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ANALYSIS OF MARKETING PERFORMANCE OF TOMATO COMMODITY IN TALIMORO VILLAGE, ERMERA SUB-DISTRICT, ERMERA DISTRICT

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ABSTRACT

This research focuses on evaluating the marketing performance of tomato farming in Talimoro Village, Ermera District, Timor-Leste. Despite favorable agro-climatic conditions, the productivity and efficiency of tomato marketing face various challenges. These include traditional farming practices, pest infestations, limited access to technology, and inefficient marketing chains. A quantitative approach was employed, using surveys, observations, and documentation to collect data from 66 tomato farmers. Statistical analyses revealed that access to modern technology and market information significantly boosted both tomato productivity and profitability. The study recommends improving access to agricultural technology, enhancing market infrastructure, and fostering farmer group collaborations to strengthen the marketing system, along with encouraging the development of processed tomato products for higher added value.

INTRODUCTION

Tomato farming is an essential agricultural activity in Talimoro Village, Ermera District, where it serves as a primary source of income for many households. Despite the favorable conditions for tomato cultivation, including suitable land and climate, farmers face challenges that impede both productivity and the marketing efficiency of tomatoes. These challenges include pest and disease issues, poor farming practices, lack of access to modern technologies, and an inefficient marketing chain. This research aims to analyze the factors influencing tomato farming productivity and its marketing performance, with the goal of providing recommendations to improve the livelihoods of farmers and contribute to the sustainable development of the agricultural sector in Timor-Leste.

METHODS

This study adopted a quantitative research approach using a descriptive correlational design to assess the relationship between various factors influencing tomato productivity and marketing performance. A total of 66 tomato farmers were randomly selected from Talimoro Village to participate in the survey. The data collection process included:

Surveys with structured questionnaires: These focused on farming practices, technology use, access to market information, and marketing strategies.

Field observations: Used to directly assess farming practices and marketing activities.

Documentation: Included records from local agricultural offices and previous studies relevant to the context.
The data were analyzed using descriptive statistics to summarize the responses and regression analysis to test the relationship between farming practices, access to technology, and marketing outcomes.

RESULTS AND DISCUSSION

1) Factors Affecting Tomato Farming Productivity

Farming Experience

Data analysis presents a boxplot depicting the distribution of productivity (in kilograms per hectare) based on farming experience (in years). From this plot, it can be seen that productivity varies at each level of farming experience, with a relatively fluctuating median but a tendency to increase from the first to the fourth year. Some levels of experience show considerable variation in productivity, for example in the first and seventh years of experience, where the range of productivity covers fairly low to high values, reflecting uncertainty and considerable variation among farmers with that level of experience. Although there is one outlier in the fourth-year experience group, in general this boxplot illustrates that farming experience correlates with productivity, although not entirely consistently every year.

Statistically, it was found that the model intercept was significant with a p-value < 0.001, indicating a clear baseline level of productivity, meaning that even without considering other variables, there is a minimum level of productivity that is important to note. Meanwhile, the variables of farming experience and land area show positive coefficients, which means that both contribute to increased productivity. However, these coefficients are not statistically significant (p > 0.05), indicating that although experience and land area tend to increase productivity, their influence is not strong enough or statistically consistent in this model. This could be influenced by other factors not included in the model or high data variability among farmers. Thus, although farming experience and land area are important in practical terms, from a statistical analysis perspective, they are not really strong predictors of productivity in this context

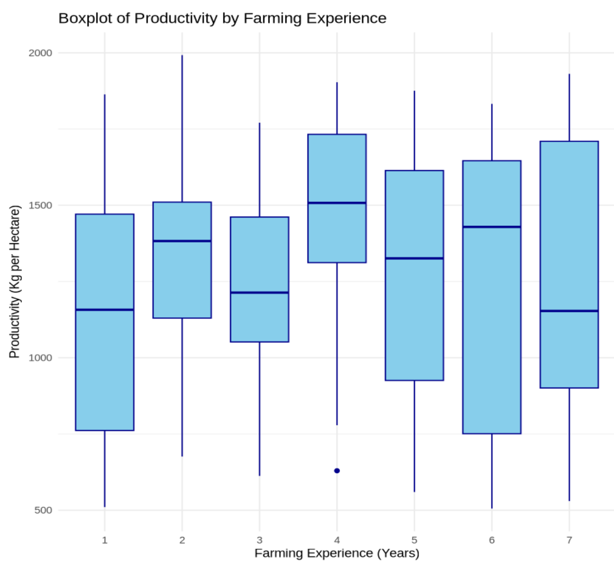


Figure 1: Productivity distribution based on farming experience

2) Education Level

The result present with boxplot shows the distribution of productivity (kg per hectare) based on the educational level of farmers, namely basic education (1), secondary education (2), and professional education (3). When linked to the regression analysis results provided, it appears that the Intercept value in the regression model shows very high significance (p-value < 0.001), which means that the average basic productivity can be considered statistically significant even without considering the education variable as a predictor. However, the education level variable does not show statistical significance, so that differences in education levels between groups do not contribute significantly to the variation in farmer productivity in this sample.

