CWE-8
June 7-11, 2026
London, ON, Canada

AI-Assisted Satellite Detection of Tornado and Downburst Forest Damage in Canada

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SUMMARY

This study outlines an AI-assisted pipeline to accelerate the Northern Tornadoes Project's end-of-season satellite analysis for detecting remote, often unreported tornado and downburst damage in Canada. Utilizing Planet Labs' annual August RGB basemap tiles (~4.7 m/pixel), the pipeline first creates filtered "difference images" masking clouds, water, and urban areas, while highlighting red-band increases associated with summer forest damage. Next, this mask is refined using a ResNet-50 CNN that compares before-and-after imagery through overlapping 32x32-pixel patches to identify potential forest damage for manual review. Trained on over 100,000 patches from more than 300 storm tiles, the model achieved approximately 98% validation accuracy and Dice score. Screening approximately 10,000 tiles across Canada's forested regions, the model flagged approximately 25% for inspection. After manually inspecting these tiles, early 2025 findings include 47 tornadoes, 85 downbursts, and 59 unclassified wind-damage cases. Future work aims to develop better architectures and expand training data.

Keywords: *Deep Learning, Tornadoes, Satellite, Automation*

1. INTRODUCTION

The Northern Tornadoes Project (NTP), a division of the Canadian Severe Storms Laboratory (CSSL), aims to detect and analyze every tornado and downburst that occurs in Canada (Sills et al., 2020). Because of Canada's vast area, the only significant damage from these severe storms often occurs in remote forested regions that frequently go unreported. To detect these remote, unreported storms, researchers at the NTP conduct an end-of-season systematic sweep of Canada's forested areas using satellite imagery. By comparing satellite imagery from different dates, large swaths of damaged trees can be detected and classified as tornado- or downburst-related damage, among other severe storm impacts (Kunkel et al., 2023).

Various other groups have also greatly benefited from satellite analysis in research on tornadoes and other severe storms (Kingfield and de Beurs, 2017; Burow et al., 2020). Moreover, many studies have found various satellite products beneficial for tornado damage detection, including the Normalized Difference Vegetation Index (NDVI) (Miller et al., 2025) and Synthetic Aperture Radar (SAR) (Slabon et al., 2025). For the NTP specifically, however, performing a systematic sweep of satellite imagery across all tornado-prone forested regions of Canada (over 3 million km^2) is time-consuming and currently requires multiple months for a team of researchers to complete. Recent advancements in deep learning and computer vision have made significant strides in automating various aspects of object detection in both everyday and satellite imagery (Agrawal et al., 2024). Consequently, to expedite this process, this study describes an automated computer vision model that was experimentally employed during the 2025 storm season to help detect both tornadoes and downbursts.

2. METHODOLOGY

For this study, Planet Labs' monthly base map imagery (Planet Labs, 2025) is used to compare August imagery from consecutive years. This RGB visual imagery has a resolution of 4.7m per pixel and is divided into approximately 19.25 x 19.25 km (4096 x 4096 pixels) basemap tiles, with more than 10,000 tiles covering Canada's forested regions.

2.1. Difference Image Generation Pipeline

To compare with the later discussed AI model and refine its predictions, the first step is to generate a filtered difference image that highlights the changes between the before and after images. Initially, both images are filtered using land-cover maps (Government of Canada, 2020) and Planet Labs' usable data masks (UDMs). These land-cover maps and UDMs are based on their own machine-learning models and are used to exclude cloud cover and land types unlikely to contain damage areas, such as bodies of water and urban regions. Next, the before image is subtracted from the after image, with all pixels that do not have an increase in the red band being removed (set to black). Similar to NDVI and the near-infrared band used for crop damage, damage to trees in summer RGB imagery shifts from green to brown/tan, requiring an increase in the red band. Finally, the absolute value of this difference is taken, and the image is contrast-enhanced for visual clarity. Figure 1 shows an overview of the difference image generation pipeline.

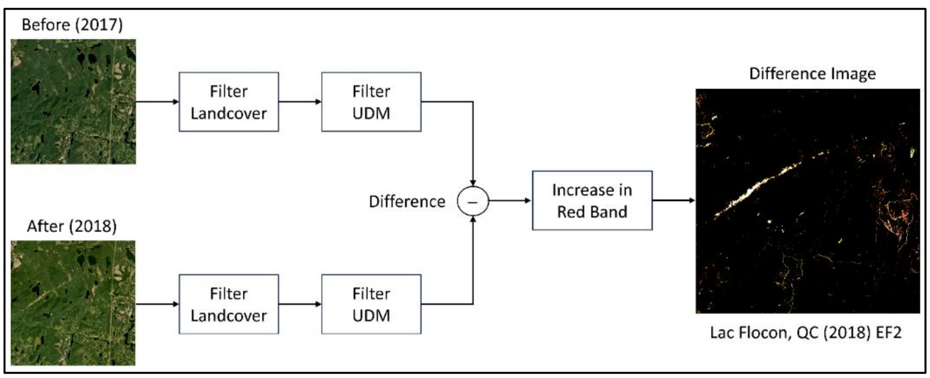

Figure 1: Overview of the difference image generation pipeline for the Lac Flocon, QC, 2018 tornado.

