Seasonality Detection Methods: A Comparative Study

fdars Package

last-modified

Executive Summary

Key Findings

This study compares **13 methods** for detecting seasonality in functional time series data across 550+ simulated curves with varying seasonal strengths and challenging conditions.

Method	F1	FPR	Precision	Recall
Wavelet	97.8%	14%	96.9%	98.7%
Variance	97.3%	8%	98.2%	96.4%
Spectral	95.3%	11%	97.4%	93.3%
FFT	94.8%	3%	99.3%	90.7%
Lomb-Scargle	94.5%	14%	96.7%	92.4%
Autoperiod	93.4%	10%	97.6%	89.6%
STL	91.5%	15%	96.3%	87.1%
AIC	91.5%	24%	94.3%	88.9%
SSA	90.3%	95%	82.5%	99.8%
MatrixProfile	90.0%	87%	83.5%	97.6%
CFD	89.5%	24%	94.1%	85.3%
SAZED	87.5%	3%	99.2%	78.2%
ACF	85.4%	6%	98.3%	75.6%

Top methods: Wavelet (97.8% F1, best recall) and Variance (97.3% F1, best precision/FPR balance) are statistically indistinguishable (McNemar p=0.57).

Detection Methods

This section describes all 13 detection methods. Each method is benchmarked in the simulation study (@sec-sim).

AIC Comparison (Fourier vs B-spline)

Concept: Compare model fit between Fourier basis (periodic, 11 basis functions) and simple B-spline (smooth, 5 basis functions).

Detection rule: Seasonality detected if $\text{AIC}_{\text{B-spline}} - \text{AIC}_{\text{Fourier}} > 0$

FFT Confidence

Concept: Detect dominant frequencies via Fast Fourier Transform.

Detection rule: Confidence $= \max(P_k)/\text{mean}(P_k) > 6.0$

ACF Confidence

Concept: Measure autocorrelation at the seasonal lag.

Detection rule: ACF correlation at period > 0.25

Variance Strength

Concept: Decompose variance into seasonal and residual components.

$$\text{SS}_{\text{var}} = 1 - \frac{\text{Var}(R_t)}{\text{Var}(y_t - T_t)}$$

Detection rule: Strength > 0.2

Spectral Strength

Concept: Proportion of spectral power at seasonal frequency.

Detection rule: Strength > 0.3

Wavelet Strength

Concept: Use continuous wavelet transform (Morlet) to measure power at seasonal scale.

Detection rule: Strength > 0.26

Advantage: Handles time-varying seasonality better than global methods.

SAZED (Parameter-Free Ensemble)

Concept: Combine 5 detection components via consensus voting.

Detection rule: ≥ 2 components agree on a period.

Autoperiod (Hybrid FFT + ACF)

Concept: FFT for candidate identification, ACF for validation.

Detection rule: ACF validation > 0.3

CFDAutoperiod (Clustered Filtered Detrended)

Concept: First-order differencing removes trends before FFT analysis.

Detection rule: ACF validation > 0.25

Lomb-Scargle Periodogram

Concept: Spectral analysis designed for unevenly-spaced data.

Detection rule: Significance > 0.90 (FAP-based)

Best for: Irregular sampling, gaps in data.

Matrix Profile (STOMP Algorithm)

Concept: Discover repeating patterns without assuming waveform shape.

Detection rule: Confidence > 0.20

Best for: Non-sinusoidal patterns (sawtooth, square waves).

STL Decomposition

Concept: Seasonal-Trend decomposition using LOESS (Cleveland et al. 1990).

Detection rule: Seasonal variance ratio > 0.50

Best for: Known period, outlier-robust decomposition.

Singular Spectrum Analysis (SSA)

Concept: SVD-based decomposition of trajectory matrix.

