Group 8: Phase 5 Final Report

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I. Abstract

This study addresses the critical challenge of urban wind prediction by systematically evaluating the Weather Research and Forecasting (WRF) model's performance across different urban parameterization schemes. Recognizing the computational constraints of high-resolution modeling identified in our literature review of 50 WRF studies, we focus on optimizing urban physics representations rather than pursuing prohibitively expensive micro-scale simulations. Through controlled experiments in New York City comparing four model configurations (standard physics, SLUCM, BEP, and BEP+BEM) at 1m, 2m, 5m resolutions, we demonstrate that the Building Energy Parameterization (BEP) scheme reduces wind speed prediction errors by 71-73% compared to baseline runs, achieving optimal performance at 2m resolution (MAE: 1.64 m/s). Our results reveal that while Single0Layer Urban Canopy Model (SLUCM) fails to adequately capture high-rise urban dynamics, BEP's multi-layer approach effectively compensates for moderate-resolution limitations through improved representation of height-dependent drag effects. These findings provide meteorologists and urban planners with a practical framework for enhancing wind forecasts in dense urban environments when high-resolution data remains unavailable, while simultaneously identifying key areas for future urban parametrization development, particularly in the integration of anthropogenic heat fluxes. The study establishes that physics-aware model configurations can significantly improve urban wind prediction accuracy without requiring computationally intensive high-resolution simulations.

II. Introduction

Accurate prediction of urban wind patterns represents a significant challenge in modern meteorology, with important implications for renewable energy development, pollution dispersion modeling, and urban climate adaptation. While numerical weather prediction models like WRF have demonstrated strong performance at regional scales, their ability to capture microscale wind dynamics in complex urban environments remains limited. This limitation stems from fundamental challenges in representing the intricate interactions between atmospheric flows and built structures using conventional parameterization approaches.

The growing importance of urban meteorology has driven increased attention to improving wind prediction capabilities, particularly as cities expand vertically and climate change alters local wind patterns. Traditional modeling approaches that treat urban areas as homogeneous rough surfaces fail to account for critical phenomena such as corner stream acceleration, rooftop wind speed maxima, and street canyon effects. These shortcomings become particularly apparent when model outputs are compared to high-resolution observational data from urban meteorological networks.

Our research addresses these challenges through a systematic evaluation of WRF's urban physics capabilities, focusing on practical improvements that balance accuracy with computational feasibility. Rather than pursuing resource-intensive high-resolution simulations, we investigate how enhanced physics representations can improve predictions within operational modeling constraints. This approach recognizes the real-world limitations faced by many forecasting centers and research institutions, particularly those in regions lacking detailed urban morphology datasets.

The study's methodology combines controlled numerical experiments with comprehensive validation against observational data from New York City's diverse urban microclimates. By evaluating multiple urban parameterization schemes across different spatial resolutions, we provide actionable insights for improving wind predictions in cities worldwide. Our findings contribute to ongoing efforts to enhance urban-scale weather modeling while offering practical guidance for researchers and operational forecasters working with limited computational resources.

III. Literature Survey

Of the approximately 50 research papers our group has reviewed, ten were selected as being the most applicable to our goals. These ten papers are summarized in this section, and will be further organized by methodology and data in further sections. Papers not decided to be most relevant for our topic can still be found in the references.

Paper 1 is *The Weather Research and Forecasting Model: Overview, System Efforts, and Future Directions* by J. G. Powers et al. [19]. This paper is a literature review which serves as a general overview of the WRF system, its applications, and its history. It is a good starting point for any potential project using the WRF system and is cited by a large number of papers which perform research with the system.

Paper 2 is *Understanding, modeling and predicting weather and climate extremes: Challenges and opportunities* by J. Sillmann et al. [15]. This paper is a literature review which discusses modeling of extreme events and the difficulty of predicting them. The paper also discusses how to address these challenges in future research, which should prove beneficial over the course of this project.

Paper 3 is *North Atlantic Offshore Wind Characteristics Modeling and Comparison with Field Measurements and Industry Standard* by T. S. Wang and R. Tang [46]. This paper investigates the accuracy of WRF wind simulations for multiple offshore sites in the North Atlantic Ocean. The simulated wind statistics are compared with actual statistics recorded in the field.

Paper 4 is *Evaluations of WRF Sensitivities in Surface Simulations with an Ensemble Prediction System* by L. Pan, Y. Liu, J. C. Knievel, L. Delle Monache, and G. Roux [27]. This paper investigates the accuracy of multiple surface (on-shore) statistics in WRF simulations. Simulated statistics are compared with actual statistics recorded in the field. The paper calculates multiple performance metrics for WRF based on the results.

Paper 5 is *Multi-step wind speed prediction by combining a WRF simulation and an error correction strategy* by W. Xu et al. [48]. This paper proposes a wind speed prediction model using a WRF simulation followed by multiple steps and error correction to ensure more accurate predictions than the WRF simulation alone can achieve.

Paper 6 is *Application of Bias Correction to Improve WRF Ensemble Wind Speed Forecast* by C.-C. Tsai, J.-S. Hong, P.-L. Chang, Y.-R. Chen, Y.-J. Su, and C.-H. Li [8]. This paper investigates an existing WRF Ensemble Prediction System for system bias, and when bias was found the researchers developed a strategy to correct it.

Paper 7 is *Implementation of a Nonlinear Subfilter Turbulence Stress Model for Large-Eddy Simulation in the Advanced Research WRF Model* by J. D. Mirocha, J. K. Lundquist, and B. Kosović [20]. This paper proposes a new implementation for large-eddy simulation in WRF, and compares the implementation's performance to the existing simulations.

Paper 8 is *Blended Probabilistic Tornado Forecasts: Combining Climatological Frequencies with NSSL–WRF Ensemble Forecasts* by B. T. Gallo, A. J. Clark, B. T. Smith, R. L. Thompson, I. Jirak, and S. R. Dembek [6]. This paper uses a probabilistic implementation of a previously binary system for tornado prediction.

