Predictability of Precipitation in Complex Terrain using the WRF Model with Varying Physics Parameterizations

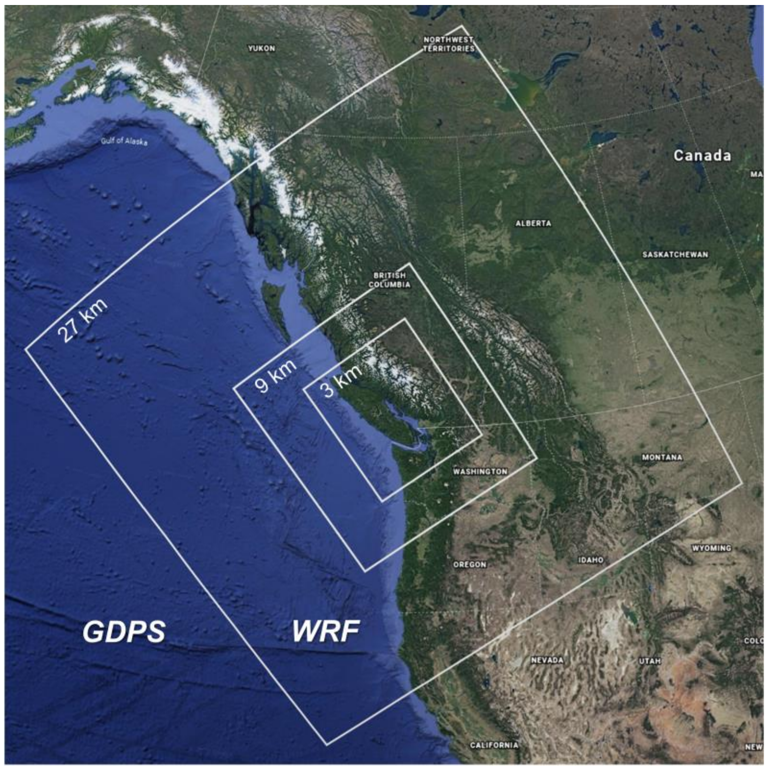
Julia Jeworrek[1], Gregory West[2], Roland Stull[1]

[1] The University of British Columbia, Vancouver BC, Canada
Department of Earth- Ocean and Atmospheric Sciences
[2] BC Hydro, Vancouver BC, Canada

Contact: jjeworrek@eoas.ubc.ca

Abstract: https://doi.org/10.5194/egusphere-egu2020-599

Verification of WRF with Systematically Varying Parameterizations



Model Configurations:

General	Initial Condition	GDPS	
	NWP Model	WRF v3.8.1	
	Grid Spacings	27 – 9 – 3 km	3 grids
	Vertical Levels	65	
	Time Period	2016	1 year
	Forecast Horizon	3 days	
Physics Parameterizations	Microphysics	Thompson Morrison WSM5	Thom Morr WSM5
	Cumulus Cloud	Kain-Fritsch Grell-Freitas	KF GF
	Land Surface	Noah Noah MP	Noah N MP
	PBL & Surface Layer	YSU + MM5 ACM2 + MM5 GBM + MM5	YSU ACM2 GBM
	Radiation	RRTM (LW) + Dudhia (SW)	

