Evaluation of PV Snow Loss Models in the East Coast of Canada using AI Computer Vision

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Introduction

Quantification of operational snow loss and evaluation of snow loss models for ground mounted systems has been conducted in the literature for several high latitude inland locations in North America but there is limited information available on the level of snow loss expected for high latitude coastal sites with high wind conditions. This study explores the performance of existing snow loss models for the Wind Energy Institute of Canada's (WEICan's) site which has these characteristics using AI Computer Vision to detect site snow losses.

WEICan's Solar Photovoltaic (PV) site description:

- Fixed 30° tilt system
- 85 monofacial and 187 bifacial panels
- 1.14 AC : 1 DC ratio - no clipping losses.
- Northwest tip of PEI, Canada, with 15 m altitude, 300 degrees of ocean exposure, high winds and harsh winter conditions.

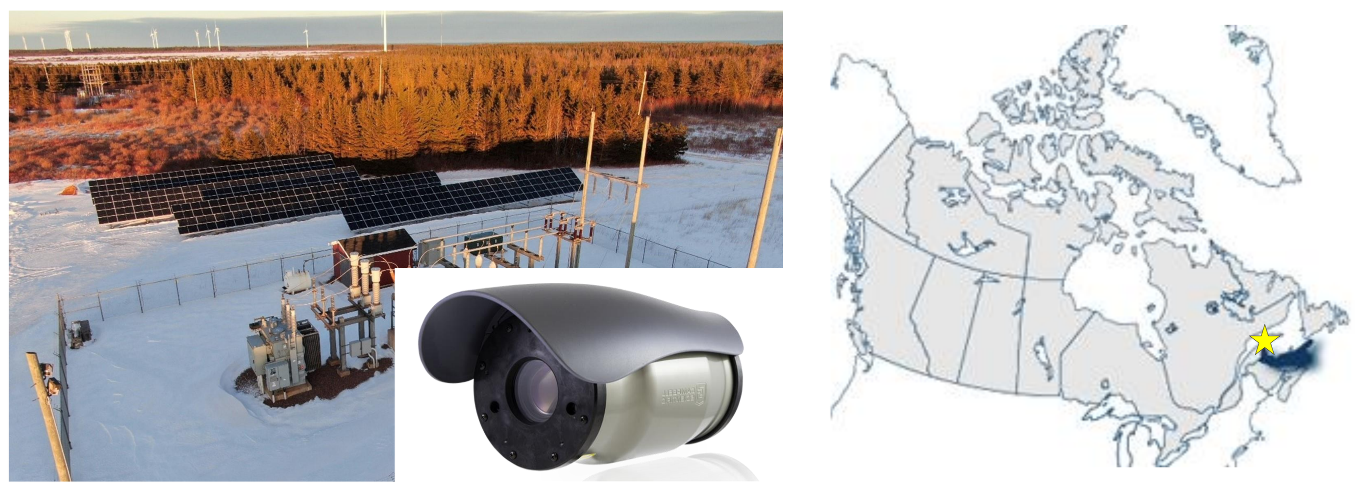

Fig. 1 Image of WEICan PV site and camera (left) and site location (right)

WEICan Snow Loss

AI Computer Vision Snow Detection

A camera was placed with view of the solar array to monitor snow cover over the winter months. Images of the array are captured and stored every 2 minutes. AI computer vision was used to assess the images and a machine learning algorithm [1] was used to determine whether the panels were impacted by snow cover and to provide an indication of snow reduction rates.

a)

b)

c)

