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Respiratory Illness, Weather and Air Pollution in Greater Jakarta During Indonesia's Fire and Haze Season: An Ecological Assessment With National Influenza Forecasting

Ahmad Nadim Shahab

dr.nadim@vaxcorpindo.com

Vaxcorp Indonesia, Indonesia

Research Article

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Respiratory Illness, Weather and Air Pollution in Greater Jakarta During Indonesia's Fire and Haze Season: An Ecological Assessment With National Influenza Forecasting

Ahmad Nadim Shahab

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1 Vaxcorp Indonesia, North Jakarta, DKI Jakarta, Indonesia; hello@vaxcorpindo.com

* Correspondence: dr.nadim@vaxcorpindo.com; Tel.: +62888806383838

Abstract

Background: Indonesia's 2026 forest-fire and haze season began early and has coincided with concerns about respiratory illness and rising influenza activity. While we know that exposure to PM2.5 in fire-affected areas may increase respiratory health risks and compromise airway defenses, influenza A detections have also risen in areas not yet directly affected by the consequences of fires, including Greater Jakarta and its surrounding areas. These concurrent trends suggest that respiratory illness in Greater Jakarta should be interpreted in light of infection, particulate exposure, and weather-related changes.

Objective: We aim to provide an exploratory national influenza A positivity forecast through publicly accessible data on respiratory and environmental indicators within the range of 16 July 2026 to 16 October 2026, and offering a repeatable methodology for ongoing local monitoring.

Methods: We compared 13 national surveillance reports and local public communications within an equal 28-day windows and examined 92 complete days of ECMWF IFS weather and Jakarta CAMS atmospheric fields. In contrast to persistence and random–walk baselines, a beta-binomial state model with damped logit drift was supported by eleven overlapping specimen weeks. We also provided separate weather and particulate model forecasts for environmental context.

Results: Relative temperature in Jakarta went from 29.24°C to 29.36°C, relative humidity went from 61.0% to 68.4%, and wind speed went from 6.59 km/h to 5.49 km/h. Modeled PM2.5 rose from 42.7 μg/m³ to 50.3 μg/m³; though not a station-confirmed increase. The national influenza A positive cases increased from 12/115 (10.4%) to 2025/337 (60.8%) in the August 15, 2026, and October 3, 2026, reports, respectively. An unresolved difference in the percentage denominator was found in a later study. The approximate projection of the exploratory model estimates 72% positivity for the week ending October 24, 2026 (95% prediction interval, range 49% - 89%). However, this refers to specimens collected and tested for national surveillance, not Jakarta population risk. Errors rose with lead time and there was a limitation for back-testing.

Conclusions: Available evidence does not prove a local causal relationship or a smoke-attributable illness burden, but it does show contemporaneous viral activity and shifting environmental conditions. Geographically-matched disease counts, pathogen-specific testing denominators, calibrated pollution measures, and report-vintage tracking are all necessary for ongoing monitoring needs. The forecast is a research example that has to be evaluated in the future.

Keywords: influenza A; acute respiratory illness; air pollution; peatland fires; haze; humidity; Greater Jakarta; surveillance; probabilistic forecasting.

1. Introduction

During periods of climate and weather catastrophes such as the ongoing forest fires and their repercussions, e.g., haze, greenhouse gas emissions, and air pollution, respiratory symptoms can have overlapping etiology and facilitating factors. Influenza and other viruses can circulate alongside exposure to urban emissions, smoke, or other airborne particles. When a rise in non-specific respiratory complaints is shrugged of as proof of a single pathogen or pollutant source, communication for public health becomes weakened. The dense population of Jakarta and its surrounding cities (Depok, Tangerang, Bogor, and Bekasi) make a coordinated metropolitan approach useful.

Official Indonesian reporting, published in late September 2026, has described a significant rise in influenza activity, with A(H1N1)pdm09 as the dominating pathogen strain, while reports in Jakarta show an increase in acute respiratory infection outpatient and inpatient visits. BMKG's Outlook in October elucidates continuing regional fire-related and weather concerns with a probable chance of local rainfall. While these simultaneous observations may motivate surveillance, their timing alone does not demonstrate causation. [1-5]

While weather can affect viral seasonality, human contact patterns, as well as the dispersion or elimination of pollutants in the atmosphere, tropical influenza patterns are generally heterogeneous, and extrapolations of observed patterns in cold-temperate winter regions cannot be conducted arbitrarily. On top of that, breathing dust and soot (collectively: particulates exposure) can irritate the lungs and exacerbations of pre-existing conditions, such as asthma. [10,20]

We prepared this report in order to increase public awareness as well as to enable professionals and researchers with the tools to continue with transparent monitoring. Our goals are to describe available evidence, address data source constraints, apply a clearly defined exploratory forecast, and outline the specific data required for a more robust local study. As an independent secondary-data assessment, this report should not be treated as an official outbreak declaration.

2. Methods

2.1 Design, setting and observation window

Our descriptive ecological assessment focuses on Greater Jakarta (Jabodetabek) regions, tracking data across five environmental sampling points representing Jakarta, Tangerang, Depok, Bekasi, and Bogor. The target review window ranges from July 16, 2026 to October 16, 2026. However, we concluded the retrospective environmental comparisons on October 15, 2026, to avoid the distortion of an incomplete final day. Because of source constraints, we could not obtain a complete, directly comparable series of local weekly outcomes; therefore, we integrated National Virological Surveillance data as essential contextual evidence.

In managing the data, we preserve weekly reports in their original published format, carefully distinguishing report dates from specimen-week labels. Because the first retained national week (July 12, 2026 to July 18, 2026) overlaps the start of our study by four days, its aggregate figures could not be precisely broken down by day. For our primary forecast model, we utilize 11 specimen weeks up to the inferred week ending September 26, 2026, while we reserved the most recent, inconsistent report for sensitivity analysis. [1]

2.2 Source identification and eligibility

Our study sources include the Indonesian Ministry of Health (Kemenkes) respiratory surveillance data, official Jakarta health and environmental communications channels, and climate metrics from BMKG. We also integrated

WHO surveillance documentation, sourced atmospheric and weather data from ECMWF and CAMS products via the Open-Meteo API, as well as verifiable public reports of local health advisories. Rather than a systematic review governed by a registered search protocol, this study was structured as a targeted review. All data were retrieved using public search engines and provider portals, ensuring that no restricted surveillance accounts or private patient records were used. [1-9,17-19,22]

2.3 Definitions, extraction and quality assessment

In our study, we made distinctions between acute upper respiratory tract infection (Infeksi Saluran Pernapasan Atas; ISPA), influenza-like illness (ILI), SARI (severe acute respiratory infection), pathogen-confirmed influenza and noninfectious exacerbations. We constructed national influenza A-positive counts by aggregating A(H1N1)pdm09, A(H3N2), and unsubtyped A detections, while extracting and tracking influenza B figures separately. We defined sample positivity as the number of positive specimens relative to the total tested; we did not interpret this value as general population prevalence. [1,2,22]

During data cleaning, to ensure data integrity, we systematically audited arithmetic consistency between numerators and denominators, subtype totals, correct timeline, and flagged placeholder or static text, and changes in institutional surveillance configurations. Any missing local data points were left missing rather than imputed. While we identified FluNet as a useful resource for national validation, we chose not to merge an independently reconciled FluNet export into our primary dataset. Finally, we treated public news reports strictly as contextual events rather than new patient counts, and we interpreted Google Trends data purely as an indicator of public attention rather than a direct measure of disease incidence. [9,14]

