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CROP PRODUCTION

# Productive trajectory of vineyards over time and comparative analysis of mathematical models for the Campanha Gaúcha region, RS, Brazil

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## Trajetória produtiva de vinhedos ao longo da idade e análise comparativa de modelos matemáticos para a região da Campanha Gaúcha

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**ABSTRACT**: Commercial vineyards are perennial agricultural systems where productivity varies non-linearly over time, reflecting the growth, maturity, and senescence of the plants. Understanding this trajectory is crucial for supporting management decisions and identifying the need for vineyard renewal. This study evaluated the productive behavior of commercial vineyards in the Campanha Gaúcha region (RS), Brazil, using four non-linear mathematical models: Gamma, Beta, Logistic with a decline term, and bilateral Gompertz. The database comprised eight *Vitis vinifera* L. cultivars (four red and four white), including vineyards of different ages, with observations extending up to 37 years after planting. Models were assessed for goodness of fit and biological consistency regarding estimates of maximum productivity, peak productive age, and the duration of the period in which productivity remains at least 90% of the maximum. While the Beta model was significant, it tended to overestimate productive longevity. The Gamma model was more suitable for representing the trajectory of red varieties, whereas the Logistic model with a decline term performed better for white varieties and the overall average. Estimates indicated that the productive peak occurs for all varieties more than 10 years after planting. Generally, red cultivars showed greater longevity, while white cultivars exhibited shorter high-productivity windows—a pattern corroborated by the early elimination of Gewürztraminer and Riesling vineyards due to economic infeasibility. These results demonstrated that the choice of mathematical model directly influences the interpretation of longevity, demonstrating that mathematical modeling is a robust tool for planning vineyard renewal on a commercial scale.
**Key words**: commercial vineyards, nonlinear modeling, productive senescence, vineyard longevity, *Vitis vinifera*.

## Trajetória produtiva de vinhedos ao longo da idade e análise comparativa de modelos matemáticos para a região da Campanha Gaúcha

**RESUMO**: Vinhedos comerciais são sistemas agrícolas perenes nos quais a produtividade varia de forma não linear ao longo do tempo, refletindo processos de crescimento, maturidade e senescência das plantas. Compreender essa trajetória é fundamental para subsidiar decisões de manejo e identificar o momento ideal para a renovação dos vinhedos. Neste sentido, o presente estudo teve como objetivo compreender o comportamento produtivo de vinhedos comerciais da região da Campanha Gaúcha (RS), no período de 1992 a 2022, por meio de quatro modelos matemáticos não lineares (Gamma, Beta, Logístico com termo de declínio e Gompertz bilateral). O banco de dados compreendeu oito cultivares de *Vitisvinifera* L., sendo quatro variedades tintas e quatro brancas, abrangendo um gradiente de idades, com observações de vinhedos de até 37 anos após o plantio. Além disso,os modelos foram avaliados quanto à qualidade de ajuste e à coerência biológica das estimativas de produtividade máxima, idade de pico produtivo e duração do período em que a produtividade permanece igual ou superior a 90% da máxima. Os resultados evidenciaram queo modelo Beta, embora significativo, tendeu a superestimar a longevidade produtiva. Os demais modelos apresentaram melhor desempenho, sendo o Gamma mais adequado para representar a trajetória produtiva de variedades tintas e o Logístico com termo de declínio para as brancas e para o a média de todas as variedades. As estimativas indicaram que o pico produtivo ocorre, para todas as variedades, acima de 10 anos após o plantio. De modo geral, as cultivares tintas apresentaram maior longevidade produtiva, enquanto as cultivares brancas exibiram janelas mais curtas de alta produtividade, padrão corroborado pela eliminação antecipada dos vinhedos de Gewürztraminer e Riesling por inviabilidade econômica. Desse modo, a escolha do modelo matemático influencia diretamente a interpretação da longevidade produtiva e destacam a modelagem matemática como ferramenta adequada para apoiar o planejamento da renovação de vinhedos em escala comercial.
**Palavras-chave**: vinhedos comerciais, modelagem não linear, senescência produtiva, longevidade do vinhedo, *Vitis vinifera*.

## INTRODUCTION

Commercial vineyards are perennial agricultural systems that require a high initial investment, with management decisions influencing productivity for decades. The grapevine (*Vitis vinifera* L.) has a productive life that can vary from 20 to 60 years under commercial conditions (ZHU

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et al., 2021). Although, this longevity allows for the dilution of implementation costs, it also requires a precise understanding of the productive dynamics throughout the vineyard aging, especially to support renewal decisions (GRIGG, 2018).