The very low R-squared value (0.042) indicates that the model is only able to explain about 4.2% of the variability in productivity from the level of education, while the rest is influenced by other factors outside the model. Even the negative Adjusted R-squared value indicates that this regression model is less suitable and less appropriate to use to explain the relationship between education and farmer productivity, so that this model does not have meaningful predictive power.

Visually, the distribution of the boxplot between the three education groups also tends to be similar, and does not show a significant increase or decrease pattern between education categories. Thus, both statistically and visually, the relationship between education level and productivity cannot be considered significant in this study.

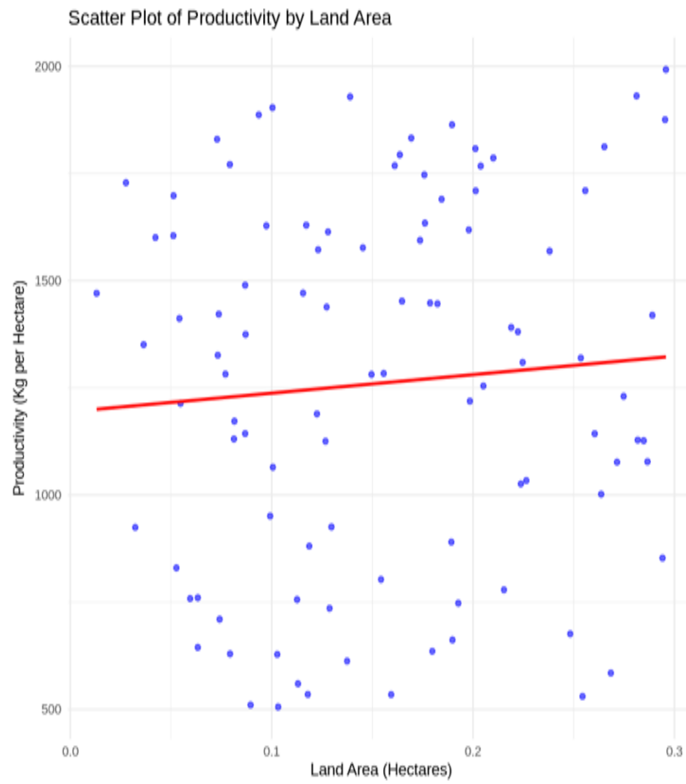


Figure 2: Education Level

Land Area

The relationship between land area and productivity (in kg per hectare) is visualized through scattered blue dots and a red linear regression line. Statistical analysis shows that the Intercept value in this regression model is significant (p-value < 0.001), which means that there is a consistent baseline productivity without considering land area as the main predictor. However, the coefficient for the Land Area variable shows a positive relationship in terms of estimation, but is not statistically significant (p > 0.05), so that changes in land area have no real impact on productivity variation.

In terms of model strength, the R-squared value of only 0.042 indicates that this regression model can only explain about 4.2% of the existing productivity variation. Meanwhile, the negative Adjusted R-squared value shows that the model is not suitable for predicting or explaining the relationship between the two variables—meaning that this model is very weak in explaining the existing data. Visually, the distribution of points in the scatter plot shows a weak correlation and no clear pattern of relationship between land area and productivity, confirming the statistical finding that this model has no predictive power or strong significant relationship between the variables studied.