2.4 Historical environmental analysis

We retrieved hourly data fields using a fixed ECMWF IFS model selection across five specific coordinates: Jakarta (-6.20, 106.84), Tangerang (-6.18, 106.63), Depok (-6.40, 106.82), Bekasi (-6.24, 107.00), and Bogor (-6.60, 106.80). All timestamps were standardized to Asia/Jakarta time (UTC +07:00). From these 24-hour cycles, we calculated daily means, total rainfall, and temperature extremes. We also estimated absolute humidity from temperature and relative humidity based on the saturation vapor pressure. Crucially, these values represent gridded model estimates rather than direct weather station observations or population-weighted district exposures. [6]

To evaluate shifts within our study window, we compared two distinct 28-day blocks: July 16, 2026, to August 12, 2026, and September 18, 2026, to October 15, 2026. This comparison highlights changes directly within the observed timeframe rather than climate anomalies measured against a multi-decade baseline. Furthermore, because the underlying geographic populations do not align, we deliberately chose not to fit correlation coefficients or perform weather-disease regressions between local Jakarta weather and national virological data.

2.5 National influenza A forecast model

To account for overdispersion in specimen positivity, we developed a beta-binomial state-space model. The latent logit probability is governed by a Gaussian state process with an estimated constant historical drift. Beyond the final observation period, we multiplied this drift by 0.7h (where h is the forecast lead week) to systematically diminish its influence over time. This approach serves strictly as a modeling assumption; it does not mechanistically forecast an epidemic peak.

Mathematically, we defined the system as follows:

Historical state transition : $z_t = z_{t-1} + \varepsilon_t$, where $\varepsilon_t \sim \text{Normal}(0, \sigma^2)$

Observation process : tBeta(pt,(1-pt)) and ytBinomial(nt,t), where pt=logistic(zt)

Future state drift : h, with a damping factor of =0.7

For statistical inference, we utilized a discrete logit grid ranging from -12 to 12 with a step size of 0.04, applying a uniform initial prior over the probability space and performing discrete parameter averaging. We evaluated a grid of hyperparameter values: {0.10,0.20,0.35,0.55,0.80} and {10,25,60,150}. The drift parameter () took values of -0.6,-0.3,0,0.3,0.6, and 0.9, weighted by a Normal(0,0.52) prior distribution. To project future dynamics, we sampled future test volumes directly from the four most recent observed denominators. Our final prediction intervals account for conditional process stochasticity, parameter uncertainty, and specimen-level variation, though they do not encompass all potential structural or data source biases.

2.6 Back-testing, sensitivity and forecast timing

Our model's performance is evaluated by comparing the damped-trend architecture against two reference models: a zero-drift beta-binomial random walk and a persistence benchmark that applies beta-binomial sampling uncertainty to the most recently observed proportion. We implemented expanding-window back-tests starting with five initial training weeks. Due to the timeframe constraints, our analysis leveraged six one-week targets and five two-week targets, with progressively fewer targets available for longer lead times. We evaluated predictive accuracy using mean absolute error (MAE), weighted interval score (WIS), and empirical interval coverage, minimizing MAE and WIS to identify better model accuracy.

Methodological Disclaimers: Because we developed the damped-trend candidate after analyzing the initial random-walk outcomes, these performance scores reflect iterative model development rather than independent external validation. Furthermore, because our back-tests utilized a frozen data extraction rather than original, historic report archives, we cannot entirely rule out reporting-vintage data leakage. Consequently, we make no formal claims of superior forecasting capability.

Sensitivity Analysis & Projections: While our primary model excluded the most recent discrepant report, we evaluated its impact through a sensitivity run that integrated its count-derived numerator and denominator. We evaluated alternative damping parameters of 0.5 and 0.85. Finally, we categorized any predictions for weeks that had already elapsed or were currently underway as reporting-gap estimates; only the weeks ending October 24 and 31 constitute true future projections relative to our October 16, 2026, issue date. Given the constraints of the data, these represent four- and five-step forecasts from the final primary observation, rather than ordinary one- or two-step horizons built on fully completed surveillance records.

2.7 Prospective environmental model products

We retrieved a 51-member ECMWF IFS 0.25-degree weather ensemble on October 16, 2026. To process this dataset, we aggregated each member's hourly fields into daily maximum temperatures, mean humidity, total rainfall, and average wind speed before calculating member-specific quantiles. To maintain data integrity, we restricted our analysis to include only complete days containing all required hourly stepos and ensemble members, analyzing a final displayed window from October 17, 2026 to October 29, 2026. We emphasize that the visual shading represents the central 80% ensemble spread, which should not be interpreted as a locally calibrated 80% prediction interval. [17]

CAMS global fields provided historical composition estimates for atmospheric data, covering the same 92-day period, alongside a separate short-range particulate forecast. We plotted future hours starting from 13:00 UTC +07:00 (Western Indonesia Time; WIB) on October 16, 2026, and summarized only complete subsequent days. Due to a relative coarseness of the global grid for highly localized urban emissions, we applied no local bias corrections, fire-specific

particulate matter attributions, or artificial confidence bands to the data. Finally, because the API snapshots did not explicitly expose a definitive run-initialization field, we preserved all raw retrieved payloads and requests to ensure methodological reproducibility. [18,19]

2.8 Exploratory environmental covariation

We calculated Spearman correlation coefficients between local Jakarta weather fields and modeled PM2.5 levels, subsequently repeating this analysis on daily first differences to minimize common-trend distortions. To establish approximate 95% confidence intervals, we implemented a paired moving–block bootstrap with 2,000 resamples using a seven-day block length. Because these four comparisons are strictly exploratory — they remain unadjusted for multiplicity and rely on overlapping modeling frameworks — they do not provide independent validation of underlying meteorological drivers or clinical health outcomes.

The exploratory correlations between weather variables and modeled PM2.5, including first-difference estimates and bootstrap intervals, are summarized in Table 4.

For future panel designs, we recommend that a localized disease surveillance panel permanently track testing and clinical care denominators, employ a clearly defined causal adjustment framework, and evaluate delayed associations using longer historical baselines. We propose initial lag windows of 0-7 days to capture pollutant–related exacerbations and 0-21 days for viral dynamics, supplemented by a 28-day sensitivity analysis. We emphasize that these specific local health associates were not parameterized, involved, and/or fitted within the scope of this study. [11]

3. Results

3.1 Historical weather in Greater Jakarta

Our retrospective environmental dataset comprised 2,208 hourly records across each of the five coordinates, totaling 11,040 location-hours or 460 daily location-specific summaries. The four retrieved weather variables were fully intact, with no missing values across the entire observation period. During evaluation of the two comparison windows, we observed that mean humidity and cumulative rainfall were systematically higher, while average wind speeds were lower, across all five regional locations during the recent period. In contrast, shifts in temperature displayed distinct spatial variability rather than a uniform regional trend. The daily weather patterns and corresponding seven-day moving averages are shown in Figure 1.

