Visibility Prediction Study in China Based on Chemistry Weather Coupling Model

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EGU General Assembly 2025

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Introduction

Low visibility (VIS) events, as typical disastrous weather, have great impacts on traffic and transportation, aircraft, and people's daily lives. Although the overall $PM_{2.5}$ concentration in China has declined in recent years, large-scale low visibility events (LVEs) closely related to haze/fog pollution still occur occasionally. Timely and accurate low visibility predictions are urgently needed and meaningful.

A reasonable atmospheric extinction algorithm in the atmospheric chemistry model is the basis for quantitatively predicting low visibility. The original IMPROVE atmospheric extinction algorithm (OIMP) in the chemistry-weather (CW) interacted model CMA_Meso5.1/CUACE CW shows reasonable performance in visibility modeling in general but tends to overestimate the extremely low visibility (VIS <3 km) under high relative humidity (RH) and light $PM_{2.5}$ conditions.

Incorporating the revised IMPROVE atmospheric extinction algorithm (RIMP) into the CMA_Meso5.1/CUACE CW model to improve the prediction of low visibility in eastern China

Atmospheric Extinction Algorithm: IMPROVE

OIMP

$$b_{ext} = 3f(RH)[SF] + 3f(RH)[NI] + 4[OM] + 10[EC] + [Soils] + 0.6[CM] + b_{rayleigh}$$

RIMP

$$b_{ext} = 2.2f_s(RH)[Small\ SF] + 4.8f_L(RH)[Large\ SF] + 2.4f_s(RH)[Small\ NI] + 5.1f_L(RH)[Large\ NI] + 2.8[Small\ OM] + 6.1[Large\ OM] + 10[EC] + 0.6[CM] + 1.7f_{ss}(RH)[SS] + [Soils] + 0.33[NO_2(ppb)] + b_{rayleigh}$$

Note. $[SF]$, $[NI]$, $[OM]$, $[EC]$, $[SD]$, and $[CM]$ represent sulfate, nitrate, organic carbon, elemental carbon, soil dust, and coarse mass concentrations ($\mu g \cdot m^{-3}$), respectively. $b_{rayleigh}$ represents Rayleigh scattering of air molecules.

Differences between RIMP and OIMP

- Develop a Split components extinction efficiency model ($Large, Small$);
- Provide more detailed aerosol hygroscopic growth factor ($f_L(RH)$, $f_s(RH)$);
- Add the extinction of *Sea Salt* and NO_2;
- Change the assumed *OM* to Organic Carbon (OC) mass ratio.

