



Research Overview: From Atmospheric Aerosols to Fog Forecasting

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Introduction

Appointments and Positions

- University of North Dakota, Department of Atmospheric Sciences
 - o **2024 Present:** Research Assistant Professor
 - 2020 2023: Postdoctoral Research Fellow
 - 2019 2020: Research Assistant

Professional Preparation

- University of Paris-East (France)
 - PhD in Atmospheric Sciences, received in December 2018
 - MESC in Environmental Quality, received in June 2015



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Introduction

Research Interest Overview

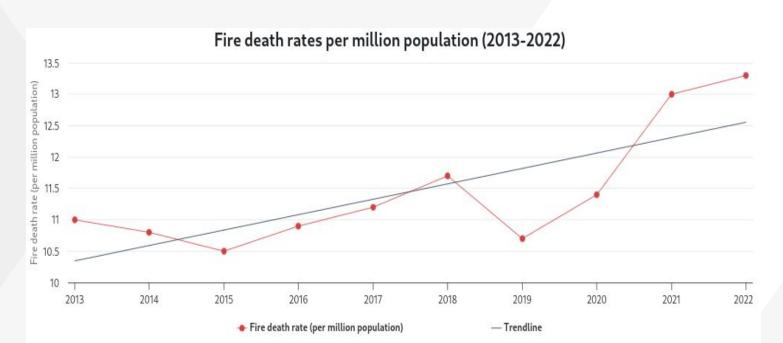
- Atmospheric Aerosols : Aerosol Chemistry in Chemical Transport models
- Fog & Cloud Microphysics
- Weather Forecasting, Weather for Uncrewed Aircraft Systems
- Machine Learning for Weather Prediction



Wildfires

- Intense and sporadic events
- Caused by natural factors (lightning, volcanic eruptions) or human activities (campfires, electrical malfunctions)
- Impact on human health (respiratory problems and cardiovascular issues)
- Impact still difficult to quantify



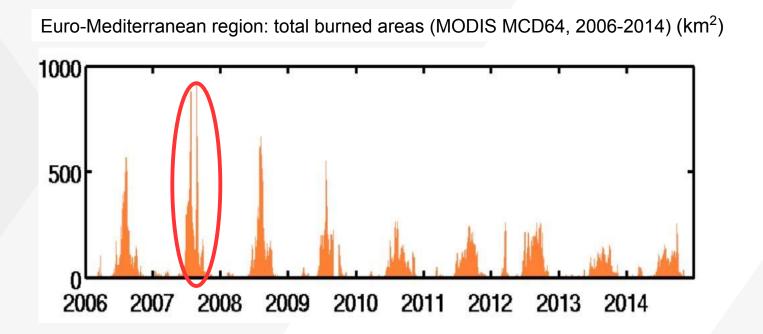




Wildfires over Euro-Mediterranean region

- Fire season: June-October with maxima in July and August (Turquety et al., 2014)
- Duration of fires: 2-10 days

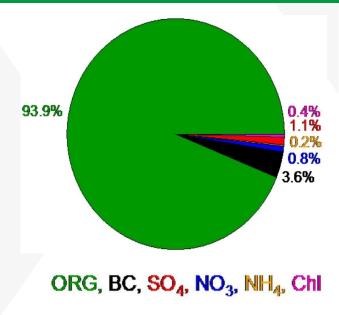
2007: the largest year in terms of burned areas according to MODIS





