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Sectoral development or vintage-year thermal conditions? An exploratory analysis of Polish wine-sector indicators, 2009/2010–2024/2025

Abstract. The Polish wine sector has expanded quickly over the past fifteen years, during a period of clear climate warming. Because the two trends move together in time, it is hard to tell whether the rise in sector-level output indicators is linked mainly to the sector's own development or to warmer vintage years. This is a standard attrib-ution problem. The study examines whether sector-level production and productivity indicators differ across de-velopment stages and across vintage-year thermal-class groups, and whether any thermal-class difference re-mains once the time trend is taken into account. Data come from the public KOWR series and the ordinal IMGW-PIB thermal classification for sixteen vintage years (2009/2010–2024/2025). The analysis uses Welch's ANOVA, Games-Howell post-hoc tests, control regressions, and influence diagnostics. The three a priori periods differ strongly on all output indicators ($p < 0.001$; $\omega^2 \approx 0.81$–0.83), and segmented models confirm a change in the growth path. Output intensity differs across thermal groups, but the result is borderline (Welch $F = 4.50$; $p = 0.047$; $\omega^2 = 0.33$) and only the extreme pair is significant; harvest per hectare gives the same ordering without reaching the 0.05 level ($p = 0.072$). In the control regressions the thermal-class coefficient is not significant once the time trend is included ($p = 0.339$ and $p = 0.408$), and time and thermal class are strongly correlated ($r = 0.73$); the result is stable across all leave-one-out refits. The findings state a limit on identification in these data rather than the absence of a thermal effect.

Keywords: viticulture, climate warming, vineyard productivity, analysis of variance, attribution

INTRODUCTION

Over less than two decades, the Polish wine sector has moved from a niche activity run by a few enthusiasts to a recognized segment of the agri-food economy. The number of entities in the register kept by the National Support Centre for Agriculture (KOWR) rose from 21 in 2009/2010 to 703 in 2024/2025; the area under vines grew from 36 to over 1 068 ha; and wine production rose from 41 to more than 2140 m³. The growth is therefore close to thirty-fold for area and more than fifty-fold for production volume. (As later context, the KOWR register reached 771 growers by the end of July 2026;

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the analysis below uses only complete vintage years through 2024/2025.) In absolute terms the sector is still small next to European producers, but its growth rate is among the fastest in specialized Polish agriculture.

Climate warming in Poland has been clear over the same period. In the IMGW-PIB thermal classification, years labeled “very”, “anomalously”, and “extremely warm” have become common since 2014, and mean annual air temperature has risen by roughly 0.3 °C per decade. The literature sometimes points to warming as one factor that favors winegrowing in a cool, marginal country [Maciejczak and Mikiciuk 2019, Galin 2023, Brodnicka 2024], in line with the wider view that moderate warming can help grapes ripen at the cool edge of the growing range [Jones et al. 2005, Schultz 2016].

The two trends occur together and in the same direction, which raises a methodological problem. The observed rise in output indicators may reflect warmer vintage years, but it may also reflect the sector’s own development: more area, better growing and winemaking practices, and a maturing market. Separating these two explanations is not simple. It is a standard case of confounding, in which two possible causes change in parallel and carry similar information. The problem is not specific to Poland. It is a recurring theme in the climate-and-wine literature, where changes in yield and quality are hard to attribute to temperature alone when technology, plant material, and water availability change at the same time [Schultz 2016].

This study uses an exploratory statistical framework, based on Welch’s ANOVA and a control regression, to ask whether changes in Polish wine-sector indicators are more plausibly linked to development stages or to vintage-year thermal conditions. It does not aim to prove a causal effect of thermal conditions on production, because the secondary data do not allow that inference. The article contributes by showing how hard it is to separate sectoral development from thermal conditions in a young, fast-growing wine sector, and by reporting the full analysis, including effect sizes, confidence intervals, and assumption checks.

The grapevine as a temperature-dependent crop

Wine is one of the few farm products whose link to place of origin is built into the product rather than added by marketing. The grapevine (*Vitis vinifera* L.) is a perennial woody plant whose timing of growth (phenology), yield, and fruit quality depend strongly on temperature, at the regional, local, and near-ground scales [Anderson et al. 2008]. Among environmental factors, temperature has the strongest influence: it affects the timing of the annual cycle, flowering and fruit set, photosynthesis, and the buildup of sugars and aroma compounds in the berry [Anderson et al. 2008].

Quality winegrowing is concentrated in fairly narrow temperature ranges. World wine regions are usually placed between growing-season mean-temperature isotherms of about 12–22 °C (April--October in the Northern Hemisphere); this seasonal measure fits real growing regions better than the older mean-annual measure [Jones et al. 2012]. Schultz [2016] adds that the vine is grown across very different climates, from oceanic to continental, Mediterranean, and arid. The practical point is that the kind and severity of climatic limits differ widely between regions, so global generalizations are risky. Poland sits at the cool, lower end of this range, which is a different setting from the warm regions of Australia or California that much of the literature describes.