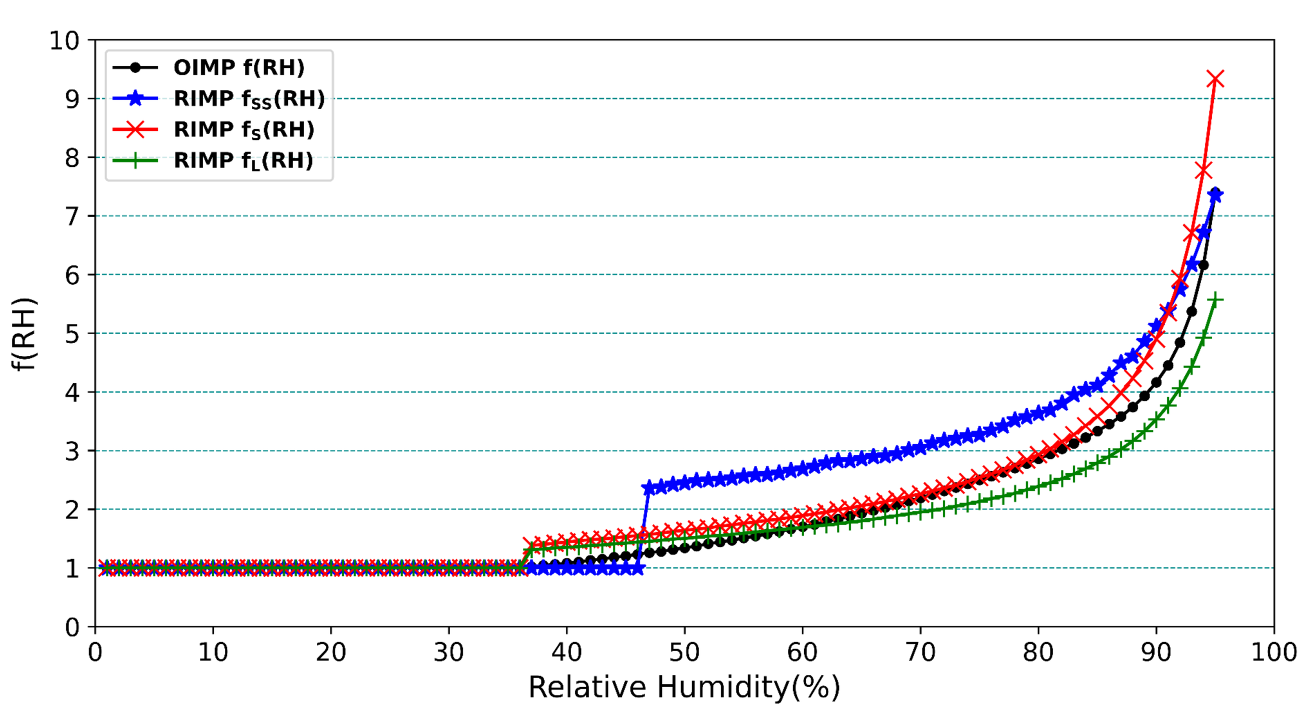

Fig1. $f(RH)$ (hygroscopic growth factor) curve used

Experiment Design

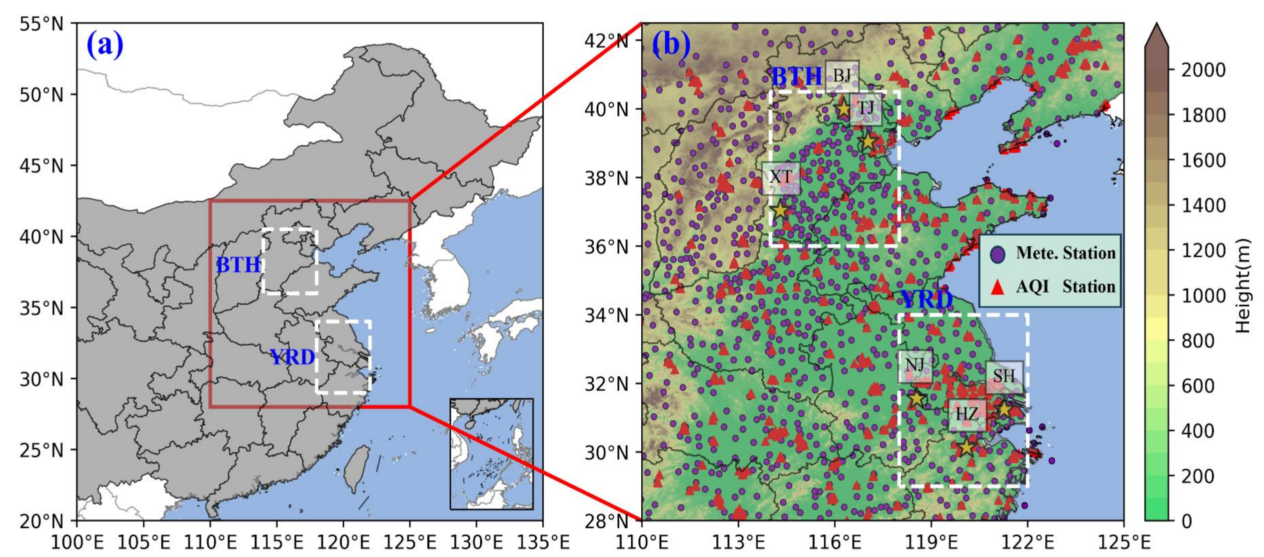

Fig 2. Model domain (a) and the study region (b), as well as its geographic location and topography.

