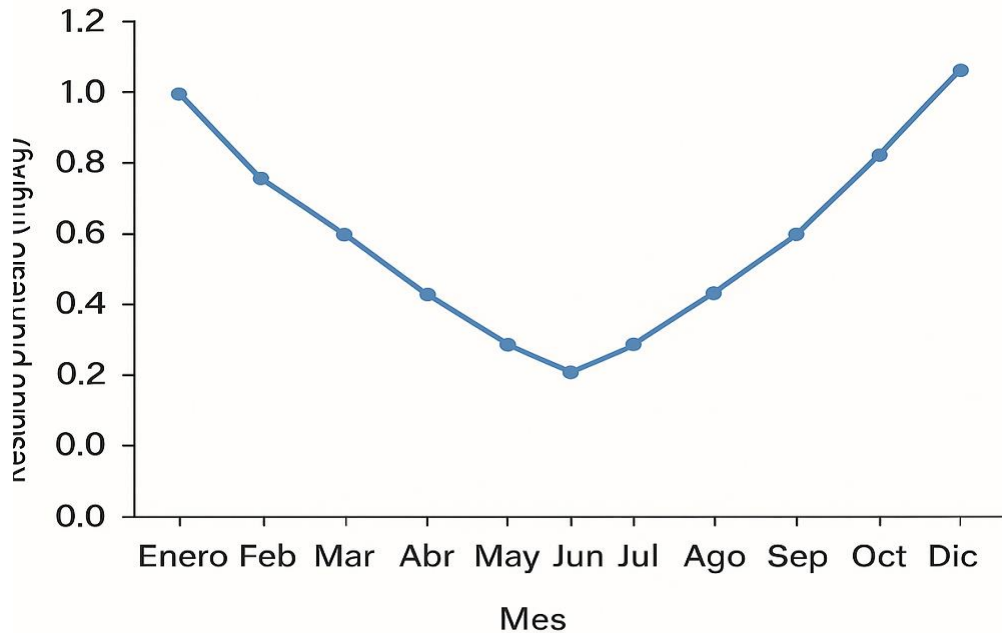


**Description:**

Boxplots of chlorpyrifos concentrations by month, indicating seasonal fluctuation and dispersion.