[Insert Table 1 here]

Table 1. Early-to-recent changes: July 16, 2026 - August 16, 2026 versus September 18, 2026 - October 15, 2026. All values are derived from fixed-model gridded historical fields. RH = relative humidity. [6]

Location	Mean T, °C	Mean RH, %	Rain, mm/day	Wind, km/h
Jakarta	29.24 → 29.36	61.02 → 68.37	0.93 → 4.03	6.59 → 5.49
Tangerang	28.24 → 28.71	68.24 → 73.15	1.32 → 4.41	7.13 → 6.04
Depok	28.08 → 28.49	65.07 → 72.03	1.24 → 4.58	6.28 → 5.10
Bekasi	28.91 → 29.58	62.64 → 66.83	0.90 → 3.84	7.45 → 5.83
Bogor	27.46 → 28.01	64.45 → 71.35	0.78 → 3.40	6.38 → 5.42

[Insert Figure 1 here]

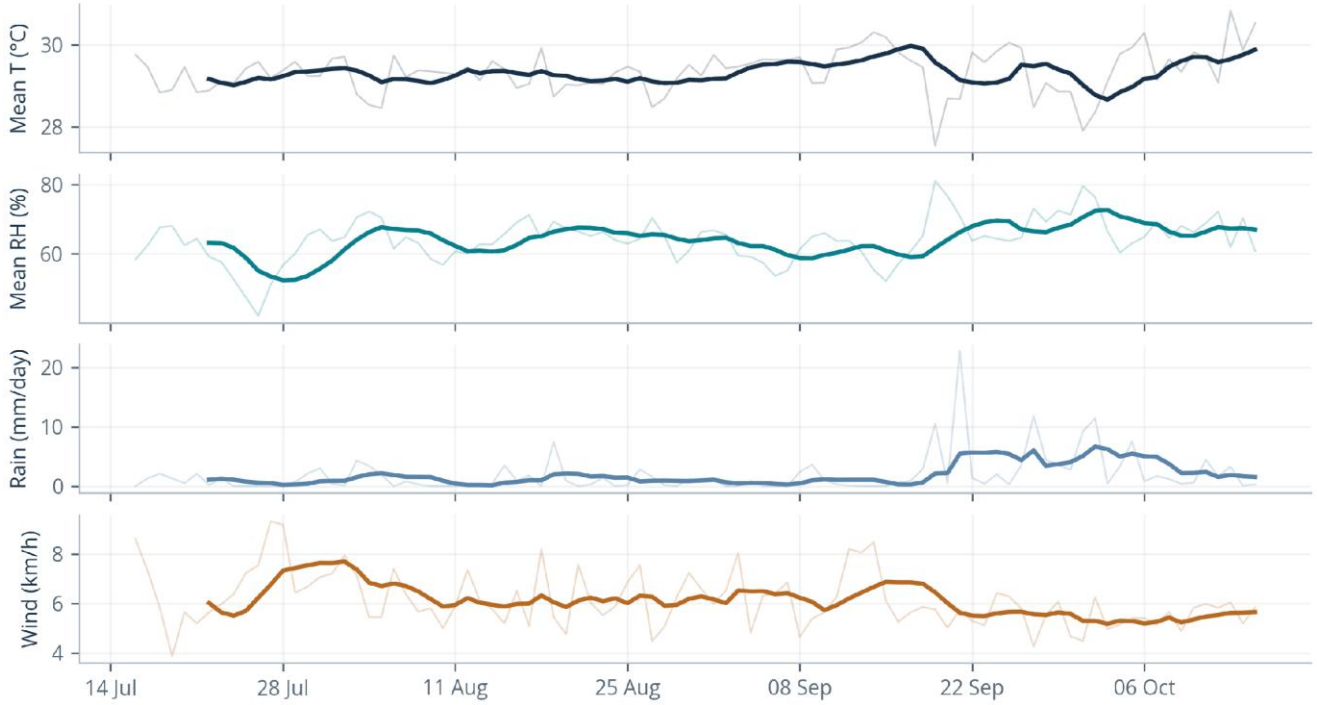


Figure 1. Jakarta historical weather fields. Thin lines show daily values and heavier lines show trailing seven-day means. The panels share time but represent separate physical variables. Source: ECMWF IFS via Open-Meteo; calculations by the preparers. [6]

In Table 1, we show our findings that Jakarta's estimated mean temperature increased by 0.12°C, accompanied by a 7.35 percentage-point rise in mean relative humidity (RH). This corresponds to a notable shift in estimated absolute humidity, which climbed from 17.77 g/m3 to 20.04 g/m3 (Δ 2.27 g/m3). Meanwhile, the surrounding regional monitoring locations experienced a more pronounced warming trend, with mean temperatures increasing by approximately 0.41°C to 0.67°C. We emphasize crucially that these environmental observations or microclimate shifts represent macro-level modeling estimates and should not be used to establish and/or infer individual personal exposure or define causal pathways for disease transmission.

3.2 National virology and local respiratory signals

National influenza A positivity, derived from raw laboratory counts, increased across the selected surveillance reports. The majority of type A detections in the late observation period consisted of A(H1N1)pdm09 subtype, a trend that aligns with the national characterization published by the Indonesian Ministry of Health (Kemenkes RI). It is, however, important to note that this epidemiological pattern portrays only the observed dynamics within submitted surveillance specimens rather than true general population prevalence. [1,2]

The selected national surveillance reports, including the corresponding laboratory counts and positivity estimates, are summarized in Table 2.

[Insert Table 2 here]

Table 2. Selected national laboratory reports; report dates are not specimen dates. *Latest row used only in sensitivity analysis. Counts refer to the national laboratory stream; ILI and SARI summaries have different denominators. [1]

Report date	All influenza / tests	Influenza A / tests	A positivity, %
2026-07-25	9 / 145	6 / 145	4.1
2026-08-15	17 / 115	12 / 115	10.4
2026-09-12	66 / 175	65 / 175	37.1
2026-09-19	86 / 185	84 / 185	45.4
2026-09-26	148 / 265	144 / 265	54.3
2026-10-03	206 / 337	205 / 337	60.8
2026-10-10	245 / 449	245 / 449	54.6 *

On September 22, 2026, public health communications from the Jakarta Health Office (*Dinas Kesehatan DKI Jakarta*) issued a statement noting a 15.7% increase in regional acute upper respiratory infections (*infeksi saluran pernapasan atas; ISPA*) cases. However, this announcement lacked the detailed, granular, statistical data required to reconstruct a standardized weekly incidence series. The agency also emphasized that ISPA clinical classifications are not synonymous with laboratory-confirmed influenza A cases. A following official local update on October 16, 2026 reinforced the importance of sentinel monitoring networks but stopped short of publishing a comprehensive, three–month weekly data series. [3,4]

At the broader national level, surveillance records documented the circulation of SARS-CoV-2, respiratory syncytial virus (RSV), rhinovirus, parainfluenza, and adenovirus; nonetheless, no parallel local time series demonstrated a simultaneous spike across all of these pathogens. Additionally, certain public references to human metapneumovirus (HMPV) were found to stem from 2025 reports, and we consequently excluded them as evidence of a concurrent 2026 surge in Jakarta. [1]

