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Pistachio nut diffusion in Spain: Growth models

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Abstract

Aim of study: To analyse the diffusion of the crop by producing forecast models, that intend to help farmers in their decision-making.

Area of study: Spain. The area dedicated to pistachio cultivation in Spain has multiplied by 36 in the period 2010 to 2020, reaching 44,244 ha.

Material and methods: This study brings together data on the evolution of pistachio cultivation based on the following parameters: cultivated area, yield, and price. Methods are based on internal, external influence models and on an influence-price-crop yield pattern.

Main results: The results indicate that given a constant crop yield, raising pistachio prices, will bring a production increase that generate the saturation level of the system. Similarly, with a constant pistachio price and an increment of the crop yield, the saturation level of the system increases. Regarding the pattern of influence, it is shown that in a context of suitable market prices for pistachio and an optimal synergy of the production factors that favour the crop yield not only increases the level of saturation of the system but also the duration of the diffusion process.

Research highlights: The diffusion curve is sigmoidal with a well-defined inflection point and three well-defined phases. The adoption of pistachio in Spain responds to a model of internal influence (logistic) and never to models of external influence. According to the results, the process has a zero-innovation effect, while the dynamics of the process is completely determined by an imitation effect.

Additional key words: innovation; logistics curve; competitive advantage; perennial crops; *Pistacia vera*.

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Introduction

The pistachio (*Pistacia vera* L.) is a crop that is limited to latitudes between 30º and 45º N which corresponds to those areas where Mediterranean countries are found. It withstands extreme temperatures, both maximum temperatures, up to 50º C, and minimum temperatures, down to -30º C. It adapts well to a rainfall level between 500 and 600 mm/year, thus not requiring additional irrigation in Spain, although irrigation improves yields (Couceiro-López et al., 2017). The average yield of the crop is between 800-1,500 kg/ha under natural rainfed conditions and 1,900-2,500 kg/ha under irrigated conditions (Couceiro-López et al., 2017). Regarding market prices, maximum prices per kilogram of open pistachio typically range between 8-15 EUR/kg as a conventional and around 20 EUR/kg as an organic crop. In 2021, the total production in Spain reached 16,725 Mg (ESYRCE-MAPA, 2021)). In the period 2010 to 2020, the area dedicated to pistachio cultivation in Spain has multiplied by 36, reaching 44,244 ha (ESYRCE-MAPA, 2020), thus sowing that this crop has lately become a very interesting option for investors in the primary sector. The diffusion of pistachio cultivation is an example of a general increase of perennial crops as a response to lower profitability of herbaceous commodities (Expósito & Berbel, 2020).

The adoption of pistachio cultivation in Spain is an innovation. According to Rogers (1995), a diffusion process takes place, when an innovation is implemented. This diffusion process occurs when the innovation is communicated over time through members of a social group. The speed of the diffusion process depends on a wide range of variables that stimulate or limit the innovative attitude of potential adopters and their final decision. In the field of business management several diffusion models have been proposed to study how new products become adopted in a population (Floyd, 1968; Easingwood et al., 1981; Skiadas, 1985; Bass, 2004). Similar work has been carried out in the industrial sector (Mansfield, 1968). Concerning agriculture, the technological change brought about by the introduction of hybrid maize seed in the USA, has been described as an innovative process of a pioneering nature (Griliches, 1957).

The study of the acquisition of new technology is known as the study of diffusion (Karshenas & Stoneman, 1995). Innovations, new products, new processes, or methods in management spread within and through a production system, so that the influence of change on the state of the system depends on the degree to which innovations diffuse, diffusion being the main driver of economic growth (Stoneman, 1986). It is necessary to stress that diffusion in an essential step of technological change, and its rate is largely determined by the structural characteristic of the early adopters of the innovation (Lamorte, 2019). The literature describes two types of non-exclusive works concerning the adoption of innovations: those that try to explain, at the individual level, why certain farmers follow the adoption process by identifying the factors that guide them to adoption, and those that try to describe the process of technology diffusion over time and its possible and probable evolution (Carmona et al., 2005). The work presented here follows the second approach.

One example is the *logistic curve* introduced by Verhulst in 1838 (Muñoz-Valencia, 2017), with the purpose of studying population growth. It describes the development and evolution of many growth phenomena and has multiple variants, which can be adapted to processes characteristic of diffusion. Another example is the *exponential model*, which has been proposed in order to study the diffusion of organic farming (Carmona et al., 2005).

This paper presents eight alternative models. The first three models are based on internal influence factors, where diffusion takes place only through interaction between farmers. The fourth model is a hybrid influence model, where potential adopters of the innovation can be divided into two distinct groups: either imitators, who are influenced by other farmers, and innovators, who are motivated by agricultural development agencies and/or academic institutions. The next three models are based purely on external motivation (development agents, media, and/or universities). Finally, the eighth model is based on a pattern of influence of external factors (pistachio prices and crop yield).