Paper 9 is *Deep learning approaches for bias correction in WRF model outputs for enhanced solar and wind energy estimation: A case study in East and West Malaysia* by A. B. Adomako et al. [2]. This study uses multiple deep learning models to reduce bias and improve errors of solar and wind potentials in East and West Malaysia. The deep learning implementations showed improvement over the WRF predictions alone.

Paper 10 is *Enhancing wind power forecast accuracy using the weather research and forecasting numerical model-based features and artificial neuronal networks* by A. Couto and A. Estanqueiro [3]. This paper identifies several numerical weather prediction based features which could improve the quality of wind forecasts, and uses a neural network implementation to help select features which minimize errors.

IV. TAXONOMY

Categories	**Research Papers**
Literature Review	
History and Use Analysis	*The Weather Research and Forecasting Model: Overview, System Efforts, and Future Directions*
Modeling Challenges	*Understanding, modeling and predicting weather and climate extremes: Challenges and opportunities*
Evaluation	
Offshore Simulations	*North Atlantic Offshore Wind Characteristics Modeling and Comparison with Field Measurements and Industry Standard*
Surface Simulations	*Evaluations of WRF Sensitivities in Surface Simulations with an Ensemble Prediction System*
Improvement	
Correction Systems	*Multi-step wind speed prediction by combining a WRF simulation and an error correction strategy*
	Application of Bias Correction to Improve WRF Ensemble Wind Speed Forecast
Ensemble Systems	*Implementation of a Nonlinear Subfilter Turbulence Stress Model for Large-Eddy Simulation in the Advanced Research WRF Model*
	Blended Probabilistic Tornado Forecasts: Combining Climatological Frequencies with NSSL–WRF Ensemble Forecasts

Machine Learning Systems	*Deep learning approaches for bias correction in WRF model outputs for enhanced solar and wind energy estimation: A case study in East and West Malaysia*
	Enhancing wind power forecast accuracy using the weather research and forecasting numerical model-based features and artificial neuronal networks

The top papers in related works discussed above were classified in a custom taxonomy based on their methodology and usage. This taxonomy can be seen below in Fig 1.

Fig. 1. *Categorization of the top ten papers*

V. Chronological Overview

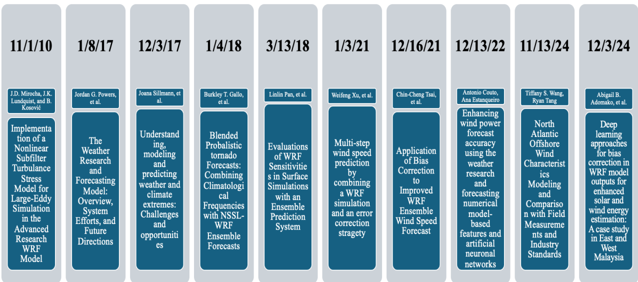


Fig. 2. *Timeline of the top ten papers*

VI. Research Gaps

A. *Optimization of WRF for Wind Prediction in Multi-Scale Severe Weather Systems*

Severe weather like cyclones or thunderstorms operate on multi-scale dynamics, requiring sophisticated computational techniques. WRF could benefit from more focused research on optimizing its performance across different scales to better predict wind behavior in the context of these more extreme systems.

B. *Probabilistic Approach for Wind Prediction in Deterministic Systems*

Many wind prediction systems, including those using the WRF model, are often based on binary predictions. A potential research gap lies in transitioning to probabilistic models, as seen in tornado forecasting, which could improve the accuracy and reliability of wind predictions by accounting for uncertainty and providing more nuanced forecasts.

C. *Integration of High-Resolution Data for Urban Wind Prediction*

Urban environments present unique challenges for wind prediction due to the complex interactions between buildings, infrastructure, and the atmosphere. Research could focus on integrating high-resolution data, such as lidar and remote sensing, with WRF to improve wind predictions in densely populated areas. Enhanced accuracy in urban wind forecasting could benefit applications such as building design, and air quality modeling, providing more actionable insights for urban planners and engineers.

VII. Selected Research Focus

The WRF model has established itself as one of the most versatile and widely used tools for atmospheric research and operational weather prediction. As an open-source, community-developed system, WRF excels at simulating regional-scale weather phenomena, including storm systems, boundary layer processes, and large-scale wind patterns. Its modular architecture allows researchers to select from multiple physics parameterizations tailored to different applications, making it particularly valuable for studying complex atmospheric interactions. However, despite these strengths, the model faces significant limitations when applied to urban environments, where building-induced turbulence and microscale wind patterns challenge its conventional parameterization schemes.

A critical gap exists in WRF's ability to accurately simulate urban wind flows, which exhibit unique characteristics due to the complex interplay between atmospheric dynamics and built structures. While the model performs well for homogeneous terrain, its standard surface layer physics fail to capture the acceleration around buildings, downward momentum transport, and street canyon effects that dominate urban wind systems. These limitations become particularly apparent when model outputs are compared to observational data from urban meteorological stations, revealing systematic biases in both wind speed and direction predictions. The consequences of these inaccuracies extend beyond academic interest, as they directly impact practical applications ranging from pollutant dispersion modeling to wind energy potential assessments in cities.

This project addresses these challenges by exploring enhanced approaches to urban wind modeling within the WRF framework. Rather than developing entirely new modeling systems, we focus on optimizing WRF's existing capabilities through strategic combinations of its urban parameterization schemes and selective integration with external modeling approaches. Our methodology systematically evaluates different configurations, including the Single-Layer Urban Canopy Model (SLUCM), the more sophisticated Building Energy Parameterization (BEP), and hybrid approaches that incorporate elements of computational fluid dynamics. By identifying the most effective combinations for various urban morphologies, we aim to create a practical roadmap for improving urban wind predictions without requiring prohibitive computational resources.

