## Modeling of Atmospheric Pollution Due to Marine Traffic in Marseille

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Inspirer un air meilleur

## Objectives

#### Build a model to predict air pollution based on detailed ship traffic data

- What is the contribution of ships to air pollution in Marseille and its surroundings ?
- How ship pollution is influenced by local meteorological conditions ?
- How Machine Learning can be used for operational purpose ?

## Introduction

## **Atmospheric Pollution**

WHO air quality guidelines (AQGs)

$\operatorname{Pollutant}$	Averaging period	AQG
$PM_{10}$	$1  \mathrm{day}$	$45 \ \mu g.m^{-3}$
	calendar year	$15 \ \mu g.m^{-3}$
$PM_{2.5}$	1 day	$15 \ \mu g.m^{-3}$
Ĺ	calendar year	$5 \ \mu g.m^{-3}$ )
$O_3$	Maximum daily 8-h mean	$100 \ \mu g.m^{-3}$
	peak season	$60~\mu g.m^{-3}$
$NO_2$	1 hour	$200 \ \mu g.m^{-3}$
	$1  \mathrm{day}$	$25~\mu g.m^{-3}$
	calendar year	$10~\mu g.m^{-3}$
$SO_2$	10 minutes	$500 \ \mu g.m^{-3}$
L	$1  \mathrm{day}$	$40 \ \mu g.m^{-3}$
CO	1 hour	$30 \ mg.m^{-3}$
	Maximum daily 8-hour mean	$10\ mg.m^{-3}$
	$1  \mathrm{day}$	$4 \ mg.m^{-3}$
BaP	calendar year	_
$C_6H_6$	calendar year	_
Pb	calendar year	$0.5 \ \mu g.m^{-3}$
As	calendar year	
Cd	calendar year	$5 \ ng.m^{-3}$
Ni	calendar year	

Particulate Matter
 DM = 357,000 promoture doot ho in 20

 $PM_{2.5} = 253\ 000\ \text{premature deaths in } 2020\ \text{in Europe}^1$ 

• Gas-phase Species

 $O_3 = 22\,000$  premature deaths in 2020 in Europe<sup>1</sup>

 $NO_2 = 52\ 000\ \text{premature deaths in } 2020\ \text{in Europe}^1$ 

<sup>1</sup> European Environmental Agency (EEA), 2022

#### **Port of Marseille-Fos**













Ferries



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# **Numerical Set-Up**



### Numerical set up



## (Weather Research and Forecasting + Chemistry)

NCAR = National Center for Atmospheric Research

#### WRF-CHEM (Weather Research and Forecasting + Chemistry)

NCAR = National Center for Atmospheric Research

#### Non-hydrostatic compressible Euler equations (Flux-form)

- Continuity Equation  $\partial_t \mu_d + (\nabla . \mathbf{V}) = 0$
- Momentum Equation

$$\begin{split} \partial_t U &+ (\nabla . \mathbf{V}u) + \mu_d \alpha \partial_x p + (\alpha/\alpha_d) \partial_\eta p \partial_x \phi = F_U \\ \partial_t V &+ (\nabla . \mathbf{V}v) + \mu_d \alpha \partial_y p + (\alpha/\alpha_d) \partial_\eta p \partial_y \phi = F_V \\ \partial_t W &+ (\nabla . \mathbf{V}w) - g(\partial_\eta p - \mu_d) = F_W \end{split}$$

• Thermodynamic Equation  $\partial_t \Theta + (\nabla . \mathbf{V} \theta) = F_{\Theta}$ 

- Humidity and Geopotential  $\partial_t Q_m + (\nabla \cdot \mathbf{V} q_m) = F_{Q_m}$  $\partial_t \phi + [(\mathbf{V} \cdot \nabla \phi) - gW]/\mu_d = 0$
- State and mass volume equation  $p = p_0 (R_d \theta_m / p_0 \alpha_d)^{\gamma}$  $\partial_\eta \phi = -\alpha_d \mu_d$

Where:  $\mathbf{V} = \mu_d \mathbf{v}$   $\phi = gz$  $\alpha = 1/
ho$   $\mu_d = p_{dhs} - p_{dht}$ 

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#### Non-hydrostatic compressible Euler equations (Flux-form)

- $\longrightarrow$  Finite Difference 5<sup>th</sup> order Runge-Kutta 3<sup>rd</sup> order  $\Delta t = 5 \text{ s}$ 
  - Continuity Equation  $\partial_t \mu_d + (\nabla . \mathbf{V}) = 0$

#### • Momentum Equation

 $\begin{aligned} \partial_t U + (\nabla \cdot \mathbf{V}u) &+ \mu_d \alpha \partial_x p + (\alpha/\alpha_d) \partial_\eta p \partial_x \phi = F_U \\ \partial_t V + (\nabla \cdot \mathbf{V}v) &+ \mu_d \alpha \partial_y p + (\alpha/\alpha_d) \partial_\eta p \partial_y \phi = F_V \\ \partial_t W + (\nabla \cdot \mathbf{V}w) - g(\partial_\eta p - \mu_d) = F_W \end{aligned}$ 

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4. Machine Learning

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MOZART

(Model for OZone And Related chemical Tracers)

- 85 gas-phase species  $\bullet$
- 157 chemical reactions
- 37 photochemical reactions

(Model for Simulating Aerosol Interactions and Chemistry)

- 4 aerosol size sections (bins)
  - bin, = [39 156] nm 0
  - bin<sub>2</sub> = [156 625] nm 0
  - bin<sub>3</sub> = [0.625 2.5] μm 0
  - bin<sub>4</sub> = [2.5 10] μm 0

## **Chemical inputs**



$$E_h = E_a \times C_m \times C_d \times C_l$$

2.

Model

Crippa et al. (2020)

Introduction



## **Chemical inputs**





### Numerical set up



Introduction

2. Model Ship Contribution

Conclusion

# **Ship Contribution**

"Zero-Out" method :  $[C_{ship}]_{\%} = \left[\frac{C_{bg+ship} - C_{bg}}{C_{bg+ship}}\right]_{\%}$ 

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 $SO_2$ 



Time-averaged NO<sub>2</sub> and SO<sub>2</sub> ship contribution for June 2021 at 8m above ground level.

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IMO-2020

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 $\overline{PM}_{2.5}$ 





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 $PM_{2.5}$ 





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**Ship Contribution** 

#### **Sea-Land Breeze Mechanism**





Time series of average scalar product between sea-land breeze vector and wind direction over Marseille

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Chevet et al. (2024) - Modeling of air pollution due to marine traffic in Marseille

# **Machine Learning**

## Machine / Deep Learning

#### **Objective** : Build a supervised hybrid Deep Learning model

#### Dataset



PM2.5 concentration for 2021 from WRF-CHEM

• Spatial Dimension :

64 x 64 = 4096

• Temporal Dimension :

7107 snapshots  $\sim$  10 months

#### **RNN** (Recurrent Neural Network)







### **Multivariate POD-RNN**



#### Built a numerical setup based on hourly ship traffic data

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• How Machine Learning can be used for operational purpose ?

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- How Machine Learning can be used for operational purpose ?
  - Development of a POD-RNN model for operational purpose : Univariate and Multivariate

5.

# Questions