Resolution of Lower-Level Boundary Layer Turbulent Processes Using WRF and Machine Learning

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SUMMARY:

Lower-level turbulence has a significant impact on the wind environment, pollutant dispersion, thermal comfort, and vehicle and low-rise structure performance. However, capturing small-scale changes in low-level turbulence is challenging due to its high variability and sudden transient nature. To address this issue, a long period nested LES with input from a mesoscale WRF model was performed for 25 days, and deficiencies were highlighted and corrected using a field inverse machine learning technique. The model's performance was verified by comparing results with data from a 60m sonic anemometer tower, with a focus on turbulent quantities' magnitude. The study was conducted during late afternoon and sunset when turbulent processes are most volatile. Incorporating machine-trained data allowed the model to resolve eddy energy within the first tens of meters of the ground, even with a lifetime of only a few hours. Although LES underestimates turbulent kinetic energy during the day, this model addresses critical gaps in LES models of environmental flows.

Keywords: Turbulence, machine learning, WRF-LES

1. INTRODUCTION

To study atmospheric conditions over complex terrain and account for land use and land cover change on atmospheric boundary layer flow, a combination of Large Eddy Simulation (LES) and Weather Research and Forecasting (WRF) models (Kosović et al., 2020) is necessary. The WRF model's 1D parameters are only applicable to scales of a few kilometers, so LES is needed to model turbulent fluxes at smaller scales. However, there are still gaps in modeling fluxes over wide scale ranges and simultaneously resolving mean quantities of turbulence and heat flux (Moeng et al., 2007). Adding a layer of machine-trained data using an inverse ML model can help address these gaps by modeling operational quantities such as eddy viscosity and turbulent kinetic energy as physical processes (Muñoz-Esparza et al., 2014;). A long-term LES-WRF combined with an inverse ML model is conducted for 25 days to resolve very low-level turbulence properties, verified against anemometer tower data at 60m height within 110m height. This study summarizes previous theoretical work and highlights the need for additional high-resolution satellite data.

2. SITE AND METHODS

2.1 Field Location

The site selected for the study was the Andaman strait, that has a complex terrain, consisting of plains, hills and valleys. The location of the tower is labelled D4 in Fig. 1, and the measurement sensors of the tower are listed in Table 1, to measure the 3 wind directional components, *u*,*v*,*w* at 10 Hz frequency. The measurements were not taken during rainfall periods. The measurement period was from 14 June 2022 to 8 July 2022, with measurements at heights of z_{30}, z_{45} and z_{60}. Filters and corrections were applied as per the study by (Lee et al., 2017).

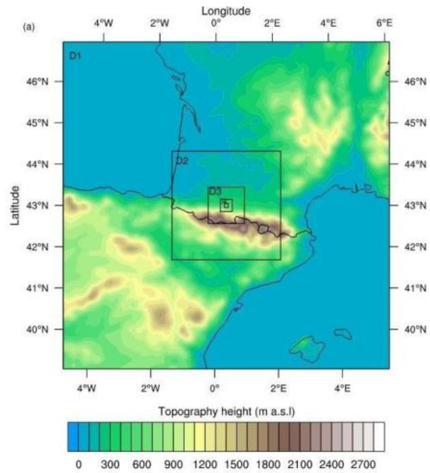

Figure 1. Terrain and site location of model location (Andaman Strait)

Table 1. Tower Sensor Data

Level	Height(m)	Sensors	Time period
Z_{30}	29.4	3D sonic anemometer	
Z_{45}	45.8	Sonic anemometer wind vane	14 June 22-8 July22
Z_{60}	61.4	3D sonic anemometer	

2.2 Application of Inverse ML

The field inverse model, works along the existing turbulence models of LES and augments them. The approach provides resolution of inverse problems to replace the discrepancies in LES parameters and minimizing the difference between data and predictions. Wherein, the quantities like TKE from LES is reproduced using backpropagation ML algorithm to replace k in $k - \omega$ equation, and so on in other governing equations of LES. The entire process is depicted in Fig. 2 (a). Deterministic mode of solving is utilized along with discrete adjoints optimization is conducted (Constantine et al., 2016). The process involves, feature selection, cross validation and a backpropagation based neural network algorithm.

