Model Evaluation

Yang Zhang, Khanh Do, and Daniel Schuch Northeastern University

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Outline

- Importance
- Model Evaluation
 - Datasets for Model Evaluation
 - Types of Model Evaluation
 - Current Status of Model Evaluation
- Preliminary Evaluation of Initial WRF-Chem Application over Africa
 - Specific Datasets Used for Model Evaluation
 - Evaluation Metrics and Protocols
 - Meteorological Evaluation (WRF only, Jan-April 2023)
 - Chemical Evaluation (WRF-Chem, Jan, 2023)
- Summary

Major sources: Zhang et al., 2006a,b, 2019, Zhang (2024), Dennis et al., 2010; Emery and Tai, 2001; Emery et al., 2017

Why is Model Evaluation Important?

- Evaluate model performance skill in terms of accuracy and reliability
- Assess if the ambient air quality meets the air quality standards
- Identify model biases and missing processes for potential model improvement
- Perform accurate source apportionment to support decision-making
- Evaluate model sensitivity to model parameters and processes
- Evaluate uncertainties in model inputs, representations, and configurations
- Establish creditable baseline for projection of future air quality
- Deepen process-level understanding of sciences

Datasets for Model Evaluation (Zhang, 2024)

- Emission Measurements
- Deposition Measurements
- Ground- and Upper Air Meteorological and Chemical Concentration Observations
- Satellite-Based Observations
- Reanalysis Datasets
- Relevant data generated using data fusion and ML

Merits and Limitations of Datasets

- Ground truth from ground monitoring stations
 - Most accurate
 - Sparse and limited access
- Low-cost air quality sensors
 - PurpleAir, Clarity, MODULAIR Air
 - Low-cost sensor evaluation: <u>https://www.aqmd.gov/aq-spec</u>
 - Require collocation and calibration
- Satellite products (e.g., gaseous column abundance, AOD)
 - Moderately accurate
 - Widely available, but requires extra steps for evaluation
- Re-analysis data
 - Coarse resolution but long-term
 - Acceptable quality
 - Widely available
- ML/data fusion-based data
 - high resolution, high fidelity
 - Limited time period





https://www.aqmd.gov



https://earth.gsfc.nasa.gov/cli mate/data/deep-blue



https://gmao.gsfc.nasa.gov/reanalysis/MERRA-2/datacube/

AirNow International

(https://www.airnow.gov/international/us-embassies-and-consulates/)



AirNow Department of State



AERONET (https://aeronet.gsfc.nasa.gov/)



PM_{2.5} from MERRA-2 (https://gmao.gsfc.nasa.gov/reanalysis/MERRA-2/)

24 Hour Average PM_{2.5}



Types of Model Performance Evaluation

Operational: Assessing the main output variable (e.g., T, WS, O_3 , and $PM_{2.5}$)

Discrete and Categorical (CW-AQF)

Diagnostic:Assessing the precursors/oxidants or components for
the main output variable, model inputs, and major
processes and parameters

Mechanistic: Assessing the responses of the output variables to changes in input variables and model parameters

Probabilistic: Assessing uncertainties in model outputs and observations

Model Evaluation Framework and Objectives (Dennis et al., 2010)



Schematic Representation of the Four Levels of Model Evaluation (Zhang, 2024)

Model Performance Evaluation

Model Analysis Technique



PDF – probability distribution function

Operational Discrete Evaluation (Zhang, 2024)

• Variables evaluated

- All raw outputs: meteorological variables, concentrations of gases and PM_{2.5}
- Processed variables: column abundance, species ratios
- Statistics commonly used
 - Accuracy of peak (matched and unmatched in space)
 - Bias (or fractional bias)
 - Gross error (or fractional gross error)

The mean bias (MB)
$$MB = \frac{1}{N} \sum_{i=1}^{N} (M_i - O_i) = \overline{M} - \overline{O} \quad \overline{M} = (1/N) \sum_{i=1}^{N} M_i \quad \overline{O} = (1/N) \sum_{i=1}^{N} O_i$$

The mean error (MAGE)

$$MAGE = \frac{1}{N} \sum_{i=1}^{N} |M_i - O_i|$$
$$MNB = \frac{1}{N} \sum_{i=1}^{N} [(M_i - O_i) / O_i] = \frac{1}{N} \sum_{i=1}^{N} (M_i / O_i - 1)$$

The mean normalized bias (MNB)

The mean normalized gross error (MNE)

The normalized mean bias (NMB)

The normalized mean gross error (NME)

$$MNE = \frac{1}{N} \sum_{i=1}^{N} [(|M_i - O_i|) / O_i]$$

$$NMB = \left[\sum_{i=1}^{N} (M_i - O_i)\right] / \sum_{i=1}^{N} O_i = \left(\frac{\overline{M}}{\overline{O}} - 1\right)$$

$$NME = \left[\sum_{i=1}^{N} \left| M_i - O_i \right| \right] / \sum_{i=1}^{N} O_i = MAGE / \overline{O}$$

where N is the number of samples (by time and/or location), M_i and O_i are values of model prediction and observation at time and location, respectively.