In Spain, several studies of agricultural diffusion models have been undertaken in the last two decades. Examples are the study carried out by Parra-López (2003) on organic, integrated and conventional production systems in olive groves, and the research by Parra-López & Calatrava-Requena (2002) on factors influencing the adoption of organic farming in the Spanish olive grove. Other examples are almond tree cultivation in Andalusia (Cárdenas-Polonio et al., 2022), localized irrigation (Alcón et al., 2006), organic farming (Carmona et al., 2005; Franco-Martínez & Rodríguez-Entrena, 2009), water-saving technologies in agriculture (Alcón et al. 2009) and the adoption and diffusion of no-tillage practices in olive groves in the province of Granada (Franco & Calatrava, 2010).

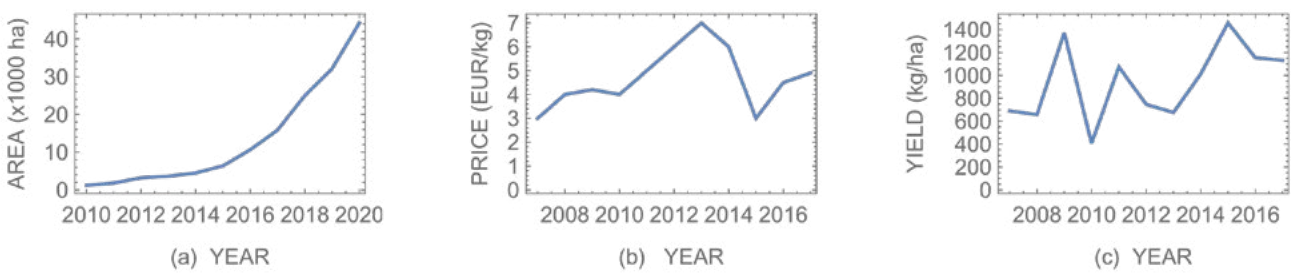

Figure 1. Evolution of pistachio areas in Spain: cultivated (a), prices (b) and yield (c). Source: Grupo IBEROPISTACHO (2019); ESYRCE-MAPA (2020, 2021)

At an international level, there are several studies that stand out: (i) the effect of price-induced patterns on the diffusion of improved pasture in Uruguay by Jarvis (1981); (ii) the adoption of drip irrigation by Fishelson & Rymon (1989) in Israel; (iii) the spread of precision agriculture in the semi-arid central Pampean region by Corró-Molas (2007); and (iv) the effect of using no-tillage practices (direct-seeding) by doing a comparison study in Argentina and Brazil (Durán et al., 2011).

The originality of the work presented here lies in the fact that it refers to the diffusion of an *emerging* crop. The pistachio crop was previously relegated to marginal lands but is now considered a valid alternative to other traditional crops. It is important to emphasize, that this study analyses the diffusion of pistachio cultivation rather than the implementation of a technology or agricultural practice. Therefore, this research should not only be considered innovative but is also justified, since it fills a current gap in the literature on diffusion models of emerging crops in Spain.

Material and methods

This study brings together data on the evolution of pistachio cultivation based on the following parameters: cultivated area, yield, and price (Fig. 1).

Internal influence models

Model 1: Logistic or internal influence model

Diffusion takes place only through interaction between farmers (interpersonal communication between adopters of the innovation and non-adopters). It is assumed that farmers interact with each other in a homogeneous fashion, and information is transmitted at a constant rate a > 0 (Carmona et al., 2005).

The diffusion pattern follows a curve as represented by the following equation:

$$Y[t]=\frac{F}{(1+\exp[-at+b])} \tag{1}$$

where Y[t]: cumulative number of hectares put under cultivation at time t; F: system saturation level; a: diffusion rate; and b: constant of integration.

The calibration of this model has been carried out by means of a non-linear regression using the program developed by Wolfram (2015).

Model 2: Giovanis-Skiadas logistic

It is assumed that the rate of growth in a cultivated area is the product of two functions, the first being proportional to the current growth in the area in question and the second proportional to the magnitude of the remaining growth (Giovanis & Skiadas, 1999):

$$\frac{df(t)}{dt}\simeq g(f(t),p)[h(F)-h(f(t))] \tag{2}$$

where df(t)/dt: growth rate of the process; F: total cultivated area to be reached: saturation level; f(t): function describing growth; h(F) – h(f(t)): residual growth of the process; p: vector of parameters.

Equation (1) can be written in the form:

$$\frac{df(t)}{dt}=b\frac{f(t)}{F}[F-f(t)] \tag{3}$$

where b is called the imitation coefficient.

Equation 3 represents one of the characteristic patterns of logistic growth. It envisages the amount of growth that can occur in a stable environment, once the degree of saturation of the system F is known.

The growth process can become unstable due to variables such as economic uncertainty and/or political uncertainty. This leads to the introduction in the growth (Eq. 2) of a random component factor which is proportional to the infinitesimal variance of the diffusion process.

Therefore, Eq. (2) is as follows:

$$\frac{df(t)}{dt}=b\frac{f(t)}{F}[F-f(t)+qu(t)] \tag{4}$$

where u(t) describes a one-dimensional white noise process and q is the parameter controlling the magnitude of the random noise.