Quantifying Wildfire Impact

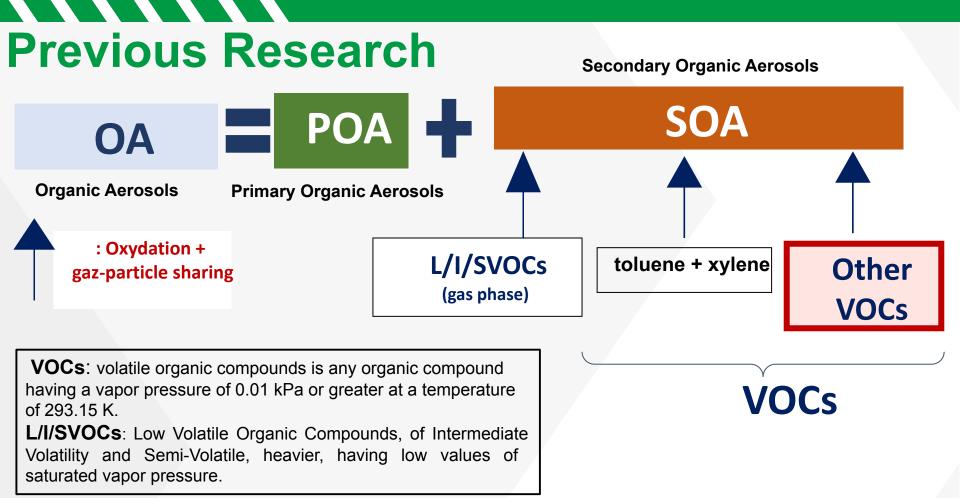
- By measurements: physico-chemical (mass, composition, size) and optics.
- In-situ: AIRBASE/AERONET
- Satellite: MODIS
- Intensive fire campaigns



LI Kleinman and AJ Sedlacek, January 2016 BBOP Final Campaign Report

- By modeling: 3D Eulerian Chemistry Transport Models (CTMs)
- Major sources of uncertainty linked to the formation of aerosols as well as their chemical evolution.





- → What are the main precursors responsible for the formation of SOA during the two fire episodes of summer 2007 in the Euro-Mediterranean region?
- → What is the contribution of SOA precursors to the formation of OA?



Secondary Organic Aerosol Formation from Wildfires in the Euro-Mediterrane and Region 0-19-5543-2019

Methodology

- Development of a new chemical mechanisms to represent the SOA Formation (H2Oaro):
 - Based on smoke chamber experiments with different VOC precursors.
 - Parameterized SOA formation in high- and low-NOx conditions.
 - Master Chemical Mechanism (MCM): oxidation reactions of VOCs with atmospheric oxidant
- Implementation of the new developed chemical mechanism in a French CTM
 - Simulate OA over the Mediterranean region during the fire events of 2007.

