Machine Learning for Cloud Detection in Sentinel-2 Imagery: Enhancing Arctic Visibility to Support Indigenous Sea Ice Navigation

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Introduction

Arctic satellite remote sensing faces a major challenge, with over 60% of days affected by cloud cover (Meraner et al., 2020). Sentinel-2's cloud mask, the Scene Classification Layer (SCL), often misclassifies snow as cloud, reducing usable imagery and creating a 'geographic data blindness' in Arctic monitoring (Qiu et al., 2019). Reliable cloud detection is essential for Inuit communities, whose hunting and navigation depend on sea ice (Rantanen et al., 2022).

Therefore, this study evaluates machine learning models to address snow-cloud confusion in Sentinel-2 data, supporting UCL's Inuit-led mapping platform (SIKU) in Pond Inlet (Fig. 1).

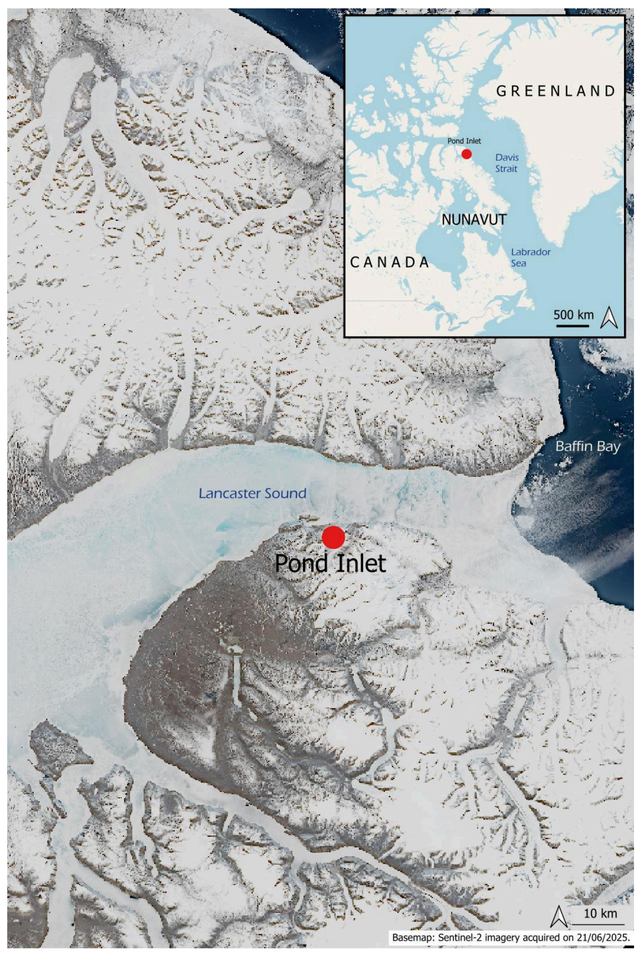

Fig. 1. Study area: Pond Inlet, Nunavut.

Consequently, the research aims are:

- Evaluate CNN, K-Means, and brightness-based methods.
- Compare performance against SCL
- Support SIKU with more reliable cloud detection in the Arctic.

