

## ASSOCIATION BETWEEN SATELLITE-DERIVED PM<sub>2.5</sub> AND CONJUNCTIVITIS CONSULTATION RATES IN A HAZE-PRONE AREA OF NORTHERN THAILAND: A LONGITUDINAL SPATIAL ANALYSIS

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### ABSTRACT

Ocular health may be impacted by air pollution, especially fine particulate matter (PM<sub>2.5</sub>), but evidence remains limited in the haze-prone area. This study investigated the spatiotemporal relationship between conjunctivitis consultation rates and satellite-derived PM<sub>2.5</sub> in Chiang Rai Province, northern Thailand, from 2021 to 2023. Meteorological factors and satellite-derived Aerosol Optical Depth (AOD) were used to predict ground-level PM<sub>2.5</sub>. A linear mixed-effects model (LMM) with month and year as fixed effects and subdistrict as a random intercept evaluated relationships with predicted PM<sub>2.5</sub>, temperature, and planetary boundary layer height (PBL). Geographic Information Systems and Global Moran's I were used to characterize spatial patterns. Predicted PM<sub>2.5</sub> was statistically significantly inversely associated with conjunctivitis consultation rate in the primary log-transformed LMM ( $\beta = -0.000420$ , 95% CI:  $-0.000806$  to  $-0.000033$ ,  $p = 0.033$ ). While the untransformed sensitivity model showed the same direction but did not reach statistical significance ( $\beta = -0.000523$ , 95% CI:  $-0.001074$  to  $0.000028$ ,  $p = 0.063$ ), however. PBL was positively associated with conjunctivitis consultant rate ( $\beta = 0.000084$ , 95% CI:  $0.000010$  to  $0.000158$ ,  $p = 0.026$ ). Significant regional clustering (Moran's I =  $0.149$ ,  $p < 0.001$ ). Given potential exposure misclassification, healthcare utilization, reporting patterns, and residual confounding, the negative association should be interpreted as an ecological association rather than evidence of a protective or causal effect.

**Keywords:** *Aerosol Optical Depth; Conjunctivitis consultation rate; Linear mixed-effects model; Satellite-derived PM<sub>2.5</sub>; Spatial epidemiology.*

### 1. INTRODUCTION

Globally, air pollution is a major threat to human health and is associated with a wide range of adverse health outcomes, including cancer, cardiovascular and respiratory diseases (Kan, 2022). Fine particulate matter (PM<sub>2.5</sub>; particles with aerodynamic diameters less than 2.5  $\mu\text{m}$ ) is particularly concerning because it can penetrate deep into the respiratory system and enter the bloodstream. Both short-term and long-term exposure to PM<sub>2.5</sub> are associated with increased morbidity and mortality (Cohen et al., 2017; Pope & Dockery, 2006). Increasing evidence also suggests that PM<sub>2.5</sub> may affect the ocular surface in addition to the cardiovascular and respiratory systems (Manisalidis et al., 2020).

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The eye is highly vulnerable to environmental pollutants, as particulate matter can induce oxidative stress, irritation, and inflammation. Conjunctivitis, one of the most common ocular disorders, involves inflammation of the conjunctiva and may result from environmental pollutants, allergens, infectious agents, or chemical irritants (Azari & Barney, 2013). Epidemiological studies have reported associations between short-term exposure to particulate matter and increased conjunctivitis-related hospital visits (Chen et al., 2019). Experimental studies further suggest that PM<sub>2.5</sub> can damage corneal epithelial cells, promote inflammatory cytokine release, and disrupt the ocular surface barrier (Air Pollutant Particulate Matter 2.5 Induces Dry Eye Syndrome in Mice (Niu et al., 2024). These findings support the potential role of air pollution as an environmental risk factor for ocular health.

One of the Southeast Asian regions that regularly suffers from extreme seasonal haze pollution is the northern part of Thailand. During the dry season, elevated PM<sub>2.5</sub> concentrations are influenced by biomass burning from both domestic sources within Northern Thailand, including forest fires and agricultural or other open biomass burning, and regional transport of smoke and particulate matter. (Punsompong et al., 2021) showed that forest fires predominated among biomass-burning sources in northern Thailand, while studies of rural and urban sites in the region have also identified open burning and biomass-burning aerosols as important contributors to PM<sub>2.5</sub>. (Chansuebsri et al., 2022) identified prominent open-burning influences at regional scale and mixed biomass-burning, traffic, and transboundary sources in Northern Thailand. In Chiang Rai specifically, both local and transboundary sources were reported to influence PM<sub>2.5</sub> during haze episodes (Niampradit et al., 2022).