Perennial fruit crops are expected to exhibit a non-linear productive trajectory, characterized by a juvenile phase of low production, progressive increase to a peak, and subsequent decline associated with senescence. This unimodal or asymmetrical pattern reflects underlying structural and physiological processes, including changes in vascular functionality, the accumulation of wood diseases, and shifts in the source–sink balance (PÉREZ-LLORCA & MUNNÉ-BOSH, 2021; GUERIN-DUBRANA, 2019; MARTÍNEZ-LÜSCHER & KURTURAL, 2021). These biological dynamics require mathematical functions capable of adequately representing the growth, peak, and decline phases over time.

For the grapevine, an increase in productivity is observed in the first productive years, followed by stabilization or reduction in older vineyards (NADER et al., 2019). However, most available studies are based on short-term time series, which limits the complete characterization of the productive trajectory throughout the vineyard's lifespan (FERNANDEZ-MENA et al., 2025). Consequently, the age of peak production and the intensity of decline remain poorly quantified, especially in subtropical systems. In the Campanha Gaúcha region, situated in Brazil's southernmost territory, the expansion of viticulture since the 2000s has led to the establishment of vineyards that are now entering their phase of productive maturity (MANFIO, 2019). This context reinforces the need for quantitative approaches capable of estimating productive longevity and supporting strategic renewal decisions.

The decision to maintain or renew a vineyard is strongly dependent on the expectation of future productivity. In this context, mathematical modeling is a central tool for describing productive trajectories and estimating biologically relevant parameters, such as age of maximum productivity and intensity of decline (ARCHONTOULIS & MIGUEZ, 2015). Models that overestimate productive stability can delay renewal and reduce the system's profitability, while excessively conservative models can anticipate the replacement of still productive vineyards, compromising the return on initial investment (ARCHONTOULIS & MIGUEZ, 2015). Different parametric nonlinear functions have been used to represent growth and senescence in biological systems, varying in terms of geometric structure and the interpretation of their parameters. Models such as Gompertz and logistic, as well as their generalizations, differ in the position of the inflection point and the shape of the curve (TJØRVE & TJØRVE, 2017; TSOULARIS & WALLACE, 2002), while Gamma and Beta functions offer greater flexibility to represent unimodal curves with different degrees of asymmetry (BRILHANTE et al., 2023). Due to these structural differences, different functional forms can generate divergent estimates for peak productive age and decline rate, characterizing relevant structural uncertainty (CHAPAGAIN et al., 2022; WALLACH et al., 2025).

Studies that systematically compare different nonlinear functions for describing vineyard productivity using extensive historical datasets remain scarce. Yet long-term assessments are essential for fully capturing the dynamics of productive aging and for reducing uncertainties in estimating the optimal timing for vineyard renewal (YANG et al., 2023; MÉROT et al., 2023). Even rarer are long-term analyses that evaluate potential differences among cultivars—both white and red—and their implications for production planning (OGER et al., 2025).

Thus, the present study aimed to understand the productive behavior of vineyards of different cultivars over the years using non-linear mathematical models. Specifically, it sought to: (i) evaluate the statistical fit and biological consistency of each model; (ii) estimate the age of peak production and subsequent decline rates; and (iii) investigate differences between white and red cultivars. The hypothesis is that the choice of functional form significantly influences estimates of peak productive age and decline rate, potentially altering the agronomic interpretation of productive longevity and the optimal time for vineyard renewal.

## MATERIALS AND METHODS

The study was conducted in commercial vineyards located in the municipality of Santana do Livramento, within the Campanha Gaúcha region, Brazil (30°48′31″ S; 55°22′33″ W). The region's climate is classified as humid subtropical (Cfa), according to ALVARES et al. (2013). The predominant soils are classified as Dystrophic Red Argisols, according to the Brazilian Soil Classification System (FLORES et al., 2007; STRECK et al., 2008).

The vineyards were progressively established over time in different plots, resulting in the coexistence of areas with different ages in each harvest. The plants were trained in a trellis system, with mixed pruning (spur pruning with

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runners) predominating, used in approximately 95% of the cultivated area. After pruning, an average of approximately 30 productive buds per linear meter of trellis was maintained. In plots trained in the Guyot system, a similar density of buds per meter was sought. Eight cultivars of *V. vinifera* were evaluated, four of which were red grapes (Cabernet Franc, Cabernet Sauvignon, Merlot, and Tannat) and four were white grapes (Chardonnay, Gewürztraminer, Riesling, and Sauvignon Blanc), grown under commercial conditions representative of the Campanha Gaúcha region.

The formative pruning was carried out according to the vegetative development of the plants, which can take four to eight years for the complete formation of the spur cordon. Fertilization was carried out in accordance with the official recommendations for grapevine cultivation in southern Brazil (CQFS-RS/SC, 2016). Before planting the vineyards, base fertilization was carried out based on soil analyses, while annual maintenance fertilization followed recommendations for average yields of approximately 12 Mg ha$^{-1}$.

