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Trends in PM_{2.5} and chemical components at the French EMEP sites

Anna FONT, Aude BOURIN, Corentin GOUILLOU, Cécile DEBEVEC, Stéphane SAUVAGE

5 May 2022

23rd EMEP Task Force on Measurements and Modelling (TFMM)



Background

- Fine particles (PM_{2.5}) are well-known to have an impact on climate, ecosystems as well as human-health
- Background sites in western and central Europe exceeding the WHO limits (5 μg m⁻³ as annual limit; 15 μg m⁻³ as daily mean) (Bressi et al., 2021)
- Chemical composition of PM_{2.5} essential to assess the sources contributing to mass concentrations
- In France, five background sites monitored PM_{2.5} mass concentrations and chemical composition between
 2014 2020
- Temporal trends in PM_{2.5} is a common tool to evaluate changes over time and assess the impact of any
 possible policy aiming to reduce primary emissions
- Trends in atmospheric components not only influence by changes in emissions but also changes in meteorology and transport patterns that might occur





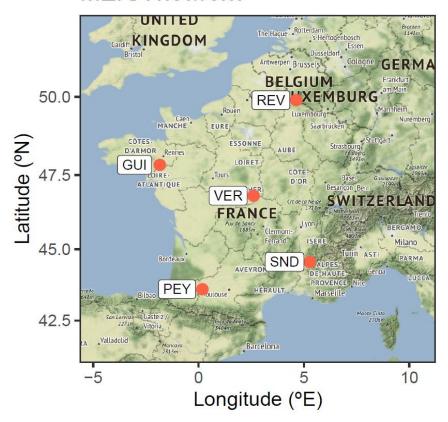
Aims

- To undertake the chemical mass balance of $PM_{2.5}$ mass concentrations based on the main ions along the years at the five remote sites monitoring $PM_{2.5}$ and chemical composition in France in 2014 2020.
 - To review conversion factors used to calculate source concentrations especially that used to account organic matter (OM) from organic carbon (OC)
- To evaluate trends in PM_{2.5} concentrations in association with changes in emission patterns removing
 any possible influence from meteorological and long-range transport characteristics



French EMEP network (MERA): PM_{2.5} chemical composition

MERA network

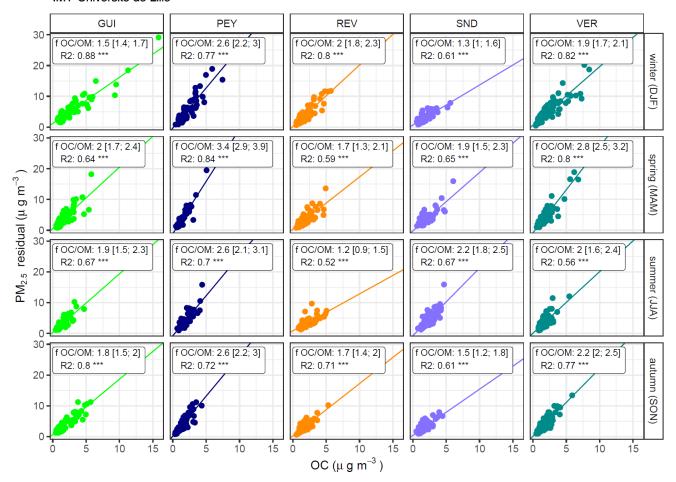


- MERA / EMEP sites where PM_{2.5} chemical composition is available for 2014 - 2020
- PM_{2.5} hourly mass concentrations (TEOM, TEOM-FDMS, BAM, FIDAS)
- Daily chemical composition every 6th day (14% year)
 - quartz filters (Pallflex Tissuquartz 2500 QAT-UP, 47 mm in diameter) + Partisol 2025i
 - OC & EC measurements: punch of 15 cm² is analysed by the Sunset instrument following EUSAAR2 protocol
 - Ca²⁺, K⁺, Mg²⁺, Na⁺, NH₄⁺; and Cl⁻, NO₃⁻, SO₄²⁻: digestion in pure water of a punch of 15.85 cm² and analysis ion chromatography
 - Monthly field blanks; averaged by season and removed from filter measurements except for OC & EC
 - No LOD correction applied