3.3 Source discrepancies and particulate exposure context

During data cleaning, we identified a clear arithmetic discrepancy from the October 10, 2026 report, describing an influenza positivity rate of 43% while simultaneously listing 245 positive specimens out of 449 tested — a fraction equivalent to 54.6%. All recorded positive cases were classified as influenza A. Due to this irreconcilable conflict on our part between the reported percentage and the raw denomintor, we omitted this specific week from our primary model fit. This issue compounded broader structural limitations in the dataset, including stale narrative text, low denominator volumes, shifting week labels, and variations in Hajj-related sampling protocols highlighted in the source documentation. [1]

Additionally, we were unable to obtain a complete, quality-controlled 92-day monitoring station history for local air pollutants. While the municipal environmental portal identified both reference-grade and low-cost sensor instruments, a formal advisory issued on September 6, 2026 noted that volcanic ash was affecting parts of the Greater Jakarta area. We retained this official advisory strictly as a contextual exposure alert, rather than treating it as a quantified individual dose or definitive proof of sustained ground-level exposure duration. [7,8]

Results — modeled pollution retrospective

The historical CAMS data archive was completely intact when we accessed it, providing all 2,208 requested hourly records. An evaluation of equal-window baselines revealed an upward shift in the mean concentrations of $PM_{2.5}$, PM_{10}, and other extracted aerosol constituents during the recent period. Crucially, we emphasize that these upward shifts reflect adjustments internal to the atmospheric simulation software. They do not constitute verified station-observed trends on the ground, nor do they isolate the specific contribution of regional Indonesian forest fires.

[18,19] The comparison of modeled atmospheric constituent concentrations between the two observation windows is presented in Table 3.

[Insert Table 3 here]

Table 3. CAMS historical model means, μg/m³, using the same 28-day windows as Table 1. Changes are descriptive and have not been calibrated to local monitoring stations. [19]

Modeled constituent	Earlier mean	Recent mean	Relative change
$PM_{2.5}$	42.7	50.3	+17.6%
PM_{10}	46.8	53.6	+14.4%
NO_2	38.0	44.4	+17.0%
O_3	94.2	107.5	+14.1%

Figure 2 shows the daily modeled particulate concentrations and their trailing seven-day averages.

[Insert Figure 2 here]

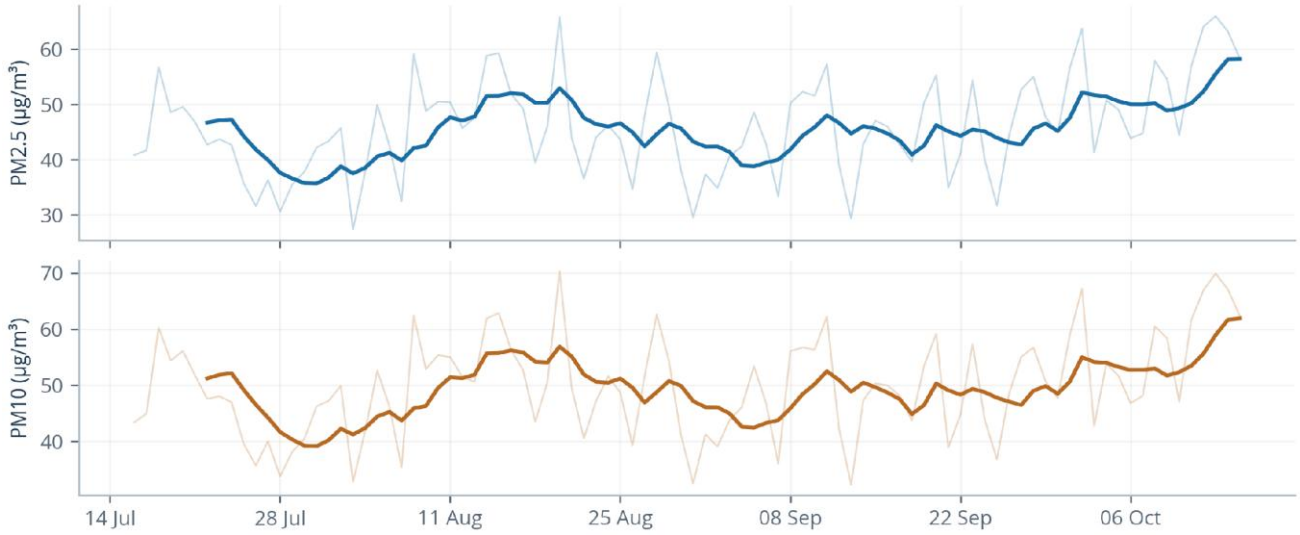


Figure 2. Historical modeled particulate concentrations. Thin lines show daily CAMS means and heavier lines their trailing seven-day averages. This product is not an independently measured exposure series. [18,19]

[Insert Table 4 here]

Table 4. Exploratory model-internal covariation. First differences use 91 paired changes. Block intervals are approximate and not corrected for four comparisons; none establishes an illness association or pollutant source. [19,23-25]

Weather versus modeled PM2.5	Raw rho	First-difference rho	Bootstrap 95% interval
Rainfall	0.25	0.07	-0.14 to 0.30
Wind speed	-0.57	-0.28	-0.47 to -0.07
Relative humidity	0.30	0.12	-0.10 to 0.32
Temperature	-0.16	-0.08	-0.29 to 0.12

Results — Modeled influenza outlook

The fitted national influenza A positivity trajectory and its conditional prediction intervals are shown in Figure 3.

[Insert Figure 3 here]

