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Improving urban flow predictions through data assimilation

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ABSTRACT

Detailed aerodynamic information of local wind flow patterns in urban canopies is essential for the design of sustainable and resilient urban areas. Computational Fluid Dynamics (CFD) can be used to analyze these complex flows, but uncertainties in the models can negatively impact the accuracy of the results. Data assimilation, using measurements from wind sensors located within the urban canopy, provides exciting opportunities to improve the quality of the predictions. The present study explores the deployment of several wind sensors on Stanford's campus to support future validation of CFD predictions with uncertainty quantification and data assimilation. We focus on uncertainty in the incoming wind direction and magnitude, and identify optimal sensor placement to enable accurate inference of these parameters. First, a set of Reynolds-averaged Navier-Stokes simulations is performed to build a surrogate model for the local velocity as a function of the inflow conditions. Subsequently, artificial wind observations are generated from realizations of the surrogate model, and an inverse ensemble Kalman filter is used to infer the inflow conditions from these observations. We investigate the influence of (1) the sensor location, (2) the number of sensors, and (3) the presence of noise or a bias in the measurement data. The analysis shows that multiple roof level sensors should enable robust assimilation of the inflow boundary conditions. In the future field experiment, sensors will be placed in these locations to validate the methodology using actual field measurement data.

1. Introduction

The continuous growth of urban areas, nearly tripling from the year 2000–2030 [1], presents a challenge for cities striving to maintain a sustainable, healthy and comfortable environment [2]. In increasingly dense and complex urban canopies, detailed aerodynamic information on local wind flow patterns will be essential to determine pedestrian wind comfort, air quality, ventilation strategies, and deployment of wind turbines. Computational Fluid Dynamics (CFD) can be used to study these complex urban canopy flow and transport processes (e.g. Refs. [3–6]), but the accuracy and reliability of the solutions remain a concern that requires further validation efforts [7]. CFD studies commonly rely on wind tunnel measurements for model evaluation and validation, e.g. Refs. [8,9]. While these have contributed significantly to our understanding of urban flow phenomena, it should be acknowledged that a wind tunnel experiment cannot fully represent the complexity of urban canopy flows. The use of idealized and controlled boundary conditions, the introduction of geometrical simplifications, and in some cases the missing of physics in the experiment, can lead to discrepancies between wind tunnel and field measurements. For example, Klein et al. [10] demonstrated significant differences between wind tunnel and field data, which were partially attributed to the large-scale variability in the atmospheric boundary layer (ABL). García-Sánchez et al. [11] further demonstrated that this inherent variability in the incoming ABL can significantly influence the predicted flow patterns. Hence, to assess the true predictive capabilities of CFD models, it is essential to consider validation with field measurements. These validation studies should account for the inherent uncertainty in the definition of the boundary conditions. Uncertainty quantification (UQ) frameworks [12,13] provide a formal method to quantify the influence of these uncertainties on the quantities of interest and provide results with confidence intervals [14].

Our previous UQ studies for urban flow have relied on an upstream sensor measurement, or on mesoscale simulation input, to characterize the uncertainty in the incoming ABL. Since these studies modeled a short-term field experiment with one dominant wind direction, measurements from a single upstream sensor, or results from mesoscale simulations for this specific wind direction, provided sufficient information. However, if we want to consider a variety of dominant wind directions, this process is more complicated. Commonly, one would rely on recordings at the most nearby weather station and directly impose the recorded wind conditions as boundary conditions for simulations at

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the location of interest. This can introduce considerable errors, since it doesn't account for potential deviations between the undisturbed incoming and measured wind conditions. The alternative of performing upstream measurements to define inflow boundary conditions would be cumbersome, since exploring all possible wind directions would require long-term deployment of multiple weather towers.

In this study, we explore the use of an inverse modeling approach that assimilates data from strategically placed sensors within the urban canopy to iteratively estimate the probability distribution for the inflow boundary condition. This distribution can then be used in a forward UQ analysis to provide predictions with quantified confidence intervals. The approach could render urban flow simulations more flexible and more accurate, in particular given the increasing trend to deploy wind and air quality sensors in cities [15].

As a starting point, we numerically evaluate the capabilities of the inverse model, and we use the results to guide the design of a field experiment on Stanford's campus. By using the campus as our test case, we have considerable flexibility to place the sensors in different locations at pedestrian, terrace, and roof level, with the possibility to easily perform long term measurements. In addition, the campus geometry has all the elements of a small urban environment, and Fig. 1 demonstrates the importance of the inflow boundary conditions: a variation of 20° in the incoming wind direction significantly alters the flow field.