Table B3. Reactions leading to SOA formation added to CB05

| Reactions | Kinetic rate parameter (molecule ⁻¹ cm ³ s ⁻¹ | | | |
|--|--|--|--|--|
| PHEN + OH \rightarrow 0.75 CAT + OH | $4.7 \times 10^{-13} \exp(1220/T)$ | | | |
| $CAT + OH \rightarrow 0.28 \text{ ACIDMAL} + OH$ | 9.9×10^{-10} | | | |
| $BENZ + OH \rightarrow 0.53 PHEN + OH$ | $2.3 \times 10^{-12} \exp(-190/T)$ | | | |
| $CRESp + OH \rightarrow 0.73 MCAT + OH$ | 4.65×10^{-10} | | | |
| $MCAT + OH \rightarrow 0.39 DHMB + OH$ | 2×10^{-10} | | | |
| $FUR + OH \rightarrow 0.87 \text{ ButDial} + OH$ | 4.19×10^{-11} | | | |
| ButDial + OH → 0.83 RADButenalCOO + OH | 5.20×10^{-11} | | | |
| RADButenalCOO + $HO_2 \rightarrow 0.15$ ButenalCOOH + HO_2 | $5.20 \times 10^{-13} \exp(980/T)$ | | | |
| RADButenalCOO + NO \rightarrow NO | $7.5 \times 10^{-12} \exp(290/T)$ | | | |
| RADButenalCOO + $XO_2 \rightarrow 0.3$ ButenalCOOH + XO_2 | 1.0×10^{-11} | | | |
| ButenalCOOH + OH → 0.3 RADButenCOOHCOO + OH | 2.12×10^{-11} | | | |
| RADButenCOOHCOO + HO ₂ → 0.15 Buten2COOH + HO ₂ | $5.20 \times 10^{-13} \exp(980/T)$ | | | |
| RADButenCOOHCOO + NO → NO | $7.50 \times 10^{-12} \exp(980/T)$ | | | |
| RADButenCOOHCOO + $XO_2 \rightarrow 0.3$ Buten2COOH + XO_2 | 1.0×10^{-11} | | | |
| SYR + OH → RADSYR+ OH | 9.63×10^{-11} | | | |
| RADSYR+ $HO_2 \rightarrow 0.57$ PSYR+ HO_2 | $2.91 \times 10^{-13} \exp(1300/T)$ | | | |
| RADSYR + NO → 0.36 PSYR+ NO | $2.70 \times 10^{-13} \exp(360/T)$ | | | |
| $RADSYR + NO_3 \rightarrow 0.36 PSYR + NO_3$ | 2.30×10^{-12} | | | |
| GUAI + OH → RADGUAI+ OH | 7.53×10^{-11} | | | |
| RADGUAI + $HO_2 \rightarrow 0.37GHDPerox + HO_2$ | $2.91 \times 10^{-13} \exp(1300/T)$ | | | |
| RADGUAI + NO → 0.32GHDPerox + NO | $2.70 \times 10^{-13} \exp(360/T)$ | | | |
| RADGUAI + NO ₃ → 0.32GHDPerox + NO ₃ | 2.30×10^{-12} | | | |
| NAPH + OH → NAPHP+ OH | 2.44×10^{-11} | | | |
| NAPHP + HO ₂ → 0.44 BBPAHIN+ HO ₂ | $3.75 \times 10^{-13} \exp(980/T)$ | | | |
| NAPHP + MEO ₂ → 0.44 BBPAHIN+ MEO ₂ | $3.56 \times 10^{-14} \exp(708/T)$ | | | |
| NAPHP + $C_2O_3 \rightarrow 0.44$ BBPAHIN+ C_2O_3 | $7.40 \times 10^{-13} \exp(765/T)$ | | | |
| NAPHP + NO → 0.26 BBPAHhN+ NO | $2.70 \times 10^{-11} \exp(360/T)$ | | | |
| NAPHP + NO ₃ → 0.26 BBPAHhN+ NO ₃ | 1.2×10^{-12} | | | |
| MNAPH + OH → 0.26 MNAPHP+ OH | 2.44×10^{-11} | | | |
| MNAPHP + HO ₂ → 0.46 BBPAHIN+ HO ₂ | 2.44×10^{-11} | | | |
| MNAPHP + MEO2 → 0.46 BBPAHIN+ MEO2 | $3.56 \times 10^{-14} \exp(708/T)$ | | | |
| MNAPHP + $C_2O_3 \rightarrow 0.46$ BBPAHIN+ C_2O_3 | $7.40 \times 10^{-13} \exp(765/T)$ | | | |
| MNAPHP + NO → 0.37 BBPAHhN+ NO | $2.70 \times 10^{-11} \exp(360/T)$ | | | |
| MNAPHP + NO ₃ → 0.37 BBPAHhN+ NO ₃ | 1.2×10^{-12} | | | |
| $USC > 6_{phen} + OH \rightarrow 0.75 USC > 6CAT + OH$ | $4.7 \times 10^{-13} \exp(1220/T)$ | | | |
| USC>6CAT + OH → 0.28 USC>6ACIDMAL + OH | 9.9×10^{-10} | | | |
| USC>6 _{NAPH} + OH → USC>6NAPHP+ OH | 2.44×10^{-11} | | | |
| USC>6NAPHP + HO ₂ \rightarrow 0.44 USC>6BBPAHIN+ HO ₂ | $3.75 \times 10^{-13} \exp(980/T)$ | | | |
| USC>6NAPHP + MEO ₂ \rightarrow 0.44 USC>6BBPAHIN+ MEO ₂ | $3.56 \times 10^{-14} \exp(708/T)$ | | | |
| USC>6NAPHP + $C_2O_3 \rightarrow 0.44$ USC>6BBPAHIN+ C_2O_3 | $7.40 \times 10^{-13} \exp(765/T)$ | | | |
| USC>6NAPHP + $C_2O_3 \rightarrow 0.44$ USC>6BBPAHhN+ C_2O_3 USC>6NAPHP + NO $\rightarrow 0.26$ USC>6BBPAHhN+ NO | $2.70 \times 10^{-11} \exp(360/T)$ | | | |
| USC>6NAPHP + NO ₃ \rightarrow 0.26 USC>6BBPAHhN+ NO ₃ | 1.2×10^{-12} | | | |

