



BAYESIAN SPATIO-TEMPORAL MODELING WITH CHANGE-POINT ANALYSIS OF CRIMES IN SOCCSKSARGEN

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In SOCCSKSARGEN alone...

171,785

crime incidents were recorded
from January 1, 2015 to November 30, 2025

5

provinces & cities

11

years of data

~43

incidents per day

Why spatial, temporal, and structural-change questions matter?

Reported totals answer “how many”, but not where counts differ or when the pattern shifts

Regional totals hide local variation

Smooth trends may not capture abrupt shifts

Crime as Spatio-Temporal Problem

Knowing where and when crime concentrates is essential for prevention. Index crimes in the Philippines declined from 2016 to 2020, with homicide and carnapping disproportionately associated with SOCCSKSARGEN (Leikuma-Rimicane et al., 2022).

Crime as Spatio-Temporal Problem

Bayesian hierarchical and spatio-temporal models capture spatial and temporal variation with uncertainty (Liu et al., 2021; Mosammam et al., 2022; Nacion & Tubo, 2022), and **change-point analysis** locates when a process shifts (Monyeki et al., 2020; Konstantinou et al., 2023).

Objectives

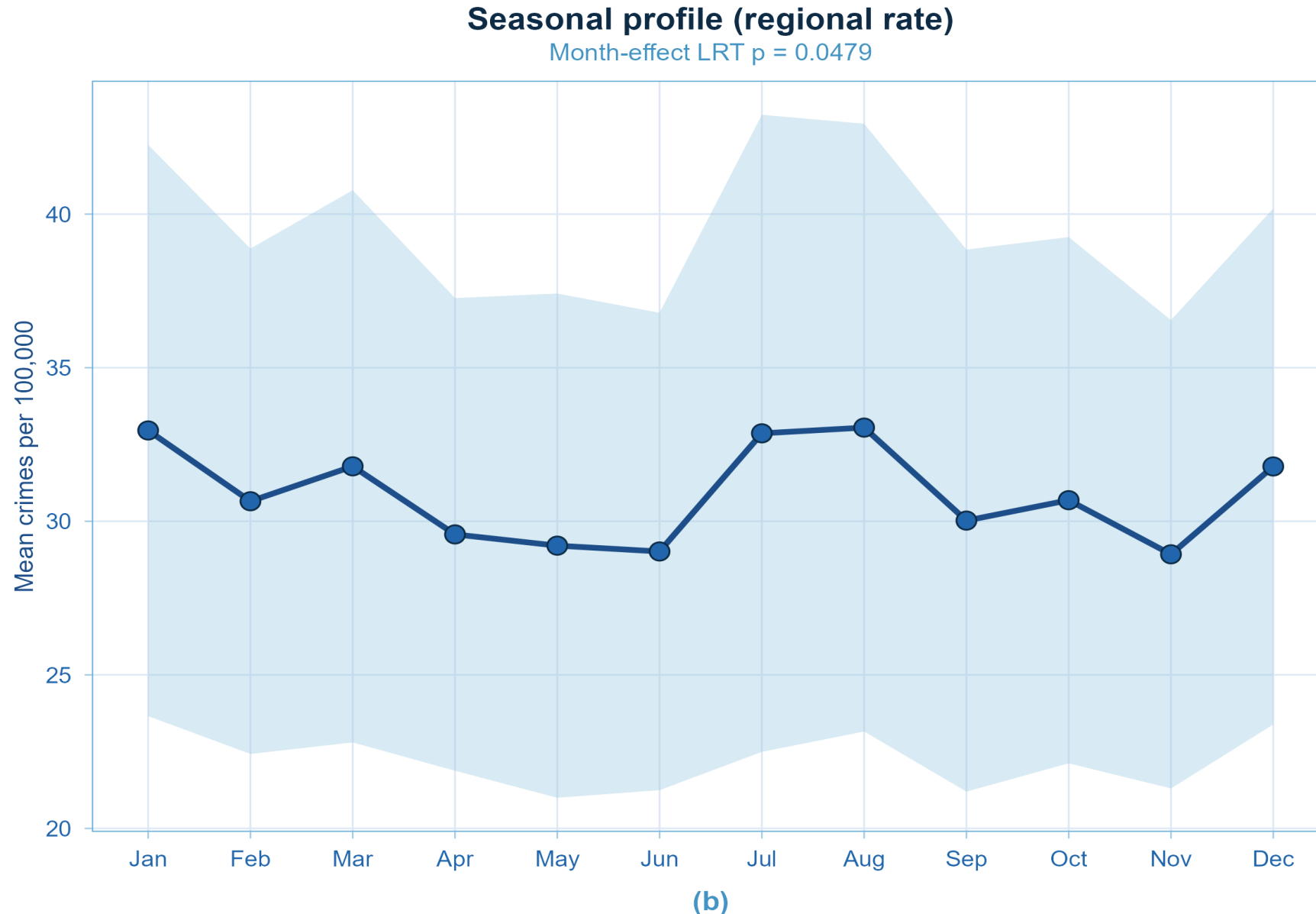
This study aims to employ Bayesian spatio-temporal modeling and change-point analysis to examine the trends, spatial distribution, and temporal shifts of crimes in SOCCSKSARGEN from January 1, 2015 to November 30, 2025.

- 1. Estimate baseline counts and area-level variation with a Bayesian hierarchical model.**
- 2. Examine Spatio-temporal patterns with a Bayesian spatio-temporal model.**
- 3. Detect structural change in crime trends through Bayesian change-point analysis.**
- 4. Compare all models with Bayesian selection criteria and assess the sensitivity of the conclusions to hyperpriors.**
- 5. Provide an R Shiny dashboard for stakeholder exploration.**

Data Acquisition and Aggregation

- Secondary data obtained via personal request from **Police Regional Office 12 (PRO-12)**
- **171,785** crime records spanning January 1, 2015 to November 30, 2025 across South Cotabato, Cotabato, Sultan Kudarat, General Santos City, Sarangani.
- **Aggregated** to 5 spatial units x 131 months = 655 observations.
- Monthly population denominators interpolated/extrapolated; models include a **log-population offset**.
- **No personally identifiable information** was released.

