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## Comparative Analysis of GEOS-Chem, SAPRC99, and MOZART Mechanisms in WRF-Chem for Simulating Pollutant Dispersion from Forest Fires

# Analisis Perbandingan Mekanisme GEOS-Chem, SAPRC99, dan MOZART dalam WRF-Chem untuk Simulasi Dispersi Polutan dari Kejadian Kebakaran Hutan

#### ADE AYU OKTAVIANA<sup>1,2</sup>, ALVIN PRATAMA<sup>1\*</sup>, PRAWIRA YUDHA KOMBARA<sup>3</sup>, LESI MARETA<sup>1</sup>

<sup>1</sup>Department of Atmospheric and Planetary Science, Sumatera Institute of Technology, South Lampung, Lampung Province, 35365, Indonesia <sup>2</sup>Department of Environmental Engineering, Sepuluh Nopember Institute of Technology, Jalan Arief Rahman Hakim,

Surabaya, East Java, 60111, Indonesia

3Research Centre for Climate and Atmosphere, National Research and Innovation Agency of Indonesia, Jalan Cisitu Sangkuriang, Bandung,
West Java, 40135, Indonesia

\*alvin.pratama@sap.itera.ac.id

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#### ABSTRAK

Mekanisme kimia polutan dan parameter meteorologi merupakan bagian penting dalam menentukan sebaran polutan. Dengan mengetahui parameter tersebut, maka dapat diestimasi arah persebaran polutan dan besaran dampak yang ditimbulkan di lingkungan. Hal ini dapat diestimasi menggunakan pemodelan numerik seperti WRF-Chem. Model ini merupakan kombinasi dari prediksi cuaca dan proses kimia atmosfer. Penggunaan mekanisme kimia yang berbeda dalam menjalankan model WRF-Chem akan berdampak pada keluaran model. Oleh karena itu, perlu dilakukan analisis lebih lanjut tentang penggunaan mekanisme kimia yang berbeda dalam model WRF-Chem. Penelitian ini memanfaatkan fire inventory untuk mekanisme kimia polutan yang dikeluarkan oleh NCAR, yaitu GEOS-Chem, SAPRC99, dan MOZART. Studi kasus yang digunakan dalam penelitian ini adalah saat kejadian kebakaran hutan di Provinsi Riau pada bulan September 2019, dengan fokus analisis pada karbon monoksida dan particulate matter (PM10). Metode yang digunakan dalam penelitian ini adalah melakukan analisis menggunakan parameter statistik, seperti korelasi, bias, dan RMSE untuk mengetahui tingkat akurasi model. Dari hasil simulasi, skema MOZART merupakan skema terbaik dengan korelasi sedang hingga kuat. Namun, seluruh skema dalam simulasi ini cenderung underestimate dan memiliki nilai error yang tinggi terhadap observasi. Hal ini menunjukkan bahwa skema kimia dari fire inventory masih mempunyai tantangan besar dalam memprediksi nilai konsentrasi polutan. Untuk arah sebaran, MOZART, dan SAPRC99 menunjukkan pola spasial yang mirip dengan citra satelit.

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#### **ABSTRACT**

The chemical mechanisms of pollutants and meteorological parameters play a crucial role in determining the distribution of pollutants. Understanding these factors enables the estimation of pollutant dispersion direction and its potential environmental impact. It can be estimated using numerical models, such as WRF-Chem, a coupled system integrating weather prediction and atmospheric chemical processes. The use of different chemical mechanisms within WRF-Chem influences the model output. This study aimed to evaluate the spatial and statistical performance of the WRF-Chem model using three different chemical mechanisms—MOZART, GEOS-Chem, and SAPRC99—from the FINN emission inventory, during a forest fire episode in Riau Province in September 2019. The analysis focused on carbon monoxide (CO) and particulate matter (PM<sub>10</sub>), using statistical metrics such as correlation, bias, and RMSE, along with spatial validation against Sentinel-5P satellite imagery. Simulation results showed that the MOZART mechanism provided the best overall performance, exhibiting moderate to strong correlation with observational data. However, all chemical schemes tended to underestimate pollutant concentrations and showed relatively high error margins. Spatially, MOZART and SAPRC99 demonstrated dispersion patterns closely aligned with satellite observations. These findings highlight the potential and limitations of current chemical mechanisms in accurately simulating pollutant dispersion during forest fire events.

