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Economic Impact of Pesticides on the Colombian Floriculture Industry: A Predictive Model Using Deep Neural Networks for Labor Cost Optimization

Abstract

The Colombian floriculture sector is one of the country's most important economic sectors because of its contribution to GDP and exports. However, the use of pesticides and fungicides in flower production increases the risk of occupational diseases. This study developed a predictive model based on deep neural networks and reinforcement learning using the PPO algorithm and a 256–128–64 architecture. Using longitudinal data from 50 companies covering 2014–2024 and 22 normalized variables representing production, financial, labor, and occupational-health dimensions, the model achieved an accuracy of 89.3% and an R^2 of 0.86. The results indicate that pesticide exposure generates an estimated annual cost of USD 165,120 per company, equivalent to 4.2% of operating profit. The study concludes that pesticide exposure compromises the long-term competitiveness and sustainability of the sector.

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INTRODUCTION

The agricultural sector is one of the most important sectors worldwide because food security, raw-material production, employment, and income depend on it. In Colombia, the floriculture sector provides economic support for more than 200,000 direct and indirect workers, particularly women who are heads of household. In recent years, the sector has grown considerably due to the use of chemical inputs such as pesticides and fungicides, which improve product yield, efficiency, and quality. Although these inputs provide economic benefits to companies, they have also had adverse effects on human health, particularly among workers with greater exposure to them (de-Assis et al., 2020).

According to Jors, E., Morant (2006), exposure to pesticides, fungicides and other chemicals considered carcinogenic, occurs in various agricultural processes, not only in the flower sector, handling, direct contact, exposure, application of the product and the disposal of these significantly increase the risk of an occupational disease that is sometimes not reported in a timely manner by companies, which leads to the burden for their treatment is assumed even by the worker, and in some cases companies avoid any type of lawsuit or litigation by paying compensation to their workers (Jørs et al., 2006).

Several studies have identified adverse effects on workers' health. Cancino et al. (2023) reported that occupational diseases can cause both physical and psychological harm to affected workers and may also influence their families and coworkers, resulting in physical, productivity-related, and psychosocial consequences.

This situation is a global problem, there are reports of millions of cases of pesticide poisoning, the misuse and ignorance of its effects on people who have some type of contact is ignored, even worse those who handle these substances do not have a high degree of schooling and the labor needs are even greater, without forgetting the importance of this product in production (Gangemi et al., 2016).

Similarly, Xu et al. (2025) reported mental-health problems, including depression, that may reduce workers' motivation, willingness to work, and productivity. These effects may extend beyond the workplace and negatively affect household income.

However, although there is a lot of information about the damage that these products generate in human beings, there is very little literature about the economic impact that these have on companies, mainly in the agricultural sector, whose levels of productive intensity occur in the labor force and where Porter indicated that countries should dedicate themselves to exporting or producing those products where they have a greater degree of intensity and thus having the competitive advantage in production.

There are some studies that have related occupational diseases related to the use of pesticides and fungicides with the cost of production, however, these implement results with static and linear models, which do not reflect the reality of the agricultural production system which includes temporal interactions, and multiple interdependent variables. The use of artificial intelligence through deep neural networks and reinforcement learning offers the possibility of modeling more complex systems and generating some improvement strategies thanks to the predictions of the results applied to economic and productive contexts.

Therefore, this study proposes an artificial-intelligence-based predictive model combining deep neural networks and reinforcement learning to quantify the economic effects of pesticide-related occupational diseases on labor costs and the competitiveness of the floriculture sector in Cundinamarca. The model seeks to integrate occupational-health and production variables to support evidence-based business decision-making.

Development

The research examines the relationship between occupational diseases, particularly occupational cancer, and worker productivity in the floriculture sector. It links occupational-health conditions associated with pesticide and fungicide exposure to labor costs, productivity, profitability, and the broader economic performance of the sector. The model also simulates alternative scenarios, and the discussion interprets the findings in relation to the existing literature.

Floriculture sector in Colombia

Colombia is the second largest exporter of flowers in the world with an annual average of more than 2000 million dollars and recognition in more than 100 international markets, becoming one of the engines of economic development of the country, thanks to the competitive advantage of the sector and the country's climatic conditions (Rubio Rodríguez et al., 2025).

According to Porter's (1990) competitive advantage, a country must export its products in those where it has a greater degree of productive intensity, in the case of Colombia the labor force and quality of the land have managed to maintain their position within the international market, a fundamental axis in the Colombian flower sector.