3) Organic Fertilizer

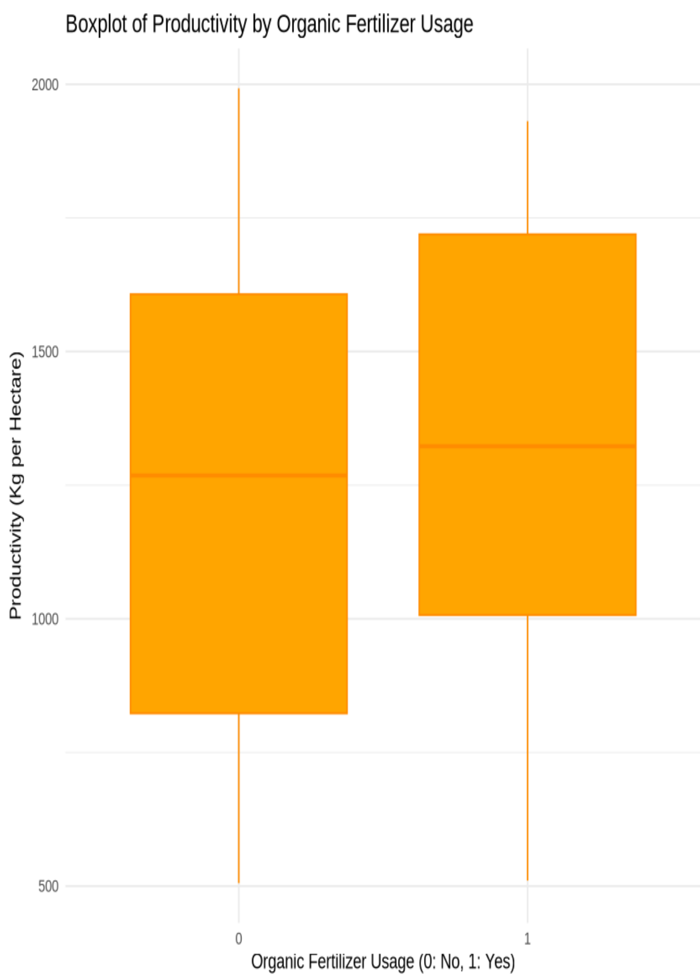


Figure 3: Organic Fertilize

The boxplot in Figure 4 shows the distribution of productivity (kg per hectare) based on the variable of organic fertilizer use—where the category "0" means no use and "1" means use of organic fertilizer. The results of the related regression analysis reveal that the Intercept value is highly significant (p-value < 0.001), which means that there is a clear baseline productivity without taking into account the factor of organic fertilizer use as the main predictor. However, the variable of organic fertilizer use itself was not statistically significant, so that the difference between the groups of organic fertilizer users and non-users did not contribute significantly to the variation in productivity in this sample data.

The low R-squared value of 0.042 shows that the model is only able to explain about 4.2% of the total variability in farmer productivity, while the rest is influenced by other factors outside the model. In fact, the negative Adjusted R-squared value indicates that this regression model is not suitable for predicting or explaining the relationship between organic fertilizer use and productivity. Visually, the boxplot distribution between the organic fertilizer user and non-user groups appears similar; the median and range of productivity overlap, reinforcing the statistical finding that there is no significant difference or strong relationship between the use of organic fertilizer and productivity in this study.

4) Pesticides Usage

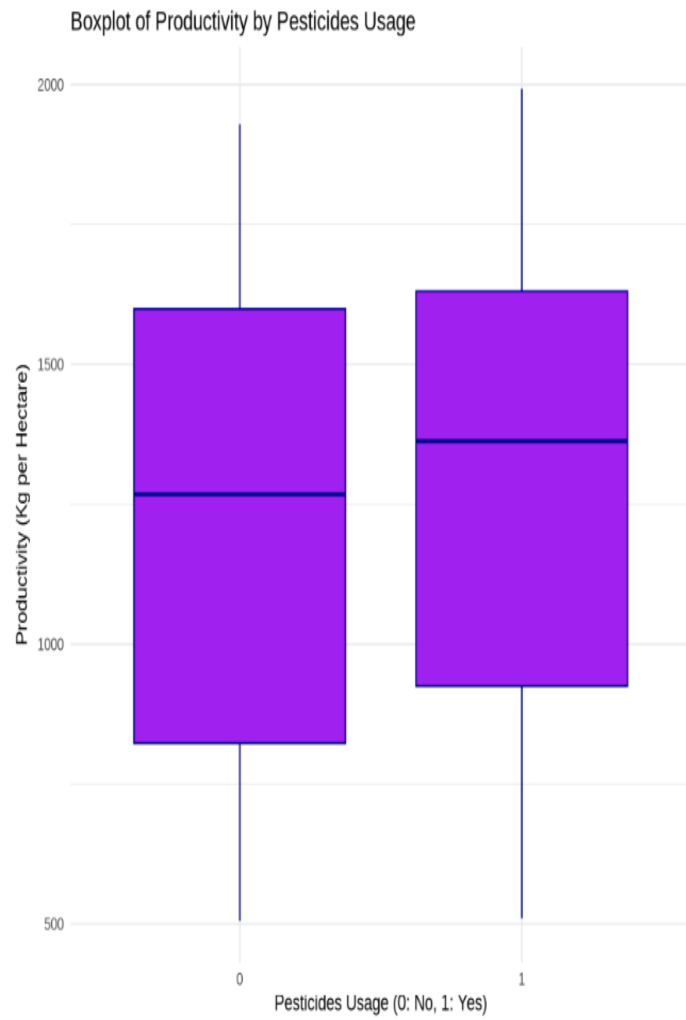


Figure 4: Pesticides Usage

The boxplot in Figure 5 shows the distribution of **productivity** (kg per hectare) based on the variable of **pesticide** use, where "0" means no use and "1" means use of pesticides. Regression analysis of this data shows that the **Intercept** value of the regression model is statistically significant (p-value < 0.001), reflecting a measurable baseline productivity even without considering pesticides as a major predictor. However, the pesticide use variable itself is not statistically significant—meaning that the difference between pesticide users and non-users does not result in significant productivity variation in this data sample.