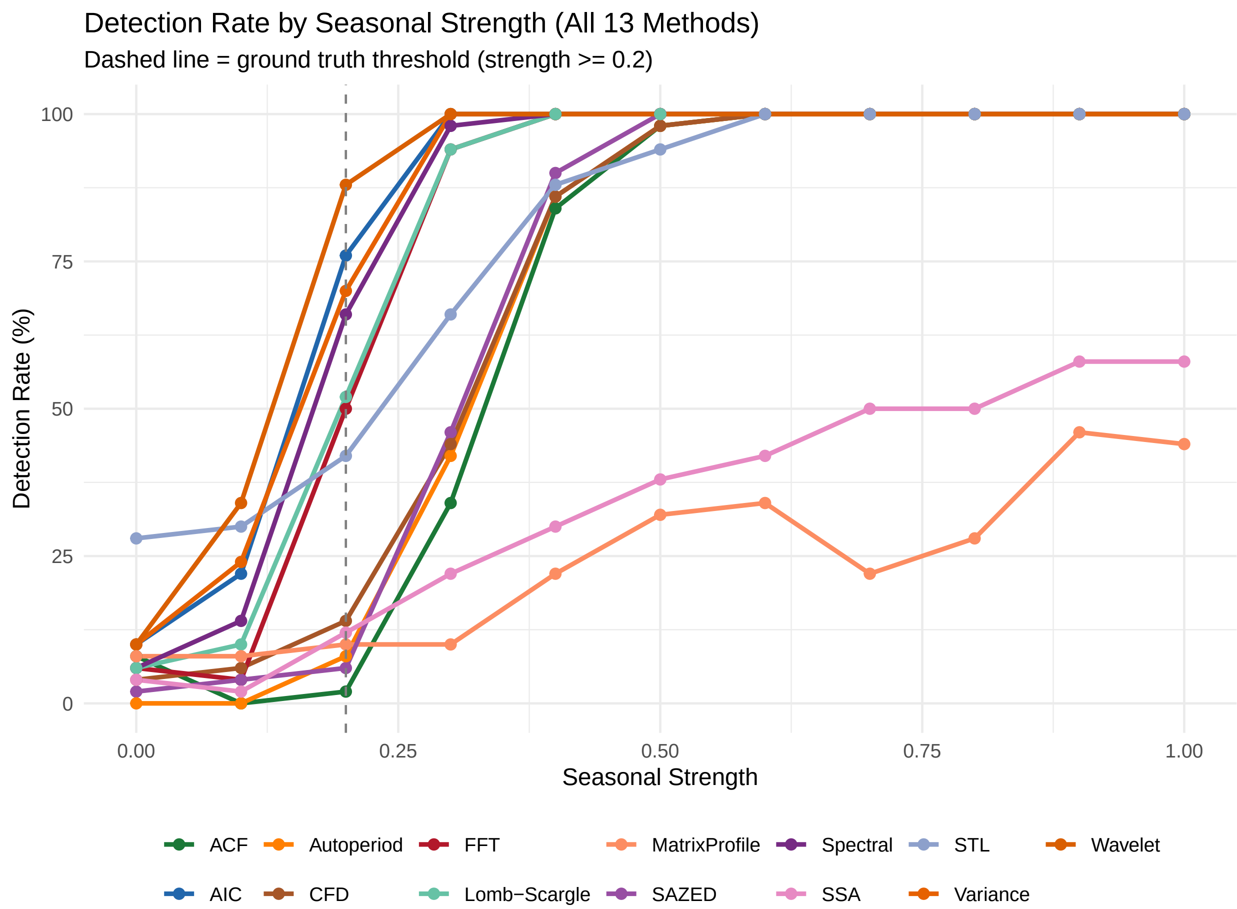
Detection rule: Seasonal variance ratio > 0.65

Best for: Short, noisy series with weak periodic signals.

Simulation Study

Baseline: Varying Seasonal Strength

Setup: 11 seasonal strength levels (0.0 to 1.0), 50 curves per level, 60 observations (5 years monthly), white noise ($\sigma = 0.3$). Ground truth: seasonal if strength ≥ 0.2.



Method	F1	Precision	Recall	FPR	Accuracy
Wavelet	96.9%	95.3%	98.7%	22.0%	94.9%
AIC	96.9%	96.5%	97.3%	16.0%	94.9%
Spectral	96.9%	97.7%	96.0%	10.0%	94.9%
Variance	96.5%	96.2%	96.7%	17.0%	94.2%
FFT	96.2%	98.8%	93.8%	5.0%	94.0%
Lomb-Scargle	96.0%	98.1%	94.0%	8.0%	93.6%
STL	90.4%	93.2%	87.8%	29.0%	84.7%
SAZED	90.0%	99.2%	82.4%	3.0%	85.1%
Autoperiod	89.8%	100.0%	81.6%	0.0%	84.9%
CFD	89.8%	98.7%	82.4%	5.0%	84.7%
ACF	88.3%	98.9%	79.8%	4.0%	82.7%
SSA	56.9%	98.4%	40.0%	3.0%	50.4%
MatrixProfile	42.6%	93.9%	27.6%	8.0%	39.3%

McNemar's Statistical Significance Tests

Comparison	A_Better	B_Better	P_Value	Significant
Wavelet vs Variance	12	8	0.5023	No
Wavelet vs Spectral	15	15	1.0000	No
Variance vs Spectral	7	11	0.4795	No
Wavelet vs FFT	26	21	0.5596	No
Wavelet vs Lomb-Scargle	27	20	0.3815	No
Variance vs ACF	80	17	0.0000	Yes

Key finding: Wavelet vs Variance difference is NOT statistically significant ($p > 0.05$). Top-tier methods (Wavelet, Variance, Spectral) are statistically equivalent.