Domain: 15.0°- 65.0° N, 70.0° - 145.0° E **Time:** Dec., 2016 to Feb., 2017

Region: Beijing-Tianjin-Hebei (**BTH**); Yangtze River Delta (**YRD**)

Typical City: Beijing, Tianjin, Xingtai; Shanghai, Hangzhou, Nanjing

Dependence Relationship of VIS on RH and $PM_{2.5}$

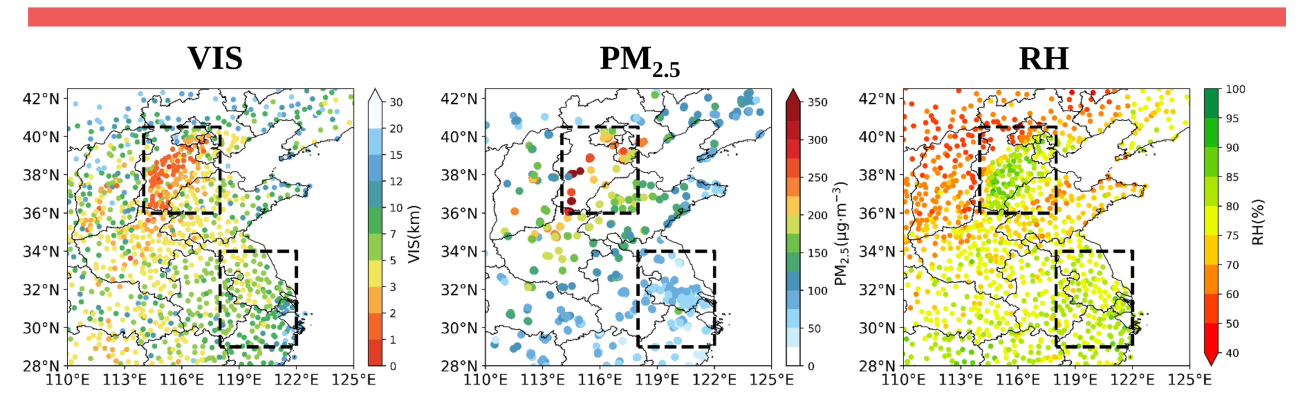

Fig 3. Mean observed VIS, $PM_{2.5}$ and RH in BTH and YRD of the three regional LVEs.

