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Spatial-aware source estimation in building downwash environments

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ABSTRACT

This paper introduces a concept called ”spatial-aware” source-term estimation (STE), which utilizes the acquired knowledge of how the forward model (FM) predictions compare against observations spatially to enhance the overall quality of source estimation. We evaluated the effectiveness of the proposed method against a wind tunnel experiment simulating low-stack plume dispersion in a building downwash environment with known source locations and varying building aspect ratios and building angles relative to wind direction, selected to achieve the balance of physical complexity and environmental controllability. Specifically, we adopted AERMOD as the FM, constructed spatially-resolved error models by comparing the FM predictions against measured concentrations for one configuration, referred to as the training case. Then the error models were applied to the rest of the configurations, referred to as test cases, for estimating emission rates. The results show that the spatial-aware STE can improve the estimation results, due to closer agreement between the error models and error distribution in terms of shapes and/or magnitudes. For example, using the vertical measurements around the $H/W = 1/2$ building with wind direction perpendicular to the building as the training case and applying the spatially-resolved error models, the estimated emission rates for all test cases with same building aspect ratio differ from the true emission rate by less than 30%, compared to 63.2%–236% without applying any error models. We argue that parallel efforts, i.e., improving the accuracy of FMs and quantifying the FM performance are needed to further advance the science and applications of source estimation.

1. Introduction

Source-term estimation (STE) refers to techniques of detecting air pollutant source locations and/or magnitudes, using observations of air pollutant concentrations and knowledge of meteorological fields [1]. There are many real-world STE applications such as estimating the toxic releases from industrial combustion sources [2], fugitive air emissions from oil and gas production [3–5], ash and other materials released from volcanoes [6,7], global emission inventory of air pollutants [8], and airborne contaminant emissions in indoor environments [9,10].

Various STE methods have been proposed over the years, as summarized by two review papers [11,12], which generally fall into two major categories: deterministic and probabilistic. A deterministic approach treats source parameters as variables with certainty. The estimated source parameters are acquired through minimizing a cost function representing the differences between measurements and forward model (FM) predictions [5,13,14]. A probabilistic approach treats source parameters as variables with specific probability density functions. For example, Bayesian inference is the most widely adopted probabilistic STE method [3,15], in which a likelihood function of the difference between the measurements and FM predictions is constructed and a posterior probability density function of the source parameters is established based on the constructed likelihood function with any available prior information.

As described above, either the deterministic or probabilistic method requires a forward model (FM) to link source parameters and receptor observations, where ”forward” means the process from source parameters to receptor observations, and the opposite direction is usually referred to as ”inverse”. The more accurately the FM captures the atmospheric processes, the better source estimation results we can expect. Equally important is a thorough understanding of the FM performance, i.e. under what conditions it performs well and poorly. As many STE applications occur in complex environments, the FM performance often has strong spatial dependence. For example, small hydrocarbon-fueled distributed generation units such as diesel backup generators [16,17], distributed combined heat and power units [18], and residential wood combustion [19] located in street canyons can potentially lead to a so-called building downwash problem, where the entrainment of exhaust from low stacks into or near the wakes of buildings can result in ground-level concentrations that are significantly larger than those from exhaust released at the same height in the absence of the buildings [20]. Estimating the emission rates of low-stack sources can assist in

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enforcing regulations and protecting public health. While FMs designed to capture the impact of building downwash often perform well in the far-wake regions, they face challenges in the near-wake regions [20].

The main objective of our study is to describe the development and evaluation of a ”spatial-aware” STE method that utilizes the acquired knowledge of the spatially-dependent FM performance to enhance the overall quality of source estimation. To the best of our knowledge, this approach has not been reported in STE research. By contrast, spatial information has been implemented in data assimilation techniques to predict the spatial and temporal variations of air pollutants by dispersion or chemical transport modeling [21,22].

The ”spatial-aware” STE methods can be applied to problems with both unknown source locations and emission rates, but in the current study we limit the scope to STE problems with known source locations and unknown emission rates. We evaluate the proposed method against sensor data in a wind tunnel experiment simulating low-stack plume dispersion in a building downwash environment [23], which was selected to achieve the balance of physical complexity and controllability. On one hand, plume dispersion with building downwash is inherently more complex to model than that over flat terrains. On the other hand, an evaluation against field measurement data will nevertheless introduce many uncertainties when source and environmental parameters are not well characterized, which may inhibit further understanding of the STE method itself. Therefore, we argue that the wind tunnel downwash experiment is appropriate for the initial evaluation of the proposed method. Moreover, the different building configurations and relative wind directions in the wind tunnel experiment allow us to develop the method in one case, and test the method in different cases for rigorous evaluations. Note that historically the development of Gaussian-based dispersion models have benefited from parameterization and evaluations against wind tunnel experiments.

This paper is organized as follows. We first describe the wind tunnel experiment and formulate the STE problem, followed by an introduction of the FM used to simulate the wind tunnel experiment. Next, we elaborate the process to construct spatially-dependent error models. Two versions of the error models are presented, referred to as ”error models” and ”modified error models” (constructed with additional information on the positions of the peak concentrations), respectively. Finally, we discuss the estimation results in the order of without error modeling, with error modeling and with modified error modeling to evaluate the proposed spatial-aware STE methods.