Eq. (4) can be written as follows:

$$\frac{df(t)}{dt}=b\frac{f(t)}{F}[F-f(t)+cf(t)u(t)] \tag{5}$$

Using Itô's (1944) differential equation formulation, the stochastic growth model is determined by the following equation:

$$df(t)=b\frac{f(t)}{F}[F-f(t)dt]+qf(t)dW(t)[23] \tag{6}$$

where W(t) describes a one-dimensional Wiener process and c = (b · q) / F. Eq. (6) is a self-contained non-linear stochastic differential equation with multiplicative noise, which satisfies the assumption, that the infinitesimal variance of the process is proportional to the growth of the process.

The solution of this Eq. (6) is given by the following expression (diffusion curve formula):

$$f(t)=\frac{F}{1+(\frac{F}{x_0}-1)(\exp(-b(t-1)))} \quad (7)$$

Parameters b, c and F are estimated from model 2.

According to the formulation of Giovanis & Skiadas (1999), the estimator of the parameters b and b/F is determined by the following expression:

$$\begin{pmatrix} b \\ \frac{-b}{F} \end{pmatrix}=ST^{-1}HT \quad (8)$$

where ST is a 2×2 matrix and HT is a two-element vector:

$$ST=\frac{1}{c^2}\begin{pmatrix} T-1 & \int_0^T f(t)dt \\ \int_0^T f(t)dt & \int_0^T (f(t))^2dt \end{pmatrix}$$

$$HT=\begin{pmatrix} \int_0^T \frac{dt}{c^2 f(t)} & \frac{1}{c^2}(f(T)-f(0)) \end{pmatrix}$$

The terms of the ST matrix (definite integrals) can be approximated using the corresponding summands, while the integral in HT can be replaced by the Riemann-Stieltje integral using Itô's (1944) equation, resulting in:

$$\int_0^T \frac{dt}{c^2 f(t)} = \ln(f(T) - \ln(f(0)) + \frac{c^2}{2}(T-1) \quad (9)$$

Additionally, the coefficient c can be estimated using an extension of the approximation procedure proposed by Chesney & Elliot (1993). This method is used to estimate the noise parameter for an autonomous non-linear stochastic differential equation with multiplicative noise:

$$\hat{c}=\frac{1}{T-1}\sum_{i=2}^{T}\frac{f(t)-f(t-1)}{\sqrt{f(t)f(t-1)}} \quad (10)$$

Model 3: Gompertz model

Although there are several models in the literature associated with different Gompertz-type growth curves, in this paper we refer to the Gompertz diffusion process described by Gómez & Carmona (2003), as the Gompertz diffusion process.

This is a sigmoidal diffusion model defined by the following function:

$$Y[t]=F^{-k-bt} \quad (11)$$

where F: saturation level of the system; Y[t]: cumulative number of hectares brought under cultivation at time t; k, b > 0: constants.

The parameters of this model are not as easily interpretable as those of the Bass model, because they are not derived from a certain individual probability of adoption (Gómez & Carmona, 2003).

Model 4: Bass model

The Bass model (2004) also called generalised static model is a mixed-influence model (Alcón et al., 2006). It is based on the effect that personal relationships and mass media have on the adoption of innovations, dividing potential adopters into imitators (internal influence) and innovators (external influence).

The adoption rate depends on the interaction between adopters and potential adopters. In this case, a stochastic version of the Bass model is used to describe the growth pattern of the cultivated area. The form of the diffusion model takes the following expression (Bass formula):

$$df(t)=\{a(F-f(t))+(b/F)(F-f(t))f(t)\}dt+k \; k(a/b+f(t)/F)dW(t) \quad (12)$$

where f(t): cumulative magnitude of growth; F: saturation level of the system; a: innovation coefficient; b: imitation coefficient; W(t): a Wiener process that helps us to determine the fluctuation of growth of a random nature; and k: noise parameter.

It can be shown that for all 0 ≤ s < t, Wt −Ws has a normal distribution with expectation E (Wt − Ws) = 0 and variance V (Wt − Ws) = t – s.

The solution of Eq. 12 is solved by reduction of stochastic differential equations as described by Skiadas & Giovanis (1997):

$$f(t) = \frac{F}{\exp\left[-\left(a+b-\frac{k^2}{2}\right)t\right]\left(\frac{1}{\frac{a}{b}+\frac{f_0}{F}}+\frac{b}{a+b-\frac{k^2}{2}}(\exp\left[\left(a+b-\frac{k^2}{2}\right)t\right]-1\right)} - \frac{Fa}{b} \quad (13)$$

The parameters a, b, k, F can be estimated indirectly through other related parameters a·F, b-a, -b/F, as described in the formulation by Skiadas & Giovanis (1997).