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Mass closure calculations and OC to OM conversion factor



station 🖊 GUI 🖊 PEY 💉 SND 🗲 REV 🖊 VER



$$PM_{2.5} = [OM] + [EC] + [SIA] + [sea salt] + [mineral dust] + [trace elements] + ϵ (1)$$

$$[SIA] = [NO_3^-] + [nss-SO_4^{2-}] + [NH_4^+]$$
 (2)

$$[OM] = f_{OC:OM} * [OC]$$
 (3)

Determination of $f_{OC:OM}$ by **site**; and by **season** and **site**: $f_{OC:OM} = ([PM_{2.5}] - ([EC] + [SIA] + [sea salt] + [mineral dust] + [trace elements])/OC (3) Fitted by OLS$

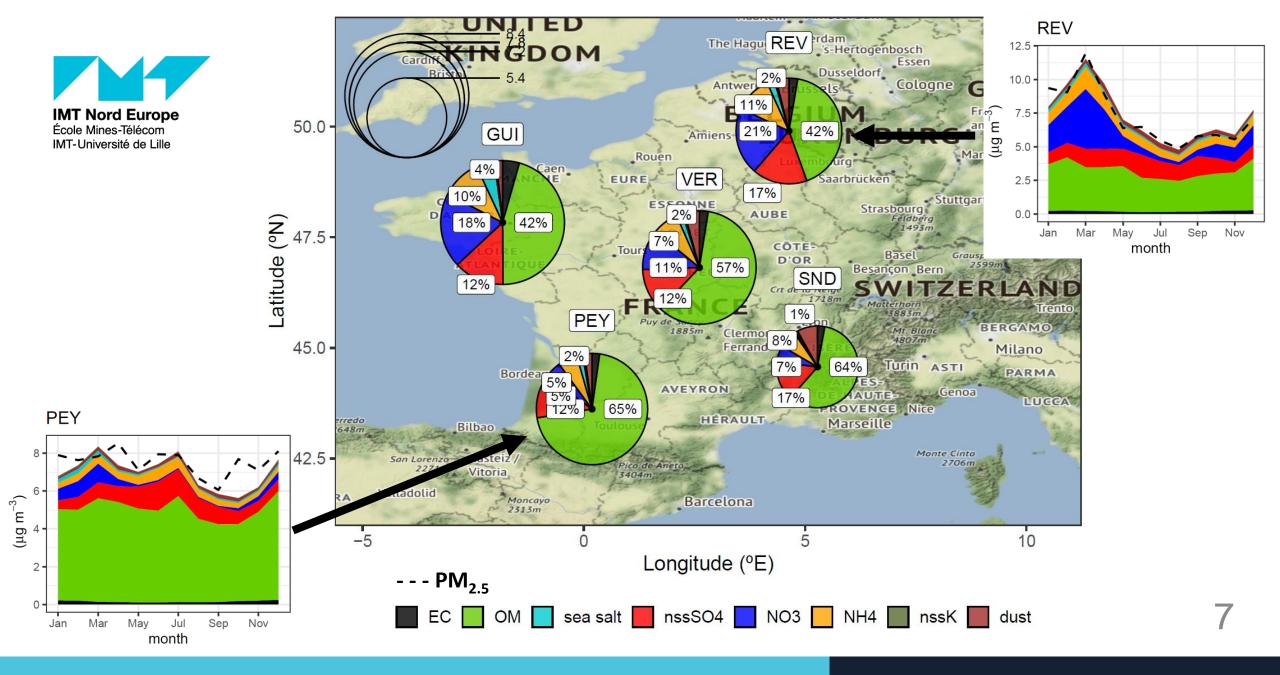


Mass closure calculations and OC to OM conversion factor

PM_{2.5} mass closure: comparison with measurements

		GUI	PEY	REV	SND	VER
Fived	Slope	0.94 [0.91 – 0.98]	0.71 [0.67 – 0.76]	0.94 [0.91 – 0.98]	0.95 [0.90 – 1.00]	0.84 [0.82 – 0.87]
Fixed $f_{\text{OC:OM}} = 1.8$	R^2	0.88***	0.70***	0.88***	0.72***	0.89***
	Avg res (%)	0.6 (7%)	2.1 (28%)	-0.4 (-6%)	-0.6 (-11%)	1.2 (16%)
Single $f_{\text{OC:OM}}$	Slope	0.90 [0.87 – 0.94]	0.90 [0.84 – 0.95]	0.93 [0.90 – 0.96]	0.95 [0.90 – 1.00]	0.91 [0.88 -0.95]
per site	R^2	0.88***	0.69***	0.89***	0.72***	0.88***
	Avg res (%)	1.0 (12%)	0.5 (7%)	-0.2 (-3%)	-0.6 (-11%)	0.4 (5%)
	Slope	0.91 [0.88 – 0.95]	0.91 [0.85 – 0.97]	0.95 [0.92 -0.98]	0.99 [0.94 – 1.04]	0.93 [0.90 – 0.97]
$f_{\rm OC:OM}$ season &	R^2	0.88***	0.71***	0.88***	0.73***	0.88***
site	Avg res (%)	0.6 (7%)	0.4 (5%)	-0.1 (-1%)	-0.5 (-9%)	0.4 (5%)

Better PM_{2.5} mass closure achieved → reduction unaccounted mass





Methods: linear trends



- Mann-Kendall test to evaluate if monotonic trends
- Theil-Sen method to calculate the temporal trend (rate of change): median of all possible trends for all x-y date points combinations.
 - Monthly means from hourly PM_{2.5} data
 - Monthly means from daily PM_{2.5} and chemical composition data

