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From Simulations to Models: Predicting Natural Ventilation

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Summary

Natural ventilation uses wind and buoyant forces to passively drive outside air through buildings. Bringing in cooler outside air with natural ventilation can reduce or eliminate the need for mechanical cooling during hotter times of day. However, the potential of natural cooling is difficult to quantify because it involves complex turbulent flow taking place across multiple scales: outdoor wind through the urban canopy and indoor flow through building interiors. Large-eddy simulations (LESs) can accurately predict these flows, but the computational cost is too large for use across large areas and many interior configurations. In this study, we use LESs to establish a fast model that combines data-driven predictions for outdoor pressure fields with a 1-D airflow network model for interior flow. We demonstrate that this model can provide realistic estimates for natural ventilation flow rates across large urban areas.

Keywords: *Large Eddy Simulations, Natural Ventilation, Natural Cooling, Machine Learning*

1 INTRODUCTION

Wind-driven natural ventilation is a key component of effective natural cooling, an efficient alternative to energy intensive mechanical cooling. However, the potential for natural ventilation can be difficult to predict. Interior flow fields experience an array of complex processes, including flow through multiple openings, through various interior layouts, and with different turbulent properties. Additionally, this flow is directly coupled to the exterior flow field, which contains its own set of flow features and turbulent properties. We recently investigated this coupling through a series of Large Eddy Simulations (LESs) resolving both interior and exterior flow fields (Bachand et al. 2025). These indoor-outdoor LESs used idealized domains which attempted to replicate important characteristics of natural ventilation in urban areas, including various wind directions, indoor-outdoor temperature differences, canopy densities, and window configurations. In all simulations, we measured the ventilation rates through each window and skylight. Through these simulations, we found very strong interactions between ventilation rates and outdoor canopy flow.

Interactions between the outdoor canopy flow and ventilation rates are usually not accounted for in building energy models (BEMs). BEMs often represent natural ventilation with 1-D pressure-driven airflow networks derived from potential flow through sharp openings (Ramponi et al. 2014). These models require pressures prescribed at openings to predict ventilation rates. Often, these pressures are calculated using a scaling factor applied to pressures measured on an isolated building in a wind tunnel (ASHRAE 2017).

The objective of this work is twofold. First, we compare ventilation rates from airflow network models to indoor-outdoor LESs under complex canopy flow. Second, we investigate whether data driven models can learn from LESs to predict exterior pressures within real urban canopies.

2 METHODS

1-D airflow network model For each indoor-outdoor LES (Bachand et al. 2025), we conducted an equivalent LES of only the outdoor flow field. Instead of measuring ventilation rates through windows and skylights, we measure pressures on the corresponding surfaces. With these pressures, we used 1-D airflow networks to predict ventilation rates (Etheridge 2012).

Data-driven outdoor pressure model The surrounding urban canopy influences the exterior flow field through a variety of mechanisms including wakes, shear layers, and their interactions (Bachand et al. 2025). The complexity of these interactions makes the exterior flow field and pressure prediction problem well suited to a machine learning method, given a significantly large dataset. To establish a dataset, we ran 200 LESs of urban areas across the San Francisco Bay Area. Each of theses LESs simulated the wind field within a 500 m^2 urban area. Figure 1 shows the sampling strategy for selecting urban geometries and subdividing the dataset. Adapting an architecture proposed by Vargiemezis and Gorlé (2025), we trained a U-net using LES results to predict pressure fields at 2 m height.