*Vineyard productivity dataset*

The dataset comprises productivity records for eight *V. vinifera* varieties collected over 30 consecutive harvests, from 1992 to 2022 (Table 1). At the beginning of the evaluation period, the vineyards were at different developmental stages, including newly planted areas as well as mature and old vineyards. Due to the progressive establishment of vineyard blocks and the coexistence of plots of varying ages in each harvest, it was possible to obtain productivity records for vineyards of different ages, with observations extending up to 37 years after planting. Thus; although the monitoring period spans 30 harvests, the resulting database represents a broader age gradient, enabling the characterization of virtually the entire productive lifespan of the vineyards. In contrast, for the white cultivars Gewürztraminer and Riesling, the historical series included vineyards up to 29 and 28 years old; respectively, because older vineyards of these varieties were removed during the evaluation period due to persistently low productivity at advanced ages.

Each plot constituted an annual observation unit, resulting in multiple productivity observations for different plant ages within each cultivar. Productivity was expressed in Mg ha$^{-1}$ and calculated annually from the total production and the area harvested in each plot. Due to plantings and eliminations, the area cultivated by each variety varied throughout the analyzed period. However, in all harvests, each cultivar occupied a minimum area of approximately 0.3 ha, ensuring sample representativeness.

*Modeling and comparison of models*

The analyses were performed in the R statistical environment (R CORE TEAM, 2024). Adjustments were made using non-linear regression via least squares, employing the Levenberg–Marquardt algorithm through the minpack.lm package (ELZHOV et al., 2023). The comparison was conducted on data organized in the format productivity × age for each cultivar, which allowed for evaluation under the same observational basis between different functional forms. Model parameters were estimated by nonlinear least squares using the Levenberg-Marquardt algorithm implemented in the minpack.lm package. Initial parameter values were defined from exploratory analyses of the productivity-age relationship and adjusted according to the biological meaning of each model. Parameters related to productivity magnitude and age were constrained

Table 1 - Characterization of the productivity database by cultivar throughout the 1992-2022evaluation period, including the number of evaluations, plant age range, area of evaluated plots, and observed productivity range.

| Variety | Group | Evaluations (n) | Age (years) | ------Area(ha)------- | | -----Productivity(Mg ha$^{-1}$)----- | |
|---|---|---|---|---|---|---|---|
| | | | | min | max | min | Max |
| Cabernet Franc | Red | 143 | 37 | 1.0 | 13.4 | 0.1 | 18.7 |
| Cabernet Sauvignon | Red | 548 | 37 | 1.9 | 7.7 | 0.2 | 21.0 |
| Merlot | Red | 232 | 37 | 1.0 | 9.2 | 0.1 | 22.3 |
| Tannat | Red | 424 | 37 | 1.5 | 8.2 | 0.1 | 24.8 |
| Chardonnay | White | 177 | 37 | 1.5 | 7.7 | 0.1 | 17.8 |
| Gewürztraminer | White | 79 | 29 | 0.3 | 6.5 | 0.2 | 18.0 |
| Riesling | White | 221 | 28 | 1.0 | 6.8 | 0.3 | 19.0 |
| Sauvignon Blanc | White | 254 | 37 | 1.2 | 8.0 | 1.1 | 24.0 |

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to biologically plausible ranges whenever necessary. Convergence was assessed using the default stopping criteria of the optimizer, based on changes in parameter estimates and residual sum of squares between successive iterations. When convergence was not achieved, alternative starting values were tested to reduce the possibility of local minimum and improve numerical stability.

Based on the above methodology, four models with different degrees of flexibility and biological interpretation were investigated:

1. Gamma (asymmetric unimodal trajectory):

$$P(t) = \alpha t^{\beta} exp^{-\gamma t}, \alpha, \beta, \gamma > 0$$

2. Beta (unimodal trajectory in a normalized domain):

$$P(t) = \alpha \left(\frac{t}{T}\right)^{\beta} \left[1 - \left(\frac{t}{T}\right)\right]^{\gamma}, \ 0 \leq t \leq T, \ \alpha, \beta, \gamma > 0$$

where$T = max\ (t)$for the respective cultivar (time normalization).

3. Logistic with decline term (sigmoidal growth followed by senescence):

$$P(t) = \frac{A}{1+\exp[-k(t-t_0)]} \exp[-d(t-t_0)], \ A, k, d > 0$$

4. Bilateral Gompertz (initial growth and late decline with distinct asymmetries):

$$P(t) = P_{\max} \exp\{-\exp[-k_1 (t-t_1)]\} \times \exp\{-\exp[k_2 (t-t_2)]\}, P_{\max}, k_1, k_2 > 0$$

The selection of these models was based on biological consistency, enabling the description of an initial increase in productivity, a peak, and a subsequent decline at advanced ages, as expected for vineyards (ARCHONTOULIS & MIGUEZ, 2015). Models were fitted individually for each cultivar, for the averages of white and red groups, and for the entire dataset. Where appropriate, specific parameter limits and constraints were applied. For the Beta model, time was normalized. For the Logistic model with a decline term, a lower bound of zero was imposed on predictions during post-processing to prevent biologically unrealistic negative productivity values.