Operational Evaluation of PM_{2.5} (2006) (IMPROVE, STN, SEARCH) (Yahya et al., 2014)



Taylor Diagrams for PM_{2.5} Performance at Rural Sites (Solazzo et al., 2012)



- Each symbol indicates a different model run
- The position of the symbol on the diagram indicates:
 - the correlation between observations and model (as angle counter-clockwise from the "east" position"
 - the ratio of modeled-to-observed standard deviation (radial distance from the origin)
 - •the centered pattern RMSE (distance from light blue symbols on the horizontal axis

(triangle: domain1; circle: domain2; square: domain3)

Operational Categorical Evaluation for CW-AQF Model (Zhang, 2024)

• Accuracy (A)

Percentage of forecasts that correctly predict an exceedance or a nonexceedance

• Critical Success Index (CSI)

Indicate how well actual exceedances are predicted, accounting for both missed events and false alarms

• Probability Of Detection (POD)

Percentage of actual exceedances that are forecasted, accounting for only missed events

• Bias (B)

Judges if forecasts are underpredicted (< 1) or overpredicted (> 1)

• False Alarm Ratio (FAR)

Measures the percentage of times an exceedance was forecasted when none occurred

$$A = \left(\frac{b+c}{a+b+c+d}\right) \times 100\%$$
$$CSI = \left(\frac{b}{a+b+d}\right) \times 100\%$$
$$POD = \left(\frac{b}{b+d}\right) \times 100\%$$
$$B = \left(\frac{a+b}{b+d}\right)$$
$$FAR = \left(\frac{a}{a+b}\right) \times 100\%$$



Categorical Evaluation Against AIRNow (2009-2014) (Zhang et al., 2016)

O₃ Season

Winter Season



• Overall good performance in terms of A and B, but with relatively low CSI and POD and high FAR

Diagnostic Evaluation (Zhang, 2024)

Analyses of PM chemical composition

Sulfate, nitrate, ammonium, elemental carbon (EC), organic carbon (OC), total nitrate (HNO_3 + PM nitrate), and total ammonium (NH_3 +PM ammonium)

Analyses of precursors of secondary PM

Primary precursors (SO₂, NO, NO₂, HNO₃, NH₃, and VOC) and oxidants and radicals (O₃, OH, NO₃, and H₂O₂)

• Analyses of shorter time average concentrations

Nitrate, ammonium, and OC for diurnal variation; seasonal variation for annual PM

Analyses of light extinction

Scattering and absorption

Analyses of mass fluxes and governing processes

Emissions, transport, transformation, and dry and wet deposition fluxes

Analyses of model inputs and parameters

Boundary conditions, rate coeff., vertical eddy diffusivity

Analyses of PM size distribution

modes (peaks and standard deviations), size intervals, and distribution shapes

Impact of the floor value of K_{zz} on O₃ during the SOS99 episode



Sensitivity simulation, $K_{zz, min} = 0.1 \text{ m}^2 \text{ s}^{-1}$

Diagnostic Evaluation: Process Analysis of O_3 (top) and $PM_{2.5}$ (bottom) (Liu et al., 2010)



■ Horizontal Transport ■ Vertical Transport □ Emissions □ Dry Deposition ■ Aerosol Processes ■ Cloud Processes

Mechanistic (Dynamic) Evaluation (Zhang, 2024)

- Simulation of several episodes: model responses to meteorology
- Simulation of different areas: model responses to various emission mixtures
- Simulation of different time periods: model responses to changes in emissions (e.g., weekday vs. weekend)
- Simulation under different emission scenarios: NO_x- vs. VOC-limited O_3 chemistry
- Simulation of different emission sectors/areas: source appointment

NO_x- vs. VOC limited O₃ Chemistry in China in 2008 (Liu et al., 2010)

Changes in simulated O_3 mixing ratios in Jul, 2008

50% reduction in NO_x emissions



Min= -27.69 at (99,37), Max= 69.64 at (50,3)

Photochemical indicator PH₂O₂/PHNO₃

Jan.