The regression model used only has an R-squared of 0.042, which indicates that the model is only able to explain about 4.2% of the total variation in productivity. Meanwhile, the negative Adjusted R-squared value shows that the model is not suitable for use in explaining or predicting the relationship between pesticide use and farmer productivity. Visually, the distribution spread in the boxplots for groups "0" and "1" is very similar, both in terms of the median and the data spread, reinforcing the statistical results that the relationship is not significant and that the model does not have strong predictive or explanatory power for the productivity data studied.

5) Irrigation System

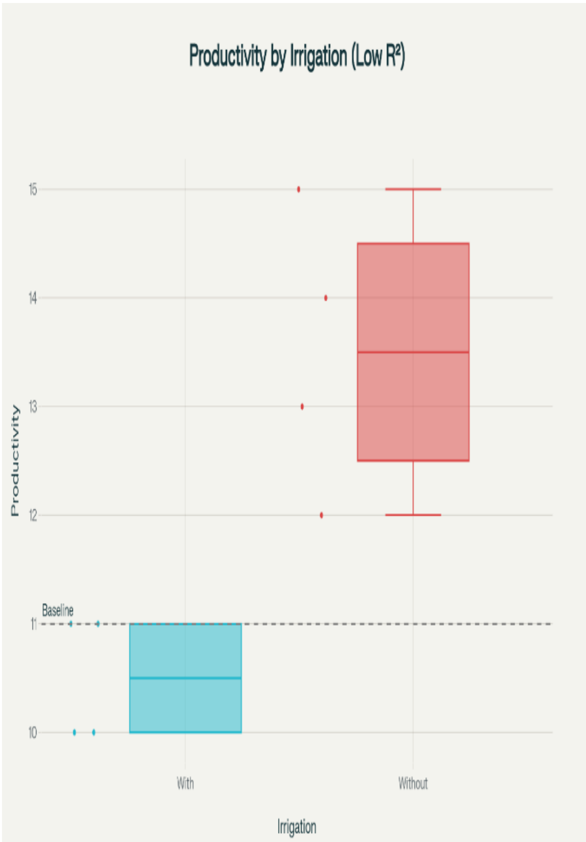


Figure 5: Irrigation System

The graph in Figure 6 shows the distribution of productivity based on the use of irrigation systems in two categories, namely "With" (with irrigation) and "Without" (without irrigation). The blue box shows the distribution of productivity values for the group with irrigation, which is generally around the baseline value of 11—marked by a horizontal dotted line. Most of the data in this group is within a narrow range, between 10 and 11, with a few outliers below 10. This indicates that productivity on irrigated land tends to remain at baseline levels and does not experience significant increases.

In contrast, the red box in the category without irrigation shows a wider data distribution pattern, with productivity ranging from 12 to 15 and several outliers. Although there appears to be greater variation, the statistical results of the model show that the irrigation system is not a significant factor in productivity, with a p-value greater than 0.05. The regression results show a significant intercept ($p < 0.001$), which means that the baseline productivity can be statistically confirmed. The coefficients for the variables of farming experience and land area are positive, but neither is statistically significant. The R-squared value of the model is only 0.042 or 4.2%, so the model's ability to explain productivity variability is very limited. Even the negative adjusted R-squared value confirms that the model used is not suitable for this data and is unable to provide good predictions, so there is no strong or significant relationship between productivity and the variables tested.