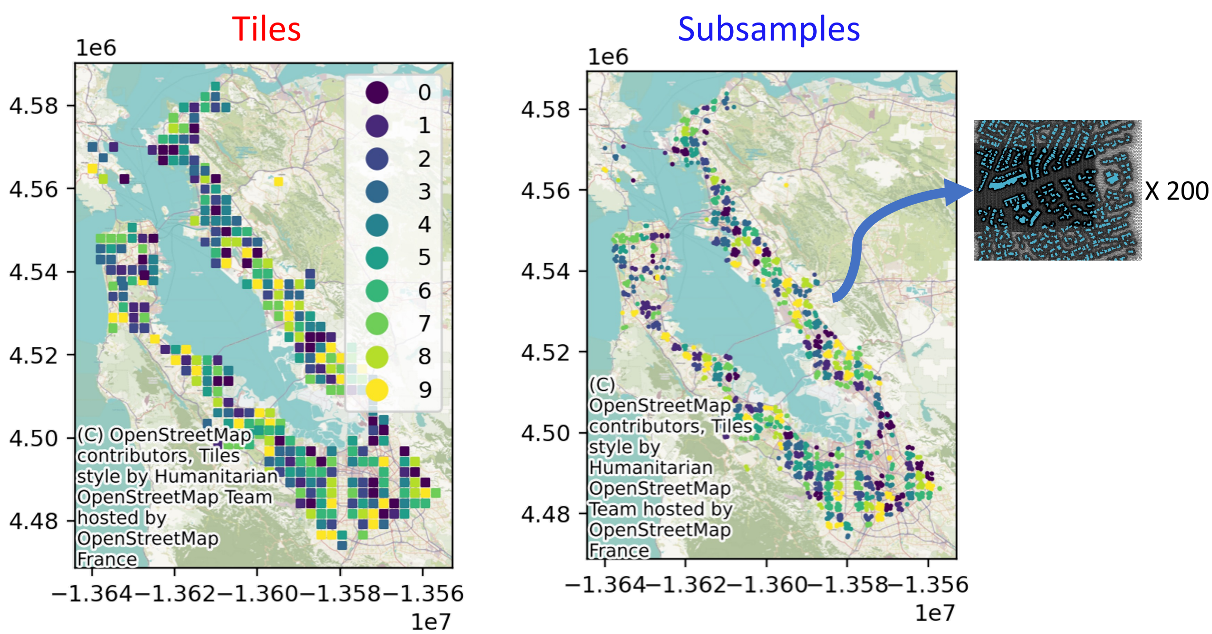

Figure 1: Sampling of Bay Area urban areas. The left panel shows 2 km^2 gridded tiles assigned to 10 data folds. The right panel shows subsamples (500 m^2) taken randomly within these tiles, each inheriting the parent tile's fold. This sampling method distinctly separates data folds without cross-contamination. Each LES simulation includes one subsampled urban area and a 250 m buffer of surrounding buildings.

3 PRELIMINARY RESULTS

Evaluation of 1-D airflow network model Figure 2 plots ventilation rates from the 1-D airflow network model against ventilation rates measured in indoor-outdoor LESs. Despite the various complex flow phenomena in the coupled indoor-outdoor flow fields, ventilation rates from the 1-D airflow network predictions agree well with the indoor-outdoor LESs. The main discrepancy observed is that the 1-D airflow network consistently overpredicts small ventilation rates. The reason for these predictive errors remains subject to investigation, but one hypothesis is that there might be a change in ventilation behavior at low Reynolds numbers (Chew et al. 2022). Using a piecewise linear regression, we were able to adjust for this low-Reynolds number behavior and