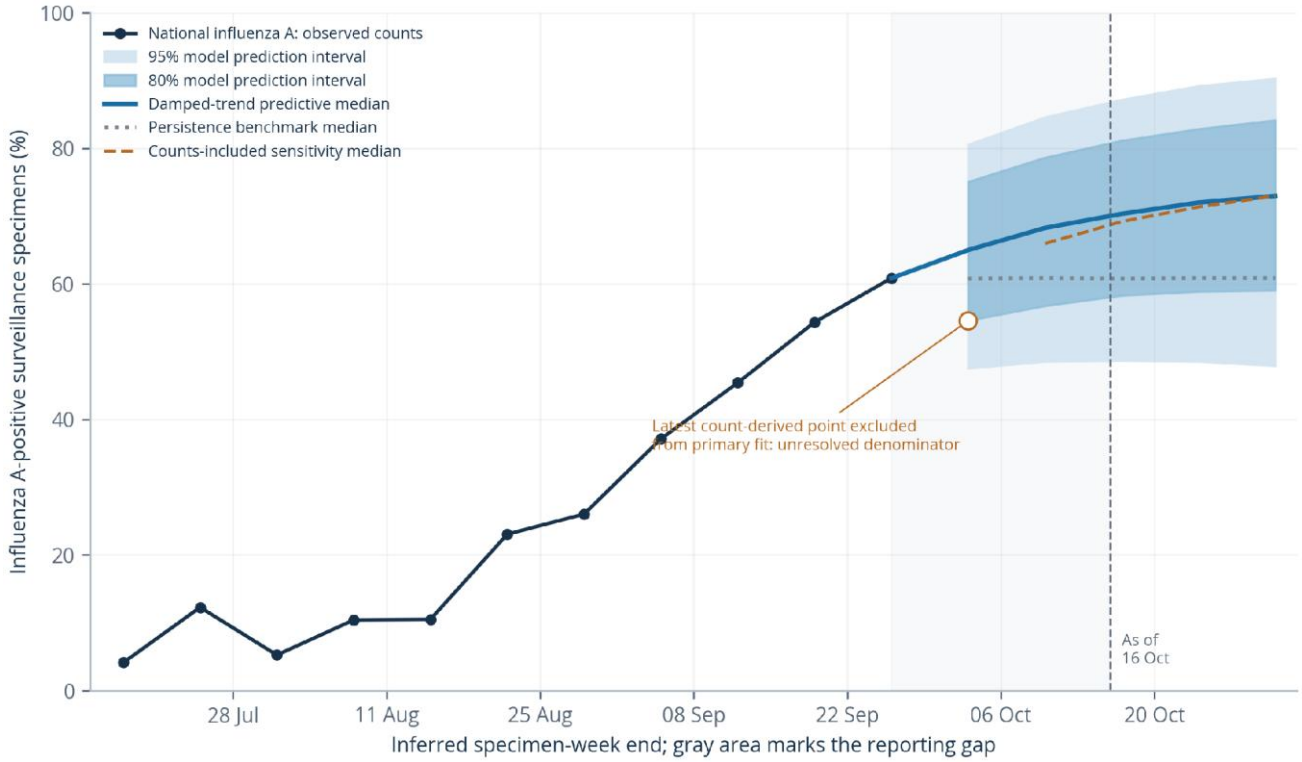


Figure 3. Fitted exploratory national influenza A forecast. Historical surveillance counts were extracted from Kementerian Kesehatan RI reports [1].

Note: The fitted trajectory and conditional 80% and 95% prediction intervals are the authors' calculations using the exploratory beta-binomial latent-state model described in Section 2.5. The gray interval denotes the reporting gap, not observed data. The open orange point represents the unresolved latest count-derived estimate, excluded from the primary fit and retained for sensitivity analysis. Results describe positivity among national surveillance specimens, not population prevalence or a Jakarta infection-rate forecast.

[Insert Table 5 here]

Table 5. Conditional future national surveillance positivity. Authors' forecasts derived from the exploratory beta-binomial latent-state model fitted to national surveillance data from Kementerian Kesehatan RI [1]. Medians and 80% and 95% prediction intervals are model-generated estimates described in Section 2.5, rather than observations reported by the source. Forecasts are conditional on the model assumptions and available surveillance data.

Future week ending	Median, %	80% prediction interval	95% prediction interval
24 Oct 2026	72.0	58.9-82.9%	48.6-89.2%
31 Oct 2026	73.0	59.1-84.2%	47.9-90.3%

We emphasize that the apparent rise in our model's projected median (see Table 5 and Figure 3) is strictly conditional on our decision to extend the fitted recent drift while progressively damping its influence over time. This projected trend must not be interpreted as an epidemiological transmission–model estimate of the reproduction number (R_0 or R_t), a prediction of actual population prevalence, or a simple proof that

environmental pollution actively perpetuates the transmission of influenza (and/or other respiratory pathogens). To maintain analytical transparency and depict with illustration the impact of alternative assumptions, we have preserved both the persistence benchmark and the date-quality sensitivity runs visible across our findings.

Results — forecast evaluation and sensitivity

3.4 Developmental back-test performance

The expanding-window predictive performance of the persistence, random-walk, and damped-trend models is compared in Table 6.

[Insert Table 6 here]

Table 6. Expanding-window developmental scores. pp = percentage points. The damped model improved WIS (weighted-interval score) at these origins, while its one-week MAE (mean absolute error) was essentially the same as that of persistence. Six or fewer targets cannot establish calibration or generalizable superiority. At four and five steps, damped-model MAE was 32.53 and 42.10 pp, respectively. [1]

Model	Lead	Targets	MAE, pp	WIS, pp	80% coverage
Persistence	1 wk	6	8.27	4.54	33%
Persistence	2 wk	5	16.16	9.39	20%
Random walk	1 wk	6	14.11	6.26	67%
Random walk	2 wk	5	22.76	10.45	40%
Damped trend	1 wk	6	8.31	3.79	100%
Damped trend	2 wk	5	14.10	6.07	100%

While incorporating the problematic surveillance week into our sensitivity analysis, the count-inclusive model yielded median positivity estimates of 71.4% and 73.0% for October 24, 2026, and October 31, 2026, respectively. Furthermore, shifting the structural damping factor from 0.5 to 0.85 resulted in the escalation of the October 31, 2026 median projection from 66.8% to 79.5%. Given this pronounced structural sensitivity and the availability constraints of acquiring longer-lead evaluation targets during back-testing, these findings emphasize that this outlook should be utilized with caution and restricted solely to research purposes.

The sensitivity of the projected national influenza A positivity median to alternative structural damping factors is illustrated in Figure S1.

[Insert Figure S1 here]

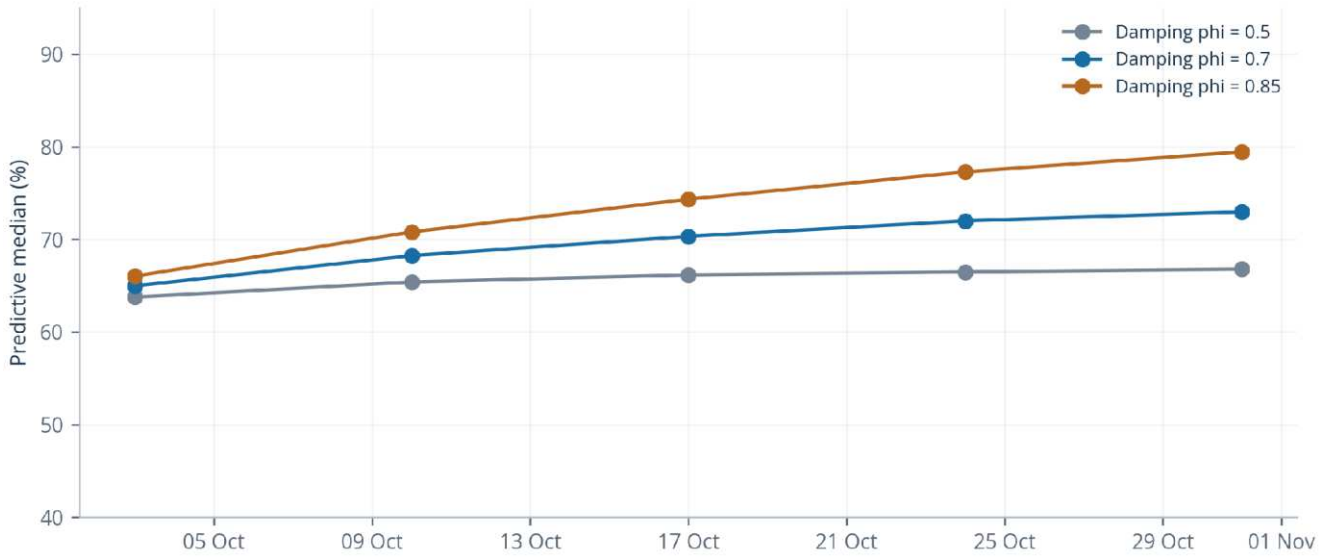


Figure S1. Structural sensitivity of the national forecast median to the assumed damping factor. Lines are alternative model assumptions, not probability bounds. Similar-looking medians can conceal substantial uncertainty about turning points and future specimen selection. [1]

Moving forward, to ensure the validity of continued monitoring, the essential next step must be prospective. Researchers should freeze each dated forecast, preserve the original data vintage, and systematically compare these outputs against subsequently reconciled observations. Ultimately, we argue that increased model complexity architecture is unjustified unless the more sophisticated framework consistently outperforms simpler benchmarks over successive reporting periods and across clinically meaningful outcomes.

