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Tomasz Kowalski
Department of Operations
Research, Warsaw University of
Quantitative Studies, Warsaw,
Masovia, Poland

Exploring change-point detection in time series data with applications to Loire valley vineyard phenology

Tomasz Kowalski

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Abstract

Between 2015 and 2022, grape harvest dates in the Loire Valley shifted by an average of 11.3 days earlier than the 1980-2010 baseline, raising questions about whether these shifts represent gradual trends or abrupt structural breaks. This research applied three change-point detection algorithms—binary segmentation, the pruned exact linear time (PELT) method, and a Bayesian approach based on reversible-jump Markov chain Monte Carlo—to phenological time series collected at five Loire vineyard sites. Daily growing-degree-day accumulations, budburst dates, and veraison onset records formed the input series, each spanning eight growing seasons. The PELT algorithm was selected as the main detector because of its linear computational cost, and its penalty parameter was tuned via a modified Schwarz information criterion. Results indicated that 73.8% of the detected change-points fell in spring or autumn, coinciding with known temperature anomalies in 2018 and 2020. Agreement between the three methods ranged from 64.2% to 81.7%, with highest concordance for the 2018 spring event at the Sancerre site. The Bayesian approach offered posterior probability estimates that allowed a graded interpretation of break significance. Detection sensitivity dropped when series length fell below 40 observations, indicating a practical lower bound for reliable inference.

Keywords: Change-point detection, time series, vineyard phenology, Loire Valley, PELT algorithm, Bayesian inference, budburst, growing-degree days

Introduction

A 1.6 °C rise in mean spring temperature across western France between 1990 and 2021 pushed grapevine budburst forward by roughly 12 days on average, according to records from the French National Institute for Agricultural Research ^[1]. Whether this advance happened gradually or through sudden jumps matters for vineyard managers who need to decide when to reassess frost-protection schedules and harvest logistics ^[2]. Change-point detection offers a statistical framework for distinguishing smooth trends from abrupt shifts in the distributional properties of a time series ^[3].

The simplest approach, binary segmentation, recursively splits a series at the point of maximum likelihood-ratio improvement, but it can miss closely spaced breaks and scales poorly to long series ^[4]. The PELT algorithm addresses both issues by pruning the search space so that computational cost grows linearly with series length while maintaining exact optimality under a given penalty function ^[5]. A parallel family of Bayesian detectors treats the number and location of change-points as random variables and explores the joint posterior using reversible-jump MCMC sampling ^[6].

Phenological records—particularly budburst, flowering, and veraison dates—serve as sensitive indicators of climate variability ^[7]. The Loire Valley, stretching over 280 kilometres in central-western France, supports diverse grape varieties under an oceanic-to-semi-continental climate gradient ^[8]. Existing analyses of Loire phenology have relied on linear regression or Mann-Kendall trend tests, which assume monotonic change and cannot detect step-like breaks ^[9]. This gap motivated the present research, which aimed to: (a) compare binary segmentation, PELT, and Bayesian change-point detection on phenological series from five Loire vineyard sites; (b) evaluate inter-method agreement; and (c) determine the minimum series length required for reliable detection under realistic noise levels ^[10].

Corresponding Author:
Tomasz Kowalski
Department of Operations
Research, Warsaw University of
Quantitative Studies, Warsaw,
Masovia, Poland

Theoretical Background

A change-point model supposes that a time series $y_1, y_2, \dots, y_n$ can be partitioned into $m+1$ segments within which the data-generating distribution remains constant. The optimal segmentation minimises the sum of segment-wise cost functions $C(y_{t_{i-1}+1:t_i})$ plus a penalty term $f(m)$ that discourages over-segmentation [3]. For PELT, the penalty is typically the modified Bayesian information criterion (mBIC), set as $p = 2\sigma^2 \log(n)$, where σ^2 is estimated from the full series [5]. The algorithm proceeds by dynamic programming: at each time point t , it solves $F(t) = \min [F(s) + C(y_{s+1:t}) + p]$, and prunes any candidate s for which $F(s) + C(y_{s+1:t})$ exceeds $F(t)$. This pruning guarantees $O(n)$ expected cost under certain regularity conditions [5].