#### 1. INTRODUCTION

#### 1.1 Background

Natural or artificial phenomena can cause forest and land fires and contribute to global warming. On the other hand, meteorological factors significantly impact the intensity and duration of forest fires. It is projected that the increased risk of forest fires is due to climate change. It is reported that more than 420 million hectares of forest burned globally from 2002 to 2016 (Giglio et al., 2018; Robinne & Secretariat, 2021). In 2015, the Indonesian health ministry said that in 18 years, the worst disaster in Indonesia was the forest fires (Yusuf et al., 2019). In 2019, forest and land fires in Riau Province ranked first as the largest land area burned in the Sumatra island region, with the total burned area of about 27,683.47 ha (Kadir et al., 2022). The burned biomass from forest fire contains concentrated particulate matter (PM) (organic matter, graphitic carbon, toxic metals, and acidic species) that are hazardous to health, such as to the lungs, heart, and circulatory systems (Hanafi et al., 2018; Heriyanto et al., 2015; Sicard et al., 2021). In addition, forest and land fires can also emit carbon, which is the dominant element in forest fires (Kadir et al., 2022).

Riau Province is one of Indonesia's most severely affected regions by forest and land fires due to its vast peatlands, agricultural practices, and meteorological vulnerability during dry seasons. In 2019, Riau experienced the largest burned area on Sumatra Island, with over 27,000 hectares destroyed. The resulting air pollution caused an increase in respiratory illness cases and led to the temporary closure of schools and airports (Crippa et al., 2016). Moreover, Riau often contributes significantly to transboundary haze pollution affecting neighbouring countries like Malaysia and Singapore, prompting international diplomatic responses. Therefore, modelling pollutant dispersion accurately in this region is critical for informing local health advisories and regional environmental policy interventions.

The long dry season can generally cause forest and land fires in Indonesia. The phenomena such as El Niño and positive IOD (The Indian Ocean Dipole) have strongly influenced the high probability of hotspots and forest fires (Nurdiati et al., 2022). In addition, it also hurts the environment and the economy in Indonesia and neighbouring countries such as Singapore, Malaysia, the Philippines, Thailand, Vietnam, and Brunei, which can be referred to as a transnational disaster (Hanafi et al., 2018). The movement of complex atmospheric interactions makes the distribution of pollutants difficult to predict. Unpredictable and difficult-tocontrol forest and land fires will have a profound impact on endangering the community. However, simulations can estimate this, such as using WRF-Chem (weather research and forecasting model with chemistry) (Pratama & Sofyan, 2020). It is a weather research and prediction model combined with chemical processes that can estimate the movement of pollutants. The composition of atmospheric chemical mechanisms is obtained from satellite data collection. The differences in satellite data sources for emissions and their interpretation can cause differences in WRF-Chem simulation output.

WRF-Chem is a weather research and forecasting model combined with chemical parameters. This model simulates the emission, transportation, mixing, and chemical transformation of gases and aerosols with meteorological parameters (Peckham et al., 2017). The chemical mechanisms of pollutants and meteorological parameters such as temperature, boundary layer, wind speed and direction, etc., play an important part in determining the distribution of pollutants (Bossioli et al., 2016; Xu et al., 2018).

Despite the extensive use of WRF-Chem in modelling pollutant dispersion from biomass burning, limited studies have systematically compared the impacts of different chemical mechanisms (model for ozone and related chemical tracers (MOZART), Goddard Earth Observing System Chemistry (GEOS-Chem), and Statewide Air Pollution Research Center (SAPRC)) under the same spatiotemporal forest fire scenario in Southeast Asia. Prior research focuses on one mechanism or broad regional simulations without highlighting localised implications. This study addresses this gap by comparing the three chemical schemes within the same emission inventory framework (FINN v1.5) adjusted to reflect the 2019 forest fires in Riau. The specific contribution lies in assessing how the choice of chemical mechanism affects modelled pollutant transport and distribution, particularly carbon and aerosols, which are key determinants of air quality forecasts and public health risk assessments.