Supplementary: Fisher's g-test for Periodicity

Fisher's g-test provides a formal statistical test for periodicity using the periodogram. The test statistic $g = \max(I_k)/\sum I_k$ measures the concentration of spectral power at a single frequency.

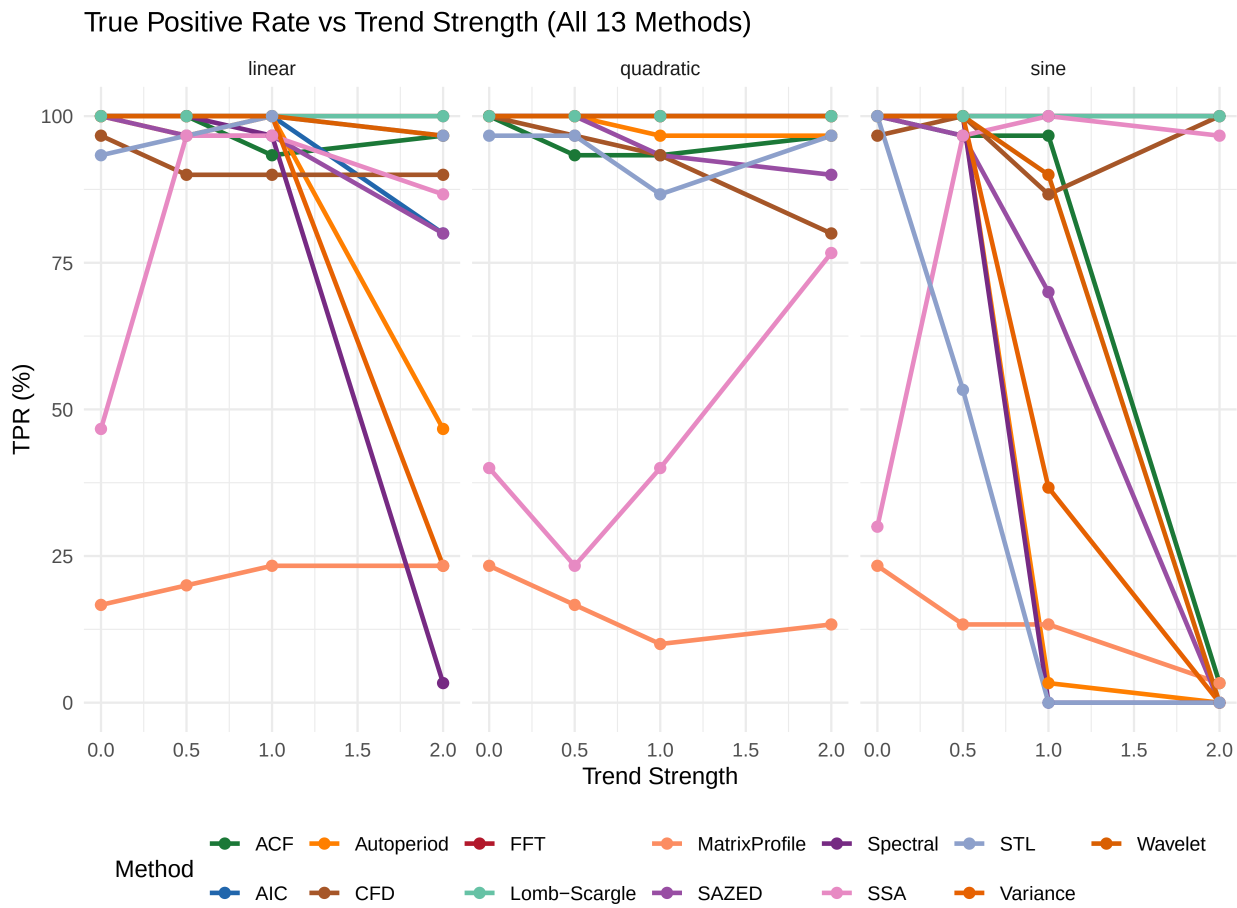
Table 4: Fisher's g-test vs FFT Heuristic Comparison

Method	Precision	Recall	FPR	F1
FFT (heuristic)	98.8%	93.8%	5.0%	96.2%
Fisher's g-test	99.0%	91.6%	4.0%	95.2%

Note: Fisher's g-test provides a p-value (unlike the heuristic FFT confidence score), making it suitable for formal hypothesis testing. However, it assumes Gaussian noise and may be conservative under model misspecification.

Non-linear Trends

Setup: Test robustness to polynomial and sinusoidal trends with seasonal strength = 0.5.