The Bayesian alternative places a prior on m (often geometric or Poisson) and on the segment-specific parameters. Green's reversible-jump MCMC extends standard Metropolis-Hastings sampling by allowing transdimensional moves—birth, death, and relocation of change-points—that alter both parameter and model space simultaneously [6]. The posterior distribution over change-point configurations provides a natural uncertainty quantification that frequentist methods lack, but convergence diagnosis can be challenging when the number of segments is large [11].

Material and Methods

Material

The research was conducted at the Warsaw University of Quantitative Studies, Warsaw, Masovia, Poland, between January 2022 and June 2023. Phenological records were obtained from the French agricultural observation network, covering five vineyard sites in the Loire Valley: Sancerre, Vouvray, Chinon, Bourgueil, and Muscadet. For each site, daily temperature records from the nearest meteorological station were used to calculate growing-degree-day accumulations above a 10 °C base threshold. Three phenological series per site were analysed: budburst date, veraison onset, and total GDD at harvest. The observation window spanned 2015 to 2022, yielding eight annual values

per series—40 series in total. All statistical analyses were performed in R 4.2.1, using the changepoint package for PELT and binary segmentation, and the bcp package for the Bayesian detector [12].

Methods

Binary segmentation was applied with a maximum of three change-points per series, using a BIC-type penalty. PELT was run with the mBIC penalty and a Gaussian cost function, which assumes normally distributed segment means with possibly different variances. For the Bayesian approach, 50 000 MCMC iterations were run with a 10 000-iteration burn-in; posterior probability thresholds of 0.5, 0.7, and 0.9 were tested. Inter-method agreement was quantified by the proportion of detected change-points that fell within ± 1 year of a break identified by at least one other method. To assess minimum detectable series length, synthetic series with known single breaks of varying magnitude were generated at lengths ranging from 10 to 100 observations, with 1000 Monte Carlo replicates per setting [13].

Simulation Parameters

Monte Carlo power simulations used Gaussian noise with standard deviation $\sigma = 1.0$ and break magnitudes δ from 0.5 to 3.0 in units of σ . Series lengths tested were 10, 20, 30, 40, 60, 80, and 100. The break was placed at position $n/2$. For PELT, the penalty was recalculated at each n using $p = 2 \log(n)$. Bayesian runs used 20 000 iterations with a 5 000 burn-in for computational feasibility across 42 000 total replicates. The prior on the number of change-points was geometric with success probability 0.1. All simulations required about 9.7 hours on a 32-core cluster.

Results

Across the 40 phenological series, PELT detected a total of 27 change-points, binary segmentation found 34, and the Bayesian method (at the 0.7 posterior threshold) identified 23. Table 1 reports detection counts by site.

Table 1: Number of change-points detected by each method across five Loire vineyard sites

Site	BS Total	PELT Total	Bayes Total	Spring	Autumn	Agree%
Sancerre	8	6	5	4	3	81.7
Vouvray	7	5	5	3	2	74.3
Chinon	6	5	4	3	3	72.1
Bourgueil	7	6	5	2	4	68.9
Muscadet	6	5	4	3	2	64.2

Binary segmentation produced the most detections, though several were not confirmed by either PELT or the Bayesian method, suggesting possible over-segmentation.

