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ARTICLE

RESEARCH ARTICLE

Predicting prices and boosting digitalization to reinforce the farmer position in the agrifood value chain: Huelva strawberry case, Spain

Impulsar la digitalización para reforzar la posición del agricultor en la cadena de valor agroalimentaria: el caso de la fresa de Huelva, España

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Abstract: *Aim of study*: A real-time monitoring and prediction system for Huelva strawberry (Spain) price is proposed, based on data from the Andalusian Observatory of Agrifood Prices (AOAP) of the Regional Ministry of Agriculture, Fisheries, Water, and Rural Development of the Government of Andalusia, Spain. This system can support farmer decisions to increase their revenues and accelerate digitalization adoption aiming at improving equity and sustainability of the agrifood value chain. *Area of study*: Huelva province (Spain) is leading Europe's strawberry sales from January to April and the sector is highly relevant in economic and development terms for this territory. *Material and methods*: Analysis of AOAP data and value chain of the strawberry sector, development of a statistical predictive model and monitoring real-time surveillance system to create the seed of a dashboard to support farmer market decisions, in the context of artificial intelligence predictive models and data space requirements. *Main results*: AOAP includes important sectoral data under a reasonable governance model that can be a starting point to develop useful decisions support tools. The developed predictive price model based on traditional tools allows for maximizing farmer revenue and thus becomes a framework to build transdisciplinary knowledge joining the agricultural domain expertise and the artificial intelligence tools in parallel with the needed big data and data spaces development. *Research highlights*: 1) The proposed predictive and monitoring system can improve the farmer's position in the value chain and thus it can also be useful to foster the adoption of digital tools by farmers. 2) Predictive systems require a huge amount of data that is not currently available. AOAP have some interesting characteristics as starting point for a data space that can contribute to fill this gap.

Keywords: agricultural data observatories and spaces; agrifood sector; artificial intelligence; predictive models; traditional vs new data technologies.

Resumen: *Objetivo del estudio:* Se propone un sistema de monitorización y predicción en tiempo real del precio de la fresa de Huelva (España), basado en datos del Observatorio Andaluz de Precios y Mercados (OAPM) de la Consejería de Agricultura, Pesca, Agua y Desarrollo Rural de la Junta de Andalucía, España. Este sistema puede apoyar la toma de decisiones de los agricultores para aumentar sus ingresos y acelerar la adopción de la digitalización, con el objetivo de mejorar la equidad y la sostenibilidad de la cadena de valor agroalimentaria. *Área del estudio:* La provincia de Huelva (España) lidera las ventas de fresa en Europa entre enero y abril, y el sector es muy relevante para la economía y el desarrollo de este territorio. *Material y métodos:* Análisis de los datos de fresa del OAPM y de la cadena de valor de este producto, desarrollo de un modelo estadístico predictivo y un sistema de monitorización en tiempo real para crear las bases de un cuadro de mando que apoye las decisiones de mercado de los agricultores, en el contexto de los modelos predictivos de inteligencia artificial y la necesidad de un espacio de datos. *Resultados principales:* OAPM incluye datos sectoriales importantes bajo un modelo de gobernanza razonable que puede servir de punto de partida para desarrollar herramientas útiles de apoyo a la toma de decisiones. El modelo predictivo de precios desarrollado, basado en herramientas tradicionales, permite maximizar los ingresos de los agricultores y, por lo tanto, se convierte en un marco para construir conocimiento transdisciplinar que combine la *expertise* en el ámbito agroalimentario con las herramientas de inteligencia artificial, en paralelo con el desarrollo necesario de *big data* y espacios de datos. *Aspectos destacados de la investigación: 1)* El sistema propuesto de predicción y monitorización puede mejorar la posición del agricultor en la cadena de valor y, por tanto, también puede ser útil para fomentar la adopción de herramientas digitales por parte de los agricultores. 2) Los sistemas predictivos requieren una gran cantidad de datos que actualmente no están disponibles. Las AOAP presentan algunas características interesantes como punto de partida para un espacio de datos que puede contribuir a cubrir esta carencia.

Palabras clave: inteligencia artificial; modelos predictivos; observatorios de datos y espacios de datos agrarios; sector agroalimentario; tecnologías de datos tradicionales versus nuevas.

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Supplementary information ↓

1. INTRODUCTION

The formation of agrifood product prices along the value chain and its influencing factors interest both stakeholders and policymakers. Many initiatives promote fair value distribution and prices for farmers (Herrero Velasco, 2021; Sarkki et al., 2022). Price observatories, created to monitor prices across the chain (Oosterkamp et al., 2013), are among the most common. However, most lack versatile decision-support systems, despite the current digitalization context offering great opportunities to develop them.

In 2003, the Regional Ministry of Agriculture of the Andalusian Government established an agrifood price and market observatory, intending to increase price transparency throughout the value chain (Junta de Andalucía, 2024a). This observatory contains extensive price data from various agrifood sectors and trade positions, making it a valuable source of information for Andalusia and a good starting point for developing associated digital tools.

In the context of a fair value chain, predicting prices in advance and explaining them through the identification of contributing factors across the different stages of the chain could improve decision-making in different ways. For example, it could help align with the requirements of the European Green Deal (European Commission Strategy and Policy, 2024) and the Farm to Fork Strategy (European Commission Food, 2024). The challenge is even greater for perishable products, especially those with high value.

Traditional statistical methods for estimating prices based on different factors and analyzing their contribution are well known (Wang et al., 2020). Digitalization offers a wide array of possibilities for using new information sources, technologies, and processing methods to improve predictions (Lezoche et al., 2020) However, digitalization adoption faces diverse challenges and is not happening as fast as anticipated. Parra-López et al. (2024) refer to several factors that difficult or inhibit digitalization adoption: lack of infrastructure, need for training and lack of clear returns among others. In addition, farmer perceptions and attitudes also play a very important role.

This paper analyzes the possibilities of predicting the price perceived by farmers for their productions and the impact of this price on subsequent positions in the value chain. The goal is to propose the inclusion of predictive information in price observatories in the short and long term to support decision making, reinforce farmers' position and boost the digitalization process. The predictive information model will be developed:

- In the short-term, by establishing a real-time monitoring system to maximize farmers' benefits by maximizing revenue.
- In the long-term, by identifying variables that explain the price perceived by farmers and quantifying their influence to inform market production strategies.

This paper uses data from the "Observatory of Prices and Markets of the Regional Ministry of Agriculture, Fishing, Water and Rural Development of Andalusia", hereafter the Andalusian Observatory of Agrifood Prices (AOAP), and it focuses on the strawberry sector in Huelva (Spain), a high-value perishable product.

Data are analyzed using multivariate techniques, and potential new data sources, technologies, and some processing methods that could contribute to the goal are also identified. Additionally, strategic political initiatives that align with this objective are discussed with especial reference to the European Data Space for Agriculture (García, 2023).