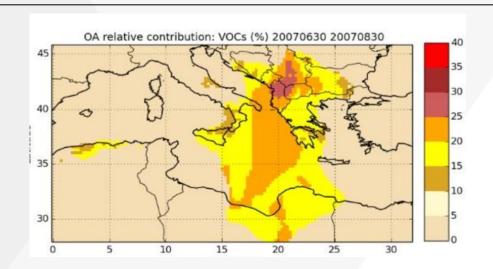


Previous Research Euro-Mediterranean Region

majdi et al. (2019) https://doi.org/10.5194/acp-19-5543-2019

Results – Key SOA Precursors

- Main VOC contributors to SOA: phenol, benzene, catechol, cresol, syringol and toluene/xylene.
- The contribution of the oxidation of VOCs to the OA concentrations is locally significant (it reaches 30 % in the area close to where wildfires are emitted and 20 % in the fire plume).



Contribution to OA from VOC oxidation (%)- 20070630 20070830

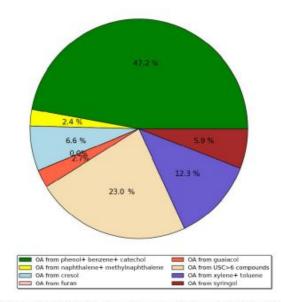


Figure 12. Distribution of the OA concentrations formed from the different VOCs emitted by wildfires over the subregion during the summer of 2007 (simulation Multstep-withVOC).



Fog

- Dense, low-lying cloud composed of tiny water droplets that suspend in the atmosphere near the Earth's surface.
- Results in reduced visibility to less than 1km.
- Vary in thickness and duration, influenced by local weather conditions, humidity levels, and geographical features.

General Impacts of Fog

- Reduced Visibility: Creates hazardous travel conditions.
- Transportation Delays: Affects schedules for public transport, including trains and buses and for commercial flights.









Impact of Fog on Aviation

- Flight Delays and Cancellations: Low visibility conditions can ground flights, leading to significant delays.
- Increased Safety Risks: Takeoff and landing maneuvers become more hazardous, requiring enhanced pilot training and procedures.
- Instrument Dependency: Pilots must rely more heavily on instruments, increasing the complexity of operations.

Impacts on Uncrewed Aircraft Systems Operations

- Navigation Challenges: Reduced visibility complicates
 UAS navigation and obstacle avoidance.
- Regulatory Restrictions: Many jurisdictions restrict UAS flights in foggy conditions due to visibility concerns.

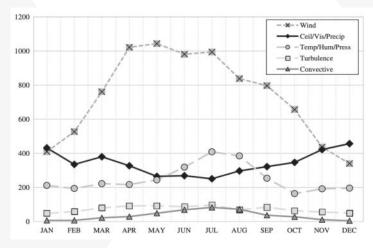


Figure 1: Weather-related general aviation accidents for each weather hazard category that occurred within the United States from 1982 through 2013 by month. Adapted from (Fultz and Ashley 2015).

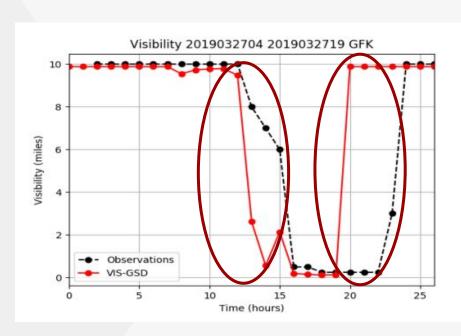


Need for a robust forecasting and safety measures to mitigate Fog impacts.



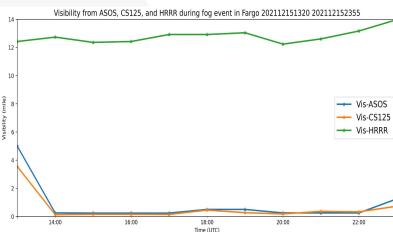
Fog Forecasting Challenges

1) Delays in predicting both the onset and dissipation times of fog



Need for better understanding and modeling of the atmospheric conditions that contribute to fog formation

2) Failure in capturing some fog events



Fog Event of December 15th, 2021 in Fargo ND





Previous/Current Research

Fog Field Campaign: MetTrailer

(Spring-Fall 2021 Fargo Jet Center, ND)