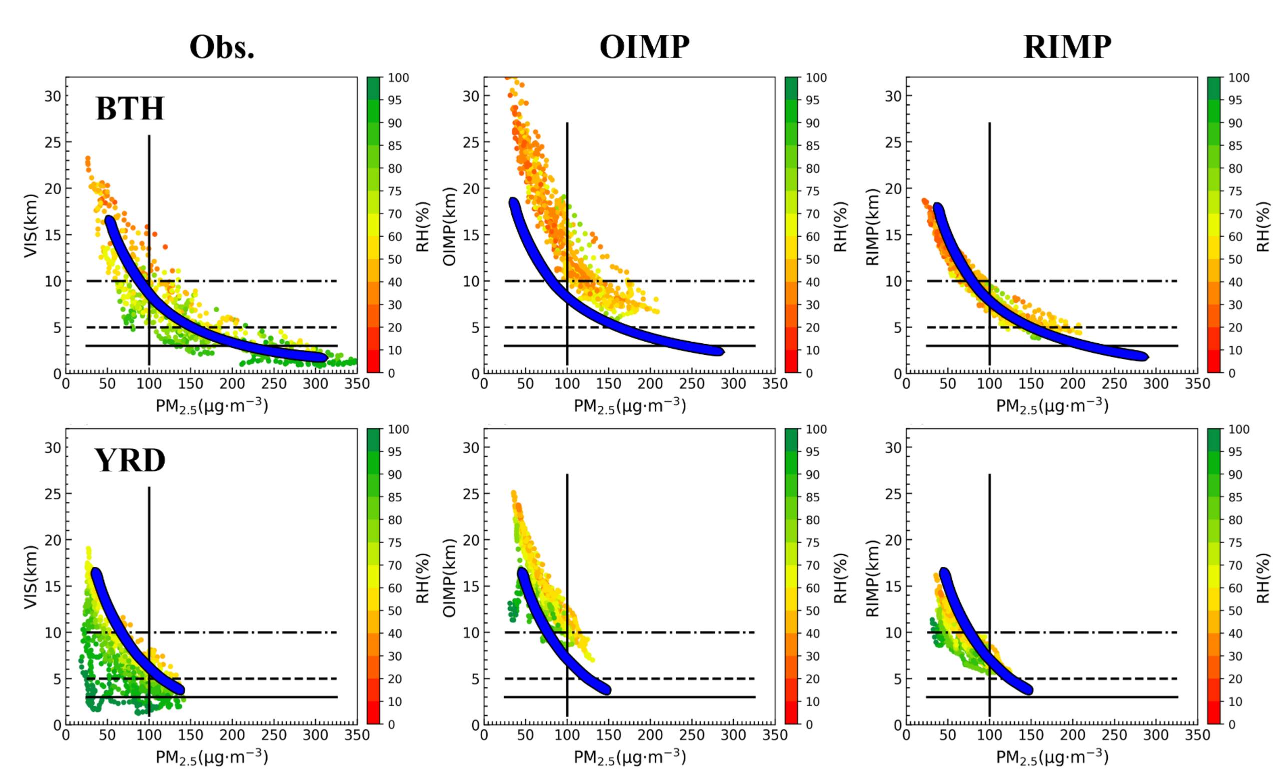

Fig 4. The relationships between the hourly $PM_{2.5}$ and VIS under different RH conditions in BTH and YRD in December 2016.

- RH and $PM_{2.5}$ show different effects on visibility variation in BTH and YRD;
- RIMP shows a **better description of the dependence relationship** of VIS on $PM_{2.5}$ and RH than that by OIMP.

Spatial Distribution and Hourly Changing

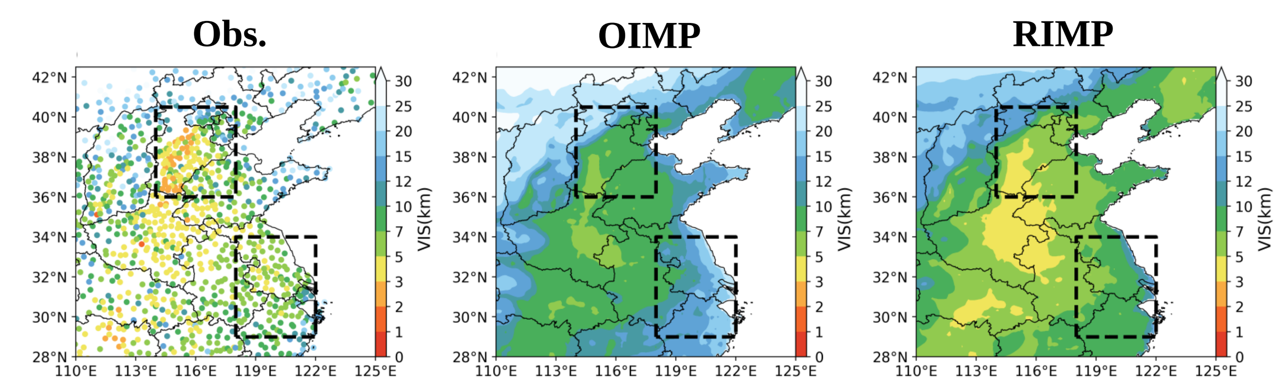

Fig 5. Mean observed and modeled (OIMP and RIMP) VIS in BTH and YRD of the three regional LVEs.