MOZART is designed for global and regional scale modelling with a simplified representation of tropospheric chemistry, making it suitable for long-range transport simulations (Emmons et al., 2020). On the other hand, GEOS-Chem is a highly detailed chemical transport model emphasising trace gas interactions and strongly competes with satellite data products (Bey et al., 2001). SAPRC99 is a detailed mechanism for simulating photochemical smog and urban air quality, incorporating numerous volatile organic compounds (Carter, 2000). These structural differences influence how each mechanism represents the transformation and fate of pollutants in the atmosphere.

This research will examine the carbon and aerosol distribution during forest and land fires in Riau Province in 2019. The WRF-Chem is a chemical model widely used to simulate regional air quality. This study will compare WRF-Chem results using the emission inventory with different chemical mechanisms (MOZART, GEOS-Chem, and SAPRC99) from the Fire Inventory from NCAR (FINN). FINN provides high-resolution, global emission estimates from open biomass burning (Peckham et al., 2017). The combustion of biomass fuels produces biomass burning emissions through either natural (e.g., wildfires) or planned processes (e.g., residential wood combustion in fireplaces and woodstoves) (Xu et al., 2018). Different chemical mechanisms from FINN will affect the model output results. This simulation uses the emissions inventory (MOZART, GEOS-Chem, and SAPRC99), version 1.5, updated in 2021. We adjusted the emissions inventory to reflect the 2019 forest fire period in Riau Province. Several studies about the dispersion of smoke from forest fires can be carried out using the WRF-Chem model (Heriyanto et al., 2015; Kombara et al., 2023; Nuryanto, 2015), stating that 'FINN' fire inventory data from the US National Centre for Atmospheric Research (NCAR) enabled the WRF-

Chem model to effectively simulate the dispersion of smoke haze caused by forest fires.

#### 1.2 Research Objectives

The objective of this study is to evaluate and compare the spatial patterns and statistical performance of WRF-Chem simulations using three chemical mechanisms (MOZART, GEOS-Chem, and SAPRC99) based on the FINN emission inventory, to enhance the accuracy of pollutant dispersion modelling during the 2019 forest fire event in Riau Province.

#### 2. METHODOLOGY

#### 2.1 Data Sources

The WRF-Chem simulation was conducted from September 21 to 25, 2019. It is based on the peak of forest fire phenomena in Riau Province. This study utilised three primary data sources.

#### a. Global Forecast Systems (GFS)

This research uses GFS data for initial conditions and as input to the WRF-Chem model. This data has a spatial resolution of 0.25 degrees and a temporal resolution of 3 hours. This data is available on the UCAR website (NCAR/UCAR, 2025; Wiedinmyer et al., 2023). GFS is suitable for this study due to its global coverage, timely availability, and compatibility with WRF-based atmospheric models. Additionally, GFS has been widely used in previous WRF-Chem simulations in Southeast Asia for biomass burning and air quality assessments, further supporting its applicability to this domain (Duc et al., 2021; Zhang et al., 2019).