Support Blocks -

All Sky Camera

3 Axis Sonic Anemometer

3D-PAWS

Weather Transmitter

Aerosol Inlet

Present Weather Sensor

2 Axis Sonic Anemometer

iMet-XQ2 UAV Sensor

MiniOFS Visibility Sensor

Pressure Transducer

Deeplens Camera

MetTrailer

http://mettrailer.atmos.und.edu/







Previous/Current Research

Fog field Campaign: Tripods







Deployed Location: Gorman Field Small UAS Airport, Emerado, ND

Deployed Date: December 2023 -Present



Data collection and processing: Fog Database

http://camera.atmos.und.edu/



Weather Cameras Database

About Weather Cameras Database

List of Cameras

Fog Events

Contact us



List of Cameras



Deeplens Camer



All Sky Car



Web Camera



aenhorm Di Camor



UND Sky Cameras





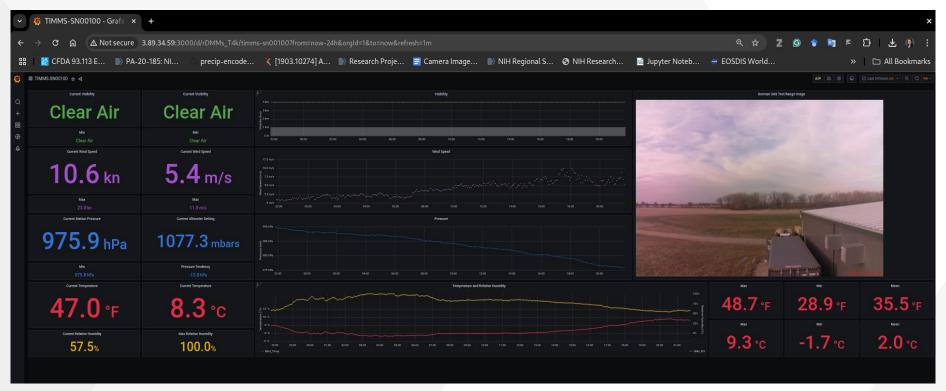






Data collection and processing: Fog Database

Grafana website to display all the collected fog observations



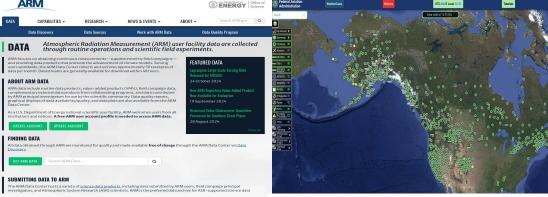


Data collection and processing: Publicly available Weather Data

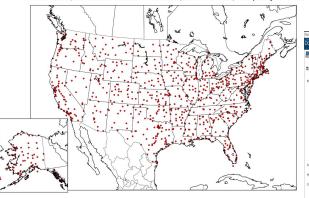
METAR/ASOS

ARM database

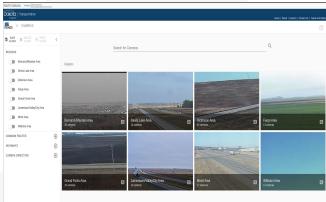




Real-Time ASOS/AWOS Observations in MesoWest (with HF-METARs) - Frequency $<= 5 \min$



NDDOT cameras



Other available live cameras





Fog Detection and Camera-based Real-Time Visibility Estimation

Camera-based Real-Time Visibility System Relative Humidity (RH) from Sensor Campbell RH< 95% RH≥ 95% visibility + No Precipitations sensor + Low Wind Speed **Fog Conditions Non-Fog Conditions** Deep Learning Model Deep Learning Model **Non-Fog Conditions Fog Conditions** Deep Learning Model Deep Learning Model 20075 Data Points 2800 Data Points during 10 Fog Events 20% Testing 80% Training 20% Testing 80% Training Visibility Measurements Relative Humidity Camera Image Features: · Change Point Real-Time Visibility Mean Brightness Mean Number of Edges Regression-based Neural Networks

Majdi et al. (2024) in prep

Motivation

- Flying in low visibility from fog reduces Unmanned Aircraft System (UAS) performance.
- Lack of visibility data or the inability to communicate visibility data to UAS operators due to the high cost of existing instruments and the required maintenance.
- There exists a high density of low-cost cameras with the potential of providing visibility data.

