

Integrated long-term snow accumulation prediction using a coupled snowdrift–snowmelt framework with OpenFOAM

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Summary

Snow accumulation strongly influences winter wind engineering and environmental planning in cold regions, affecting road maintenance, roof-load assessment, and urban design. While many studies have used high-resolution CFD to capture short-term snowdrift processes, predicting snow accumulation over multi-week to seasonal periods remains challenging due to the need to consider snow transport, deposition, erosion, and melting under time-varying meteorological conditions. Existing coupled mesoscale-microscale or quasi-steady approaches have demonstrated promising results but still require frequent steady CFD simulations and detailed time-resolved meteorological inputs, leading to high computational demand. In this study, we develop an integrated long-term snow-accumulation prediction framework within OpenFOAM couples snowdrift and snowmelt processes and is driven by statistical rather than continuous meteorological data. This enables seasonal-scale simulations while preserving detailed airflow and snow distribution around buildings. The method is initially validated using a rare, multi-month field dataset, demonstrating its potential as a practical approach for predicting long-term snow accumulation.

Keywords: *Snowdrift model, Erosion and accumulating, Snowmelt, Snow distribution, Computational fluid dynamics (CFD)*

1 INTRODUCTION

Snow accumulation plays a crucial role in winter wind engineering and environmental assessment in cold regions. Accurate prediction of snow distribution helps us understand the localized snow hazards and make plans for long-term operational strategies. Although Numerous studies have investigated snowdrift processes using computational fluid dynamics (CFD) simulations in short-term predictions. A long-term (over a week to several months) prediction of snow accumulation remains a significant challenge. The difficulty arises from the need to model the combined effects of snowdrift transport, snow deposition, erosion, and melting processes driven by temporal variations in meteorological conditions, which requires extremely large computational resources for the temporal simulation, that few studies applied to the seasonal snow accumulation using CFD simulation (Tominaga, 2018).

Early efforts to build unified long-term snow prediction systems include the work of Tominaga et al. (2011a), who coupled a mesoscale meteorological model with microscale CFD and successfully reproduced key snowdrift features such as windward erosion and sheltered deposition. Zhou et al. (2018) further advanced this direction by developing a coupled snowdrift-melt model and introducing a quasi-steady approach that groups meteorological conditions into discrete stages for separate steady CFD runs. However, both methods still depend on meteorology-driven boundary conditions and require frequent steady-state simulations, resulting in high computational cost and complex data handling. In addition, long-term field datasets with detailed meteorological and snowdrift measurements are extremely limited, making model validation difficult.

In the present study, the objective is to develop an integrated framework for long-term snow accumulation prediction couples snowdrift and snowmelt models in the OpenFOAM environment.

This framework is designed to be driven by not continuous but statistics meteorological data, enabling seasonal-scale simulations while retaining high-resolution representations of wind flow and snow distribution around buildings. The system is to be validate using a rare, long-term field observation dataset by Tsutsumi et al. (2010) that includes detailed meteorological conditions, wind fields, and snowdrift fluxes.

2 FIELD OBSERVATION FOR VALIDATION

Field observations (Tsutsumi et al., 2010) were conducted on the campus of the Hokkaido Institute of Technology from December 2008 to March 2009. As shown in Figure 1a, a full-scale two-story isolated building facing WNW was monitored, with snow depth, wind speed at reference height, z_R (=3 m), and drifting snow flux measured continuously using a sonic anemometer and a snow particle counter positioned 20 m and 50 m windward of the building, respectively. Moreover, snow depth was recorded daily using a snow-depth gauge (Figure 1b) as well as at several snow-depth observation points (Figure 1c) located around the building. Such spatially detailed snow-depth observations are extremely rare, and they provide invaluable data for validating numerical snowdrift models.

3 NUMERICAL MODEL

3.1 Analysis procedure

The snowdrift and snowmelt models developed by Tominaga et al. (2011a,b) were implemented in the solver of OpenFOAM v2112, which is an open-source CFD platform. As illustrated in the flowchart (Figure 2), the analysis procedure consists of four main steps: classifying weather-snow conditions into scenarios, conducting snowdrift and snowmelt analyses for each, and integrating their results to obtain the total snow depth.

