Machine Learning Framework for Extending SMOS Surface Soil Moisture Observations over Canada

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Background of the study

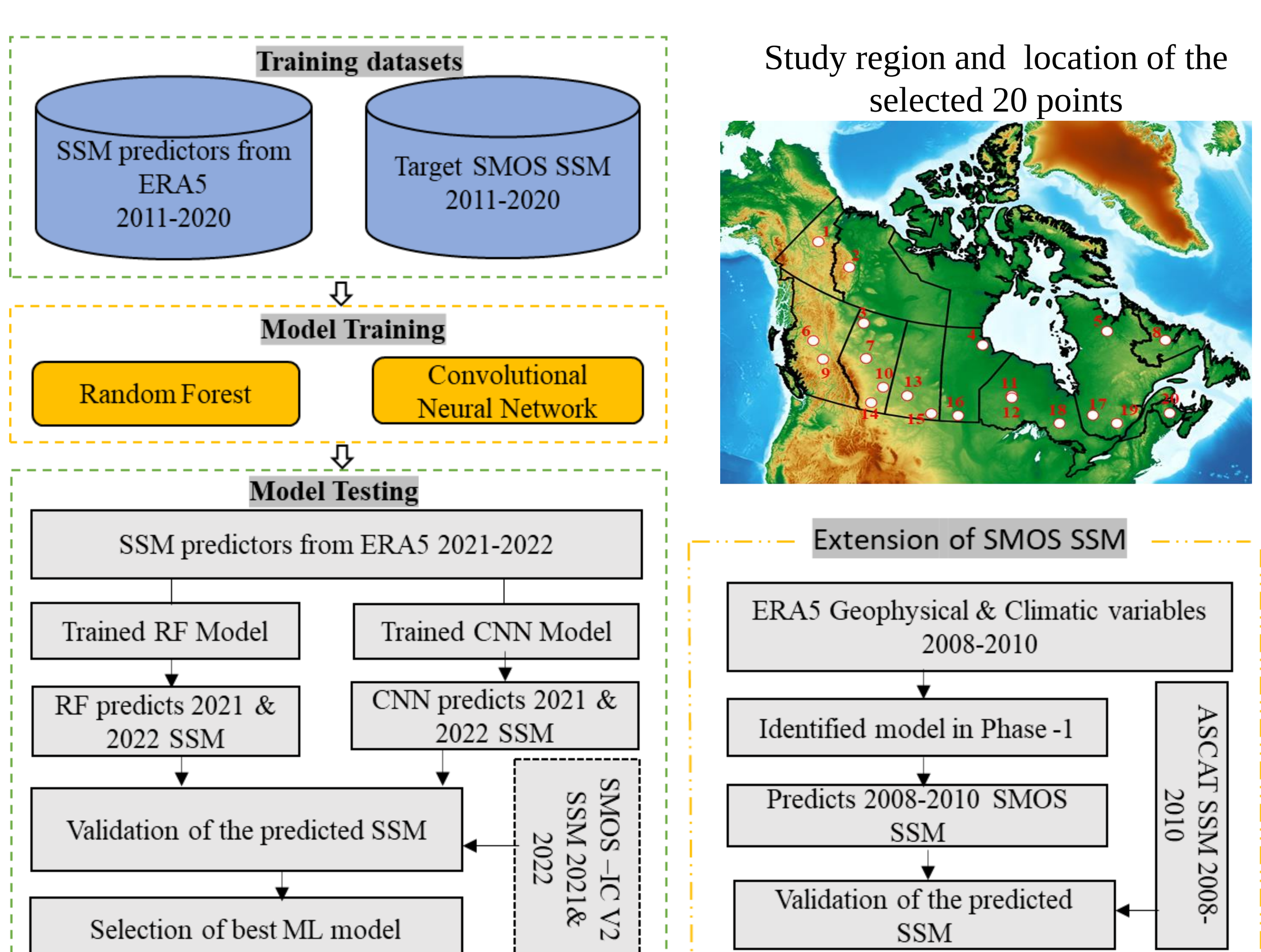
- The launch of several satellite missions has expanded research possibilities in the area of soil and vegetation interactions, both regionally and globally.
- These missions exhibit data deficiency in regions with complex topography, snow-covered and densely forested regions.
- Machine learning algorithms are effectively used to fill data gaps in various soil moisture products.

Objective: To develop a novel framework using ML approaches for the spatiotemporal extension of the SMOS observations over Canada.