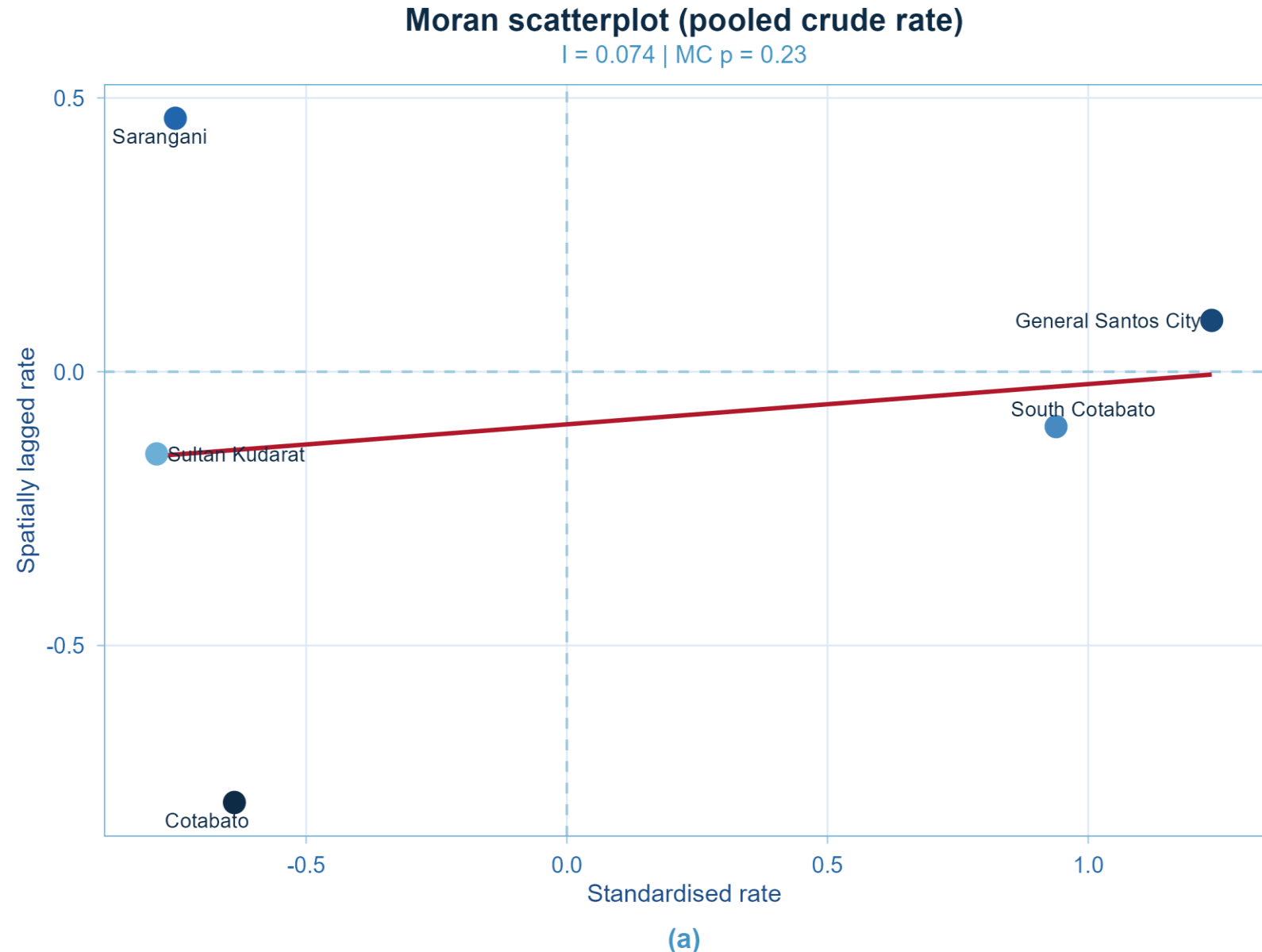
EDA: Temporal Pattern



- The regional crime rate is **slightly higher in Jan and July–August** and **lower in April–June and Nov.**
- The month effect is borderline ($p = 0.0479$) and the 95% bands overlap across all months. Seasonality is weak next to the long-term decline, so **no seasonal term was included in the models.**

EDA: Spatial differences and unusual observations

- **Pattern:** The fitted line is nearly flat ($I = 0.074$, $p = 0.23$), so a province's crime rate is not related to its neighbors' rates.
- **Interpretation:** There is no significant spatial clustering, only differences between provinces. With five provinces, the test has low power.



Why Proceed with a Spatial Model Despite a Non-Significant Moran's I ?

- **Result:** Moran's I was not significant (crude rates: $I = 0.074$, $p = 0.23$; NB residuals: $I = 0.073$, $p = 0.18$).
- **Low power:** With only five areas, the test cannot rule out spatial dependence.
- **Flexible model:** The BYM model lets the data decide the weight of its spatial and unstructured components (Besag et al., 1991; Riebler et al., 2016).
- **Safe fallback:** If there is no spatial dependence, it reduces to a hierarchical model with province-specific effects, which still suits population-adjusted risk estimation under strong overdispersion (Blangiardo & Cameletti, 2015).
- The data support provincial heterogeneity, not spatial clustering.

Model Specification: Likelihood and Spatial Structure

NEGATIVE BINOMIAL LIKELIHOOD

$$Y_{it} \sim \text{NB}(\mu_{it}, r), \quad \log(\mu_{it}) = \log\left(\frac{P_{it}}{100000}\right) \eta_{it}$$

- Negative-binomial likelihood for overdispersed counts.
- $\log(\text{population})$ offset adjusts for exposure.
- BYM combines structured ICAR and unstructured area effects.
- INLA used for inference.

Model Specification: Model Hierarchy

Bayesian Hierarchical Modeling Framework

Model 0: β_0 Intercept only

Model 1: adds BYM spatial effects

Model 2: BYM + year effects relative to 2015,

$$\eta_{it} = \beta_0 + \sum_{k=2016}^{2025} \beta_k I(\text{year}(t) = k) + u_i + v_i$$

- β_k is the log relative risk of year k versus 2015, where $I(\cdot) = 1$ if month t falls in year k .
- u_i is the spatially structured effect (shared with neighbors).
- v_i is the unstructured province-specific effect.

Model Specification: Model Hierarchy

Bayesian Spatio-Temporal Framework

Model 3: BYM + RW1

Model 4: BYM + RW2

Model 5: BYM + RW2 + Space-Time Interaction,

$$\eta_{it} = \beta_0 + u_i + v_i + \gamma_t + \delta_{it}$$

- γ_t is temporal effect of month t . It follows a second-order random walk (RW2), so the trend evolves smoothly.
- δ_{it} is space-time interaction. It has an independent normal (IID) prior, so it flags unusual province-months.

Model Specification: Model Hierarchy

Change-Point Analysis Framework

Model 5: Model 4 + Candidate Step at τ ,

$$\eta_{it} = \beta_0 + \beta_\tau I(t \geq \tau) + u_i + v_i + \gamma_t, \quad \tau \in \{2, \dots, 130\}$$