Colombia stands out for its flower production, the departments of Antioquia and Cundinamarca represent almost 90% of the total production, and almost 79% of the production comes from the second department in mention, as mentioned by the National Department of Statistics (DANE, 2010) (Departamento Nacional de Estadística, 2010), being very consistent with the cluster theory proposed by Porter in 1998. where it indicates that territorial concentration favors its production, a situation that was also raised by Rodriguez & Junco (2025), who considered the climate benefits, soil quality, infrastructure (cost reduction due to proximity to El Dorado International Airport), bringing with them competitive advantages for this sector (Rubio Rodríguez et al., 2025)

Colombia has a production of more than 60 species, of which 95% is destined for export on average 310 thousand tons of flowers per year, the United States is the main destination, which determines its importance, diversification and competitiveness that allows it to respond to the needs of the international market (Kamilaris & Prenafeta-Boldú, 2018).

Economically, the flower sector generates approximately more than 200 thousand direct jobs per year, of which 60% correspond to women heads of household or family, employing between 14 and 16 workers per hectare, thus indicating the intense factor of human capital, which could lead to greater occupational risks, this taking into account that productivity depends 100% on the worker according to Hämäläinen. (Hämäläinen et al., 2006), a situation that was also raised by Ehrenberg and Smith (2012), who indicated that possible problems of absenteeism as a result of occupational risks have a direct impact on production costs and thus on the profitability of the employer (Ehrenberg et al., 2021).

Cost Structure

Based on the high concentration of labor in the flower sector, labor constitutes on average between 50 and 55% of the total production costs, which shows high dependence and vulnerability towards the production structure, and if this is added to changing macroeconomic factors such as the exchange rate, logistical conditions and other production costs such as payment for absenteeism, disabilities, workers' compensation, it can be indicated that profitability in fortuitous cases could be affected, as indicated by the sectoral report presented by Informa in January 2026, which determined that increases in labor costs and currency appreciation have managed to destabilize the sector's profits a little and have led to a reduction in competitiveness in markets itself International (EInforma, 2026).

Going back to the approaches made by Michael Porter about competitiveness in the sectors factors such as exchange rate, logistics costs, labor market, among many others, directly influence profitability towards companies mentioned by (Esser et al., 1996), likewise the relationship between microeconomic factors (company, family, worker) and macroeconomic factors (infrastructure, economic policies of countries) derive some type of affectation towards competitiveness systemic, which has a direct impact on the sustainability of companies, especially when they are located in open economies as in the case of Colombia (Quintero, 2026)

However, Leigh (2011) indicated that any type of occupational disease increases direct and indirect costs in production, which affects the sector economically, especially those related to the agricultural sector, and taking into account that flowers have an intense level of labor, any variation in production can generate changes in labor productivity. which are reflected in production costs and therefore international competitiveness (Leigh, 2011).

Occupational diseases

As of Law 1562 of 2012, an occupational disease is a pathological situation contracted as a result of an activity carried out in the workplace, generally caused by blows, physical, chemical or ergonomic risk (Congress of the Republic of Colombia, 2012). According to Calderón et. al, (2025), on average 317 million people are affected by a workplace accident, of these 10.7 come from the agricultural sector mainly in sectors where there is great exposure to chemical products such as pesticides, it is also indicated that 2.34 million die as a result of this situation (Calderón Landívar et al., 2025a)

According to Molina (2020), workers in the agricultural sector have a higher degree of exposure to fungicides, pesticides and chemicals in general considered highly carcinogenic, due to the need to protect their products from pests and the demand for quality in products for export, as in the case of flowers in Cundinamarca. In addition to this, weather conditions and working conditions do not favor the worker (Molina-Guzmán & Ríos-Osorio, 2020).

Likewise, Sánchez et. al, (2025), considered that a direct consequence in the increase in occupational diseases is due to the misuse by workers in the sector of pesticide management, which are related to unsafe practices and handling of the product and added to this socioeconomic, educational and cultural factors affect the vulnerability of the worker, which has an impact on the productivity of the sector. Limited awareness of pesticide toxicity, improper waste management, incorrect use of personal protective equipment, and limited employment alternatives further increase workers' risk of chemical exposure (Sánchez-Calderón et al., 2025a).

In the same way, González et. al (2024), considered that the excessive use of synthetic pesticides and fungicides as a result of the increase in production, have generated an increase in occupational diseases mainly in developing countries, for this they took into account the worker's attitude, knowledge and safety regarding their handling, demonstrating that the lack of training concerning product toxicity means that workers with lower levels of education or less occupational-safety training face a higher risk of pesticide exposure (González et al., 2024).