These parameters can be expressed in matrix form as follows:

$$\begin{pmatrix} aF & b-a & \frac{-b}{F} \end{pmatrix}^T=ST^{-1}HT^T$$

where ST is a 3 × 3 matrix and HT is a three-element vector:

$$ST=\begin{pmatrix} \int_0^T \frac{dt}{f(t)^2} & \int_0^T \frac{dt}{f(t)} & T \\ \int_0^T \frac{dt}{f(t)} & T & \int_0^T f(t)dt \\ T & \int_0^T f(t)dt & \int_0^T f(t)^2dt \end{pmatrix}$$

$$HT=\begin{pmatrix} \int_0^T \frac{df(t)}{f(t)^2} & \int_0^T \frac{df(t)}{f(t)} & \int_0^T df(t) \end{pmatrix}$$

The terms of the ST matrix can be approximated using the corresponding summations, while the terms of the HT vector can be substituted with the Riemann-Stieltjes integral, using Itô's formula (1944). In this way one obtains:

$$\int_0^T \frac{df(t)}{f(t)} = \ln(f(T)) - \ln(f(0)) + \frac{k^2}{2}T$$

$$\int_0^T \frac{df(t)}{f(t)^2} \frac{1}{f(0)} - \frac{1}{f(T)} + k^2 \int_0^T \frac{dt}{f(t)}$$

Finally, the coefficient k can be estimated using the procedure proposed by Chesney & Elliot (1993):

$$k = \frac{1}{T-1} \sum_{i=2}^{T} \frac{f(t) - f(t-1)}{\sqrt{f(t) f(t-1)}} \quad (14)$$

External influence models

Model 5: Exponential model (Carmona et al., 2005).

In this case the information reaches the adopters through a communication channel external to the system (official development agencies or academic research channels). The diffusion curve is given by the following equation:

$$Y[t] = k - \exp[-(c + bt)] \quad (15)$$

where Y[t]: cumulative number of hectares brought under cultivation at time t; F: system saturation level; b: integration constant; and a: diffusion rate.

The diffusion curve is a negative exponential function, whose trajectory is an increasing curve with no inflection point. A higher value of the parameter **a** implies a higher diffusion rate and a higher value for constant **b** (integration cost), in absolute value. This model assumes that the diffusion rate depends on the number of potential adopters present at time **t**, not attributing a relationship between previous and potential adopters (Alcón et al., 2006).

Model 6: Weibull model (Gómez & Carmona, 2003).

Here a sigmoidal but flexible diffusion model is presented. This means that it is non-symmetric, it depends on the value of the parameters, and it is defined by the following function:

$$Y[t] = k(1 - Exp[-\left(\frac{t}{c}\right)^b) \quad (16)$$

where Y[t]: cumulative number of hectares brought under cultivation at time **t**; F: system saturation level, with b, d constants b≥1, d>0.

The time at which the adoptions reach a maximum depends on parameter b: the curve will be symmetric when b=1/(1–ln2).

Model 7: de Bertalanffy model (Gómez & Carmona, 2003). This is a flexible model defined by the equation:

$$Y[t] = k(1 - \exp[-bt])^{\left(\frac{1}{1-c}\right)} \quad (17)$$

where Y[t]: Cumulative number of hectares brought under cultivation at time **t**; F: system saturation level, with b, d constant, d≠0, b>0.

The curve will be symmetric or asymmetric depending on the value of the **d** parameter.

Model 8: Jarvis model (influence-price-crop yield pattern) (Jarvis, 1981).

Given that the diffusion process lasts several years, it is assumed that the following parameters, product price, and crop yield improvement (because of using innovative technology and a better interaction of the production factors) will have an influence on the process of crop diffusion. In this context, the price and yield data have been deferred in the non-linear regression analysis for a total of three years, in respect to the area and time data. This allows the calculation to consider the delayed effects of the first two variables on the evolution of the cultivated area.

The diffusion curve corresponds to the following equation:

$$f[t] = k_0 + \frac{k_1 \cdot p[t] \cdot Y[t]}{(1 + \exp[-c - f_1 \cdot t])} \quad (18)$$

where f[t]: number of hectares brought under cultivation at time t, with k_0, k_1, c integration constants, f_1: diffusion rate; p[t]: pistachio price (EUR/kg) in year t: market prices to the producer; Y[t]: crop yield = production (kg)/cultivated area in year t.

It should be noted that the process of adoption of the crop and its subsequent diffusion is not a spontaneous process, but one that is treated with caution by farmers. The calibration has been made with a nonlinear model using the program MATHEMATICA v. 12 (Wolfram Research).

A series of fit indices must be considered to proceed with the validation of the mathematical models that describe crop diffusion. Eight error indices and one fit index will be considered here (Camarillo-Peñaranda et al., 2013). These are as follows:

— Mean absolute error: $MAE = (\frac{1}{n}) \sum_{i=1}^{n} Abs(y_i - \hat{y}_i)$,

where y_i is the measured (observed) value, $\hat{y}_i$ is the value estimated using the model and n is the amount of data.

Table 1. Parameters of models 1, 2, 4 and 8

Model	a	b	c	F (ha)	k	k_0	k_1	f_1
1	0.44	5.79		120,232				
2		0.47	0.36	125,112				
3		-0.34	-3.1	∞	30.06			
4	0.0025	0.266		215,444	0.36			
5		0.0056	-13	638,479 ≈ ∞	638,479			
6				Overflow in computing				
7				Overflow in computing				
8			7.03			2.594	9.4	0.76

Source: Own elaboration

— Mean error: ME = (1/n) * $ME = \left(\frac{1}{n}\right) \sum_{i=1}^{n} (\hat{y}_i - y_i)$.