Mean trends (95% confidence interval)

	Hourly P	M _{2.5} data	Daily MERA filters		
	Trend	Trend	Trend	Trend	
site	(µg m ⁻³ year ⁻¹)	(% year ⁻¹)	(µg m ⁻³ year ⁻¹)	(% year ⁻¹)	
GUI ^A	-0.4 [-0.8, -0.1]*	-4.3 [-7.5 <i>,</i> -0.8]*	-0.5 [-0.9, -0.2]**	-5.7 [-8.8 <i>,</i> -2.3]**	
PEY	-0.5 [-0.7 <i>,</i> -0.3]***	-5.5 [-7.2 <i>,</i> -3.8]***	-0.5 [-0.7 <i>,</i> -0.3]***	-5.7 [-6.9 <i>,</i> -3.3]***	
REV	-0.5 [-0.7 <i>,</i> -0.4]***	-6.1 [-7.5 <i>,</i> -4.6]***	-0.7 [-0.9, -0.4]***	-7.2 [-8.9 <i>,</i> -5.1]***	
SND	-0.3 [-0.5, -0.1]**	-4.7 [-6.9 <i>,</i> -2.4]**	-0.3 [-0.5, -0.1]**	-5.3 [-7.8 <i>,</i> -2.7]**	
VER	-0.6 [-0.9, -0.3]***	-6.5 [-9.0 <i>,</i> -4.1]***	-0.7 [-1.0, -0.4]***	-8.0 [-9.9 <i>,</i> -5.3]***	

A trends calculated for 2014-2019

^{***} p < 0.001 ** p < 0.01 * p < 0.05 + p < 0.1



Methods: random-forest modelling for de-weathered time series

Primary emission rates, meteorological conditions and long-range transport patterns influence PM_{2.5} concentrations as well as its chemical components



- Random-forest modelling is a machine-learning method based on decision-trees (Grange et al., 2017)
- Multiple trees were built to reproduce concentrations using temporal, meteorological and transport
 explanatory variables using 70% of the data time series; the remaining 30% of the data is used to
 evaluate the performance of the model
- De-weathered algorithm calculates the time series for a given atmospheric component based on an iterative
- Limitation: chemical composition is based on daily filter measurements sampled every 6th day while meteorological and long-range transport data is available at a higher time resolution
 - <u>Proposed solution</u>: use 3-hourly met data and long-range transport data to predict 3 —h chemical data; daily averages to compared modelled vs daily measured data



