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Climatic variability and routine childhood vaccine uptake in high-risk urban settlements of Karachi, Pakistan: a longitudinal fixed-effects panel analysis

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Climatic variability and routine childhood vaccine uptake in high-risk urban settlements of Karachi, Pakistan: a longitudinal fixed-effects panel analysis

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Abstract

Climate variability may disrupt routine immunization in rapidly growing cities, where informal settlements combine high climatic exposure with fragile health services, yet longitudinal urban evidence from low- and middle-income countries is limited. We examined associations between monthly climatic conditions and routine childhood vaccine doses in 14 public and private health facilities serving nine high-risk urban union councils of Karachi, Pakistan, using 266 facility-month observations (June 2023–December 2024). Monthly doses of Bacille Calmette–Guérin (BCG), pentavalent (Penta-1 to Penta-3), inactivated poliovirus (IPV-1) and measles–rubella (MR-1) vaccines were linked with reanalysis-based maximum temperature, relative humidity and wind speed, satellite-based rainfall, night-time light (NTL) and catchment population. One-way fixed-effects panel models with facility-clustered standard errors were fitted for each vaccine, with five sensitivity analyses. In the main models, wind speed was negatively associated with doses of all six vaccines (standardized $\beta = -0.150$ to -0.491), maximum temperature with five, and relative humidity positively with all six. Rainfall was negatively associated with BCG doses ($\beta = -0.285$, $p < 0.001$) in every specification, whereas its positive associations with Penta-2 and MR-1 did not persist after lagged climatic terms were added. The temperature association persisted only for BCG and Penta-2 when the start-up months were excluded. NTL was associated with the multi-visit doses Penta-2, Penta-3 and IPV-1. Climatic associations with routine immunization in urban informal settings therefore differ by vaccine, supporting vaccine-specific, climate-informed urban immunization planning.

Keywords Urban health · Informal settlements · Childhood immunization · Climate variability · Fixed-effects panel model · Karachi

Introduction

Childhood immunization is one of the most effective and cost-efficient public health interventions; it currently prevents an estimated 3.5–5 million deaths each year [1–4]. In Pakistan, the Expanded Programme on Immunization (EPI) provides free childhood vaccination through fixed facilities, outreach sessions, mobile teams and supplementary campaigns [5, 6]. Maintaining consistently high coverage nevertheless remains challenging, particularly in rapidly urbanizing settings where socioeconomic inequalities, infrastructure limitations, population mobility and environmental stressors disrupt healthcare delivery.

Climate change has emerged as an additional threat to health-system resilience: rising temperatures, changing rainfall patterns, flooding and other extreme weather affect healthcare accessibility, workforce availability, transport networks and cold-chain maintenance [7–9]. Most existing evidence concerns acute events such as heatwaves or floods [10]. Routine immunization is, however, likely to be influenced also by persistent seasonal fluctuations in temperature, humidity, rainfall and wind, acting through reduced health-worker productivity in extreme heat, electricity interruptions affecting vaccine storage, damaged transport infrastructure after rainfall and reduced caregiver attendance during adverse weather.

Cities are where these pressures converge. Urban populations in low- and middle-income countries are particularly vulnerable because rapid urbanization often outpaces improvements in infrastructure, sanitation, transport and health services [11–14]. Informal settlements commonly experience poor drainage, unreliable electricity, overcrowding, urban heat and limited access to primary healthcare, conditions that amplify both socioeconomic vulnerability and exposure to climate-related hazards, and that make urban immunization equity a climate-sensitive problem. Karachi, Pakistan's largest city, exemplifies these challenges through recurrent heatwaves, monsoon flooding and persistent inequalities in healthcare access across densely populated informal settlements.

Previous studies of climate and immunization have largely relied on cross-sectional or ecological designs [15, 16], limiting the ability to distinguish temporal from spatial variability. Longitudinal facility-level analyses incorporating gridded climatic data remain scarce, particularly in cities of low- and middle-income countries, and few studies have examined whether climatic associations are uniform across the vaccines of a routine schedule. This study linked monthly vaccine-dose data from 14 health facilities in nine high-risk urban union councils of Karachi with gridded climatic and socioeconomic data and used fixed-effects panel models, which remove all time-invariant facility-specific confounding, to estimate the associations of maximum temperature, relative humidity, wind speed, rainfall and a night-time light (NTL) index of local development with doses of six EPI vaccines, each modelled separately. The aim was to inform climate-resilient urban immunization planning.