The article is structured as follows: Following this introduction, Section 2 presents the general and current context of the agrifood value chain, with a focus on farmers, monitoring tools, and the opportunities offered by digitalization. Section 3 presents the case study of the Huelva strawberry sector and the current data provided by the AOAP in the digitalization context. Section 4 describes the methodology used to explain and predict prices as the basis for the strawberry decision support systems and to analyze the AOAP in the framework of the Agricultural Data Spaces. Section 5 presents the results of the predictive model and monitoring system developed, called Berrydashboard, the possibilities of improving it by adding new data and data technologies and the results of the analysis of AOAP as a use case of a Data Space. Finally, the conclusions from the strawberry case study and the developed tool are presented, with the ambition of being useful for future developments and generalization to other products with the necessary adaptations.

2. THE POSITION OF FARMERS IN THE AGRI-FOOD VALUE CHAIN

The price farmers receive for their products has been a constant source of controversy, advocacy from farmers and governmental initiatives aimed at contributing to solving the problem. Protests and demonstrations by farmers across Europe in the first half of 2024 are a good example of the situation.

The most significant governments initiatives to address this issue include the creation of price observatories and the development of agrifood value chain legislation. Briz Escribano et al. (2010) emphasized the importance of the value chain as an analytical tool for transparency in the sector and for other aspects such as environmental impact, integration, trust, or risk.

2.1. Value chain approach

The value chain concept was defined by Porter (1985). In the specific case of the agrifood sector, Briz Escribano et al. (2010) noted that the value chain represents a comprehensive approach involving all stakeholders, from production to consumption, including the farmers, wholesalers, the processing industry, retailers and consumers.

According to the same authors, the main goal of the value chain is to create value along the chain, which must be competitive and efficient. However, the value distribution is equally important, and it must provide fair revenues to all the actors, aiming for what is known as "economic sustainability", particularly to the farmer, who is often in the weakest position and requires special attention.

Nowadays, the chain is also expected to be environmentally and socially sustainable, taking care of natural resources and minimizing the negative environmental impacts, while ensuring that value creation along the chain occurs under fair and socially acceptable conditions for all workers involved. FAO adopts a similar approach when applying this reality to developing countries (Neven, 2015).

However, the market does not always economically reward all the factors, often failing to reflect the full reality. Many current studies focus on analyzing the consumer's perception —or that of other intermediate actors— regarding the environmental and social conditions under which production occurs. If the market were able to pay for these factors, it would strengthen the farmer's position while helping to achieve many of the European strategies' objectives associated with the Green Deal, such as improving carbon and energy footprints (Moreno Marcos, 2019; Taufique et al., 2022) or the social impact (Rossi et al., 2024).

2.2. Price observatories and other governmental actions

Various European governments and the European Union itself have established and developed price observatories for monitoring agrifood product prices to determine the factors affecting price volatility and introduce transparency into the price structure along the value chain.

Oosterkamp et al. (2013) cited Spain and France's price observatories as the two best-known examples. They explained that both observatories have permanent staff monitoring price trends in the agrifood production chain also conducting various types of studies to investigate price transmission and formation mechanisms within the value chain.

In 2009, EU Member States implemented the European Food Prices Monitoring Tool to compare price trends across different countries and sectors. The EU now also operates an agrifood product observatory (European Commission Agriculture and Rural Development, 2024) that monitors many products and publishes short- and medium-term outlook reports. This observatory, which includes a group of experts, aims to provide sectors with greater transparency by disseminating data and publishing outlook reports.

But the EU itself notes that its outlook reports are based on assumptions that imply relatively smooth market developments, while markets are often much more volatile, meaning these outlook reports do not constitute predictions.

In response to low price episodes and farmer protests, governments have approved legislation to protect farmers and guarantee them a fair income. For example, in 2013, Spain approved Law 12/2013, of August 2, on measures to improve the functioning of the food chain, which was modified in 2021. In 2024, a package of measures was also introduced to strengthen the application of the Food Chain Law in response to farmer demonstrations.

Also in 2024, recognizing the need for such tools, the EU took another step by launching the creation of the Agricultural Food Chain (European Commission, 2024a) to strengthen farmers' positions in the food supply chain and reinforce trust among all chain stakeholders.

2.3. The need for price prediction and explanation systems. Real-time monitoring systems

Price prediction and other variables that describe market conditions for agrifood products would be highly beneficial for farmers decision support, helping them to improve their income. However, this type of prediction is very complex, as acknowledged by the EU regarding the tools available in its agrifood price observatory.

Although agrifood markets, like other markets, are governed by the laws of supply and demand, agricultural product supply, unlike non-living system production, is influenced by natural conditions and climate, making accurate predictions challenging and dependent on the availability of data (Wolfert et al., 2017).

One option for tackling this problem, as a first step, is the use of real-time monitoring systems, short-term predictive systems that are continuously updated with real data as they become available, adjusting the models accordingly. These systems are used for various purposes to improve decision-making in uncertain situations, as seen for example in the Eco-ready project for assuring food security (Manikas, 2022).

In price observatories, short-term predictions of production quantities and agrifood product prices could be based on recent real data. In contrast, long-term price predictions must rely on identifying, quantifying, and modelling explanatory variables. Short-term predictions can be used to support short-term decisions —the season or campaign decisions— while the later ones should serve as a general reference for decision-making regarding factors affecting the business model and not being used as exact tools for revenue or profit quantification.

2.4. Price transmission in advanced positions of the chain. Consumer preferences

All factors that contribute to explain, through cause-effect relationships, the price of agrifood products will positively influence decision-making by farmers, provided that accessible tools are designed and developed for them. Oosterkamp et al. (2013) call for scientific studies on the exact nature of price transmission and ask for data that must be collected specifically for this goal in certain production chains.

Analyzing price transmission along the value chain requires studying whether the price paid by other stakeholders in the chain depends on the price received by the farmer. It involves analyzing how the price changes downstream and to what extent the price paid by the consumer is related to that perceived by the farmer. The objective of determining whether this cause-effect relationship exists is to assess whether the farmer can influence consumer prices and what is more interesting whether the farmer's production decisions —such as adopting good environmental or social practices, like implementing organic farming strategies (Kumar et al., 2018), reducing plastic use (EIP-AGRI Focus Group, 2021), using reclaimed water for irrigation (Gómez-Lucena et al., 2024) or adopting good labor conditions— are compensated by the market and, from this perspective, whether it is worthwhile for the farmer to implement them.

Farmer preferences for adopting different kind of strategies have been the focus of many analyses (Dessart et al., 2019; Blasch et al., 2022; Gars et al., 2024). On the other hand, it seems clear that consumers have the power to compel the food production industry to consider these social and environmental issues beyond mere price or convenience. The evolution of labelling is a prime example, as environmental, health, ethical, and other concerns have become increasingly important (van Bussel et al., 2022). Another example is the boycott by German supermarkets of strawberries from Huelva (Spain) in 2023 due to the controversy over irrigation in the Doñana National Park.