**Purpose:** Highlights agronomic seasonality effects on residue behavior.

**Figura 6. Gráfico de tendencia mensual del residuo promedio (12 meses)**



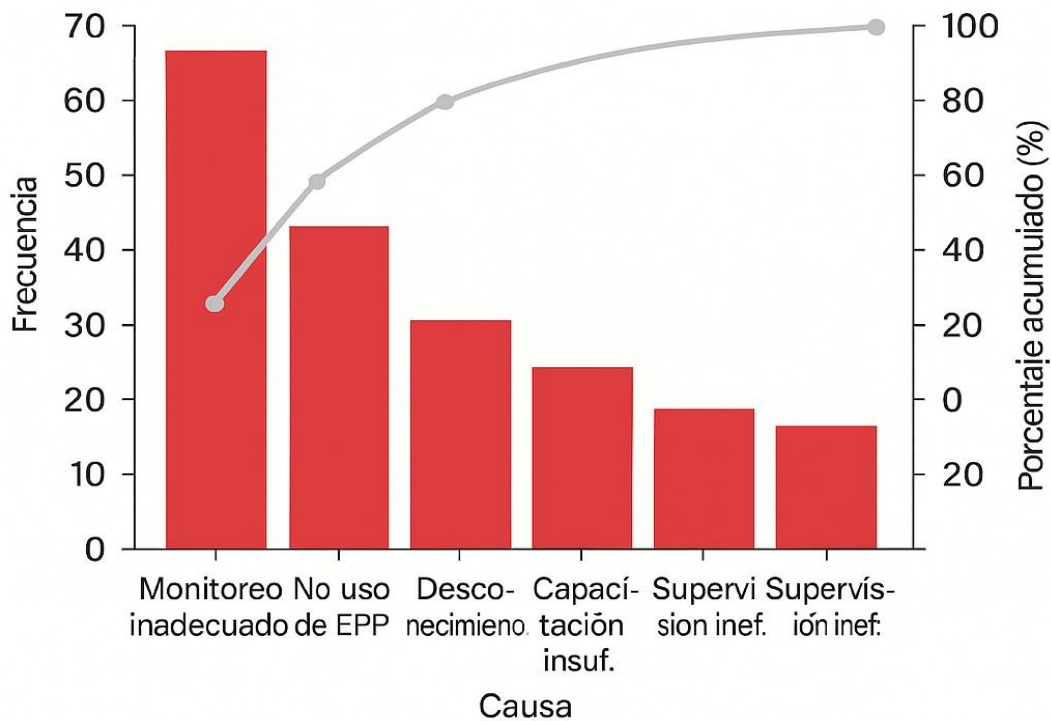
**Description:**

Correlation heatmap showing Pearson and Spearman coefficients for GAP compliance, documentation completeness, traceability levels, and chlorpyrifos results.

**Purpose:** Quantifies upstream behavioral drivers of chemical variability.

S7. Pareto Chart of Root Causes Identified in Analyze Phase

Figura 7. Gráfico de Pareto de causas raíz vinculadas a BPA incumplidas

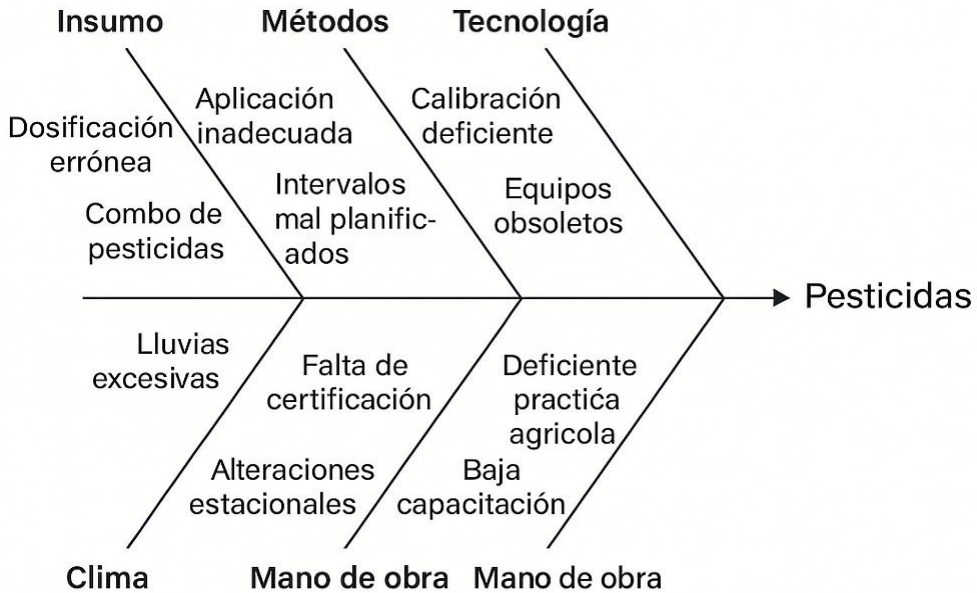


**Description:**

Pareto chart ranking main causes of non-conformities (pesticide misuse, PHI non-compliance, documentation gaps, equipment calibration issues).