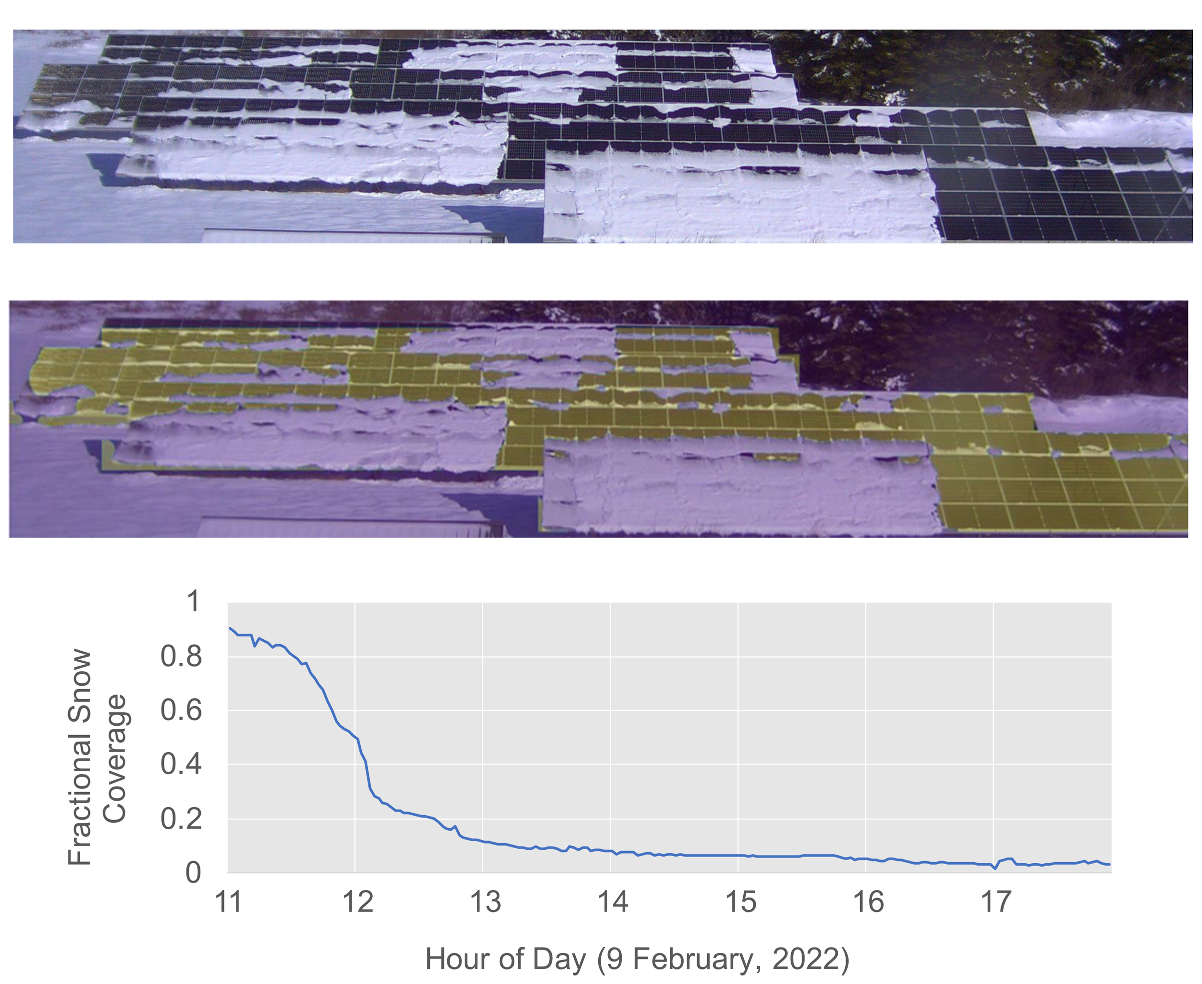

Fig. 2 AI computer vision snow detection for 9 February 2022. a) original image for 12:04 am b) algorithm results for 12:04 am c) diurnal snow coverage plot showing snow melt throughout the day

WEICan Snow Loss (cont.)

Production Loss Data Analysis

A multi-linear regression model considering screened and filtered power production, irradiance, wind speed and air temperature was assessed for the site on a rolling six-week basis [2]. As the PV system is a mix of monofacial and bifacial panels, reflected irradiance was accounted for in the irradiance term, as recommended in [3]. The resulting baseline performance model was compared to unfiltered SCADA power production as shown in Fig. 3 and Fig. 4 and was used to quantify the snow cover production loss for the site.