Datasets

DATASET	RESOLUTION	ALGORITHM
SMOS-IC V2	25 KM , DAILY	L-MEB
ASCAT	25 km, 1-3 days	Change Detection Algorithm

Methodology

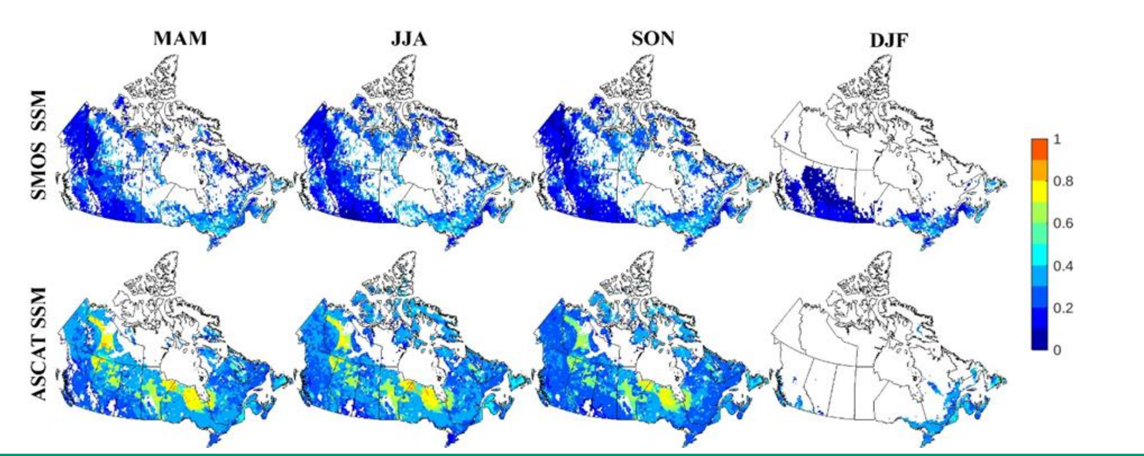


ERA5 Variables

- **Total precipitation,**
- **Evaporation,**
- **2-m air temperature,**
- **2-m dewpoint temperature,**
- **dewpoint depression (proxy for humidity),**
- **snowmelt,**
- **snow depth and**
- **water availability**
- **Soil type, vegetation type and their fractional areas lake fraction**