**Purpose:** Confirms 80/20 patterns and focuses Improve-phase interventions.

### Figura 8. Diagrama Ishikawa para causas de variabilidad en residuos



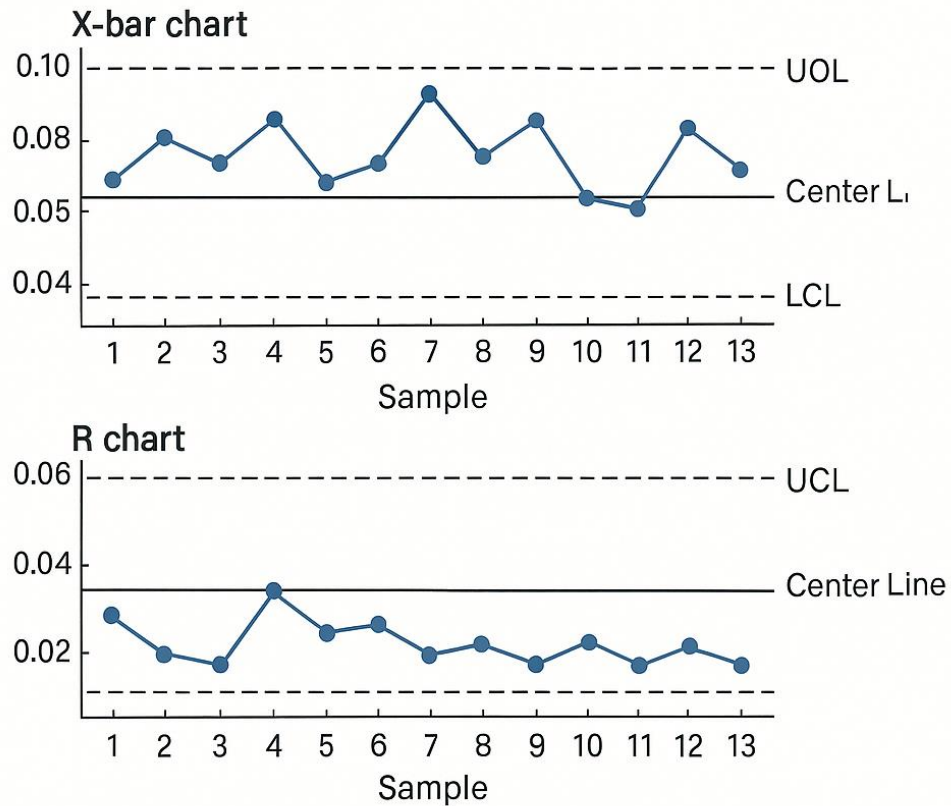
**Description:**

Six-category diagram (Materials, Methods, Manpower, Machines, Measurement, Environment) detailing hypothesized root causes.