Regional modeling has also demonstrated substantial contributions from transboundary biomass-burning PM<sub>2.5</sub> in northern Thailand, with Chiang Rai among the provinces showing the highest estimated contributions (Inlaung et al., 2024). More recent source-apportionment evidence likewise indicates that both local and regional biomass-burning sources contribute to haze in Northern Thailand (Saksakulkrai et al., 2026). These findings indicate that seasonal haze in Northern Thailand should be understood as the result of interacting domestic and regional sources, rather than being attributed exclusively to transboundary transport. Significant health effects, such as respiratory complaints and an increase in hospital admissions, have been associated with haze events in Northern Thailand. However, despite numerous reports of eye irritation and pain during haze situations, relatively little attention has been dedicated to the possible ocular health effects of air pollution in this region.

Assessing population exposure to air pollution accurately remains difficult, especially in places with limited or no ground-based monitoring. An efficient method for measuring particle pollution across wide areas was satellite remote sensing (Hoff & Christopher, 2009; Laosuwan et al., 2024). Aerosol Optical Depth (AOD) from satellite observations is widely used to estimate ground-level PM<sub>2.5</sub>, particularly when combined with meteorological variables such as temperature, relative humidity, wind speed, and planetary boundary layer height (Gupta & Christopher, 2009; Hongthong & Nakapan, 2023; Van Donkelaar et al., 2015; Xie et al., 2015). Such satellite-based estimates are increasingly applied in environmental health studies, especially in areas without monitoring networks. Spatial epidemiological approaches, including Geographic Information Systems (GIS) and spatial statistics, can further identify geographical patterns, clustering, and heterogeneity in health outcomes (Elliott & Wartenberg, 2004). However, there is still some evidence, especially in Southeast Asia, that exposure to PM<sub>2.5</sub> causes eye diseases. Few research have used satellite-derived PM<sub>2.5</sub> and spatial statistical techniques to investigate the geographical epidemiology of conjunctivitis in haze-affected locations.

By combining satellite-derived PM<sub>2.5</sub> data with spatial epidemiology analysis in an area with limited ground monitoring, this work provides novel insights into the relationship between air pollution and conjunctivitis in a haze-prone area. By integrating health surveillance data, satellite-derived aerosol observations, meteorological variables, and spatial statistical analysis, this research aims to identify spatial patterns of conjunctivitis consultation and evaluate the potential role of air pollution as an environmental factor associated with ocular health in haze-prone areas.

## 2. STUDY AREA

The province of Chiang Rai, which is in northern Thailand, covers approximately 11,678 km<sup>2</sup>. Eighteen districts constitute the administrative division of the province with 1,161,263 population. The region borders Laos and Myanmar and is defined by valleys and rocky landscapes. It is situated between latitude 19.9105 degrees North and longitude 99.8406 degrees East, 829 kilometers from Bangkok. The mountain ranges range in elevation from 1,500 to 2,000 meters above sea level, as shown in Fig. 1.

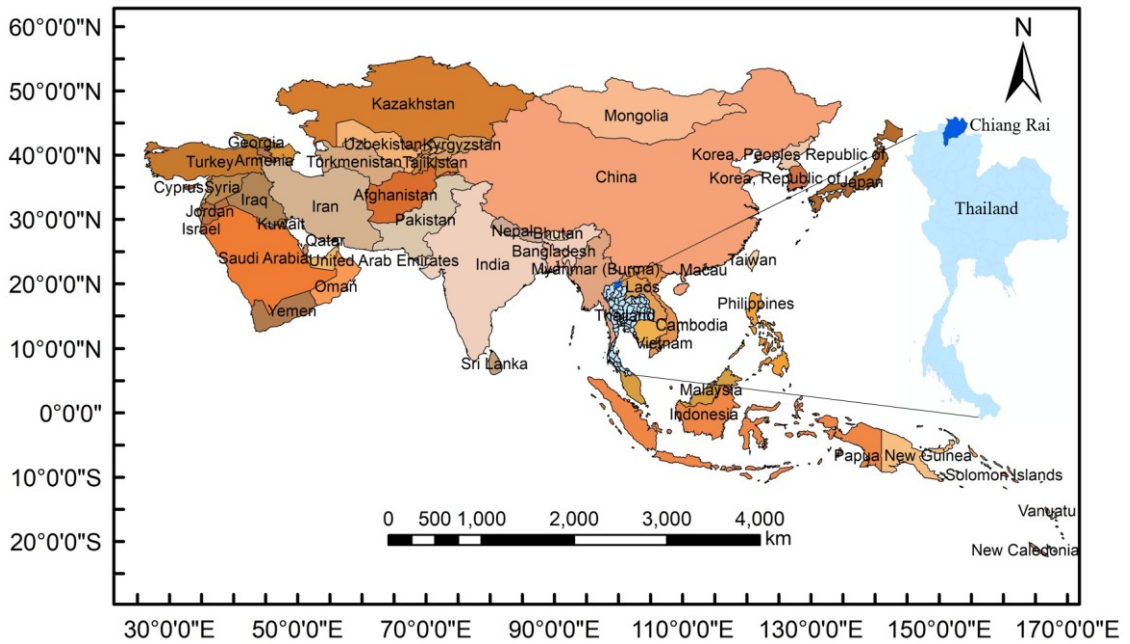


Fig. 1. Study area.