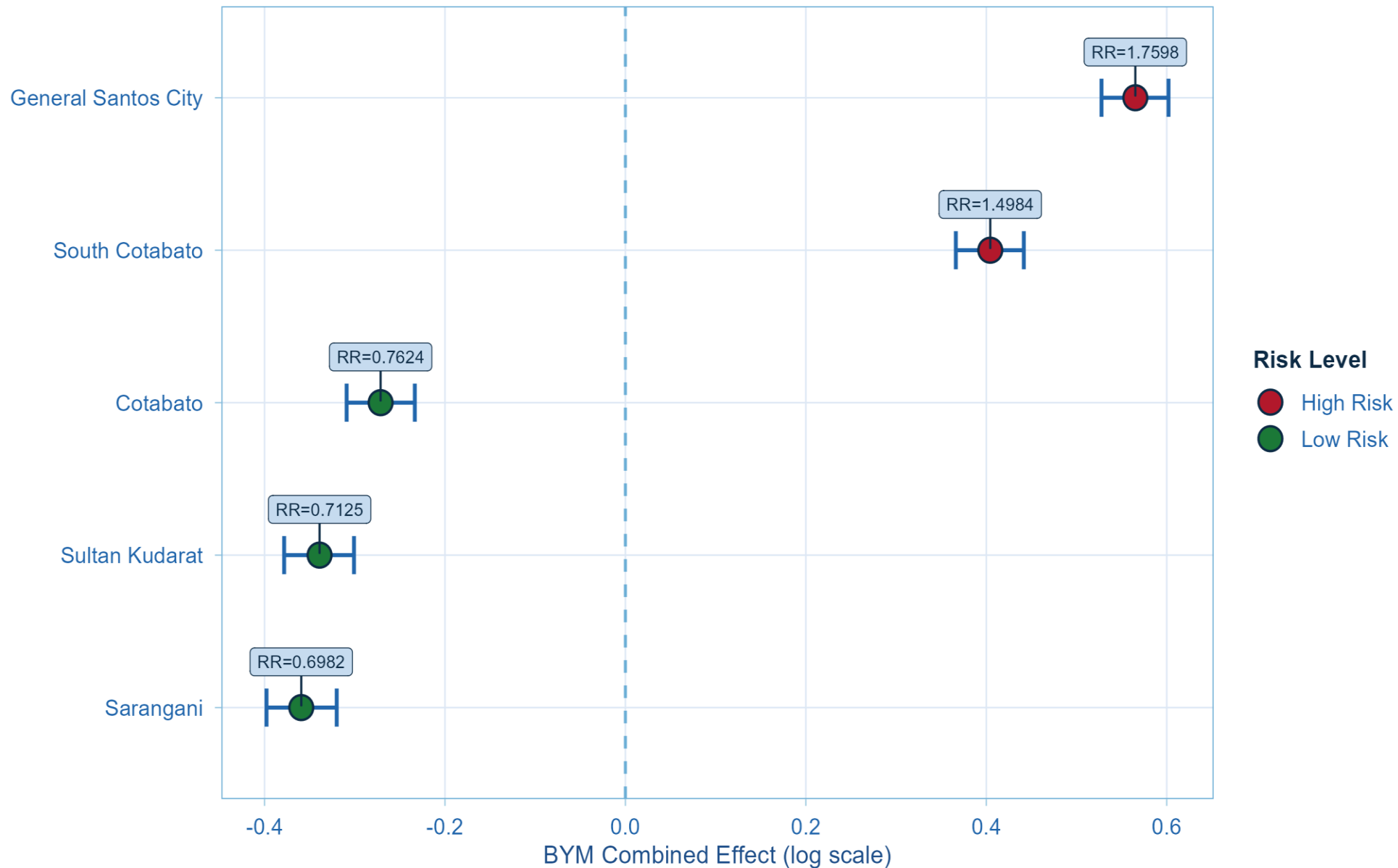
The optimal break was

$$\tau^* = \operatorname{argmin} WAIC(\tau), \quad \tau \in \{2, \dots, 130\}$$

Model Comparison				
Model	DIC	WAIC	pWAIC	LPML
M0: Intercept only	8343.51	8343.3	1.77	-4171.65
M1: BYM	8066.3	8067.72	7.32	-4033.85
M2: BYM + year	7094.9	7103.17	22.87	-3551.11
M3: BYM + RW1	7077.08	7088.95	44.04	-3543.2
M4: BYM + RW2	7083.92	7093.53	25.89	-3546.08
M5: BYM + RW2 + interaction	6461.68	6360.7	343.94	-3575.04
M6: M4 + a candidate step at τ	7059.34	7070.15	27.7	-3534.62

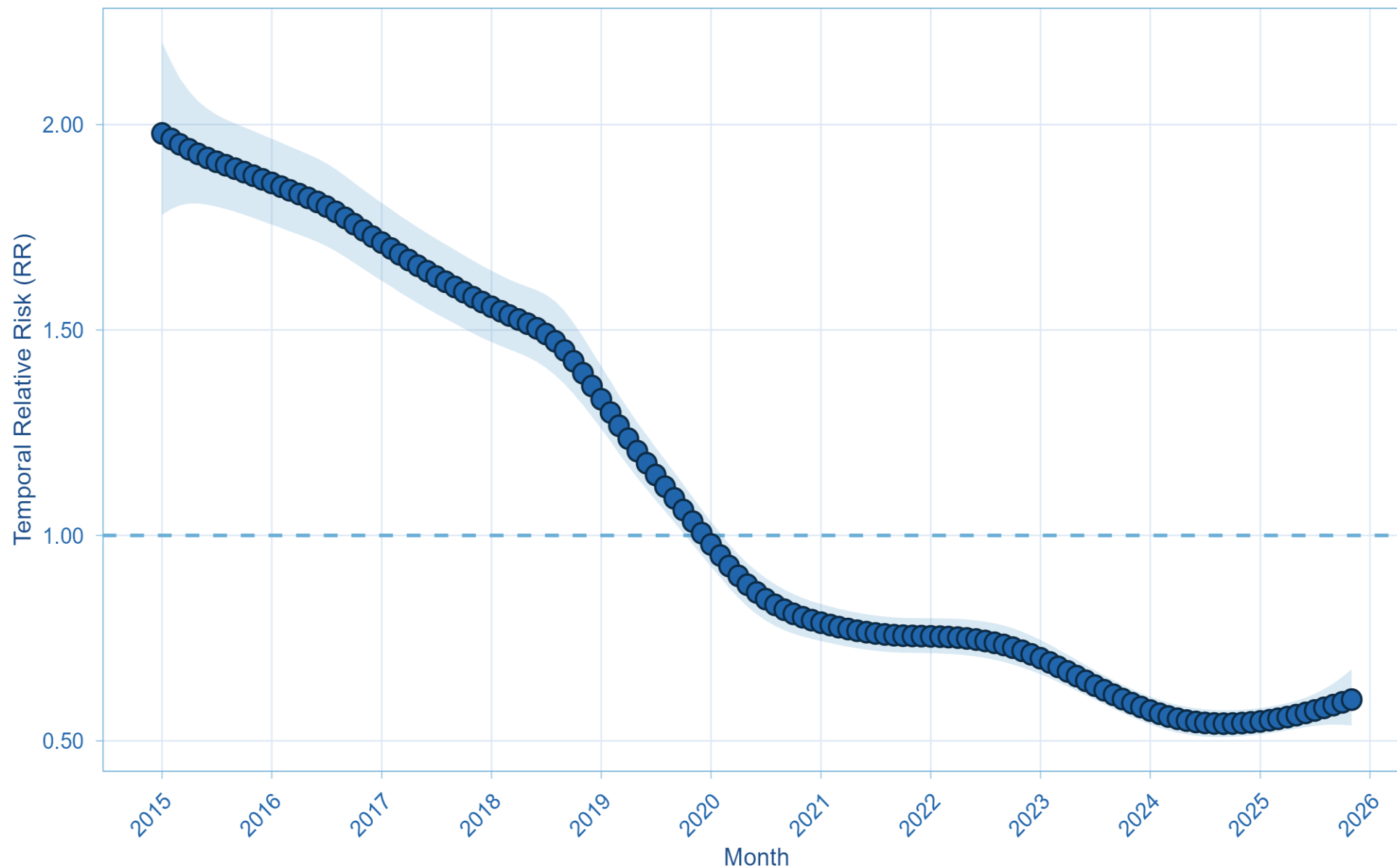
Prior Sensitivity					
Prior	Δ WAIC	Max $ \Delta$ RR	Spearman ρ	Max $ \Delta\gamma $	Class changes
PC(1, 0.01) [baseline]	0	0	1	0	0
PC(0.5, 0.01)	-0.12	0.0003	1	0.0002	0
PC(2, 0.01)	-0.039	0.0014	1	0.001	0
PC(3, 0.01)	-0.126	0.0016	1	0.001	0
PC(1, 0.05)	-0.024	0.002	1	0.0007	0
Gamma(1, 5×10^{-5})	-1.529	0.0005	1	0.0024	0
Gamma(1, 0.01)	-10.599	0.0053	0.9	0.1645	0
Gamma(0.5, 5×10^{-4})	-5.473	0.0021	0.9	0.053	0

Results: Spatial Risk



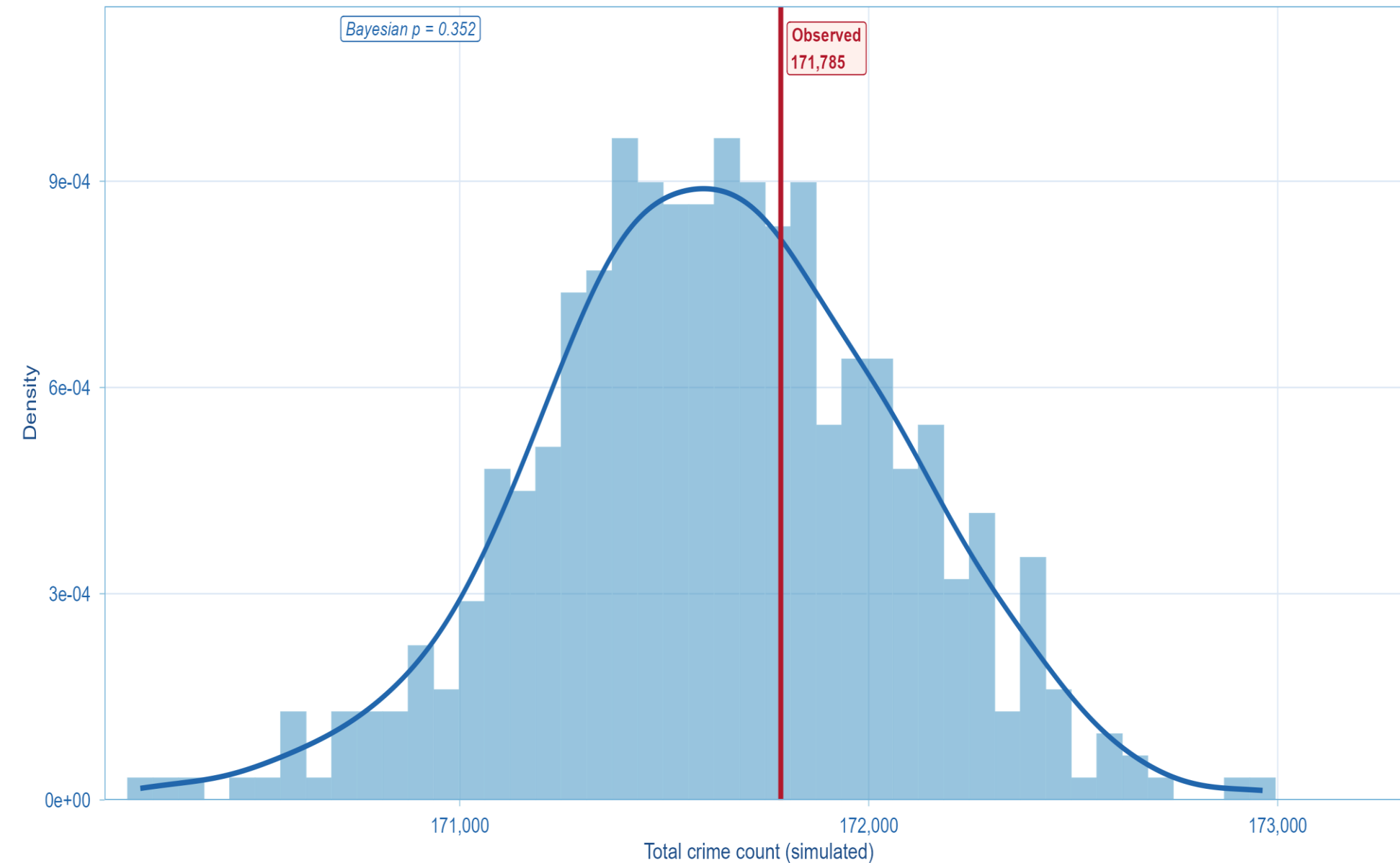
- **General Santos City:** $RR \approx 1.76$, credibly above five-area average.
- **South Cotabato:** $RR \approx 1.50$, credibly above average