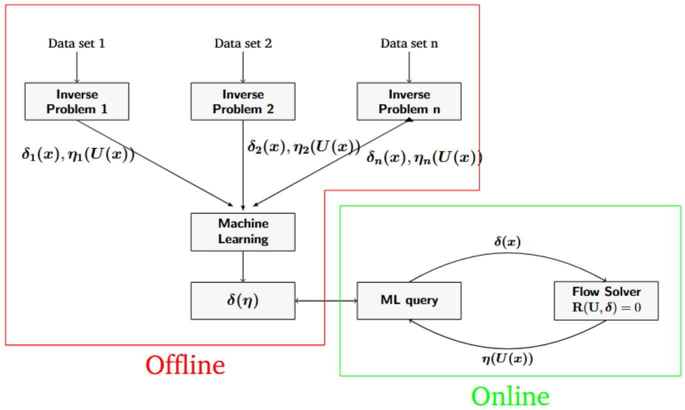

Figure 2. LES-ML workflow and adjoint backpropagation algorithm

2.3 Coupled WRF-LES

The WRF modelling is carried out in two stages; first is a meso scale 9 km to 1 km two-way nestled feedback ensemble. And a microscale stage (LES) of 333 m to 111 m by applying meso output in the lateral and initial boundaries. In LES, a 3D turbulence closure, along with a prognostic TKE equation is used (Lilly, 1967). The WRF-LES model setup with the domain parameters are given in Table 2.

Table 2. WRF-LES model setup (n*x** n*y**nz are number of grid points)

Domain	n*x** n*y**nz	Grid	Mode	PBL scheme
D1		9km	RANS	MYJ(Mellor–Yamada–Janji´c)
D2		3km	RANS	MYJ
D3	99*99*38	1km	RANS	MYJ
D4		333m	LES+ML	
D5		111m	LES+ML	

3. CONCLUSION

This section provides basic model outputs. Fig. 3 shows wind roses at 30 m, with similar results at 45 m and 60 m verified by tower observations. The LES-ML output fits closely. Mean bias and RMSE values were calculated and will be presented in the full paper.

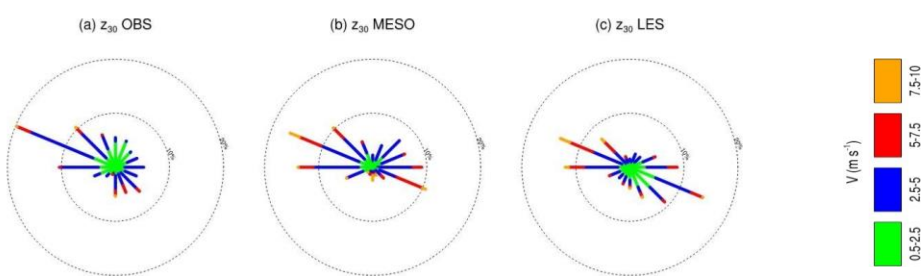

Figure 3. Wind rose of (a) tower data (b) MESO output (c) LES-ML model output

Wind speed differences between MESO and LES-ML were minimal (0.5-1.2 m/s), but MESO under- presented wind direction by 4˚ at 111 m. Fig. 4 shows the TKE plot, indicating MESO failed to capture turbulence peaks, while the LES-ML model reproduced them.

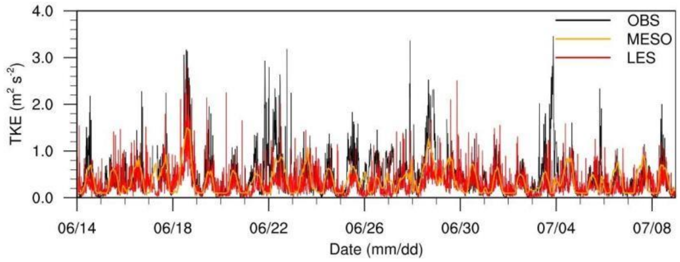

Figure 4. TKE spectrum from tower, MESO and LES-ML output at z_{30} for 111m grid

Fig. 5, depicts the power spectrum of turbulent velocity field, the field ranges from 25 days to10 mins. It can be inferred that the LES-ML reproduces and sustains the eddies with lifetime lessthan 2-3 hrs, whereas it decays in MESO alone. MESO is unable to resolve energies for frequency higher than 10^{-4}(periods lesser than about 2hrs).

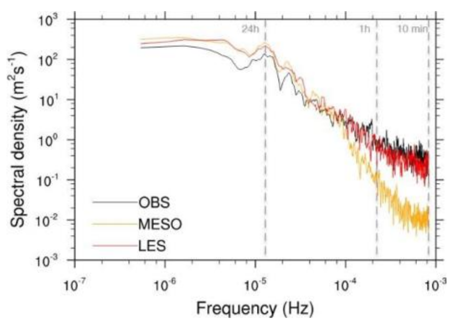

Figure 5. Turbulence spectrum at z_{30}

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