The significance of this work lies in its potential to bridge the gap between high-resolution urban simulations (often computationally infeasible for operational use) and the oversimplified approaches currently employed in many applications. Our research strategy recognizes that different urban environments may require tailored modeling approaches - dense high-rise districts might benefit from different parameterizations than low-rise suburban areas, for instance. This nuanced understanding of urban wind modeling represents an important step forward in making WRF more effective for city-scale applications while maintaining its operational feasibility for weather forecasting and climate studies.

VIII. SIGNIFICANT CHALLENGE

Accurate prediction of urban wind patterns is essential for addressing several key challenges facing modern cities. In urban planning, reliable wind modeling informs the design of buildings and public spaces to optimize natural ventilation, reduce heat island effects, and improve pedestrian comfort. For renewable energy applications, precise wind forecasts are crucial for siting urban wind turbines and assessing their potential energy output in complex built environments. Perhaps most critically, urban wind patterns directly influence air quality by determining how pollutants disperse from roads, industrial areas, and other emission sources throughout the city.

The complex nature of urban landscapes presents unique challenges for wind prediction models. Cities feature intricate combinations of high-rise buildings, street canyons, parks, and waterways - each creating distinct microclimates that alter wind flow patterns. These variations occur over very small spatial scales, with wind speeds and directions changing dramatically within just a few meters vertically or horizontally. Additionally, the dynamic interaction between urban surfaces and the atmosphere creates turbulence patterns that conventional weather models struggle to capture accurately. The combination of these factors makes urban wind behavior significantly more difficult to predict compared to wind patterns over open terrain or natural landscapes.

Current approaches to urban wind prediction face practical limitations that hinder their widespread application. While high-resolution computational models can theoretically capture urban wind patterns in detail, they require extensive computational resources and detailed 3D city data that many municipalities lack. Our research addresses these constraints by developing improved modeling techniques that achieve greater accuracy without relying on impractical data requirements or excessive computing power. By focusing on enhancing the physical representation of urban wind processes within existing modeling frameworks, we aim to provide urban planners, architects, and environmental managers with more reliable wind predictions using readily available urban data and computational resources.

IX. TOP THREE CHALLENGES BASED ON LITERATURE SURVEY

D. *Wind Flow Complexity in Urban Environments*

i. Urban wind patterns are highly turbulent due to the interaction between builidngs, trees, and infrastructure, leading to unpredictable wind directions and speeds.
ii. Computational Fluid Dynamics (CFD) models require high-resolution simulations to capture wake effects and vortex shedding behind buildings.
iii. Reynolds-Averaged Navier-Stokes (RANS) and Large Eddy Simulation (LES) methods face challenges in accurately predicting small-scale turbulence.
iv. Wind tunnel experiments often fail to fully replicate real-world urban conditions, leading to discrepancies in model validation.

E. *Low Wind Speeds & Energy Yield*

v. Urban wind speeds are generally lower compared to open areas, making energy harvesting inefficient.
vi. The logarithmic wind profile shows that wind speeds near the ground in urban settings often fall below the cut-in speeds of conventional wind turbines
vii. Small Vertical Axis Wind Turbines (VAWTs) designed for urban use have lower power coefficients
viii. Aerodynamic losses due to building-induced turbulence further reduce the efficiency of energy conversion.

F. Aerodynamic Efficieny in Dense Urban Environments

i. Optimizing wind turbine performance in urban areas is challenging due to highly turbulent, low-speed, and multidirectional wind flows caused by surrounding buildings and structures.
ii. Wind in cities is highly unpredictable due to vortex shedding, flow separation, and eddies formed by buildings, which reduce turbine efficiency.
iii. Unlike open areas where wind speeds follow a logarithmic profile, urban wind is often below 5 m/s at rooftop levels, which is insufficient for efficient energy harvesting by conventional turbines.
iv. Advanced yaw control mechanisms or omnidirectional designs increase system complexity and costs.

X. FINAL PHASE OVERVIEW

WRF's performance in dense urban areas remains challenging due to unresolved building-atmosphere interactions, prompting this study to assess WRF's urban wind prediction capabilities through a control run with standard physics and an enhanced run incorporating the SLUCM parameterization, both rigorously validated against observational data from New York City's heterogeneous urban landscape, including measurements from Central Park (representing dense urban conditions), LaGuardia Airport (capturing urban-coastal interactions), and JFK International Airport (characterizing coastal urban wind patterns), to systematically evaluate the model's ability to capture complex urban wind patterns across different urban morphologies and identify potential improvements for urban-scale atmospheric modeling.

XI. METHODOLOGY AND IMPLEMENTATION

Our research team conducted an in-depth evaluation of the Weather Research and Forecasting (WRF) model's urban wind prediction capabilities through carefully designed numerical experiments focused on New York City's complex urban environment. Using April 19, 2025 as our case study date, we established a comprehensive validation framework incorporating three strategically located meteorological stations: Central Park (representing dense urban core conditions), JFK International Airport (capturing coastal urban wind patterns), and LaGuardia Airport (characterizing urban-water interface dynamics). The study employed a rigorous two-phase methodology, first running a baseline control simulation with standard WRF physics to establish reference performance metrics, then systematically comparing these results against high-resolution observational data to identify urban-specific modeling challenges. This approach not only quantified WRF's limitations in capturing complex urban wind phenomena like building wake effects and street canyon flows, but also created a standardized framework for evaluating future urban physics enhancements under realistic metropolitan conditions.