Several bioclimatic indices describe the thermal suitability of a site. The simplest is the sum of active temperatures (SAT); related measures are growing degree-days (GDD) and the Huglin heliothermal index, which adds day length and radiation [Jones et al. 2012, Schultz 2016]. For Poland, a SAT of roughly 2500 °C is treated as an approximate threshold for commercial growing [Brodnicka 2024].

These growing-season indices are more informative than a single annual thermal class, a point we return to in the methods and discussion.

Jones et al. [2012] also group varieties by the growing-season temperature at which they ripen best, from cool (about 13–15 °C) to hot (about 19–24 °C). Early, cool-climate varieties such as Müller-Thurgau, Pinot Gris, Riesling, and Pinot Noir sit at the lower end. The suitability window of a single variety is narrow, on the order of 2–3 °C, so even moderate warming can move a region from one group to the next. This framework also warns against a simple "warmer is better" rule: the link between temperature and quality is shaped like an inverted U, with an optimum above which quality falls through loss of acidity and excess sugar [Anderson et al. 2008, Jones et al. 2012]. Cool regions such as Poland mostly sit on the rising part of this curve, which is why warming is often described as potentially favourable for them.

Warming in cool-climate wine regions: potential benefits and attribution limits

The view that warming has uneven effects is supported by both historical records and model projections. In the analysis of 27 leading wine regions, growing-season temperature rose by about 1.3 °C over recent decades, with higher vintage ratings and less year-to-year variation in quality [Jones et al. 2005]. Two features matter for cool regions. First, warming is uneven across the day and year: the largest gains are at night and in winter and spring, which shortens the frost period and lengthens the frost-free season. For marginal regions, lower frost risk can matter more than higher heat sums. Second, climate models project a poleward shift of the 12–22 °C isotherms, with a relatively larger gain in suitable area in the Northern Hemisphere [Jones et al. 2012].

On the economic side, warming may raise the number of good vintages in cool regions while lowering it in hot regions [Ashenfelter and Storchmann 2016]. Poland sits on the cool side of this divide, which makes the idea of a favourable warming effect plausible at first glance. At the same time, annual classification is a coarse measure: a national, year-level thermal class can hide the within-season events that often decide yield [White et al. 2006].

The most relevant theme for this study is attribution, developed most fully by Schultz [2016]. He notes that linking observed warming to changes in yield is hard, because growing practices, plant material, and production goals changed at the same time. Long German records show yields rising with temperature from about 1910, but the parallel growth of agronomy, plant protection, and plant material likely played at least as large a role [Bock et al. 2013]. In California the temperature signal was weaker, and in parts of Australia yields fell, more in line with water availability than with temperature. Schultz concludes that water, rather than temperature alone, may be the deciding factor for future yields.

A related caution concerns thermal thresholds. The upper temperature limits for many varieties are not actually known, yet suitability charts have been used to declare varieties "unsuitable" when future temperatures exceed values seen in current regions. Field evidence from the Rheingau, Burgundy, and the Rhône shows that growing-season temperatures already passed these presumed limits without harm to quality, which points to real varietal flexibility [Van Leeuwen et al. 2013]. In some cases, changes in practices and demand explained rising must sugar more than climate did [Alston et al. 2011]. The lesson is methodological: in observational data, where warming overlaps with technological and market change, attributing output changes to temperature alone is not justified. The present analysis gives a clear, if simple, illustration of this point for Poland.

The Polish wine sector

Studies of the Polish wine sector are mostly descriptive. Brodnicka [2024] identifies warming as a factor behind new vineyards, especially in warmer voivodeships, but does not test its quantitative link to productivity. Galin [2023] and Maciejczak and Mikiciuk [2019] place Polish winegrowing within the wider effects of climate change on farming, noting both opportunities (a longer growing season) and risks (frost, drought). The present study addresses the gap by treating the question as a problem of statistical inference and its limits, rather than description.

The KOWR data show development along two linked tracks. The first is the professionalization of production: a roughly thirty-fold rise in area and a more than fifty-fold rise in volume within a decade, with white wines predominating and a growing number of registered entities. The second is a maturing of the sector's institutions and reputation. For the present analysis, one feature is central: productivity, measured as output per hectare, is not a smooth function of scale. It varies markedly between years, with clear declines in 2017/2018 and 2024/2025 despite continued growth in sector size. This non-linearity is what makes the question of vintage-year conditions, including thermal conditions, worth testing, and it motivates the statistical separation of the development effect from the thermal-class difference that is the focus of this study.

Aim, research questions, and hypotheses

The aim of this study is to examine whether changes in sector-level production and productivity indicators in Polish winemaking can be more plausibly associated with sectoral development stages or with vintage-year thermal conditions, using an exploratory statistical framework based on Welch's ANOVA and a control regression model. The study does not aim to prove a causal effect of thermal conditions on wine production, because the available secondary data do not allow such an inference.

Three research questions follow. RQ1: do sector-development indicators (production, area, and the logarithm of production) differ across development stages? RQ2: does output intensity (production per hectare) differ across vintage-year thermal-class groups? RQ3: does any thermal-class difference remain after the time trend is taken into account in a control regression?

