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Assessment of atmospheric environments prone to damaging downbursts in Canada

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SUMMARY
Strong winds including downbursts are the most severe weather hazard in Canada based on the recent analysis of insured losses. Hence, this study uses machine learning models to investigate environments prone to damaging downbursts across Canada. Our analyses use the Northern Tornado project database of damaging downbursts over Canada together with the ERA5 reanalysis data and lightning observations for the period 2019–2022. A double-stage verification process was used to train 30 machine learning models for differentiating environments preceding 1) damaging downburst, 2) lightning without damaging downburst, and 3) neither a downburst nor lightning events. Combining two indices—one representing thermodynamics (vertical gradient of equivalent potential temperature) and another dynamics (effective bulk shear) features of the atmosphere—this research proposes a new and robust downburst diagnostics index called the Downburst Precursor Parameter (DPP). A DPP value higher than 2 indicates a high risk of downburst development. We further demonstrated that damaging downbursts were not observed from the Rockies westward while ~45% of the total 294 events occurred in southeastern Canada, in which case squall lines were the dominant storm type (~57%). Considering downbursts accompanied by lightning (~70% cases), nearly half of the events were supercell thunderstorms. The rest 30% of the events were mostly dry downbursts without deep moist convection.

Keywords: Downburst, Instability index, Canada, Machine learning, Atmospheric science.

1. MOTIVATION

Downbursts are strong downdrafts of negatively buoyant air that descends from a thunderstorm cloud and impinges upon the earth's surface (Fujita, 1985). Downburst can produce a severe outflow of locally intense winds that pose treat to human safety and cause damage to the built and natural environments.

In Canada, six of the ten most costly disasters were related to severe thunderstorms (Sills & Joe, 2019). Hadavi et al. (2022) investigated insured losses in Ontario and Quebec during 2008–2021 and demonstrated that nearly three-quarters of all natural catastrophes were associated with severe straight-line winds, which include downbursts. Moreover, they identified that winds associated with convective storms were most disastrous by causing about CA$3.5 billion in insured losses. This figure is roughly 67% of the total wind damage in these two Canadian provinces.

Compared to the United States, Europe, and Australia, climatology of thunderstorms and environments prone to deep moist convection was considerably less investigated in Canada mainly due to the limited data availability. This study fills this research gap by combining reports of damaging downburst over Canada, lightning detection observations, reanalysis data and upper air measurements using Machine Learning (ML) models as well as by using traditional methods of analysing the profiles of equivalent potential temperature.

2. METHODOLOGY

Fig. 1 summarizes the overall workflow of this study.

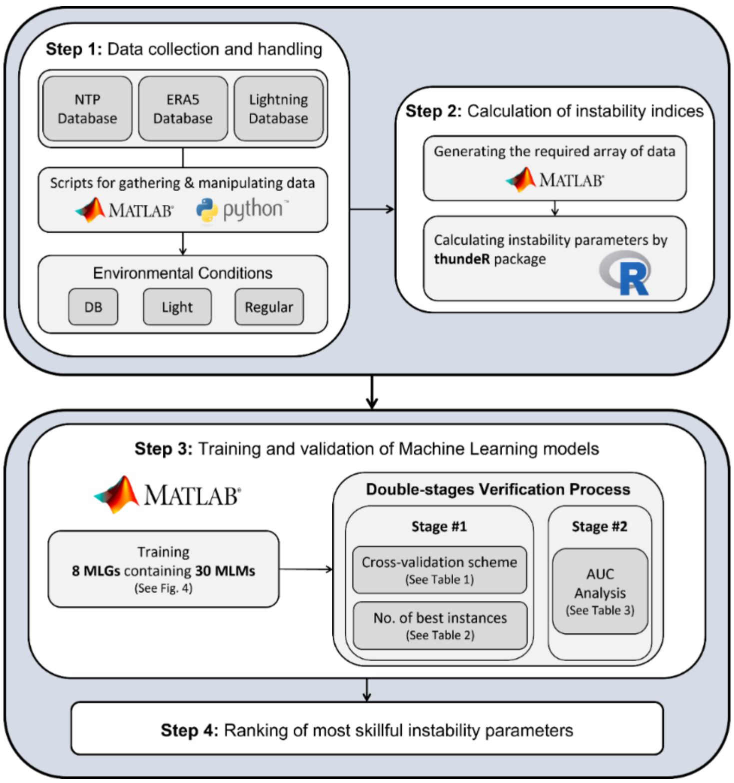

Figure 1. Overall workflow of the present study.

Downburst data for 2019–2022 were obtained from the Northern Tornado Project database (NTP, 2022), and lightning data were provided by Environment Canada's Canadian Lightning Detection Network. 30 ML models were trained based on ERA5 reanalysis data for discriminating environments preceding 1) damaging downburst [294 cases], 2) lightning without downburst [218,131 cases], and 3) neither downburst nor lightning [618,163 cases] and a total of 108 instability parameters was evaluated in the process. Firstly, the cross-validation scheme was employed to examine the predictive accuracy of the fitted models by partitioning the dataset into five folds. In the second stage, we investigated Receiver Operating Characteristic (ROC) curves and the associated geometrical Area Under Curve (AUC). This analysis provided a suitable summary statistic for the performance of different ML models and instability parameters.

3. HIGHLIGHTED RESULTS

Three ML models of (1) Ensemble Boosted Trees, (2) Decision Tree with maximal decision splits of 20, and (3) Tri-layered Neural Network outperformed the rest models. As presented in Table 1, six instability parameters were identified as the most skilful based on the average AUC values for the selected ML models for 100 iterations. Other operational forecasting parameters, like CAPE or WINDEX, showed less-reliable AUC scores indicating the distinction of environments leading to downbursts in Canada from the ones in the United States.