2.2. Deep Learning Pipeline

Due to the rarity and diversity of tornado tracks, existing computer vision instance segmentation architectures, such as Mask R-CNN models (He et al., 2017), may not achieve sufficient accuracy to detect every tornado across the extensive search area. Instead of directly predicting tornadoes, a forest-damage detection model will be employed. This model utilizes a convolutional neural network (CNN) to automatically compare small sections of satellite imagery taken at different times and identify regions with significant changes in the forest. Consequently, only areas with detected forest damage need to be manually examined for tornado tracks, greatly reducing the search time, while aiming to balance the model's accuracy and precision to prevent missing any tornadoes. First, the before-and-after images are stacked into a single 6-channel image, which is then split into overlapping 32x32-pixel (~150x150m) patches. Next, a ResNet-50-based CNN (He et al., 2015) was trained to classify whether each patch contains forest damage consistent with a tornado or downburst. After all patches are predicted, the overlapping patch predictions are merged and averaged to create the overall model's prediction for a given tile. The predicted tile is then filtered to remove pixels absent from the difference image. Figure 2 shows an overview of the deep learning prediction pipeline.

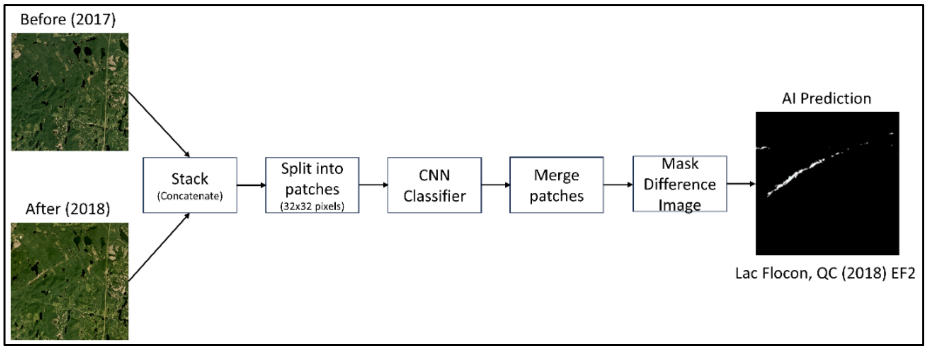

Figure 2: Overview of the full AI-model prediction pipeline for the Lac Flocon, QC, 2018 tornado.

3. PRELIMINARY RESULTS

To train the model, a dataset of over 100,000 32x32-pixel patches were collected from more than 300 tiles containing tornadoes and downbursts, with half of the patches representing forest damage and the other half randomly selected from non-forest-damaged areas. The tiles were split 80/20% for training and validation, respectively. Given the simplicity of this binary classification task, the current model achieved a validation accuracy and Dice score of approximately 98%. Figure 3 shows two example test cases for both the generated difference image and the AI model's prediction of the tornado track. Both cases were excluded from the training and validation data.

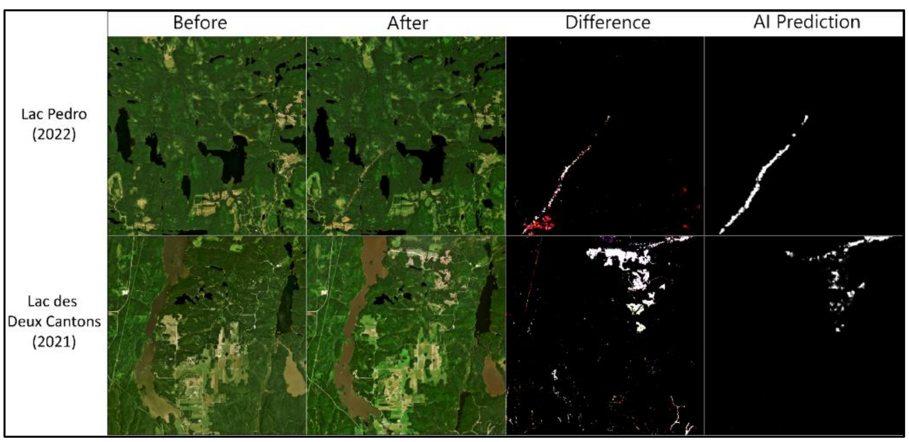

Figure 3: Two example test cases displaying both the difference image and the AI model's prediction.

Once the current model had finished training, it was run on approximately 10,000 tiles spanning Canada's forested regions. Roughly 25% of tiles were flagged as potentially containing storm forest damage. The AI's prediction for these tiles were then manually examined to determine if they contain a tornado, downburst, or other unclassified wind-related damage. Table 1 provides a preliminary overview of the storm damage found using AI-assistance for Canada in 2025. The model performs effectively at identifying tornado- and downburst-related damage, but also inevitably predicts many false positives from non-storm-related forest damage, such as logging or forest fires. Overall, the model saves a considerable amount of time by reducing the number of tiles that must be searched and by highlighting the parts of a tile most likely to contain damage.

Table 1: Preliminary results for AI-assisted satellite sweep of Canada 2025

Event Type	Newly Found	Previously Known	Total
Tornado	32	15	47
Downburst	59	26	85
Unclassified	47	12	59

4. CONCLUSIONS AND FUTURE WORK

This study introduces an automated computer vision model used during the 2025 storm season to detect tornadoes and downbursts. The model has significantly enhanced the efficiency of the NTP's end-of-season satellite sweep across Canada. Future efforts will focus on developing new CNN architectures to improve the model's accuracy. In addition, data from U.S. and European tornadoes and downbursts will be added to expand the training dataset's size and diversity, potentially broadening the model's use beyond Canada.

ACKNOWLEDGEMENTS

This research was funded by ImpactWX, Western University, and the Natural Sciences and Engineering Research Council of Canada (NSERC).

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