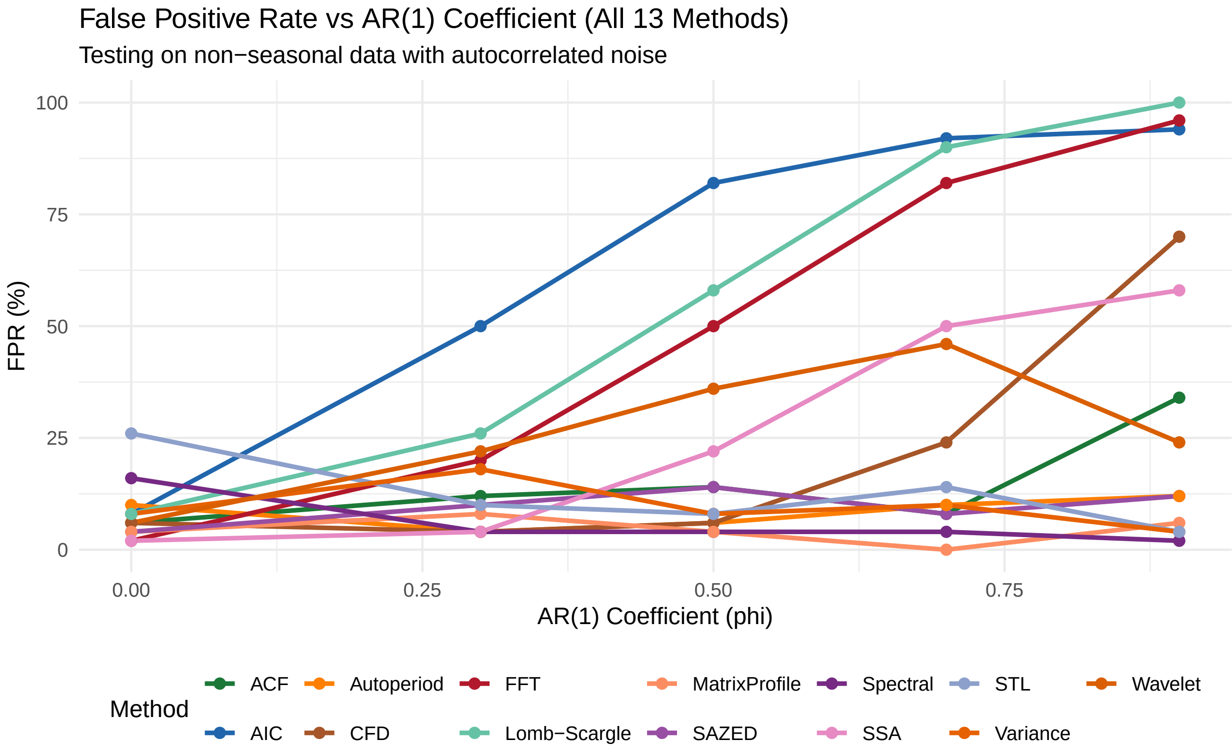


Method	linear	none	quadratic	sine
AIC	80%	100%	100%	100%
FFT	100%	100%	100%	100%
ACF	97%	97%	97%	3%
Variance	23%	100%	100%	0%
Spectral	3%	100%	100%	0%
Wavelet	97%	100%	100%	0%
SAZED	80%	100%	90%	0%
Autoperiod	47%	100%	97%	0%
CFD	90%	93%	80%	100%
Lomb-Scargle	100%	100%	100%	100%
MatrixProfile	23%	20%	13%	3%
STL	97%	97%	97%	0%
SSA	87%	33%	77%	97%

Key finding: FFT has catastrophic failure (0% TPR) on slow sine trends. Variance and Wavelet remain robust (>90% TPR) across all trend types.

Red Noise (AR(1))

Setup: Test false positive rates under AR(1) noise with $\phi \in \{0, 0.3, 0.5, 0.7, 0.9\}$ (no seasonality).