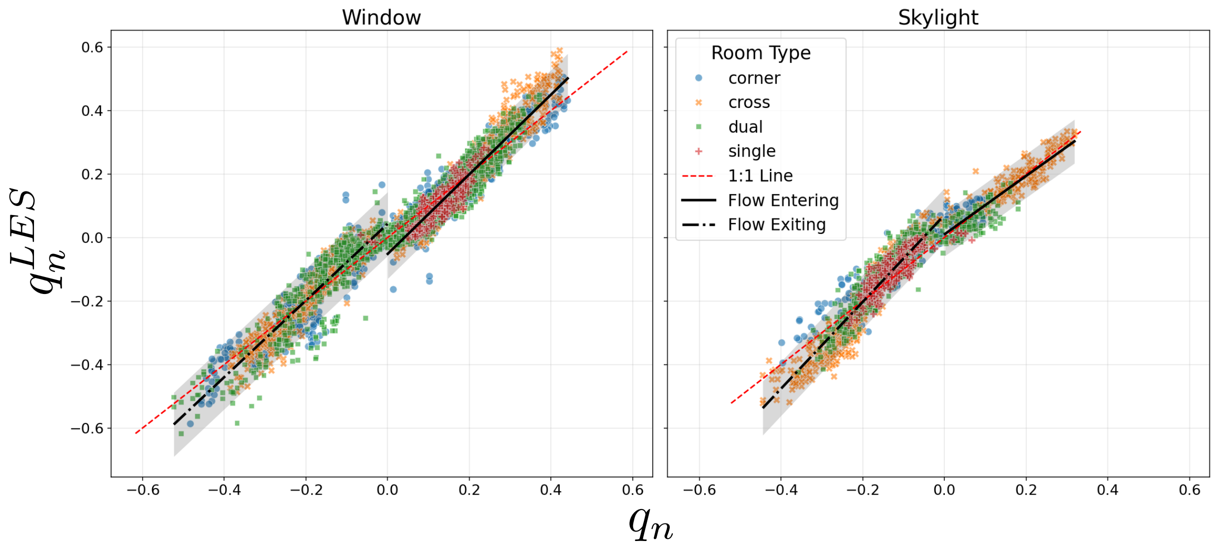

Figure 2: Ventilation rates from 1-D airflow network (q_n) vs ventilation rates measured in simulated building interior (q_n^{LES}). The left plot shows flow through windows, while the right plot shows flow through skylights. Black lines show secondary linear regressions to improve airflow network predictions. Note that ventilation rates are normalized by the window area and the velocity at 10 m height.

achieve improved ventilation predictions. The remaining errors in ventilation rates were further investigated to identify correlations with other flow properties, but no significant benefit from regressing against other components of the exterior flow field, such as the shear velocity, were observed. This finding indicates that the pressure field is the primary predictor of ventilation rates.

The success of the 1-D airflow network unlocks accurate large scale ventilation predictions since the model is very fast to evaluate and can be quickly applied to a very large number of buildings. Furthermore, the model avoids explicitly simulating geometrically complex interior layouts. However, the model does require an accurate prediction of the pressures at the openings, and these pressures highly depend on complex local outdoor wind flow characteristics.

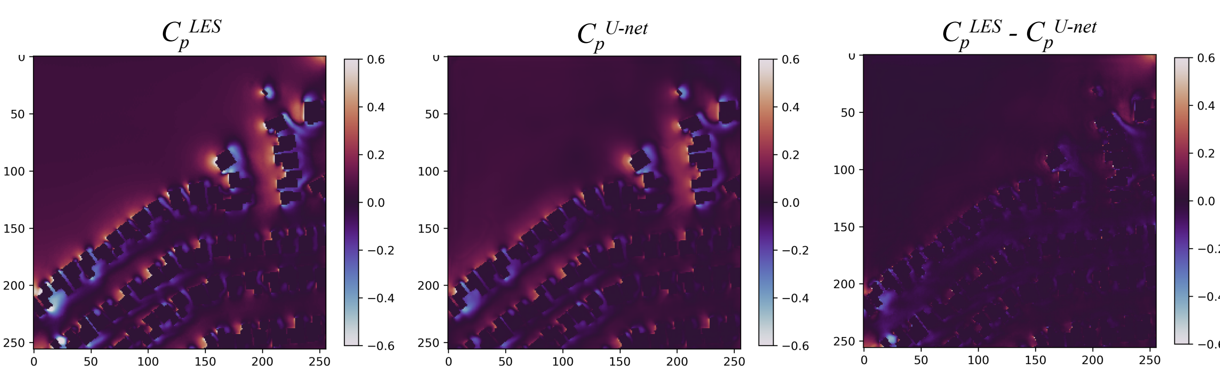

Figure 3: Pressure coefficients (C_p) from LES and U-net for one example in validation dataset.

Evaluation of data-driven outdoor pressure model Figure 3 compares LES pressure coefficients (C_p) with U-net predictions for one example within the validation dataset. Visually, the

U-net prediction shows good agreement with the LES. We observe the largest error near large positive or negative pressure regions, as well as near boundaries, where the U-net does not have as much context on the surrounding canopy. Overall, the root mean squared error for C_p predictions around buildings in the validation dataset was 0.8, approximately 10% of the C_p range.

4 CONCLUSION AND FUTURE WORK

Using LES results, we develop a modeling framework for natural ventilation predictions that can account for the influence of local urban canopy flow. First, we show that a 1-D airflow network model agrees well with ventilation rates from indoor-outdoor LESs. Second, we propose a U-net trained on LES data to predict pressures within the urban canopy. In ongoing work, we are combining these pressure predictions with 1-D airflow networks to enable fast large-scale predictions for wind-driven natural ventilation and cooling.

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