Investigating Chemical Component Relationships in Submicron Aerosol Composition Using Time-of-Flight Aerosol Chemical Speciation Monitoring (ToF-ACSM)

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Abstract

This study examines the chemical composition of fine particulate matter (PM2.5) in Chiang Mai, Thailand, using data from a Time-of-Flight Aerosol Chemical Speciation Monitor (TOF-ACSM) operated by the National Astronomical Research Institute. The analysis focuses on five major non-refractory components: chloride (Chl), ammonium (NH_4), nitrate (NO_3), organic compounds (Org), and sulfate (SO_4). After rigorous quality control and outlier removal using the Rolling Sigma-Clipping method, relationships among the components were analyzed using Spearman's rank correlation ($\alpha = 0.05$). Results show significant positive correlations among all species, particularly between nitrate and organic compounds, suggesting common sources or formation pathways influencing air quality in Chiang Mai.

Introduction

In early 2019, Thailand experienced severe air pollution, particularly PM2.5, which significantly affected public health, causing nasal irritation, breathing difficulties, and skin rashes. Research by the National Astronomical Research Institute of Thailand used a TOF-ACSM instrument to continuously measure the chemical composition of PM2.5 over 24 hours. The study focused on five major components: chloride (Chl), ammonium (NH_4), nitrate (NO_3), organic compounds (Org), and sulfate (SO_4). Understanding the relationships among these components helps identify pollution sources and supports the development of effective PM2.5 control policies.

Objectives

To study the relationship between the chemical composition of small dust particles from the TOF-ACSM device

Methodology



Data Characteristics

Mass Loadings analyzed by the TOF-ACSM machine are recorded every 10 minutes, 24 hours a day, and recorded in text file format (.txt), including the state information of the machine at that time, to determine if the machine is malfunctioning and the time.

Statistical Methods

(1) Rolling Sigma clipping method – outlier detection

$MA_t \pm k \cdot SD_t$

MA_t: rolling mean

SD_t: rolling standard deviation

k: a constant used to define the width of the boundary. Commonly used values are 1.5, 2, 2.5, and 3.

(2) Kolmogorov-Smirnov test – Normal distribution test

(3) Spearman's sequence correlation coefficient - Analysis of the mass loadings relationship of 5 chemical elements in small dust particles

Results

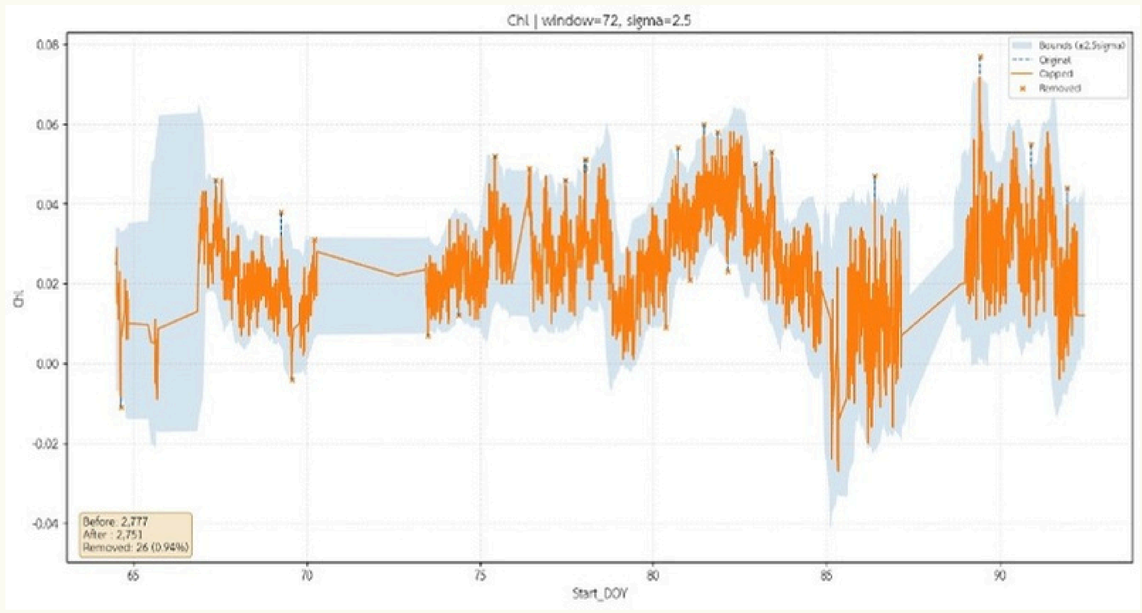


Figure: Time series of chloride after rolling sigma-clipping ($\sigma = 2.5$)

Table: Spearman's Rank Correlation Matrix for Mass Loadings of Five Chemical Constituents

	Chl	NH_4	NO_3	Org	SO_4
Chl	1.000	0.597*	0.710*	0.789*	0.401*
NH_4		1.000	0.612*	0.781*	0.723*
NO_3			1.000	0.852*	0.218*
Org				1.000	0.496*
SO_4					1.000

Remark: * p-value < 0.01

Conclusion

It was found that every pair of chemical elements (Chl, NH_4, NO_3, Org, and SO_4) showed a positive correlation in the same direction, meaning that when one variable increased, the others increased accordingly, and when one decreased, the others decreased as well (p-value < 0.01). These findings support PM2.5-related air pollution research and enhance the effectiveness of fine particulate matter management strategies.

References [1] Pandas Development Team. (2024). Pandas user guide: Rolling window endpoints. Retrieved from https://pandas.pydata.org/docs/user_guide/window.html#rolling-window-endpoints
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