— Mean squared error: $MSE = \left(\frac{1}{n}\right) \sum_{i=1}^{n} (y_i - \hat{y}_i)^2$.

— Root mean squared error: $RMSE = \sqrt{(1/n) * \sum_{i=1}^{n} (y_i - \hat{y}_i)^2}$.

— Mean absolute percentage error:

$$MAPE[\%] = \left(\frac{100}{n}\right) \sum_{i=1}^{n} Abs((y_i - \hat{y}_i)/\, y_i).$$

The interpretation of the MAPE statistical rate can be made using Nafidi´s (2019) criteria: the lower the values the better the fit (a rate lower than 10 can be considered a high fit and a rate ranging from 10 to 30 indicates a good one).

— Modified normalised sum of quadratic errors:

$$MNSSE[\%] = 100 \sqrt{\sum_{i=1}^{n} (y_i - \hat{y}_i^{\,2}) / \sum_{i=1}^{n} y_i^2}.$$

— Mean relative error:

$$MRE = \left(\frac{1}{n}\right)^5 \sum_{i=1}^{n} (\hat{y}_i - y_i)/y_i .$$

— Sum of standardised sum of squared errors:

$$\text{NSSE}=100\left(\sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \,/\, \sum_{i=1}^{n} y_i^2 \right).$$

— Best fit: $FIT[\%] = 100(1 - \sum_{i=1}^{n} Abs(y_i - \hat{y}_i) / \sum_{i=1}^{n} Abs(y_i - \overline{y}))$, where $\overline{y}$ is the average value of the measured data. Its result is a percentage, where 100% represents a perfect fit.

Results

Table 1 shows the parameter values for models 1, 2, 4 and 8. In this framework, it should be noted that only models 1, 2, 4 and 8 provided analysable results. In addition, all the external influence models and the Gompertz model showed a non-significant level of the p-value statistic in the regression analyses performed.

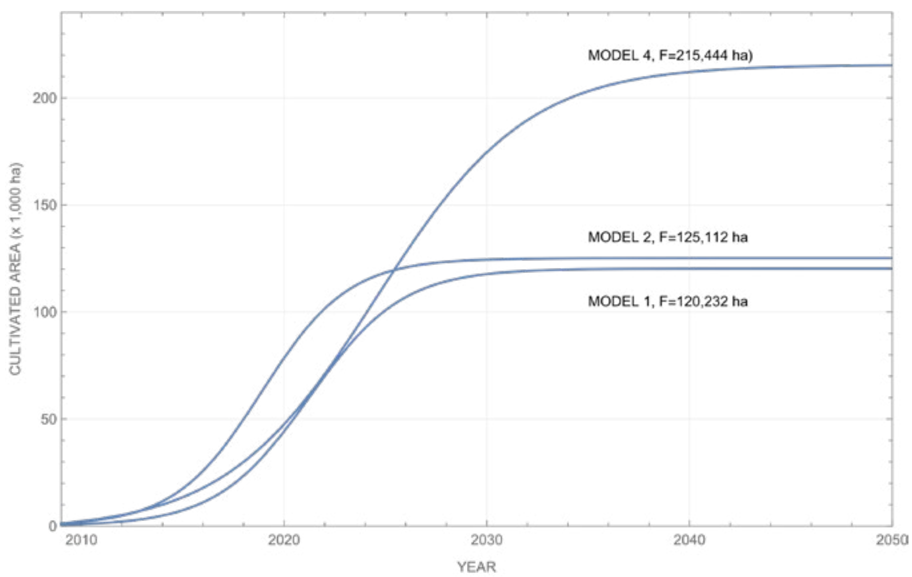

Figure 2. Diffusion curve for models 1, 2 and 4. F: level of system saturation. Source: Own elaboration.

Table 2. Statistical error rates for models 1, 2, 3, 4, 5, 6, 7 y 8

Model/Index	MAE	ME	RMSE	MAPE (%)	MNSSE	MRE	NSSE	FIT (%)
1	598	-115	716	14.7	1.67	-0.09	0.15	95
2	6.89	6.86	9.69	42	22	0.41	25.4	40
3	670	119	968	9.6	2.25	0.05	0.27	94
4	4.49	4.49	5.01	66	11.2	0.66	6.8	61
5	5.18	-85.7	6.2	154	14.3	-0.7	1.35	54
6	Overflow	--	--	--	--	--	--	--
7	Overflow	--	--	--	--	--	--	--
8	1.22	-0.01	1.63	22.6	3.6	0.12	0.7	89

MAE: mean absolute error. ME: mean error. RMSE: root mean squared error. MAPE: mean absolute percentage error. MNSSE: modified normalised sum of quadratic errors. MRE: mean relative error. NSSE: sum of standardised sum of squared errors. FIT: best fit. Source: Own elaboration.