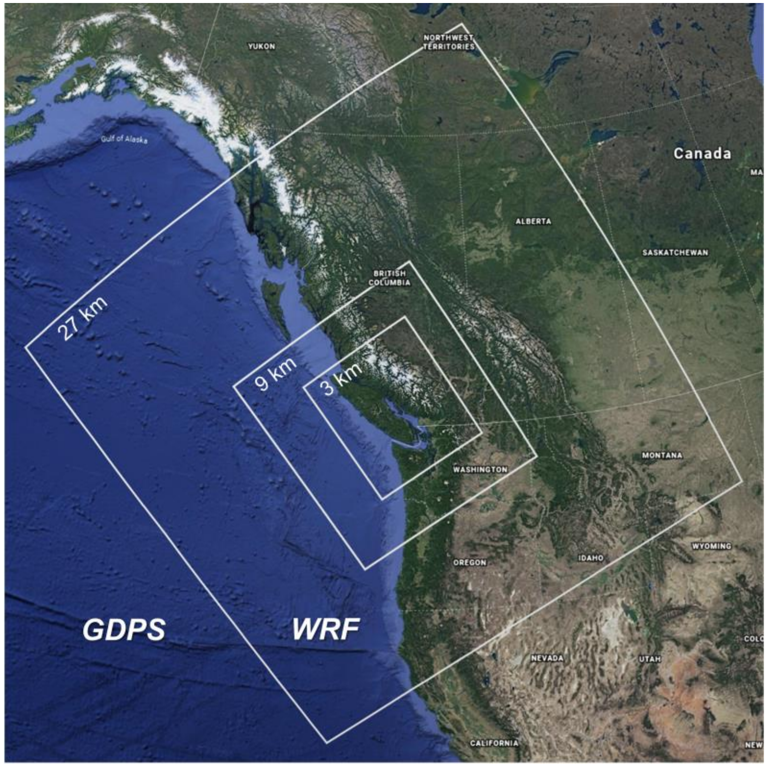
The systematical variation of all combinations results in

>100 configurations

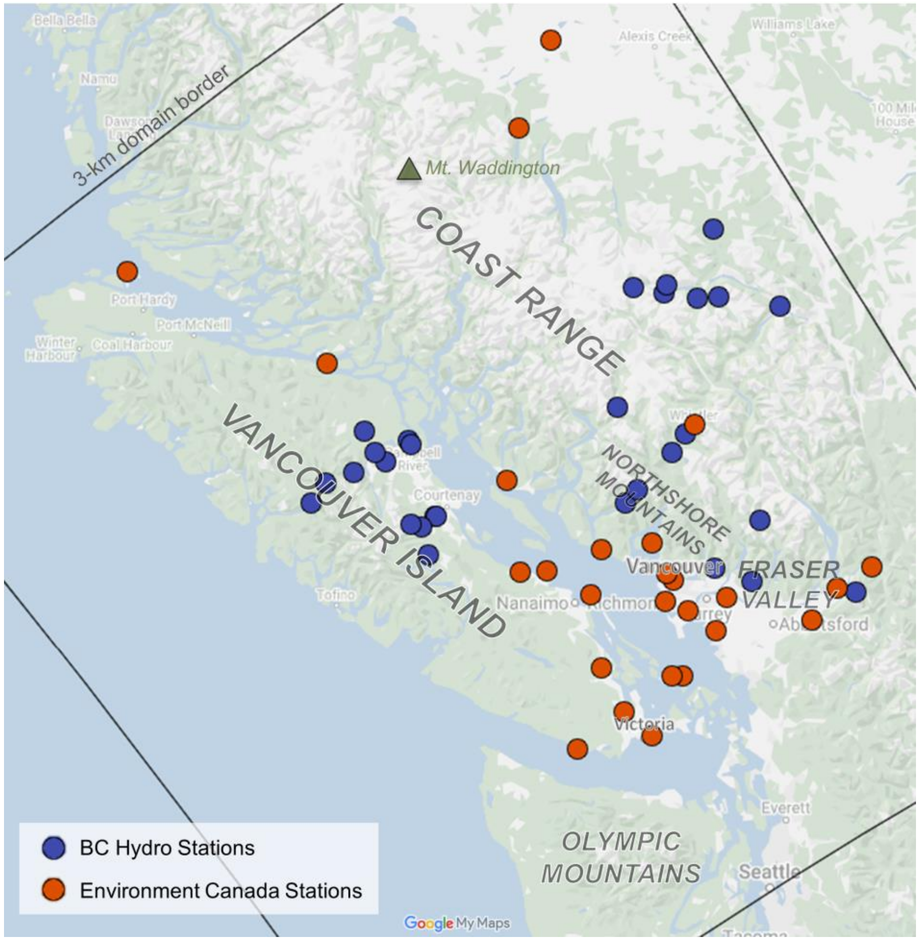
compute canada | calcul canada

for which
Compute Canada provided
the resource allocations

Verification of WRF with Systematically Varying Parameterizations



55 Stations with Hourly Observations:



Verification of the Individual Configurations

Overall best performing models:

- WSM5 | KF | YSU | NoahMP
- WSM5 | KF | GBM | NoahMP
- Thom | KF | YSU | NoahMP
- Thom | KF | ACM2 | NoahMP
- Thom | GF | YSU | NoahMP

However, the ‘best-performing’ model is unique to the user, based on which verification metric(s) are most important to their application.