## 3. DATA AND METHODS

### 3.1. Health Data

Monthly conjunctivitis records (ICD-10 H10) between January 2021 and December 2023 were obtained from the Health Data Center (HDC), Ministry of Public Health, Thailand. In this study, a conjunctivitis case was defined as an outpatient consultation recorded in the HDC database with an ICD-10 diagnosis code within the H10 category. The available HDC data were aggregated at the subdistrict level and did not include individual clinical information or diagnostic subtypes. Therefore, conjunctivitis cases were analyzed as the overall H10 category rather than further classified by etiology or clinical subtype. Because individual identifiers were unavailable, repeated visits by the same patient could not be distinguished. Consequently, the outcome represented the monthly conjunctivitis consultation rate rather than disease prevalence. The population data for each subdistrict was obtained from the Chiang Rai Provincial Office for each study year. Monthly consultation rates were calculated as by Eq. (1).

$$\text{Consultation rate} = \frac{\text{Cases}}{\text{Population}} \times 1,000 \quad (1)$$

where: Population means the registered number in each subdistrict  
Cases means the patient's residential subdistrict in the HDC database

### 3.2. Satellite Aerosol Data

The MODIS MAIAC-AOD product was used in this study (Hongthong & Nakapan, 2023). An algorithm method called the multi-angle implementation of atmospheric correction (MAIAC) produces a high resolution AOD result (1 km). This algorithm simultaneously retrieves atmospheric aerosols and bidirectional reflectance from MODIS data. It further detects clouds and corrects atmospheric effects over both dark vegetated surfaces and bright desert targets. Collection-6 MAIAC products are in Stage-1 validation. This entails that their product accuracy has been predicted using a small number of independent measurements derived using data from selected locations, time periods, and ground-truth/field programs. MODIS Terra and Aqua satellites, which pass over the study area at approximately 10:30 a.m. and 1:30 p.m. local time, respectively. Only data with quality assurance flags greater than 0.5 were used.

To address missing AOD values, a spatiotemporal interpolation was employed to generate spatially continuous AOD fields before  $PM_{2.5}$  prediction. (Xiao et al., 2021; Yan et al., 2021). Finally, the AOD value of each 1 km grid cell was displayed by mapping the spatial distribution of AOD in GIS.

### 3.3. Meteorology collection

Daily temperature, relative humidity, and wind speed were obtained from the Thai Meteorological Department, and the planetary boundary layer height (PBL) was obtained from the ERA5 atmospheric reanalysis dataset provided by the European Centre for Medium-Range Weather Forecasts (ECMWF).

### 3.4. $PM_{2.5}$ Predictive Model Development

Satellite-derived aerosol optical depth (AOD) and meteorological variables, including temperature and planetary boundary layer height, were used to predict daily ground-based  $PM_{2.5}$  concentrations. To assess the predictor variables' incremental contribution, three potential multiple linear regression models were created: AOD alone was included in Model 1, AOD and PBL were included in Model 2, and AOD, PBL, and temperature were included in Model 3. Model 3 showed the best overall performance, with the highest  $R^2$  (0.702), and the lowest RMSE ( $20.63 \mu g/m^3$ ), and lowest AIC (6234.29) compared with Models 1 and 2. The regression model's general form was shown in Eq. (2). Then, the ten-fold cross-validation was subsequently used to evaluate its out-of-sample predictive performance.

$$PM_{2.5} = \beta_0 + \beta_1 AOD + \beta_2 PBL + \beta_3 Temp + \varepsilon, \quad (2)$$

where  $PM_{2.5}$  is the ground-observed concentration,  $\beta_0$  is the intercept,  $\beta_1$ – $\beta_3$  are regression coefficients, and  $\varepsilon$  is the residual error.

### 3.5. Model validation

The 10-fold cross-validation was used to assess the predictive performance of the candidate  $PM_{2.5}$  models. Using a fixed random seed (random state = 42), the dataset was randomly split into ten roughly equal sections. Nine subsets were utilized for model fitting in each iteration, with the remaining subset being used for prediction. Until every observation had been utilized once for validation, this procedure was repeated. The pooled out-of-fold predictions were used to compute cross-validated  $R^2$  (CV- $R^2$ ) and RMSE (CV-RMSE). Model 3, incorporating AOD, PBL, and temperature, showed the best predictive performance among the three candidate models. It achieved a CV- $R^2$  of 0.670 and a CV-RMSE of  $22.30 \mu g/m^3$ .