Methods: random-forest modelling for de-weathered time series

Longitude (°E)

Temporal variables

- Day of the week
- Julian date (to capture seasonal variability)
- Decimal date (to capture long-term trends)

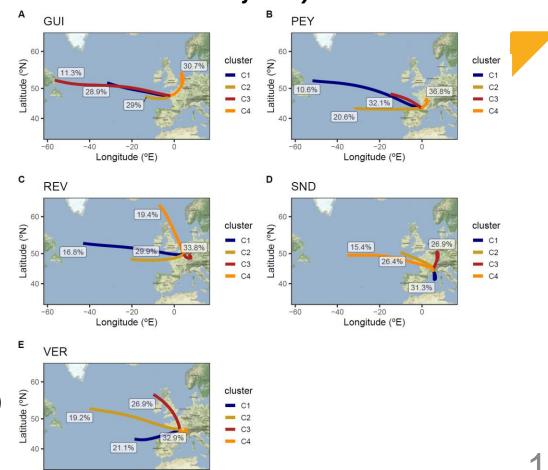
Meteorological variables

- Wind speed
- Wind direction
- Temperature
- Atmospheric pressure
- Relative humidity
- Mixing layer height (from GFS model)
- Precipitation at the site (from GFS model)

Long-range transport

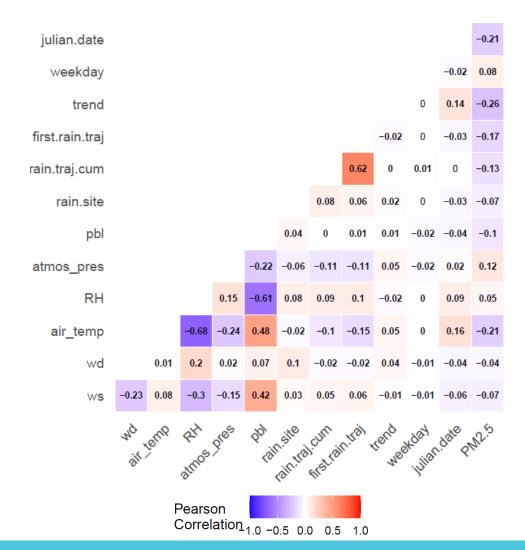
- Backtrajectory cluster (Hysplit GFS; release at 500 m)
- Cumulative rain along the trajectory
- Hour back main rain episode (> 0.2 mm)

Main backtrajectory cluster





Methods: Pearson correlation between explanatory variables





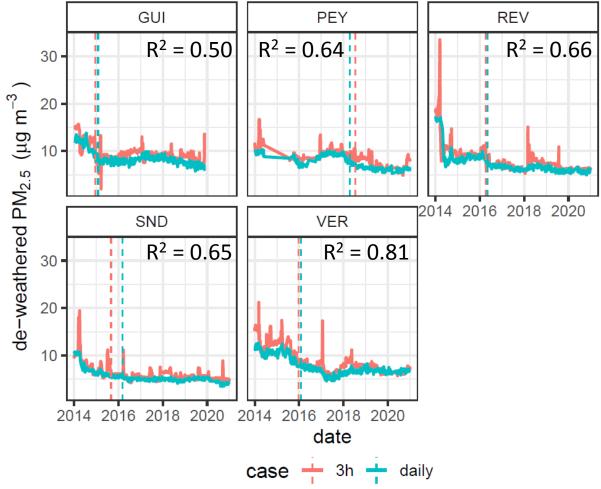
Variables chosen:

- Wind speed
- Wind direction
- Air temperature
- Atmospheric pressure
- Cluster
- Cumulative rain along back-trajectory
- Trend
- Weekday
- Julian date



Comparison de-weathered time series: daily vs 3 h explanatory

data



Vertical line: change point (based on the Buishand Range Test)