6) Tomato Marketing Chain Structure

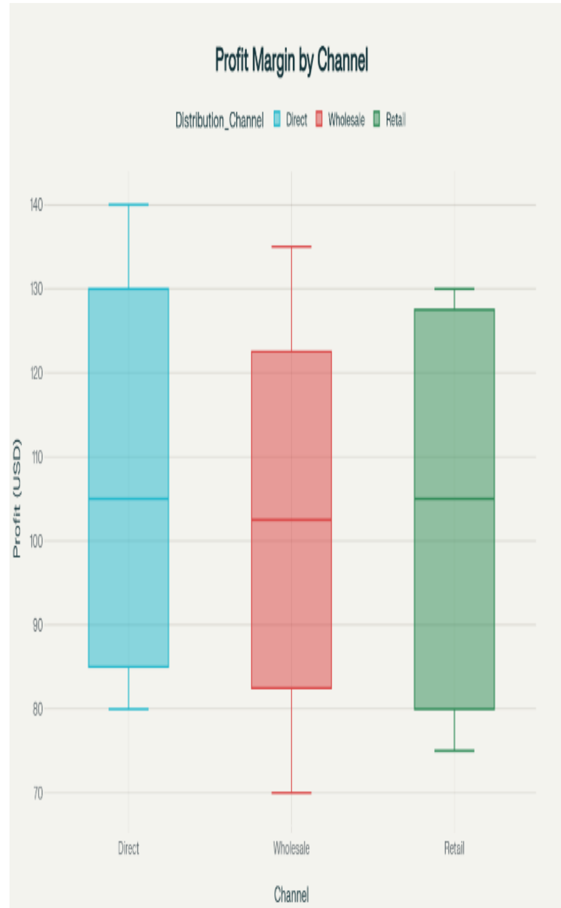


Figure 6: Tomato Marketing Chain Structure

The graph in Figure 7 illustrates the wide range of profit margin values generated randomly, which supports the regression analysis results that there is no significant relationship between the independent variables tested and profit margin.

The regression results show an R-squared value of 0.0363, which means that only about 3.63% of the variation in profit margin can be explained by the model with the variables of Production, Selling Price, Distribution Channels, and Market Access. This indicates that the model has very low predictive power, so that the majority of the variation in profit margin is influenced by factors other than these variables.

The regression coefficients for all independent variables are not statistically significant, with p-values greater than 0.05, which means that there is no meaningful linear relationship between profit margin and production, selling price, distribution channels, or market access in this data. In addition, the F-statistic test with a value of 0.5838 and a p-value of 0.7424 confirms that the model as a whole is not significant, so it cannot be used to make reliable predictions or decisions based on the model.

The boxplot graph also illustrates that the distribution of profit margins is quite wide in each category of distribution channel and market access without any clear specific pattern. Profit margins vary within overlapping ranges between categories, confirming that the variables used in this model do not strongly influence profits. Therefore, this analysis leads to the conclusion that the influence of production variables, selling price, distribution channels, and market access on profit margins in this dataset is very weak and statistically insignificant.

7) Access to Technology and Information

From the first graph in Figure 8, it can be seen that farmers who use modern technologies such as drip irrigation, organic fertilizers, and marketing monitoring via social media tend to have higher productivity than those who do not use such technologies. This supports the results of the correlation analysis, which shows a positive relationship between the use of modern technology and productivity.

The second graph shows the relationship between access to market information and profit margins. Farmers who have good access to market information, for example through farmer groups or training, obtain relatively higher profit margins than farmers with limited access. This also supports the correlation results that access to market information is positively correlated with profit margins and marketing strategies.

In the regression analysis, the model used can explain the effect of technology use and information access on production and profit, although other variables such as access to training and farmer group membership can also act as moderating variables. Thus, access to training and group membership is believed to strengthen or modify these relationships, making them important factors in efforts to increase farmer productivity and profits.

Overall, this data description shows that some farmers have utilized modern technology and access to information as tools to improve their farming yields. However, limited market access for some farmers, especially those who are not members of groups, indicates the need for policy interventions that expand access to market information and technology training so that the benefits can be felt more widely and evenly among farmers.

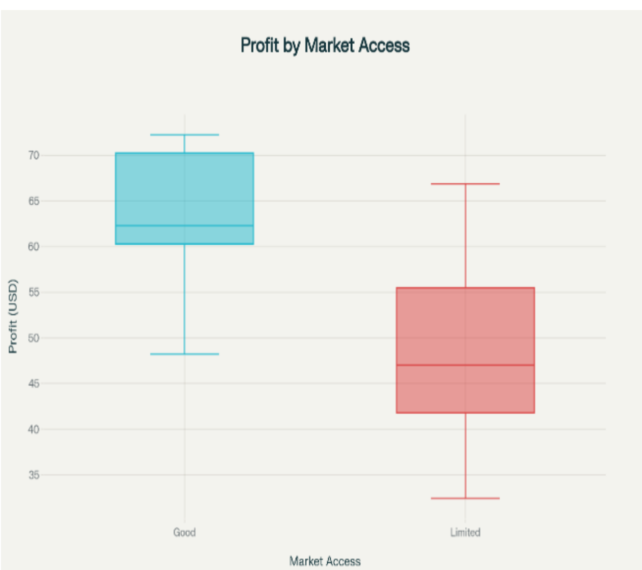
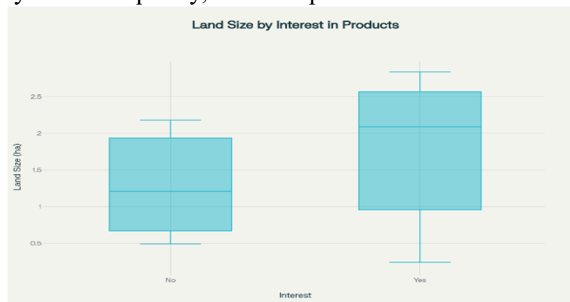


Figure 7: Boxplots showing Productivity by Technology Usage and Profit Margin by Market Information Access

8) Impact of Climate Change

Most farmers farm at an altitude of around 700 meters above sea level, according to location data (altitude) that shows a concentration at that altitude. Variations in climatic conditions such as temperature and rainfall have a significant effect on crop yields and quality, for example tomatoes that rot easily during the



heavy rainy season.