### 3.6. Temporal analysis

The R software (version 4.5.3) was used to examine monthly and seasonal variation in PM<sub>2.5</sub> concentrations and conjunctivitis consultation rates. Months were treated as categorical fixed effects in the mixed-effects analysis. The data was organized in long format, with repeated monthly observations for each subdistrict. Seasonal classification was retained for descriptive and spatial analyses: summer (February–April), rainy season (May–September), and winter (October–January).

### 3.7. Spatial Analysis

Spatial analyses were performed using Geographic Information Systems (GIS) and spatial statistical techniques to evaluate the geographical distribution of conjunctivitis consultation rates and PM<sub>2.5</sub> exposure by ArcMap version 10.5. Subdistrict-level consultation rates and predicted PM<sub>2.5</sub> concentrations were mapped to visualize spatial and seasonal variability. Global Moran's I applied to assess overall spatial autocorrelation of monthly consultation rates across Chiang Rai Province, using a queen-contiguity spatial weight matrix in ArcMap. Global Moran's I provide a measure of overall spatial dependence across the study area but does not identify specific local clusters or fully account for spatial heterogeneity. Its results may also depend on the specification of the spatial weight matrix. Spatial autocorrelation of the residuals from the final linear mixed-effects model was not formally assessed.

### 3.8. Association between conjunctivitis and PM<sub>2.5</sub>

Because health records were aggregated at the subdistrict level, the 1 km predicted PM<sub>2.5</sub> grids were spatially averaged within each subdistrict for each month. The resulting subdistrict-month dataset was used for the longitudinal analysis. The relationship between predicted PM<sub>2.5</sub> and conjunctivitis consultation rates was then determined using a linear mixed-effects model, accounting for temporal and meteorological variables. The monthly conjunctivitis consultation rate (cases per 1,000 people) was the primary outcome. Predicted PM<sub>2.5</sub> was the main exposure in the LMM, along with month and year as fixed effects, temperature and PBL as meteorological variables, and a random intercept for subdistrict.

The major health-outcome model employed log (1 + consultation rate) due to the substantially right-skewed consultation-rate distribution. As a sensitivity/comparison model, a Gaussian LMM was fitted using the untransformed consultation rate. Normal Q-Q plots and residual versus-fitted plots were used to assess the model's adequacy. The final analytical dataset comprised 2,958 subdistrict-month observations from 124 subdistricts over 2021–2023. The repeated observations were analyzed using a linear mixed-effects model, with subdistrict included as a random intercept to account for within-subdistrict correlation, by the missing data being caused by the missing conjunctivitis consultation.

## 4. RESULTS

The descriptive statistics of environmental variables and the conjunctivitis consultation rate from 2021 to 2023 are shown in **Table 1**. The mean PM<sub>2.5</sub> concentration rose from 31.64 µg/m<sup>3</sup> in 2021 to 49.01 µg/m<sup>3</sup> in 2023. Severe pollution occurrences were indicated by extreme values of 374 µg/m<sup>3</sup>. AOD levels also increased from 0.48 in 2021 to 0.63 in 2023, showing a higher concentration of atmospheric aerosols. These discrepancies could be partially caused by large-scale climate phenomena: El Niño conditions developed in 2023, which are typically linked to warmer and drier weather that may encourage biomass burning and pollutant accumulation in Southeast Asia, while La Niña conditions prevailed in 2021–2022, which typically bring cooler and wetter conditions that can help disperse pollutants. Therefore, the increased PM<sub>2.5</sub> levels and environmental exposure seen in 2023 may

Table 1.

Summary statistics of study variables.

| Variable                                        | Mean   |        |        | SD     |        |        | Min    |        |        | Max    |        |        |
|-------------------------------------------------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|
|                                                 | 2021   | 2022   | 2023   | 2021   | 2022   | 2023   | 2021   | 2022   | 2023   | 2021   | 2022   | 2023   |
| Measured PM <sub>2.5</sub> (µg/m <sup>3</sup> ) | 31.64  | 26.49  | 49.01  | 28.87  | 12.40  | 55.10  | 4.00   | 5.00   | 2.60   | 259.00 | 64.00  | 374.00 |
| AOD                                             | 0.48   | 0.43   | 0.63   | 0.36   | 0.30   | 0.56   | 0.01   | 0.01   | 0.06   | 2.10   | 1.40   | 2.70   |
| Temperature                                     | 24.29  | 24.80  | 25.10  | 3.34   | 2.80   | 3.35   | 13.10  | 17.40  | 17.70  | 31.10  | 30.50  | 32.40  |
| PBL (m.)                                        | 447.49 | 441.20 | 497.09 | 152.51 | 141.97 | 213.62 | 143.35 | 140.67 | 175.86 | 855.58 | 795.36 | 968.84 |
| Conjunctivitis consultation rate                | 1.56   | 1.31   | 1.40   | 0.79   | 0.71   | 0.73   | 0.43   | 0.34   | 0.41   | 2.65   | 3.22   | 3.23   |