The proposed inverse Bayesian technique is based on the inverse Ensemble Kalman Filter (EnKF) proposed by Iglesias et al. [16]. We assume an incoming boundary layer with a logarithmic profile corresponding to a neutral surface layer with a roughness height of 0.3 m, [17]. The non-dimensional velocity in the urban canopy is solely a function of the incoming wind direction, hence we focus on inferring a distribution for the inlet flow angle. Wind measurements from a nearby weather station are used to investigate a prior distribution for the wind direction. Subsequently a set of CFD simulations are used to construct polynomial chaos expansions [18] for the quantities of interest, i.e. the velocity vector throughout the urban canopy. These expansions serve as a reduced order model to make the inverse approach computationally affordable. The sensitivity of the inverse model to the locations of the sensors, and to noisy and biased measurements, is tested to draw conclusions on the optimal placement of the sensors in the future experimental campaign.

Previous studies on the use of inverse Bayesian techniques for modeling the built environment have primarily focused on identifying pollutant source characteristics [19–21]. The EnKF has also been used to quantify and reduce turbulence model uncertainties in RANS simulations of the flow over periodic hills [22]. The current study extends the use of inverse methods in flow simulations of the built environment to infer the incoming ABL, taking into account its natural variability. The use of a polynomial chaos expansion surrogate model addresses some of the concerns related to the cost of the data assimilation process mentioned in Ref. [21]. The approach is therefore well suited for increasing the practical use of CFD simulations with data assimilation and uncertainty quantification in urban areas. Future extensions to the framework could also leverage the EnKF to further improve confidence in the results by compensating for the modeling errors and lack of flow physics [23].

The remainder of the paper is organized in three sections. The following section introduces the data assimilation framework, along with the set-up of the CFD simulations and the construction of the surrogate model. In section 2, we first identify the optimal sensor locations for data assimilation. Subsequently, we characterize the effect of noisy and biased flow measurements and investigate the use of a multi-sensor assimilation to mitigate the effect of inaccurate measurements and numerical models.

2. Methodology

2.1. Proposed data-assimilation framework

The objective of the data-assimilation framework is to estimate the boundary condition set by the incoming wind direction and velocity solely based on local measurements of the 2D wind vector within the modeled urban canopy. We first infer the incoming wind direction based on the local flow direction in the urban canopy. Subsequently, we use measurements of the local velocity magnitude to obtain the inlet velocity magnitude. This second step uses the local reduced velocity, U_R obtained from the simulation. U_R is the ratio between the local wind speed (U_{sensor}) and the reference velocity at the inlet, and it is only a function of θ_{inlet}. Hence the following linear relation can be used to infer the inlet velocity magnitude: $U_{inlet} = U_{sensor}/U_R(\theta_{inlet})$, once θ_{inlet} is inferred. Throughout the remainder of the paper most of the analysis is focused on data obtained on a horizontal plane at a height of 5 m. This height was selected to match the tripod height that will be used for the ground level measurements during the experimental campaign [24].

Fig. 2 presents the iterative data assimilation framework to infer the inflow wind direction. It is based on an ensemble Kalman [25] filter and comprises four main steps:

1. Definition of a prior (first step) or updated (following steps) ensemble of particles with the probabilistic distribution for the inlet wind direction. The variability of the inlet conditions represents the natural behavior of the ABL.
2. Compute the Reynolds averaged flow field at the locations where experimental data is available for each particle, using a computational fluid dynamics or a surrogate model.
3. Compare the propagated ensemble to the data from the field measurements.
4. Use a Bayesian updating procedure to minimize the difference between the experimental and the propagated state and update the ensemble of inlet flow angles.

The following sections provide further information on each of these

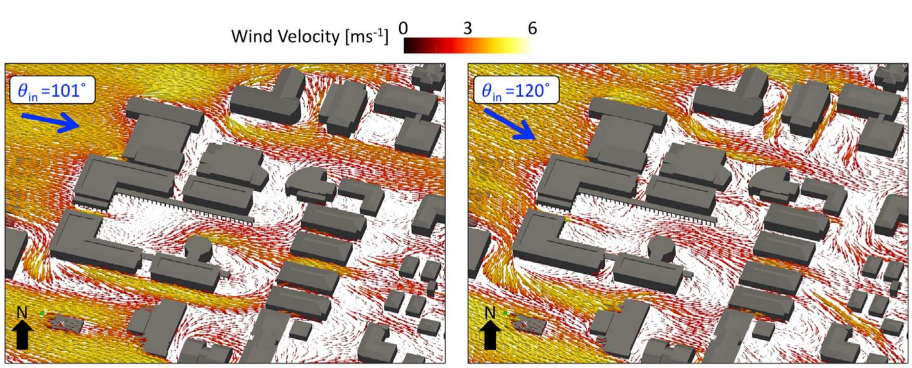

Fig. 1. Numerical predictions of the flow field on Stanfords campus showing the different flow patterns for two different wind directions.