#### b. Emission Inventory

In simulating air pollution in WRF-Chem, three emission input inventories are required: anthropogenic, biogenic, and biomass burning emissions. In this study, anthropogenic combustion emissions were incorporated using the EDGAR-HTAP dataset. Biogenic emissions were modelled using the Model of Emissions of Gases and Aerosols from Nature (MEGAN), which estimates natural emissions from terrestrial ecosystems (Emmons et al., 2020). Biomass burning emissions were derived from the Fire Inventory from NCAR (FINN v1.5), using three chemical mechanisms (MOZART, GEOS-Chem, and SAPRC99) for comparative analysis. These data serve as the initial condition for the emission loading in the WRF-Chem simulation. The emission inventory is accessible on the UCAR website (UCAR, 2025). The selection of MOZART, GEOS-Chem, and SAPRC99 is justified by their distinct characteristics and wide usage in atmospheric chemistry modelling. MOZART (model for ozone and related chemical tracers) is well-suited to represent large-scale tropospheric chemistry. It has been integrated with WRF-Chem for regional air quality studies involving longrange pollutant transport (Danabasoglu et al., 2020). GEOS-Chem is a global 3D chemical transport model known for its detailed treatment of trace gases and satellite data assimilation. It makes it effective for evaluating biomass burning emissions and their atmospheric transformation (Bey et al., 2001). SAPRC99, developed by Carter (2000), is optimised for simulating complex photochemical reactions in polluted and urban environments with extensive representation of volatile organic compounds (VOC) species. Including these three schemes allows for a comprehensive assessment of how chemical mechanism selection affects simulation outcomes, particularly in the context of intense biomass burning events in Southeast Asia.

#### c. Observational Data

Observation data from air quality monitoring stations (AQMS) were used to validate the WRF-Chem simulation outputs. This data was obtained from the Ministry of Environment and Forestry of Indonesia. The monitoring instruments are in Padang, Pekanbaru, and Batam, serving as representative stations for the western Sumatra region and surrounding areas affected by transboundary haze. Specifically, carbon monoxide (CO) and particulate matter (PM $_{\rm 10}$ ) concentrations were observed in Padang, Pekanbaru, and Pekanbaru. These parameters were selected due to their strong association with biomass burning emissions and health-related air quality impacts.

#### 2.2 Model Configuration

The configuration of the WRF model was initiated with the domain setup. The modelling framework included a parent domain (D1) with a spatial resolution of 9 km and a nested area (D2) with a resolution of 3 km, as shown in Figure 1. WRF-Chem version 3.6 simulated carbon monoxide (CO) concentrations and particulate matter ( $PM_{10}$ ). Meteorological and chemical parameterisation schemes were applied, as detailed in Table 1. These schemes have been validated in previous studies and are considered appropriate for the study region, given its atmospheric dynamics and regional characteristics (Kombara et al., 2023; Nuryanto, 2015).



Figure 1. Domain configuration for WRF-Chem

Table 1. Configuration options in WRF-Chem

Scheme	1st domain	2nd domain	
Spatial resolution	9 km x 9 km	3 km x 3 km	
Number of vertical	34 levels	34 levels	
levels			
Microphysics	Lin et. al	Lin et. al	
Cumulus	Grell 3D (5)	Grell 3D (5)	
Boundary layer	YSU (1)	YSU (1)	
Longwave radiation	RRTM (1)	RRTM (1)	
Shortwave radiation	Dudhia (1)	Dudhia (1)	
Diamasa humnina	Mozart, GEOS-	Mozart, GEOS-	
Biomass burning emissions	Chem	Chem	
EIIIISSIOIIS	and SAPRC99	and SAPRC99	
Biogenic emission	Megan	Megan	

#### 2.3 Model Verification

The outputs of WRF-Chem must be evaluated before interpretation and application (Kombara et al., 2023; Pratama & Sofyan, 2020). This study verified the model using ground-based observation data from air quality monitoring stations in Padang, Pekanbaru, and Batam. The primary objective of this verification process was to assess the model's performance in simulating pollutant concentrations and to identify the most accurate chemical mechanism. Additionally, spatial validation was performed by comparing the simulated pollutant dispersion patterns with Sentinel-5P satellite imagery. The statistical parameters employed for model validation include correlation coefficient, bias, and root mean square error (RMSE).