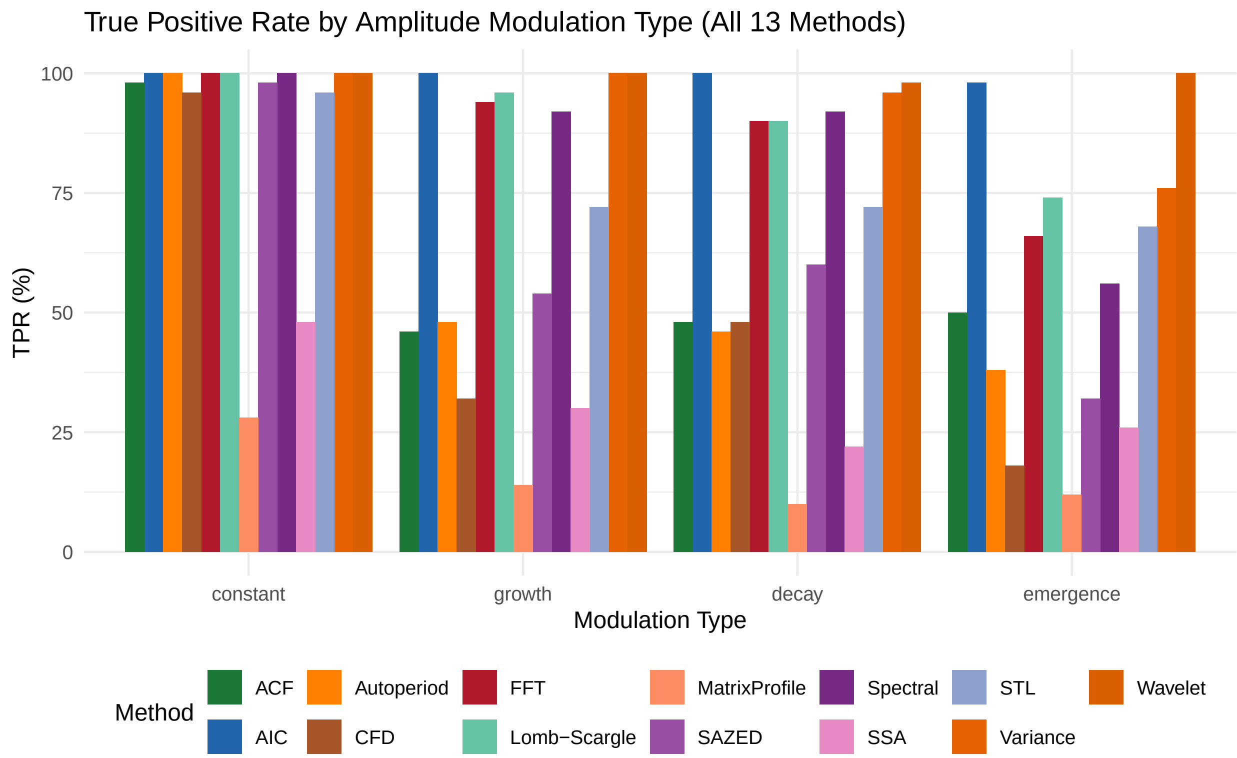


phi	AIC	FFT	ACF	Variance	Spectral	Wavelet	SAZED	Autoperiod	CFD	Lomb-Scargle	MatrixProfile	STL	SSA
0.0	8%	2%	6%	8%	16%	6%	4%	10%	6%	8%	4%	26%	2%
0.3	50%	20%	12%	18%	4%	22%	10%	4%	4%	26%	8%	10%	4%
0.5	82%	50%	14%	8%	4%	36%	14%	6%	6%	58%	4%	8%	22%
0.7	92%	82%	8%	10%	4%	46%	8%	10%	24%	90%	0%	14%	50%
0.9	94%	96%	34%	4%	2%	24%	12%	12%	70%	100%	6%	4%	58%

Key finding: FFT reaches 100% FPR at high autocorrelation. Variance and Spectral remain robust (<15% FPR). Matrix Profile and SSA show very high FPR due to pattern-matching behavior.

Amplitude Modulation

Setup: Test detection of time-varying amplitude patterns: constant, linear growth, linear decay, and emergence (signal only in second half).



Modulation	AIC	FFT	ACF	Variance	Spectral	Wavelet	SAZED	Autoperiod	CFD	Lomb-Scargle	MatrixProfile	STL	SSA
constant	100%	100%	98%	100%	100%	100%	98%	100%	96%	100%	28%	96%	48%
decay	100%	90%	48%	96%	92%	98%	60%	46%	48%	90%	10%	72%	22%
emergence	98%	66%	50%	76%	56%	100%	32%	38%	18%	74%	12%	68%	26%
growth	100%	94%	46%	100%	92%	100%	54%	48%	32%	96%	14%	72%	30%