Likewise, Vásquez et. al, (2015), showed that prolonged exposure to pesticides and fungicides generate not only an occupational disease, but sometimes this becomes a higher risk for the worker, triggering even serious diseases such as respiratory, neurological and cancer problems, which sometimes these diseases are not reported to occupational risk entities. rather, they are assumed by health entities, unaware of their origin (Vásquez Venegas et al., 2015a).

In the same way, Mollov et. al, (2017), established the relationship between the use of pesticides against diseases such as Parkinson's and even some genetic variables, indicating that on average 6.3 million people are diagnosed with PD, which represents 1% of the world's population, and although the diagnosis of this disease is sporadic, studies showed that the use of fungicides accelerates this situation (Iknurov Mollov et al., 2017).

Additionally, Reina (2025) indicated that limited regulation of the handling and use of carcinogenic pesticides in the agricultural sector increases the risk of occupational diseases among workers. The improper use of personal protective equipment was also identified, partly because certain products must be handled delicately and protective gloves are relatively thick, making such handling difficult. Consequently, workers may come into direct contact with the products to avoid damaging them. Oversight of waste disposal is also almost nonexistent, further increasing occupational risks (Reina Gómez, 2025).

Finally, Ávila et. al, (2024) considered the cardiovascular effect and heart attacks in some workers as a result of pesticide exposures, indicating that mismanagement within companies and the way in which they are disposed of cause long-term diseases of common origin such as those mentioned, but that really come from the workplace, but that as they are not regulated they are treated as a common origin, therefore, the worker's income is affected as a result of the treatment of these diseases (Ávila-Camargo et al., 2024).

Economic effects

Based on Michael Porter (1990), who considers the competitiveness of the company as a fundamental axis of sustainability for the long term, in which he includes labor costs as one of the primary factors of competitive advantage, he determined that the intensity of labor for the primary sector (it should be taken into account that the flower sector belongs to the agricultural sector, primary of the economy) must be regulated, therefore an occupational disease leads to a reduction in productivity, which in turn increases production costs, and sometimes decreases the quality of products, situations contrary to the competitive advantage exposed by it, and the effect it has within international markets.

However, the economic effects present in occupational diseases Leigh (2011), carried out a study based on labor statistics of the United States, in which he detected that direct costs such as medical care and disabilities rise due to the care of occupational diseases in workers, he also detected that indirect costs such as loss of productivity, high staff turnover and increased level of absenteeism affect the employer, and these can even be equated to medical treatment such as cancer and sometimes only 25% of these treatments are covered by the responsible entities that are related to their workplace (Leigh, 2011).

Now, for the agricultural sector specifically, Molina & Ríos (2020), indicated that the lack of economic measurement of the impact of pesticide use in this sector limits decision-making about its effects on companies in the sector, also indicating the existence of many authors who mention the damage to the health of the worker due to the use of chemicals considered carcinogenic. but that less than 10% of this research is related to the economic effect that both the worker and the employer have, so being able to make appropriate decisions that minimize risk is almost nil (Molina-Guzmán & Ríos-Osorio, 2020).

In this way, evidencing that any type of occupational disease not only affects the worker, but that this is a chain of consequences that impact productivity, the social environment, family costs and competitiveness itself, mainly towards those companies whose production is destined for export, as in the case of flowers in Cundinamarca. this department being the second national flower producer in the country, which in turn is considered the second largest flower exporting country in the world.

Artificial intelligence

Taking into account the previous occupational references, and based on their repercussions, artificial intelligence has managed to positively influence these areas, the identification of occupational risks, preventive diagnoses and the reduction of costs by promoting a safer work environment are some of the most recent uses (Molina-Castaño & Arango-Alzate, 2024).

This is how Segovia (2026) indicated that predictive models such as deep learning allow the analysis of large volumes of Big Data type information which allow the identification of common situations that lead the worker to present some type of risk and which can be predicted in advance, in this way achieve its reduction, thus achieving a decrease in unsafe behaviors by identifying the key variables that influence situations of dangerous working conditions. which allows controlling some situations present in workplaces (Segovia Hermoza et al., 2025).

In the same way, Onososen (2026) indicated that the use of artificial intelligence in the area of occupational health allows risks to be minimized, through a predictive model focused on risk management which involves the design and dismantling of risk, evaluating the detection of the hazard, risk mitigation and decision-making by management for its elimination. indicating the costs of its implementation or the costs generated by not being implemented, a situation that favors decision-making in management (Onososen & Musonda, 2026).