#### 4.1. Conjunctivitis distribution

**Fig. 2** shows the seasonal distribution of conjunctivitis consultation rates from 2021 to 2023, with repeated higher-rate areas in several districts, particularly the central-eastern (Wiang Chiang Rung, Phaya Mengrai, and Khun Tan) and southern (Phan and Wiang Pa Pao) districts. Consultation rates were more widespread during the dry season, whereas more localized patterns were observed during the rainy season. Persistent spatial patterns across seasons suggest that both local and seasonal factors may contribute to the observed distribution.

#### 4.2. Predicted PM<sub>2.5</sub>

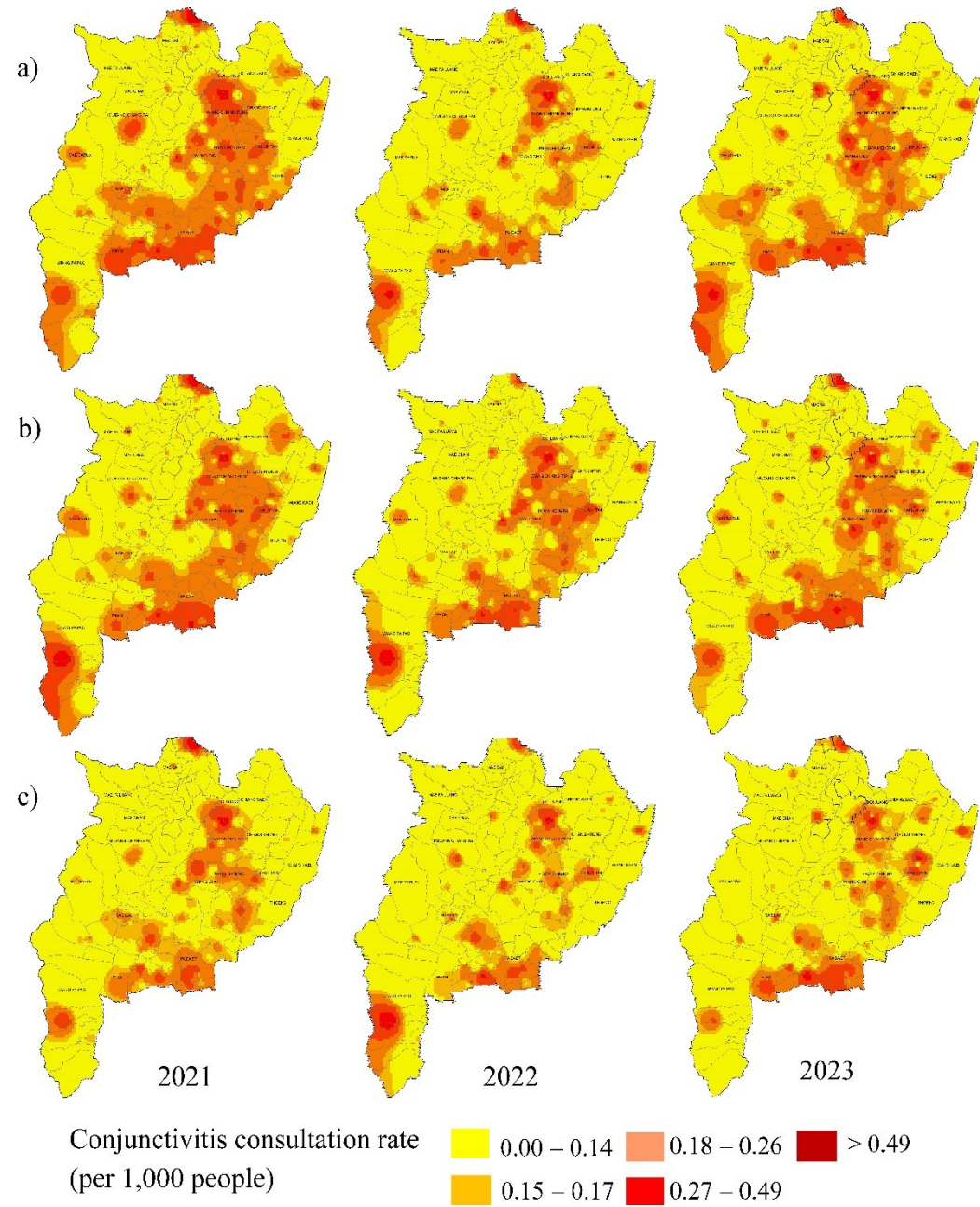
**Fig. 3** shows the predicted PM<sub>2.5</sub> distribution in Chiang Rai for the summer and winter of 2021–2023. The selected prediction model, incorporating satellite-derived AOD, PBL, and temperature, demonstrated an  $R^2$  of 0.702 and RMSE of 20.63 µg/m<sup>3</sup>, while 10-fold cross-validation yielded a CV- $R^2$  of 0.670 and CV-RMSE of 22.30 µg/m<sup>3</sup>, indicating consistent out-of-sample predictive performance. PM<sub>2.5</sub> levels were higher during the summer, especially in 2023, consistent with the seasonal influence of biomass burning and transboundary haze in Northern Thailand (Adam & Balasubramanian, 2021). During the rainy season, cloud cover and high humidity can reduce the availability and retrieval quality of satellite AOD, which may introduce uncertainty into PM<sub>2.5</sub> prediction (Gupta & Christopher, 2009; van Donkelaar et al., 2016). The available subdistrict-month observations with matched exposure predictions were used to examine the health association by taking temporal and meteorological variation in the LMM into consideration.