Each fitted model generated predictions and residuals, which served as the basis for calculating standard goodness-of-fit metrics. Although $R^2$ was reported as a descriptive measure of explained variability, model selection was primarily based on AICc and residual diagnostics because the interpretation of $R^2$ in nonlinear regression is not always straightforward. These metrics were used to diagnose fit quality and verify the consistency of the estimated curves over time.

Model selection was primarily guided by the Corrected Akaike Information Criterion (AICc), which accounts for model complexity and is particularly suited for small to moderate sample sizes. The AICc was derived from the residual sum of squares and the number of estimated parameters. The model with the lowest AICc was deemed most suitable. However, in instances of a technical tie, defined by BURNHAM & ANDERSON (2002) as $\Delta AICc \leq 2$, the more parsimonious model with fewer parameters was selected. To ensure that the selected models adequately represented the observed data, residual diagnostic analyses were also conducted. Residual normality was assessed using the Lilliefors and Shapiro-Wilk tests, residual independence was evaluated using the Durbin-Watson test, and homoscedasticity was assessed using the Breusch-Pagan test. Additionally, mean residual values and residual standard deviations were calculated to evaluate model bias and residual dispersion. These diagnostics were used to verify the adequacy of the selected models beyond their relative ranking based on AICc.

## RESULTS AND DISCUSSION

In general, the four models were able to adequately describe the productive trajectory of the vineyards, with an initial phase and a decline phase that are asymmetrical and separated by a productive peak. To characterize productive longevity, a high-productivity phase was defined as the period during which productivity remained equal to or greater than 90% of the estimated maximum. This threshold was adopted as a practical indicator of near-maximum productive performance under the conditions evaluated in this study; although, alternative thresholds may be more appropriate in other regions or for different management objectives. However, Beta was the most discrepant model. Its curve was shifted to the right, indicating a delay in the estimated point of maximum productivity compared to the other models (Figure 1 and Supplementary Material).This pattern likely reflects the high flexibility of the Beta function, which may produce delayed peak estimates when applied to asymmetric productivity trajectories (BRILHANTE et al., 2023). This model also showed the poorest fit according to the adjustment criteria (Table 2), yielding the lowest $R^2$ and the highest Root Mean Square Error (RMSE). Furthermore, its significantly higher AICc values indicate a greater loss of information relative to the alternatives.

The remaining models performed similarly. The Logistic model with a decline term and the

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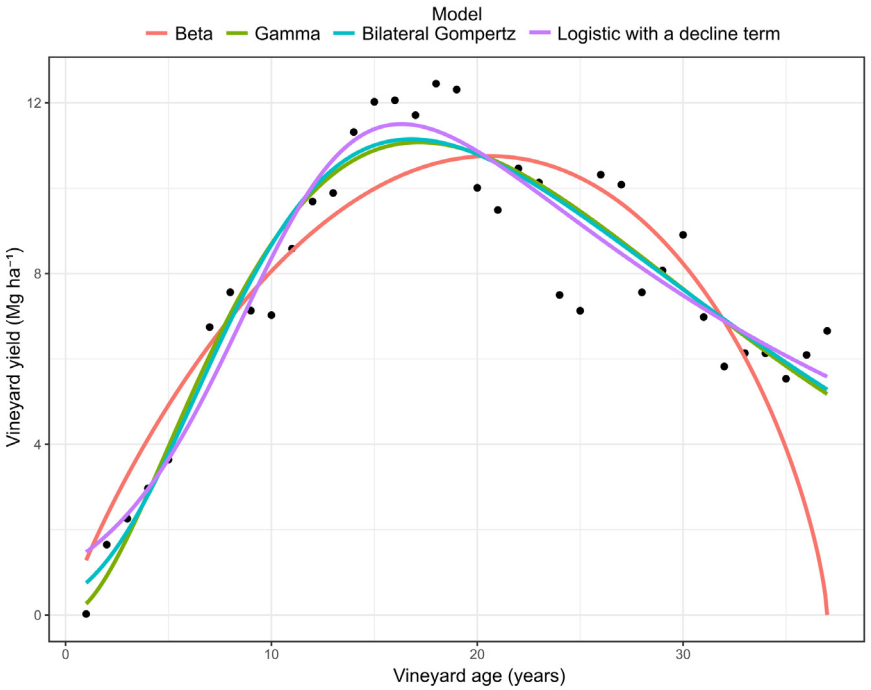