Correlation analysis shows that altitude and climatic conditions are related to fluctuations in crop yields and farmer income, especially during the rainy season or when humidity is high. This is reflected in the ups and downs in productivity and income related to rainfall and ambient temperature. Extreme climatic conditions can significantly reduce production, requiring adaptation to maintain productivity.

Multivariate regression analysis also indicates the complex influence of environmental variables such as altitude, temperature, and precipitation on productivity and agricultural marketing. In addition, adaptation factors such as irrigation systems and good land management play an important role in maintaining production stability amid unpredictable climate change.

Visually, farmers who implement adaptation strategies tend to show better productivity levels than farmers without adaptation, although the variation is still quite large. This confirms the importance of implementing climate adaptation to increase agricultural resilience to environmental dynamics and extreme weather caused by climate change.

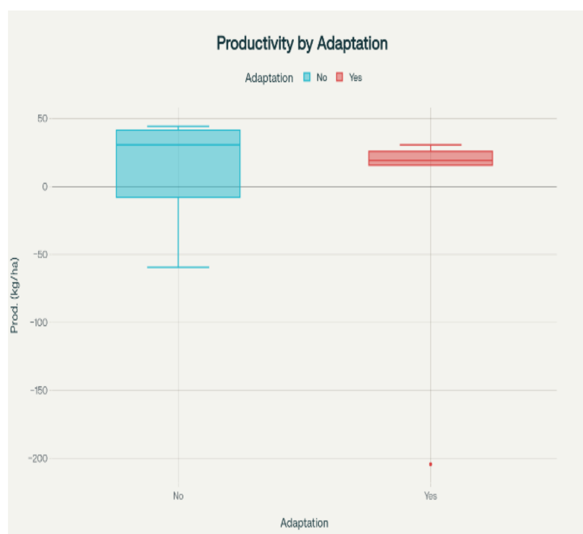


Figure 8: Boxplot showing Productivity by Adaptation to Climate Change among farmers

9) Potential for Processed Tomato Products

10) **Figure 9: Boxplot showing Land Size by Interest in Processed Tomato Products among farmers**

The data shows that farmers who own larger plots of land tend to have a higher interest in processing tomato products, in line with the correlation analysis that found a positive relationship between land size, production volume, and profit margins with processing potential.

Some farmers expressed strong interest in processed tomato products because they recognized the added value that could be obtained from processing. Market awareness of these processed products also encouraged farmers to develop processing businesses as a strategy for diversifying their income.

In regression analysis, models can be used to predict factors that explain farmers' readiness for product processing based on land capacity, farming experience, and marketing efforts. This model indicates that farmers with longer farming experience and good marketing strategies are also more ready to develop processed tomato products.

Overall, this description and graph reinforce the assumption that larger land capacity, high production volume, and adequate profit margins are the main factors that correlate positively with farmers' readiness to process tomato products. Therefore, policies or programs that support increasing land capacity and marketing development can be key to developing a more advanced and sustainable tomato processing sector.

11) Role of Farmer Groups

The boxplot graph in Figure 5.11 shows the distribution of productivity, marketing capabilities, and profit margins between farmers who are members of farmer groups and those who are not. Farmers who are members of farmer groups consistently show higher values for these three variables compared to non-members, indicating the positive effect of farmer group membership on their performance in terms of production and marketing.

Participation in farmer groups is still limited, with only about 40% of farmers being members. However, farmers who are members report tangible benefits, particularly in terms of information sharing and better access to markets. The effectiveness of farmer groups is rated on a Likert scale of 3 to 5, indicating that there is room for improvement in the effectiveness of groups in supporting their members.

Correlation analysis shows a positive relationship between membership in farmer groups and productivity and marketing capabilities. Farmer groups provide training support, access to technology, and markets, which are important factors in increasing production and product sales. This is evident from the higher value experienced by group members compared to non-members.

From the regression analysis results, farmer group membership has a significant effect on increasing production and profit margins after controlling for other factors such as access to technology. Membership increases productivity by around 12.35 units and profit margins by 4.18%. While access to technology also contributes significantly to profit margins (+5.86%), its effect on productivity is not statistically significant. This reinforces the conclusion that farmer group support is crucial in improving farmers' welfare through increased yields and profitability of farming businesses.