**Purpose:** Structures root cause analysis consistent with LSS methodology.

S9. SPC Charts ( $\bar{X}$ -R) with Annotations

Figura 9. Control chart ( $\bar{X}$ -R) para el comportamiento del proceso

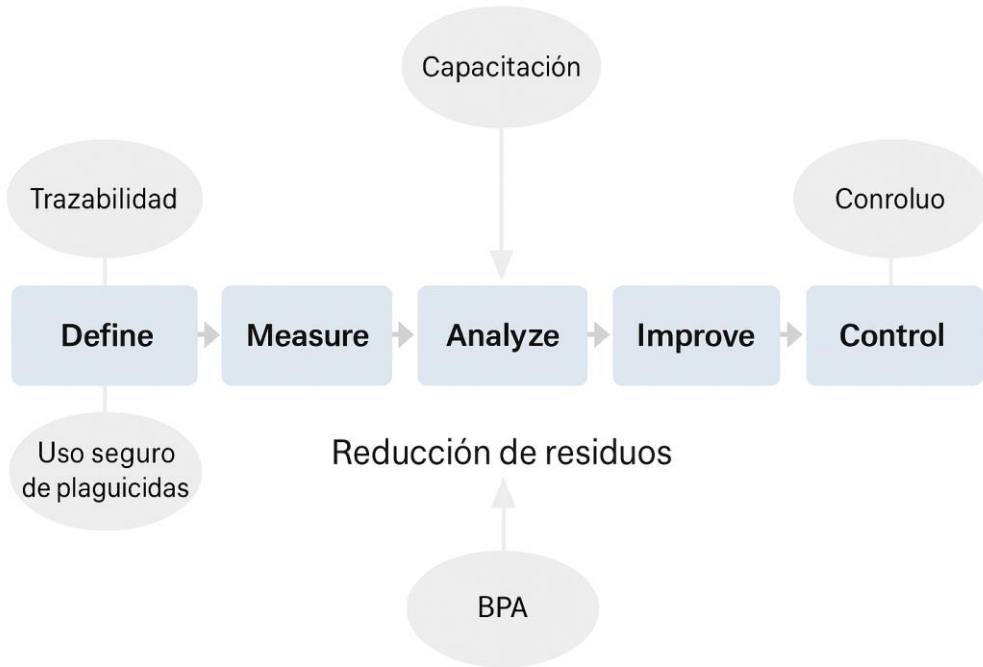


**Description:**

X-R control charts annotated with points outside control limits, runs, and shifts.

**Purpose:** Demonstrates process instability and presence of special-cause variation.

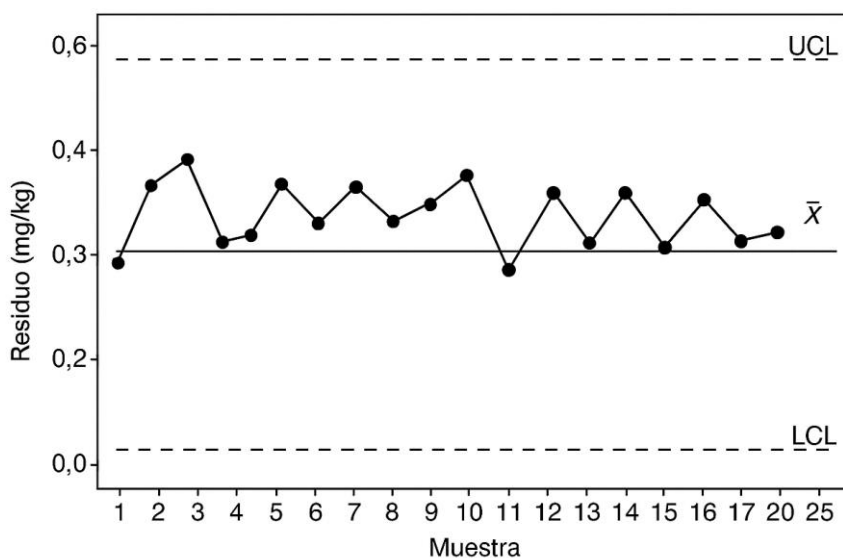
*S12. Extended Capability Analysis (Cp, Cpk, Pp, Ppk)*



**Description:**

Tables and graphs showing capability indices with 95% confidence intervals, fitted distributions, and sigma level estimates.

**Purpose:** Strengthens statistical validity of conclusions regarding process incapability.



**Figure 11.** Proyección del proceso después de implementar controles SPC

*CRedit Author Contributions*

**Fiorella del Carmen Valdivia Rosas:** Conceptualization, Literature review, Methodology, Data curation, Initial draft writing.

**Julio César Carrasco Bocangel:** Supervision, Methodology, Statistical analysis, Validation, Writing – review & editing, Project administration.

*Declaration of Conflicts of Interest*

The authors declare no conflicts of interest.

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*Ethics Statement*

This study uses historical and non-sensitive operational data provided by AGRIPROCESS S.A.C. No human or animal subjects were involved. Ethical approval was not required.

*Data Availability*

Data supporting this study are subject to commercial confidentiality. Anonymized datasets may be made available upon reasonable request to the corresponding author.

*AI Use Statement*

Artificial intelligence tools were used only for editorial assistance (language refinement and formatting). All scientific ideas, analyses, interpretations, and conclusions were generated, reviewed, and validated by the authors.

### Highlights

- Lean Six Sigma and GAP integration reduces pesticide variability in quinoa.
- Analysis of 312 industrial lots reveals chlorpyrifos as the critical CTQ.
- Process capability is insufficient:  $C_p = 0.597$  and  $C_{pk} = 0.560$ .
- Low GAP compliance suppliers explain most upstream variability.
- DMAIC-based model enhances control, traceability, and chemical risk reduction.

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