The Farm to Fork Strategy and the Biodiversity Strategy (European Commission Energy, 2024), both part of the European Green Deal, propose an agricultural model focused on environmental protection with significant requirements for producers. From a political point of view, it is crucial to consider who bears the cost of implementing these measures, especially given the European Commission's interest in ensuring that no one is left behind (European Commission, 2023a) in this transition and that the possible impacts of applied measures and policies are distributed equitably across all chain actors.

2.5. Digitalization context

Digitalization is a strong trend that offers enormous unimagined opportunities as well as challenges. Briz Escribano (2011) pointed to the capacity of ICT to empower small producers of the agrifood sector while Wolfert et al. (2017) referred possibilities of predictive models and big data to support decisions and improve the farmer's position in the value chain.

The digitalization of all sectors of the economy is a political and strategic priority for the EU within the 2021-2027 framework, as it is for other administrations. In the context of agrifood in Spain, the

Strategy for the Digitalization of the Agrifood, Forestry, and Rural Environment sectors (MAPA, 2019), as well as various digitalization initiatives and projects led by the Andalusian Government (Junta de Andalucía, 2024b) are good examples.

But as pointed out before, digitalization adoption is not as easy and fast as foreseen, due to multiple factors. Some of the most important are available data and infrastructure, training and skills, trust, lack of returns, governance and privacy issues (Wolfert et al., 2017; MIT Technology Review, 2023; Oluwafunmi Adijat Elufioye et al., 2024; Parra-López et al., 2024).

Regarding this situation and taking into account these factors, Gallardo (2024) pays attention to the need for digital technology development to be sector-oriented. Focusing on the producer, on the industry and its conditions is a key factor to increase adoption and to overcome the obstacles that limit the adoption.

The availability of data grows exponentially daily, and its exploration, study, interpretation, and potential use open and complement lines of work that have historically suffered from a lack of data. Although the quantity of needed data —especially for predictive models— is still very important and, in most cases, they are not available, some new techniques, including Artificial Intelligence, are helping to overcome this difficulty (MIT Technology Review, 2023).

At the European level, two particularly ambitious and interesting initiatives are developing:

1. The Agriculture of Data Partnership (European Commission, 2023b), under the EU's Horizon Europe Research and Innovation Programme, aims to achieve sustainable agriculture in the EU and the implementation and monitoring of policies based on the use of digital and data technologies in environmental and land observations.

2. The European Data Space for Agriculture, under the Digital Europe Programme, aims to create a secure and reliable space for sharing and accessing data transparently, supporting the agricultural sector's economic and environmental progress (European Commission Shaping Europe's digital future, 2023).

These initiatives require real-world use cases to articulate and support their development process. The Agriculture of Data Partnership investigates new data-based solutions for agrifood sector problems, while the Agricultural Data Space generates and makes available to different stakeholders the necessary data to implement these solutions. This agricultural data space proposed and fostered by EU is a framework where to add and share data in a secured and trusted manner and in this way can help to overcome some of the difficulties for digitalization and for the use of predictive models and in particular for the artificial intelligence predictive models that are part of the data spaces (Deroo & Maes, 2023).

3. CASE STUDY: HUELVA (SPAIN) STRAWBERRY

This study proposes using Huelva strawberry, a high-value perishable product, as a case study for price prediction as a tool to support farmer position in the value chain and the digitalization process. The price will be estimated using data from the AOAP

First, we will discuss the enormous importance of the strawberry sector in Huelva (Andalusia) and the functioning of the corresponding value chain, highlighting the interest in predicting its price and the specific characteristics of this product.

In second place, we will describe how the AOAP works, detailing the information available on various products and focusing on the available price data for strawberries, their origin, significance, and frequency, and focusing on the observatory as a potential case use or building block for the development of agricultural data spaces.

3.1. Huelva strawberry value chain

According to the AOAP, almost all of Andalusia's strawberry production comes from the province of Huelva, which produced 97.3% of Spanish strawberries and nearly 29% of EU-27 strawberries in 2021. This makes Spain the top strawberry producer in the EU and the second-largest exporter worldwide in 2022. The value of the Andalusian strawberry production rose 407.830 million € for the year 2021 contributing with 2.9% to the Andalusian agricultural production.

Strawberries are an annual seasonal crop, with the harvest extending from November to June of the following year. Production is minimal in the early months, reaching a peak in the central months of the season (typically March and April) before declining again in June (Figure 1).

Figure 1. Strawberry prices and production along the season. Andalusian Observatory of Agrifood Prices.

One of the key characteristics of strawberry production in Huelva is the use of early season varieties, which entry into markets earlier than others, placing this production in a highly competitive position. However, since European and Spanish harvests overlap from May onwards, the commercialization of Andalusian strawberries drops sharply due to competition and the impact of high temperatures on fruit quality.

Prices follow a pattern related to these circumstances, starting with very high values in the early months of the season and declining as the season progresses.

The strawberry crop system introduces continuous innovation and presents differences even within the same season. Sustainability receives particular attention (90% of production is either organic or integrated), positioning the strawberry sector to grow and face the future with a focus on improving profitability and sustainability in its social, economic, and environmental dimensions. Sector association Freshuelva has developed an ethical, labor and social responsibility plan, which aims to improve the social and working conditions of immigrants who work in the sector. This initiative is welcomed by German importers who care about social aspects.

Like other berries, strawberries have increasingly desirable characteristics in agrifood markets, making them high-value crops with significant growth potential. To capitalize on this, it is essential to know and take into account consumer demands and respond through research and innovation.

In the 2022/2023 season, the planted strawberry area reached 6,778 hectares, 0.7% less than the 6,828 hectares planted the previous season. Prices were favorable for farmers, likely due to climate adversities that contributed to lower production, although, according to the sector, these higher prices did not offset the reduced yield or increased cultivation costs.

It should be noted that the excessive increase in costs that began in the 2021/2022 season and intensified in 2022/2023 —particularly following Russia's invasion of Ukraine— has had severe consequences for agricultural activity.

The ability to predict the farmer's price based on the quantity produced in advance would allow farmers to make collective decisions about the quantities to put on the market, impacting the revenue they obtain.

The AOAP tracks the different stages strawberries go through, from production to the consumer, as shown in Figure 2.

Figure 2. Strawberry Value Chain. Andalusian Observatory of Agrifood Prices.

The strawberry value chain has traditionally been made up of the following agents or trading positions:

- Farmer who produces strawberries on their farm.
- From there, the production goes to the fruit and vegetable center where it is conditioned.
- The next position is the wholesale market or *Merca*, that distributes to the traditional retail store where the consumer purchases it.

Currently, this chain is still active, but the modern chain has also been developed that, from the horticultural center, replaces the mentioned above stakeholders by the distribution platform and the supermarket[1].

3.2. The Andalusian observatory of agrifood prices. Strawberry data.

The AOAP was established in 2003 with the following objectives:

- To improve knowledge of the sectors analyzed.
- To provide transparency regarding prices along the commercialization chain.

1 The chain has different configurations depending on the product, the transformation or preparation required, as well as the channels reaching the market. Traditionally these channels were wholesale markets, but currently, large distribution has logistics platforms that give rise to more modern value chains, parallel to the traditional ones.