Results — prospective weather context

Figure 4 presents the ECMWF IFS ensemble outlook for Jakarta, including the member median and the 10th–90th percentile spread.

[Insert Figure 4 here]

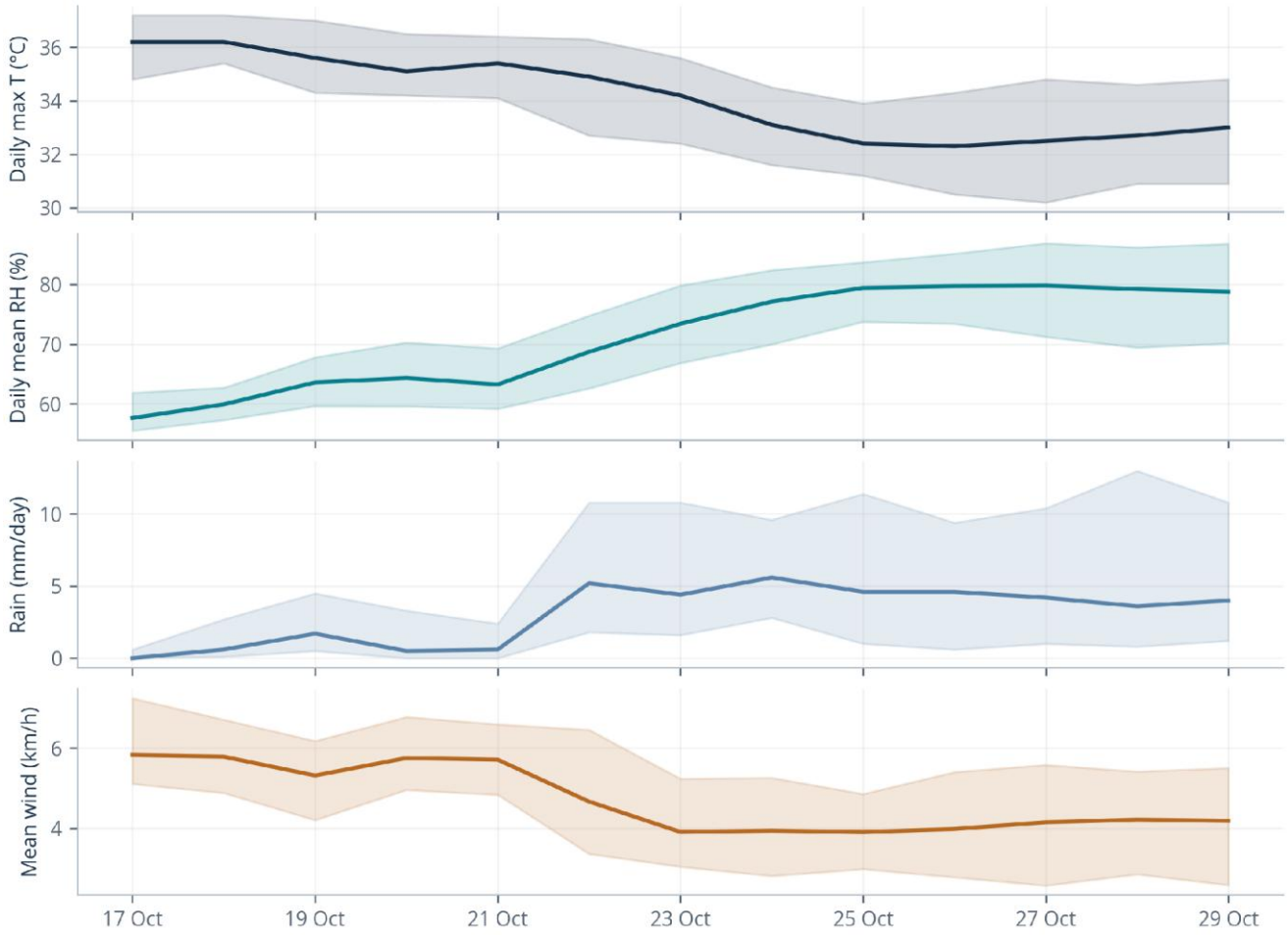


Figure 4. Jakarta ECMWF IFS weather ensemble retrieved 16 October 2026. Curves show the member median and shaded areas the 10th-90th member percentiles. Every displayed day has complete inputs for all 51 members. The spread is not a locally calibrated probability interval and does not quantify respiratory-disease risk. [17]

It is important to note that the ensemble supplies a physical–weather outlook entirely independent of the national disease model. Consequently, a forecast of high humidity or increased rainfall does not imply a corresponding rise or fall in influenza transmission. Other confounding variables, such as social contact patterns, population immunity, intrinsic pathogen dynamics, and clinical ascertainment rates, are equally vital. Conversely, structural environmental shifts, such as declining rainfall or reduced wind speeds, lack the specificity required to identify which distinct pollutant source is responsible for localized exposure.

To safeguard the integrity of our quantifications, we did not replace missing forecast hours with arbitrary null values. Although the raw API request subsumed a 16-day window, we systematically removed incomplete boundary days to isolate a clean comparison period from October 17, 2026 to October 29, 2026. For operational accuracy, these predictive outlooks must be updated on a daily basis and continuously validated against subsequent physical readouts from municipal weather stations.

How to interpret this figure for public awareness

Local weather factors — like temperature, humidity (RH), rainfall, and wind speeds — often shift at the same time. These combined changes can affect how comfortable you feel outdoors, how trapped air pollution becomes, and how easily respiratory infections might spread. This ensemble chart is designed to give you a broad, reliable look at upcoming weather conditions so you can stay informed and plan ahead. However, please keep in mind that this tool cannot predict your individual risk of getting sick. Because of its reliance on a large geographic grid, the data represents

regional trends and cannot account for the unique microclimates inside your specific neighborhood or indoor environment.

Results — prospective particulate context

The short-range CAMS particulate forecast for the Jakarta sampling point is shown in Figure 5.