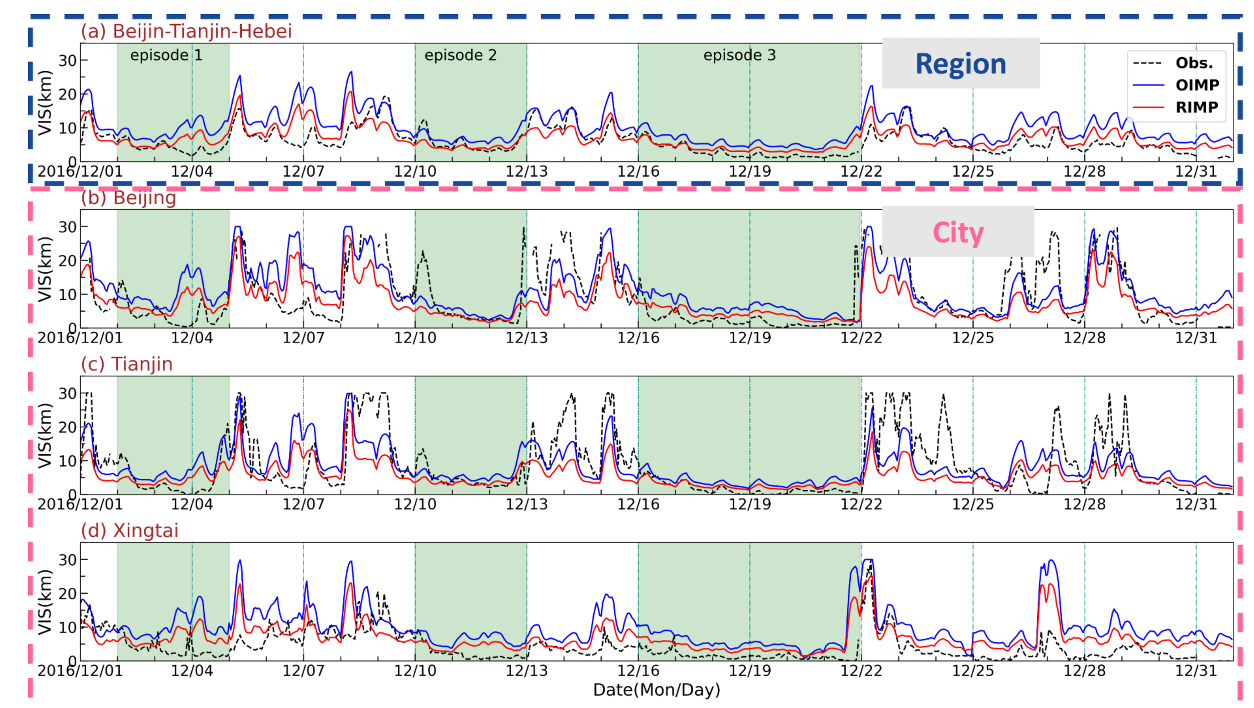

Fig 6. Hourly changing visibility at regional (a: BTH) and city scales (Beijing, c:Tianjin, d:Xingtai)

- RIMP reduces the VIS overestimation by OIMP in general;
- The VIS modeled by RIMP is much **more consistent with observations** than that by OIMP, and shows better performance at regional and city scales.