Referring to Table 1 it is observed that the diffusion coefficients for models 1 and 2 are very close (0.44 and 0.47 respectively), hence the diffusion curves are very similar (Fig. 4), displaying comparable saturation levels (120,232 ha and 125,112 ha).When considering model 4 (Bass model), the values of the parameters give an idea of the characteristics of the diffusion process: innovation coefficient = 0.0025 and imitation coefficient = 0.266, i.e., the imitation factor (diffusion by contagion) is more important in the process than the innovation factor (0.0025).

Table 2 shows the statistical error rates for models 1, 2, 3, 4, 5, 6, 7 and 8. Considering the MAPE and FIT values, it can be concluded that only models 1 and 8 provide a good fit between the expected and observed data.

From the study of the goodness of fit, it can be concluded that among the first three models, the first one meets the requirements as a suitable forecasting model for the development of the cultivated area.

— MAE: A lower value indicates that the estimated data fit well with the measured data. Among models 1, 2 and 4, the first one has the lowest value and hence, a better fit.

— ME: Its value measures whether the model has overestimated or underestimated the observed data. The first model has the lowest value, indicating a good goodness of fit.

— RMSE: It is a measure of the differences between those values predicted by a model and the observed. values. This index weights the forecasts that are furthest away from the observed value. The first model is the one that brings the forecasts closest to the observed data.

— MAPE: Only the first model presents a MAPE value that ensures a good prognosis with 14.7% MAPE. In this sense, also model 8 (influence pattern) presents a MAPE value that ensures a good prognostic fit with 22.6%. To interpret this index, the criteria of Nafidi et al. (2019) should be considered.

— MNSSE (%): Its lower value, in order of magnitude, indicates a better fit. For this index, the first model is the best performing of the first three models.

— MRE: It measures the relative bias between the estimates and the observed data. In absolute value, the first model has the smallest bias.

— NSSE: This index measures the percentage of squared error between the estimates and the observed data. The model 8 presents the lowest value.

— Best fit: FIT (%): This index is a comparison between the observed and estimated data, with respect to the average of the observed data. Its result is a percentage, 100 indicating a perfect fit. The first model represents an excellent fit (95%), while the second and third models represent an insufficient fit. Model 8 presents an almost perfect fit with 89%.

Table 3 shows the saturation level and the tipping point for models 1, 2 and 4. Figure 2 represents the diffusion curve for models 1, 2 and 4. Table 4 shows the saturation level and the tipping point for model 8 for an average yield of 1,000 kg/ha and different values of the pistachio price variable (7, 10, 12 and 14 EUR/kg). Figure 3 shows the diffusion curve of Jarvis' model 8, for an average yield of

Table 3. Saturation level and inflection point for Models 1, 2 and 4.

Model	System saturation level F (ha)	Inflection point	
		Year	Cultivated area
1	120,232	2021	59,039 ha
2	125,112	2020	62,555 ha
4	215,444	2024	106,685 ha

Source: Own elaboration.

Table 4. Saturation level and inflection point for Model 8, Yield = 1,000 kg/ha, and for different values of the price variable

Yield (kg/ha)	p_{pi}	F (ha)	Inflection point	
			Year	Cultivated area
1,000	7	68,452	2018	35,523 ha
1,000	10	96,676	2018	49,635 ha
1,000	12	115,493	2018	59,072 ha
1,000	14	134,310	2018	68,451 ha

Source: Own elaboration.

1,000 kg/ha, and for different values of the price variable (7, 10 and 14 EUR/kg). Finally, Figure 4 displays the diffusion curve of model 8, for a pistachio price of 12 EUR/kg, for different values of the variable crop yield: 700, 1,000 and 1,400 kg/ha.

Model 8 (Jarvis model) indicates that the price level of pistachio and the evolution of the crop yield have a positive influence on the diffusion rate (0.76), being greater than those measured in models 1, 2 and 4. In other words, a multiplicative effect of an upward evolution of prices and yield on the magnitude of the aggregate cultivated area can be affirmed. In this sense, looking at Table 4 and Figs. 3 and 4, it can be observed that in a favourable price environment, with a greater synergy of the production factors which lead to an increase in crop yield (irrigation regime, fertiliser regime, climate, soil, flowering control, choice of rootstock, pruning, soil maintenance system, pest and disease control, etc.), there is a contrasting trend towards a higher level of saturation of the system (F).

The current work proves that for a constant crop yield of 1,000 kg/ha, raising pistachio prices from 7-10-12 to 14 EUR/kg, brings about an increase in the saturation level of the system from 68,452 ha to 96,676 and then up to 134,310 ha.

Similarly, with a constant pistachio price of 12 EUR/kg and an increment of the crop yield from 700 to 1400 kg/ha, the saturation level of the system increases from 81,624 ha to 115,493 ha and finally to 160,653 ha.

Regarding model 8 (pattern of influence), it is shown that in a context of suitable market prices for pistachio and an optimal synergy of the production factors that favour the crop yield not only increases the level of saturation of the system but also the duration of the diffusion process.