Figure 1 - Productive trajectory of vineyards derived from the average yield values of eight *Vitis vinifera* cultivars, estimated with four nonlinear models—Beta, Gamma, Bilateral Gompertz, and Logistic with a decline term—fitted to the age-specific means. Black points show the observed mean productivity for each vineyard age.

bilateral Gompertz model exhibited high $R^2$ values and low RMSE values. However, model adequacy was also supported by residual diagnostic analyses, while model selection was primarily based on AICc and model parsimony. The Gamma model also proved to be very competitive, with low AICc values. It is a solid alternative, especially if the data distribution favors asymmetric probability density functions, a trend observed in this dataset. The Gamma model was considered the best fit for all red varieties and for Riesling (Table 3). The Logistic model with a decline term proved to be the most suitable for white varieties. Although the bilateral Gompertz model offered a strong fit, it did not outperform the others; following the principle of parsimony, it was rejected in cases of equal performance, as observed in Sauvignon Blanc, due to its higher parametric complexity. Residual diagnostic analyses supported the adequacy of the selected models, with the Lilliefors test indicating no significant departures from normality ($P > 0.05$) and the Breusch-Pagan test supporting homoscedasticity across all datasets. Mean residuals were close to zero, indicating negligible bias, while the mild residual autocorrelation detected in some datasets is consistent with the age-structured nature of nonlinear growth data (Supplementary Material available at https://doi.org/10.5281/zenodo.19092284).

Table 2 - Variation of fit criteria for the models.

| Model | $R^2$ | RMSE | AICc |
|---|---|---|---|
| Beta | 0.3234 – 0.7524 | 1.4838 – 3.2145 | 35.9322 – 93.1352 |
| Gamma | 0.5029 – 0.8993 | 0.9722 – 2.7552 | 4.6458 – 81.7279 |
| Logistic with a decline term | 0.5245 – 0.9060 | 0.9389 – 2.6946 | 4.5891 – 82.6029 |
| Bilateral Gompertz | 0.5172 – 0.9051 | 0.9438 – 2.7153 | 7.6611 – 85.8550 |

The results show that the productive trajectory of the evaluated vineyards presents a clearly unimodal behavior. This pattern is widely described for perennial crops and reflects cumulative physiological and structural processes, including changes in source-sink balance and carbon allocation, reduced vascular efficiency, and increased incidence of wood diseases (PÉREZ LLORCA & MUNNÉ

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Table 3 - Best-fit model selection and estimated parameters for vineyard production trajectories by variety and group. P(t) represents productivity at age t; $R^2$: coefficient of determination; RMSE: root mean square error; AICc: corrected Akaike information criterion.

| Variety | Best Model | Equation | R2 | RMSE | AICc |
|---|---|---|---|---|---|
| Cabernet franc | Gamma | P(t) = 0.5503 * t^1.6768 * exp-0.0985 * t | 0.634 | 2.282 | 67.785 |
| C. Sauvignon | Gamma | P(t) = 0.2514 * t^2.0459 * exp(-0.1226 * t) | 0.832 | 1.223 | 21.613 |
| Merlot | Gamma | P(t) = 0.0480 * t^2.9491 * exp(-0.1681 * t) | 0.786 | 1.831 | 51.489 |
| Tannat | Gamma | P(t) = 0.5896 * t^1.5414 * exp(-0.0817 * t) | 0.503 | 2.755 | 81.728 |
| Red | Gamma | P(t) = 0.2630 * t^2.0016 * exp(-0.1134 * t) | 0.867 | 1.142 | 16.582 |
| Chardonnay | Logistic | P(t) = (17.0142/(1+exp(-0.4299 * (t - 11.3837)))) * exp(-0.0602 * (t - 11.3837)) | 0.864 | 1.332 | 30.439 |
| Gewürztraminer | Logistic | P(t) = (14.8946/(1+exp(-0.5745 * (t - 8.1468)))) * exp(-0.0451 * (t - 8.1468)) | 0.707 | 2.185 | 55.006 |
| Riesling | Gamma | P(t) = 0.2940 * t^2.1244 * exp(-0.1516 * t) | 0.691 | 1.775 | 39.135 |
| Sauvignon blanc | Logistic | P(t) = (19.9099/(1+exp(-0.4646 * (t - 7.7335)))) * exp(-0.0370 * (t - 7.7335)) | 0.842 | 1.733 | 49.923 |
| White | Logistic | P(t) = (16.0018/(1+exp(-0.4111 * (t - 8.8358)))) * exp(-0.0381 * (t - 8.8358)) | 0.880 | 1.153 | 19.793 |
| Overall | Logistic | P(t) = (17.2629/(1+exp(-0.3006 * (t - 10.2892)))) * exp(-0.0422 * (t - 10.2892)) | 0.906 | 0.939 | 4.589 |

BOSCH, 2021; GUERIN DUBRANA ET AL., 2019; MARTÍNEZ LUSCHER & KURTURAL, 2021).

