STATISTICAL ANALYSIS OF GROUND SURFACE TEMPERATURE SIMULATIONS IN THE NORTHWEST TERRITORIES TUNDRA.



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INRODUCTION / BACKGROUND

Permafrost modelling can contribute to informing adaptation in permafrost regions by characterizing the subsurface thermal regime at different points in time. However, as models vary in their representation of physical phenomena, they also differ in performance at each location. This can make it difficult to make a justifiable comparison of two simulation products, or to distinguish improvement in the representation of permafrost processes in modelling software.

Consistency in metrics for model evaluation provides an opportunity to better compare the relative strengths of multiple models. In this study, we evaluate models under a range of accordance measures, for differing terrain types, and temporal subsets. Through review and experimental testing, we aim to develop a ranking of simulation quality that accounts for the specific characteristics of ground surface temperatures (GST) in permafrost areas.

METHODOLOGY

- Ground surface temperature simulations are produced using the modelling software GEOtop² **SIMULATIONS** forced with JRA55, MERRA-2, and ERA5 reanalysis data.
- Observational ground temperature data from the NWT is collected from Carleton permafrost **Observations** database (COLDASS) and NSERC PermafrostNet ERDDAP.
- The python package used to partition simulation and observational datasets and produce a ACCOMATIC suite of summary statistics used to generate model rankings is called accomatic³. Each simulation will be tested against a range of accordance measures, then split by season and terrain type.



SIMULATED VARIABLE: GST

Ground surface temperature is measured roughly 10 cm below the ground surface. GST is inexpensive to measure relative to other permafrost variables while remaining 13 cm highly representative of the underlying thermal regime. Characteristics to represent when modelling include:

(1) Topography

(2) Ground type *i.e.* subsurface materials (3) Surface vegetation

t - INTERVAL BOOTSTRAPPING

Observational datasets that can be used to test simulations are often spatially sparse and incomplete. To make use of incomplete datasets, we implement a t-interval bootstrap Θ approach⁴. Fig 3 shows a visualization of how \Im *n* windows of *t* days are randomly selected.

The bootstrap test provides a confidence interval around each mean accordance measure, showing that rankings between models can overlap.



TESTING CONDITIONS



OBSERVATIONS

RESULTS: SIMULATION PERFORMANCE ACROSS TESTING CONDITIONS

Mini loggers that are

used to measure GST.

Accordance Measures

Figure 4 below shows the results of three different accordance measures being used to evaluate simulation performance. While the JRA-55 simulation performs best across each accordance measure shown here (*RMSE*, R^2 , BIAS), it ranges in performance considerably, overlapping with the worst performing simulation

Seasonal Subsetting

Figure 5 shows *RMSE* bootstrap results with a 0.95 confidence interval shown around each RMSE mean. While the JRA-55 model performs best over all (Fig 4), it has a greater *RMSE* value than the *MERRA-2* simulation in Winter and Spring.

WINTER	SPRING	SUMMER	AUTUMN
		т	ERA5
			JRA-55

Figure 5: Seasonal *t*-interval bootstrapping results using the *RMSE* metric for four

different simulations.

Additionally, though the MERRA-2 model is ranked

second in Fig 4, here in Fig 5 we see that it has a large



Terrain Type



Seasonal Subsetting



Measure how **seasonality** influences model performance.

SIMULATIONS

Terrain Type



Evaluate how models perform in different terrains.

Figure 2: Visualization of testing conditions for GST simulation ranking, including a variety of accordance measures, seasons and terrain subsetting.



Figure 4: *t*-interval bootstrapping results for *RMSE*, *R*² and *BIAS* accordance measures. While *RMSE* and *BIAS* show interpretable results, the tinterval bootstrap approach does not seem effective at capturing correlation (*R2* in Fig 4).

FUTURE WORK

This poster summarizes the findings of only the first iteration of using *accomatic* to evaluate model simulations and uses only a small subset of GST data. Future work includes:

RMSE of 10.1 in the Summer.

- **1.** Larger amount of GST data to allow for meaningful terrain type analysis (Fig 1)
- 2. More rigorous parameterization of individual sites in GEOtop.
- **3.** Addition of CLASSIC model, driven by all three reanalysis datasets.
- 4. More in depth description of terrain type subsetting and classification metrics.
- **5.** Additional analysis of seasonality (How do we define a season?)

MERRA-2

ENSEMBLE

Figure 7: Terrain-type subsetting *t*-interval bootstrapping results using the *RMSE* metric for four different simulations.

COLLABORATORS / ACKNOWLEDGEMENTS



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