Methods

Study Design and Setting

This facility-based longitudinal panel study used monthly observations from June 2023 to December 2024 for 14 health facilities (five public-sector primary health centres and nine private-sector facilities) located within nine urban high-risk union councils (HRUCs) of Karachi: Safoora, Pehlwan Goth, Malir Cantt, Gulzar-e-Hijri, Yousuf Goth, Mamarabad, Frontier Colony, Baloch Goth and Qasba Colony (Fig. 1). These union councils were designated as high risk because of persistent polio transmission and comprise densely populated neighbourhoods with informal settlements, limited public infrastructure and high social vulnerability. The facilities are part of an implementation research pilot jointly executed by the Department of Health Sindh, EPI Sindh and the Aga Khan University to address vaccine inequities in Karachi's urban squatter settlements. Each facility was observed monthly, forming a balanced panel of 266 facility-month observations.

Karachi has a semi-arid subtropical climate with hot summers (monthly mean maximum temperatures above 35 °C), mild winters and a monsoon from July to September; rapid urbanization and poor drainage make the city highly susceptible to flooding and heatwaves. Pakistan's EPI schedule begins at birth (BCG and OPV-0), followed by pentavalent vaccine (Penta-1 to Penta-3), OPV and IPV at 6–14 weeks, and measles–rubella vaccine from 9 months of age, which allows early- and later-schedule doses to be compared.

Data Sources

Monthly vaccination data were obtained from facility immunization registers maintained under EPI Sindh, recording the number of doses administered each month for BCG, Penta-1, Penta-2, Penta-3, IPV-1 and MR-1. Because these vaccines target different age cohorts and are delivered at different contacts, each vaccine was analysed as a separate outcome; an aggregate model of total doses is provided for reference only in Online Resource 1.

Monthly maximum temperature, relative humidity and wind speed were obtained from the ERA5-Land reanalysis of the European Centre for Medium-Range Weather Forecasts [17] at 0.1° × 0.1° resolution (approximately 11 km × 11 km), and monthly precipitation from the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) [18]. Climatic values were matched to each facility's location. Because the facilities fall within a small number of grid cells, several share identical climatic values (four distinct series for wind speed and relative humidity and eight for rainfall); the climatic exposures therefore vary predominantly over time rather than between facilities.

Night-time light intensity, a proxy for local economic activity and infrastructure development, was obtained from the Visible Infrared Imaging Radiometer Suite (VIIRS) Day/Night Band monthly composites (Google Earth Engine dataset NOAA/VIIRS/DNB/MONTHLY_V1/VCMCFG) [19] at approximately 464 m resolution.

Baseline catchment populations, included as a demographic control, were based on the 2023 Population and Housing Census [20] and projected forward at a constant annual growth rate of 1.9%, so that population increased at an identical rate in every facility (2.86% over the 19 months); within facilities this term therefore captures a smooth secular trend and is interpreted as a control rather than a substantive determinant.

Statistical Analysis

Associations were estimated with one-way fixed-effects (within-estimator) panel regression models, fitted separately for each vaccine, for facility $i = 1, \ldots, 14$ and month t:

$$Y_{it} = \alpha_i + \beta_1 \mathrm{Rain}_{it} + \beta_2 \mathrm{Tmax}_{it} + \beta_3 \mathrm{Wind}_{it} + \beta_4 \mathrm{RH}_{it} + \beta_5 \mathrm{NTL}_{it} + \beta_6 \mathrm{Pop}_{it} + \varepsilon_{it} \qquad (1)$$

where Y_{it} is the number of doses of a given vaccine, α_i is a facility fixed effect absorbing all time-invariant facility characteristics (e.g. staff capacity, baseline catchment behaviour and service quality), β_1–β_6 are the coefficients of interest and ε_{it} is the error. Standard errors were clustered by facility.

Fixed effects were preferred to random effects on the basis of a Hausman-type test [21] implemented through the Mundlak correlated random-effects approach [22], which remains valid with clustered standard errors; an F-test assessed the poolability of facility effects. Coefficients are reported as within-facility standardized betas (raw coefficient multiplied by the ratio of the within-facility standard deviations of predictor and outcome), which does not alter fit or significance. Multicollinearity was assessed with variance inflation factors (VIFs).

Five sensitivity analyses were conducted (Online Resource 2): (i) inference based on a *t*-distribution with 13 degrees of freedom to account for the small number of clusters; (ii) a common linear time trend; (iii) exclusion of the programme start-up months, June–August 2023 (N = 224); (iv) one-month lagged climatic terms (N = 252); and (v) a Poisson fixed-effects model with incidence rate ratios per within-facility standard deviation. The false

discovery rate across the 36 main-model coefficients was controlled with the Benjamini–Hochberg procedure [23]. Analyses were conducted in Python with the linearmodels and statsmodels packages.