50% reduction in VOCs emissions



Min= -25.54 at (112,42), Max= 5.53 at (98,34)

< 0.2, VOC-limited chemistry \geq 0.2, NO_x-limited chemistry Jul.



Min= 0.0 at (100.65). Max= 292.5 at (37.15)

Source Contributions to O₃ and PM_{2.5} over SE U.S. in July 2002 (Burr and Zhang, 2011)



Probabilistic Evaluation (Zhang, 2024)

- Probability distribution functions (PDFs) for uncertainty and variability of model inputs
- PDFs of model output (PM_{2.5}) compared with probability distribution or confidence intervals of observations
- Possible approach to quantify model uncertainty: ensemble modeling with different model configurations or model inputs
 - Talagrand Diagrams (Rank Histograms)
 - Reliability Diagrams



Current Status of Model Evaluation (Zhang, 2024)

- Operational evaluation for meteorology and air quality has been extensively performed; increasing numbers of diagnostic and process analysis as well as mechanistic evaluation have been performed; probabilistic evaluation has been less frequently performed but is gaining increasing attentions.
- Various testbeds in the U.S. and in other countries (e.g., Canada, Europe); Community testbeds established by multi-organizations (e.g., the Aerosol InterComparison project (AeroCom), the Air Quality Model Evaluation International Initiative (AQMEII))
- Good performance for O₃ and PM_{2.5} mass concentrations. Relatively poor performance for nitrate and organic aerosols. The performance evaluations, however, are mostly operational. Large uncertainties in predictions of PM number conc. and size distribution.
- Relatively good understanding of oxidant chemistry, but limited understanding of PM_{2.5}, particularly organic PM.
- Large uncertainties in model predictions of radiative properties and total column mass conc., due mainly to uncertainties in model treatments of aerosol/cloud microphysics.
- Uncertainties in model inputs (emissions, meteorology, boundary conditions) limit model accuracy, and corroborative modeling techniques have developed and applied to verify model results.

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Data for Model Evaluation in Africa

Africa Air monitoring networks

Network	Region	Total	Variable measured	Temporal resolution	Measurement
		site #			method
SAAQIS	South Africa	175	CO, NO, NO ₂ , SO ₂ , O ₃ , PM _{2.5} , PM ₁₀ , meteorology	Hourly / - Present	Research grade
RBCAA	South Africa	10	PM _{2.5} , PM ₁₀ , SO ₂ , meteorology	Hourly / - Present	Research grade
AirNow	Egypt	1	PM _{2.5}	Hourly/2022 - Present	FEM & low-cost
EEAA	Egypt	120	PM_{10} , NO, NO ₂ , SO ₂ , O ₃ , CO	1998 – Present	Research grade
CAIP	Egypt	37	PM _{2.5} , PM ₁₀	1998 – 2007	Research grade
AfriqAir	Ivory Coast	2	$PM_{2.5}, NO_x, O_3$	Hourly/ - Present	FEM&low-cost
AirQo	Africa	>250+	PM _{2.5} , PM ₁₀	Hourly/ 2023-Present	Low-cost sensor
EMA	Egypt	1	PM ₁₀	Hourly/- Present	Research grade
ISD	Worldwide	20,000	Meteorology	Hourly/1929 - Present	Research grade

Ground AOD

Products	Region	Species	Temporal resolution/time period
AERONET	Worldwide	AOD	Daily and Monthly / 2014 – Present

Satellite AOD

Products	Region	Resolution	Species	Temporal resolution/time period
MODIS	Worldwide	1-km	AOD	Daily / 2014 – Present
CERES-MODIS	Worldwide	1°x1°	SWR	Daily / - Present
CLARA	Worldwide	0.25°x0.25°	Surface radiation budget	Daily / 1979 - Present

Reanalysis MERRA-2

Model	Region	Resolution	Species	Temporal resolution/time period
MERRA 2	Worldwide	0.625°x0.5°	Surface: BC, dust, OC, PM _{2.5} , sulfate, sea salt, SO ₂	Hourly / - Present
			Total Column: BC, dust, OC, O ₃ , sulfate, sea salt, SO ₂	





Data used for the African Testbed Evaluation

- Meteorology NOAA Global Hourly Integrated Surface Database
 - 20,000 stations worldwide
 - Data includes wind speed (WS), wind direction (WD), temperature (T), and dew point temperature (DT)
- Air quality
 - AirNow: ground observations for PM_{2.5}
 - **EMA:** ground observationPM₁₀ data
 - **AERONET**: ground truth for AOD
 - MERRA-2: reanalysis data for PM_{2.5}