- To enhance knowledge of competition and destination markets.

Currently, the observatory covers a wide variety of products grouped into 14 sectors, with price data available along the value chain for all of them.

For each product, different types of prices are recorded based on the analyzed value chain. Generally, as defined on the sector-specific web pages of the AOAP, four types of prices can be identified,

- Farmer prices (prices at the point of production).
- Handling and conditioning center prices / Transformation center prices (in the case of livestock).
- Wholesale market prices.
- Consumer prices.

The prices published by the observatory for different products are aggregated and weighted values, so each price is associated with its corresponding volume.

The definitions of farm and handling and conditioning center prices are specific to each sector and exclude taxes and commissions. Wholesale and consumer prices are conceptually homogeneous across all products and sectors included in the AOAP. Each price is provided by several informants, as established in the AOAP methodology.

In the case of strawberries, the AOAP provides price data by season (monthly or weekly) at the following commercial stages: farm prices, wholesale market prices (*Mercas*), and consumer prices (which may appear associated with different distribution channels or sales points and formats).

The AOAP allows for market trend analysis, providing greater transparency and serving as a strategic decision-making support tool. In the current context, the AOAP could be improved by adding useful and farmer-adapted tools.

In addition, the AOAP has a structure, objectives and governance that to a great extent help to deal with and overcome the problem of sharing data that farmers not organized in a collective way find to be able to develop support decision tools.

From this point of view, the AOAP can be useful to be considered as a use case, starting point or building block of an agricultural data space (María Isabel Ruiz García, 2024 Personal Communication). AOAP manages and shares data of different stakeholders of the strawberry sector in a trust environment, respecting privacy and allowing monitoring of value chain and decision support.

Predictive models can support decision-making in the short term and make the AOAP more attractive for farmers and support digitalization process. However, the development of automatic predictive models for agrifood production, based on big data, has not given the expected results or at least not in the expected time (easytosee, 2024; Hormigo, 2024): "The development of predictive solutions to real farming challenges are still in its infancy" (Oluwafunmi Adijat Elufioye et al., 2024)

Predictive models need real big data to be accurate, and the current context is approaching this big data availability, so applications are going "beyond primary production influencing the entire value chain" (Wolfert et al., 2017).

Potential contribution of artificial intelligence works in the same direction significantly improving the accuracy and efficiency of demand forecasting and supply chain operations in agriculture.

Predictive models are one of the main objectives of Artificial Intelligence (Oluwafunmi Adijat Elufioye et al., 2024). However agricultural domain expertise is also very important for predictive model development (José Emilio Guerrero Ginel, 2024 Personal Communication). Traditional statistics and econometric models —unlike the automatic models that work as black boxes— have the ability to develop models including causal relationships (Storm et al., 2020).

The complementary use of new data sources derived from digitalization but also from traditional sources and models, is also a key point. Development of data spaces can be a cornerstone and, in this sense, it must be worthy analyzing the characteristics of AOAP that can lead to this goal.

4. MATERIAL AND METHODS

This section explains the proposed methodology to develop tools to incorporate into price observatories with the aim of explaining and predicting the price perceived by farmers, thereby supporting decision-making and helping to boost digitalization adoption.

First, the proposed model for predicting the price perceived by various stakeholders along the strawberry value chain is presented. The model is based on the variables involved in price formation which are available in the AOAP.

Since one of these variables is the quantity marketed, it is necessary to predict this in advance to build a real-time monitoring system. This requires developing a short-term predictive model for the quantity produced.

Finally, based on the literature and available online data, other variables that could improve the models will be suggested together with the analysis of the AOAP as use case for the development of an agricultural data space.

4.1. Price prediction model along the value chain

The goal is to develop a model that explains the price of strawberries (€/kg) to anticipate future values at different positions within the value chain: the farmer, the wholesale market, and the consumer, always focusing on providing useful information for the farmer.

Initially, traditional tools (classical statistical analyses) will be applied, to later explore new tools that emerge in the context of digitalization.

The potential explanatory variables will initially be those available in the AOAP: the quantity produced by the group of farmers providing price data (thousands of tons) and the period in which it is produced (week, month, season), which captures the seasonality of strawberry production based on the month of harvest.

Monthly data for the mentioned variables are available for different periods depending on the commercial position. For farm prices, data are available from the 2002/2003 to 2022/2023 seasons, while for wholesale market and consumer prices, monthly price data are available from 2006/2007 to 2022/2023 seasons.

Using this data, various descriptive analyses are conducted to understand the relationships between the different variables over time and the relationships between prices at different positions of the value chain (Table 1).

Table 1. Descriptive measures for prices (euro per kg) and quantity (thousands of tons): January 2003 to June 2021

	Observations	Mean	Standard deviation	Minimum	Maximum
Farm prices	113	1.23	0.60	0.34	2.83
Wholesale prices	90	1.98	0.73	1.03	4.38
Consumer prices	90	2.75	0.67	1.72	4.63
Farmer Quantity produced	113	12.06	11.13	0.01	44.85

Considering the sequence of the value chain, it seems reasonable to opt for a simultaneous equations model to relate prices at the three positions of the chain. Thus, to explain the behavior of the strawberry monthly farm price (P_{F_t}), the potential explanatory variables are the quantity produced (C_{F_t}), in thousands of tons and the seasonality determined by the months of the strawberry season (November to June). This is shown in Figure 3, which illustrates the evolution of the strawberry farm price during the period analyzed (2002/2003 to 2020/2021 seasons).

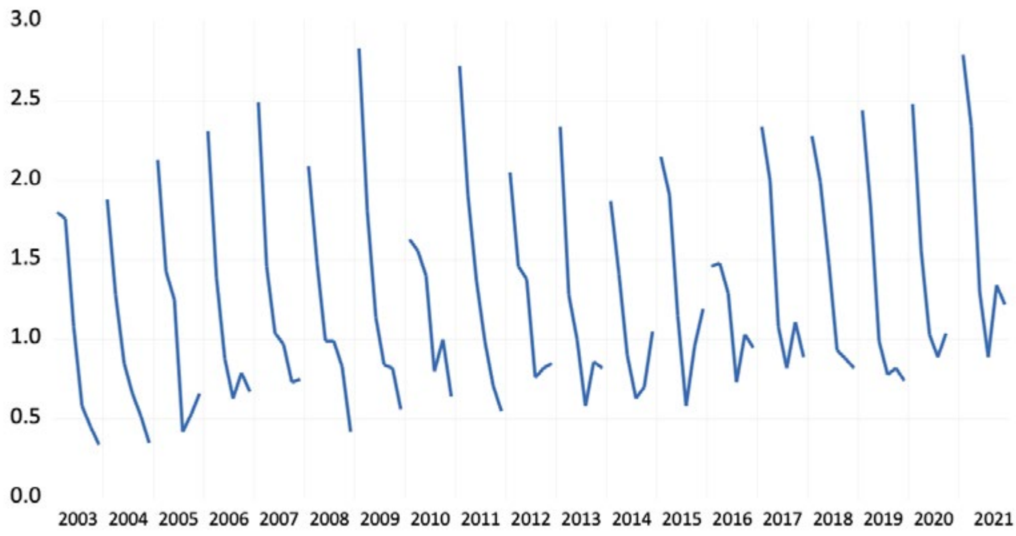


Figure 3. Strawberry farm monthly prices (€/kg) evolution (2002/2003 to 2020/2021).