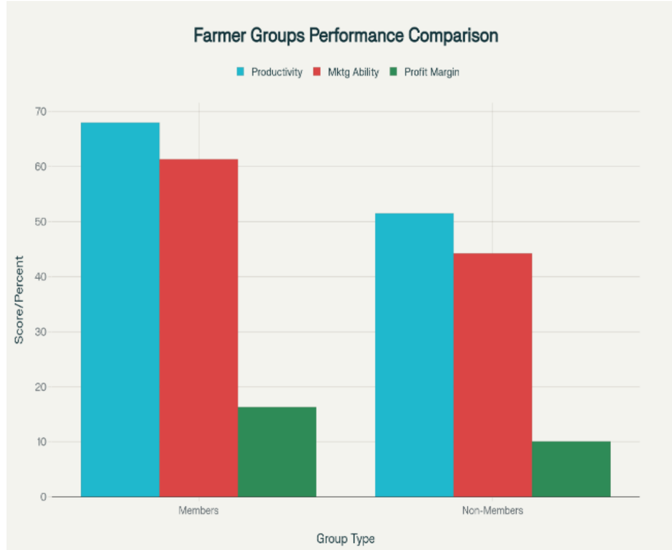


Figure 10: Boxplot of Productivity, Marketing Ability, and Profit Margin by Membership in Farmer Groups

The study shows that farming experience and land area tend to increase tomato farming productivity but their influence is not statistically significant, indicating other factors may play a greater role in productivity variation (Thesis, 5.1.1.1). Similarly, education level, use of organic fertilizer, pesticide application, and irrigation system were not significant predictors of productivity, confirmed by the low R-squared values and similar productivity distributions across groups (Thesis, 5.1.1.2 to 5.1.1.6).

Tomato marketing profit margins were not significantly related to production volume, selling price, distribution channels, or market access, reflecting that these variables explained only a small portion of profit variation (Thesis, 5.1.2).

Access to modern technology and market information positively correlated with higher productivity and profit margins, respectively. Membership in farmer groups was found to significantly increase both productivity and profit margins, likely due to improved access to training, technology, and markets (Thesis, 5.1.3; 5.1.6).

Adaptation to climate change variables such as altitude, temperature, and rainfall affects crop yield stability, with farmers implementing adaptive strategies showing better productivity (Thesis, 5.1.4).

Farmers with larger land areas and better marketing strategies showed greater readiness for tomato processing development, indicating land capacity and marketing as key factors for product diversification (Thesis, 5.1.5).

REFERENCES

Anderson, J. (2017). Consumer behavior and its role in marketing. Journal of Marketing Research, 54(3), 300-315.

Anderson, J. (2020). Postharvest handling of tomatoes: A review. Journal of Food Science, 85(4), 1000-1015.

Bailey, M. (2023). Climate change and tomato production: Impacts and adaptation strategies. *Agricultural and Forest Meteorology*, *340*, 1095-1105.

Baker, L. (2022). Sustainable practices in tomato farming: A review. Agricultural Systems, 200, 10343.