[Insert Figure 5 here]

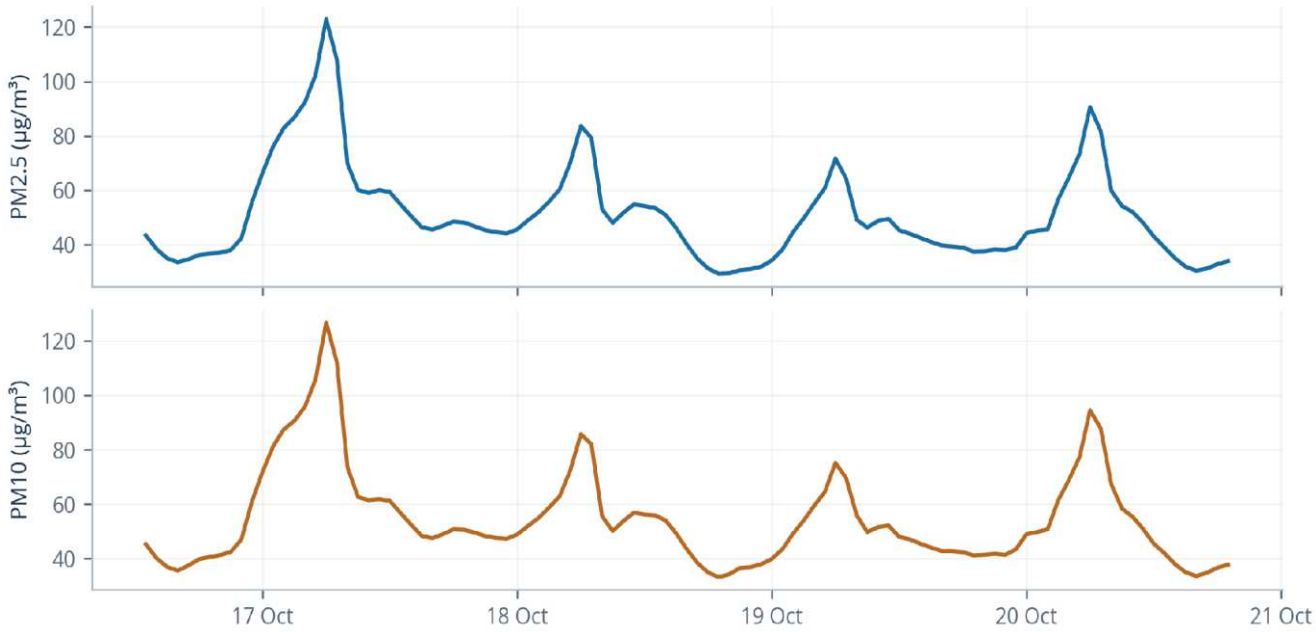


Figure 5. Hourly CAMS global particulate forecast at the Jakarta sampling point, obtained through Open-Meteo on 16 October. These are model concentrations, not observed station values. No uncertainty band was supplied by this deterministic product. The global grid cannot resolve street-level traffic or establish the fraction attributable to forest fires. [18,19]

The corresponding daily mean PM2.5 and PM10 forecasts for complete future days are summarized in Table 7.

[Insert Table 7 here]

Table 7. Model-only daily particulate summaries. Partial days are omitted. Values should be checked against calibrated local monitors; hourly concentrations are not interchangeable with a daily AQI category. [19]

Complete future day	Mean PM2.5, µg/m³	Mean PM10, µg/m³
17 Oct 2026	65.3	68.4
18 Oct 2026	48.6	51.9
19 Oct 2026	45.6	49.4

These forward-looking fields serve to fill a critical gap in our prospective environmental context. However, they cannot reconstruct the missing historical weather station records. We emphasize that a direct attribution linking the recent rise in respiratory cases to regional haze remains unestimated within this study. Furthermore, potential model biases may stem from discrepancies in emissions inventories, active fire data, aerosol chemistry, transport dynamics, and overall spatial resolution.

To achieve a more full-bodied smoke–attribution framework, future studies should combine surface-level pollutant concentrations with independently verified plume boundaries, NASA FIRMS thermal anomalies, and multi-altitude backward trajectories. Relying solely on an isolated thermal hotspot or a single backward trajectory

is methodologically insufficient to quantify the degree to which wildfire smoke actually contributes to an individual's inhaled dose.

4. Discussion

4.1 Interpreting concurrent changes

The most supportable observation from our data is the concurrent shift in local environmental conditions alongside rising positivity rates within the national influenza surveillance stream. However, because of the underlying geographic mismatch between these datasets, it is not possible to isolate a specific Jakarta-weather effect from these series. While higher relative humidity or increased rainfall frequently coincide with elevated influenza (and other ILI-causing pathogen) activity, this relationship does not demonstrate a direct causal pathway. Instead, shared seasonal calendar patterns and changes in indoor contact behaviors may drive these trends. [10]

The historical CAMS fields introduce a modeled pollution baseline that allows for limited checks on environmental covariation. In these models, wind speed demonstrated a negative relationship with modeled PM2.5 concentrations, whereas other first-difference associations remained weak. Because these atmospheric products rely on shared physical modeling inputs and lack validation from local monitoring stations in this study, these findings are best treated as hypothesis requiring prospective tracking rather than independent validation of exposure mechanisms.

Furthermore, the high proportion of positive specimens reported nationally directly reflects the specific cohort of patients selected for clinical testing. This metric does not imply that a similar percentage of the general Jakarta population is infected with influenza. Nevertheless, an increasing trend in test positivity remains a valuable indicator for tracking pathogen circulation, provided that testing eligibility criteria, sentinel sites, and laboratory methods remain sufficiently comparable. [1,9,22]

Finally, localized surges in respiratory health demands likely reflect a combination of infectious transmission, tissue irritation, and noninfectious exacerbations. The recent volcanic-ash advisory underscores exactly why tracking PM10 and characterizing particle sources remain vital alongside standard PM2.5 monitoring. Moving forward, surveillance frameworks should keep influenza A, as well as other respiratory viruses, pneumonia, and asthma as independent tracking outcomes before attempting to build any composite metric for health–service demand. [7,8,20]

4.2 Forecast meaning and practical limits

Rather than relying on a static scenario table, the fitted model converts recent national specimen dynamics directly into a continuous probability distribution. The upward trajectory of its median is a direct mathematical consequence of the estimated historical drift and the specified damping factor. Because the model contains no local meteorological coefficients, its structural shape must not be used as evidence that weather conditions or regional haze are driving the forecast.

Furthermore, the systemic reporting gap significantly extends the effective forecast horizon. The resulting intervals remain strictly conditional on this specific model family and the observed surveillance process; they cannot account for unmodeled real-world shifts, such as changes in healthcare access, patient case mixes, pathogen importation strains, or systemic reporting biases. Finally, because we conducted model development and performance assessment using the same short epidemiological episode, achieving a smooth curve, a lower WIS, or apparently adequate interval coverage across a handful of evaluation targets cannot, on its own, establish true operational reliability. [12,13]

4.3 Public-health communication

From a public health perspective, communities should be advised to regularly monitor local air quality indicators (AQIs), minimize outdoor exposure during periods of high particulate pollution, and utilize well-fitting particulate

respirators when necessary. At the same time, individuals should follow established influenza prevention protocols, such as receiving updated vaccinations, staying home when symptomatic, and seeking professional medical evaluations. It is crucial to frame these as distinct preventive interventions; vaccination offers no protection against the physical irritation caused by atmospheric pollutatnts, just as wearing a mask does not vonfirm or rule out a viral infection. [2,7,8]

Finally, public communications must transparently state what variables were measured, alongside the exact locations, timeframes, and lingering uncertainties. A definitive outbreak assessment requires a rigorous comparison against baseline historical expectations of disease occurrence, rather than relying on an arbitrary, one-size-fits-all percentage-increase threshold. Consequently, neither the reported 15.7% shift in local ISPA cases nor the national test positivitiy forecast is sufficient on its own to declare an official outbreak in Jakarta. [3,21]

5. Limitations

This study's findings are subject to five core methodological limitations, primarily involving incomplete local disease surveillance records, localized meteorological data sampling and constrains, and a short 11-week primary statistical model window [1]. These structural boundaries means that our results should be treated as exploratory rather than an operational evaluation of transmission dynamics. [1]

5.1. Incomplete Local Disease Data

A comprehensive, unified weekly data series for the Greater Jakarta area (Jabodetabek) was unavailable. The current records lack integrated data combining patient residence, age, testing denominators, illness onset timelines, and clinical severity. Broad national surveillance data cannot substitute for this missing, localized epidemiologic information.