#### 4.3. Association between conjunctivitis consultation rate and predicted PM<sub>2.5</sub>

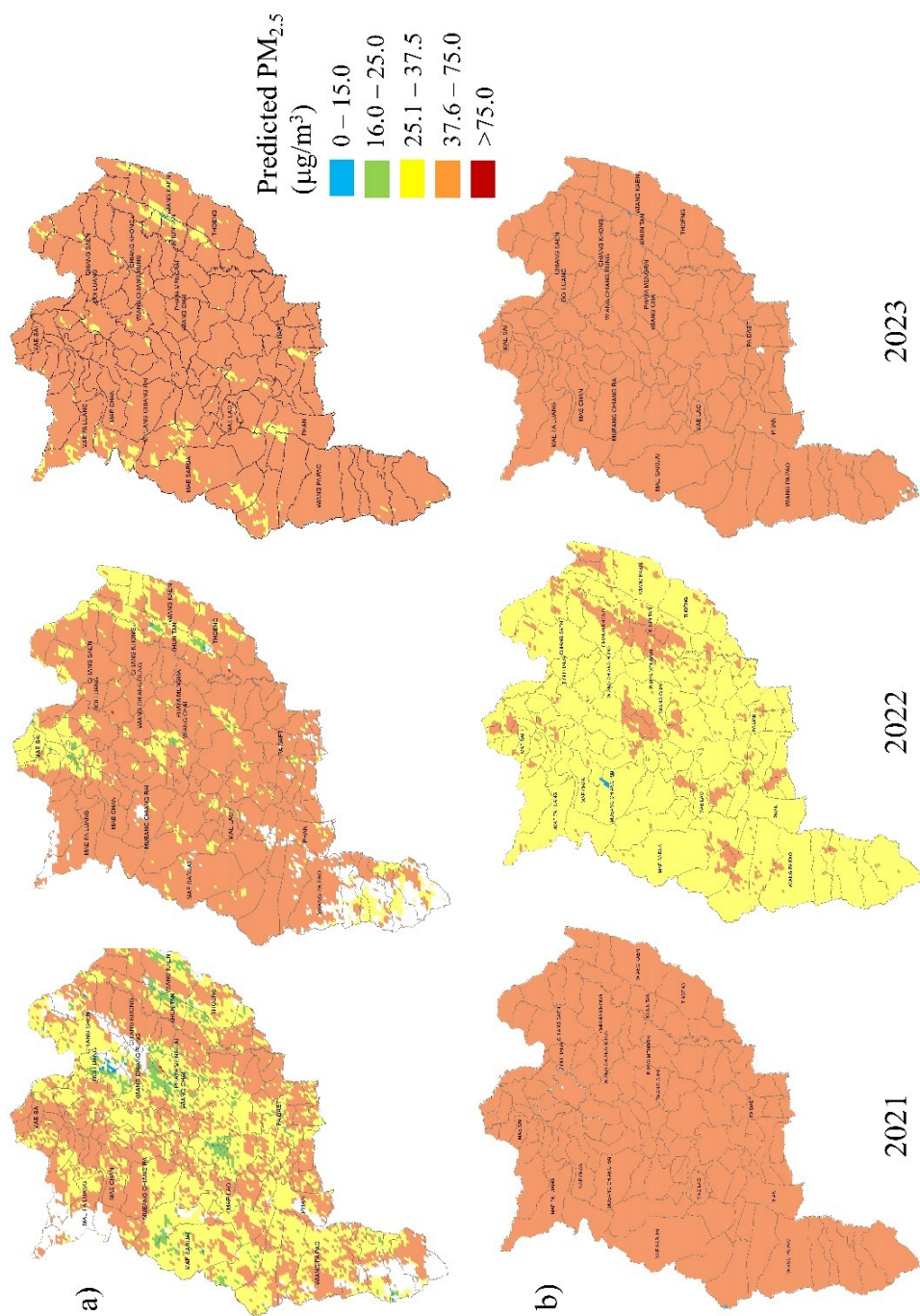
The estimates from the log-transformed linear mixed-effects model are shown in **Fig. 4**. Predicted PM<sub>2.5</sub> was inversely associated with conjunctivitis consultation rate after adjustment for temperature, PBL, calendar month, and year, with a random intercept for subdistrict ( $\beta = -0.000420$ , 95% CI:  $-0.000806$  to  $-0.000033$ ,  $p = 0.033$ ). PBL was positively associated with conjunctivitis consultation rate after adjustment for predicted PM<sub>2.5</sub>, temperature, calendar month, and year, with a coefficient of  $\beta = 0.000084$ , 95% CI:  $0.000010$  to  $0.000158$ ,  $p = 0.026$ . However, this association should not be interpreted as evidence of a direct effect of PBL on conjunctivitis. Rather, the coefficient may reflect residual meteorological or exposure-related patterns that were not fully captured by the model. Whereas temperature was not associated with the outcome ( $\beta = -0.000495$ , 95% CI:  $-0.005407$  to  $0.004416$ ,  $p = 0.843$ ).