Model Evaluation Metrics and Protocols

Meteorological variables	MB	IC	DA	RMSE	N	МВ	References
Т2	≤ ±0.5 ≥ 0.8					Emery et al. (2001)	
WS10	WS10 ≤ ±0.5 ≥		≥ 0.6				Emery et al. (2001)
WD10	≤ ±10						Zhang et al. (2006a, 2019)
Precipitation	cipitation —				< ±30%		Zhang et al. (2006a, 2019)
Air pollutant variables	N	NMB N		1E R		R	
All pottutant variables	Goal	Criteria	Goal	Criteria	Goal	Criteria	
Max 8h O ₃	< ±5%	< ±15%	< 15%	< 25%	> 0.75	> 0.5	
24-hr SO ₄ ²⁻ , NH ₄ ⁺ , PM _{2.5}	< ±10%	< ±30%	< 35%	< 50%	> 0.7	> 0.4	
24-hr NO ₃ -	< ±15%	< ±65%	< 65%	< 115%			Emery et al. (2017), Zhang et al. (2006b)
24-hr OC	< ±15%	< ±50%	< 45%	< 65%			
24-hr EC	< ±20%	< ±40%	< 50%	< 75%			

- Good model performance falls within the range of the benchmark values
- Benchmarks vary by regions
- Newer models tend to produce higher benchmark scores
- Seasonal variations result different metrics

WRF Spatial Evaluation (WRF only)



January

April

WS10 is overpredicts in January but underpredicts in April

January Timeseries - Cairo, Egypt (WRF only)

2013.02.01

2023:02:01



- WRF exhibits cold bias in temperature predictions for Cairo
- The model shows good correlation with RH
- WRF underpredicts wind speed, but has good correlation with wind direction

April Timeseries - Cairo, Egypt (WRF only)





- WRF captures temperature trends and RH in Cairo during April
- Good performance on wind speed

PM_{2.5} Evaluation

- Time conversion: local time to UTC
- Monitoring networks: no conversion is needed for ground observations
- MERRA-2: PM_{2.5} can be calculated using Buchard et. el., 2016

$$PM_{2.5} = PM_{2.5}^{DU} + PM_{2.5}^{SS} + PM_{2.5}^{OC} + PM_{2.5}^{BC} + \left(\frac{132.14}{96.06}\right)PM_{2.54}^{SO_4}$$

- $PM_{2.5}^{DU}$ is dust, $PM_{2.5}^{SS}$ is sea salt, $PM_{2.5}^{OC}$ is organic carbon, $PM_{2.5}^{BC}$ is black carbon, and $PM_{2.54}^{SO_4}$ is sulfate
- AOD evaluation
 - AOD from AERONET
 - Interpolate AOD 550nm from AERONET dataset
 - AOD from WRF-Chem

WRF
$$AOD550 = \sum_{n=1}^{N} EXTCOF55 * Z$$

where $Z = \frac{PH+PHB}{9.8}$

PM_{2.5} Timeseries (January)



Abuja, Nigeria

Cairo, Egypt

AOD Evaluation Against AERONET (January)



 Reasonably good correlation between predicted and observed AOD

MBE

 WRF-Chem shows moderate underprediction in AOD, due likely to the underpredictions in PM

PM_{2.5} Spatial Evaluation Against MERRA-2 (January)



20

0

60

-20



- WRF-Chem shows a good agreement in terms of NMB
- Low MB in the North and East Africa regions

R	MB	NMB%	
0.26	-9.27	-2.33	

PM_{10} Evaluation at the EMAsite in Cairo (January)



- Reasonably good agreement during Jan 1-12
- Largely PM₁₀ overpredictions during Jan 13-15

Summary

- Model evaluation is a critical step to establish model fidelity to support decision-making and create creditable baseline for future projection.
- Increasing number of datasets are available for model evaluation in many regions, including Africa, each having its own merits. Only calibrated data should be used, and QA/QC is critical to ensure the data quality.
- Major types of model evaluation include operational, diagnostic, mechanistic (aka dynamic), and probabilistic, offering complementary information to comprehensively assess the model's skill and associated sensitivity and uncertainties.
- Preliminary evaluation of the initial application of WRF and WRF-Chem in Africa shows some skills but more work remain to identify sources of errors and improve the performance

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