#### a. Pearson Correlation Coefficient (R)

The correlation coefficient measures the level of linearity between WRF-Chem results and observational data. Its values range between -1 and +1. A negative sign means the relationship between WRF-Chem results and observational data is inversely proportional.

$$r = \frac{\sum_{i=1}^{N} (F_i - \bar{F}_i)(O_i - O_i)}{\sqrt{\sum_{i=1}^{N} (F_i - \bar{F}_i)^2} \sqrt{\sum_{i=1}^{N} (O_i - \overline{O_i})^2}}$$
 (1)

Where:

Fi: the pollutant value of WRF-Chem

Oi: the observation data

These are the categories of correlation coefficients (see Table 2).

Table 2. The category of correlation coefficients

Coefficient Interval	Correlation
0.00 - 0.19	No Correlation
0.20 - 0.39	Week
0.40 - 0.69	Medium
0.70 - 0.89	Strong
0.90 - 1.00	Very Strong

#### b. Root Mean Square Error (RMSE)

RMSE determines the error generated between the WRF-Chem output and observation data. The following formula calculates the error value.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(F_i - O_i)^2}....(2)$$

#### c. Relative Bias

Bias is a statistical indicator to measure the tendency of WRF-Chem results to match observational data. Positive bias values indicate overestimated models, and negative values indicate underestimated models based on observational data.

$$Bias = \frac{\sum_{i=1}^{N} (F_i - O_i)}{\sum_{i=1}^{N} (O_i)}.$$
 (3)

#### d. Sentinel-5p Satellite Imagery

Satellite imagery (Sentinel-5p) is used to validate the output of WRF-Chem spatial. Model validation is done qualitatively, using Sentinel-5p satellite data to see the dispersion pattern of carbon monoxide (CO) and aerosol emissions. This data can be obtained from the Copernicus Open Access Hub (European Space Agency, 2022).

#### 3. RESULT AND DISCUSSION

## 3.1 Statistical Performance of WRF-Chem Over Observation Data

Between September 21–25, 2019, an increase in PM<sub>10</sub> concentrations was observed at the Global Atmosphere Watch (GAW) stations in Kototabang and East Singapore. This rise corresponded to a forest fire in several areas surrounding Riau Province. At the GAW station, the air quality index reached a value of 180, while in East Singapore, it reached 85, both categorised as unhealthy conditions (see Figure 2). The worst air quality conditions were recorded on 22 September 2019. In response to this event, a WRF-Chem simulation was conducted to evaluate the model's performance in capturing severe air pollution events in Riau Province and its surrounding regions.

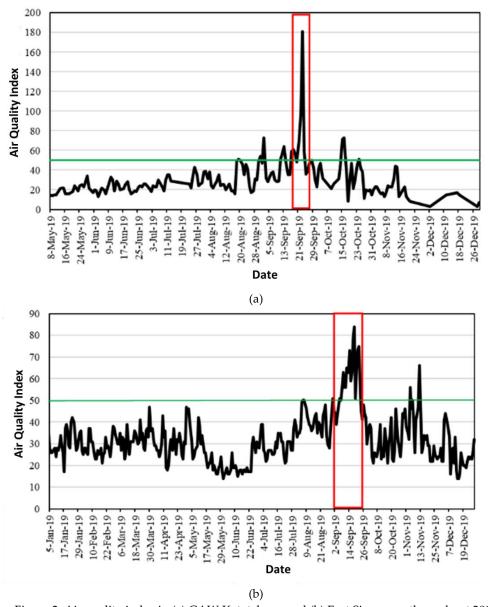


Figure 2. Air quality index in (a) GAW Kotatabang and (b) East Singapore throughout 2019

The WRF-Chem simulation aimed to predict the concentration levels of  $PM_{10}$  and CO resulting from the forest fires. Before further analysis, model outputs were verified against observational data using statistical metrics, as suggested by previous studies (Kombara et al., 2023; Pratama & Sofyan, 2020). The model performance was assessed using the correlation coefficient (R), root mean square error (RMSE), and bias (see Table 3). This verification aimed to evaluate the model accuracy and the impact of different emission mechanisms (SAPRC99, MOZART, and GEOS-Chem) on pollutant prediction. According to Table 3, the correlation

coefficients between the WRF-Chem outputs and observation data ranged from 0.39 to 0.65 for  $PM_{10}$  and 0.37 to 0.80 for CO, across stations in Batam, Padang, and Pekanbaru. These values indicate a moderate to strong relationship. Overall, WRF-Chem demonstrated a reasonable capability in capturing the temporal variation patterns of  $PM_{10}$  and CO concentrations. Among the emission mechanisms, the MOZART scheme showed better performance in simulating  $PM_{10}$ , while either the GEOS-Chem or MOZART schemes performed better for CO simulations.