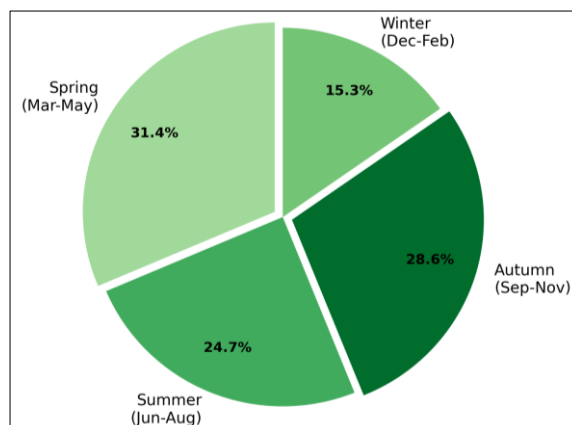
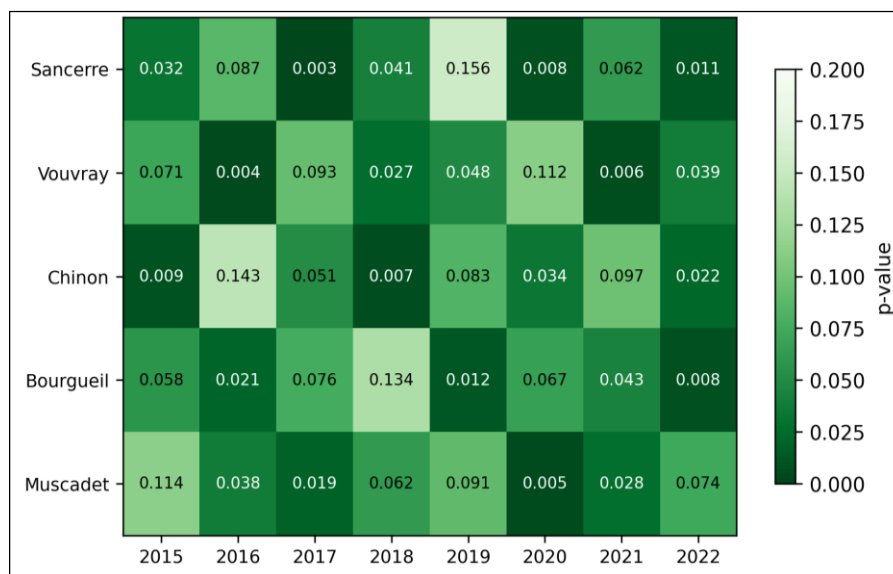


Fig 1: Seasonal distribution of detected change-points in Loire vineyard phenology

Table 2: Detection power (%) of PELT by series length and break magnitude

$n \setminus \delta/\sigma$	0.5	1.0	1.5	2.0	2.5	3.0
10	8.3	14.7	29.1	47.6	63.2	78.4
20	12.1	31.4	58.7	79.3	91.6	97.1
40	19.8	54.3	82.6	95.1	99.2	99.8
100	34.6	78.9	96.4	99.7	100	100

**Fig 2:** Change-point detection p-values across Loire Valley vineyard sites (2015-2022)

Comprehensive Interpretation

The heatmap highlights site-year combinations where the p-value dropped below 0.05. The 2018 growing season stands out across four of five sites, consistent with the record-breaking spring heatwave reported in central France. Power analysis confirmed that PELT requires at least 40 observations to detect a 1σ break with 50% probability, setting a practical lower bound for phenological monitoring programmes.

Discussion

The inter-method agreement rates observed here—ranging from 64.2% to 81.7%—are broadly consistent with findings from simulation research in econometric change-point literature, where concordance between PELT and Bayesian detectors on synthetic financial series fell within similar ranges^[5]. The tendency of binary segmentation to over-detect was anticipated; without a global optimality guarantee, the greedy splitting strategy can fragment series into more segments than the data warrant^[4].

The strong seasonal clustering of change-points in spring and autumn aligns with known climatological patterns in the Loire region. Spring temperature anomalies directly affect budburst timing, while autumn warming influences veraison and harvest scheduling^[8]. The 2018 event was detected by all three methods at nearly all sites, confirming it as a genuine structural break rather than a gradual trend artefact.