White colors indicate average values of the ensemble; values better than the average are highlighted in green; values worse than the average are highlighted in red.

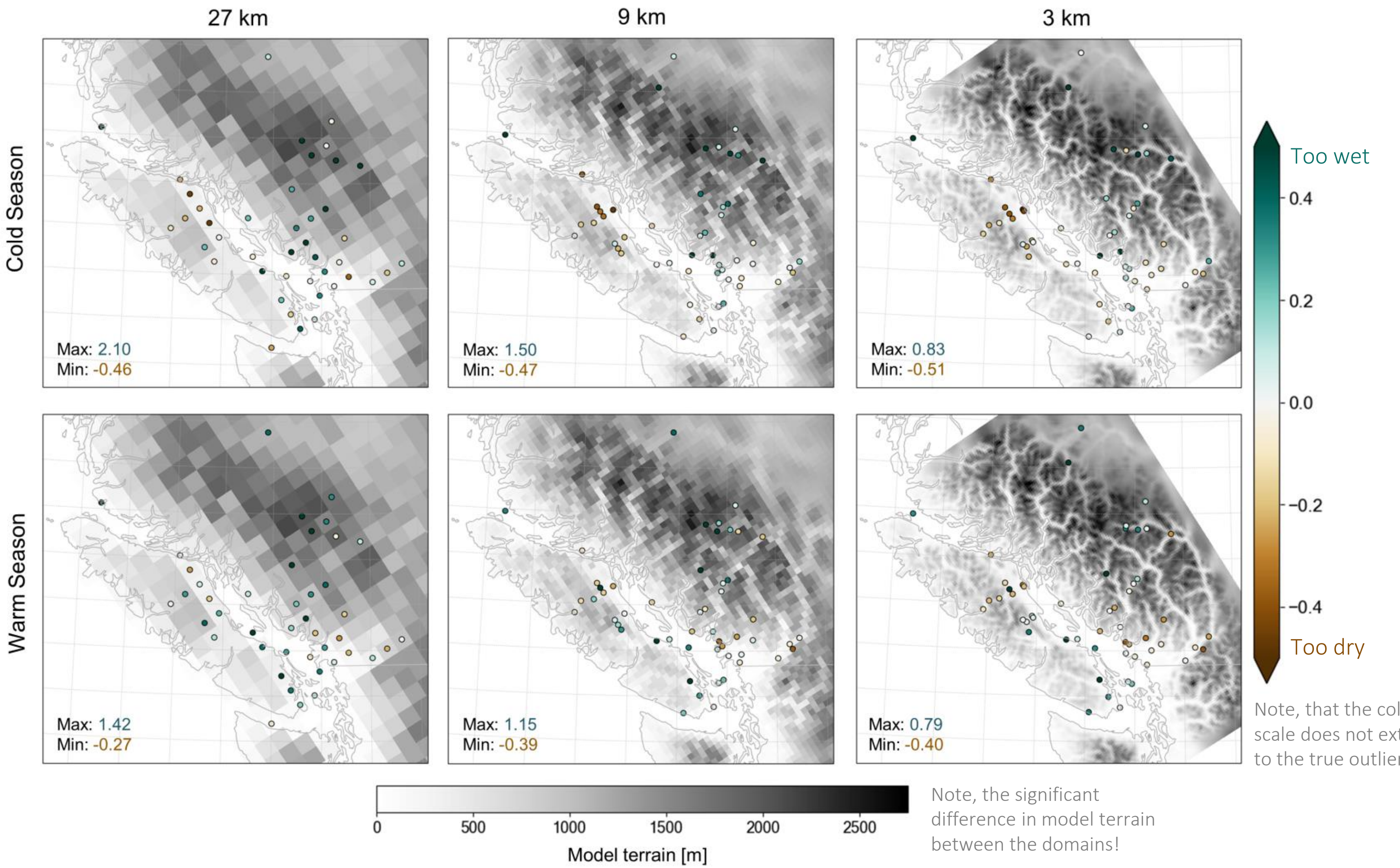
Metrics for Continuous Forecasts* / Metrics for Categorical Forecasts*