The comparison between models revealed that the chosen function has a significant impact on the statistical fit and the estimation of key agronomic metrics, including maximum yield, age at peak productivity, and the duration of the high-productivity phase. The Beta model; although statistically significant, presented a greater residual error and a tendency to shift the peak productivity to more advanced ages, in addition to prolonging the high productivity phase. This behavior is consistent with previously identified limitations for highly flexible functions when applied to series with uneven age distributions or pronounced productive declines, potentially resulting in an overestimation of the system's functional longevity (BRILHANTE et al., 2023; CHAPAGAIN et al., 2022).

The Logistic model with a decline term and the bilateral Gompertz model exhibited high biological consistency and statistical performance, confirming that accounting for productive senescence is a robust strategy for interpreting the functional longevity of perennial crops (ARCHONTOULIS & MIGUEZ, 2015). The inclusion of a negative term to capture the productive senescence phase overcomes a widely documented structural limitation of the classical Gompertz model, whose asymptotic form describes growth with progressive deceleration but does not incorporate an explicit decline term, compromising its application in situations where productive decline occurs after the peak (TJØRVE & TJØRVE, 2017; TSOULARIS & WALLACE, 2002). Conversely, the Gamma model proved to be quite efficient and simple. As pointed out by GEA-IZQUIERDO & CAÑELLAS (2009), Gamma regression stands out for modeling the dependent variable at its original scale, eliminating transformation biases and naturally correcting for increased variance, resulting in more parsimonious models that are easy to interpret and highly effective in describing the growth trajectory of tree species, for example.

Estimates of maximum productivity, age at peak production, and duration of the period in which productivity remains at or above 90% of its maximum varied consistently among models, cultivars, and groupings (Table 4). In general, the Gamma and bilateral Gompertz models estimated similar maximum productivity values, while the Logistic model with a decline term estimated some higher values, and the Beta model presented lower estimates. The Logistic model also tended to anticipate the onset of productive decline, thereby shortening the high-productivity window (at or above 90%). In contrast, the Beta model postponed the achievement of the 90% threshold, the timing of peak yield, and the age at which productivity falls below the 90% mark, estimating a more prolonged high-productivity phase.

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Table 4 - Maximum productivity and 90% threshold parameters for vineyard groups. Duration represents the interval between reaching and dropping below the 90% productivity threshold. Metrics derived from Bilateral Gompertz, Logistic, Beta, and Gamma models. Asterisks (*) denote the model with the best performance for each group.