Results

Vaccine Doses and Climatic Conditions

Table I summarizes the study variables. Mean doses per facility-month ranged from 52.9 (BCG) to 65.0 (Penta-1 and IPV-1). Doses of all six vaccines rose steeply during the programme start-up phase in mid-2023 and thereafter fluctuated from month to month (Fig. 2). BCG was the most volatile (coefficient of variation of monthly means 0.23), and MR-1 showed the strongest upward trend (approximately 1.9 additional doses per facility per month, compared with 0.5–1.1 for the other vaccines). Doses of the six vaccines were positively correlated ($r = 0.43–0.89$; Online Resource 2, Fig. S2), most strongly for the co-administered Penta-3 and IPV-1.

Monthly mean maximum temperature was highest in May–July 2024 (39.4–40.4 °C) and lowest in January 2024 (26.4 °C). Rainfall was concentrated in the monsoon (125.8 mm in July 2023; 100.9 and 129.6 mm in July and August 2024; under 15 mm in most other months) and was strongly right-skewed. Wind speed was highest in June–August 2023 (5.5–6.8 m s^{-1}), and relative humidity ranged from 42.3% to 85.4%. Almost all climatic variance occurred within facilities (97% for maximum temperature and almost 100% for rainfall), compared with 47% for NTL and under 1% for population.

Vaccine-Specific Fixed-Effects Models

Table II presents the standardized estimates. Maximum temperature was negatively associated with doses of every vaccine, significantly for BCG ($\beta = -0.315$), Penta-1 ($\beta = -0.229$), Penta-

2 ($\beta = -0.253$), Penta-3 ($\beta = -0.253$) and IPV-1 ($\beta = -0.168$; all $p \leq 0.003$), but not MR-1 ($\beta = -0.088$, $p = 0.066$). Wind speed was negatively associated with doses of all six vaccines ($\beta = -0.150$ to -0.491, all $p \leq 0.014$), most strongly for Penta-1, and relative humidity positively with all six ($\beta = 0.255$ to 0.487, all $p \leq 0.002$), most strongly for MR-1.

Rainfall differed in sign across the schedule. It was negatively associated with BCG ($\beta = -0.285$, 95% CI -0.406 to -0.163; $p < 0.001$), the only dose given at or shortly after birth, but positively with Penta-2 ($\beta = 0.139$, $p < 0.001$) and MR-1 ($\beta = 0.126$, $p = 0.003$), marginally with IPV-1 ($\beta = 0.094$, $p = 0.050$), and not significantly with Penta-1 or Penta-3; these opposing associations would offset one another if doses were summed. Catchment population was associated with BCG ($\beta = 0.186$, $p = 0.036$) and MR-1 ($\beta = 0.411$, $p < 0.001$) only. The NTL index was associated with Penta-2 ($\beta = 0.273$), Penta-3 ($\beta = 0.345$) and IPV-1 ($\beta = 0.277$; all $p < 0.001$) but not with BCG or MR-1. Within R^2 ranged from 0.200 (BCG) to 0.356 (MR-1), and all models were significant overall ($p < 0.001$).

Facility effects were jointly significant in every model (poolability $F = 9.09–14.19$, $p < 0.001$), and the cluster-robust Mundlak test rejected random effects for every vaccine ($\chi^2 = 21.36–68.11$, $df = 6$, $p \leq 0.002$). All VIFs were below 3 (largest 2.84). Coefficients with 95% confidence intervals are plotted in Online Resource 2 (Fig. S3).

Sensitivity Analyses

With small-cluster inference, every association significant at $p < 0.05$ remained significant except population for BCG ($p = 0.055$). Adding a linear time trend left every climatic and NTL association unchanged in direction and significance, whereas the population term reversed sign for five vaccines, confirming that it captured within-facility secular trends. Excluding the start-up months (N = 224), which included the windiest months, strengthened the rainfall associations (BCG $\beta = -0.384$, $p = 0.002$), and wind speed and relative humidity

remained significant for four vaccines each; maximum temperature, however, remained significantly negative only for BCG ($\beta = -0.245$) and Penta-2 ($\beta = -0.175$) and became positive for MR-1 ($\beta = 0.106$, $p = 0.045$).

With one-month lagged climatic terms (N = 252), the negative rainfall–BCG association was stronger ($\beta = -0.463$, $p < 0.001$), but the positive rainfall associations with Penta-2 and MR-1 were no longer significant. Contemporaneous temperature remained negatively associated with BCG and Penta-2, and part of the wind association shifted to the previous month (lagged wind significant for Penta-1, IPV-1 and MR-1). The Poisson model agreed with the linear model in sign and 5% significance for 35 of 36 coefficients, and 24 of 25 significant associations survived Benjamini–Hochberg correction (exception: population for BCG).