First, the simulation target is defined, relevant observational and meteorological data are collected, and these data are classified into specific wind-snow scenarios to set up the simulation cases. The wind condition was classified based on whether the surface friction velocity exceeded the threshold value u_t^* , above which snow particles become entrained and below which they remain stationary. The threshold friction velocity, set to 0.25 m/s in accordance with previous studies, was calculated using the logarithmic wind profile equation: $U_{Rt} = u_t^* / \kappa \ln(z_R / z_0)$, where U_{Rt} is the wind speed at z_R , κ is the von Karman constant (= 0.4), and z_0 is the roughness height (= 0.0024 m). The snow condition was determined from the hourly snow-depth change at the windward measurement point. An increase in snow depth indicated snowfall, in which case the inlet and top snowdrift-density boundary conditions were set based on the corresponding hourly snow-mass increase, otherwise, it was treated as a no-snowfall condition. Then, in the snowdrift model, steady-state simulations were first conducted using the Reynolds-averaged Navier–Stokes equation (RANS) method, with the realizable $k-\varepsilon$ model utilized for resolved the averaged flow field. Subsequently, unsteady simulations for snowdrift-density transport and snow-depth change were calculated using the averaged flow field as the initial condition. Snow erosion was considered in the time-dependent calculations, and the snowdrift density was updated accordingly. Third, in the snowmelt model, unsteady calculations were conducted by incorporating temporal variations in solar position and meteorological conditions, while utilizing the flow field obtained from the CFD simulations. Finally, the snow depth was obtained by integrating the results of cases under all scenarios. Further details of the model formulations can be found in the referenced literature.

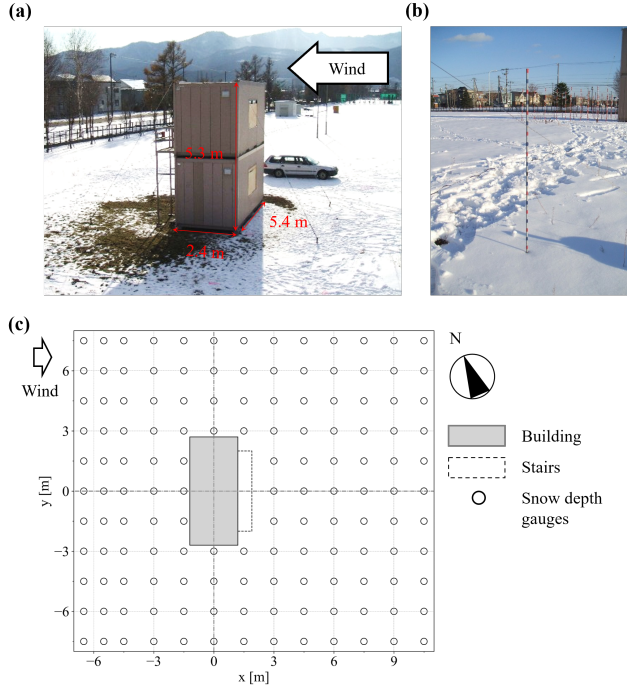


Figure 1: Schematic of the field observation site: (a) target building, (b) snow depth gauge, (c) snow depth observation point.

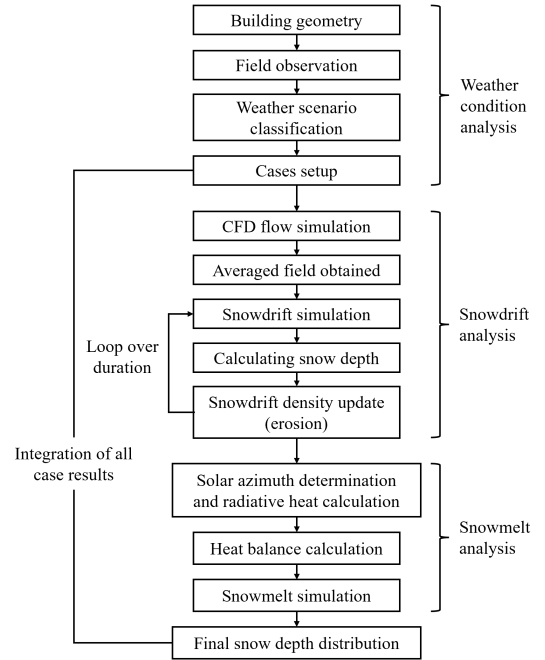


Figure 2: Flowchart of analysis procedure.