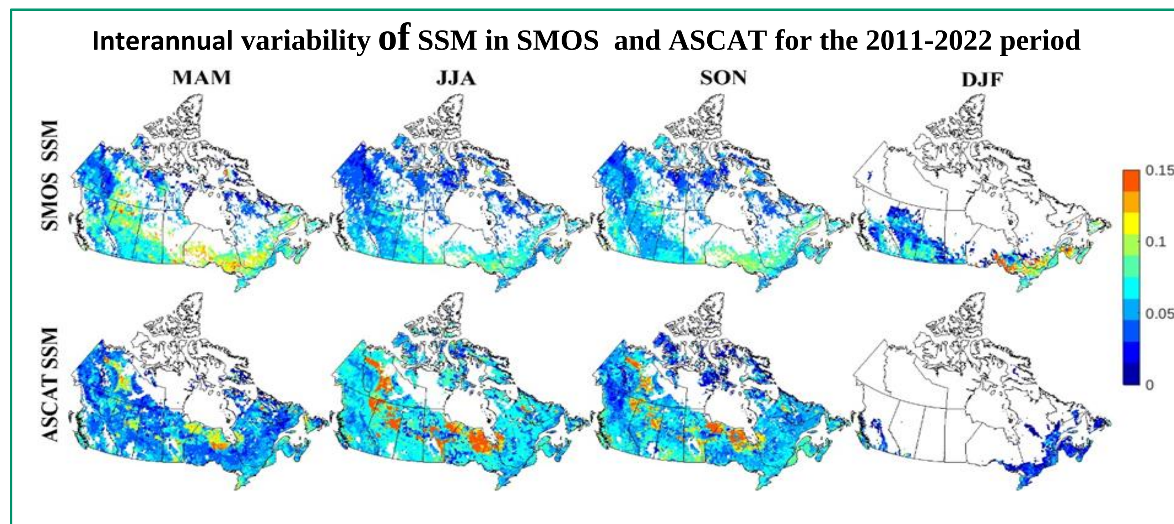
Results: Development & Validation of ML

Mean seasonal surface soil moisture for SMOS and ASCAT for the



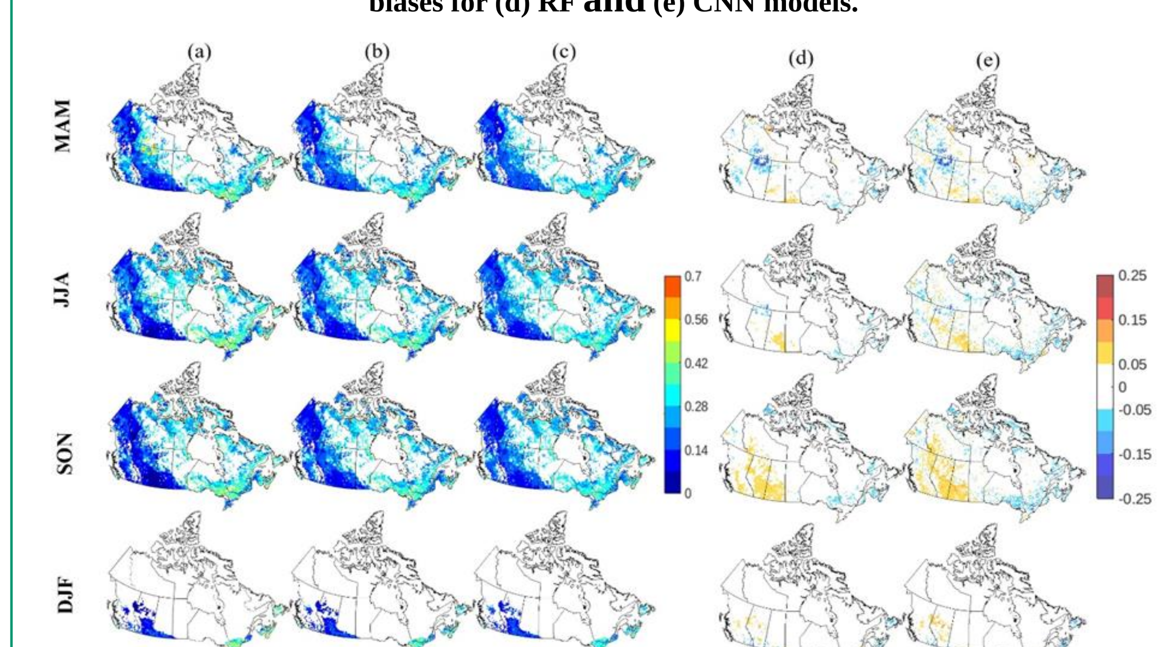
- ✓ SMOS SSM data shows high soil moisture (0.3–0.4 m^3/m^3) in southeast and maritime regions year-round.
- ✓ ASCAT data shows higher soil moisture in boreal forests and peatlands (0.6–0.9 m^3/m^3) compared to SMOS readings

Interannual variability of SSM in SMOS and ASCAT for the 2011-2022 period



- ✓ SMOS and ASCAT show high variability in southern regions.
- ✓ SMOS shows high interannual variability towards the southern limit of the boreal forest region
- ✓ In ASCAT, high interannual variability over regions characterized by organic soil

Mean seasonal SSM for (a) SMOS, (b) RF and (c) CNN for the year 2021, and the prediction biases for (d) RF and (e) CNN models.



- ✓ The bias lies in the $\pm 0.09 m^3/m^3$ range for the RF model and in the $\pm$ 0.15 range for the CNN model
- ✓ CNN model exhibits higher levels of overestimation over the Canadian prairies during SON
- ✓ Regions with biases in RF and CNN predictions are collocated
- ✓ These are also regions with higher inter-annual variability

Evaluation metrices RMSE and R for the year 2011-2020

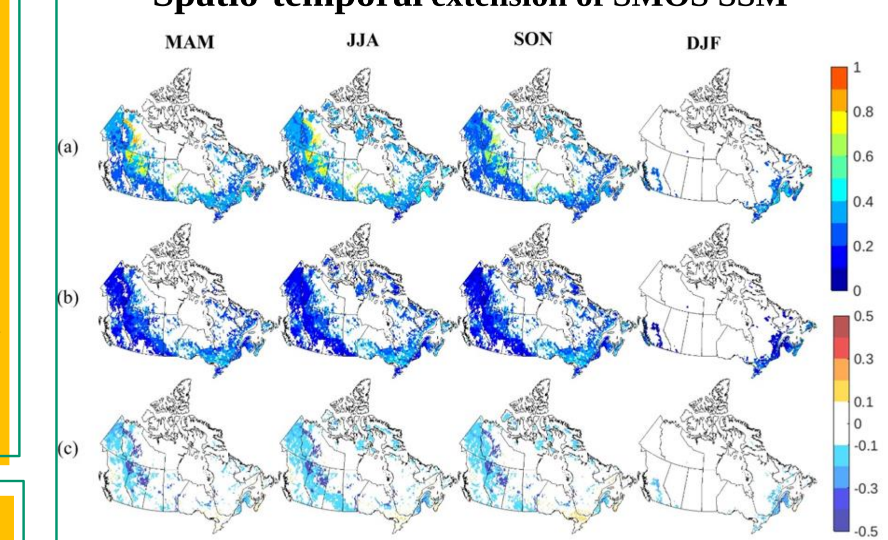
Year	Seasons	RF RMSE (m^3/m^3)	RF R	CNN RMSE (m^3/m^3)	CNN R
2011-2020	MAM	0.013	0.79	0.058	0.57
	JJA	0.011	0.95	0.042	0.66
	SON	0.017	0.81	0.093	0.36