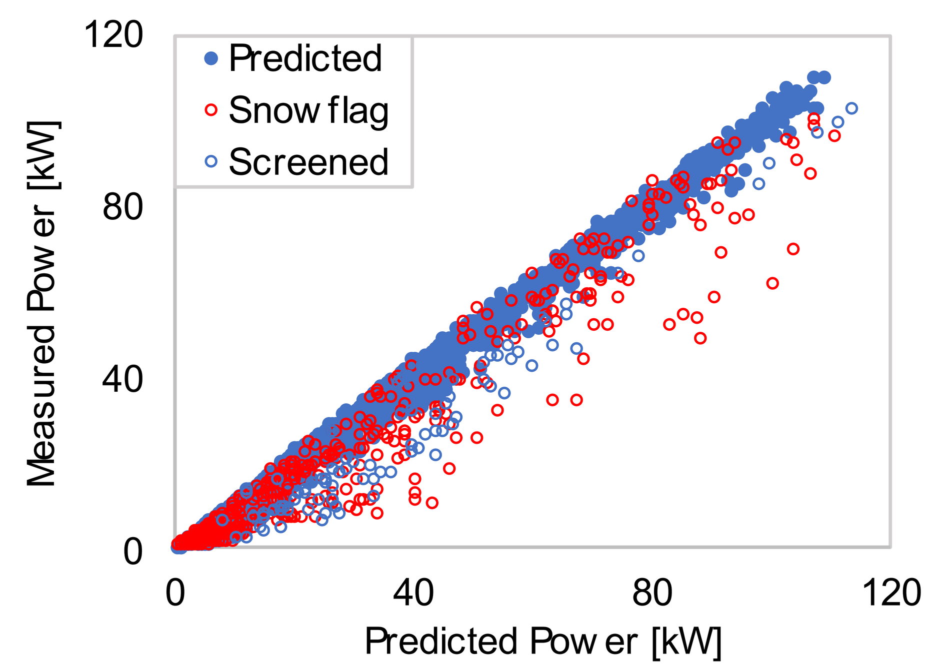

Fig. 3 Hourly Measured Power vs Predicted Baseline Power. Only data in solid blue were considered for curve fitting. Hollow data circles in red represent data records where snow was observed. Hollow data circles in blue represent data periods of underperformance with no visual indication of snow cover which were also removed from the regression analysis.

Fig. 4 presents the timeseries deviation of measured power from the baseline performance model due to snow for March 2022.

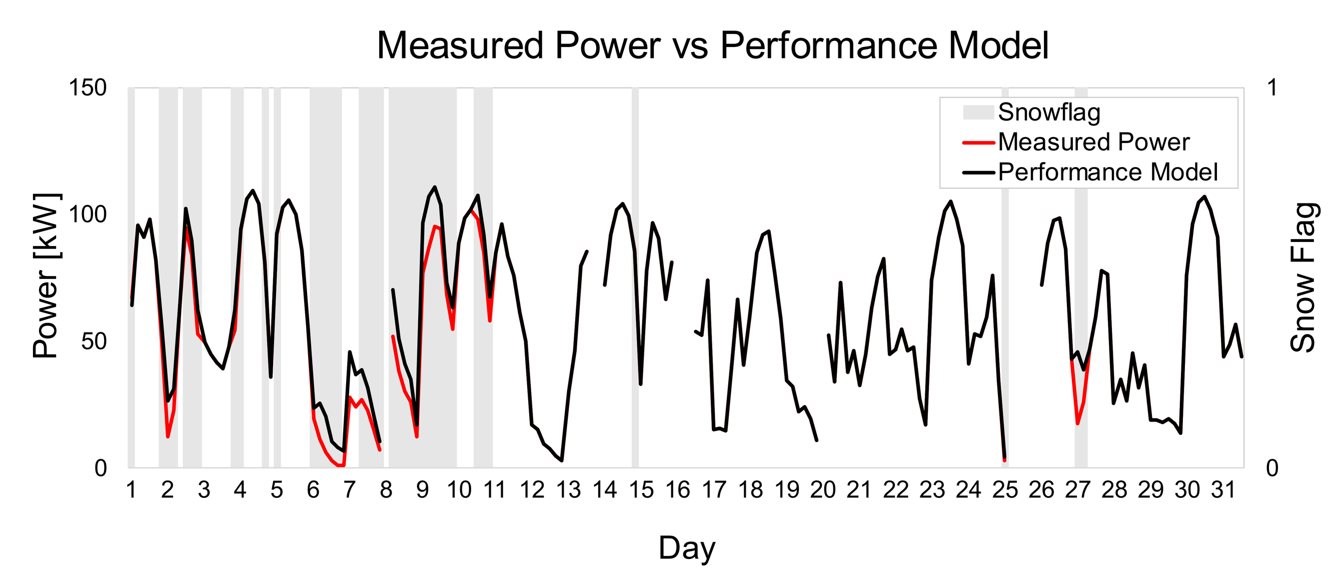

Fig. 4 Active power recorded on site vs results of the performance model for March 2022 with nighttime periods removed. Grey background indicates records flagged for snow cover.

Operational snow loss discussion

- The method outlined in this study for image capture and detection of snow on a PV system is a repeatable process that can be applied at any site with a relatively low-cost camera and system for automatically logging and storing images.
- The machine learning algorithm used to calculate snow coverage performed well for days with snow but was sensitive to rain, fog, icing on the camera and sun glare off the solar panels which in some cases produced false positives.