Methods

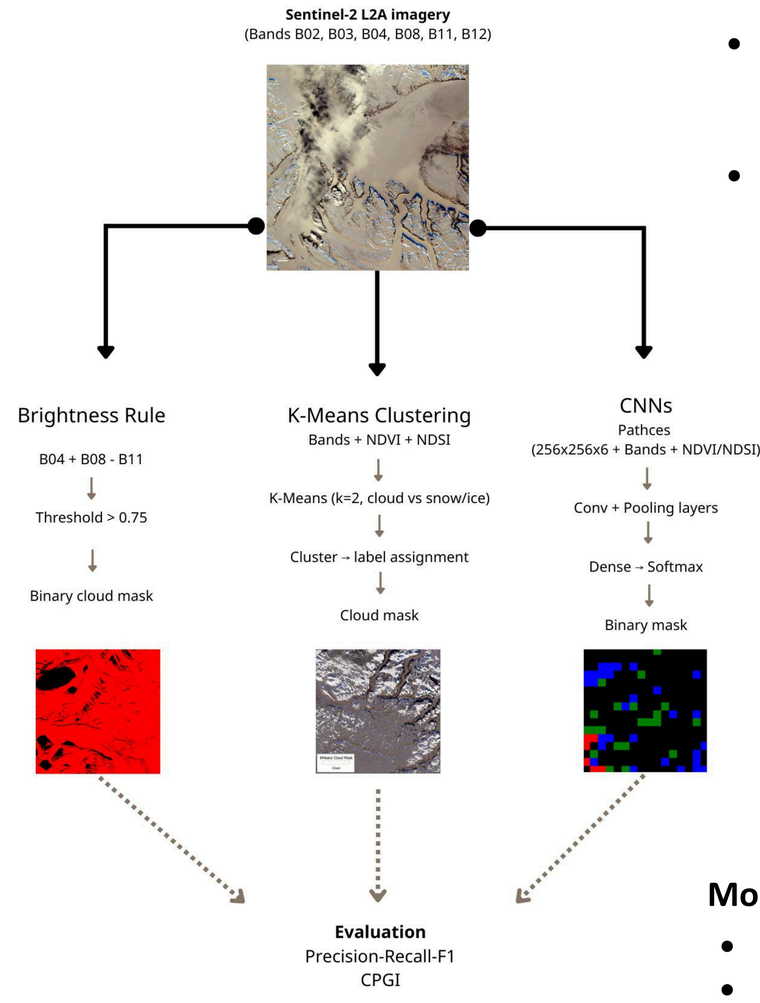

Fig. 2. Overall methodology.

- **Dataset**: 24 Sentinel-2 L2A tiles (Mar–Jun 2025).
- **Processed** as full tiles and 256x256 patches due to computational limits.
- **Manual labelling**: QGIS SCP & Python
- **Inputs**: Sentinel-2's 6 spectral bands, spectral indices (NDVI/NDSI)

Models tested (Fig. 2):

- CNN (supervised)
- K-Means (unsupervised)
- Brightness rule (B04+B08–B11 > 0.75)

Evaluation metrics:

- Precision-recall-F1
- Clear Pixel Gain Index (CPGI) to quantify gains over SCL

Results

- CNN: Strong in snow-dominated tiles → F1 ≈ 0.80 (Fig.4).
- K-Means: Strong in heterogeneous spring/summer tiles → F1 up to
- 0.90 (Fig. 4).
- Brightness rule: High recall (>0.9) but poor precision (<0.7), successfully identified clouds but also misclassified snow. CPGI: Up to +35% clear pixels vs. SCL (T18WVE; Fig. 5).

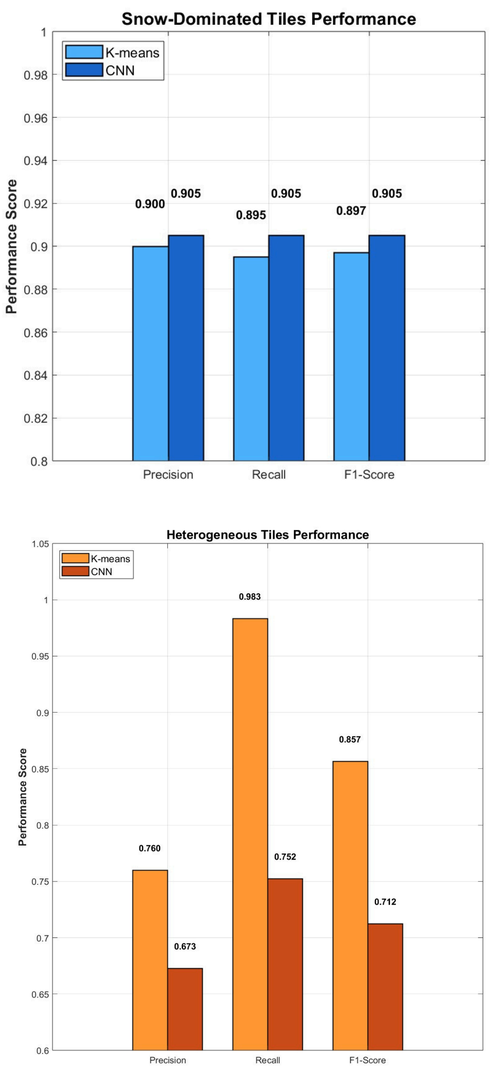

Fig. 3. Snow-dominated (top) and heterogeneous tiles performance (bottom).