Results: Temporal Trend



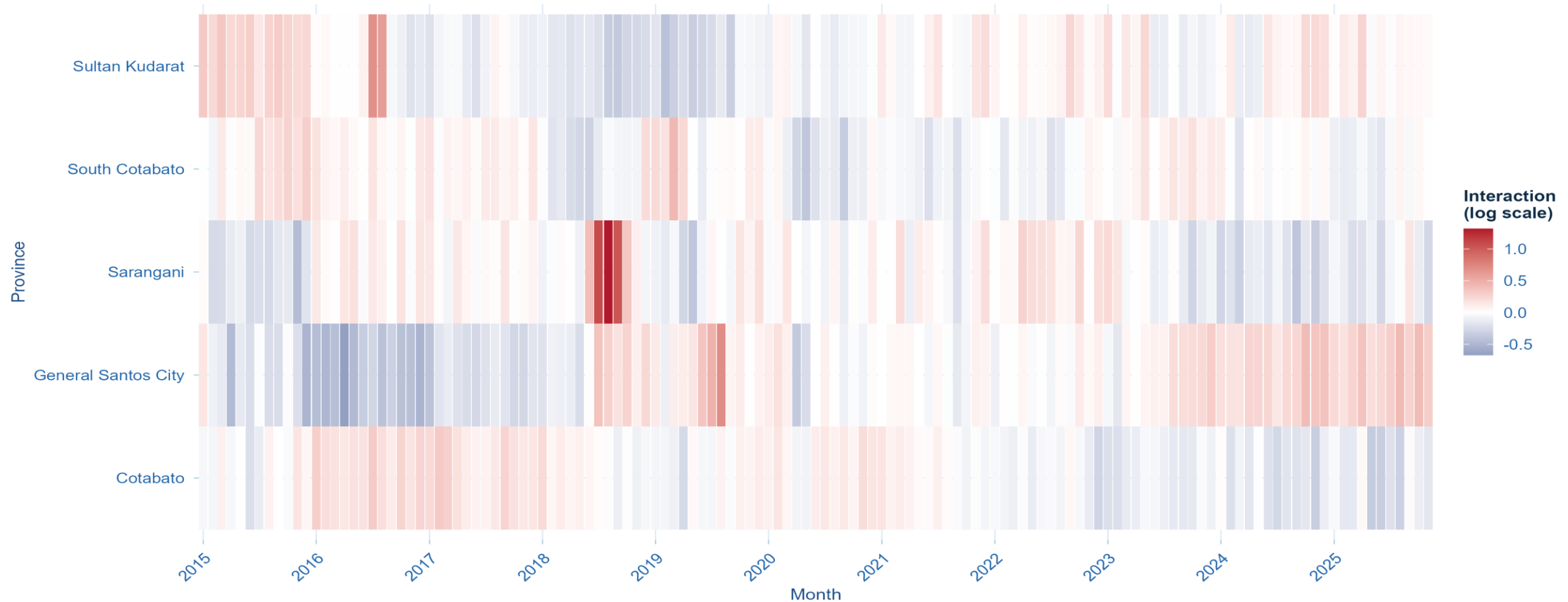
- **Risk falls from about twice the average in 2015 to about 0.55–0.60 by 2024–2025.**
- **The steepest decline occurs around 2019–2020.**

Results: Posterior Predictive Check for M5



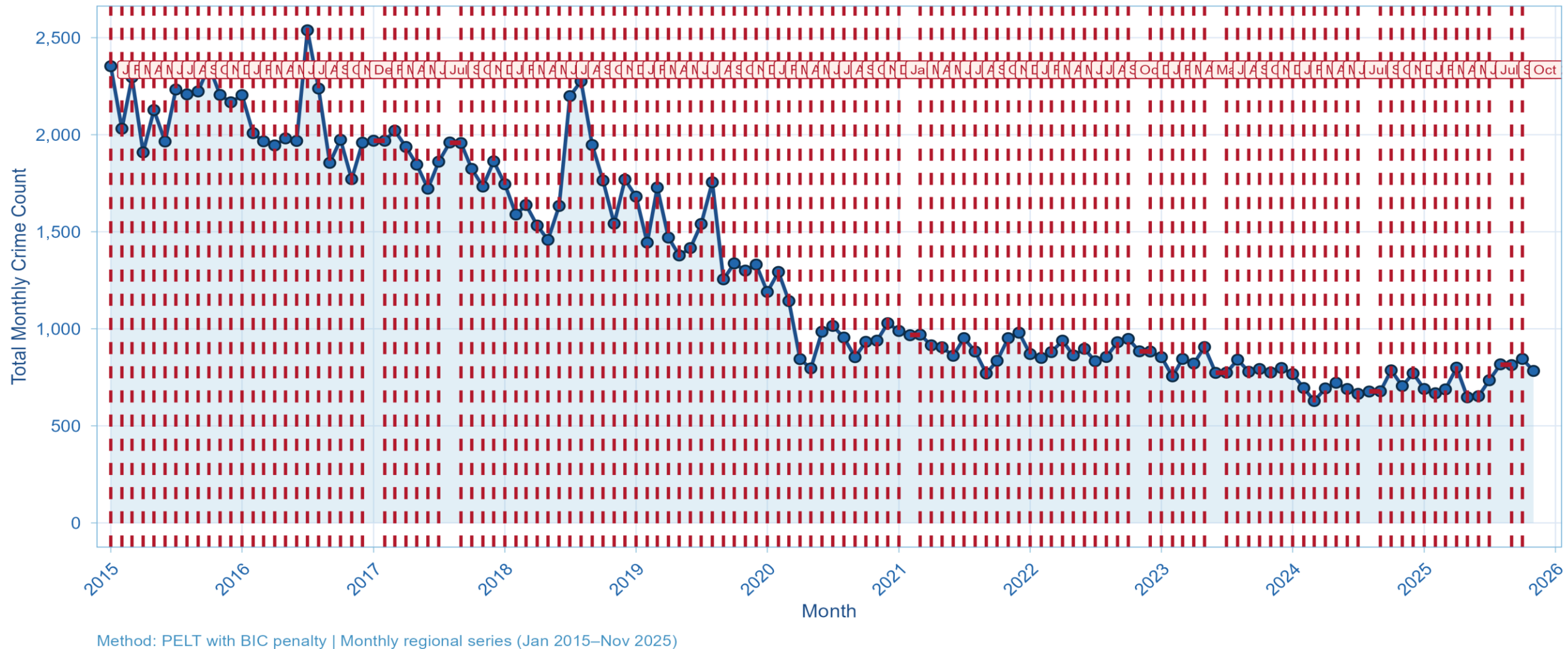
M5: Observed overall and provincial crime totals were well reproduced ($p=0.35$) and ($p=0.17-0.78$), **with no extreme values**. However, **this check is weak** because M5 includes observation-level random effects.