Therefore, in the equation that estimates the monthly price (P_{F_t}) as a function of the monthly quantity (C_{F_t}), a constant will be introduced (the observed trend), additionally the detected effect of the monthly seasonal factor (*F*) will be included. As it is a qualitative factor whose values are the months:[2]

S = {January (1), February (2), March (3), April (4), May (5), June (6)}

it will be modelled including in the model the corresponding artificial variables associated to each *F* value:

$$M_i = \begin{cases} 1 & \text{if } F = \text{month } i \\ 0 & \text{if } F \neq \text{month } i \end{cases} \qquad i = 1,2,\ldots,6$$

For simplicity and to avoid multicollinearity, June is chosen as the baseline category.

Furthermore, Figure 4 (scatterplot of wholesale (P_{M_t}) and consumer (P_{C_t}) prices vs. farm prices (P_{F_t}), considering only the months from January to June of each year) shows a clear positive linear relationship between farm prices and both wholesale and consumer prices. Both linear relationships have similar slopes, indicating that 1 euro increase in the farm price has the same impact on the prices at the other two commercial positions. However, as expected, the intercept is higher for the consumer price, reflecting the price increase at this position compared to the farmer.

2 Experts point out that November and December are not significant months in terms of the quantity sold.

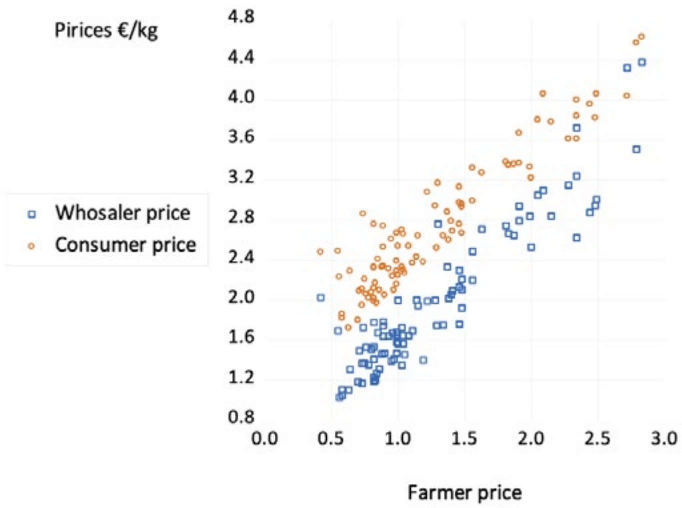


Figure 4. Relation between wholesaler and consumer prices and farmer Price (2006/2007 to 2020/2021).

Given this, it seems reasonable to specify a linear simultaneous equation model, whose structural form for *g* endogenous variables and *k* exogenous variables with *n* observations is:

$$Y = Y\Gamma + X\beta + \varepsilon \qquad (1)$$

where:

- **Y** and **X** are the arrays of observations of the exogenous and endogenous variables, and
- **Γ** y **β** are the arrays of structural parameters,

In our case, the model (with all prices deflated using the Food Price Index) can be specified as[3]:

$$\begin{cases} P_{F_t} = \beta_0 + \beta_1 C_{F_t} + \beta_2 M_1 + \beta_3 M_2 + \beta_4 M_3 + \beta_5 M_4 + \beta_6 M_5 + \varepsilon_{1t} \\ P_{M_t} = \alpha_0 + \alpha_1 P_{F_t} + \varepsilon_{2t} \\ P_{C_t} = \gamma_0 + \gamma_1 P_{F_t} + \varepsilon_{3t} \end{cases} \qquad (2)$$

Finally, to evaluate the predictive capacity of the estimated model, data from the 2021/2022 and 2022/2023 seasons are excluded from the estimation process, so they can serve as a comparison point for the predictions made for those seasons. This training methodology ensures that the model only uses information from the past to predict the future, respecting the time sequence and avoiding information leaks. This makes it possible to simulate a real forecast scenario, where the model is trained with known information and tested with unknown future data. Likewise, the cut-off point that determines the test data (the last two seasons) set is established according to the objective of the analysis and in a way that reflects the seasonality of the series.

Prediction errors in forecasting scenarios are analyzed through the mean square error (MSE) decomposition and Theil's U. Root mean square error (MSE) and mean absolute error (MAE) are used as predictive accuracy measures.

[3] The specified model does not include dynamic relationships after estimations of the model considering different lags of the price series showed that these lagged variables were not relevant (see Data Sets: http://hdl.handle.net/10396/33282).

4.2. Estimating the quantity produced: Real-time monitoring system

The model developed to determine the current month's price requires the quantity produced by farmers supplying data to the AOAP in that month as an independent or predictor variable, which is not available in advance. Therefore, to make the proposed model practically useful, it is necessary to estimate the quantity produced over time.

Weather variables like temperature and radiation that influence strawberry production has been considered. Daily data from meteorological stations close to Huelva strawberry production zone has been considered. For each day mean temperature and radiation of selected meteorological stations has been calculated and related to daily production (in particular with the difference of expected production —based on expected percentage production and total season production— and real production)

No clear relationship has been found between these meteorological variables and the production, and finally two situations are considered to estimate the quantity produced over time:

- At the start of the season: Due to the lack of information, the total production for the current season is estimated by considering three production scenarios (low, medium, high) based on past production data available from the observatory's companies.
- As the season progresses: The total production for the current season can be predicted using information from the recent past months (quantity estimation model).

In both cases, once the total predicted quantity for the season is determined, the monthly production (for the entire season or the remaining months) is estimated based on the expected monthly production distribution, which is calculated using production data from the OAOP companies for past seasons. This represents the average value, for each month, of the percentage of total production that corresponds to the production of that specific month in each season.

This provides a real-time monitoring system. If at a given moment, the model shows that prices are going to drop, the strawberry interprofessional organization can regulate production, divert some to processing, reduce the quantity reaching the market, and raise prices.

Since the main objective of predictive systems is to support farmers' decision-making to maximize profits, and the proposed system does not take costs into account, in this case, the stated objective can be equated with maximizing monthly revenue: *quantity produced × price obtained.*

5. RESULTS

5.1. Analysis and prediction of prices along the value chain. Berrydashboard —a predictive model and monitoring system— development.

5.1.1. Relationship between price at different positions in the value chain and the price perceived by the farmer

To determine how price is transmitted along the value chain, a simultaneous equation model (2) is proposed to relate prices at the three stages of the chain following its logical sequence.