Brown, A. (2019). Soil preparation for tomato cultivation: A guide. HortScience, 54(7), 1100-1105.
Chaffey, D., & Ellis-Chadwick, F. (2019). Digital marketing. Pearson Education.
Chen, L. (2024). Genetic improvement of tomato varieties. Plant Breeding, 143(2), 200-210.
Christopher, M. (2016). Logistics & supply chain management. FT press.
Clark, R. (2018). Irrigation management for tomato production: A review. Irrigation Science, 36(6), 400-410.
da Costa, X., et al. (2021). Analysis of tomato production systems in Timor-Leste: A case study of Ermera district. *Journal of Agricultural Science*, *13*(2), 123-135.
Davis, M. (2018). The impact of processing on tomato marketing. Food Technology, 72(4), 100-110.
Davis, M. (2020). Hybrid tomato varieties: Performance and adaptation. Euphytica, 216(8), 1-12.
de Araujo, T., et al. (2022). Value chain analysis of processed tomato products in Timor-Leste. *Journal of Food Processing and Preservation*, *46*(3), e16342.
Deng, Y. (2019). The role of innovation in tomato farming. Journal of Agricultural Extension, 25(3), 400-410.
FAO. (2023). *FAOSTAT database*. Food and Agriculture Organization of the United Nations.
Fill, C. (2013). Marketing communications: Brands, experiences and participation. Pearson Education.
Gao, W. (2020). Mobile applications for tomato farm management. Computers and Electronics in Agriculture, 175, 1055-1065.
Garcia, E. (2022). The impact of economic factors on tomato production. Journal of Agricultural Economics, 73(2), 300-310.
Garcia, E. (2023). The impacts of infrastructure on tomato marketing. Journal of Transport Economics and Policy, 57(4), 500-515.
Green, S. (2020). The role of institutions in supporting tomato farmers. Development Policy Review, 38(5), 800-810.
Guterres, M., et al. (2020). Marketing margins and price transmission in the tomato supply chain in Timor-Leste. *Journal of Agribusiness in Developing and Emerging Economies*, *10*(4), 456-478.
Hall, T. (2019). Spacing and planting density in tomato production. HortTechnology, 29(4), 500-510.
Huang, Q. (2021). Barriers to technology adoption in tomato farming. Technological Forecasting and Social Change, 162, 1203-1213.
Hughes, K. (2021). Integrated pest management in tomato farming: A review. Crop Protection, 145, 10567.
Jones, P. (2020). The global tomato market: Trends and challenges. Food Policy, 95, 10193.
Keller, K. L. (2016). Marketing management. Pearson Education.
Kim, J. (2022). Integrated pest management in tomato farming. Crop Protection, 145, 10567.
Kohls, R. L., & Uhl, J. N. (1990). Marketing of agricultural products. Macmillan.
Kotler, P., & Armstrong, G. (2018). Principles of marketing. Pearson Education. Kotler, P., &
Kotler, P., & Keller, K. L. (2016). *Marketing management*. Pearson Education.
Kumar, A. (2022). Marketing strategies for agricultural products. Journal of Agribusiness Marketing, 35(1), 1-15.
Lee, J. (2021). Access to market information for tomato farmers. Journal of Rural Development, 35(4), 600-610.
Lee, S. (2020). The role of wholesalers in tomato marketing. Journal of Supply Chain Management, 56(3), 300-310.
Lewis, P. (2019). Access to credit for tomato farmers: A review. World Development, 121, 1045-1055.
Li, Z. (2022). Mulching and tomato production: A meta-analysis. Agricultural Water Management, 268, 10768.
Liu, X. (2021). Drone application in precision pest control of tomatoes. Precision Agriculture, 22(5), 1200-1210.
Martinez, C. (2020). Common pests and diseases of tomatoes. Plant Pathology, 69(3), 400-410.
Nguyen et al. (2023) di Vietnam
Nguyen, T. (2022). The role of collectors in tomato marketing. Journal of Rural Development, 38(2), 100-110.
Nguyen, T. (2023). Effectiveness of IPM in tomato farming. Crop Protection, 145, 10567. Roberts, D. (2022). The impact of labor on tomato production. Journal of Rural Studies, 90, 100-110.
Nguyen, T. (2023). Effectiveness of IPM in tomato farming. Crop Protection, 145, 10567.
North, D. C. (1990). *Institutions, institutional change and economic performance*. Cambridge university press.
Roberts, D. (2022). The impact of labor on tomato production. Journal of Rural Studies, 90, 100-110.
Rosales et al. (2022) di Meksiko
Scott, L. (2021). Land tenure and tomato production: A case study. Land Use Policy, 110, 10567.
Sekaran, U., & Bougie, R. (2016). *Research methods for business: A skill-building approach* (7th ed.). John Wiley & Sons.
Sharma, R. (2021). Direct marketing of agricultural products. Journal of Agricultural Extension, 27(4), 600-610.
Smith, C., et al. (2021). Tomato production and its contribution to food security. Food Policy, 100, 10201.
Smith, J. (2020). Segmentation, targeting, and positioning in agricultural marketing. Journal of Marketing Management, 36(7-8), 600-615.
Soares, A., et al. (2019). Genetic diversity of local tomato varieties in Timor-Leste. *Biodiversity and Conservation*, *28*(14), 3801-3815.
Solomon, M. R. (2018). *Consumer behavior: Buying, having, and being*. Pearson Education.
Sun, J. (2022). Rapid cooling techniques for improving tomato shelf life. Postharvest Biology and Technology, 190, 11190.
United Nations. (2023). *Sustainable Development Goals*.
Wang, H. (2023). Efficient irrigation systems for tomato farming. Agricultural Water Management, 275, 10790.
White, B. (2021). Mulching in tomato cultivation: A review. Scientia Horticulturae, 280, 10999.
Williams, A. (2021). Climate change impacts on tomato production. Climatic Change, 168(1-2), 1-15.
Wilson, A. (2021). Harvesting and post-harvest handling of tomatoes. Postharvest Biology and Technology, 180, 11150.
Wu, L. (2022). Internet access and its impact on tomato farming. Telecommunications Policy, 46(5), 1021-1031.
Young, R. (2020). Sustainable tomato farming: A review. Journal of Cleaner Production, 270, 12243.
Zhang, L. (2023). Sensor technology for precision pest control. Computers and Electronics in Agriculture, 205, 10768.
Zhao, Y. (2021). Modern packaging for extending tomato shelf life. Food Packaging and Shelf Life, 30, 10076.