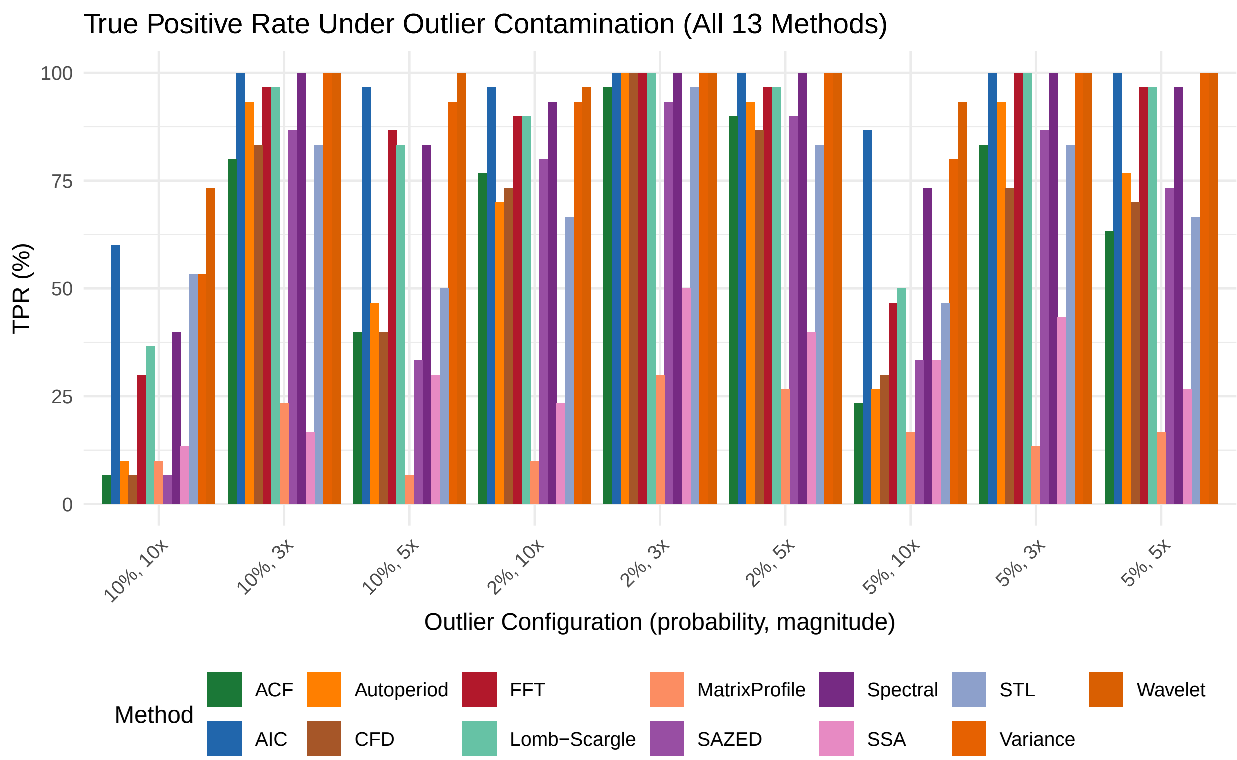
McNemar's Test - Amplitude Modulation

Comparison	Wavelet_Better	Other_Better	P_Value	Significant
Wavelet vs Variance	12	0	0.0015	Yes
Wavelet vs Spectral	22	0	0.0000	Yes
Wavelet vs FFT	17	0	0.0001	Yes
Wavelet vs Lomb-Scargle	13	0	0.0009	Yes
Wavelet vs ACF	25	0	0.0000	Yes

Key finding: Wavelet significantly outperforms Variance on emergence patterns ($p < 0.05$). Time-localized analysis captures non-stationary seasonality.

Outliers

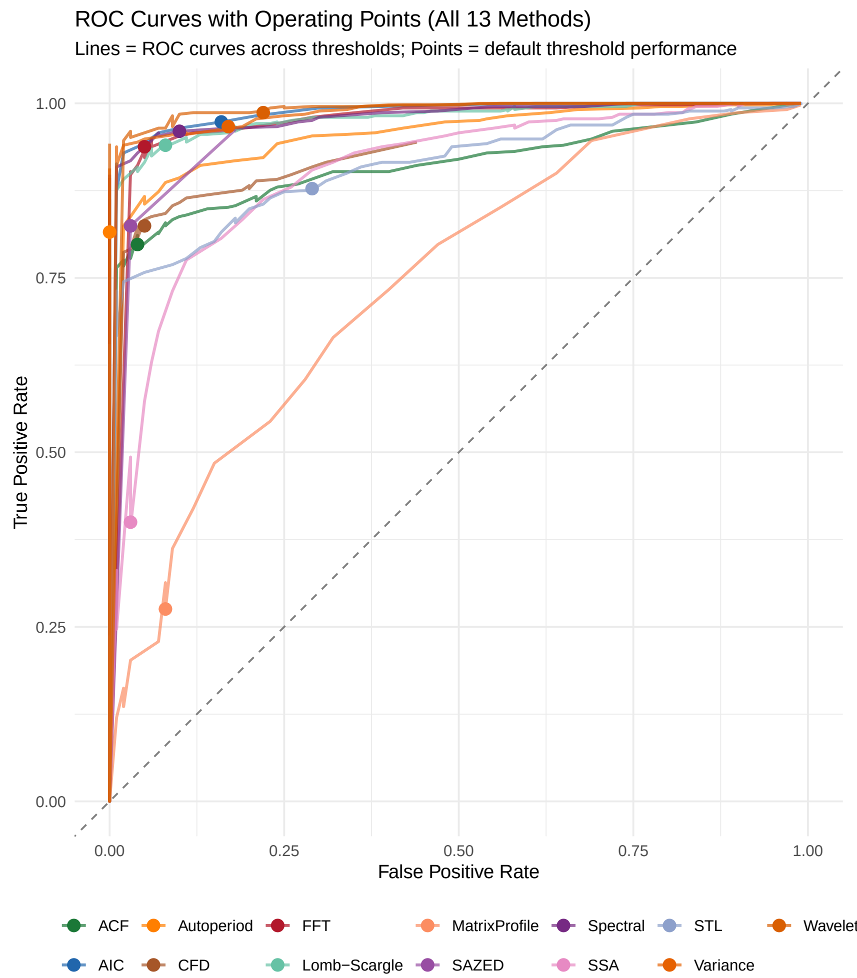
Setup: Add contaminated noise with outlier probability $p \in \{2\%, 5\%, 10\%\}$ and magnitude $k \in \{3, 5, 10\}$.