In comparison, the untransformed Gaussian LMM yielded an inverse association between predicted PM<sub>2.5</sub> and conjunctivitis consultation rate, but the association did not reach statistical significance ( $\beta = -0.000523$ , 95% CI:  $-0.001074$  to  $0.000028$ ,  $p = 0.063$ ). Therefore, only the log-

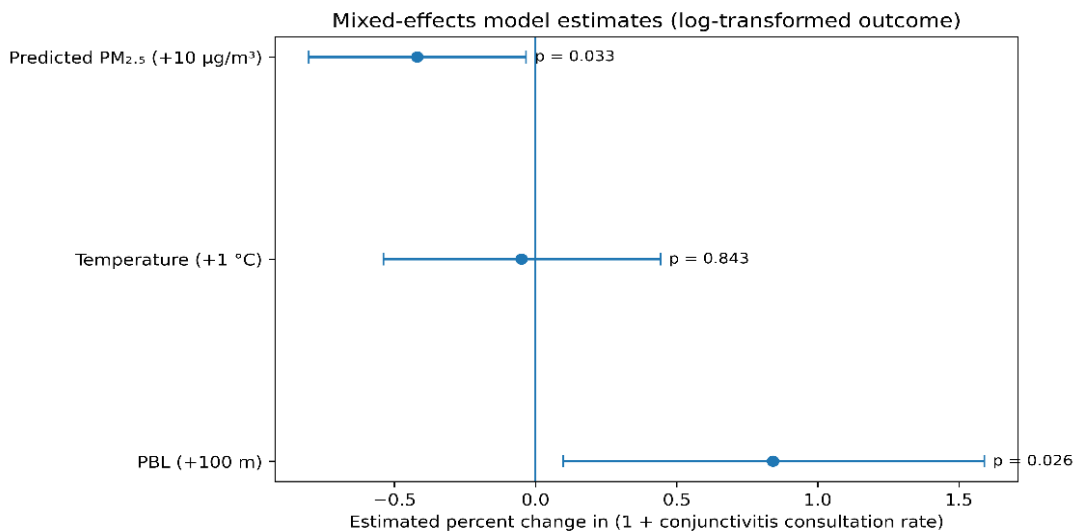
transformed model showed statistical significance, but the direction of the PM<sub>2.5</sub> connection was consistent across the two model assumptions. Its selection as the main model was supported by residual diagnostics, which showed an enhanced residual pattern and decreased residual dispersion following log transformation.



**Fig. 2.** Seasonal distribution of conjunctivitis consultation rate 2021–2023:  
a) Summer, b) Rainy, c) Winter.



**Fig. 3.** Seasonal distribution of predicted  $PM_{2.5}$  concentrations in Chiang Rai Province, 2021–2023: a) Summer, b) Winter.