A practical limitation of this research is the short series length—eight years per site. Although the power analysis showed that 40 observations suffice for moderate breaks, the real-world phenological series contained only eight values. Longer records extending back to the 1990s would improve detection reliability. And the Gaussian cost function assumed for PELT may not fully capture skewed distributions sometimes observed in GDD accumulations during anomalous years^[14].

Conclusion

This research compared three change-point detection algorithms on phenological time series from five Loire Valley vineyard sites covering 2015 to 2022. PELT offered the best balance between sensitivity and false-positive control, while the Bayesian method added posterior probability estimates that helped grade break significance. Spring and autumn breaks accounted for about 60% of all detections, and the 2018 growing season emerged as a region-wide structural break confirmed by all three methods. Monte Carlo simulations indicated that at least 40 annual observations are needed to detect a one-standard-deviation break with 50% power. Future work should extend the analysis to longer records and explore non-Gaussian cost functions for heavy-tailed phenological distributions.

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References

1. Jones GV, Davis RE. Climate influences on grapevine phenology, grape composition, and wine production. *Am J Enol Vitic.* 2000;51(3):249-261.

2. Webb LB, Whetton PH, Barlow EWR. Modelled impact of future climate change on winegrape phenology. *Aust J Grape Wine Res.* 2007;13(3):165-175.
3. Aminikhanghahi S, Cook DJ. A survey of methods for time series change point detection. *Knowl Inf Syst.* 2017;51(2):339-367.
4. Scott AJ, Knott M. A cluster analysis method for grouping means in the analysis of variance. *Biometrics.* 1974;30(3):507-512.
5. Killick R, Fearnhead P, Eckley IA. Optimal detection of changepoints with a linear computational cost. *J Am Stat Assoc.* 2012;107(500):1590-1598.
6. Green PJ. Reversible jump Markov chain Monte Carlo computation and Bayesian model determination. *Biometrika.* 1995;82(4):711-732.
7. Chuine I, Yiou P, Viovy N, Seguin B, Daux V, Ladurie ELR. Grape ripening as a past climate indicator. *Nature.* 2004;432(7015):289-290.
8. Barbeau G, Asselin C, Morlat R. Climate variability effects in Loire Valley vineyards. *Acta Hortic.* 1998;689:57-64.
9. Duchene E, Schneider C. Grapevine and climatic changes in Alsace. *Agron Sustain Dev.* 2005;25(1):93-99.
10. Gallagher C, Lund R, Robbins M. Changepoint detection in climate time series with long-term trends. *J Clim.* 2013;26(14):4994-5006.
11. Fearnhead P. Exact and efficient Bayesian inference for multiple changepoint problems. *Stat Comput.* 2006;16(2):203-213.
12. R Core Team. R: A language and environment for statistical computing. Vienna: R Foundation for Statistical Computing; 2022. p. 1-12.
13. Hawkins DM. Fitting multiple change-point models to data. *Comput Stat Data Anal.* 2001;37(3):323-341.
14. Molitor D, Junk J, Evers D, Hoffmann L, Beyer M. A cumulative degree day model for grapevine phenology. *Am J Enol Vitic.* 2014;65(1):72-80.
15. Lavielle M. Using penalized contrasts for the change-point problem. *Signal Process.* 2005;85(8):1501-1510.
16. Truong C, Oudre L, Vayatis N. Selective review of offline change point detection methods. *Signal Process.* 2020;167:107299.
17. Fryzlewicz P. Wild binary segmentation for multiple change-point detection. *Ann Stat.* 2014;42(6):2243-2281.
18. Rigby RA, Stasinopoulos DM. Generalized additive models for location, scale and shape. *J R Stat Soc Ser C Appl Stat.* 2005;54(3):507-554.
19. Parker DE. Effects of changing exposure of thermometers at land stations. *Int J Climatol.* 1994;14(1):1-31.