The matching hypotheses are stated as group differences, because ANOVA tests differences between means rather than a directional trend. RH1: sector-development indicators differ across development stages. RH2: output intensity differs across thermal-class groups. RH3: after the time trend is taken into account, thermal class does not remain an independent predictor of output intensity. RH2 and RH3 are deliberately in tension: RH2 is a simple group difference, while RH3 concerns whether that difference survives control for the time trend. The null hypotheses are equality of group means (RQ1, RQ2) and a zero thermal-class coefficient after controlling for time (RQ3). The significance level is $\alpha = 0.05$.

Table 1. Statistical hypotheses: null hypothesis H_0 and alternative hypothesis H_1

Test	H_0	H_1
ANOVA · development stage → production_m3 (and area_ha, log_production)	group means are equal	at least one group mean differs
ANOVA · thermal class → intensity_dm3_ha (and harvest_Mg_ha)	group means are equal	at least one group mean differs
Regression · intensity_dm3_ha ~ year_c + temp_ord_c	thermal-class coefficient = 0 (after controlling for time)	thermal-class coefficient ≠ 0

MATERIAL AND METHODS

Data and study period

The data cover sixteen complete vintage years from 2009/2010 to 2024/2025; the year 2025/2026 is left out as incomplete. Production data come from the KOWR series "The Wine Market in Figures" [KOWR 2010–2025] and include the number of registered entities, the area under vines, the volume of wine production, and the size of the harvest. One definitional break should be noted: through 2021/2022 the register counted "producers", and from 2022/2023 it counts "growers", which limits the comparability of that single series over time.

Each year's thermal class comes from the IMGW-PIB thermal classification for Poland, an ordinal scale from "extremely cool" to "extremely warm" [IMGW-PIB 2010–2025]. The classification is quantile-based: a year is ranked against the distribution of annual mean air temperature over the current climatological normal period (1991–2020), and the eleven classes correspond to fixed quantile bands of that distribution. The class is assigned by harvest year, that is, the calendar year that contains most of the growing season. This annual, national class is a coarse proxy for the growing-season indices (SAT, GDD, the Huglin index) used in climate-and-wine research; this limitation is discussed in Section 4.

The split into development stages (2009–2014 early; 2015–2019 transition; 2020–2024 new) is an a priori periodisation. It is theoretically motivated rather than estimated from the data, and reflects a common reading of a young sector's path from start-up through fast area expansion to consolidation. It is used here as a descriptive frame for comparing periods, not as a claim that discrete stages exist. A comparison of consecutive periods of a strongly rising series will show differences whether or not distinct stages are present, so the periodisation was additionally checked against the data with a segmented model, described in Section 2.3 and reported in Section 3.1.

Variables

The analysis uses two grouping variables (factors): development stage (three periods) and thermal class (three groups: normal/cool; warm; anomalously/extremely warm). The dependent variables are wine production (m^3), area (ha), the logarithm of production, output intensity ($dm^3\ ha^{-1}$), and harvest per hectare ($Mg\ ha^{-1}$). The control variables in the regression are the centred year (year_c) and the centred ordinal thermal class (temp_ord_c). The variable temp_ord is the position of the vintage year on the eleven-point IMGW-PIB ordinal scale, coded from 1 for an extremely cool year to 11 for an extremely warm year. The classes that occur in the study period take the values 1 (extremely cool), 5 (slightly cool), 6 (normal), 7 (slightly warm), 8 (warm), 9 (very warm), 10 (anomalously warm), and 11 (extremely warm); the coding of every year is given in Appendix A. Both control variables were centred on their sample means, so that year_c = year – 2016.5 and temp_ord_c = temp_ord – 7.875.

Output intensity is defined as intensity_dm3_ha, the total wine production in cubic decimetres divided by the total registered vineyard area in hectares. It should be read as sector-level output intensity rather than pure agronomic yield, because the denominator includes vineyards at different stages of maturity, including young plantings not yet in full production. Any positive link between this indicator and temperature should therefore be read in terms of output intensity, not value or quality. Harvest per hectare (harvest_Mg_ha) is reported alongside it because it stands closer to agronomic productivity. The logarithm of production is used only for the development-stage factor, to stabilize variance; it is not used for the thermal analysis, because it rises mainly with sector size rather than with weather.

Table 2. Construction of the three thermal-class groups

Original IMGW class	Analytical group	N
Normal, slightly cool, extremely cool	normal/cool	6
Slightly warm, warm, very warm	warm	5
Anomalously warm, extremely warm	anomalously/extremely warm	5

Statistical procedure

Because the sample is small (n = 16) and group variances are not equal, the main test is the one-way Welch's ANOVA [Welch 1951], which does not assume equal variances. Pairwise differences are examined with the Games-Howell post-hoc test [Games and Howell 1976], which also allows unequal variances and group sizes; the confidence intervals reported for pairwise differences are simultaneous intervals based on the studentized range, so that they are consistent with the accompanying p-values. The third step is a control linear regression in which output intensity is explained jointly by the time trend (year_c) and thermal class (temp_ord_c), with the coding given in Section 2.2. Both explanatory variables were centred to improve the interpretability of the intercept. Centring does not remove the substantive collinearity between time and thermal class. Collinearity is assessed with the variance inflation factor VIF [O'Brien 2007]. The regression is decisive for the study: it shows whether the thermal-class difference seen in the simple group comparison still holds once the parallel time trend is included. The same regression is also fitted with harvest per hectare as the dependent variable, as a check that the conclusion does not depend on the choice of indicator.