Results: Space-Time Interaction effects of M5



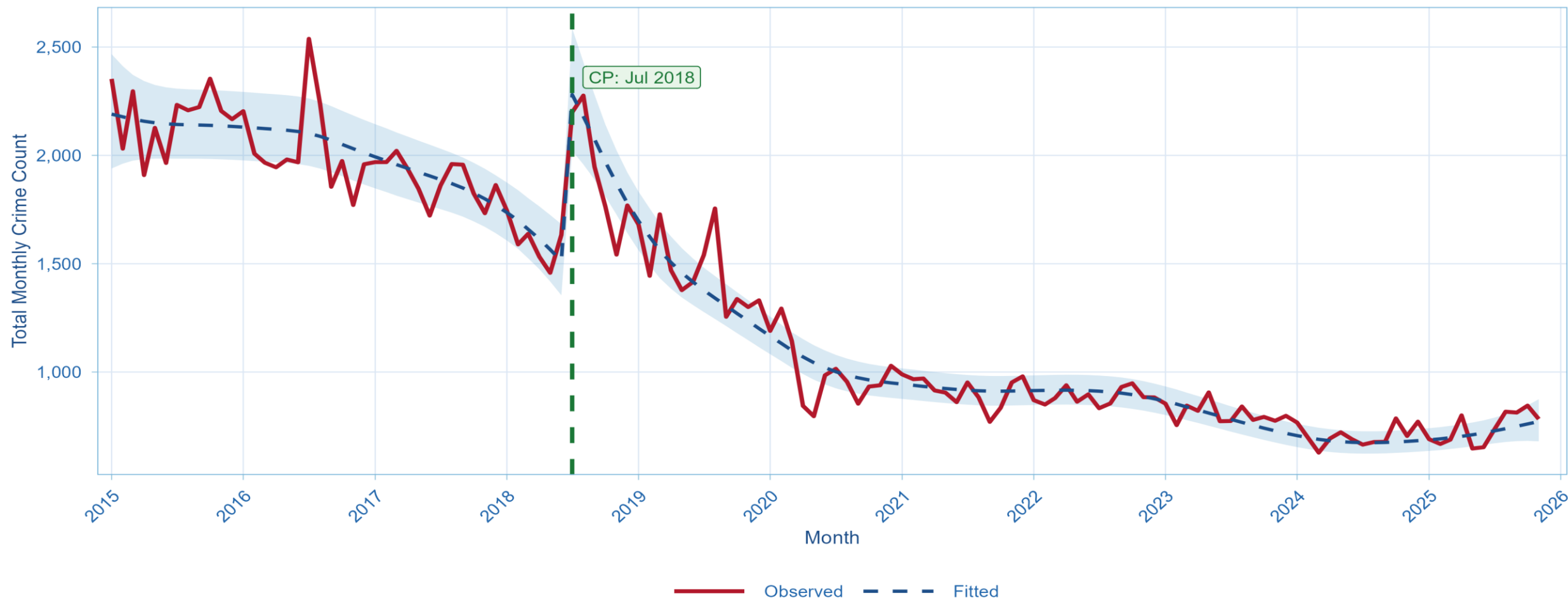
- M5 interaction effects were **mostly small**, with notable increases in Sarangani (mid-2018) and Sultan Kudarat (mid-2016), elevated Cotabato effects in 2016–2017, and shifting General Santos City effects across periods.

Results: Preliminary PELT (mean-shift variant, BIC penalty)



- PELT on the regional totals was **uninformative**, returning 123 breaks in 131 months
- variance-shift variant found two breaks , mean-and-variance variant nine

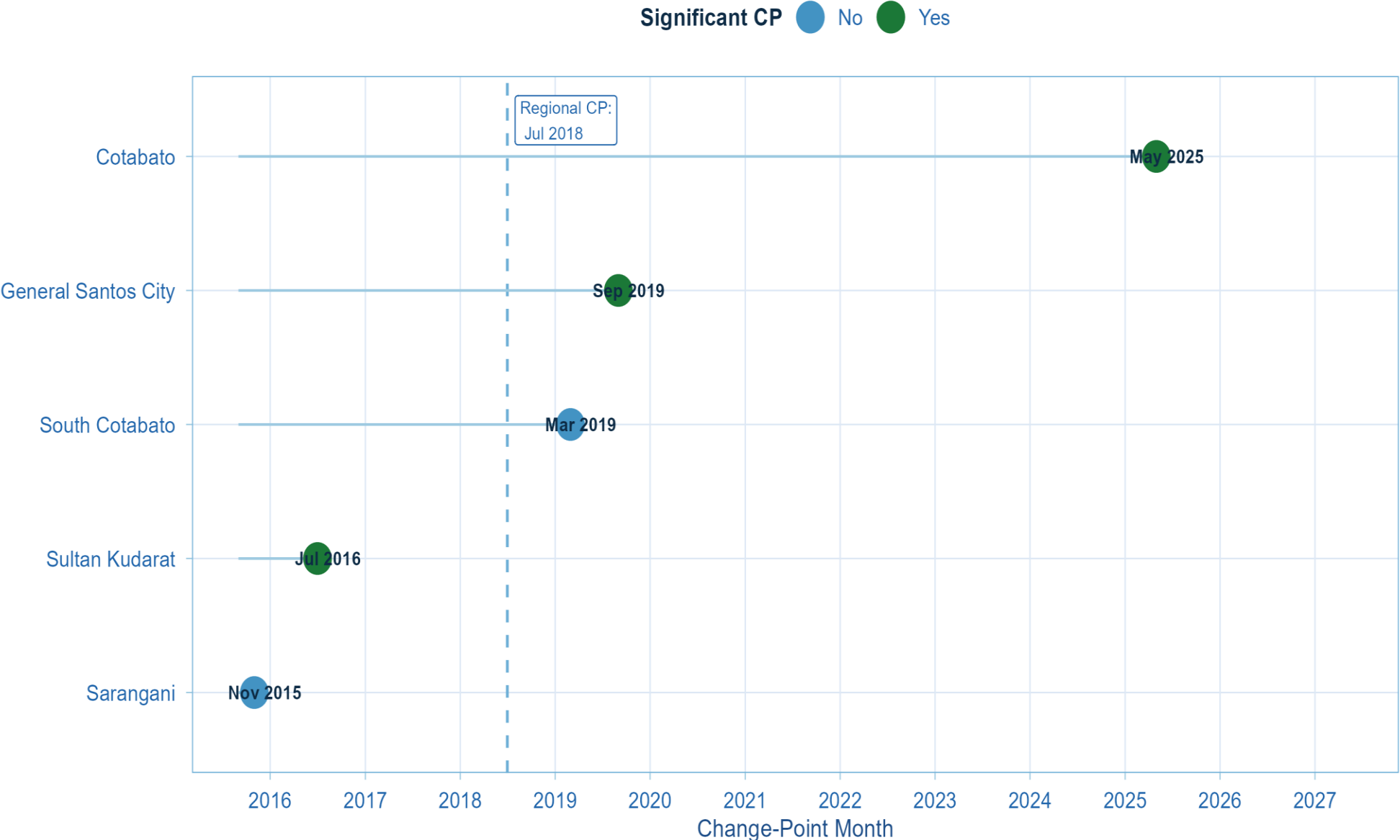
Results: Regional Change-Point



Dashed green line = WAIC-optimal change-point (Jul 2018). Jan 2015–Nov 2025.