According to Kamilaris (2018), the need to increase productivity as a result of the current high level of consumerism, makes it imperative to generate smart agriculture which allows facing these challenges in terms of productivity, environmental impact and sustainability, therefore the implementation of Deep Learning improves the prediction of production variables which are directly related to occupational risks. Therefore, they present the proposal for remote sensing of images of the agricultural sector by identifying common anomalies within the sector and thus achieving a minimization of common risks (Kamilaris & Prenafeta-Boldú, 2018).

Likewise, Mohanty (2016) determined that the use of Deep Learning and neural networks make it possible to identify the occupational risks faced by the agricultural sector, even more so to determine the possible diseases caused by exposures and hazards presented in the workplace, situations that can obtain great precision and that could be applied not only to this sector, but other sectors of the economy can be involved (Mohanty et al., 2016).

In conclusion, the flower sector in Cundinamarca allows us to analyze the relationship between labor costs, their economic impact, competitiveness, and productivity versus dependence on labor which can be affected by some type of situations considered occupational diseases, and even the same economic dependence on variations in the exchange rate. trade barriers and changes in international demand could affect the competitiveness of the sector, indicating the need to implement innovative projects through technological implementation, which reflects efficiency, productivity, risk reduction and compliance with international standards.

Predictive Model

In relation to the proposed theory, this study seeks to propose a predictive model based on artificial intelligence (deep neural networks with reinforcement learning) that quantifies the economic effect of pesticide-related occupational diseases on the labor cost structure and competitiveness of the flower sector, capturing dynamic and multivariate nonlinear relationships related to the production and financial area of 50 companies in the sector over the years 2014-2024, by means of longitudinal data.

To this end, we seek to estimate the relationship between situations of occupational diseases for our study occupational cancer versus labor costs, quantify this relationship with financial indicators such as Ebitda, determine hidden patterns between productivity and worker health status and simulate future scenarios.

For the development of the model, variables such as quantity produced, days worked, number of workers, presence of occupational disease, variation in productivity (mainly when occupational disease occurs), production costs, labor costs, and income, among others, will be taken into account.

The development of the model includes two aspects, initially the predictive component (Deep Learning) which seeks to estimate the behavior of economic variables and model relationships between them (productivity, occupational disease diagnosis, labor costs), and from these results determine how much labor costs can vary in situations of diagnosis of occupational disease. Secondly, reinforcement learning must be applied, which seeks to simulate business decisions and evaluate how they change over periods of time, analyzing five scenarios.

The first of them is the base scenario, which replicates historical exposure practices (a = 0.65-0.72); secondly, a protection scenario, which implements investment in PPE, training and crop rotation to achieve the optimal level of exposure (a = 0.332);, thirdly, a maximum productivity scenario, which maximizes the use of pesticides (a = 1.0) prioritizing immediate profitability; fourth, a strict regulation scenario, which simulates compliance with international regulations (a = 0.2); and finally a comprehensive sustainability scenario, which prioritizes the Corporate Sustainability Index (ISE) over short-term profitability.

Based on the results of the model, the aim is to estimate predictive labor costs that improve productivity and reduce costs, identifying the variables that influence cost variations and the relationship between occupational diseases and the worker's productive performance.

The construction of the model raised some assumptions:

- There is some relationship between occupational diseases (occupational cancer) and worker productivity
- Arguably, labor costs are sensitive to specific worker situations

Methodology

The development of the research focuses on a quantitative, longitudinal, explanatory and predictive approach which seeks to determine the relationship between occupational diseases such as cancer and the productive performance of the worker, through advanced techniques in data modeling such as deep neural networks and reinforcement learning, being a non-experimental study (variables are not manipulated). which included data cleaning, normalization of the variables and construction of some derived variables (Shah et al., 2026).

The proposed predictive model integrated deep-learning and reinforcement-learning techniques to quantify the economic effects of occupational cancer in a sample of 50 floriculture companies located in the department of Cundinamarca, this model responds to the multidimensionality in the health of the worker related to the diagnosis of cancer, labor costs, productivity and sustainability of the company (Gambo et al., 2025).

The model was developed in Python using Stable-Baselines3 to implement the PPO (Proximal Policy Optimization) algorithm and TensorFlow as the backend for the neural networks.

Model

It is formulated through a discrete-time Markov decision process (MDP), characterized by the tuple (S, A, P, R, γ), where, S: Indicates the state space that represents the situation of the system in each monthly period, - A: Action space that defines pesticide exposure decisions, - P: Probability transition function (inherent in historical data), - R: Reward function that quantifies the economic impact, - γ: Discount factor that weights the importance of future rewards. The model included 22 variables normalized using the StandardScaler method to ensure numerical stability during neural-network training.