Because the dataset is a short annual time series, the ANOVA results are read as descriptive group comparisons rather than as evidence of independent treatment effects. The analysis is exploratory and illustrative, not causal. For the same reason, and because several tests are run on a small sample, p-values are read descriptively and were not treated as confirmatory; no formal multiple-testing correction was applied. The Welch ANOVA, the Games-Howell comparisons, the control regressions, and the Shapiro-Wilk, Levene, Durbin-Watson, and collinearity checks were computed in jamovi [The jamovi project 2024], which runs on R [R Core Team 2020]. The procedures that lie outside the standard jamovi output were computed in R itself, using base functions only: the simultaneous confidence intervals for the Games-Howell comparisons, the per-observation leverage values, externally studentized residuals, Cook's distances and DFFITS, the leave-one-out refits, and the segmented models. Effect sizes (η^2, ω^2) were derived from the sums-of-squares decomposition of the corresponding fixed-effects analysis of variance. The script that reproduces every value reported in this article, together with the input data, is provided as supplementary material.

Because sixteen observations leave the estimates exposed to individual years, the control regression was subjected to influence diagnostics: leverage (hat values), externally studentized residuals, Cook's distance, and DFFITS, assessed against the conventional reference values 2k/n for leverage, 4/n for Cook's distance, and $2\sqrt{(k/n)}$ for DFFITS. A leave-one-out analysis was also run, in which the model was refitted sixteen times with one vintage year omitted in turn, in order to establish whether the result depends on any single year.

To check whether the a priori periodisation is compatible with the data, continuous piecewise-linear (segmented) models were fitted to the logarithm of production and to the logarithm of area, with the calendar year as the running variable. Models with no breakpoint, one breakpoint, and two

breakpoints were compared; breakpoint positions were chosen by exhaustive search over all admissible configurations with a minimum segment length of four years, and the models were compared by the Bayesian information criterion. Because sixteen annual observations do not support reliable inference on break dates, this is reported as a descriptive compatibility check and no confidence intervals for the breakpoints are given.

Assumption checks

Normality was checked with the Shapiro-Wilk test [Shapiro and Wilk 1965] and equal variances with Levene's test [Levene 1960]. The choice of the Welch test and Games-Howell follows from these checks rather than the reverse. The regression was checked for residual normality (Shapiro-Wilk), residual autocorrelation [Durbin and Watson 1950], and collinearity (VIF). With group sizes of 5–6, the power of these tests is limited, so the absence of a significant departure from an assumption is read with caution.

RESULTS

Development stages

For the development-stage factor, the Shapiro-Wilk test showed no significant departure from normality for any of the three dependent variables ($p > 0.4$), while Levene's test indicated unequal variances for production and area; the Welch ANOVA and Games-Howell tests are therefore appropriate. All three variables differ strongly across stages, with very large effect sizes (Table 3).

Table 3. Welch ANOVA across development stages

Dependent variable	Welch F	df1/df2	p	η^2	ω^2
production_m3	34.00	2/5.67	<0.001	0.845	0.812
area_ha	32.84	2/5.95	<0.001	0.856	0.825
log_production	38.36	2/7.81	<0.001	0.863	0.834

Note. Levene p = 0.072 (production_m3), 0.021 (area_ha), 0.106 (log_production); Shapiro-Wilk on residuals p = 0.865, 0.975, 0.492

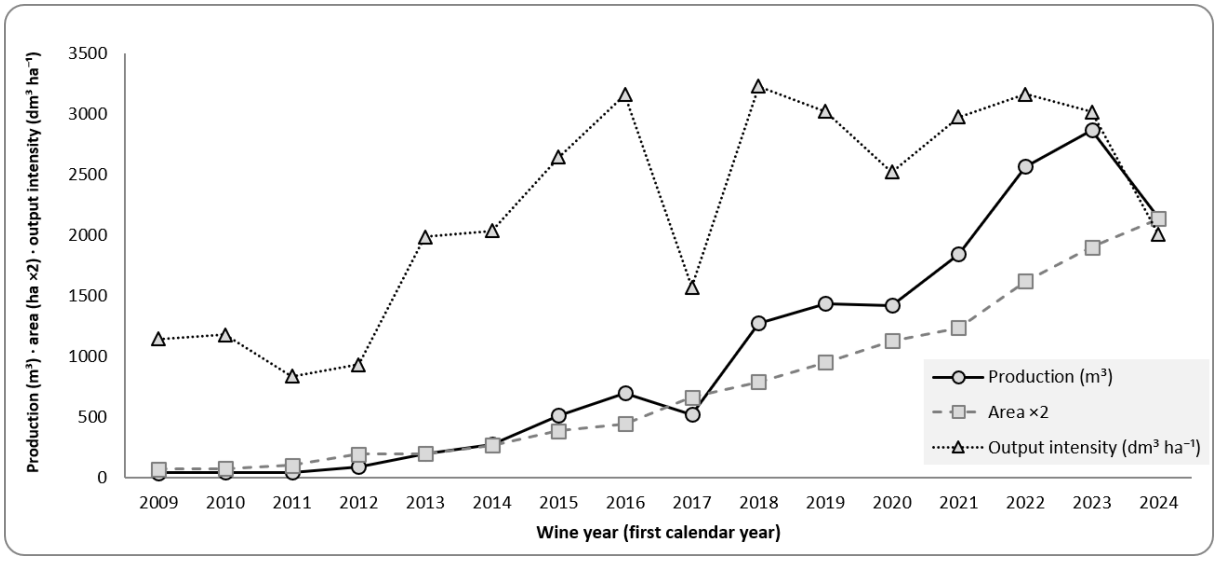
Group means rise sharply across stages. For production, the mean increases from 115.0 m^3 in the early period (95% CI: 11.7, 218.2) to 889.0 m^3 in the transition period (347.4, 1 430.5) and 2 169.4 m^3 in the new period (1457.9, 2880.8). Mean area rises from 75.8 ha to 803.0 ha over the same periods. The Games-Howell test finds every pair of periods significantly different (Table 4).