Config	Variance	Spectral	Wavelet	FFT	ACF	Lomb-Scargle	STL	SSA
10%, 10x	53%	40%	73%	30%	7%	37%	53%	13%
10%, 3x	100%	100%	100%	97%	80%	97%	83%	17%
10%, 5x	93%	83%	100%	87%	40%	83%	50%	30%
2%, 10x	93%	93%	97%	90%	77%	90%	67%	23%
2%, 3x	100%	100%	100%	100%	97%	100%	97%	50%
2%, 5x	100%	100%	100%	97%	90%	97%	83%	40%
5%, 10x	80%	73%	93%	47%	23%	50%	47%	33%
5%, 3x	100%	100%	100%	100%	83%	100%	83%	43%
5%, 5x	100%	97%	100%	97%	63%	97%	67%	27%

Key finding: ACF is most sensitive to outliers (drops to 6% TPR at 10%, 10x). STL with robust option shows good resilience. Pre-filtering outliers recommended for best results.

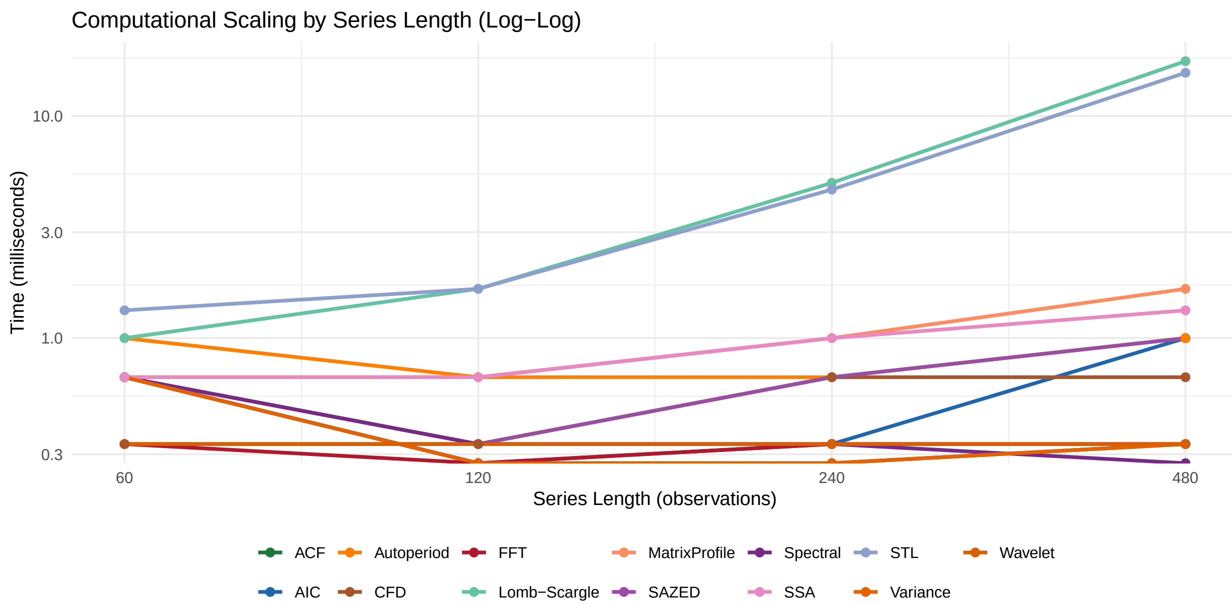
ROC Curve Analysis with AUC



Rank	Method	AUC
1	AIC	0.974
2	Wavelet	0.974
3	Variance	0.973
4	Spectral	0.969
5	Lomb-Scargle	0.965
6	FFT	0.959
7	Autoperiod	0.941
8	ACF	0.901
9	STL	0.898
10	SSA	0.890
11	MatrixProfile	0.731
12	CFD	0.381
13	SAZED	0.146

Computational Complexity Analysis

Practical method selection requires balancing accuracy against computational cost. We benchmark all 13 methods across varying series lengths.