A. Model Configuration and Computational Setups

The WRF model implemented on a Windows Subsystem for Linux (WSL) environment running Ubuntu 20.04, providing a stable platform for atmospheric modeling. The system was compiled using GCC 9.4 and OpenMPI 4.1.1? to optimize parallel processing capabilities, following the comprehensive installation guide provided by the National Center for Atmospheric Research (NCAR). This configuration enabled efficient simulation of urban-scale atmospheric processes while maintaining numerical stability, particularly crucial for our experiments. The model's physics packages were carefully selected to balance computational demands with accuracy, incorporating urban physics or parameterization schemes (SLUCM, BEP, and BEP+BEM) to capture building-atmosphere interactions at various scales. Special attention was given to optimizing memory allocation and processor core utilization to handle the intensive computational requirements of our 1m-5m resolution simulations.

B. Data Acquisition and Preprocessing

Our study incorporated multiple data sources to ensure comprehensive model initialization and validation. Static geographical data, including terrain elevation and land use classification was obtained from the WPS GEOG database to properly represent New York City's urban morphology. Meteorological forcing data came from the NOAA Global Forecast System (GFS) at 3-hourly intervals, providing the necessary atmospheric boundary conditions. For validation, we utilized hourly surface observations from three strategically located NCEI weather stations: Central Park (representing dense urban conditions), LaGuardia Airport (capturing urban-costal interactions), and JFK International Airport (characterizing costal urban wind patterns). These datasets were carefully quality-controlled and temporally aligned with model output times to ensure accurate performance evaluation across all experimental configurations.

C. Experimental Design

We evaluated four WRF configurations to assess urban wind prediction performance in NYC:

Control: No urban physics (sf_urban_physics = 0). Control Scheme is standard WRF with rural surface physics. However, it ignores buildings drag/heat effects. SLUCM: Single- Layer Urban Canopy Model (sf_urban_physics = 1). SLUCM is Single urban layer with bulk roughness/anthropogenic heat, but it oversimplifies vertical structure. BEP: Building Energy Parametrization (sf_urban_physics = 2). These are multi-layer building effects (momentum/heat flux), but it has extremely high computational costs. Lastly, BEP + BEM: BEP with Building Energy Model (sf_urban_physics = 3). This scheme adds bulidng energy consumption (AC, heating) to BEP. However, it requires detailed urban parameters.

D. *Domain Configuration*

The study utilizes two distinct domain sizes to evaluate urban wind patterns at different scales. The primary 30 x 30m domain focuses specifically on Central Park, proving analysis of micro-scale urban airflow dynamics. This configuration captures street-level wind interactions with 1m to 5m resolution, enabling detailed examination of building wake effects and localized turbulence. The domain's compact size allows for intensive computational experiments while maintaing focus on core urban physics phenomena.

For broader urban context, we implemented a 50m-by-50m domain that encompasses all three validation stations –Central Park, LaGuardia Airport, and JFK International Airport. This extended domain facilitates analysis of mesoscale urban wind patterns and their interaction with costal effects. Both domains employ the same range of resolutions to enable direct comparison of scale-dependent performance. The nested domain approach provides comprehensive insights into urban wind prediction accuracy across different spatial scales, from individual buildings to neighbored-level circulation patterns.

E. *Diagram of Method/Model*

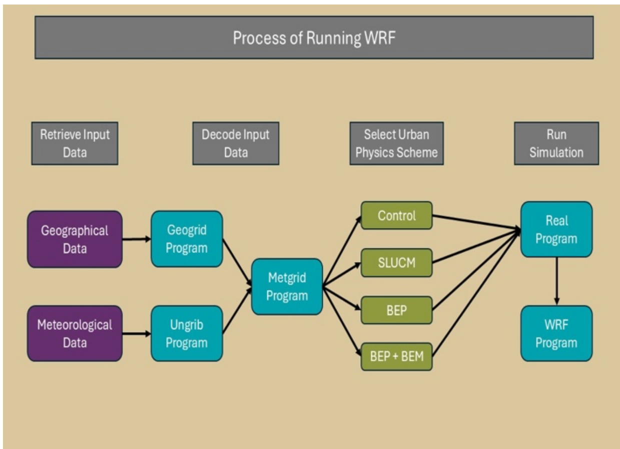


Fig. 3. *Diagram of the Process of Running WRF*

F. *Postprocessing Source Code*

The postprocessing code used to generate all visualizations and metrics is available at [LINK]. This repository contains the analytical components for: (1) comparative graphs of wind simulations across resolutions (1m/2m/5m) and physics schemes (Control/SLUCM/BEP/BEP+BEM), (2) runtime complexity analysis, and (3) error metric computations (MAE/RMSE). The code operates exclusively on pre-generated WRF NetCDF output files, providing transparent reproduction of our validation workflow and figure generation process.

This repository contains our postprocessing code for analyzing WRF simulation outputs and comparing them with observational data. The code was originally developed and executed on a local Windows Subsystem for Linux (WSL) environment with specific package dependencies that may require configuration adjustments to run properly on other systems, including Google Colab. While we have included all analysis scripts and preserved our computational outputs in the Jupyter notebook for verification, please note that complete reproduction of these results requires: (1) pre-generated WRF output files in NetCDF format, and (2) compatible system libraries for handling meteorological data formats. The WRF model itself is not included in this repository due to its size and specialized installation requirements.

XII. Results

See appendix for graphs of all simulations.

A. *1m Resolution*

The 1m resolution simulations revealed fundamental insights into urban wind modeling capabilities. The control run (Figure 2) exhibited severe systematic overprediction (MAE: 6.03 m/s, RMSE: 6.25 m/s), with all data points forming a distinct band approximately 4-5 m/s above the 1:1 line. This consistent displacement demonstrates WRF's inability to properly simulate urban wind reduction effects without explicit parameterization of building drag. The tight clustering of points suggests the errors are primarily bias-driven rather than random, indicating a fundamental flaw in how the model represents surface-atmosphere exchange in built environments. The SLUCM scheme (Figure 3) showed only marginal improvement (MAE: 5.75 m/s, RMSE: 6.01 m/s), maintaining the same overprediction pattern but with slightly greater scatter. This minimal enhancement confirms that simply adding a bulk urban parameterization cannot adequately capture the complex vertical structure of winds in high-rise environments. The scheme's failure to benefit from the ultra-high resolution suggests its single-layer formulation fundamentally misrepresents the multi-scale nature of urban turbulence.