Evaluation metrices RMSE and R for the year 2021 & 2022

Year	Seasons	RF RMSE (m^3/m^3)	RF R	CNN RMSE (m^3/m^3)	CNN R
2021	MAM	0.04	.91	0.05	0.85
	JJA	0.02	.97	0.04	0.93
	SON	0.04	.92	0.05	0.89
2022	MAM	0.05	.87	0.06	0.82
	JJA	0.02	.97	0.04	0.92
	SON	0.03	.95	0.04	0.90

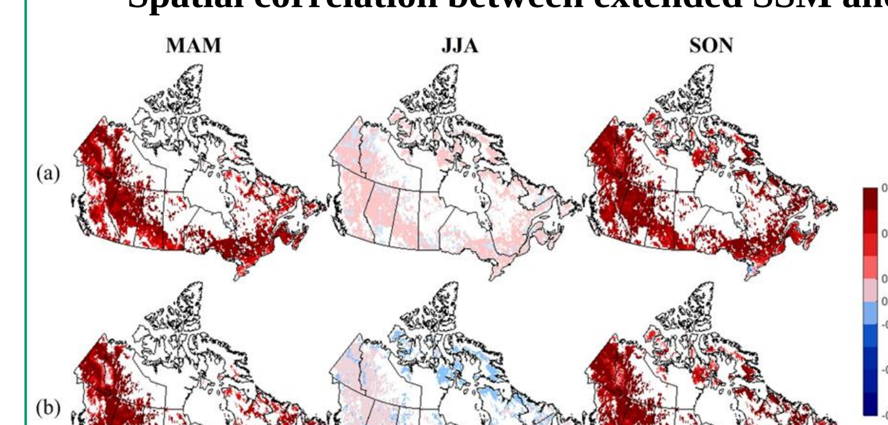
Results: Extension and Validation of SSM

Spatio-temporal extension of SMOS SSM



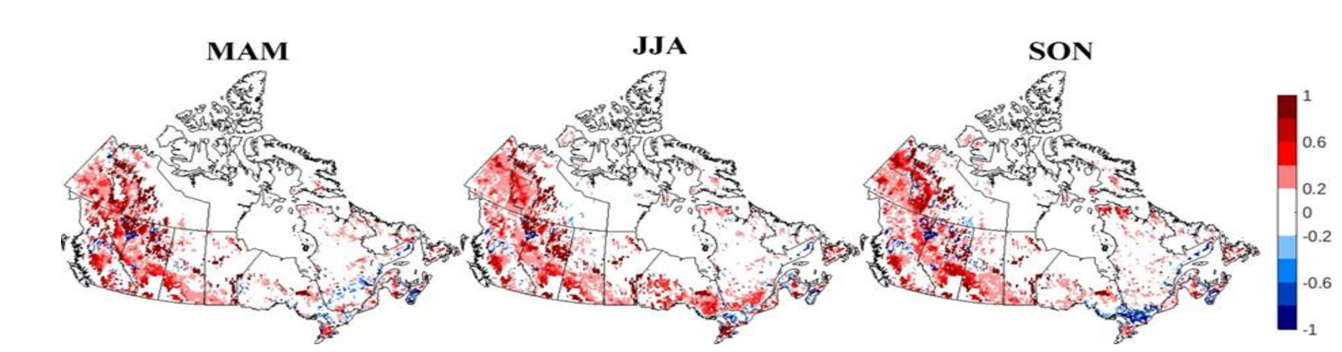
- ✓ RF model is employed for the spatiotemporal filling of SSM from 2008 to 2010.
- ✓ RF predictions of SSM are underestimated, over the boreal forest and peatland regions.

Spatial correlation between extended SSM and ASCAT SSM



- The spatial patterns for extended SSM and ASCAT SSM are very similar in the 0.4 to 0.5 range for both fall and spring

Temporal correlation between extended SSM and ASCAT SSM



- ✓ A strong temporal correlation is evident for the spring, summer, and fall seasons, with values above 0.6 for most of the regions.
- ✓ Negative correlations are noted, especially for the Great Lakes and maritime regions.

Conclusions

- ✓ This study has demonstrated the spatiotemporal extension of L band SSM observations in Canada, employing ML models using 14 ERA5 reanalysis-based predictor variables and SMOS SSM as the target variable.
- ✓ RF model showed robustness and efficiency in predicting SSM .
- ✓ Additional investigation is needed to enhance its ability to capture SSM for land surface types not included during training
- ✓ The developed framework is robust in that it can be used to resolve spatial/temporal data gaps in other SSM products and for other regions of the world.

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compute canada | calcul canada
TISED Trottier Institute for Sustainability in Engineering and Design

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