| Model | Maximum Productivity | | 90% productivity threshold | | |
|---|---|---|---|---|---|
| | Mg ha$^{-1}$ | Age (Years) | Age to Reach | Age to Drop Below | Duration (years) |
| | | | Cabernet Franc | | |
| Bilateral Gompertz | 11.8186 | 18.69 | 12.26 | 26.08 | 13.82 |
| Logistic | 12.5054 | 18.45 | 13.9 | 23.71 | 9.81 |
| Beta | 11.7893 | 21.12 | 13.98 | 27.77 | 13.8 |
| Gamma* | 11.9318 | 17.03 | 11.69 | 23.79 | 12.11 |
| | | | Cabernet Sauvignon | | |
| Bilateral Gompertz | 10.4948 | 17.77 | 13 | 23.25 | 10.25 |
| Logistic | 10.8192 | 17.58 | 13.57 | 22.29 | 8.72 |
| Beta | 10.0567 | 19.98 | 13.6 | 26.08 | 12.49 |
| Gamma* | 10.305 | 16.7 | 11.91 | 22.62 | 10.71 |
| | | | Merlot | | |
| Bilateral Gompertz | 11.8044 | 17.6 | 13.43 | 22.62 | 9.19 |
| Logistic | 12.275 | 17.28 | 13.9 | 21.47 | 7.58 |
| Beta | 11.264 | 20.58 | 14.9 | 26 | 11.1 |
| Gamma* | 11.7383 | 17.55 | 13.27 | 22.65 | 9.38 |
| | | | Tannat | | |
| Bilateral Gompertz | 11.9104 | 19.21 | 13.46 | 26.38 | 12.92 |
| Logistic | 12.1589 | 18.15 | 13.38 | 24.77 | 11.4 |
| Beta | 11.7297 | 22.51 | 15.01 | 29.16 | 14.15 |
| Gamma* | 11.6826 | 18.86 | 12.75 | 26.71 | 13.96 |
| | | | Red | | |
| Bilateral Gompertz | 11.2754 | 18.04 | 13.11 | 24.07 | 10.96 |
| Logistic | 11.5955 | 17.52 | 13.43 | 22.78 | 9.35 |
| Beta | 10.9393 | 21.09 | 14.47 | 27.28 | 12.81 |
| Gamma* | 11.1274 | 17.66 | 12.53 | 24.01 | 11.48 |
| | | | Chardonnay | | |
| Bilateral Gompertz | 10.7341 | 15.7 | 12.31 | 20.36 | 8.04 |
| Logistic* | 11.3476 | 15.61 | 12.91 | 19.32 | 6.41 |
| Beta | 10.2707 | 18.91 | 14.2 | 23.6 | 9.41 |
| Gamma | 10.6787 | 17 | 13.13 | 21.56 | 8.42 |
| | | | Gewürztraminer | | |
| Bilateral Gompertz | 10.9503 | 13.05 | 9.95 | 17.67 | 7.72 |
| Logistic* | 11.3137 | 12.44 | 10.01 | 16.37 | 6.36 |
| Beta | 10.6867 | 16.69 | 12.27 | 20.81 | 8.55 |
| Gamma | 10.9529 | 14.59 | 10.95 | 18.94 | 7.99 |
| | | | Riesling | | |
| Bilateral Gompertz | 9.5862 | 13.02 | 9.47 | 18.09 | 8.61 |
| Logistic | 9.8569 | 12.53 | 9.66 | 16.96 | 7.3 |
| Beta | 9.0218 | 19.19 | 12.81 | 24.2 | 11.38 |
| Gamma* | 9.5788 | 14 | 10.07 | 18.88 | 8.82 |
| | | | Sauvignon Blanc | | |
| Bilateral Gompertz | 14.6329 | 13.46 | 9.75 | 19.18 | 9.43 |
| Logistic* | 15.083 | 13 | 10.02 | 17.85 | 7.82 |
| Beta | 13.7038 | 18.61 | 12.34 | 24.86 | 12.51 |
| Gamma | 14.5052 | 15.48 | 10.9 | 21.18 | 10.28 |
| | | | White | | |
| Bilateral Gompertz | 11.3272 | 14.8 | 10.81 | 20.71 | 9.9 |
| Logistic* | 11.7499 | 14.39 | 11.17 | 19.35 | 8.18 |
| Beta | 10.688 | 19.68 | 13.3 | 25.86 | 12.57 |
| Gamma | 11.2575 | 16.46 | 11.74 | 22.29 | 10.55 |
| | | | Overall | | |
| Bilateral Gompertz | 11.1516 | 16.81 | 12.12 | 22.95 | 10.82 |
| Logistic* | 11.5035 | 16.32 | 12.48 | 21.61 | 9.13 |
| Beta | 10.7529 | 20.6 | 13.95 | 26.9 | 12.95 |
| Gamma | 11.0759 | 17.17 | 12.15 | 23.41 | 11.26 |

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The tendency of the Beta model to estimate later production peaks and extend the window of high productivity reinforces the impact of functional form on the agronomic interpretation of the results. If this model were the sole basis for the analysis, it would lead to the perception that vineyards reach their maximum productive efficiency only at more advanced ages. This is not always compatible with empirical field observations or analyses based on large viticultural databases (FERNANDEZ MENA et al., 2025; OGER et al., 2025). Thus, the choice of mathematical model directly influences the inference about the moment of maximum productive efficiency and, consequently, the planning of the vineyard's life cycle. Models that fail to adequately capture the intensity of productive decline tend to overestimate vineyard longevity. Such bias may delay renewal decisions for declining areas, jeopardizing system profitability. Conversely, models that explicitly incorporate productive senescence provide more realistic estimates of peak efficiency duration, offering robust support for strategic and economic planning in viticulture (ARCHONTOULIS & MIGUEZ, 2015; MÉROT et al., 2023).

Peak productive ages were estimated, in all models, to be more than a decade after planting. These estimates are consistent with long-term observations in commercial vineyards from various wine-growing regions (GRIGG et al., 2017; NADER et al., 2019). This pattern indicates that full productive maturity occurs after the structural consolidation of the plant and the training system, when a balance is established between vegetative growth and fruiting (GRIGG et al., 2017). Evidence from other viticultural contexts reinforces that vine age may be associated with productivity increases as the plant reaches full structural consolidation. In Shiraz vineyards in Australia, GRIGG et al. (2018) observed higher reproductive performance in older vines, attributing this pattern mainly to the increase in the structural size of the plant, expressed by the trunk diameter, and the greater carrying capacity of the vegetative system. These results do not contradict the unimodal trajectory observed in the present study but reinforce that age acts as an indicator of functional maturity and source-sink balance. However, maintaining high productivity levels at advanced ages can be progressively limited by cumulative environmental and sanitary factors, such as trunk diseases and abiotic stresses, which are widely recognized as drivers of productive decline over time (GUERIN DUBRANA et al., 2019; MÉROT et al., 2023).