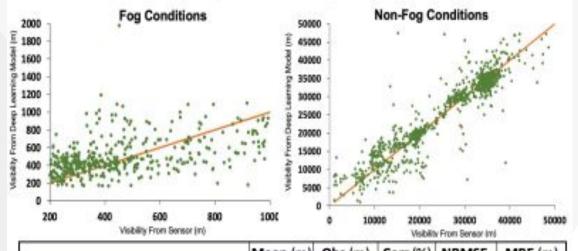
Objective

Develop and validate a Camera-based Deep Learning Model that provides a real time visibility estimation and determines the presence of fog over Grand Forks and Fargo, ND.



Fog Detection and Camera-based Real-Time Visibility Estimation

Majdi et al. (2024) in prep



| | Mean (m) | Obs (m) | Corr (%) | NRMSE | MBE (m) |
|-------------------------------------|------------|----------|----------|-------|----------|
| | Fog Condit | ions | 1 | | |
| Visibility from Deep Learning Model | 491.67 | 444.48 | 60 | 0.54 | 47.19 |
| Visibility from HRRR | 9578.92 | 444.48 | 35 | 30.17 | 9134.442 |
| No | on-Fog Con | ditions | | | 12.0 |
| Visibility from Deep Learning Model | 26039.59 | 26069.41 | 94 | 0.14 | -29.83 |
| Visibility from HRRR | 24331.6 | 26069.41 | 80 | 0.5 | -1737.82 |

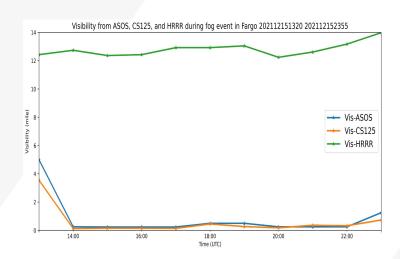
Results

- Overall, the Fog conditions and Non-Fog conditions Deep learning models show a good fit. Good agreement between the estimated visibility from the camera-based Real-Time Visibility System and visibility observations comparing to HRRR model.
- Due to the decreased computational time required and low-cost high density camera, the Camera-based Real time visibility system is suitable for UAS operations that do not want to deploy high cost-instruments.



Toward Improving the Prediction of Radiation Fog Life Cycle using WRF Model

- Numerical Weather Prediction models often fail to predict the time and location of the fog onset and dissipation with sufficient accuracy.
- The main purpose of this project is to improve the scientific understanding of fog processes that directly impact WRF performance in simulating the occurrence of radiation fog over Eastern North Dakota.
- Determine the best model setup using ensemble modeling methodology: Different model setups (coupling, utilizing meteorological observation data from the fog dataset as initial conditions, the nudging of meteorological observation data, and utilizing observed CCN concentrations) are analyzed.
- The project uses a case study of December 15th, 2021 fog event in Fargo methodology that combines observations from the created fog database with model improvements and evaluation.





Future Research

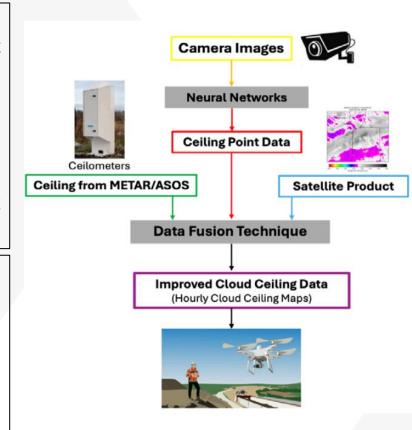
Real-time Visibility and Cloud Ceiling Estimation for UAS Operations

Motivation:

- Low cloud ceiling (measured as cloud base height relative to ground) threatens safe UAS operations and causing missions delays and cancellation.
- As UAS operations are not limited to take-off and landing at airports where cloud ceiling observations are available, a greater spatial extent of observations is required.
- There is a lack of cloud ceiling data due to the high cost of existing instruments and the required maintenance.