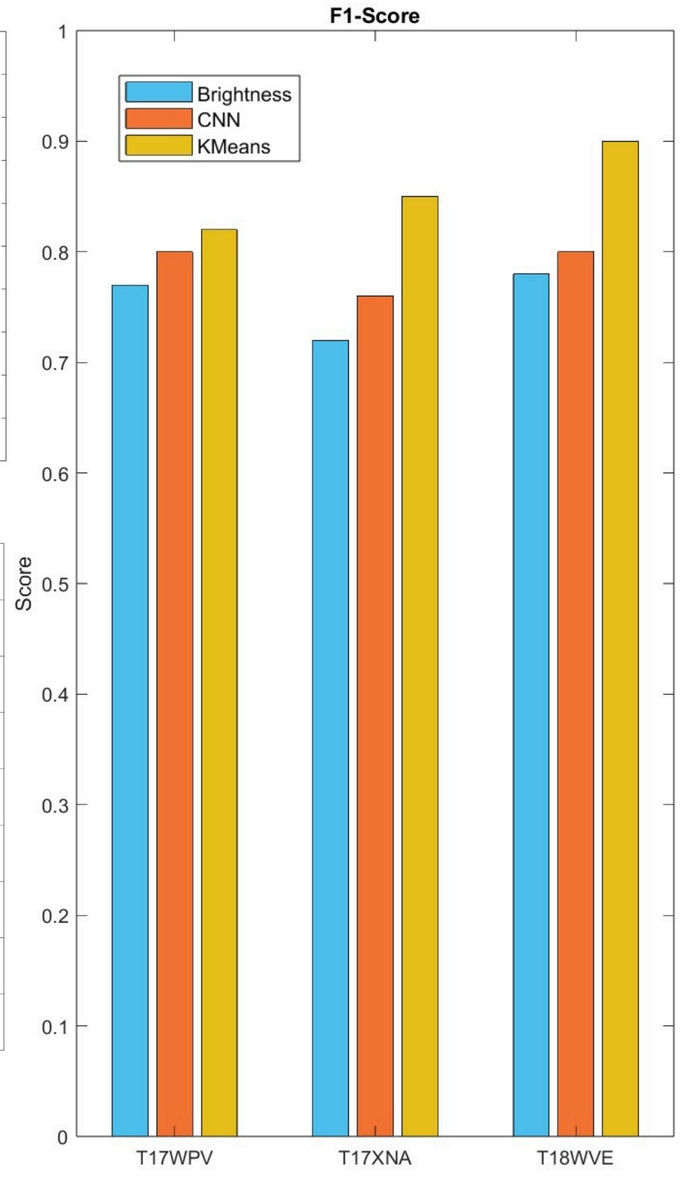

Fig. 4. Each model's F1-score on validation tiles.

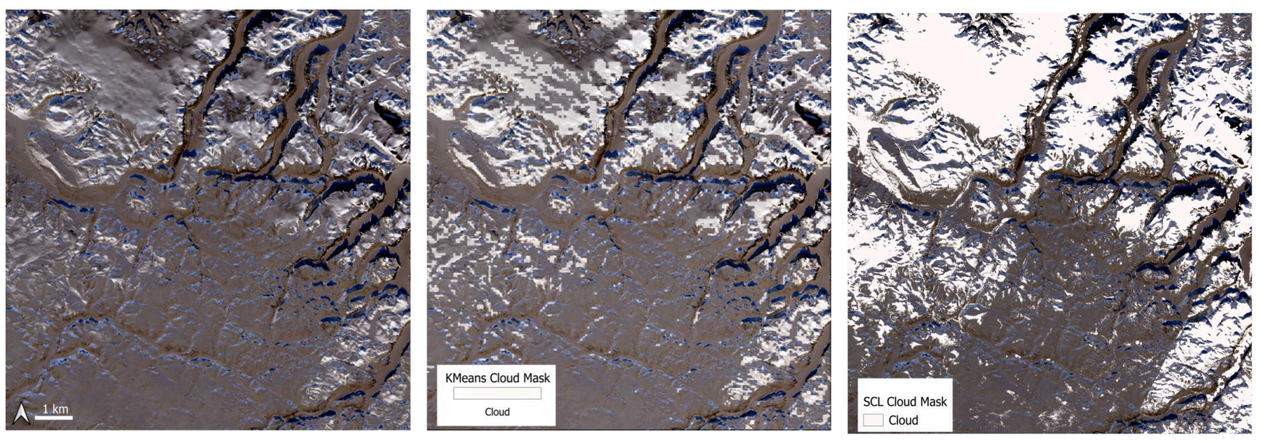

Fig. 5. Left: T18WVE RGB. Middle: K-Means mask. Right: SCL mask.

Discussion

SCL consistently underperformed. The brightness rule should be a rapid detection method integrated into workflows prioritising interpretability. CNN reduced snow-cloud confusion by learning characteristic patterns and spectral signatures but was computationally extensive. K-Means held an intermediate position, stronger than SCL and brightness thresholding but less generalisable than CNNs. An adaptive strategy is proposed: CNN for snow- dominated months, K-Means for heterogeneous surface months (Fig. 3).

Conclusion

Seasonal adaptive masking increases usable Sentinel-2 imagery, supporting Inuit-led sea-ice safety through SIKU, a mapping platform integrating satellite data with Indigenous knowledge. Future studies should implement full-tile CNNs on high-performance computing to enable year-round monitoring.

Key References

Meraner, A., Ebel, P., Zhu, X. X., & Schmitt, M. (2020). Cloud removal in Sentinel-2 imagery using a deep residual neural network and SAR-optical data fusion. ISPRS Journal of Photogrammetry and Remote Sensing, 166, 333–346. https://doi.org/10.1016/j.isprsjprs.2020.05.013.
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