Static Evaluation

Table 1. RMSE (km) of modeled visibility levels (km) by OIMP, RIMP, and the RMSE (%) and TS changing from OIMP to RIMP

Cities/Regions	Scheme / Changing	RMSE of VIS			
		VIS ≤ 3	3 < VIS ≤ 5	5 < VIS ≤ 10	VIS ≤ 10
Beijing	OIMP	4.4	5.5	5.8	5.1
	RIMP	2.7	3.5	4.1	3.3
	Changing of RMSE / TS	↓ 38.6% / ↑ 0.27	↓ 36.4% / ↑ 0.10	↓ 29.3% / ↓ 0.01	↓ 35.3%
BTH	OIMP	6.9	6.7	5.9	6.1
	RIMP	4.3	4.0	4.5	3.7
	Changing of RMSE / TS	↓ 37.7% / ↑ 0.15	↓ 40.3% / ↑ 0.21	↓ 23.7% / ↑ 0.08	↓ 39.3%
Shanghai	OIMP	9.6	12.4	11.7	11.4
	RIMP	6.1	5.9	4.2	5.3
	Changing of RMSE / TS	↓ 36.5% / 0.00	↓ 52.4% / ↑ 0.15	↓ 64.1% / ↑ 0.33	↓ 53.5%
YRD	OIMP	11.6	11.1	8.8	9.0
	RIMP	6.3	5.1	4.2	4.3
	Changing of RMSE / TS	↓ 45.7% / ↑ 0.01	↓ 54.1% / ↑ 0.13	↓ 52.3% / ↑ 0.33	↓ 52.2%

- RIMP (red) improves VIS prediction compared to OIMP (blue) at regional and city scales. **RMSE decreased >30% , TS increased 0.01~0.33**.

Summary and Discussion

1. OIMP and RIMP schemes both showed reasonable performance in aerosols-induced low VIS modeling in megacity clusters in eastern China;
2. The RIMP scheme cut down the overestimation of low VIS obviously and shows better capacity in low VIS prediction than the OIMP scheme;
3. RIMP scheme also underestimated low VIS lower than 5 km, 3 km, or even lower VIS, showing it is not enough that only the impacts of the aerosols and its hygroscopic growth on atmosphere extinction for the accurate low VIS prediction.

NEXT STEP: An atmospheric extinction coefficient algorithm involves in full extinction factors:

- **Extinction coefficients:** haze (current), fog/cloud, rain, snow, graupel, and dust, etc.

$$b_{ext} = \boxed{b_{ext\_aero} + b_{ext\_fog}} + b_{ext\_rain} + b_{ext\_snow} + b_{ext\_graupel}$$

- **Key factors:** aerosols ⇆ fog/cloud droplets (transformation and interaction)

Table 2. Several droplet extinction algorithms.

method			parameter
$\frac{K \cdot LWC^{f_b(N_D)}}{f_a(N_D)}$	LWC $< 0.1 g \cdot m^{-3}$	$f_a(N_D) = 0.242{N_D}^{-0.0617} - 0.1351$	LWC: liquid water content; N_D: droplet number concentration
		$f_b(N_D) = -0.857{N_D}^{0.0385} + 1.66$	
	LWC $> 0.1 g \cdot m^{-3}$	$f_a(N_D) = 0.14{N_D}^{-0.0226} - 0.0123$	
		$f_b(N_D) = -0.00039{N_D}^{0.7525} + 0.743$	
$\frac{K \cdot LWC^{f_b(N_D \cdot re)}}{f_a(N_D)}$	LWC > LWCcv	$f_a(N_D) = a \cdot {N_D}^{-b} - c$	a, b, c, d, e, f are fit parameters.
	LWC < LWCcv	$f_b(N_D \cdot re) = -d \cdot N_D \cdot \exp(-e \cdot r_e) + f$	
$\sum_k Q_{ext}\, n(D) \frac{1}{4} \pi D^2 \Delta D$	Q_{ext}: extinction coefficients of clouds calculated by MIE model; D: Cloud droplet diameter; n(D): cloud droplet number concentration		physical process-based cloud extinction algorithm

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More Information

This study was supported by the National Science Fund for Distinguished Young Scholars (41825011) and key project of the Basic Scientific Research and Operation Project by Chinese Academy of Meteorological Sciences (2023Z021).

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