Table 1. Selected skilful damaging downburst indicators for Canada.

Rank	Parameter name	AUC average
#1	Cold Pool Strength	0.83
#2	$\Delta\theta_e$	0.80
#3	Effective Bulk Shear	0.79
#4	WMAXSHEAR	0.79
#5	Freezing Height	0.77
#6	Mixing Ratio	0.76

We conducted the Pearson correlation analysis and investigated the probability of downburst occurrence given lightning for all possible selected parameters' combinations. It was detected that the bins with high fraction of downburst to lightning occurrences follow a linear relationship between the second and third ranked parameters in Table 1. Combining those two thermodynamic- and dynamic-related indices, this study proposes a robust Downburst Precursor Parameter (DPP) for Canada that is defined as follows:

$$\mathrm{DPP} = \frac{\mathrm{BS\ EFF} + 0.6\Delta\theta_e + 27}{25.3}. \tag{1}$$

DPP is reliable damaging downburst precursor with the associated ROC score of 0.9 when the best ML model is employed. Three considered environmental categories are separated by DPP (Fig. 2). DPP higher than 2 and lower than 1.5 indicates the maximum and minimum risk of developing a damaging downburst, respectively.

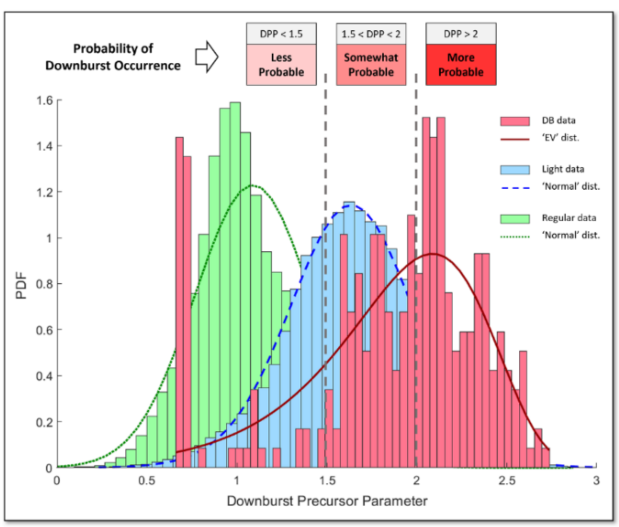

Figure 2. Probability density function of DPP values for three considered environmental categories.

The reported damaging downbursts were distributed mostly in the southern part of Canada, while there was significantly less downbursts in central Canada and no detected downburst from the Rockies westward (Fig. 3). Approximately 45% of damaging downburst events occurred in southeastern Canada.

The investigation of radar images of convective modes associated with damaging downbursts in Canada revealed that supercells and Quasi Linear Convective System (QLCS) were the most dominant storm types (Fig. 3). Supercells commonly occurred east of the Rockies and in the central parts of Saskatchewan along the northern boundary of the Great Plains. QLCS was the dominant convective mode in the southeastern Canada.

Near half of the storms associated with damaging downbursts were supercells when downburst events were accompanied with a lightning. The rest were mostly dry downbursts without deep convection (frequent around the High Plains' edge) or with disorganized convective pattern.

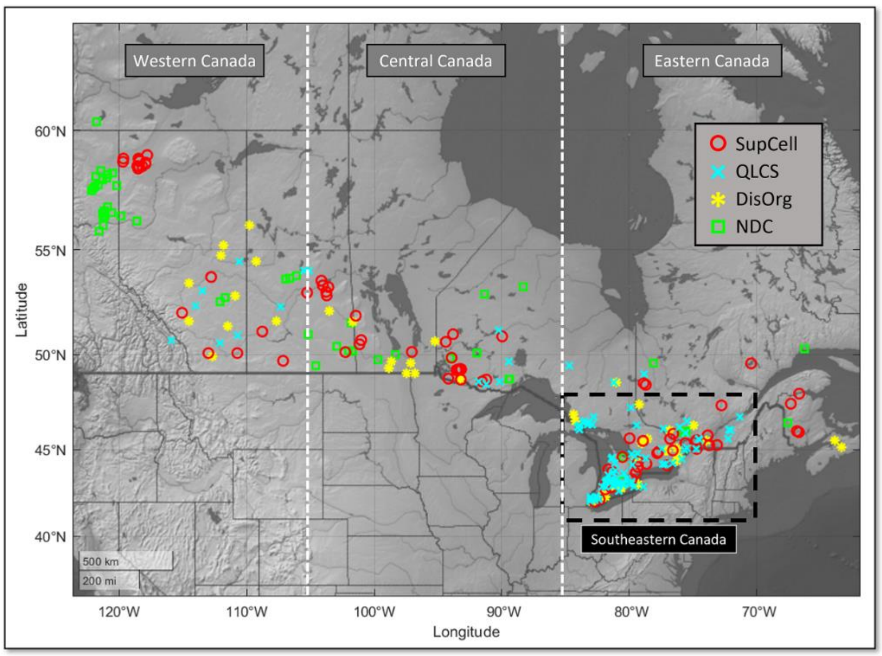

Figure 3. Storm modes that produced damaging downbursts in Canada (SupCell = supercells; QLCS = quasilinear convective systems; DisOrg = disorganized convection; NDC = no deep convection detected).

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