3.2 Computational conditions

Based on the field observation site, a computational domain of 150 m (L) \times 100 m (W) \times 80 m (H) was established, with the target building centrally located. The building dimensions were set to 2.4 m (L) \times 5.4 m (W) \times 5.3 m (H), matching the actual structure. The computational domain contained approximately 0.2 million polyhedral cells, with locally refined regions around the building (0.2 m) and ground surface to capture flow separation and snow transport. The first-layer cell height was set to 0.01 m, ensuring a $y^+ \approx 100$ for the simulation. The inflow wind condition was prescribed using a power-law ($\alpha=0.15$) velocity profile constructed from the averaged wind speed of each scenario. Other computational settings follow the guidelines provided by AIJ (Tomimaga et al., 2008). The wind direction was set to WNW, corresponding to the predominant wind during the observation period.

4 A PRELIMINARY RESULTS

Figure 3 compares a preliminary simulated with the observed snow-depth distributions around the building. This preliminary study combined results from snowy and non-snowy conditions under both mean strong and mean weak winds, considering only the dominant wind direction and evaluates the feasibility of the analysis procedure and the implementation of the model. The simulation captures the main characteristics of snowdrift formation, including surface erosion along the side shear layers and snow accumulation in the windward stagnation region. However, snow depth in the wake is noticeably overestimated. One possible reason is that the current framework relies only on mean strong and weak winds, making the results overly sensitive to one certain wind velocity,

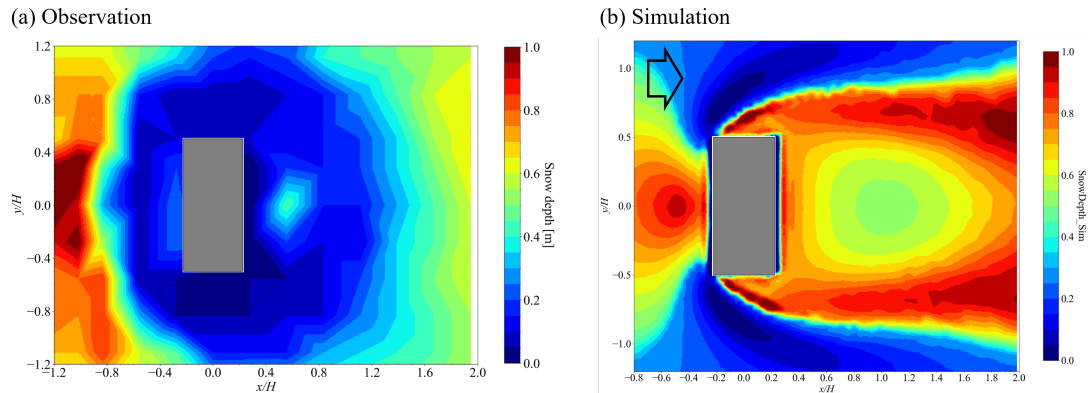


Figure 3: Comparison of simulated and observed snow depth distributions around the building at the end of the initial accumulation stage. (a) Observed snow depth, (b) simulation snow depth.

even though real wind conditions exhibit substantial variability that can strongly affect erosion patterns. Moreover, considering only a single dominant wind direction ignores directional variations that influence snow distribution. Introducing wind-speed variability and limited wind-direction diversification would help reduce these biases and improve model robustness.

5 CONCLUSIONS

This study proposed an integrated long-term snow accumulation prediction that couples snowdrift and snowmelt framework with OpenFOAM. Validation using a rare multi-month field dataset showed that the method can reproduce key features of snow distribution, though further refinement of erosion-related parameters is needed. The results demonstrate the feasibility of the proposed approach for seasonal-scale prediction, and future work will extend the validation and improve model parameterization.

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