Preliminary analyses identified abnormal residuals in the different equations (January 2009, 2010, and 2016, and June 2008), whose effect is captured by introducing corresponding dummy variables. Consequently, the final model specified is:

$$\begin{cases} P_{F_t} = \beta_0 + \beta_1 C_{F_t} + \beta_2 M_1 + \beta_3 M_2 + \beta_4 M_3 + \beta_5 M_4 + \beta_6 M_5 + \beta_7 jan_{09} + \beta_8 jan_{10} + \beta_9 jan_{16} + \varepsilon_{1t} \\ P_{M_t} = \alpha_0 + \alpha_1 P_{F_t} + \alpha_2 june_{08} + \varepsilon_{2t} \\ P_{C_t} = \gamma_0 + \gamma_1 P_{F_t} + \gamma_2 june_{08} + \varepsilon_{3t} \end{cases} \quad (3)$$

The results of the seasonal unit root tests DHF (Dickey et al., 1984) and HEGY (Hylleberg et al., 1990) provide sufficient evidence to affirm that the three price and quantity series are stationary (Table 2). Therefore, in model (3) these series are taken in levels, which reduces the risk of spurious regressions. The study of the model's identifiability confirms that it is identified (all three equations are identified). Thus, it is possible to estimate it using both limited and full information methods. The weighted two-stage least squares method[4] was chosen (as it provided best results for the standard errors when there is heteroskedasticity), and the estimation, conducted using EViews 12, resulted in the following model (standard errors in parenthesis):

Table 2. Stationary analysis of the series: Seasonal unit root tests (DHF and HEGY)

	Farm prices	Wholesale prices	Consumer prices	Farmer Quantity produced
DHF (statistic)	-3.29	-2.82	-3.08	-19.56
HEGY (statistic)	2.66	2.38	3.59	9.32
Decision*	stationary	stationary	stationary	stationary (at 1%)

5% critical values: DHF test = -2.01 HEGY test = 7.31 Deterministic term: Intercept Max. lags: 12
*value of statistic < critical value ⟹ stationary (null hypothesis)

$$\begin{cases} \hat{P}_{F_t} = \underset{(0.037)}{0.59} - \underset{(0.002)}{0.005} C_{A_t} + \underset{(0.054)}{1.23} M_1 + \underset{(0.055)}{0.77} M_2 + \underset{(0.072)}{0.42} M_3 + \underset{(0.083)}{0.15} M_4 + \underset{(0.06)}{0.13} M_5 + \underset{(0.16)}{0.43} jan_{09} - \underset{(0.16)}{0.48} jan_{10} - \underset{(0.16)}{0.72} jan_{16} \\ \hat{P}_{M_t} = \underset{(0.052)}{0.35} + \underset{(0.048)}{1.19} P_{F_t} + \underset{(0.193)}{0.88} june_{08} \\ \hat{P}_{C_t} = \underset{(0.047)}{1} + \underset{(0.043)}{1.12} P_{F_t} + \underset{(0.175)}{0.61} june_{08} \end{cases} \quad (4)$$

The residual analysis confirms the fulfilment of a priori assumptions (autocorrelation and normality), as can be seen from the results in Table 3.

Table 3. Analysis of the estimated model residuals

	Statistic	*p*-value	Decision
Ljung-Box (autocorrelation)	104.017	0.5905	No autocorrelation up to lag 12
Jarque-Bera (normality)	7.328	0.2916	Normality

The farm, wholesale, and consumer prices are explained in 89.1%, 88.6%, and 88.9%, respectively.

The estimated model allows us to conclude that for every additional 10,000 tons produced, the monthly farm price decreases by 5 cents. Similarly, the wholesale and consumer prices increase by €1.19 and €1.12, respectively, for every €1 increase in the farm price, confirming the trends inferred from Figure 4.

4 Preliminary analyses revealed heteroscedasticity in the error term of the three model equations, since in all three cases, the Breusch-Pagan-Godfrey test applied to the residuals showed *p*-value = 0.

5.1.2. Price prediction along the value chain

With the estimated model, monthly price predictions are obtained for the three positions in the value chain for the 2021/2022 and 2022/2023 seasons, compared to the real prices observed during those seasons, as shown in Figure 5.

Figure 5. Comparison of the predicted prices with the actual observed prices at the different positions of the value chain during the 2021/2022 and 2022/2023 seasons.

The results show predictions for farm prices that are very close to reality in both seasons. Most errors are due to random causes (52% and 59%, respectively). The exception occurred in February 2023, when the real price was higher than usual for that month due to a sharp drop in production caused by low temperatures at the beginning of the year. The prediction in June is not good either, the price is also higher than expected also due to an offer reduction by climatic reasons, but this month is not so important for farmer income neither in terms of quantities nor prices (see Figure 1).

Wholesale market price predictions are also reasonably aligned with reality in 2021/2022 season, with slightly less accuracy in January and June. In 2022/2023 season February effect is also detected. But overall, the estimations are more precise than the farm price predictions. The errors are largely random (71% and 84%, respectively), with very little bias.

In the 2021/2022 season, the results show a slight underestimation of the consumer price, which is consistent with the fact that fresh fruit was one of the food items that experienced the largest price increases in the food inflation context of that season.

However, in 2022/2023, the consumer price predictions behave similarly to those for the wholesale market, with low bias and errors mostly attributable to random causes (74%).

It is interesting to note that important events like Pandemia or Value Chain Law have not had an important impact on the model while to some extent —not to a big extent— they have impacted prices.

5.2. Quantity estimation model: real-time monitoring system

As mentioned in Materials and Methods, the practical utility of the proposed model depends on estimating the monthly production quantity for the current season. Two different situations are considered: the start of the season and during the season.

5.2.1.Quantity prediction system based on production scenarios

To estimate the total quantity produced at the start of the season, based on three possible production scenarios (low, medium, high), the mean production of all the AOAP companies for each season are stratified into three categories based on the corresponding terciles. The amount assigned to each scenario is the arithmetic mean of the values of each stratum multiplied by the number of companies that provide data to the observatory in the ongoing campaign

To do so, first, available data of production companies for seasons 2002/2003 a 2022/2023 are depurated eliminating data of those companies that do not continue producing in the last seasons and data of the season 2002/2003 where only two companies with not very reliable data were supplying data. Then, the average production for the set of companies supplying data to the AOAP per season stratified as explained. Table 4 shows the stratified production averages for each campaign, and Table 5 presents the assigned values for each scenario.

Table 4. Average strawberry production per season of companies set in the Andalusian Observatory of Agrifood Prices

Season	Average production per company (t)		Season	Average production per company (t)	
2006/07	2,761,288		2019/20	4,920,237	
2022/23	3,024,996		2017/18	5,006,459	
2016/17	4,256,942		2012/13	5,246,826	2nd tercile
2010/11	4,279,789		2018/19	5,414,631	
2011/12	4,471,897		2013/14	5,545,452	
2021/22	4,556,132		2008/09	5,753,920	
2020/21	4,617,613	1st tercile	2004/05	6,706,794	
2009/10	4,759,022		2003/04	7,163,666	
2014/15	4,778,577		2007/08	10,143,898	
2015/16	4,888,260				

Table 5. Average strawberry season production by company assigned to each production scenario

Scenario	Average production per company (t)
Low Production	3,891,841
Medium Production	4,828,361
High Production	6,567,884

5.2.2. Quantity prediction system based on season information

As the season progresses and production data becomes available, the total quantity can be predicted based on data from previous months. This is achieved by using a model that correlates past monthly production with total season production.