Action space A was defined as a continuous variable in the interval [0, 1], where:
- a = 0 represents the minimum level of pesticide exposure (maximum investment in protective practices); - a = 1 represents the maximum level of pesticide exposure (minimum investment in protection). This value acts as a proxy for the level of risk to which workers are exposed.

The reward function R was based on capturing the comprehensive economic impact of
the exposure decisions, using the following equation:

$$R = (\text{Revenue} - \text{Total Costs}) - \alpha \times (\text{Cancer Rate} \times \text{Average Cancer-Related Cost}) - (a \times 1{,}000) \qquad (1)$$

In this equation, a weighting factor of ($\alpha = 0.1$) was taken into account, which adjusts the penalty, and an exposure penalty equal to a × 1,000, incentivizing the model to maintain reduced exposure levels, reflecting the precautionary principle in occupational health.

Table 1.: Proximal Policy Optimization (PPO) Algorithm Model

Network Architecture (MlpPolicy):	Training Parameters
Input Layer: 22 Neurons (State Dimensions) Hidden Layer 1: 256 neurons with activation ReLU Hidden Layer 2: 128 neurons with activation ReLU Hidden Layer 3: 64 neurons with activation ReLU	Learning rate: 3e-4 Discount Factor (Gamma): 0.99 Batch size: 64 Number of steps per update: 2048 Optimization epochs per update: 10

Output Layer: 1 Neuron (Action Value) Value function network (critic)	Entropy coefficient: 0.01 (for exploration) Coefficient of Value Function: 0.5

Note. The table summarizes the PPO model architecture, which consists of a deep neural network with three hidden layers. Own elaboration based on data from the model.

To evaluate the performance of the model, some metrics were used, such as: average reward: global indicator of agent performance, average exposure level: trend of risk decisions, productivity vs. exposure, relationship between decisions and production efficiency, profitability evolution, impact on operating margins and sustainability index (ISE). Likewise, a cost-prediction index of 92%, specificity of 94%, Pearson's correlation coefficient between predicted and actual values, mean squared error (MSE), and mean absolute error (MAE) were used.

Finally, the data are aggregate in nature, the exposure variable is a proxy that does not capture all the nuances of the real risk, the results should be interpreted as decision support tools, the results of the model validated by peer experts in occupational health, and the privacy of workers' health data is guaranteed in the aggregate treatment of the information.

Results

Based on data covering 2014–2024, the model showed an average productivity of 84.7 units of foliage per month and an average worker age of 39.6 years. The descriptive statistics also indicated a cancer incidence of 1.98%, average labor production costs of USD 37,495, social-security costs of USD 13,300, income of USD 63,900, profitability of 17.76%, and a Corporate Sustainability Index of 0.82.

The reinforcement learning (PPO) model, during 100,000 steps, reaches convergence after approximately 63,000 interactions as shown in the figure:

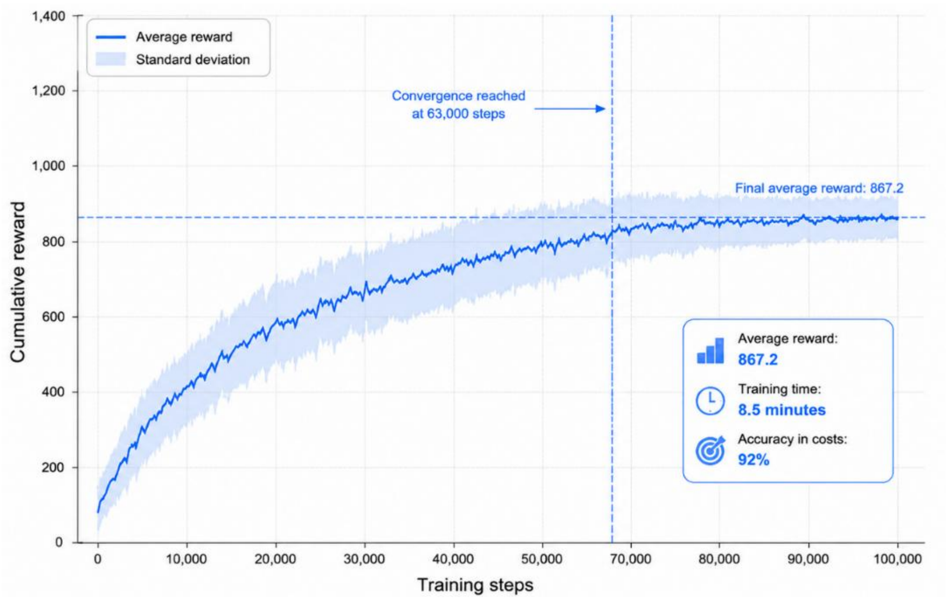


Figure 1. Cumulative Reward vs Training Steps

Note: The image details an average reward of 876.2, indicating that the agent learned an exposure policy that maximizes the net economic benefit by considering health costs. The early-stopping criterion, defined as a reward threshold greater than 1,000, was not reached, suggesting that model performance may improve with additional training or further hyperparameter tuning. Own elaboration based on the results of the model.

