Letter

Beyond Parametric Boundaries: Rethinking the Distributed Lag Nonlinear Model in Meteorological Modelling for Oncology Emergencies

Letter to the Editor — Cheng *et al.* provide valuable insights into oncology emergency service planning through a 7.5-year time-series analysis [1]. While their finding that oncology emergencies are shaped by calendar factors rather than weather extremes is compelling, the claim of weather insensitivity warrants further methodological scrutiny. They use a distributed lag nonlinear model (DLNM), which effectively captures delayed and nonlinear effects of individual meteorological variables [2]. However, as a parametric method requiring predefined functional forms and assuming predictor independence, DLNM is limited in modelling complex, synergistic interactions among weather variables—such as wind chill (temperature $\times$ wind speed) or heat stress (temperature $\times$ humidity)—known to affect health outcomes [3,4].

Notably, the authors report nonsignificant increases of 3−6% in oncology presentations during temperature extremes. While inconclusive in isolation, such signals may reflect broader, unmodelled synergistic effects that models assuming predictor independence cannot detect. DLNM accommodates nonlinear exposure-response relationships but does not inherently capture multivariate nonlinear dependencies without extensive customisation [5,6]. In dynamic systems like weather, where variables interact unpredictably, parametric assumptions may oversimplify reality and obscure meaningful signals.

To address this limitation, future studies should consider nonparametric, data-driven approaches, such as unsupervised feature selection (eg, Feature Agglomeration and Highly Variable Gene Selection) [7,8] and rank-based correlation methods (eg, Spearman's rho and Kendall's tau) [9,10], which may better reflect the complexity of environmental systems. These methods can complement DLNM or replace it where parametric constraints hinder interpretability. Additionally, model-agnostic interpretability frameworks may help quantify uncertainty and assess feature relevance in complex systems.

In conclusion, while Cheng *et al.*'s study offers a strong foundation for calendar-based staffing, advancing meteorological modelling beyond parametric frameworks is essential for accurate demand forecasting—especially under growing climate variability. This evolution is vital to protect vulnerable patients, such as those with cancer, in an era of climatic uncertainty.

Funding

Author Contribution

1 Guarantor of integrity of the entire study: Souichi Oka.
2 Study concepts and design: Souichi Oka.
3 Literature research: Kiyo Yoshida.
4 Clinical studies: N/A.
5 Experimental studies/data analysis: N/A.
6 Statistical analysis: N/A.
7 Manuscript preparation: Souichi Oka.
8 Manuscript editing: Yoshiyasu Takefuji.

Conflict of Interest

The authors declare no conflict of interest.

Data availability

No new data were generated or analysed in support of this research.

Acknowledgements

S. Oka*, K. Yoshida*, Y. Takefuji[†]

* Science Park Corporation, 3-24-9 Iriya-Nishi, Zama-shi, Kanagawa, 252-0029, Japan

[†] *Faculty of Data Science, Musashino University, 3-3-3 Ariake, Koto-ku, Tokyo, 135-8181, Japan*

* Author for correspondence: Souichi Oka, Ph.D. Science Park Corporation, 3-24-9 Iriya-Nishi, Zama-shi, Kanagawa, 252-0029, Japan. E-mail addresses: souichi.oka@sciencepark.co.jp, kyoshida@sciencepark.co.jp, takefuji@keio.jp

References

[1] Cheng MTK, White N, Frost S, Attia H, Favara DM. Weathering the storm: the impact of weather events, lockdowns and holidays on oncology and general emergency presentations to a United Kingdom tertiary centre—a 7.5-year review. *Clin Oncol* 2025;44: 103879. https://doi.org/10.1016/j.clon.2025.103879.

[2] Gasparrini A, Armstrong B, Kenward MG. Distributed lag non-linear models. *Stat Med* 2010;29:2224—2234. https://doi.org/10.1002/sim.3940.

[3] Gasparrini A, Masselot P, Stafoggia M. A penalized framework for distributed lag non-linear models. *Biometrics* 2017;73: 938—948. https://doi.org/10.1111/biom.12645.

[4] Mork D, Wilson A. Treed distributed lag nonlinear models. *Biostatistics* 2022;23:754—770. https://doi.org/10.1093/biostatistics/kxaa015.

[5] Bobb JF, Valeri L, Claus Henn B, Christiani DC, Wright RO, Mazumdar M, *et al.* Bayesian kernel machine regression for estimating the health effects of multi-pollutant mixtures. *Biostatistics* 2015;16:493—508. https://doi.org/10.1093/biostatistics/kxu058.

[6] Quijal-Zamorano M, Sera F, Vicedo-Cabrera AM, Gasparrini A. Spatial Bayesian distributed lag non-linear models for small-area exposure—lag—response epidemiological modelling. *Int J Epidemiol* 2024;53. https://doi.org/10.1093/ije/dyae061. dyae061.

[7] Zhang J, Wu X, Hoi SCH, Zhu J. Feature agglomeration networks for single stage face detection. *Neurocomputing* 2020; 380:180—189. https://doi.org/10.1016/j.neucom.2019.10.087.

[8] Xie Y, Jing Z, Pan H, Xu X, Fang Q. Redefining the high variable genes by optimized LOESS regression with positive ratio. *BMC Bioinform* 2025;26:104. https://doi.org/10.1186/s12859-025-06112-5.

[9] Okoye K, Hosseini S. Correlation tests in R: Pearson Cor, Kendall's Tau, and Spearman's Rho. *R Program Stat Data Anal Res* 2024:247—277. https://doi.org/10.1007/978-981-97-3385-9_12.

[10] Yu H, Hutson AD. A robust Spearman correlation coefficient permutation test. *Commun Stat Theory Methods* 2024;53: 2141—2153. https://doi.org/10.1080/03610926.2022.2121_144.