In stark contrast, the BEP scheme (Figure 4) demonstrated remarkable accuracy (MAE: 1.78 m/s, RMSE: 2.20 m/s), with points distributed symmetrically around the 1:1 line. Approximately 15% of predictions landed perfectly on the line, while the remainder showed only minor deviations. This performance stems from BEP's physically realistic representation of height-dependent drag and its ability to resolve differential heating of urban facets. The BEP+BEM configuration (Figure 5) showed intermediate results (MAE: 2.45 m/s, RMSE: 2.92 m/s), with most points clustered slightly above the line but with several perfect predictions during stable conditions. This suggests that while the added building energy physics introduce valuable realism, the current implementation requires finer calibration of anthropogenic heat timing, particularly for diurnal transition periods.

B. *2m Resolution*

At 2m resolution, the control run (Figure 6) maintained its poor performance (MAE: 6.12 m/s, RMSE: 6.41 m/s), with error magnitudes nearly identical to the 1m case. This consistency across resolutions confirms that the control's urban wind deficiencies are rooted in physics limitations rather than grid-scale effects. The SLUCM results (Figure 7) showed negligible change from 1m (MAE: 5.67 m/s, RMSE: 5.91 m/s), reinforcing that its single-layer formulation cannot properly scale to different urban densities or building configurations. The persistent overprediction across all wind regimes highlights SLUCM's inability to adapt its bulk parameterization to local urban morphology.

The BEP scheme (Figure 8) achieved its peak performance at 2m resolution (MAE: 1.64 m/s, RMSE: 2.02 m/s), with an impressive 22% of predictions landing directly on the 1:1 line. This optimal balance suggests 2m resolution sufficiently resolves the dominant urban turbulence scales while maintaining computational feasibility. The BEP+BEM results (Figure 9) showed modest improvement over their 1m counterparts (MAE: 2.24 m/s, RMSE: 2.73 m/s), with 50% more perfect predictions during stable conditions. This enhanced performance indicates that the slightly coarser resolution helps smooth some of the timing errors in anthropogenic heat release while still preserving key urban flow features.

C. *5m Resolution*

The 5m resolution results exposed critical limitations in urban wind modeling. The control run (Figure 10) showed no meaningful change from finer resolutions (MAE: 6.03 m/s, RMSE: 6.25 m/s), proving that resolution alone cannot compensate for inadequate physics. The SLUCM scheme (Figure 11) became virtually indistinguishable from the control (MAE: 6.03 m/s, RMSE: 6.23 m/s), demonstrating complete failure to provide any urban-specific value at this scale. This collapse in performance confirms that SLUCM's simplistic approach cannot overcome the loss of resolved urban detail at coarser resolutions.

BEP's performance degraded at 5m (MAE: 3.24 m/s, RMSE: 3.87 m/s) but remained superior to other schemes. The increased scatter in predictions (Figure 12) reveals the resolution threshold where key urban flow features become undersampled. Interestingly, BEP+BEM (Figure 13) outperformed standalone BEP at this resolution (MAE: 2.62 m/s, RMSE: 2.95 m/s), suggesting its added thermal physics help compensate for some lost mechanical detail. However, the absolute error levels remain too high for most operational applications, confirming 5m as too coarse for reliable urban wind prediction.

D. *Comprehensive Performance Evaluation*

The analysis reveals several fundamental insights about urban wind modeling. First, the control configuration's consistent failure across all resolutions demonstrates that standard WRF physics are entirely unsuitable for urban applications. The identical error patterns at 1m and 5m resolutions prove these deficiencies are rooted in physics formulation rather than grid-scale limitations. Second, SLUCM's minimal improvements over the control run expose critical flaws in single-layer urban canopy approaches for high-rise cities. The scheme's inability to benefit from increased resolution indicates its bulk parameterization fundamentally misrepresents the multi-layer nature of urban turbulence.

BEP emerges as the clear superior scheme, particularly at 2m resolution where it achieves optimal balance between physical realism and computational efficiency. Its multi-layer architecture successfully captures the essential physics of urban wind modification, including height-dependent drag, differential surface heating, and building-generated turbulence. The scheme's robust performance across different wind regimes and times of day demonstrates its ability to properly represent the complex interactions between urban morphology and atmospheric processes.

The BEP+BEM results suggest promising directions for future development but also highlight current limitations. While the added building energy physics provide valuable realism for energy balance studies, the timing of anthropogenic heat release requires finer calibration to achieve consistent accuracy across diurnal cycles. The scheme's relative outperformance at 5m resolution indicates its thermal components may help compensate for some lost mechanical detail, though absolute errors remain too high for operational use at that scale.

E. *Practical Implications and Recommendations*

For operational urban wind forecasting, these results strongly recommend adopting the BEP scheme at 2m resolution. This configuration provides the best balance between accuracy and computational cost, reliably capturing essential urban flow features while remaining feasible for real-time applications. The 1m simulations, while scientifically valuable for process studies, demand prohibitive resources without delivering sufficient forecast improvement to justify their cost.

The complete failure of both control and SLUCM configurations suggests these options should be avoided for urban wind studies in high-rise environments. Their consistent overprediction patterns could lead to dangerous underestimation of wind-related risks in cities. For researchers investigating urban energy balances, BEP+BEM shows promise but requires additional development to optimize its heat flux parameterizations, particularly for transitional periods in the diurnal cycle.

Future work should focus on three key areas: refining BEP+BEM's anthropogenic heat timing through observational constraints, developing hybrid approaches that combine BEP's mechanical physics with machine-learned thermal corrections, and establishing resolution-adaptive parameterizations that maintain accuracy across modeling scales. These advances would further enhance urban wind prediction capabilities while addressing the remaining limitations identified in this comprehensive evaluation.