This is a foreseeable conclusion since optimal product prices tend to be a determining factor for the decision making of the farmers. Furthermore, higher crop yields are an additional decision-making incentive that predisposes farmers to adopt the crop.

Therefore, this study shows that the diffusion process of pistachio cultivation in Spain follows the logistic curve pattern. This characterises the very process of adoption of the crop by farmers, and implies:

— A first stage determined by high uncertainty on crop yields, price levels and new technologies to be

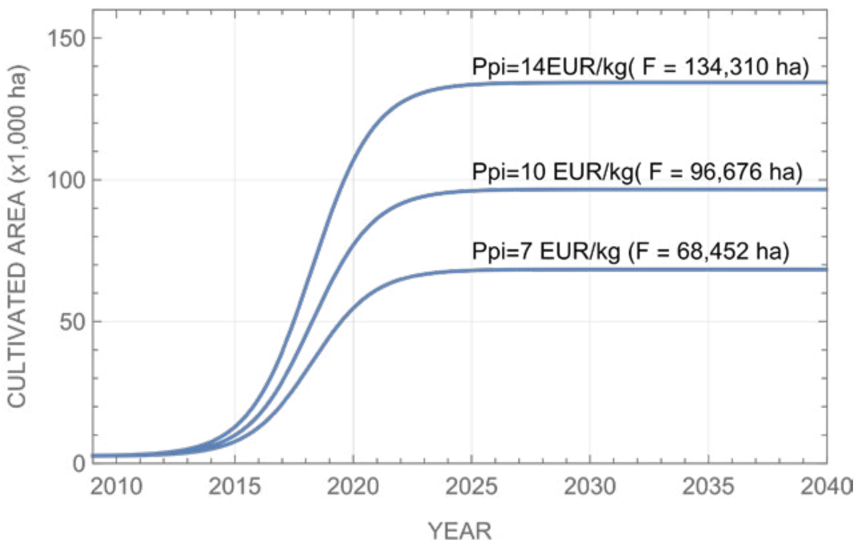

Figure 3. Diffusion curve of model 8 with constant crop yield = 1,000 kg/ha. F: level of system saturation. Ppi: pistachio price (EUR/kg). Average crop yield = 1,000 kg/ha. Source: Own elaboration.

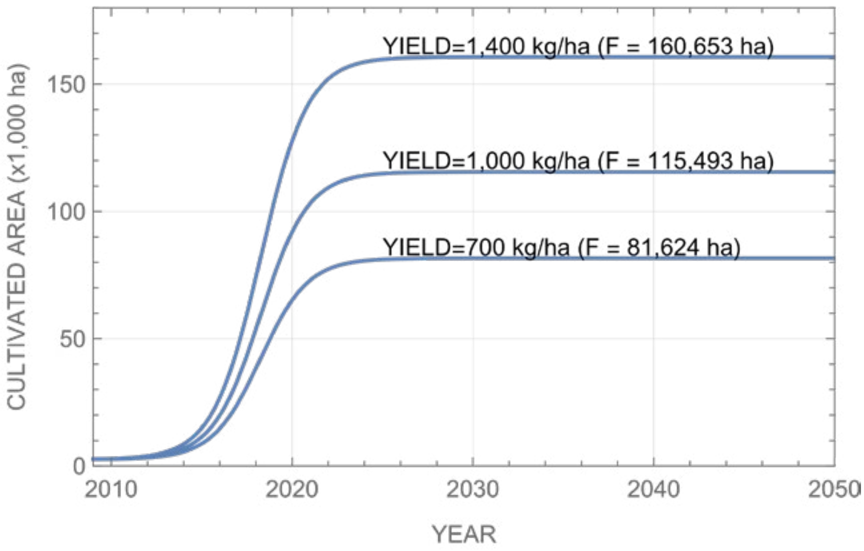

Figure 4. Diffusion curve for Jarvis Model 8 with constant price of ppi = 12 EUR/kg. F: level of system saturation. P_{pi}: pistachio price (EUR/kg). YIELD = average crop yield. Source: Own elaboration.

applied to obtain acceptable yields. In other words, uncertainty in adoption due to the existence of a high adoption risk, which is why the diffusion process is slow.

— A second stage characterised by an increase in the technological performance of the innovation and therefore a higher acceptance of the innovation by potential adopters. The speed of diffusion will also increase rapidly.

— A third stage characterised by a slower rate of diffusion mainly for two reasons: the technology is approaching its performance limit and expectations of future productivity increases are diminishing. The diffusion process approaches its saturation level (F). The shape of the diffusion curve is symmetrical sigmoidal with a well-defined inflection point, which determines the instant in time when the speed of the process starts to decrease.

Discussion

Over the last 70 years, several mathematical diffusion models have been used to describe the process of adoption of innovation in the agricultural world, revealing that all of them are based on the sigmoidal growth curve; with an initial phase presenting a relatively low growth rate, an intermediate phase of rapid growth and a final phase close to the saturation level of the system with a negligible growth rate.