Evaluation of Snow Loss Models

The impact of operational snow cover was compared to results from two predictive snow loss models. Models were calculated using inputs from the WEICan Solar PV weather monitoring station and using the National Operational Hydrologic Remote Sensing Center (NOHRSC) snow data [6]. Annual (2022) and seasonal (January 2023 to April 2023) results are shown in Table 1 and Fig. 5, respectively.

TABLE I: 2022 Assessed and Modeled Annual Snow Loss

Model	2022 Snow Loss	Description
WEICan	1.3 %	Snow loss detected from AI computer vision and site data analysis.
NREL (default)	2.7 %	Default for ground mounted systems.
NREL (site specific)	1.7 %	Slide threshold of -50 $W/m^2/°C$ calculated from site data for periods where snow was reducing.
Townsend (default)	2.7 %	Default values with no ground interference term.
Townsend (site specific)	n/a	Empirical model fit to site losses to determine a site-specific slope of 3.2E04. Results were evaluated for Jan-Apr 2022 only in Fig. 5 as Oct-Dec 2022 was used to train the model.

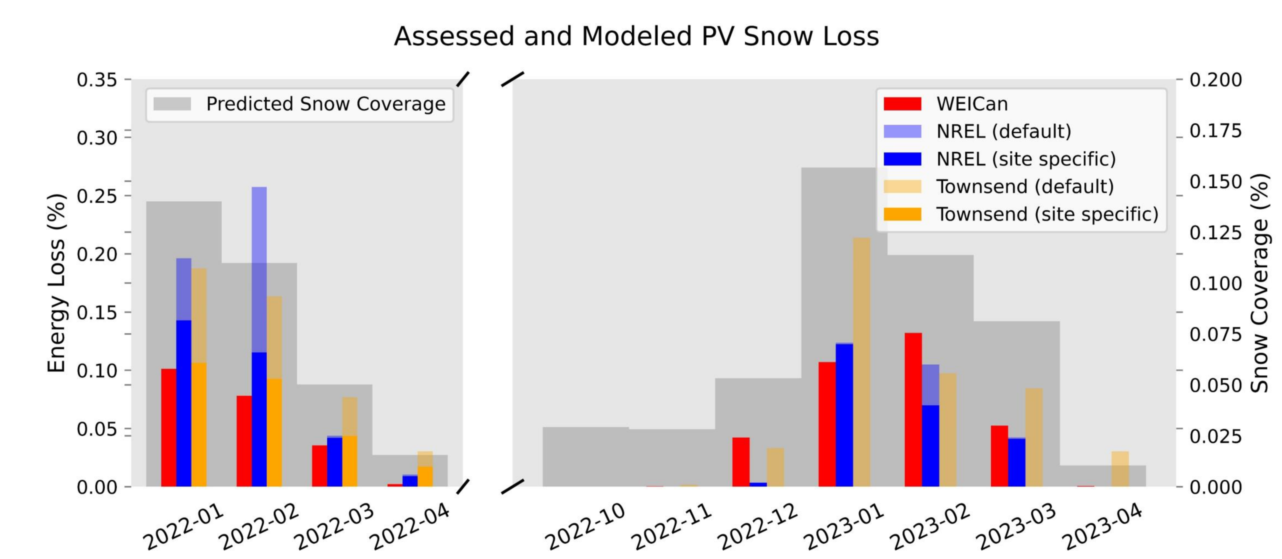

Fig.5 NREL, Townsend and WEICan energy loss estimates due to snow. WEICan's algorithm for the monthly average of snow coverage is represented with shaded gray bars.

Predictive snow loss model discussion

- The Townsend and NREL snow loss models which were developed in California and Colorado, produced similar monthly trends but overpredict absolute snow loss values on a monthly and annual basis.
- Snow reduction periods and production losses determined through AI computer vision and site data can be used to calculate site-specific model coefficients to improve the Townsend and NREL snow loss predictions for different regions and climates.

Summary

- The image analysis used in this study is a transferrable methodology that can indicate the snow losses incurred at a PV site
- Townsend and NREL models using default settings overpredict the snow losses for the coastal northern latitude WEICan site
- The proposed method can be used to measure snow reduction periods and losses required to calculate site-specific parameters for the Townsend and NREL models
- Indicative site-specific parameters for the Townsend and NREL models were calculated and presented for WEICan's PV site .

References

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