The linear correlation between monthly production and the total production of companies from the AOAP shows that the strongest correlations are observed starting in February. Table 6 illustrates these correlations for the period 2002/2003 to 2021/2022.

Table 6. Linear correlation between monthly and total production (2002/2003 to 2021/2022).

Month	November	December	January	February	March	April	May	June
Correlation	−0.408	−0.3462	0.1932	0.7757	0.905	0.9548	0.9018	0.4316

Thus, the model developed to predict the total quantity produced by the AOAP companies during season (C_j) based on the accumulated production from February to month *i* is: The estimation of this model using ordinary least squares (OLS), for the *j*=2002/2003 to 2021/2022 seasons for *i*=February, March, and April, gives the following equations:

$$C_j = \beta_0 + \beta_1 * accum\ prodquantity\ since\ Frebruary\ to\ i\ month\ in\ j\ season\ + error$$

The estimation of this model using ordinary least squares (OLS), for the *j*=2002/2003 to 2021/2022 seasons for *i*=February, March and April, gives the following equations:

$$\hat{C}_j = 12801305.7 + 7.13 * quantity\ produced\ in\ February\ in\ j\ season$$

$$\hat{C}_j = 1457094.3 + 2.43 * quant.produced\ since\ February\ to\ March\ in\ j\ season$$

$$\hat{C}_j = -2501988.7 + 1.34 * quant.produced\ since\ February\ to\ April\ in\ j\ season$$

Finally, to estimate monthly production based on the predicted total quantity under either scenario, the expected monthly production distribution is calculated. This is done by analyzing data from the 2002/2003 to 2021/2022 seasons, as described in Materials and Methods. The expected percentage of total production for each month is represented by the average percentage of total production corresponding to each month across the available seasons, as shown in Figure 6.

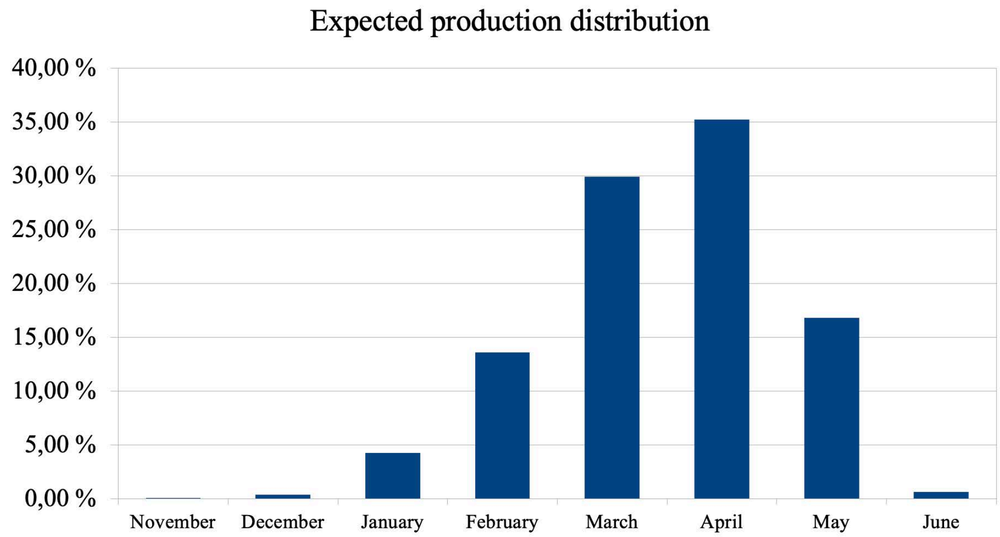
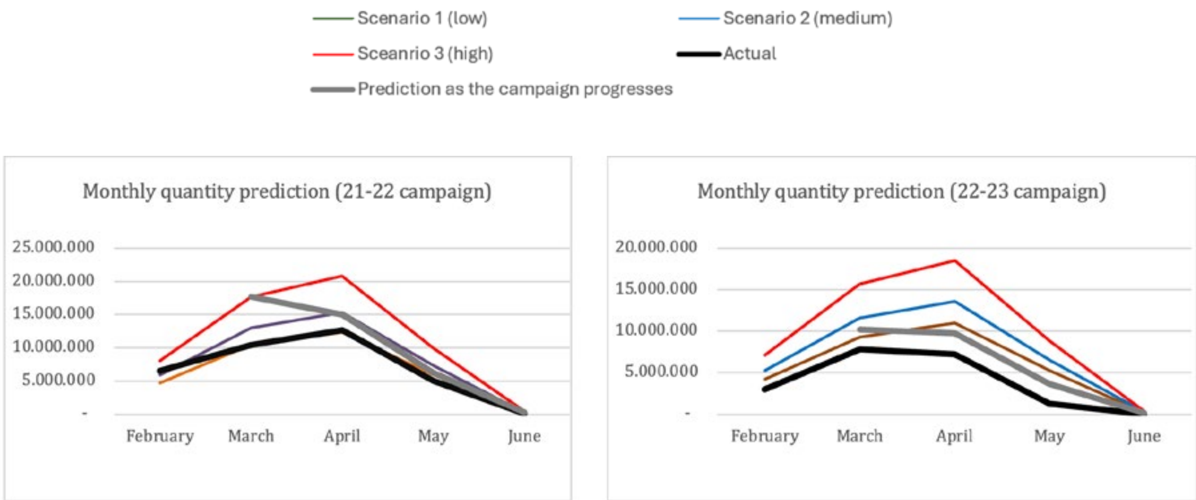


Figure 6. Expected Monthly Production Percentage.

This expected production curve allows for estimating the total monthly production under either the scenario-based or in-season prediction models. The system can then predict the monthly price and revenue (predicted price × expected production).

5.3. Estimation of monthly revenue for farmers. Berrydashboard results.

Figure 7 shows the results of applying Berrydashboard predictive system to the 2021/2022 and 2022/2023 seasons. The figure includes predictions for the monthly production of companies in the AOAP under the scenario system and the in-season production model. It also shows the estimated monthly prices derived from the simultaneous equation predictive model, based on the predicted production quantities. With these results, the monthly revenue is estimated (estimated price × expected quantity).