MP	CU	PBL	LS	Mean Absolute Error (MAE)	BIAS	Standard Deviation (STD)	Pearson Correlation	Mean Squared Difference (MSD)	MSD random/total	0.25 mm: Accuracy	0.25 mm: False Alarm Ratio	0.25 mm: Frequency Bias	0.25 mm: Probability of Detection (POD)	0.25 mm: Equitable Threat Score (ETS)	75th Percentile: Accuracy	75th Percentile: False Alarm Ratio	75th Percentile: Frequency Bias	75th Percentile: Probability of Detection (POD)	75th Percentile: Equitable Threat Score (ETS)
WSM5	KF	YSU	Noah	1.29	0.109	3.09	0.465	11.4	0.739	0.813	0.413	1.12	0.658	0.314	0.922	0.631	1.09	0.403	0.153
			N MP	1.27	0.0901	3.08	0.47	11.2	0.742	0.82	0.404	1.1	0.655	0.323	0.924	0.624	1.1	0.412	0.157
		ACM2	Noah	1.29	0.107	3.14	0.464	11.8	0.762	0.816	0.405	1.09	0.647	0.316	0.923	0.63	1.08	0.4	0.15
			N MP	1.29	0.0975	3.14	0.466	11.7	0.761	0.818	0.398	1.07	0.645	0.319	0.922	0.629	1.07	0.397	0.149
		GBM	Noah	1.29	0.115	3.14	0.465	11.7	0.761	0.816	0.413	1.12	0.655	0.316	0.923	0.628	1.09	0.405	0.152
			N MP	1.25	0.06	3.08	0.463	11.2	0.767	0.817	0.41	1.09	0.644	0.315	0.925	0.633	1.08	0.394	0.148
	GF	YSU	Noah	1.31	0.123	3.17	0.46	12	0.762	0.817	0.396	1.06	0.641	0.318	0.92	0.635	1.1	0.403	0.148
			N MP	1.29	0.0949	3.13	0.464	11.6	0.757	0.821	0.391	1.05	0.64	0.323	0.922	0.63	1.1	0.407	0.148
		ACM2	Noah	1.32	0.13	3.23	0.458	12.4	0.783	0.82	0.394	1.04	0.633	0.316	0.921	0.636	1.12	0.406	0.147
			N MP	1.31	0.125	3.22	0.461	12.3	0.785	0.821	0.39	1.04	0.633	0.319	0.921	0.634	1.13	0.413	0.149
		GBM	Noah	1.32	0.12	3.24	0.455	12.4	0.78	0.818	0.397	1.05	0.632	0.315	0.921	0.635	1.11	0.404	0.145
			N MP	1.31	0.109	3.23	0.458	12.4	0.785	0.82	0.393	1.04	0.63	0.317	0.922	0.632	1.1	0.406	0.142
Thom	KF	YSU	Noah	1.28	0.127	3.03	0.46	11	0.696	0.803	0.437	1.22	0.689	0.303	0.922	0.628	1.05	0.392	0.15
			N MP	1.27	0.105	3	0.463	10.8	0.691	0.808	0.427	1.19	0.682	0.311	0.924	0.622	1.04	0.393	0.149
		ACM2	Noah	1.28	0.127	3.05	0.459	11.1	0.711	0.805	0.434	1.2	0.681	0.303	0.923	0.626	1.05	0.393	0.153
			N MP	1.26	0.0999	3	0.467	10.8	0.708	0.809	0.424	1.17	0.676	0.311	0.924	0.621	1.05	0.398	0.155