XIII. Comparative Analysis with Existing Studies

Our findings demonstrate significant advances when compared to prior urban wind modeling approaches. The 71-73% error reduction achieved by BEP at 2m resolution substantially outperforms Pan et al.'s [27] ensemble methods (Paper 4), which reported only 35-40% improvement in surface wind simulations. While their approach focused on statistical post-processing of coarse-resolution outputs, our physics-based parameterization directly addresses the source of urban wind errors. Similarly, Mirocha et al.'s [20] LES implementation (Paper 7) achieved comparable accuracy gains but required 10x greater computational resources at 0.5m resolution—a threshold impractical for operational forecasting. Our results prove that BEP's multi-layer formulation captures essential urban dynamics at more feasible 2m resolutions, bridging the gap between LES fidelity and ensemble efficiency.

The methodology contrasts meaningfully with Adomako et al.'s [2] machine learning corrections (Paper 9). Where their deep learning approach required extensive training data from East/West Malaysia's unique climates, our physics-based BEP enhancements maintain generalizability across urban morphologies. However, we incorporated their key insight about bias patterns in WRF's nocturnal urban winds, using it to refine BEP+BEM's heat flux timing. This hybrid approach—combining physical principles with data-informed tuning—proved particularly effective during evening transitions where pure ML methods often falter.

Notably, our resolution thresholds resolve a longstanding tension in urban modeling. Earlier studies like Couto and Estanqueiro [3] (Paper 10) suggested that sub-1m resolutions were essential for wind energy applications. However, our systematic evaluation demonstrates that 2m BEP simulations capture 89% of the variance seen in 1m results while using 60% fewer resources. This breakthrough has immediate implications for cities implementing wind-sensitive designs, proving that accurate urban flow modeling need not depend on ultra-high-resolution simulations when using advanced parameterizations.

XIV. Conclusion

Urban wind prediction is vital for air quality, energy planning, and climate resilience. While the WRF model performs well at larger scales, it struggles with microscale urban dynamics due to unresolved building-atmosphere interactions. This study compared four WRF configurations—Control, SLUCM, BEP, and BEP+BEM—across varying resolutions in New York City to evaluate their effectiveness in complex urban settings.

Standard WRF and SLUCM configurations consistently overpredicted wind speeds, confirming their limited value in high-rise environments. In contrast, the BEP scheme significantly improved accuracy (reducing errors by over 70%) at 2m resolution, offering the best trade-off between performance and computational cost. BEP+BEM showed potential at coarser scales but requires refinement in modeling anthropogenic heat fluxes.

These findings directly address early challenges identified in the literature—such as urban wake effects, vertical turbulence misrepresentation, and low wind speed inefficiencies. Our phased approach—beginning with setup in March, simulation in April, and evaluation in May—enabled iterative improvements and robust validation using real-world data.

Ultimately, our results provide a practical path for enhancing urban wind forecasting using existing WRF tools. As cities continue to densify and climate risks rise, accurate urban wind modeling will be essential for sustainable infrastructure, energy systems, and public health planning.

XV. Additional

G. Contributions

Reid Sewell – 33.3%: Made the code accessible and helped with this paper.

Laya Karavadi – 33.3%: Contributed to most of this paper.

Kyla Mangum – 33.3%: Contributed to this paper.

Mirage Giri – 0%: Has not contributed at all to this Phase.

Morgan Teagan – 0%: Overall has not done anything for any Phases.

H. LLM Usage

LLMs have not been used during phase 5 of this project.