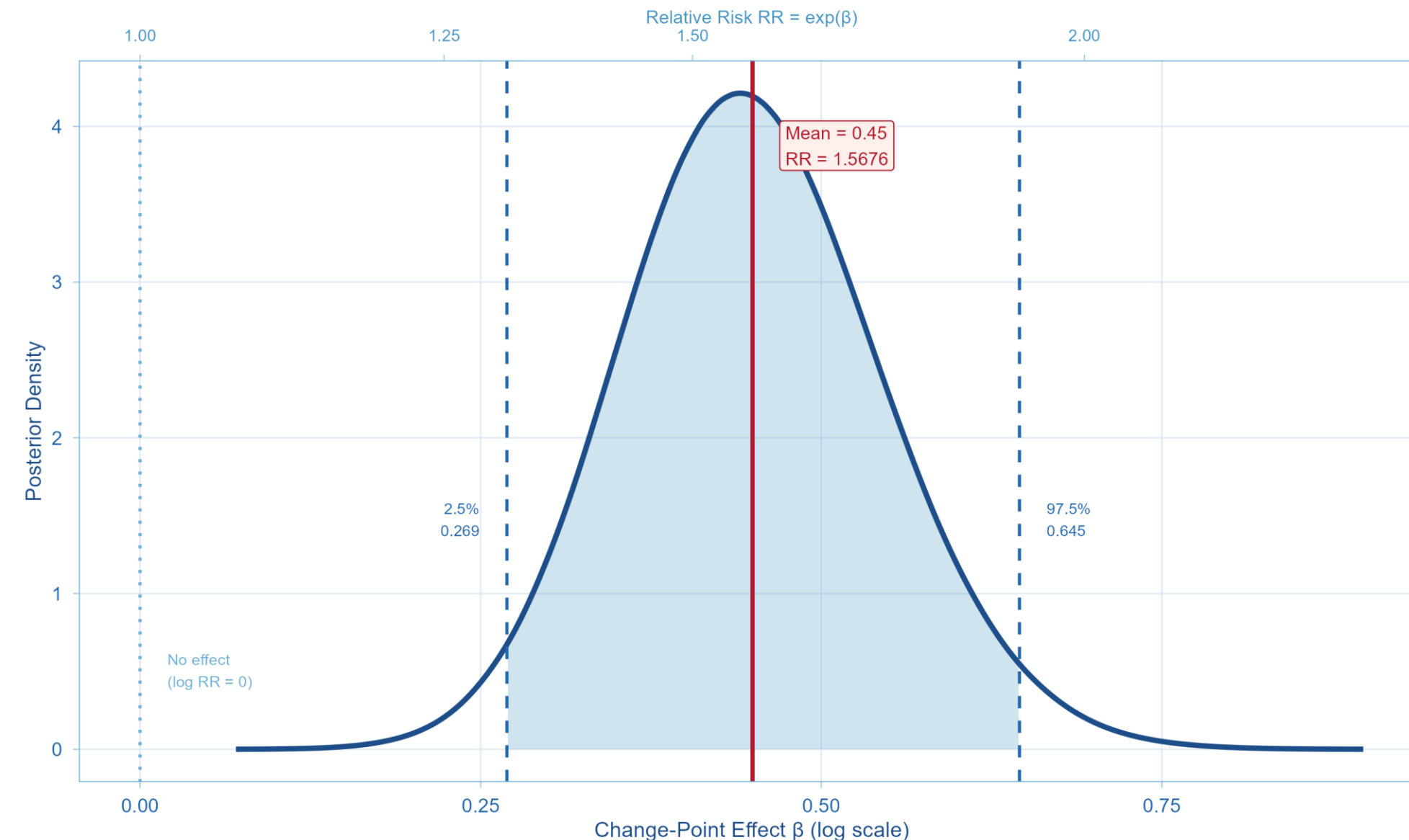
- WAIC-selected candidate: **July 2018**.
- Step **RR ≈ 1.55** relative to the smooth RW2 trend.

Results: Province-Specific Breaks



- **General Santos City: Sep 2019**, credible decrease ($RR \approx 0.51$).
- **Sultan Kudarat: Jul 2016**, credible increase ($RR \approx 1.93$).
- **Cotabato: May 2025**, decrease ($RR \approx 0.74$; short post-break period).
- **Sarangani and South Cotabato intervals include no step effect.**

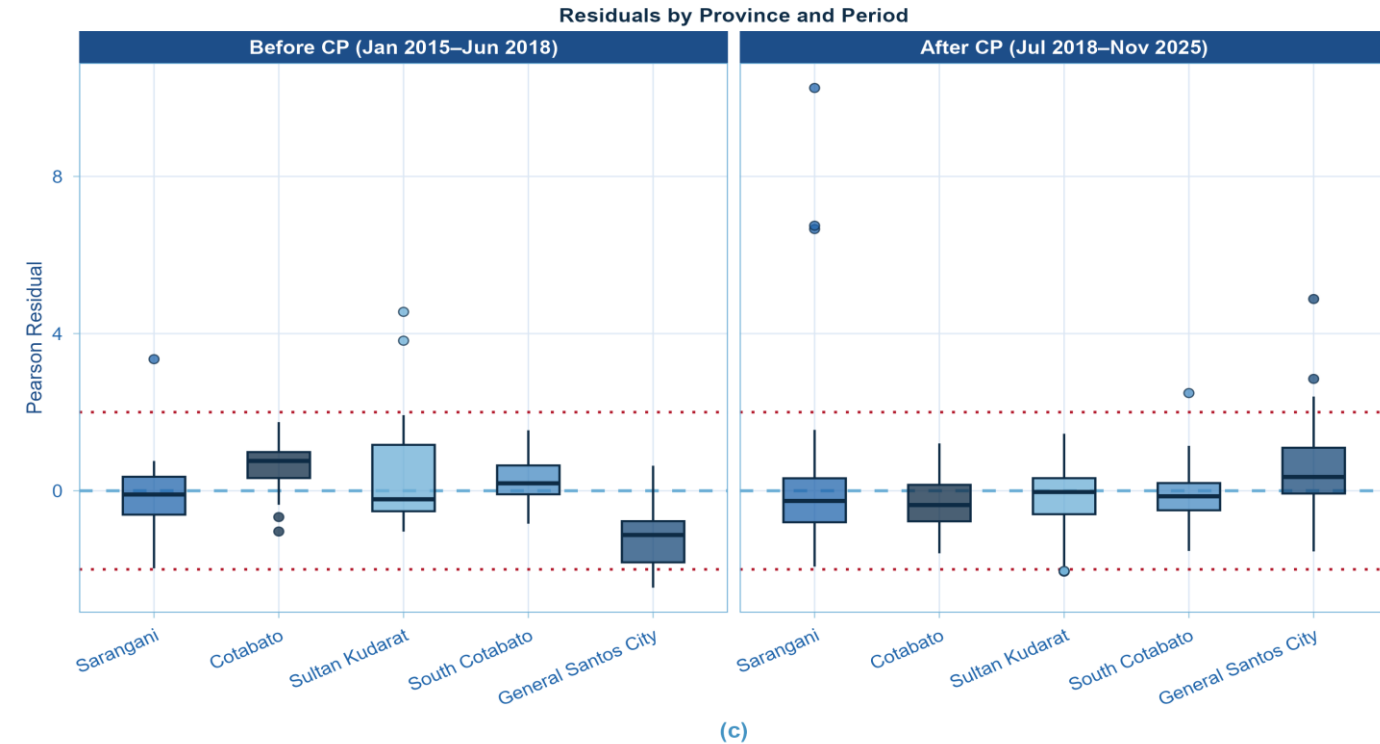
Results: Posterior Density of the Break Effect