Comparison de-weathered time series: daily vs 3 h explanatory data

Evaluation of the random-forest model

	Daily explanatory data			3 h explanatory data		
site	Slope [95% CI]	RMSE (μg m ⁻³)	R ²	Slope [95% CI]	RMSE (µg m ⁻³)	R ²
GUI ^A	0.752 [0.647, 0.873]***	5.09	0.41	0.940 [0.938, 0.942]***	1.67	0.96
PEY	0.754 [0.642, 0.884]***	3.83	0.40	0,910 [0.908, 0.912]***	1.16	0.95
REV	1.026 [0.881, 1.194]***	5.44	0.28	0.923 [0.921, 0.926]***	1.49	0.95
SND	0.679 [0.593, 0.776]***	3.37	0.44	0.905 [0.903, 0.907]***	1.10	0.94
VER	0.773 [0.687, 0.870]***	5.29	0.57	0.947 [0.946, 0.949]***	1.45	0.97

Linear trends (Theil Sen slope)

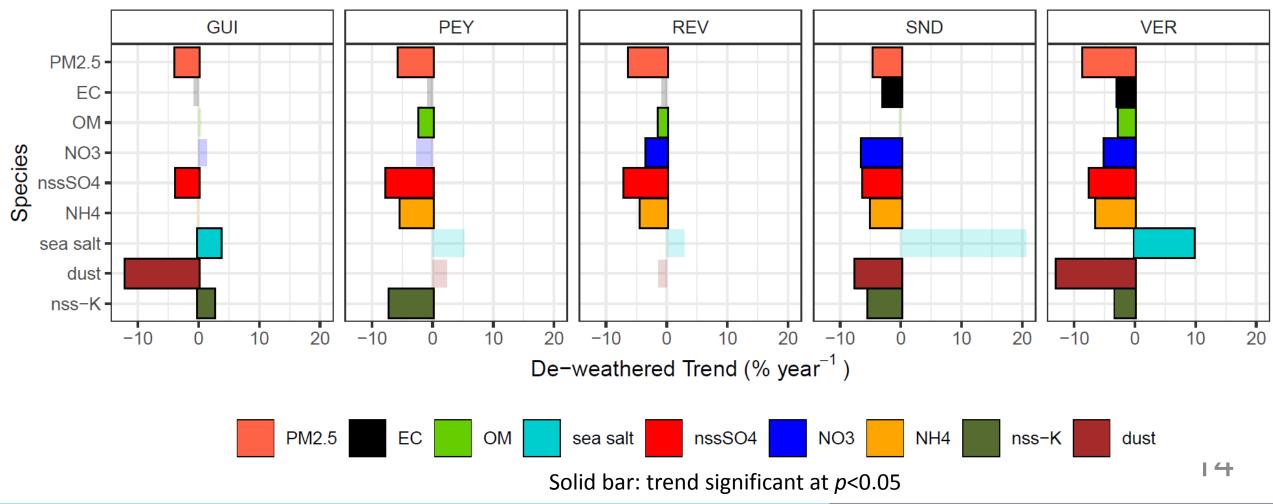
	Daily explana	itory data	3-hourly explanatory data		
	Trend	Trend	Trend	Trend	
site	(µg m ⁻³ year ⁻¹)	(% year ⁻¹)	(µg m ⁻³ year ⁻¹)	(% year ⁻¹)	
GUI ^A	-0.50 [-0.25, -0.79]***	-5 [-3, -8]***	-0.41 [-0.15, -0.69]***	-4 [-2, -6]***	
PEY	-0.57 [-0.45, -0.68] ***	-6 [-5 <i>,</i> -7] ***	-0.64 [-0.48, -0.88]***	-6 [-5 <i>,</i> -7]***	
REV	-0.51 [-0.41, -0.64] ***	-6 [-5, -7]***	-0.63 [-0.56, -0.73]***	-7 [-6 <i>,</i> -8] **	
SND	-0.36 [-0.26, -0.44] ***	-6 [-4 -7]***	-0.30 [-0.19, -0.44]***	-4 [-3, -6]***	
VER	-0.62 [-0.35, -0.84] ***	-7 [-4 <i>,</i> -9]***	-0.96 [-0.67, -1.2]***	-9 [-7, -11]***	