**Fig. 4.** Mixed-effects model estimates for the association between predicted PM<sub>2.5</sub> and conjunctivitis consultation rate.

## 5. DISCUSSION

This study used a repeated-measures mixed-effects approach to assess the relationship between conjunctivitis consultation rates and satellite-derived PM<sub>2.5</sub> and found significant temporal and geographical fluctuation in these rates in a haze-prone area. The log-transformed LMM revealed an inverse relationship between predicted PM<sub>2.5</sub> and consultation rate after controlling for temperature, PBL, month, and year ( $\beta = -0.000420$ , 95% CI:  $-0.000806$  to  $-0.000033$ ,  $p = 0.033$ ). This finding, however, is in contrast to the positive associations reported in several prior epidemiological studies that linked particulate matter exposure to conjunctivitis and ocular irritation (Chen et al., 2019). Potential explanations include exposure misclassification from spatial averaging of 1 km PM<sub>2.5</sub> prediction, differences between outpatient consultation rates and actual illness incidence, healthcare-seeking behavior, unmeasured allergens or infectious agents, and environmentally related conjunctivitis in the available H10-coded health data, as well as residual confounding.

As a result, the negative relationship should not be taken as confirmation that PM<sub>2.5</sub> lessens conjunctivitis. Instead, it suggests that exposure assessment, temporal structure, and other factors related to healthcare utilization and ocular disease may influence the direction and strength of the ecological relationship. In an area with limited ground monitoring, the satellite-derived AOD model offered helpful spatial coverage for PM<sub>2.5</sub> prediction, as also demonstrated in an application integrating MAIAC-AOD with air-quality modeling (Hongthong & Nakapan, 2023). The LMM accounted for repeated subdistrict measurements as well as meteorological and temporal variation.

The selected PM<sub>2.5</sub> prediction model achieved a CV-R<sup>2</sup> of 0.670 and a CV-RMSE of 22.30 µg/m<sup>3</sup> in 10-fold cross-validation, indicating reasonably consistent out-of-sample predictive performance. Consultation rates were spatially structured rather than randomly distributed, according to the considerable regional clustering (Moran's  $I = 0.149$ ,  $p < 0.001$ ). When considered collectively, the findings emphasize that the observed PM<sub>2.5</sub>-conjunctivitis association is ecological and should not be interpreted causally, and they encourage the use of satellite-based exposure estimates and spatial epidemiology techniques.

There are several limitations to this study. First, the health outcome was based on routinely reported outpatient consultations; because individual identifiers were unavailable, repeated visits by the same patient could not be distinguished, and the outcome therefore represents a consultation rate rather than disease prevalence. Second, healthcare access and reporting practices may vary spatially and temporally. Third, satellite-derived PM<sub>2.5</sub> predictions are subject to uncertainty from cloud contamination, aerosol vertical distribution, and model assumptions (van sDonkelaar et al., 2016). Fourth, the LMM does not explicitly control several potential confounders, including relative humidity, wind speed, allergen exposure, infectious outbreaks, socioeconomic conditions, and healthcare accessibility. Fifth, the inverse association observed in the log-transformed model may reflect ecological exposure misclassification or unmeasured factors and should not be interpreted as a causal or protective effect. And finally, PM<sub>2.5</sub> in the study area may originate from both transboundary and domestic sources, including forest fires and agricultural biomass burning (Saksakulkrai et al., 2026).

As the present analysis did not distinguish PM<sub>2.5</sub> by emission source, the relative contribution of each source could not be determined and should therefore be considered when interpreting the observed association with conjunctivitis. Future studies using individual-level health data, longer time-series observations, and additional meteorological and environmental covariates are needed to clarify the relationship between PM<sub>2.5</sub> exposure and conjunctivitis. Moreover, the evaluation of lag structures, such as lag 0, lag 1, and distributed-lag models, using finer temporal health and exposure data should be considered.

## 6. CONCLUSION

This study shows that conjunctivitis consultation rates in Chiang Rai Province vary across space and time and can be evaluated in relation to satellite-derived PM<sub>2.5</sub> using a mixed-effects framework. The log-transformed LMM identified an inverse ecological association between predicted PM<sub>2.5</sub> and consultation rate after adjustment for temperature, PBL, month, and year, while substantial spatial clustering was also observed. These findings demonstrate the value of integrating satellite-derived PM<sub>2.5</sub> predictions with subdistrict-level health surveillance and longitudinal mixed-effects modeling in data-limited haze-prone area. Further studies using individual-level or time-series designs, improved exposure assessment, and additional meteorological, allergen, infectious, and socioeconomic covariates are needed to determine whether PM<sub>2.5</sub> has a causal effect on ocular health.

## ACKNOWLEDGMENTS

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