Table 3. Statistical verification of WRF-Chem output against observation data using three chemical mechanisms

Emission -	WRF-Chem/Mozart			WRF-Chem/GEOS-Chem			WRF-Chem/SAPRC			
	R	BIAS	RMSE	R	BIAS	RMSE	R	BIAS	RMSE	
Pekanbaru Region										
CO	0.40	-625.85	626.61	0.46	-621.55	622.57	0.37	-625.09	626.03	
PM <sub>10</sub>	0.65	-447.32	568.16	0.41	-447.37	568.73	0.60	-447.19	568.1	
	Batam Region									
СО	0.74	-651.71	652.2	0.74	-648.93	649.5	0.74	-651.11	662.61	
PM <sub>10</sub>	0.58	-451.3	572.5	-0.56	-451.3	572.9	0.57	-451.3	572.5	
Padang Region										
СО	0.81	-657.09	657.31	0.80	-657.13	657.39	0.80	-638.82	639.18	
PM <sub>10</sub>	0.42	-450.06	571.47	0.01	-450.48	572.02	0.39	-450.02	571.46	

Table 4. Chemical composition of the general category of forest and land fire areas for the GEOS-Chem mechanism

Chemical type	Grassland	Tropical forest	Forest temperature	Agricultural land	Boreal forest	Shrubs
NO	0.38	0.74	0.26	0.09	0.7	0.74
C <sub>2</sub> H <sub>6</sub>	0.82	0.82	0.29	0.43	1.63	1.01
СзНв	0.18	0.1	0.1	0.08	0.13	0.37
CH <sub>2</sub> O	2.12	2.08	1.33	1.84	1.45	2.23
MEK	1.4	1.05	0.41	0.78	1.63	1.25

Source: Peckham et al. (2017)

However, mechanisms tended all three to underestimate pollutant concentrations, as indicated by the negative bias values. This underprediction is consistent with previous findings, which reported that WRF-Chem tends to underestimate surface concentrations of major air pollutants across East Asia (Zhang et al., 2016). Several factors may contribute to this discrepancy, including uncertainties in land cover classification due to satellite limitations. For instance, remote sensing often fails to detect fire events smaller than 100 hectares, despite their potential to significantly impact atmospheric emissions. Moreover, cloud and haze interference can reduce satellite visibility, leading to an underestimation of fire extent (Lopez-Noreña et al., 2019). Additional sources of uncertainty stem from the inherent differences in chemical mechanism structure. Variations in how species and reactions are defined, such as the carbon bond arrangements used in SAPRC99 versus the broader species representation in MOZART, can affect the simulation results (Wang & Zhang, 2012). The MODIS land cover type (LCT) and vegetation continuous fields (VCF) datasets were used to determine vegetation type and density for each fire pixel, which were then categorised into general land cover classes (e.g., grassland, shrubland, tropical forest). These classes were mapped to emission factors relevant to each chemical mechanism.

Table 5. Chemical composition of the general category of forest and land fire areas for the Mozart mechanism