For the red cultivars, the maximum yield estimated by the best-fitting models ranged from approximately 10 to 12 Mg $ha^{-1}$, with a group average of 11.13 Mg $ha^{-1}$. As previously noted, the Gamma model provided the best fit for this group, placing the average age of maximum productivity at 17 years and eight months. The high-yield window for these varieties occurred between approximately 9 and 14 years, with a group average duration of 11.5 years.

For the white cultivar group, estimated maximum yield ranged from approximately 9 to 15 Mg $ha^{-1}$, with a group average of 11.75 Mg $ha^{-1}$. The age at peak yield occurred between 12 and 16 years. Notably, the high-productivity window remained below 9 years for all varieties and for the group average. The narrowest window, 6.36 years for Gewürztraminer, was less than half the duration estimated for Tannat, the red cultivar with the longest productive peak.

The differences observed between the red and white groups provide relevant insights for varietal planning and the definition of vineyard renewal strategies. From agronomic and economic perspectives, the duration of the high-yield window of a vineyard is more critical than the peak yield itself. This interval defines the temporal window for the highest return on investment, particularly in capital-intensive perennial systems where establishment costs are amortized over several years (LAZZAROTTO & PROTAS, 2020). Rather than a modeling artifact, the reduced productive longevity of white cultivars aligns with actual management decisions implemented during the study period. None of the 'Gewürztraminer' or 'Riesling' vineyards maintained economically sustainable production beyond 29 years, leading to their removal before reaching three decades of age. Consequently, these varieties lacked observations in the later stages of the productive cycle. This reinforces that productive decline in certain cultivars is a functionally relevant process capable of accelerating economic in infeasibility and prompting vineyard renewal (MÉROT et al., 2023).

This divergence between groups corroborates that cultivars respond differently to aging due to physiological variation and differential sensitivity to biotic and abiotic stresses (PÉREZ LLORCA & MUNNÉ BOSCH, 2021; MÉROT et al., 2025). Xylem water transport declines with vine age, especially in perennial structures, increasing vulnerability to cavitation and limiting transpiration, canopy function, and carbon assimilation (CLAVERIE et al., 2023). This hydraulic constraint helps explain post-peak yield decline and supports the inclusion of a senescence phase in productivity models (PÉREZ LLORCA & MUNNÉ BOSCH, 2021). In the

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Campanha Gaúcha, where vineyards are mostly in the maturity phase, these differences are critical for planning varietal choice, productive longevity, and vineyard renewal (MANFIO, 2019).

Taken together, our results demonstrated that mathematical modeling is not only a statistical tool but a central element for interpreting the productive longevity and in supporting decision-making in commercial viticultural systems. Models that overestimate productive stability over time can lead to delays in renewing functionally declining vineyards, reducing the economic efficiency of the system. Conversely, more biologically consistent approaches tend to display greater predictive capacity, providing realistic estimates of the productive trajectory of vineyards.

## CONCLUSION

The productivity-age trajectory of the evaluated vineyards follows a unimodal behavior, characterized by an initial increase, peak productivity, and decline associated with plant aging. The comparison between non-linear models demonstrated that the chosen functional form directly influences both the quality of the statistical fit and the estimates of maximum productivity, age at peak productivity, and duration of the high-productivity phase. While the Beta model proved inadequate, the bilateral Gompertz, despite its good fit, is the most complex. Consequently, the Gamma and Logistic with a decline term models emerged as the most suitable models. In general, red grape varieties showed greater productive longevity, while white grape varieties exhibited shorter windows of high productivity. These results demonstrated that mathematical modeling is a robust tool for strategic planning and decision-making in commercial vineyard management.

## SUPPLEMENTARY MATERIAL

Research data is available at: <https://doi.org/10.5281/zenodo.19092284>.

## DATA AVAILABILITY STATEMENT

All relevant data are within the paper.

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## DECLARATION OF CONFLICT OF INTEREST

The authors declare no conflict of interest. The founding sponsors had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, and in the decision to publish the results.

## AUTHORS' CONTRIBUTIONS

All authors contributed equally to the conception and writing of the manuscript. All authors critically revised the manuscript and approved of the final version.

## DECLARATION OF USE OF ARTIFICIAL INTELLIGENCE

Artificial intelligence tools were used only for language refinement of the manuscript. All AI-assisted corrections were carefully reviewed by the authors to ensure that the scientific content was not altered.

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