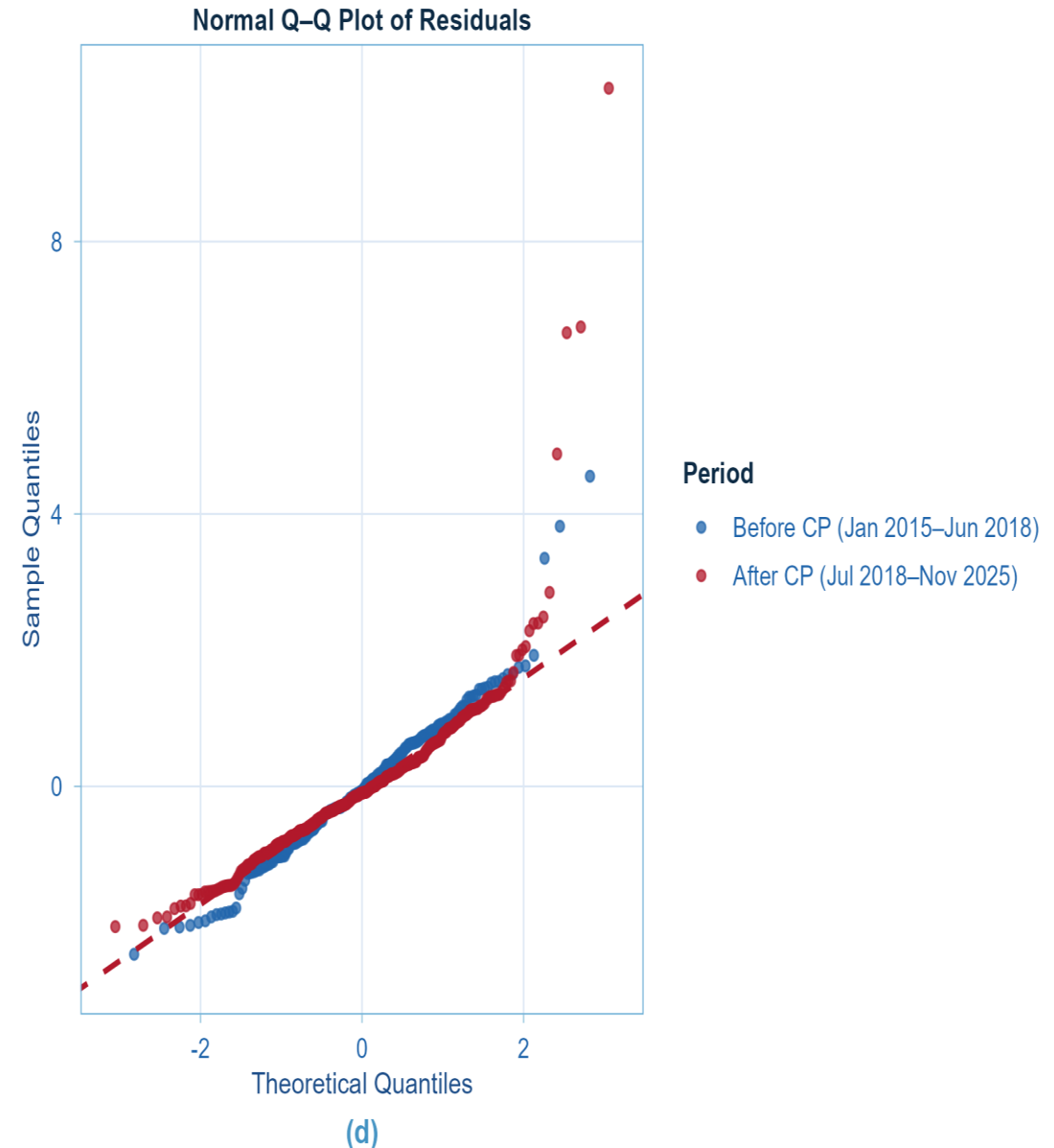
Shaded region = 95% posterior credible interval | Red line = posterior mean | CP: Jul 2018

- The posterior of β is **unimodal and nearly symmetric** (mean 0.45; RR = 1.57), and its 95% CrI lies well away from 0 (RR = 1), so the **step is credibly positive conditional on the selected month.**

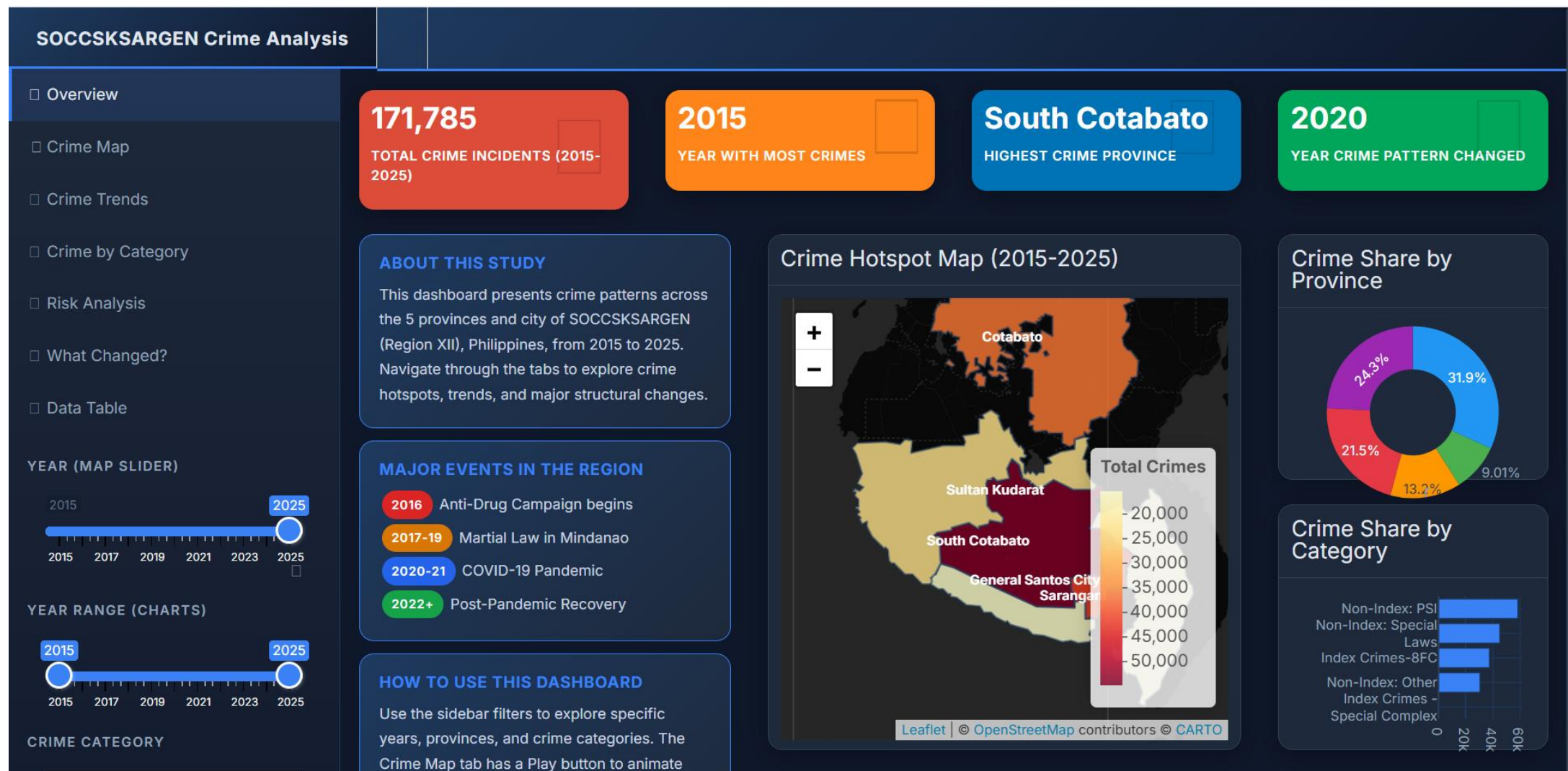
Results: Pearson Residuals Diagnostic for M6



- **Pearson residuals** showed no clear trend over fitted values or time, but **retained a heavy right tail**.
- **Q–Q plots** followed the reference line centrally, **with right-skewed outliers above +2**.
- **Provincial residuals shifted across periods**: General Santos City changed from mostly negative to positive, while Cotabato showed the opposite, **suggesting time-invariant spatial effects do not fully capture changing provincial shares**.



R shiny Dashboard



<https://tinyurl.com/3tf5v74d>

Conclusions

1. Adjusted risk is credibly higher in General Santos City and South Cotabato.
2. Temporal risk declines markedly over the study period.
3. July 2018 is a candidate upward step relative to the smooth trend; province-level shifts are heterogeneous.
4. Spatial risk rankings are robust to tested hyperpriors, while temporal smoothness is more sensitive.

Recommendations

- Prioritize prevention and monitoring in Genral Santos City and South Cotabato; monitor Sultan Kudarat's post-2016 increase.
- Ask PRO-12 to verify the Sarangani 2018 and Sultan Kudarat 2016 surges and any recording changes.
- Extend to municipal/offense-specific models; test BYM2, seasonal terms, covariates, and multiple or outlier-robust breaks.