Table 4. Games-Howell post-hoc for production (production_m3)

Comparison	Difference (m^3)	95% CI	p
Early vs transition	774.0	89.4, 1458.6	0.033
Early vs new	2054.4	1149.8, 2959.0	0.003
Transition vs new	1280.4	346.3, 2214.5	0.012

These differences confirm that the three periods differ on the output indicators, but they do not establish that the sector passed through discrete stages: a variable rising steadily over time would produce significant differences between any such periods. The segmented models give a more informative reading. For the logarithm of production, a model with a single breakpoint at 2018 fits far better than a model with a constant growth rate (residual sum of squares 0.960 against 2.497; BIC –31.15 against –21.40), which confirms that the rate of growth did change during the study period. A two-breakpoint model does not improve on this once the additional parameters are penalised: the best configuration (2012 and 2016) reaches BIC –28.08, and the configuration corresponding to the a priori periodisation (2014 and 2019) reaches BIC –26.34 while reducing the residual sum of squares only from 0.960 to 0.917. The logarithm of area behaves in the same way, with a single breakpoint at 2017 preferred. The data therefore support a change in the growth path but not the specific three-period division, which is retained as an a priori descriptive frame rather than as an estimated structure.

Figure 1. Wine production, vineyard area (×2 for scale), and output intensity (dm³ ha⁻¹), 2009/2010–2024/2025



Thermal-class groups

For output intensity, neither assumption was violated (Shapiro-Wilk p = 0.501; Levene p = 0.796). The Welch ANOVA across thermal groups is nominally significant at the 0.05 level, but borderline and sensitive to the small sample size (Welch F = 4.50; df = 2/8.43; p = 0.047; $\eta^2 = 0.435$; $\omega^2 = 0.334$). Mean output intensity rises from 1510 dm³ ha⁻¹ in normal/cool years (95% CI 643, 2377) to 2515 dm³ ha⁻¹ in warm years (1643, 3388) and 2759 dm³ ha⁻¹ in anomalously/extremely warm years (2144, 3374). The Games-Howell test, however, finds only the coolest-versus-warmest pair significant (Table 5); the other two pairs are not. This pattern argues for caution in reading the omnibus result.

Table 5. Games-Howell post-hoc for output intensity (intensity_dm3_ha)

Comparison	Difference (dm³ ha⁻¹)	95% CI	p
Normal/cool vs warm	1005	−282, 2293	0.128
Normal/cool vs anom./extr. warm	1249	105, 2393	0.034
Warm vs anom./extr. warm	243	−881, 1368	0.807

Figure 2. Output intensity (dm³ ha⁻¹) by thermal-class group. Open circles are years; diamonds are group means