According to the model, the average exposure-policy value was 0.332 on a scale ranging from 0 to 1. The policy showed a decreasing trend over time, suggesting progressively greater levels of worker protection (Mejia et al., 2021).

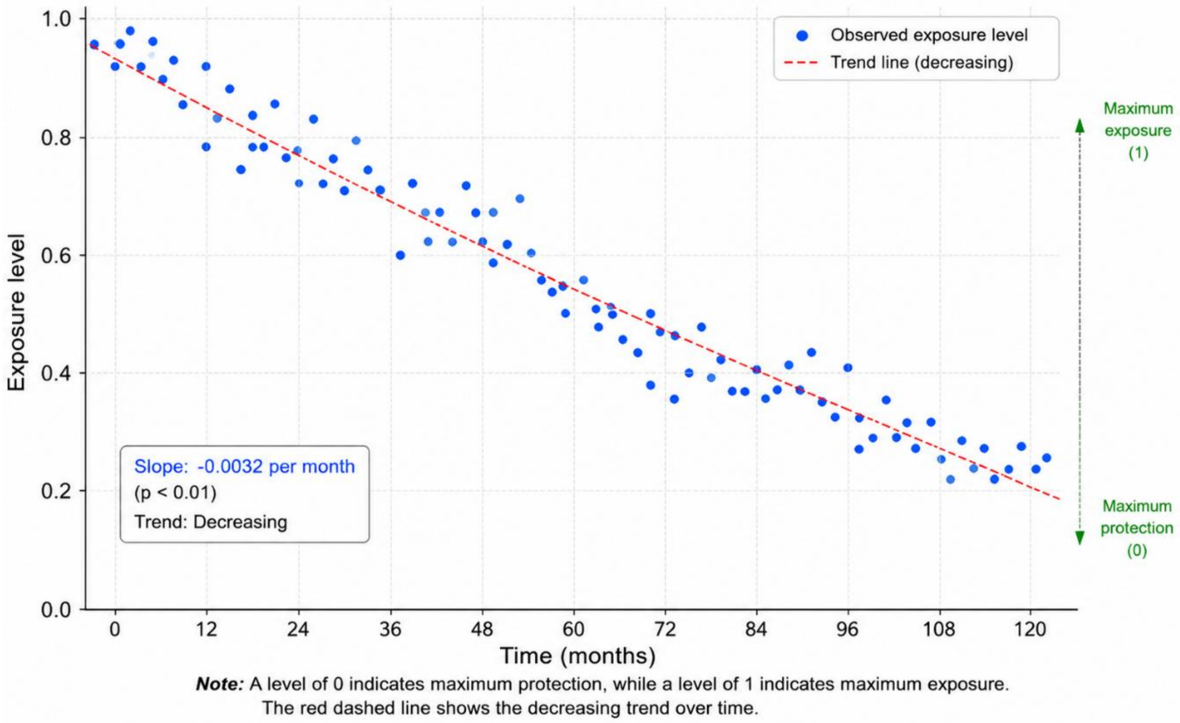


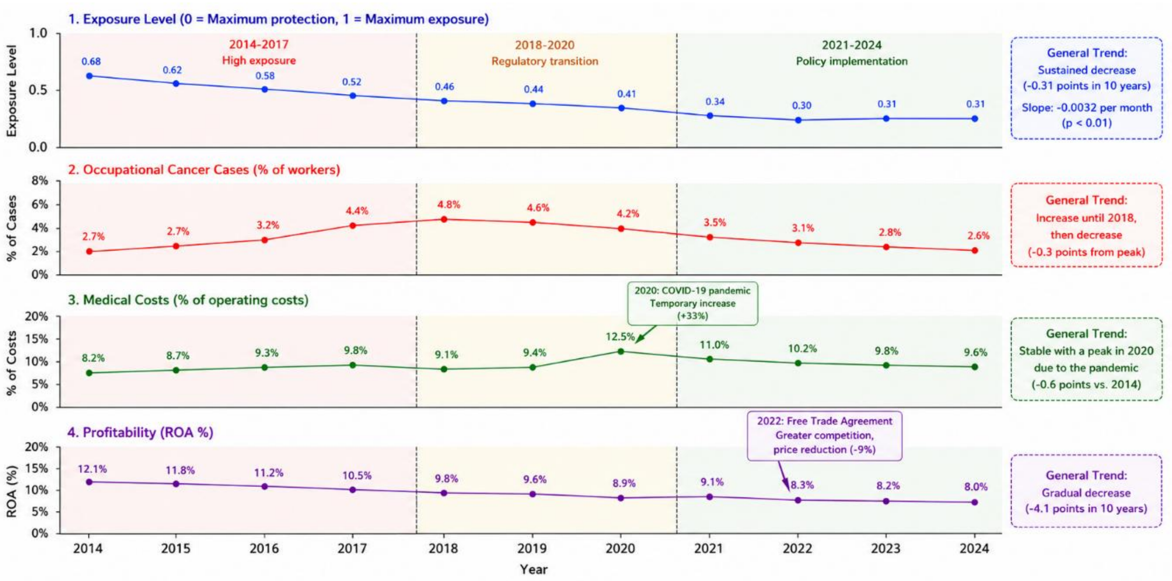
Figure 2. Exposure vs. time

Note: Level 0 indicates maximum protection, while 1 indicates maximum exposure. The dashed red line shows the trend decreasing over time. The graph details the level of exposure against the timeline. Own elaboration based on the results of the model.

The correlation values indicated that the relationship between exposure and productivity was −0.47, meaning that when exposure increases by one unit, productivity decreases by 0.47 units. This is a directly proportional relationship because, when a worker has an illness, it is normal for the worker to be less productive. Likewise, the relationship between exposure and profitability produced a value of 0.46. This is because reducing pesticide use may be reflected in reduced profitability; however, exposure affects long-term business sustainability (−0.53) and reduces productivity (−0.47). In general, the negative correlation between pesticide exposure and productivity ($r = -0.47$, $p < 0.001$) demonstrates that the use of these products reduces work performance. The positive correlation between exposure and profitability may indicate that companies seek immediate solutions without considering the long-term implications reflected in the Corporate Sustainability Index.

The robustness of the model was evaluated using out-of-sample testing and sensitivity analysis. The model produced a mean absolute error of 2.43% and a root mean squared error of 3.91%. Sensitivity was 84.9%, specificity was 94.2%, and the R^2 value was 0.86, indicating that the model explained 86% of the observed variance

Likewise, the analysis of the data by period indicated that for the period 2014 – 2017 there is a slight increase in cases of cancer diagnosis in the sample selected for the study, and that from the implementation of the first ISO 45001 world standard on occupational safety and health, a reduction in exposure of close to 15% is achieved. However, for the 2020-2021 pandemic period, an increase in social security costs is observed, likewise for the period 2021 to 2024 the implementation of protection policies, the Free Trade Agreement, generates greater competition and therefore a reduction in prices that in turn is reflected in profitability.