Discussion

In this longitudinal study of health facilities serving high-risk urban settlements of Karachi, monthly climatic conditions were associated with routine vaccine doses, in several cases for all six vaccines. Higher maximum temperature and wind speed were associated with fewer doses and higher relative humidity with more doses, whereas rainfall and the NTL index showed vaccine-specific patterns detectable only when each vaccine was modelled separately. The negative association between rainfall and BCG doses was the most robust finding; the temperature association was sensitive to exclusion of the start-up months, and the positive rainfall associations with later doses to lagged climatic terms.

The temperature finding should be interpreted with caution because, after exclusion of the start-up months, it remained significant only for BCG and Penta-2, suggesting that part of the main-model estimate reflects the coincidence of low start-up volumes with the summer of 2023. Extreme heat, which is intensified in dense informal settlements by the urban heat island, can make outdoor movement difficult for caregivers and health workers and strain

transport and cold-chain systems. Heat has been associated with reduced use of maternal and child health services and lower vaccination coverage in South Asia and sub-Saharan Africa [16, 24, 25], and with immunization shortfalls during heatwaves in Sindh [10]; our facility-level analysis complements that work by examining routine month-to-month variability rather than discrete events.

Wind speed showed the most consistent negative association. It was significant for all six vaccines in the main and Poisson models, persisted for four vaccines after exclusion of the start-up months and was partly expressed with a one-month delay. In informal settlements with unpaved roads, strong winds and accompanying dust may hinder caregiver travel and outreach; few studies have evaluated wind as a determinant of vaccination. Relative humidity is unlikely to influence vaccination directly and, conditional on temperature and wind, may mark seasonal periods with more favourable travel conditions; this interpretation remains speculative.

Rainfall was negatively associated with BCG doses in every specification. If a substantial share of BCG doses follows facility-based births, this may reflect disruption of deliveries during heavy rainfall through flooding, waterlogged streets, transport difficulties or a shift towards home births; otherwise it may reflect difficulty in bringing newborns to facilities. Urban flooding is a recurrent hazard in Karachi's low-lying informal settlements, where drainage is poor [11, 13]. The positive rainfall associations with Penta-2 and MR-1 did not persist in the lag model and may reflect the timing of catch-up visits. Because opposing associations offset one another when doses are aggregated, treating immunization as a single outcome can conceal policy-relevant relationships.

The non-climatic covariates require cautious interpretation. The population term captured a within-facility trend and reversed sign once a time trend was included, so it should not be read as evidence that catchment size drives specific doses. The NTL index was associated with

Penta-2, Penta-3 and IPV-1, the doses that require a caregiver to return for a subsequent visit, but not with BCG or MR-1, and most strongly with Penta-3, which defines the WHO/UNICEF primary-series dropout indicator. This is consistent with financial constraints, transport costs and competing household priorities affecting completion of the primary series among the urban poor. However, monthly NTL composites are affected by seasonal cloud cover and were negatively correlated with rainfall within facilities ($r = -0.52$), so this finding is hypothesis-generating.

Strengths and Limitations

The panel design with facility fixed effects controlled for all time-invariant facility-level confounding, the specification was validated for every vaccine, modelling each vaccine separately revealed sign-reversing associations that an aggregate analysis would obscure, and five sensitivity analyses addressed small clusters, secular trends, the start-up period, lags and the count outcome. Several limitations apply. The sample of 14 facilities and 266 facility-months is modest, and the 19-month period covers fewer than two seasonal cycles, so the climatic exposures, which varied mainly over time and were shared within grid cells, may be partly confounded with other time-varying factors such as the programme start-up. Lags were examined only up to one month. The facilities lie within HRUCs of one city, and findings may not generalize to other urban or rural settings. Routine dose counts may contain reporting inaccuracies and reflect service volume rather than coverage. Individual-level factors (e.g. maternal education, income, hesitancy and migration) and service-level disruptions (stock-outs, staffing, electricity interruptions) were unavailable. Catchment population was projected rather than enumerated, NTL is an indirect proxy, and the observational design precludes causal inference.

Implications for Urban Health and Conclusions

Monthly climatic variability was associated with routine childhood vaccine doses in facilities serving high-risk urban settlements of Karachi, and the associations differed by vaccine: rainfall was robustly associated with fewer birth doses, wind and heat with fewer doses across the schedule, and the NTL index specifically with the multi-visit doses that determine series completion. For urban health systems, this suggests calibrating climate adaptation to the vaccine and delivery contact at risk: protecting birth-dose delivery during the monsoon, weather-responsive outreach and catch-up scheduling, resilient cold-chain and transport arrangements, and targeted follow-up of socioeconomically vulnerable households to prevent dropout. As climate change intensifies heat and flooding in cities, longer time series, more facilities, coverage-normalized outcomes, direct socioeconomic measures and distributed-lag models are needed to confirm these associations.