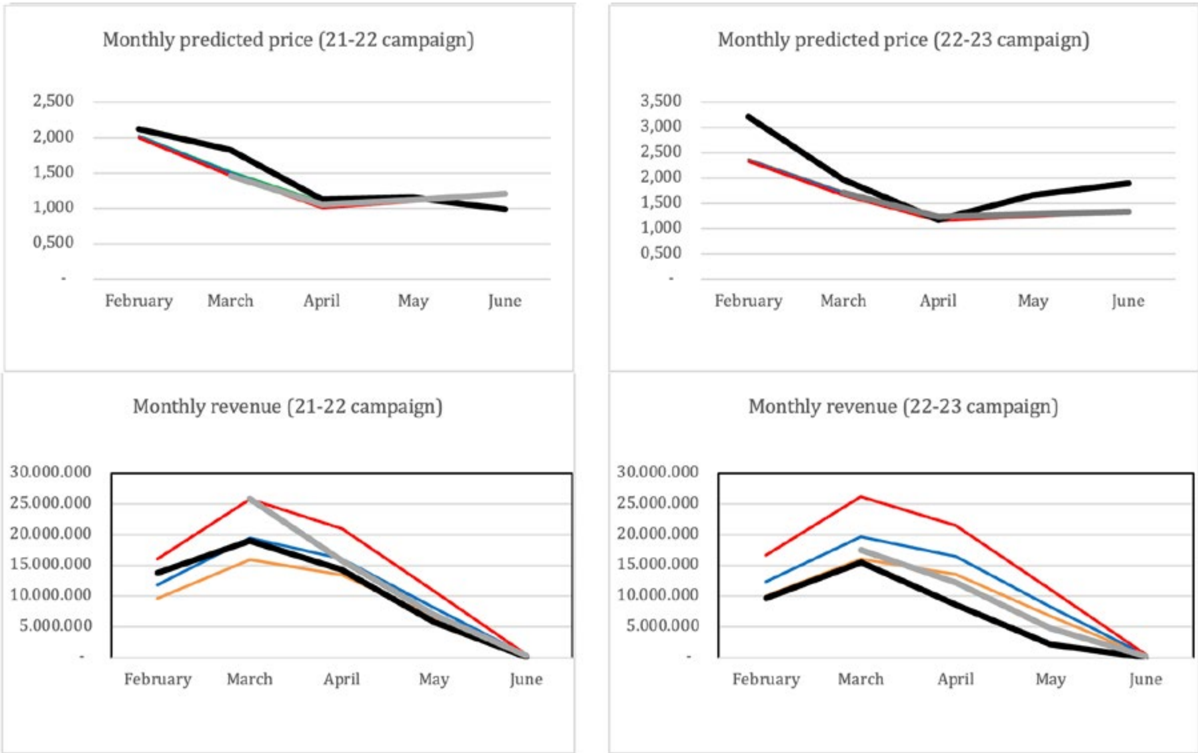


Figure 7. Comparison of predictions and actual data for Quantity, Price and Revenue in the 2021/2022 and 2022/2023 seasons.

Graphics show how as the season progresses, predictions of quantity and revenue are more accurate. It is particularly interesting in March and April when the revenue is higher. The model shows a better functioning in April and is less accurate in March, being good for the rest of the months of the season. The introduction of new variables that contribute to explaining these deviations is desirable as explained in the following section.

5.4. Proposed improvements to the model and considerations related to agricultural data spaces

To reduce error and improve the accuracy of the Berrydashboard, it is necessary to delve deeper into the model by including more explanatory variables, which the current context of data proliferation will undoubtedly make possible.

The development of the Internet of Things (IoT) in agriculture has generated a wealth of real-time data from nearby and remote sensors that can improve the prediction of strawberry production (Wolfert et al., 2017). In addition, the combination of structured and unstructured data, together with technologies such as lake houses, optimizes costs and minimizes privacy risks (Storm et al., 2020; MIT Technology Review, 2023).

A deeper analysis of the proposed and tested inclusion of climate data can improve the model as weather influences strawberry production (Inês Diel et al., 2021) and also consumption. The use of weekly rather than monthly data is suggested to take advantage of the accuracy of short-term weather predictions. Likewise, production costs, and especially those affected by disruptive changes such as the increase in the minimum wage in Spain, should be included in price prediction.

To estimate demand, it is proposed to analyze consumption trends through tools such as Google Analytics, web scraping, and artificial intelligence. These technologies make it possible to anticipate market patterns and optimize supply.

The AOAP Observatory represents a very preliminary use case for agricultural data spaces in Europe, promoting the exchange of information while ensuring data sovereignty. Its evolution can facilitate the integration of actors in these digital ecosystems, promoting open and collaborative systems as referred to by Deroo & Maes (2023), García et al. (2023), Andalucía Agrotech (2024), and Eisenträger et al. (2024).

6. CONCLUSIONS

The Berrydashboard system and the conducted analysis addressed are useful to deal with a real-world problem, the need for strengthening farmers' positions in the strawberry value chain, as well as for boosting the farmers' digitalization adoption process, and data space development.

Integrating real-time monitoring and decision-support systems into price observatories is both feasible and advisable. In the case of Huelva's strawberry sector, implementing a predictive revenue system can help farmers make informed decisions. The AOAP serves as a valuable data source and a framework supporting these tools. Due to strawberry seasonality and the strong price correlation along the value chain, farmers may pass production costs onto the market. This motivated the development of a price prediction model that performed well during the 2021/22 and 2022/23 campaigns, with low and explainable errors.

The model's practical use depends on a real-time monitoring system, based on monthly production forecasts of AOAP companies, allowing farmers to shift production to maximize revenue. Including Berrydashboard in the Observatory supports adoption and digital transformation.

The model serves as a flexible base. New variables and data sources can be added to it as needed. Climate data is especially relevant due to its production impact and availability. Work is in course to include weather variables to predict strawberry production over time. Additionally, this will enhance the model's accuracy in price predictions and increase the lead for its application.

The study has been carried out for the Huelva strawberry, but the methodology followed can be extrapolated to other regions where strawberries are also cultivated.

The observatory represents a promising data-sharing initiative with a governance system that empowers farmers and could evolve into an agricultural data space. Moreover, engaging companies that provide data would further enhance the Berrydashboard system and foster broader participation. Data business models can also be useful to develop the required data space.

Given that markets are often affected by unpredictable geopolitical or disruptive events, expert advice should complement these tools.

Prediction models must reflect the unique characteristics of each product. For strawberries, perishability, added value, and seasonality are critical. Other crops will require different considerations.

Digitalization presents great opportunities for developing decision-support models. Although agricultural predictive models are still emerging, increasing data availability —including sensor and unstructured data— will help achieve true big data potential.

Traditional modelling, causal relationships, domain expertise, and interdisciplinary collaboration remain essential. Data spaces and AI-based predictive models need further development, but rapid progress is expected, with the ability to adopt becoming a key factor.

Supplementary information ↑

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Supplementary material

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Data availability

The price data are publicly available at AOAP web page: https://www.juntadeandalucia.es/agriculturaypesca/observatorio/servlet/FrontController?ec=default&action=Static&url=openData.jsp&page=1

Software material and data are also available online in the Helvia repository (http://hdl.handle.net/10396/33282)

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Authorship contribution statement

Blanca Lucena-Cobos: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Resources, Supervision, Validation, Writing – original draft, Writing – review & editing.

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Competing interests

The authors have declared that no competing interests exist.

Statement on the use of Artificial Intelligence

Not applicable.

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