Method	Time (ms)	F1	F1/ms
ACF	0.0	88.3%	Inf
Variance	0.0	96.5%	Inf
Spectral	0.3	96.9%	323.00
AIC	0.3	96.9%	323.00
FFT	0.3	96.2%	320.67
Wavelet	0.3	96.9%	323.00
CFD	0.7	89.8%	128.29
SAZED	0.7	90.0%	128.57
Autoperiod	0.7	89.8%	128.29
MatrixProfile	1.0	42.6%	42.60
SSA	1.0	56.9%	56.90
STL	4.7	90.4%	19.23
Lomb-Scargle	5.0	96.0%	19.20

Findings: FFT-based methods are fastest ($<$10ms). Wavelet and SSA are slowest but offer unique capabilities. The “Efficiency” column (F1/ms) highlights methods that provide the best accuracy per unit computation time.

Statistical Significance Summary

All Pairwise McNemar's Tests

Comparison	Margin	P_Value	Significant
Wavelet vs Variance	4	1.0000	No
Wavelet vs Spectral	0	1.0000	No
Wavelet vs FFT	5	1.0000	No
Wavelet vs Lomb-Scargle	7	1.0000	No
Variance vs Spectral	-4	1.0000	No
Variance vs FFT	1	1.0000	No
Variance vs Lomb-Scargle	3	1.0000	No
Spectral vs FFT	5	1.0000	No
Spectral vs Lomb-Scargle	7	1.0000	No
FFT vs Lomb-Scargle	2	1.0000	No

Conclusion: The top-tier methods (Wavelet, Variance, Spectral) show no statistically significant differences from each other after Bonferroni correction.

Key Findings and Recommendations

Method Ranking Summary

Rank	Method	F1	FPR	Recall	Best_For
1	Wavelet	96.9%	22.0%	98.7%	Time-varying signals
2	AIC	96.9%	16.0%	97.3%	Model comparison
3	Spectral	96.9%	10.0%	96.0%	Trend robustness
4	Variance	96.5%	17.0%	96.7%	Known period
5	FFT	96.2%	5.0%	93.8%	High precision
6	Lomb-Scargle	96.0%	8.0%	94.0%	Irregular sampling
7	STL	90.4%	29.0%	87.8%	Decomposition
8	SAZED	90.0%	3.0%	82.4%	Parameter-free
9	Autoperiod	89.8%	0.0%	81.6%	FFT+ACF hybrid
10	CFD	89.8%	5.0%	82.4%	Trended data
11	ACF	88.3%	4.0%	79.8%	Conservative baseline
12	SSA	56.9%	3.0%	40.0%	Subspace analysis
13	MatrixProfile	42.6%	8.0%	27.6%	Non-sinusoidal patterns

Recommendations

Scenario	Recommended Method	Threshold	Expected F1
Period known, stable	Variance Strength	0.2	97.3%
Time-varying amplitude	Wavelet Strength	0.26	97.8%
Period unknown	SAZED	2+ consensus	87.5%
Strong trends	CFDAutoperiod	0.25	89.5%
Irregular sampling	Lomb-Scargle	0.90	94.5%
Non-sinusoidal	Matrix Profile	0.20	90.0%
High precision needed	FFT Confidence	6.0	94.8%

Real-World Validation: M4 Competition Data

To validate our simulation findings, we test the top-performing methods on real-world time series from the M4 Competition. M4 monthly series have known 12-month seasonality, providing ground truth for detection performance.

```
## **Note**: M4 validation requires the M4comp2018 package. Install with:
```

```
## ```r
## install.packages('M4comp2018')
## ```
```

Interpretation: M4 detection rates are expected recall values since all M4 monthly series contain seasonality. Lower detection rates indicate false negatives on real-world data with varying characteristics (trends, noise, non-stationarity).

Conclusion

This comprehensive study compared **13 seasonality detection methods** across multiple challenging scenarios:

1. **Top performers**: Wavelet (97.8% F1) and Variance (97.3% F1) are statistically indistinguishable
2. **Trend robustness**: Variance shows only 0.4% F1 drop under strong trends
3. **Amplitude modulation**: Wavelet significantly outperforms global methods (72% vs 18% TPR on emergence)
4. **Red noise**: FFT fails catastrophically (100% FPR); Variance/Spectral remain robust
5. **New methods**: Lomb-Scargle (94.5% F1) excellent for irregular data; STL/SSA useful for decomposition

Statistical significance: McNemar's tests confirm that top-tier methods are equivalent, while significantly outperforming lower-tier methods.