Supplementary Information

Online Resource 1 Fixed-effects model of total doses across the six vaccines, provided for reference only (Table S1, Fig. S1).

Online Resource 2 Correlation of vaccine doses (Fig. S2), coefficient plot of the main models (Fig. S3) and sensitivity analyses: small-cluster inference, linear time trend, exclusion of the start-up months, lagged climatic terms and Poisson fixed-effects model (Tables S2a–S2e).

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Statements and Declarations

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Author contributions All authors contributed to the study conception and design, data interpretation and critical revision of the manuscript. Ammarah Ali: conceptualization, methodology, investigation, data curation, formal analysis, writing – original draft. Wardah Ahmed: methodology, investigation, data curation, writing – original draft. Saqib-ur-Rehman: methodology, formal analysis, visualization, writing – review & editing. Zahid Memon: conceptualization, project administration, funding acquisition, supervision, writing – review & editing. Zafar Fatmi: conceptualization, methodology, supervision, funding acquisition, writing – review & editing. All authors read and approved the final manuscript.

Data availability Climatic data are publicly available from the Copernicus Climate Data Store (ERA5-Land monthly means; https://cds.climate.copernicus.eu/datasets/reanalysis-era5-land-monthly-means) and the Climate Hazards Center (CHIRPS v2.0;

https://data.chc.ucsb.edu/products/CHIRPS-2.0/), and night-time light data from the Google Earth Engine catalogue (NOAA/VIIRS/DNB/MONTHLY_V1/VCMCFG). Facility-level vaccination data were provided by EPI Sindh under a data-sharing agreement; they are not publicly available but can be obtained from the corresponding author on reasonable request with the permission of EPI Sindh.

Code availability The analysis code (Python) is available from the corresponding author on reasonable request.

Ethics approval The study involved no human participants and used only anonymized, aggregate facility-level counts of vaccine doses from routine immunization records, together with publicly available climatic and satellite datasets. The vaccination data were provided by EPI Sindh under a data-sharing agreement that permits their use for research and publication.

Consent to participate Not applicable; no individual-level data were used.

Consent for publication Not applicable.

References

1. Lindstrand A, Cherian T, Chang-Blanc D, Feikin D, O'Brien KL. The world of immunization: achievements, challenges, and strategic vision for the next decade. *J Infect Dis*. 2021;224(Suppl 4):S452-S467. doi:10.1093/infdis/jiab284

2. Shattock AJ, Johnson HC, Sim SY, et al. Contribution of vaccination to improved survival and health: modelling 50 years of the Expanded Programme on Immunization. *Lancet*. 2024;403(10441):2307-2316. doi:10.1016/S0140-6736(24)00850-X

3. World Health Organization. Global immunization efforts have saved at least 154 million lives over the past 50 years. Published April 24, 2024. Accessed November 19, 2026.

https://www.who.int/news/item/24-04-2024-global-immunization-efforts-have-saved-at-least-154-million-lives-over-the-past-50-years

4. World Health Organization. Vaccines and immunization. Accessed November 19, 2026. https://www.who.int/health-topics/vaccines-and-immunization

5. Haq Z, Shaikh BT, Tran N, Hafeez A, Ghaffar A. System within systems: challenges and opportunities for the Expanded Programme on Immunisation in Pakistan. *Health Res Policy Syst*. 2019;17(1):51. doi:10.1186/s12961-019-0452-z

6. World Health Organization Regional Office for the Eastern Mediterranean. Pakistan and WHO renew their pledge to protect millions with lifesaving vaccines. Published April 27, 2025. Accessed November 19, 2026. https://www.emro.who.int/pak/pakistan-news/pakistan-and-who-renew-their-pledge-to-protect-millions-with-lifesaving-vaccines.html

7. Ebi KL, Vanos J, Baldwin JW, et al. Extreme weather and climate change: population health and health system implications. *Annu Rev Public Health*. 2021;42:293-315. doi:10.1146/annurev-publhealth-012420-105026

8. Naser K, Haq Z, Naughton BD. The impact of climate change on health services in low- and middle-income countries: a systematised review and thematic analysis. *Int J Environ Res Public Health*. 2024;21(4):434. doi:10.3390/ijerph21040434

9. Golden CD, Childs ML, Mudele OE, et al. Climate-smart public health for global health resilience. *Lancet Planet Health*. 2025;9(8):101293. doi:10.1016/j.lanplh.2025.101293

10. Siddiqi DA, Iftikhar S, Anfossi CM, et al. Assessing the impact of heat waves on childhood immunization coverage in Sindh, Pakistan: insights from 132.4 million doses recorded in the provincial electronic immunization registry (2018-2024). *Vaccine*. 2025;61:127424. doi:10.1016/j.vaccine.2025.127424