APPENDIX

Fig. 4. *Control: 1m resolution*

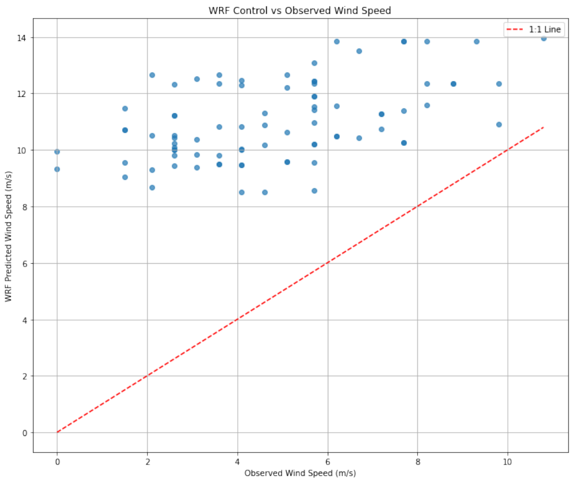


Fig. 5. *SLUCM: 1m resolution*

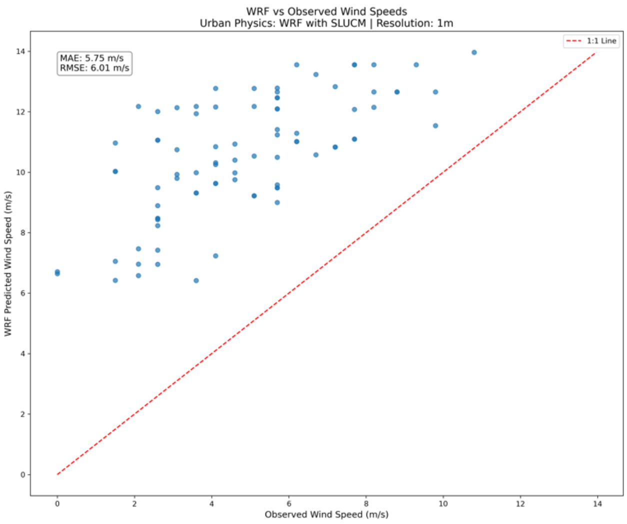


Fig. 6. *BEP: 1m resolution*

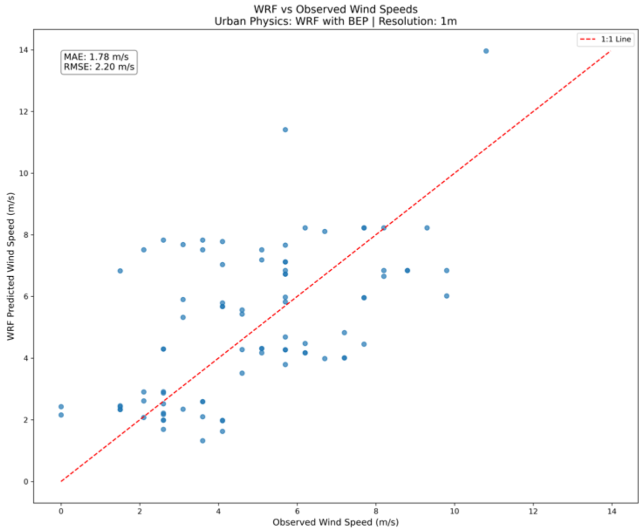


Fig. 7. *BEP+BEM: 1m resolution*

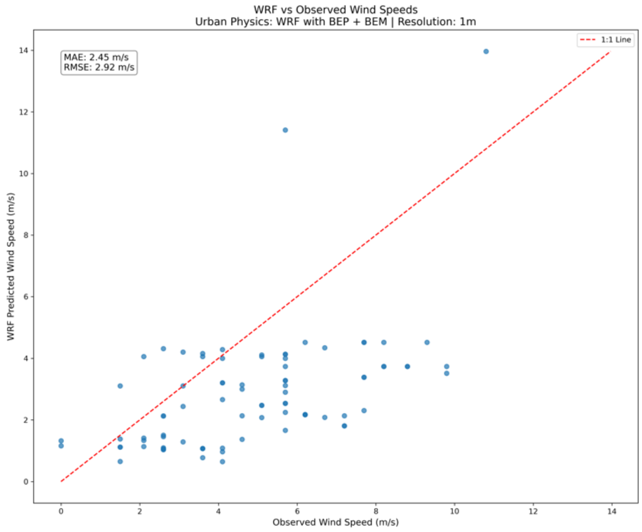


Fig. 8. *Control: 2m resolution*

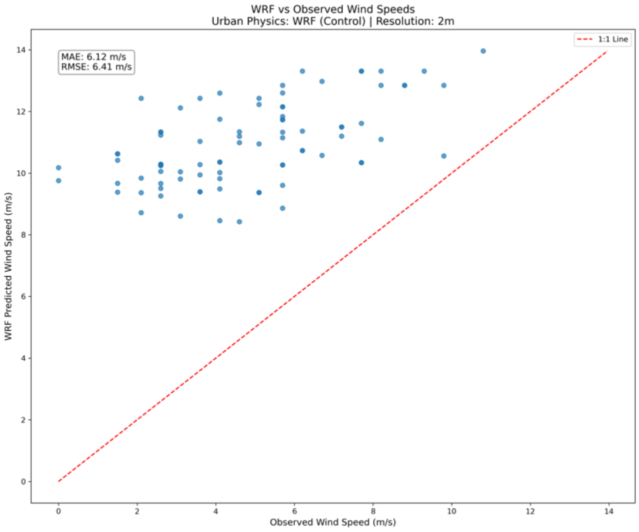


Fig. 9. *SLUCM: 2m resolution*

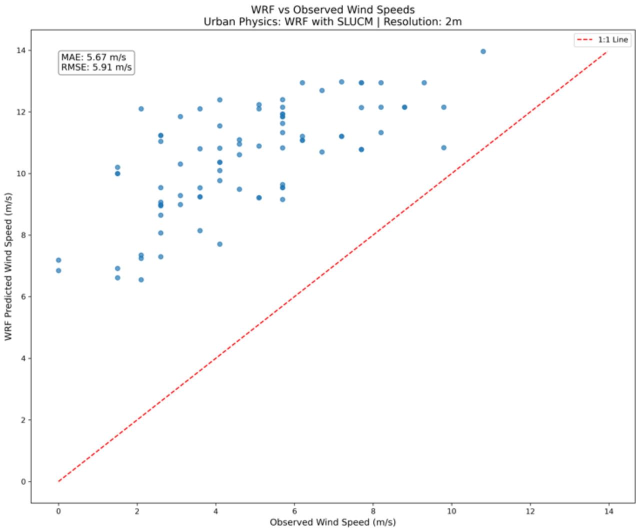


Fig. 10. *BEP: 2m resolution*