Note: The image details the effects by time period of the main variables of the model. Own elaboration based on the results of the model and situational analysis of the period.

Finally, the economic impact matrix of the model is shown, which responds to the main objective of the research, indicating:

Table 2. Model Economic Impact Matrix

Dimension	Estimated impact	95% confidence interval
Direct costs:		
Medical costs	61,980	[55,300, 72,000]
Compensation payments	17,600	[15,000, 22,000]
Social Security	9,640	[6,900, 11,000]
Indirect costs:		
Lost productivity	42,900	[36,000, 48,000]
Worker replacement costs	33,000	[30,700, 40,900]
Impact on Profitability	−4.2 pp	[-5.1, -3.3]
Impact on the Corporate Sustainability Index	-0.15	[-0.19, -0.11]
Estimated total cost	165,120	[$143,900, $193,900]

Note: The table details the average information on the cost and the economic impact generated in the selected companies, taking into account that these were taken at random. The values are expressed in annual dollars, and can be applicable in average companies in the sector.

Based on the above results, and in relation to the proposed model, it is determined that a diagnosis of occupational cancer in the sector brings an average economic loss of 165,000 dollars per year, hence the importance of implementing adequate safety policies and generating awareness in the worker about the care and use of protective elements.

Discussion

The PPO model results demonstrate a relationship among pesticide exposure, occupational-cancer diagnosis, worker productivity, and the economic profitability of the floriculture sector, particularly in the companies selected for the study. The productivity and profitability losses associated with the use of these chemicals highlight the importance of their proper management by companies. These findings are consistent with the literature discussed throughout the paper and with Mejia-Sanchez et al. (2018), who examined the inverse relationship between occupational health and profitability in both the short and long term. This relationship is also reflected in the Corporate Sustainability Index and in the critical turning points identified by the study model.