11. Williams DS, Máñez Costa M, Sutherland C, Celliers L, Scheffran J. Vulnerability of informal settlements in the context of rapid urbanization and climate change. *Environ Urban*. 2019;31(1):157-176. doi:10.1177/0956247818819694

12. Codjoe SNA, Gough KV, Wilby RL, et al. Impact of extreme weather conditions on healthcare provision in urban Ghana. *Soc Sci Med*. 2020;258:113072. doi:10.1016/j.socscimed.2020.113072

13. Borg FH, Greibe Andersen J, Karekezi C, et al. Climate change and health in urban informal settlements in low- and middle-income countries – a scoping review of health impacts and adaptation strategies. *Glob Health Action*. 2021;14(1):1908064. doi:10.1080/16549716.2021.1908064

14. Damte E, Manteaw BO, Wrigley-Asante C. Urbanization, climate change and health vulnerabilities in slum communities in Ghana. *J Clim Change Health*. 2023;10:100189. doi:10.1016/j.joclim.2022.100189

15. Utazi CE, Thorley J, Alegana VA, et al. High resolution age-structured mapping of childhood vaccination coverage in low and middle income countries. *Vaccine*. 2018;36(12):1583-1591. doi:10.1016/j.vaccine.2018.02.020

16. Zheng H, Zhu Y, Chu H, et al. Association between ambient temperature and childhood vaccination coverage in low- and middle-income countries. *BMC Med*. 2026;24(1):296. doi:10.1186/s12916-026-04743-w

17. Muñoz-Sabater J, Dutra E, Agustí-Panareda A, et al. ERA5-Land: a state-of-the-art global reanalysis dataset for land applications. *Earth Syst Sci Data*. 2021;13(9):4349-4383. doi:10.5194/essd-13-4349-2021

18. Funk C, Peterson P, Landsfeld M, et al. The climate hazards infrared precipitation with stations—a new environmental record for monitoring extremes. *Sci Data*. 2015;2(1):150066. doi:10.1038/sdata.2015.66

19. Elvidge CD, Baugh K, Zhizhin M, Hsu FC, Ghosh T. VIIRS night-time lights. *Int J Remote Sens*. 2017;38(21):5860-5879. doi:10.1080/01431161.2017.1342050

20. Pakistan Bureau of Statistics. 7th Population and Housing Census 2023: final results. Pakistan Bureau of Statistics; 2023. Accessed November 19, 2026. https://www.pbs.gov.pk/sites/default/files/population/2023/tables/table_1_sindh_provinc e.pdf

21. Hausman JA. Specification tests in econometrics. *Econometrica*. 1978;46(6):1251-1271. doi:10.2307/1913827

22. Mundlak Y. On the pooling of time series and cross section data. *Econometrica*. 1978;46(1):69-85. doi:10.2307/1913646

23. Benjamini Y, Hochberg Y. Controlling the false discovery rate: a practical and powerful approach to multiple testing. *J R Stat Soc Series B Stat Methodol*. 1995;57(1):289-300. doi:10.1111/j.2517-6161.1995.tb02031.x

24. Dey AK, Dimitrova A, Raj A, Benmarhnia T. The effect of extreme temperatures on healthcare utilization during pregnancy: findings from a nationally representative survey in India. *Environ Res*. 2025;285:122410. doi:10.1016/j.envres.2025.122410

25. Kouanda S, Kadio K, Sana A, et al. Heat and its effects on maternal and neonatal health care: evidence from Burkina Faso. *Public Health*. 2026;252:106144. doi:10.1016/j.puhe.2026.106144

Table I Descriptive statistics of vaccine doses and predictors, 14 health facilities in high-risk urban union councils of Karachi, Pakistan (N = 266 facility-months, June 2023–December 2024)

Variable	Mean	SD	Median	Min	Max
BCG doses	52.9	24.8	52.0	2	138
Penta-1 doses	65.0	19.1	64.0	15	156
Penta-2 doses	61.4	17.2	61.5	8	103
Penta-3 doses	64.7	17.5	66.0	7	116
IPV-1 doses	65.0	18.7	66.0	8	124
MR-1 doses	59.9	20.0	59.0	5	123
Rainfall (mm $month^{-1}$)	25.2	41.5	6.8	0.8	140.9
Maximum temperature (°C)	34.8	4.1	35.2	25.8	43.8
Wind speed (m s^{-1})	4.7	1.7	4.8	1.2	8.0
Relative humidity (%)	68.4	15.2	74.9	36.6	87.9
NTL radiance (nW cm^{-2} sr^{-1})	37.7	15.1	33.2	9.1	91.7
Catchment population	14,295	8,383	14,243	992	32,964