A trends calculated for 2014-2019

^{***} p < 0.001 ** p < 0.01 * p < 0.05 + p < 0.1



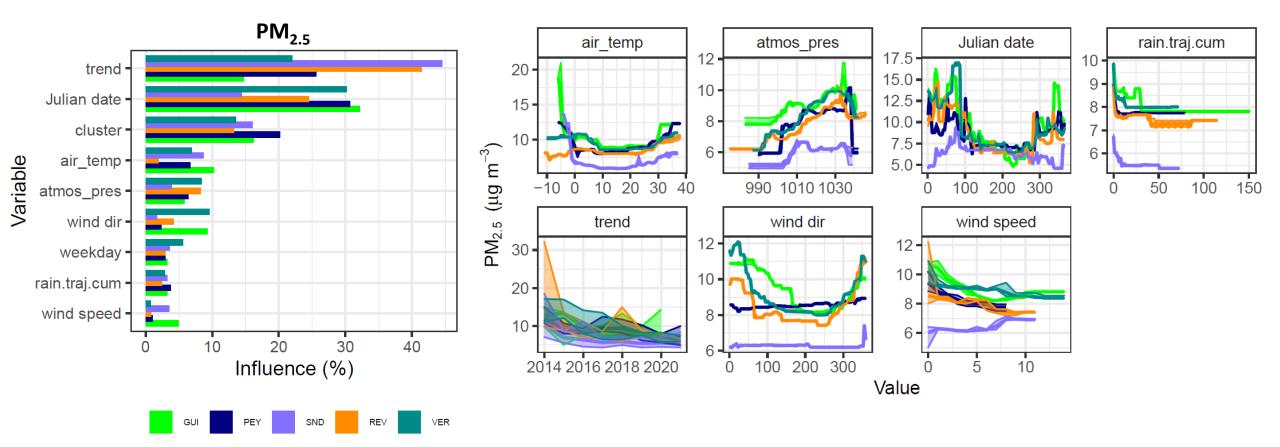
Results: Theil-Sen trends for de-weathered time series (3-h model)





Results: influence of variables & partial dependency plots







Conclusions

Annual PM_{2.5} concentrations at background sites in France ranged from 4.8 μg m⁻³ to 11.6 μg m⁻³ for the period 2014 – 2020, with the majority of sites / years exceeding the annual WHO limit value (5 μg m⁻³)



- Better PM_{2.5} mass closure was achieved when using site and seasonal specific $f_{OC:OM}$ ratios, with the unaccounted mass from -11% to 28% (fixed $f_{OC:OM} = 1.8$); to -9% to 7%.
- The chemical composition of fine aerosols was at the French EMEP sites for 2014 2020: OM (42–65%), non-sea-salt sulphate (17–21%), nitrate (5–21%), ammonium (12–5%), mineral dust (2–9%), EC (2–4%), sea salt (1–4%) and non-sea-salt potassium (~1%).
- OM was the main component of PM_{2.5} all year long
- SIA contributed mostly in spring
- The contribution of OM to PM_{2.5} was larger at the southern sites whereas the contribution of SIA was larger at the northern sites.



Conclusions

 Better reproduction of PM_{2.5} concentrations by random-forest modelling when using 3-hourly met and long-range transport information (R² > 0.90 and RMSE < 1.5 μg m⁻³)



- Temporal variables had greater role in explaining the variability in PM_{2.5} concentrations (15 45%);
 followed by the cluster variable (~15%) representing the long-range transport
- De-weathered time series for PM_{2.5} and the main components were built using the RF modelling
- All sites observed downward trends in PM_{2.5}, at a rate of -4 to -9% year⁻¹ for the period 2014 2020
- Downward trends in PM_{2.5} were coincidental with the downward trends in nss-SO₄²⁻ (-4 to -8 % year⁻¹) associated with the decrease in SO₂ emissions (mean decrease of -8% year⁻¹ between 2014 2019 in France)
- Reduction in NO₃⁻ concentrations from reduced NO_X emissions less evident at the French EMEP sites: 3 out of 5 sites observed significant downward trends (REV, SND and VER: -3% year⁻¹ to -6% year⁻¹). For 2014-2020, NO_X emissions in France decreased at a rate of -5% year⁻¹.
- Reduction in biomass burning was observed with downward trends in nss-K⁺ at three sites (VER, SND and PEY: -3 to -7 % year⁻¹). One site observed a significant upward trend (GUI) (2% year⁻¹)