References

- I. Adeyemi, R. A., Mayaki, J., Zewotir, T. T., & Ramroop, S. (2020). Demography and crime: A spatial analysis of geographical patterns and risk factors of crimes in Nigeria. *Spatial Statistics*, 41, 100485. <https://doi.org/10.1016/j.spasta.2020.100485>
- II. Arif, S. N. M., Mohsin, M. F. M., Bakar, A. A., Hamdan, A. R., & Abdullah, S. M. S. (2017). Change point analysis: A statistical approach to detect potential abrupt change. *Jurnal Teknologi*, 79(5). <https://doi.org/10.11113/jt.v79.10388>
- III. Besag, J., York, J., & Mollié, A. (1991). Bayesian image restoration, with two applications in spatial statistics. *Annals of the Institute of Statistical Mathematics*, 43(1), 1–20. <https://doi.org/10.1007/BF00116466>
- IV. Blangiardo, M., & Cameletti, M. (2015). *Spatial and spatio-temporal Bayesian models with R-INLA*. John Wiley & Sons.
- V. Cameron, A. C., & Trivedi, P. K. (1990). Regression-based tests for overdispersion in the Poisson model. *Journal of Econometrics*, 46(3), 347–364.
- VI. Drozdowski, R., Wielki, R., & Tukiendorf, A. (2023). Overlapped Bayesian spatio-temporal models to detect crime spots and their possible risk factors based on the Opole Province, Poland, in the years 2015–2019. *Crime Science*, 12, 10. <https://doi.org/10.1186/s40163-023-00189-0>
- VII. Geisser, S., & Eddy, W. F. (1979). A predictive approach to model selection. *Journal of the American Statistical Association*, 74(365), 153–160.
- VIII. Gelman, A., Hwang, J., & Vehtari, A. (2014). Understanding predictive information criteria for Bayesian models. *Statistics and Computing*, 24(6), 997–1016. <https://doi.org/10.1007/s11222-013-9416-2>
- IX. Killick, R., Fearnhead, P., & Eckley, I. A. (2012). Optimal detection of changepoints with a linear computational cost. *Journal of the American Statistical Association*, 107(500), 1590–1598. <https://doi.org/10.1080/01621459.2012.737745>
- X. Knorr-Held, L. (2000). Bayesian modelling of inseparable space-time variation in disease risk. *Statistics in Medicine*, 19(17–18), 2555–2567.

References

- XI. Konstantinou, A., Chatzakou, D., Theodosiadou, O., Tsikrika, T., Vrochidis, S., & Kompatsiaris, I. (2023). Trend detection in crime-related time series with change point detection methods. *Lecture Notes in Computer Science*, 72–84. https://doi.org/10.1007/978-3-031-42448-9_7
- XII. Leikuma-Rimicane, L., Ceballos, R. F., & Medina, M. N. D. (2022). Location and type of crimes in the Philippines: Insights for crime prevention and management. *International Journal of Criminal Justice Sciences*, 17(1), 22–33. <https://doi.org/10.5281/zenodo.4756087>
- XIII. Lindgren, F., & Rue, H. (2015). Bayesian spatial modelling with R-INLA. *Journal of Statistical Software*, 63(19), 1–25. <https://doi.org/10.18637/jss.v063.i19>
- XIV. Liu, D., Song, W., Xiu, C., & Xu, J. (2021). Understanding the spatiotemporal pattern of crimes in Changchun, China: A Bayesian modeling approach. *Sustainability*, 13(19), 10500. <https://doi.org/10.3390/su131910500>
- XV. Ljung, G. M., & Box, G. E. P. (1978). On a measure of lack of fit in time series models. *Biometrika*, 65(2), 297–303. <https://doi.org/10.1093/biomet/65.2.297>
- XVI. Monyeke, P., Naicker, N., & Obagbuwa, I. C. (2020). Change-point analysis: An effective technique for detecting abrupt change in the homicide trends in a democratic South Africa. *The Scientific World Journal*, 2020, 1–10. <https://doi.org/10.1155/2020/4158472>
- XVII. Moran, P. A. P. (1950). Notes on continuous stochastic phenomena. *Biometrika*, 37(1–2), 17–23. <https://doi.org/10.1093/biomet/37.1-2.17>
- XVIII. Mosammam, A. M., Abbasi, E., & Mateu, J. (2022). Bayesian approach for modelling spatial–temporal crime data. *Journal of Statistical Sciences*, 16(2), 435–448. <https://doi.org/10.52547/jss.16.2.435>
- XIX. Nacion, J., & Tubo, B. (2022). A Bayesian hierarchical model for COVID-19 cases in Mindanao, Philippines. *The Philippine Statistician*, 25–36.

References

- XX. Nivette, A. E., Zahnow, R., Aguilar, R., et al. (2021). A global analysis of the impact of COVID-19 stay-at-home restrictions on crime. *Nature Human Behaviour*, 5, 868–877. <https://doi.org/10.1038/s41562-021-01139-z>
- XXI. Philippine Daily Inquirer. (2020, April 22). *Crime rate drops in Soccsksargen amid COVID-19 crisis*. <https://newsinfo.inquirer.net/1263036/crime-rate-drops-in-soccsksargen-amid-covid-19-crisis/amp>
- XXII. Philippine Statistics Authority. (n.d.). *Population of Region XII – SOCCSKSARGEN (based on the 2015 Census of Population)*. <https://psa.gov.ph/statistics/population-and-housing/node/57696>
- XXIII. Philippine Statistics Authority. (2021, August 20). *Highlights of the Region XII (SOCCSKSARGEN) population: 2020 Census of Population and Housing* [Press release]. https://psa.gov.ph/system/files/phcd/2022-12/15_Press%2520Release_2020%2520CPH_RSSO%2520XII_signed.pdf
- XXIV. Philippine Statistics Authority. (2025). *Philippine Standard Geographic Code (PSGC): Region XII (SOCCSKSARGEN)* [Data set]. <https://psa.gov.ph/classification/psgc/provinces/1200000000>
- XXV. Philippine Statistics Authority. (2025). *2024 Census of Population (POPCEN) counts declared official by the President*. <https://psa.gov.ph/content/2024-census-population-popcen-population-counts-declared-official-president>
- XXVI. Police Regional Office 12. (2025). *Crime record, 2015–2025* [Unpublished dataset]. Provided through formal request.
- XXVII. Riebler, A., Sørbye, S. H., Simpson, D., & Rue, H. (2016). An intuitive Bayesian spatial model for disease mapping that accounts for scaling. *Statistical Methods in Medical Research*, 25(4), 1145–1165. <https://doi.org/10.1177/0962280216660421>
- XXVIII. Rue, H., Martino, S., & Chopin, N. (2009). Approximate Bayesian inference for latent Gaussian models by using integrated nested Laplace approximations. *Journal of the Royal Statistical Society: Series B*, 71(2), 319–392. <https://doi.org/10.1111/j.1467-9868.2008.00700.x>

References

- XXIX.Simpson, D., Rue, H., Riebler, A., Martins, T. G., & Sørbye, S. H. (2017). Penalising model component complexity: A principled, practical approach to constructing priors. *Statistical Science*, 32(1), 1–28. <https://doi.org/10.1214/16-STS576>
- XXX.Spiegelhalter, D. J., Best, N. G., Carlin, B. P., & van der Linde, A. (2002). Bayesian measures of model complexity and fit. *Journal of the Royal Statistical Society: Series B*, 64(4), 583–639. <https://doi.org/10.1111/1467-9868.00353>
- XXXI.Wang, Y., Chen, X., & Xue, F. (2024). A review of Bayesian spatiotemporal models in spatial epidemiology. *ISPRS International Journal of Geo-Information*, 13(3), 97. <https://doi.org/10.3390/ijgi13030097>
- XXXII.Watanabe, S. (2010). Asymptotic equivalence of Bayes cross validation and widely applicable information criterion in singular learning theory. *Journal of Machine Learning Research*, 11, 3571–3594.
- XXXIII.Yu, D., & Fang, C. (2022). How neighborhood characteristics influence neighborhood crimes: A Bayesian hierarchical spatial analysis. *International Journal of Environmental Research and Public Health*, 19(18), 11416. <https://doi.org/10.3390/ijerph191811416>



A map of Mindanao, Philippines, with the Cotabato region highlighted in orange and South Cotabato in maroon. Other regions shown in yellow include Sultan Kudarat, General Santos City, and Sarangani. Major cities labeled include Zamboanga City, Cotabato City, Davao City, and Taguig. The text "THANK YOU!" is overlaid in large, bold, dark blue letters.

THANK YOU!