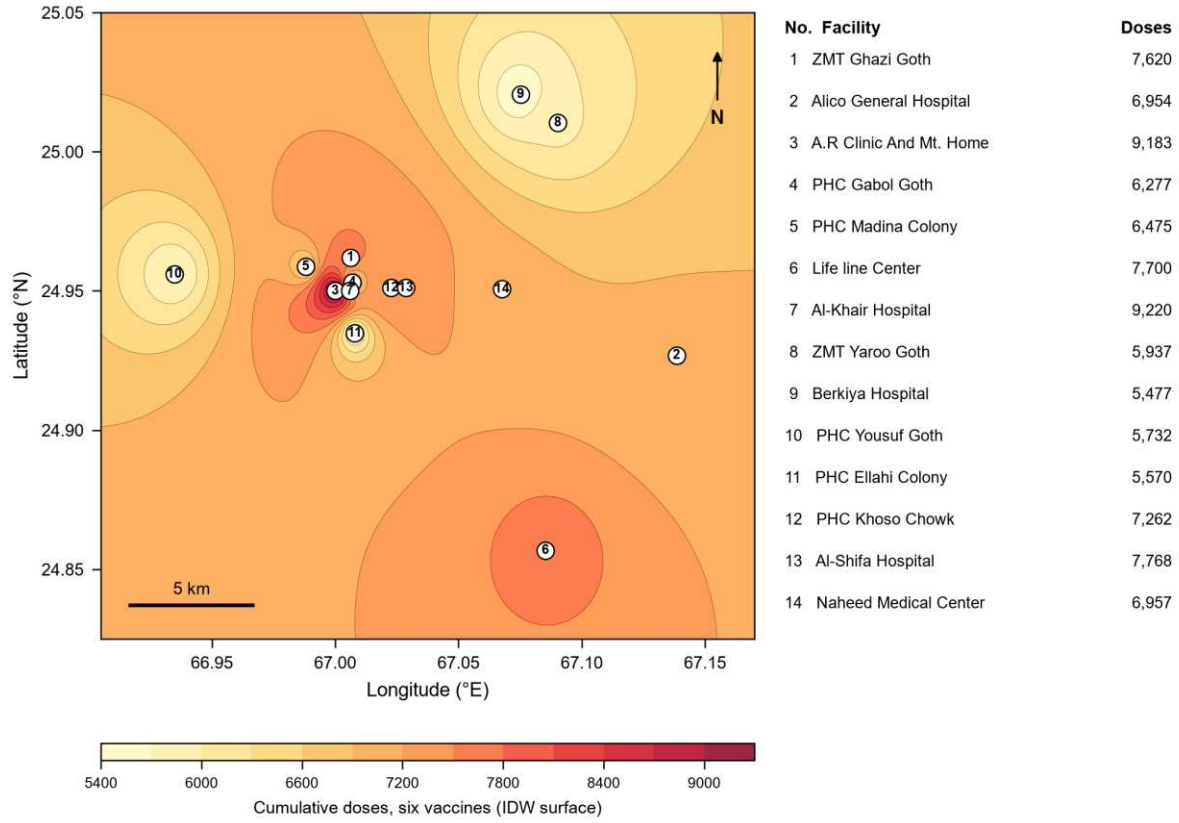
SD standard deviation; NTL night-time light

Table II Fixed-effects estimates of the association between climatic and socioeconomic predictors and monthly vaccine doses, by vaccine

Predictor	BCG	Penta-1	Penta-2	Penta-3	IPV-1	MR-1
Rainfall	−0.285*** [−0.406, −0.163]	−0.055 [−0.192, 0.082]	0.139*** [0.068, 0.209]	0.043 [−0.048, 0.134]	0.094* [−0.000, 0.189]	0.126*** [0.044, 0.208]
Maximum temperature	−0.315*** [−0.464, −0.165]	−0.229*** [−0.334, −0.124]	−0.253*** [−0.361, −0.145]	−0.253*** [−0.350, −0.157]	−0.168*** [−0.279, −0.056]	−0.088* [−0.182, 0.006]
Wind speed	−0.150** [−0.269, −0.030]	−0.491*** [−0.708, −0.273]	−0.419*** [−0.572, −0.265]	−0.265*** [−0.391, −0.140]	−0.327*** [−0.488, −0.166]	−0.378*** [−0.543, −0.214]
Relative humidity	0.262*** [0.120, 0.404]	0.368*** [0.238, 0.498]	0.273*** [0.100, 0.445]	0.284*** [0.130, 0.439]	0.255*** [0.092, 0.418]	0.487*** [0.357, 0.617]
Population	0.186** [0.012, 0.359]	0.071 [−0.051, 0.193]	0.150* [−0.012, 0.313]	0.067 [−0.059, 0.193]	0.124 [−0.041, 0.289]	0.411*** [0.235, 0.587]
NTL index	−0.061 [−0.204, 0.081]	0.121 [−0.030, 0.271]	0.273*** [0.140, 0.405]	0.345*** [0.211, 0.479]	0.277*** [0.132, 0.423]	0.103 [−0.094, 0.301]
Within R^2	0.200	0.264	0.324	0.224	0.211	0.356