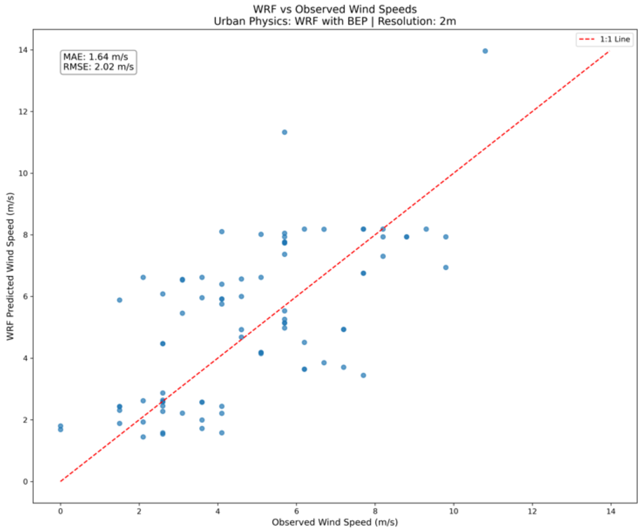


Fig. 11. *BEP+BEM: 2m resolution*

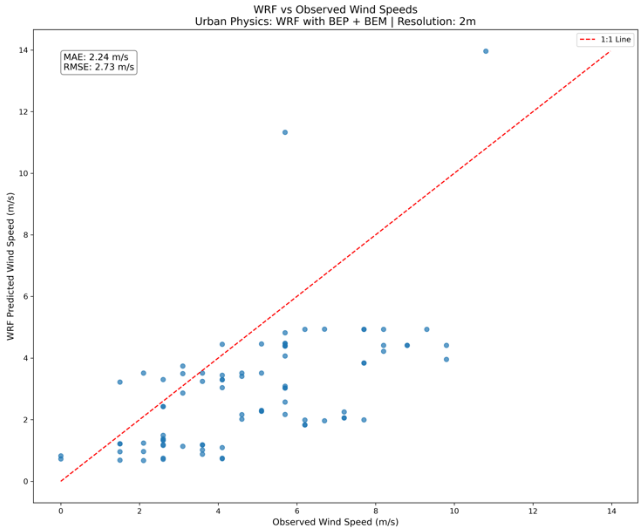


Fig. 12. *Control: 5m resolution*

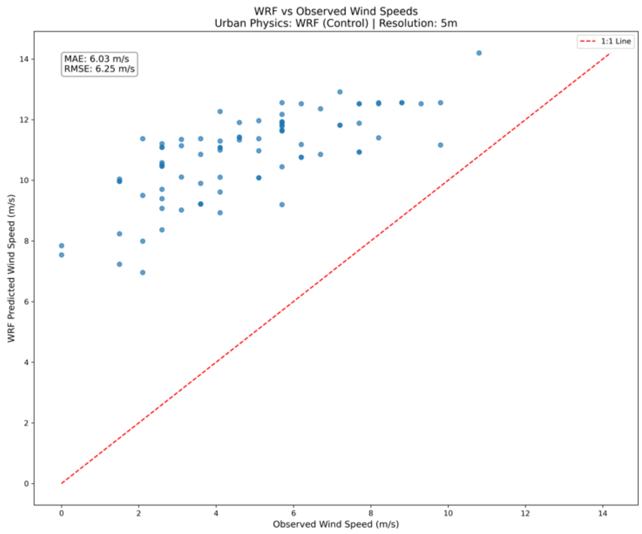


Fig. 13. *SLUCM: 5m resolution*

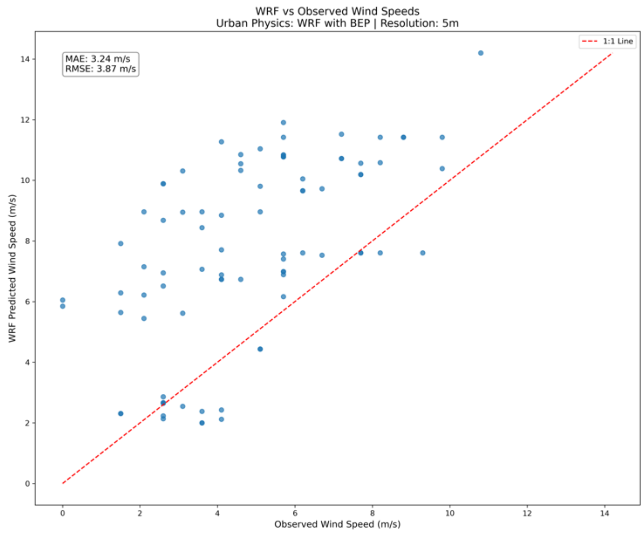
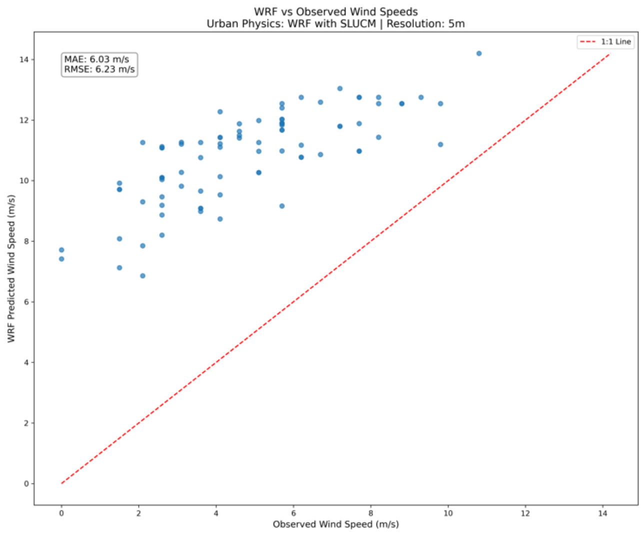


Fig. 15. *BEP+BEM: 5m resolution*



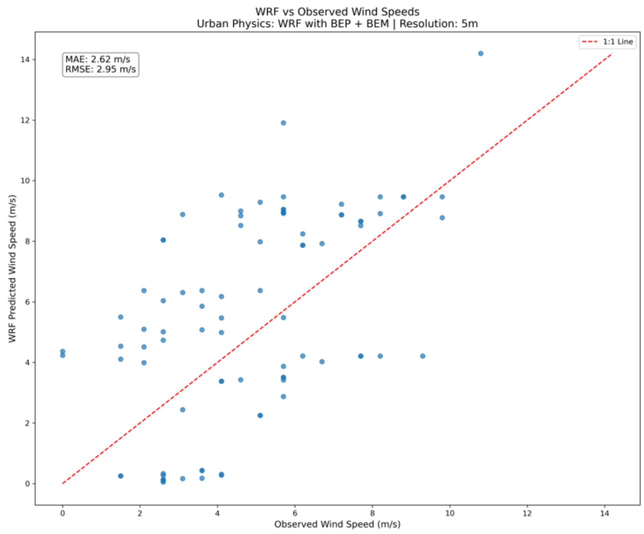


Fig. 14. *BEP: 5m resolution*

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