2. Method

2.1. Defining the STE problem

2.1.1. Wind tunnel experiment

The wind tunnel experiment was conducted at the USEPA Meteorological Wind Tunnel Facility to study the near-field dispersion of pollutants around elongated buildings. The tunnel test section is 370 cm wide, 210 cm high, and 1830 cm long, which is 1:150 to the full scale. Detailed description of the experiment can be found in Ref. [23]; and only a brief introduction is presented here.

Fig. 1 illustrates the wind tunnel experiment setup. The experimental datasets include several combinations of source locations, stack heights, building geometries and building angles. The buildings, simplified as rectangular boxes, were 150 mm in both height (H) and length (L) with different width (W). In this paper, we distinguish different building geometries by L to W ratios. For example, the building with 300 mm in width is referred to as the 1×2 building (i.e., $L/W = 1/2$). The buildings were positioned at different angles (θ) relative to the mean flow of the wind tunnel, where 0° has the long side of the buildings perpendicular to the mean flow. The reference wind speed (U_0) at the building height was 2.77 m s^{-1}. High-purity ethane (C_2H_6) at room temperature was employed as the tracer gas and emitted at the rate of 1.875 g min^{-1} (±3%) in all directions from a porous ball installed on the upper end of the capped source tube, which inhibited plume rise from either initial momentum or buoyancy. Receptors were placed along vertical ($z-$), lateral ($y-$) and longitudinal ($x-$) directions. Note that the origin ($x = 0$, $y = 0$, $z = 0$) was set directly under the source location ($x = 0$, $y = 0$, $z = h_s$). The cases with the source location in the middle of the building downwind side and the source stack height equal to $1.5H$ had the largest number of receptor locations among all configurations. Furthermore, as summarized in Table S1 in the Supporting Information (SI), vertical ($z-$) and lateral ($y-$) receptors with $x = 3H$ and $x = 10H$ were included in all the cases of 1×2 and 1×8 (i.e., $L/W = 1/8$) buildings with different building angles, and the longitudinal ($x-$) receptors were included in all the cases of 1×4 (i.e., $L/W = 1/4$) buildings with different building angles. We focus on those cases and receptor locations to perform the proposed STE method for comparison of different cases.

2.1.2. Mathematical formulation for the STE problem

In our study, we applied the deterministic approach. The estimated source parameters are acquired through minimizing a cost function representing the distances between measurements and forward model predictions.

Assuming a linearly additive error, we can express the generic relationship between the wind tunnel measurement and FM prediction as:

$$C^{WT}(x, y, z) = C^{FM}(x, y, z;\ \eta_1, \cdots, \eta_m) + \varepsilon(x, y, z;\ \lambda_1, \cdots, \lambda_n) \tag{1}$$

where $C^{WT}(x,\ y,\ z)$ denotes the concentration measured in the wind tunnel (WT) at the location $(x,\ y,\ z)$; $C^{FM}(x, y, z;\ \eta_1, \cdots, \eta_m)$ represents the concentration at the location $(x,\ y,\ z)$ obtained from a forward model (FM) with m source parameters $\eta_1,\ \cdots, \eta_m$; $\varepsilon(x, y, z;\ \lambda_1, \cdots, \lambda_n)$ refers to the error at the location $(x,\ y,\ z)$ with n error model parameters $\lambda_1,\ \cdots, \lambda_n$. We ignore the instrumentation errors (±1% full scale of range [24]) from the true values.

Source parameters can be estimated by minimizing the objective function:

$$\sum_{(x,y,z)} (C^{WT}(x, y, z) - C^{FM}(x, y, z;\ \eta_1, \cdots, \eta_m) - \varepsilon(x, y, z;\ \lambda_1, \cdots, \lambda_n))^2 \tag{2}$$

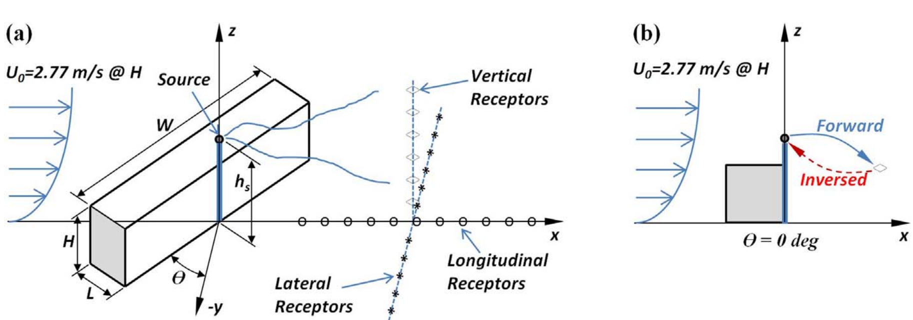

Fig. 1. Wind tunnel experiment setup to simulate low-stack plume dispersion in a building downwash environment: (a) 3D view; (b) Side view.