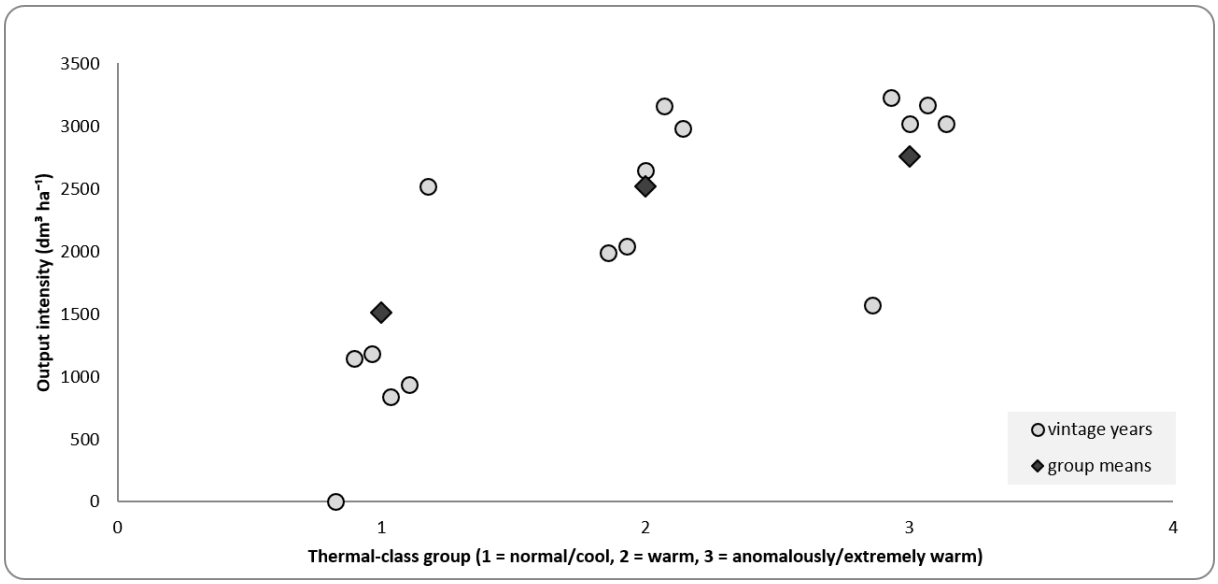
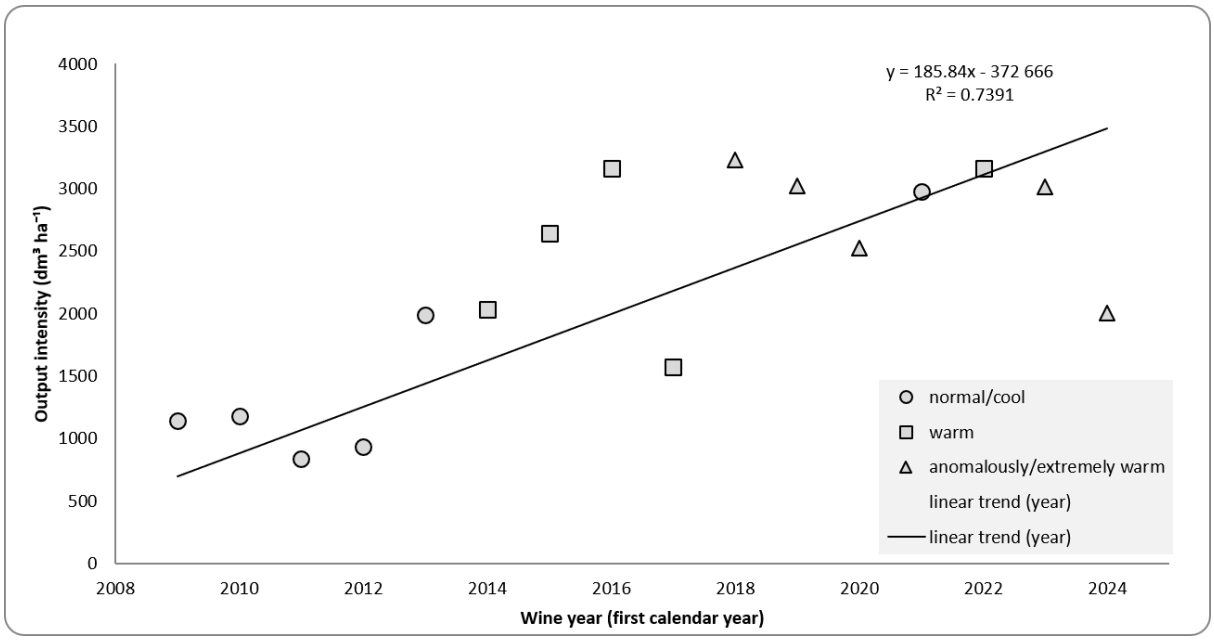


Figure 3. Output intensity (dm³ ha⁻¹) by wine year, with marker shape by thermal group and a linear trend line (year)



Harvest per hectare follows the same pattern as output intensity, with a slightly weaker test statistic. Both assumptions were met (Shapiro-Wilk p = 0.589; Levene p = 0.789) and the Welch ANOVA across thermal groups does not reach the 0.05 level (Welch F = 3.64; df = 2/8.51; p = 0.072; η^2 = 0.401; ω^2 = 0.296). Mean harvest rises from 2.38 Mg ha^{-1} in normal/cool years (95% CI: 1.00, 3.77) to 3.93 Mg ha^{-1} in warm years (2.64, 5.23) and 4.15 Mg ha^{-1} in anomalously/extremely warm years (3.16, 5.13). No Games-Howell pair is significant, the coolest-versus-warmest pair coming closest (difference 1.77 Mg ha^{-1}; 95% CI: –0.06, 3.59; p = 0.058). Because harvest per hectare stands closer to agronomic productivity than output intensity does, it is reported here rather than as supplementary material. The difference between the two omnibus p-values (0.047 and 0.072) should not be read as a substantive

difference between the indicators: with five to six observations per group the two tests are not distinguishable, and the effect sizes are of the same order ($\omega^2 = 0.334$ and 0.296). Figures 2 and 3 show output intensity by thermal group and over time.