Chemical Type	Grassland	Tropical Forest	Forest Temperature	Agricultural Land	Boreal Forest	Shrubs
СН₃ОН	1.92	2.6	1.51	2.11	2.5	2.49
CH <sub>3</sub> COCH <sub>3</sub>	0.22	0.39	0.2	0.83	0.2	0.71
СН₃СНО	1.03	1.27	0.38	3.05	0.67	0.96
CH <sub>2</sub> O	2.12	2.08	1.33	1.84	1.46	2.23
СзН8	0.18	0.1	0.1	0.08	0.13	0.37
C <sub>3</sub> H <sub>6</sub>	0.43	0.56	0.26	0.38	0.76	0.77
C <sub>2</sub> H <sub>4</sub>	2.27	1.38	1.11	1.08	1.62	2.3
MVK	0	0.2	0	0	0	0
MACR	0	0.08	0	0	0	0
ISOP	0.05	0.07	0.03	0.6	0.14	0.03
HYAC	1.01	0.55	8.03	0	0.77	0
NO	0.38	0.74	0.26	0.09	0.7	0.74
CH <sub>2</sub> COOH	2.08	1.87	0.53	2.19	1.8	1.24
СН₃СОСНО	0.81	0.37	0.17	0.19	0.28	0.86
glyald	0.5	0.79	0.28	1.68	0.25	1.39
MEK	1.31	0.85	0.41	0.79	1.64	1.16
Cresol	0.44	0.17	0.07	0.6	0.85	0

Chemical Type	Grassland	Tropical Forest	Forest Temperature	Agricultural Land	Boreal Forest	Shrubs
Toluene	1.16	2.06	0.61	1.07	1.3	1.32
C10H16	0.01	0.04	0.03	0	0.04	0.01
bigena	0.45	0.52	0.22	0.37	0.35	0.63
bigalk	0.2	0.13	0.11	0.09	0.16	0.42

Source: Peckham et al. (2017)

Table 6. Chemical composition of the general category of forest and land fire areas for the SAPRC99 mechanism

Chemical Type	Grassland	Tropical Forest	Forest Temperature	Agricultural Land	Boreal Forest	Shrubs
MEK	1.87	1.2	8.33	0.54	2.25	0.92
MVK	0.22	0.2	0	0.14	0	0

Source: Peckham et al. (2017)

MOZART produced the highest correlation with observation data among the three mechanisms, likely due to its more comprehensive chemical species inventory. For instance, including compounds such as bigalk, bigene, and toluene enhances the model's ability to simulate hydrocarbon reactions and carbon bond formation, improving its predictive capability (Emmons et al., 2020).

## 3.2 The Comparison of PM<sub>10</sub> Parameters with Satellite Imagery

In addition to statistical analysis, this study also conducted a spatial comparison between the simulated dispersion of  $PM_{10}$  and satellite imagery. Figure 3 presents the  $PM_{10}$  distribution on 22 September 2019, as simulated by all WRF-Chem emission schemes, alongside imagery from the Sentinel-5P satellite.

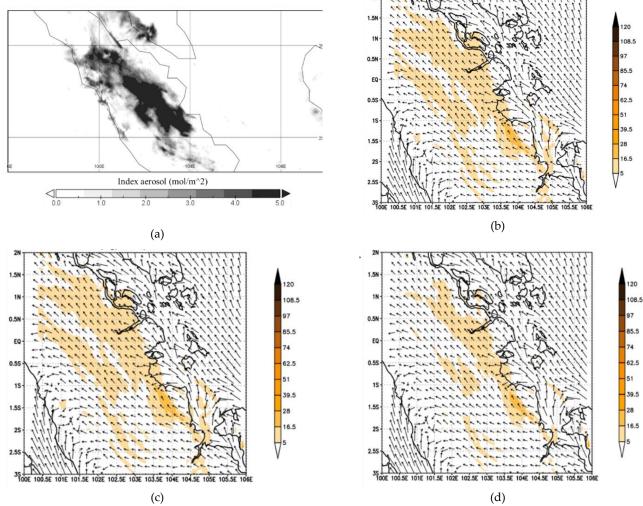


Figure 3. Comparison map of Sentinel-5p satellite PM<sub>10</sub> distribution with WRF-Chem model outputs of different chemical mechanisms on September 22, 2019 (a. Sentinel-5p satellite image, b. SAPRC99, c. MOZART, and d. GEOS-Chem)

The satellite image showed that the  $PM_{10}$  dispersion covered several regions, including Jambi, Padang, Pekanbaru, and the western part of Sumatra Island. The simulated dispersion patterns from the WRF-Chem model, particularly those generated using the SAPRC99 and MOZART schemes, closely matched the spatial trends observed in the Sentinel-5P data. In contrast, the GEOS-Chem scheme produced a more limited dispersion area and lower concentration values than the other two mechanisms. The SAPRC99 and MOZART simulations exhibited higher  $PM_{10}$  concentrations and broader affected areas, aligning more closely with the satellite-based observations. These results are consistent with previous findings that indicate WRF-Chem's capability to capture

spatial distributions and seasonal variations in pollutant abundance (Zhang et al., 2016).