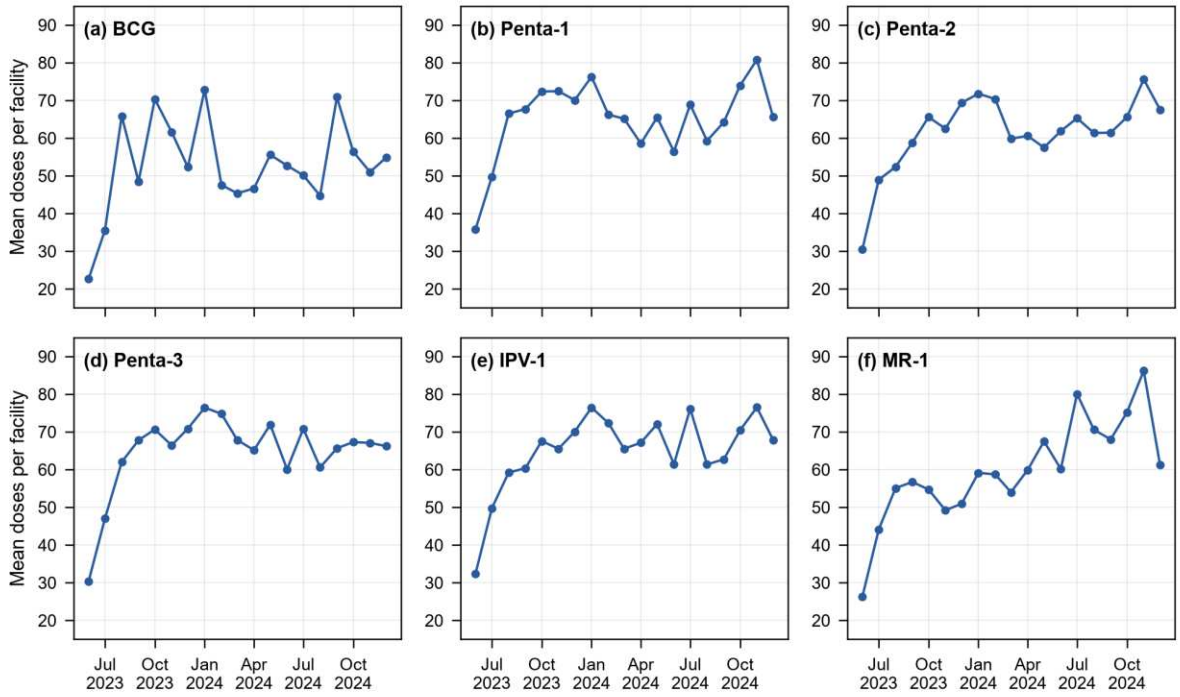
Values are within-facility standardized β with 95% confidence intervals in brackets. Standard errors are clustered by facility; N = 266 facility-months and 14 facilities for every model. NTL night-time light. *p < 0.10, **p < 0.05, ***p < 0.01

Figure Legends



No.	Facility	Doses
1	ZMT Ghazi Goth	7,620
2	Alico General Hospital	6,954
3	A.R Clinic And Mt. Home	9,183
4	PHC Gabol Goth	6,277
5	PHC Madina Colony	6,475
6	Life line Center	7,700
7	Al-Khair Hospital	9,220
8	ZMT Yaroo Goth	5,937
9	Berkiya Hospital	5,477
10	PHC Yousuf Goth	5,732
11	PHC Ellahi Colony	5,570
12	PHC Khoso Chowk	7,262
13	Al-Shifa Hospital	7,768
14	Naheed Medical Center	6,957

Fig. 1 Location of the 14 study health facilities in high-risk urban union councils of Karachi, Pakistan, with cumulative doses administered per facility (six vaccines combined, June 2023–December 2024). The background surface is an inverse-distance-weighted (IDW) interpolation of facility totals



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411 **Fig. 2** Mean monthly doses administered per facility, by vaccine, Karachi, Pakistan, June
412 2023–December 2024: (a) BCG, (b) Penta-1, (c) Penta-2, (d) Penta-3, (e) IPV-1 and (f) MR-1

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- ESM1.pdf
- ESM2.pdf