Control regression

In the control regression, output intensity is explained jointly by the centred time trend and the centred thermal class, with temp_ord coded as described in Section "Variables". Neither predictor is significant at the 0.05 level (Table 6). The model itself is significant ($R^2 = 0.557$; adjusted $R^2 = 0.489$; $F(2, 13) = 8.17$; $p = 0.005$), residuals are well-behaved (Shapiro-Wilk $p = 0.939$; Durbin-Watson = 1.81), and collinearity is moderate (VIF = 2.17). The key point is substantive collinearity: the correlation between year and thermal class is $r = 0.73$, so the two variables carry much of the same information.

Table 6. Control regression: intensity_dm3_ha ~ year_c + temp_ord_c

Predictor	B	SE	β	t	p	95% CI
intercept	2214.5	155.0	—	14.29	< 0.001	1879.6, 2549.4
year_c	95.6	49.6	0.525	1.93	0.076	−11.5, 202.7
temp_ord_c	83.6	84.2	0.270	0.99	0.339	−98.4, 265.6

The same regression was fitted with harvest per hectare as the dependent variable, as a check that the conclusion does not depend on the choice of indicator, and the pattern is identical: the model is significant ($R^2 = 0.513$; adjusted $R^2 = 0.438$; $F(2, 13) = 6.84$; $p = 0.009$), the residuals are well-behaved (Shapiro-Wilk $p = 0.733$; Durbin-Watson = 1.71), and neither predictor reaches the 0.05 level, with 0.143 Mg ha^{-1} per year for the time trend (SE = 0.079; $p = 0.093$) and 0.115 Mg ha^{-1} per ordinal step for thermal class (SE = 0.134; $p = 0.408$). In short, the simple group comparison shows a thermal-class difference, but the regression shows that this difference is not separable from the time trend. Once the time trend is included, the thermal-class coefficient is no longer statistically significant, for either indicator.

Influence diagnostics and sensitivity

Because sixteen observations leave the model exposed to individual years, the control regression for output intensity was examined for influential observations. One year exceeds the conventional thresholds: 2024/2025, with an externally studentized residual of –2.63, a Cook's distance of 0.469 against the reference value $4/n = 0.250$, and DFFITS of –1.43 against $2\sqrt{(k/n)} = 0.866$. Its leverage (0.228) is unremarkable, so the influence comes from the size of the residual rather than from an extreme position on the predictors. Two further years exceed the leverage threshold $2k/n = 0.375$ without being influential: 2010/2011, which has the highest leverage in the set (0.492) but a Cook's distance of only 0.044, and 2021/2022 (leverage 0.391, Cook's distance 0.219, below the threshold). Both are unusual in their position on the predictors rather than in how well the model fits them. The leverage of 2010/2011 follows directly from the thermal variable: it is the only extremely cool year in the study period and the only one coded temp_ord = 1, so it sits far from the remaining observations on that scale, and the model nevertheless predicts it well. The two years that depart most clearly from a mon-

otone reading of the thermal variable are 2021/2022, classified as normal yet with high output intensity, and 2024/2025, classified as extremely warm yet with the lowest output intensity of the last six years. Diagnostics for all sixteen years are given in Appendix B.

A leave-one-out analysis was run to establish whether the conclusion depends on any single year. Omitting each vintage year in turn, the coefficient on thermal class remains non-significant in all sixteen refits, with p between 0.190 and 0.475 and the point estimate between 62.4 and 140.3 $dm^3\ ha^{-1}$ per ordinal step, against a full-sample estimate of 83.6. The same holds for harvest per hectare, where the thermal coefficient stays non-significant in every refit (p between 0.202 and 0.563). The time trend is less stable: it reaches the 0.05 level when 2024/2025 is omitted (p = 0.010) and falls well below it when 2021/2022 is omitted (p = 0.337). The central conclusion of the study therefore does not rest on any single vintage year, and it is the temporal component rather than the thermal one that is sensitive to individual observations.

Table 7. Summary answers to the research questions

Question	Answer	Content
RQ1	Yes	The three a priori periods differ strongly on production, area, and log-production (p < 0.001); segmented models confirm a change in the growth path but favour one breakpoint, not two
RQ2	Partly	Output intensity differs across thermal groups, but the omnibus result is borderline (p = 0.047) and only one pair is significant; harvest per hectare shows the same ordering without reaching the 0.05 level (p = 0.072)
RQ3	Not detected	After controlling for the time trend, the thermal-class coefficient is not significant for either indicator; the result is stable across all leave-one-out refits

DISCUSSION

RQ1: development stages and sector indicators

Development stages differ strongly and significantly on all three output indicators, with very large effect sizes ($\omega^2 \approx 0.81–0.83$) and significant differences between every pair of periods. This gives a quantitative description of a process that the Polish literature has so far described qualitatively [Brodnicka 2024]. As noted in the results, the significant pairwise differences are consistent with a phased reading of growth but do not establish step-wise change; a monotonic trend over arbitrary periods would produce similar differences.