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Trends in PM_{2.5} and chemical components at the French EMEP sites

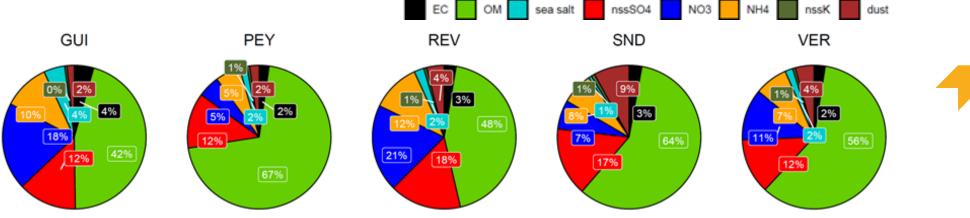
Many thanks for your attention

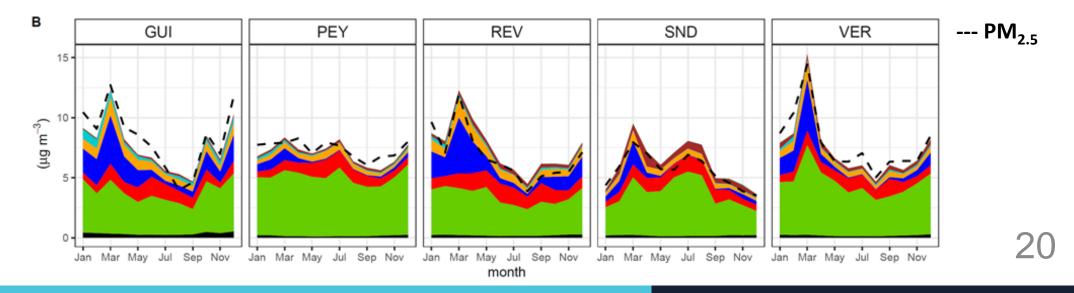
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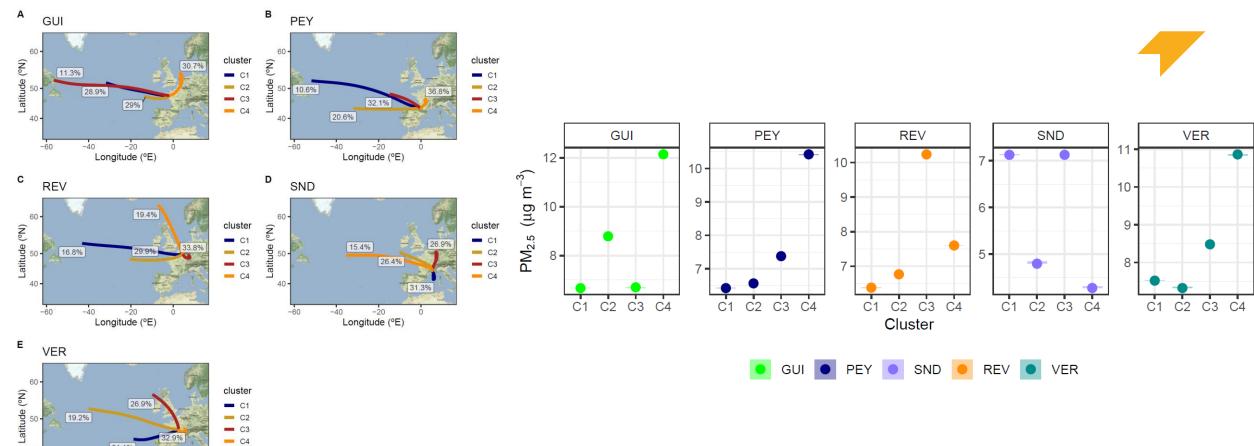
PM_{2.5} mass closure







Results: partial dependency plots for the cluster variable



21.1%

Longitude (°E)

- C4