		GBM	Noah	1.3	0.136	3.08	0.456	11.3	0.712	0.801	0.439	1.21	0.682	0.298	0.922	0.629	1.05	0.39	0.154
			N MP	1.28	0.115	3.05	0.463	11.1	0.714	0.807	0.428	1.18	0.677	0.309	0.923	0.623	1.05	0.395	0.157
	GF	YSU	Noah	1.29	0.105	3.1	0.454	11.4	0.721	0.816	0.4	1.06	0.633	0.312	0.921	0.633	1.08	0.398	0.148
			N MP	1.27	0.08	3.07	0.456	11.2	0.712	0.818	0.396	1.05	0.634	0.316	0.922	0.63	1.08	0.399	0.148
		ACM2	Noah	1.31	0.131	3.16	0.45	11.9	0.742	0.816	0.399	1.04	0.624	0.309	0.92	0.64	1.1	0.398	0.143
			N MP	1.3	0.12	3.13	0.456	11.7	0.742	0.818	0.395	1.03	0.625	0.312	0.921	0.636	1.11	0.404	0.147
		GBM	Noah	1.31	0.118	3.14	0.445	11.7	0.739	0.814	0.404	1.03	0.615	0.303	0.921	0.641	1.1	0.395	0.148
			N MP	1.3	0.115	3.13	0.453	11.7	0.737	0.815	0.399	1.03	0.616	0.307	0.921	0.636	1.1	0.402	0.147
Morr	KF	YSU	Noah	1.28	0.112	3.04	0.46	11	0.703	0.809	0.421	1.15	0.663	0.306	0.922	0.632	1.08	0.396	0.15
			N MP	1.28	0.103	3.03	0.464	10.9	0.705	0.813	0.412	1.13	0.663	0.313	0.922	0.63	1.07	0.396	0.145
		ACM2	Noah	1.29	0.109	3.07	0.459	11.3	0.723	0.812	0.415	1.12	0.654	0.308	0.923	0.63	1.07	0.394	0.15
			N MP	1.28	0.0974	3.08	0.462	11.3	0.727	0.813	0.412	1.1	0.649	0.308	0.923	0.63	1.06	0.394	0.151
		GBM	Noah	1.29	0.107	3.1	0.454	11.5	0.726	0.81	0.419	1.13	0.655	0.305	0.922	0.63	1.06	0.393	0.15
			N MP	1.29	0.106	3.1	0.459	11.5	0.733	0.812	0.413	1.12	0.657	0.309	0.922	0.628	1.06	0.395	0.151
	GF	YSU	Noah	1.31	0.146	3.11	0.455	11.5	0.726	0.812	0.411	1.1	0.647	0.307	0.921	0.636	1.1	0.399	0.135
			N MP	1.28	0.111	3.07	0.454	11.2	0.726	0.815	0.41	1.09	0.643	0.307	0.922	0.638	1.1	0.396	0.132
		ACM2	Noah	1.32	0.156	3.16	0.454	11.9	0.75	0.812	0.412	1.08	0.637	0.301	0.921	0.639	1.11	0.401	0.136
			N MP	1.32	0.157	3.16	0.457	11.9	0.755	0.812	0.41	1.08	0.638	0.304	0.921	0.636	1.12	0.408	0.138
		GBM	Noah	1.33	0.144	3.19	0.447	12.1	0.751	0.811	0.414	1.07	0.629	0.297	0.921	0.641	1.1	0.394	0.133
			N MP	1.35	0.172	3.23	0.45	12.4	0.758	0.811	0.409	1.07	0.632	0.3	0.92	0.636	1.1	0.401	0.135