RQ2: output intensity and thermal class

Output intensity rises from cooler to warmer groups, and the omnibus test is nominally significant. The result should not be over-read. It is borderline (p = 0.047) and sensitive to the small sample, and the Games-Howell test finds only the coolest-versus-warmest pair significant, with the adjacent pairs not significant. Harvest per hectare, which stands closer to agronomic productivity, gives the same ordering of group means and a comparable effect size but does not cross the conventional threshold. The two indicators should be read as telling one story rather than two: at this sample size the position of a p-value relative to 0.05 carries little information, and what the data show is, at most, a weak group difference at the extremes, not a graded thermal response.

RQ3: does the thermal difference survive control for time?

Once the time trend is added, the thermal-class coefficient is no longer significant, because year and thermal class are strongly correlated (r = 0.73) and carry much the same information. The results are consistent with RH3, but they should not be read as proof of no thermal effect. A non-significant coefficient bounds neither the sign nor the size of a possible effect: the 95% confidence interval for the thermal-class coefficient runs from –98 to 266 $dm^3\ ha^{-1}$ per ordinal step, which is wide enough to include differences that would matter agronomically. What the model establishes is a limit on identification, not a null result. The distinction between "no effect" and "effects that cannot be separated" is central to the study.

The attribution problem

This pattern is a local case of the attribution problem in the climate-and-wine literature. Schultz [2016] shows that linking output changes to temperature is hard when growing practices, plant material, and goals change in parallel; the German yield series is the clearest example [Bock et al. 2013]. In Poland, the role of "parallel change" is played by the whole process of sector development, captured here by the time variable. When that variable is added to the model, the separate thermal-class term loses significance. The reading is also bounded by the nature of the indicator: output intensity is sector-level output per hectare, not agronomic yield or quality, so even a clear positive link would not justify a claim about the economic value of warming. The clear decline in output intensity in the extremely warm 2024/2025 season (2005 $dm^3\ ha^{-1}$), below the milder 2022/2023 and 2023/2024 seasons (above 3000 $dm^3\ ha^{-1}$), is a reminder that within-season events not captured by an annual class can drive output.

Limitations

The limitations are substantial and bound every conclusion. The sample is very small (n = 16). The data are aggregated at the national level and are an annual time series. The thermal variable is a coarse, year-level, national proxy, not a growing-season climate measure. There are no regional data, no data on vine age, and no data on varietal structure. There are no data on precipitation, drought, frost, or water balance, and no quality or price data. The output-intensity indicator is not pure agronomic yield. Because of the small sample, the absence of significance does not prove the absence of an effect; the regression result is a statement that effects cannot be separated in this dataset, not that no effect exists. The collinearity between time and thermal class (r = 0.73) cannot be resolved with national, annual data, regardless of the model. The influence diagnostics add one further qualification: a single vintage year, 2024/2025, exceeds the conventional thresholds for influence, two further years exceed the leverage threshold without being influential, and the significance of the time trend depends on whether 2024/2025 and 2021/2022 are included. The thermal coefficient is stable across all leave-one-out refits, so the central conclusion does not rest on an individual year, but the estimate of the time trend itself should be treated as provisional.

Future research

A credible test of the role of thermal conditions would require: a panel of voivodeships or individual vineyards; growing-season indices (SAT, GDD, the Huglin index) for April-October; the number of days with May frosts; total precipitation and a water-balance measure; data on vine age and varietal

structure; wine-quality indicators; prices or production value; and panel or mixed-effects models. Spatial variation across a panel would help separate time effects from thermal effects, which the present national series cannot do.

Field-experimental work on Polish and Czech vineyards illustrates what such designs can deliver. Using a randomised block design with fixed cultivars across two contrasting climatic zones, Kapłan et al. [2026] show that the growing site significantly differentiates bunch and stem biometry, while Kapłan et al. [2025] and Maj et al. [2024] report the corresponding differences in the energy properties of post-production vineyard biomass. Such designs identify a thermal effect precisely because cultivar, management, and plot are held constant, which is the control that a national annual series cannot provide. They also indicate that vintage-year conditions act on the whole biomass of the vine and not only on the volume of wine, so that indicators derived from post-production material may in time offer an additional and independent window on the same question.

CONCLUSIONS

Three conclusions follow. First, the output indicators of the Polish wine sector differ strongly across the three a priori periods, with significant differences between every pair (RQ1); the segmented models confirm that the growth path changed during the study period, although they identify a single change rather than the two implied by the three-period division, so that the periodisation should be read as a descriptive frame and not as an estimated structure. Second, both output intensity and harvest per hectare are higher in warmer thermal groups, but the difference is weak: for output intensity the omnibus test is borderline and only the coolest-versus-warmest pair is significant, and for harvest per hectare no pair reaches the 0.05 level (RQ2). Third, the thermal-class difference does not survive control for the time trend, for either indicator, because time and thermal class are strongly correlated (RQ3). This is a statement about what can be identified in these data, not a finding that thermal conditions are irrelevant.

The study contributes by illustrating the methodological difficulty of separating sectoral development from thermal conditions in a young, rapidly expanding wine sector. In these data, an apparent thermal difference disappears once the development trend is taken into account. The results should be read as an exploratory, well-documented case, not as evidence of a causal effect of thermal conditions on Polish wine production. The honest message is that, with national annual data, the two explanations cannot be told apart, and that separating them will require finer, panel-level data.

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