In this study, we have been able to demonstrate that the diffusion of the pistachio crop in Spain also follows the logistic growth curve (Figs. 2, 3 and 4). The strength of our results lies in the fact that the source of the data gathered (ESYRCE-MAPA, 2020) is reliable and the historical data covers all pistachio plantations that have been adopted in Spain (100%) until now. Alcón et al. (2006) have studied the diffusion of localised irrigation in Campo de Cartagena. This work mirrors ours because it also studies the area in which the technology has been implemented. However, the relevance of our work, in pistachio cultivation, lies in the fact that it analyses the evolution of the crop area. Finally, our results are reliable because they can be validated by previous work carried out in Spain and at an international level.

In Spain, we have found similarities on work recently done by Cárdenas-Polonio et al. (2022) on almond trees in Andalusia. Here the logistic models of Giovanis & Skiadas (1999) and Bass (2004) are also analysed, presenting extrapolated results. Another significant example is the study by Parra-López (2003) on organic, integrated and conventional production systems in olive groves. He found that in cases of low productivity, the logistic curve offered a good fit with similar results to those found in the present work on pistachios (a sigmoidal curve with three well-defined phases). However, in highly productive olive groves, Parra-López (2003) concludes that the external influence is predominant in the process of adopting organic farming, causing the data to fit an exponential distribution. Work undertaken on the adoption of water-saving technologies in agriculture by Alcón et al. (2009) also shows that the technology is adopted following the logistic model (an initial phase of growth that exceeds 10% from 1980 onwards, increasing over time until 1987, from which the innovation continues to be introduced into the market until 1997, when 90% of its total diffusion is reached).

Franco & Calatrava (2010) analysed the adoption and diffusion of no-tillage practices in olive orchards in the province of Granada The diffusion process was analysed by estimating the logistic (Verhulst, 1847), Gompertz (Gómez & Carmona, 2003) and exponential (Carmona et al., 2005) model. Results obtained from the analysis of the logistic model by Franco & Calatrava (2010) and those obtained in the present work are comparable. However, concerning the other models, Gompertz and exponential, no comparable results have been obtained in the present work.

At an international level, Duran et al.´s (2011) work on the diffusion of no-tillage technology in Argentina shows that the adoption of no-tillage follows the sigmoidal curve pattern with a well-defined inflection point. This conclusion matches our findings.

A novelty in the present study is that the influence of exogenous factors (pistachio price and yield) on the cultivated area is studied following Jarvis (1981)'s methodology. The inclusion of the exogenous factors on this analysis is of paramount significance. For example, the price of the product can be considered a key factor in enabling farmers to decide on whether to plant pistachio or not.

In summary, we have demonstrated that in the pistachio crop in Spain, considering an average crop yield of 1,000 kg/ha and an average price of 12 EUR/ha, which are typical values, both the estimation of the cultivated area and the influence of the exogenous factors on the latter can be modelled using the logistic curve described by Verhulst (1838). This is confirmed by the goodness of fit of the models.

Conclusions

This paper concludes that the process of diffusion of pistachio cultivation in Spain is influenced by the profitable use of new technology by some farmers and their positive interaction with other farmers which are encouraged to adopt it. In addition, optimal production factors, leading to improved crop yields, (irrigation regime, fertiliser regime, climate, soil, flowering control, rootstock choice, pruning, soil maintenance system, pest and disease control, etc.) together with a favourable product price determine the extent of the diffusion process and the magnitude of the saturation level of the system.

Farmers will always seek to maximise their profits. Therefore, given a limited set of resources, pistachio cultivation will be extended according to a model that will only make sense by allocating resources where returns are greatest. The higher the returns, the faster the diffusion process. In this sense, the highest profitability of irrigated plantations must be considered.

The following general conclusions can be drawn from the analysis of the diffusion models studied in this paper: The diffusion curve is sigmoidal with a well-defined inflection point and three well-defined phases: an initial phase with a small diffusion rate, an intermediate phase with a very rapid growth and a final phase with a negligible diffusion rate close to the saturation level of the system. The process by which pistachio cultivation is adopted in Spain responds to a model of internal influence (logistic) and never to models of external influence. It is for this reason that the process has a null innovation effect, and all the dynamics of the processes are marked by the imitation effect between the agents of the system.

The main novelty of this work is that it assesses the spread of pistachio cultivation, a species that has historically been relegated to marginal and unirrigated land and which is currently displacing traditional crops in those farms with the greatest agronomic potential in the region.

Finally, it is worth mentioning that since the entry into force of Regulation 1308/2013 productions are grouped under a single Common Market Organisation, with a more rigorous wording. In this context, EU policies have adopted measures aimed at promoting the cultivation of nuts, among other reasons due to the beneficial effects that their consumption has on health. These incentives are linked to the area cultivated. If this incentive policy is maintained over time, it is foreseeable that a second cycle of growth, expansion and dissemination of pistachio cultivation will take place in Spain.

This paper aims to contribute to alleviate the scarcity in the literature of papers dealing with the application of explanatory models of the diffusion of a given crop by farmers.

Authors' contributions

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Writing – original draft: F. Cárdenas-Polonio
Writing – review & editing: F. Cárdenas-Polonio, J. Martínez-Dalmau, J. Berbel

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