Figure 3 also illustrates that the direction of  $PM_{10}$  dispersion generally followed the dominant wind flow from the southeast toward the northwest and north. This pattern indicated the potential for pollutant transport to neighbouring countries. During August–September, Indonesia typically experiences the Australian monsoon, characterised by dominant southeasterly winds. The simulations also showed a gradual decline in  $PM_{10}$  concentration over time (see Figure 4), likely resulting from the atmospheric dispersion of pollutants from the original fire locations to downwind areas.

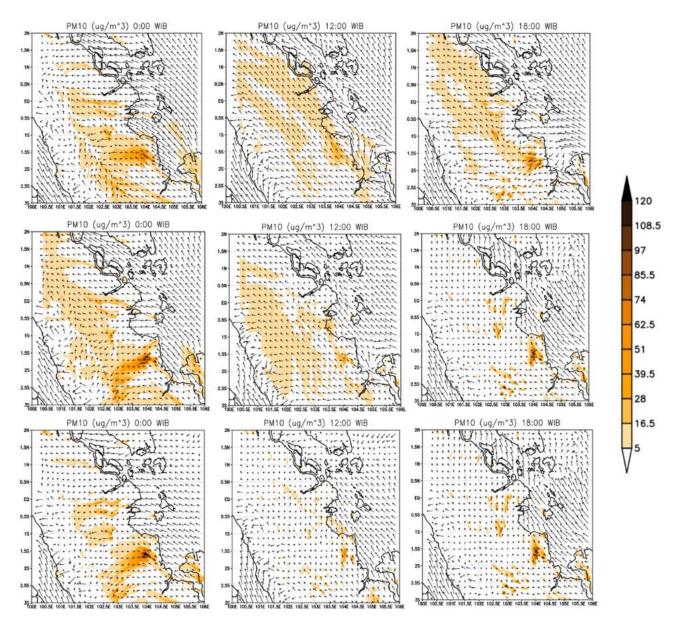


Figure 4. The dispersion pattern of PM10 during forest and land fires on September 22, 2019 to September 24, 2019

Wind speed played a significant role in determining  $PM_{10}$  concentrations. Higher wind speeds contributed to greater dispersion and lower pollutant accumulation, while lower wind speeds were associated with increased concentrations. A comparable situation occurred during the 2015 forest fire event, which led to transboundary haze affecting Malaysia and Singapore, deteriorating air quality in

both countries (Hanafi et al., 2018). A similar transboundary pollution event was also recorded in September 2019, as forest and land fires occurred in various parts of Sumatra Island.

#### 4. CONCLUSION

This study demonstrated that the WRF-Chem model, when applied to simulate pollutant dispersion during the 2019

forest fire episode in Riau Province, could capture the general spatial and temporal patterns of carbon monoxide (CO) and particulate matter ( $PM_{10}$ ) concentrations. Among the three chemical mechanisms tested (MOZART, GEOS-Chem, and SAPRC99), the MOZART scheme exhibited the best statistical performance, with moderate to strong correlation values and spatial patterns most consistent with Sentinel-5P satellite imagery. However, all schemes tended to underestimate pollutant concentrations and exhibited relatively high error margins compared to observational data, indicating persistent challenges in accurately modelling emissions from biomass burning. These findings highlight the need for improved emission inventories, enhanced chemical speciation, and better fire detection to support more accurate forecasting of pollutant dispersion and its potential transboundary impacts.

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