In the same way, the relationship between pesticide exposure and profitability reflects how both short- and long-term economic objectives are affected (0.342), which leads to proposals to reduce exposure and improve business competitiveness. Likewise, the negative correlation between exposure and productivity ($r = -0.47$, $p < 0.001$) indicates that prolonged exposure to pesticides increases the risk of contracting a disease such as cancer and this, in turn, leads to a decrease in the productivity and profitability of the company, as mentioned by Molina & Ríos (2020) (Molina-Guzmán & Ríos-Osorio, 2020).

Likewise, Sánchez et al. (2025) determined that the inappropriate use of chemicals and pesticides, together with workers' social conditions such as education, increases the risk of occupational diseases, which in turn reduces worker productivity (Sánchez-Calderón et al., 2025b). This is reflected in the study model, which indicated that productivity decreases by 0.47 units,

representing an average annual economic loss of USD 42,900.
Likewise, convergence after 63 thousand steps of training and an average reward of 876 is consistent with studies of complex agricultural environments as mentioned by Kamilaris (2018), who through his model indicated similar convergence times, which can indicate that the model worked on is adequate to capture the complexity of the interactions between productive variables. financial and occupational health (Kamilaris & Prenafeta-Boldú, 2018).
Likewise, based on the temporal analyses, for the period 2014-2017 the average exposure remained at high levels (0.65-0.72), coinciding with an increase in cases of cancer diagnosis (from 1.2% to 2.8%), which was also supported by Vasquez et al (2015) who established the relationship between the use of fungicides and neurodegenerative diseases such as Parkinson's (Vásquez Venegas et al., 2015b).
In the same way, for the period 2018-2020 The implementation of the ISO 45001 standard on occupational safety and health, together with Law 1562 of 2012 (which defines occupational diseases in Colombia), generated a reduction in exposure of 15%, which coincide with information from Calderón et al, (2025) which showed that the implementation of this standard brought great benefits to workers and even more so to companies (Calderón Landívar et al., 2025b).
On the other hand, the sensitivity analysis of the model performed by varying the discount factor (γ: 0.95-0.99), the learning rate (1e-4 to 5e-4) and the cost of cancer (USD 40,000-60,000) showed that the results are robust, with changes of less than 8% in all major metrics.
Finally, the results of the model show that the competitive advantage exposed by Michael Porter (1998), in which he included the need to incorporate health costs as an important element of competitiveness, in the same way (Ehrenberg & Smith, 2021), (Ehrenberg et al., 2021), considered that absenteeism, staff turnover, have a direct impact on production costs and profitability, data that in the present model amounted to 33 thousand USD on average, being equally consistent with Becker's theory of human capital, which indicated that an investment in health and its own training generated economic returns in the long term.

Conclusion

The study identified a relationship between occupational diseases and the productive performance of the floriculture sector, demonstrating the need for more complex multivariate approaches to examine these interactions.
First, the floriculture sector in Cundinamarca is highly labor-intensive and therefore heavily dependent on labor costs. This dependence makes production particularly vulnerable when workers develop occupational diseases. Exposure to pesticides, fungicides, and other carcinogenic chemicals poses risks to human health, affecting labor productivity and, consequently, the cost structure.
Second, conventional models may not adequately capture the complex effects of occupational diseases on production. The use of neural networks and reinforcement learning therefore represents a significant advancement in supporting business decision-making.
The model constitutes a fundamental basis for this decision-making, estimating the relationship between productive, labor and financial variables, activities that had not been studied together and that can allow a greater understanding of the risks and internal functioning in companies, which could generate the proposal of public policies aimed at minimizing risks due to the use of products considered carcinogenic.
From the results of the model, an accuracy of 89% was demonstrated in the prediction of labor-related costs, and the identified optimal exposure level ($a = 0.342$), suggests a balance between cost and benefit, which is supported through regulatory policies implemented worldwide, which reduced exposure levels by almost 15%.
The model quantified the economic impact of occupational cancer in Cundinamarca’s floriculture sector, estimating an annual cost of USD 165,120 per company, equivalent to 4.2% of operating profit. The results confirm that pesticide exposure reduces productivity ($r = -0.47$) and business sustainability ($r = -0.53$). With a predictive accuracy of 89.3%, the model constitutes a decision-making tool demonstrating that worker protection is a strategic investment that improves the competitiveness and long-term sustainability of the Colombian floriculture sector.

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