Objective:

- Demonstrate an advanced prototype system with capabilities in weather data fusion, processing and machine learning to automatically derive refined cloud ceiling, specifically tailored for UAS operations.
- Combine cloud ceiling observations from ground-based instruments and satellite to deliver refined cloud ceiling data with a greater spatial extent to UAS operators for efficient mission planning.





Future Research

Improved Model Representation of the Microphysical Processes for Droplet Formation during Fog Events over Non-Mountainous, Continental Location

Motivation

- Limitations in Current Fog Forecasting: Current fog models are insufficient, often failing to account for rapid changes in atmospheric conditions and complex interactions in fog formation processes.
- Importance of Microphysical Processes: Understanding fog's microphysical processes, including aerosol activation and interactions with atmospheric factors, is essential for accurate forecasting, which remains a challenge with current models.

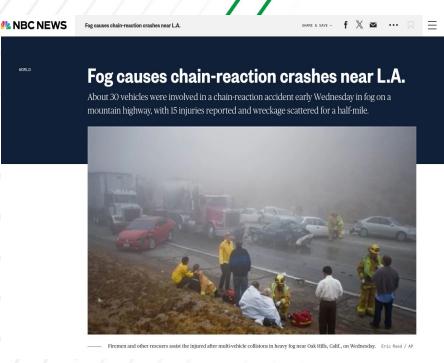
Objectives

- Developing an Advanced Aerosol Activation Scheme: Introduce a new parameterization that incorporates local atmospheric conditions such as cooling rates and water vapor flux to better model fog microphysics, particularly aerosol activation, in fog formation.
- Enhancing Predictive Accuracy for Fog: Improve fog forecasting by accurately representing droplet activation and growth conditions, focusing on droplet concentration and visibility reduction under fog conditions.
- Case Study in Eastern North Dakota: Use unique data from fog events in a non-mountainous, continental area with a specific focus on the December 2021 fog event in Fargo, ND, to validate the model.



(1973) The crash of Delta Air Lines flight 723 - Analysis





Thank you! Any questions?



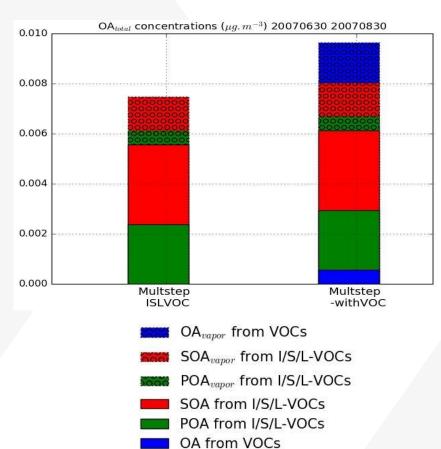


Secondary Organic Aerosol Formation from Wildfires in the Euro-Mediterranean Region

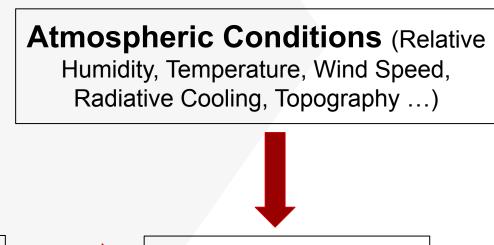
majdi et al. (2019) https://doi.org/10.5194/acp-19-5543-2019

Results - Key SOA Precursors

- VOC vs. I/S/L-VOC Contributions to SOA:
- L/I/SVOCs contribute about 10 times more to particle organic aerosol concentrations than VOCs.
- ~70% of OAtot (gas+particle) from VOCs are in the gas phase: a better understanding of gas-particle partitioning.







Atmospheric Aerosols



Fog Forecasting

Accurately forecasting fog requires a good understanding of the interplay between aerosols and atmospheric conditions.



Explainable Artificial Intelligence to Improve the Understanding of Radiation Fog Formation over Non-Mountainous, Continental Locations

- Use XAI techniques such as SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations) to analyze critical features driving the short forecast of fog in order to demonstrate how ML can be used as a tool to explain how radiation fog forms.
- Focuses on fog events that occur over Eastern North Dakota and aims at utilizing the University of North Dakota (UND) database of meteorological observations collected during previous fog field campaigns at the Fargo Airport.



Presidual Research related to the integration of Wildfires