5.2. Meteorological Sampling Constraints

Our retrospective weather data relied on a single gridded point per locality. Consequently, this approach does not estimate true population-weighted exposures, indoor humidity levels, or individual human mobility patterns. Furthermore, we lacked a quality–controlled, three-month local air pollutant history for direct linkage, and the environmental forecast fields came from external models with varying resolutions that were not locally validated.

5.3. Surveillance Reporting Inconsistencies

The underlying surveillance data contained several administrative flaws, including stale descriptive fields, shifting denominator volumes, and inconsistent epidemiological week labels. The cause of the most recent data discrepancy remains unadjudicated and could stem from a spearate data stream, an unrecorded revision, or a clerical error. Additionally, small sample sizes and Hajj-related protocol shifts complicate long-term comparisons, meaning that treating this count-derived series as a single, coherent stream remains an unconfirmed assumption. [1]

5.4. Limited Statistical Framework

The primary model relied on only 11 overlapping specimen weeks. Due to this brief timeframe, the model is yet to become capable of isolating long-term annual seasonality, estimate local transmission parameters, or identify independent weather-driven effects. Additionally, because the candidate framework was developed iteratively, it lacks prospective validation against independent datasets, suffers from sparse long-lead back-tests, and fails to account for unmodeled shifts in sampling policies.

5.5. Divergent Evidence and Metric Scope

Biomass fire detections, official ash alerts, aggregate particulate matter concentrations, and clinical syndromes represent fundamentally different categories of evidence. No single metric is sufficient on its own to calculate a localized, smoke-attributable infection burden. Ultimately, all modeled percentages within our influenza outlook describe national surveillance specimens rather than direct population infection risks.

6. Continuing surveillance: a shared research protocol

We propose an open, versioned monitoring workflow that clinicians, laboratories, environmental researchers, and public-health teams can continue using. Improve participation to enhance data comparability before expanding model complexity. A minimum weekly dataset should retain the following fields.

Domain	Minimum fields
Respiratory illness	Residence/catchment, facility ID, week, age group, ILI and total visits; SARI/pneumonia and total admissions; asthma/COPD outcomes separately.
Laboratory	Pathogen and subtype, number tested, number positive, assay, specimen date and changes in eligibility or testing policy.
Environment	Station coordinates, instrument/calibration, hourly PM2.5/PM10 and gases; local temperature, humidity, rainfall and wind.
Reporting integrity	Publication and revision timestamps, reporting completeness, source URI, version/hash and unresolved-quality flags.

Frequency	Action	Research safeguard
Daily	Archive calibrated station readings and new forecast snapshots; check weather and particulate observations.	Preserve missingness, instrument IDs, and the forecast issue vintage.
Weekly	Reconcile illness and test denominators; deduplicate public reports; publish a locality-by-week evidence summary.	Separate event date from article date and site from patient residence.
Weekly	Update eligible model inputs and freeze predictions before outcomes arrive.	Retain the old forecast, source revision, and exclusion decision.
Monthly	Evaluate MAE, WIS, and coverage against persistence; assess subgroup and reporting changes.	Report negative or deteriorating forecast performance.
Before local causal modeling	Obtain at least 2-3 comparable prior years and define the causal estimand and adjustment set.	Avoid geographic substitution and adjustment for an unintended mediator.

The supplement provides a national-model input contract, a monitoring-data template, a source issue log, forecast quantiles, back-test outputs, and executable analysis. A local model should be fitted only after a consistent local stream is available; national counts must not be relabeled as Jakarta observations. Outputs should be versioned, dated, and released with denominator definitions. [22]

7. Conclusion

The publicly vailable evidence indicates a clear rise in national influenza A specimen positivity alongside

concurrent shifts in moisture, rainfall, and wind conditions across the sampled Greater Jakarta locations during the observed date range. However, these parallel trends do not establish a localized weather-disease causal pathway, nor do they quantify the specific clinical burden attributable to regional forest-fire haze.

Ultimately, ouyr exploratory national forecast and the separate environmental model visualizations offer a transparent starting point for continued surveillance. The primary practical value of these models lies in their ability to expose foundational data gaps and bring implicit analytical assumptions to light. Moving forward, generating truly dependable local health predictions will require geographically matched surveillance infrastructure, callibrated ground-level pollutant measurements, rigorous source reconciliation, and continuous prospective forecast evaluations.

Declarations and availability

Supplementary Materials: Supporting information, including supplementary data and code, is provided with the manuscript, if applicable. No separate supplementary materials are available unless otherwise specified in the submission files.

Author Contributions: Conceptualization, A.N.S.; methodology, A.N.S.; software, A.N.S.; validation, A.N.S.; formal analysis, A.N.S.; investigation, A.N.S.; resources, A.N.S.; data curation, A.N.S.; writing—original draft preparation, A.N.S.; writing—review and editing, A.N.S.; visualization, A.N.S.; supervision, A.N.S.; project administration, A.N.S.; funding acquisition, not applicable. The author has read and agreed to the published version of the manuscript.

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Informed Consent Statement: Not applicable. This study did not involve direct participation by human subjects or the use of identifiable individual-level patient data.

Data Availability Statement: The data analyzed in this study were obtained from publicly available national surveillance reports, local public communications, and gridded meteorological and atmospheric-composition datasets. The data sources and analytical methods are described in the manuscript. Any supplementary analytical data and code are available in the accompanying supplementary materials, where provided.

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Abbreviations

Abbreviation	Full term
AQI	Air Quality Index
API	Application Programming Interface
A(H1N1)pdm09	Influenza A(H1N1)pdm09 virus

A(H3N2)	Influenza A(H3N2) virus
BMKG	*Badan Meteorologi, Klimatologi, dan Geofisika* (Indonesian Agency for Meteorology, Climatology, and Geophysics)
CAMS	Copernicus Atmosphere Monitoring Service
COVID-19	Coronavirus Disease 2019
COPD	Chronic Obstructive Pulmonary Disease
ECMWF	European Centre for Medium-Range Weather Forecasts
FIRMS	Fire Information for Resource Management System
HMPV	Human Metapneumovirus
IFS	Integrated Forecasting System
ILI	Influenza-Like Illness
ISPA	*Infeksi Saluran Pernapasan Atas* (acute upper respiratory tract infection)
MAE	Mean Absolute Error
NO_2	Nitrogen Dioxide
O_3	Ozone
$PM_{2.5}$	Particulate Matter with an Aerodynamic Diameter of 2.5 μm or Less
PM_{10}	Particulate Matter with an Aerodynamic Diameter of 10 μm or Less
RH	Relative Humidity
RSV	Respiratory Syncytial Virus
SARI	Severe Acute Respiratory Infection
SARS-CoV-2	Severe Acute Respiratory Syndrome Coronavirus 2
URI	Uniform Resource Identifier
UTC	Coordinated Universal Time
WIS	Weighted Interval Score
WIB	*Waktu Indonesia Barat* (Western Indonesia Time)
WHO	World Health Organization

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