* Metrics calculated from 6-hourly precipitation on the 9-km grids (time and location-averaged)

Verification Across the Region

Relative bias (WRF-Obs / Obs) of 6-hourly precipitation by location as ensemble and seasonal average:

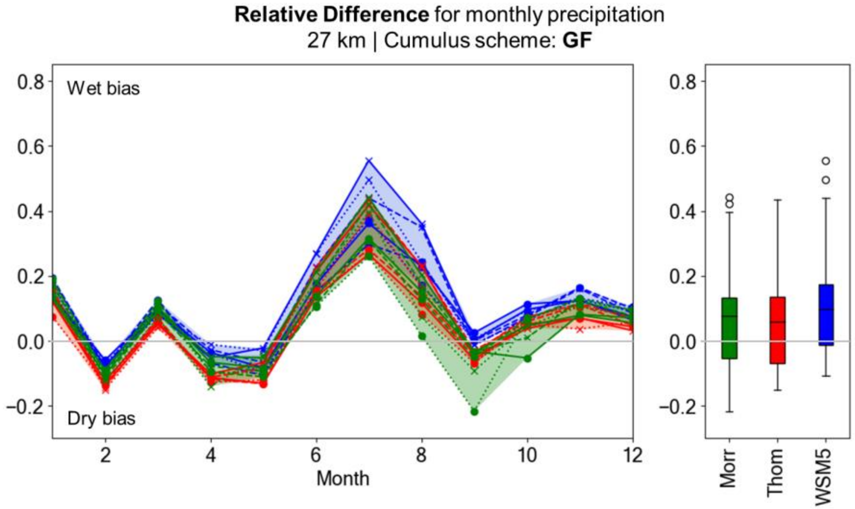


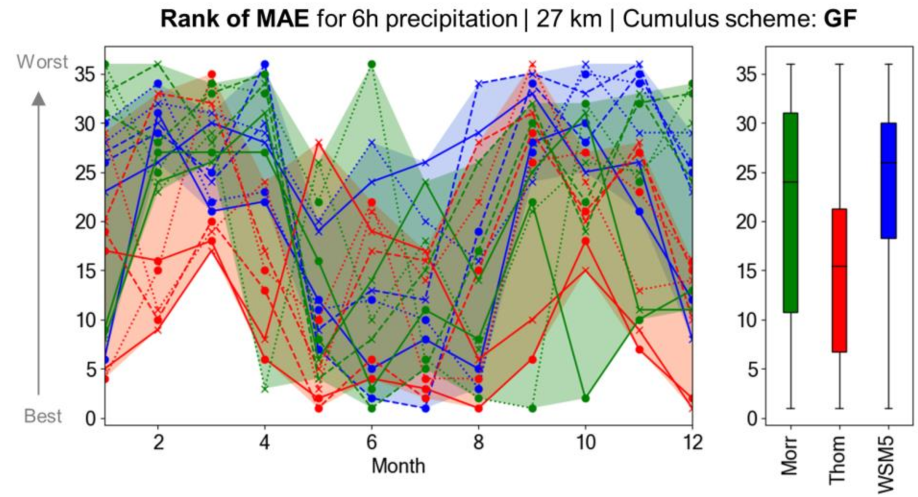
Note, that the color scale does not extend to the true outliers!

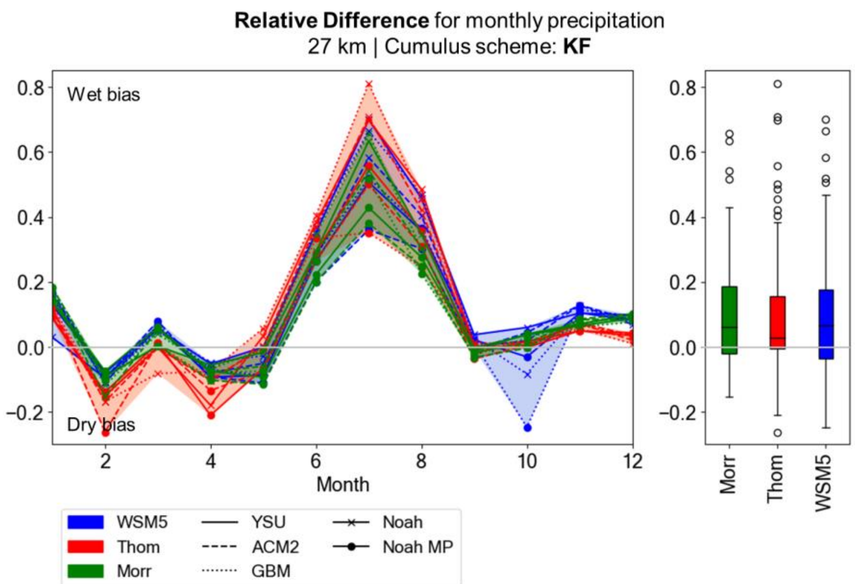
Note, the significant difference in model terrain between the domains!

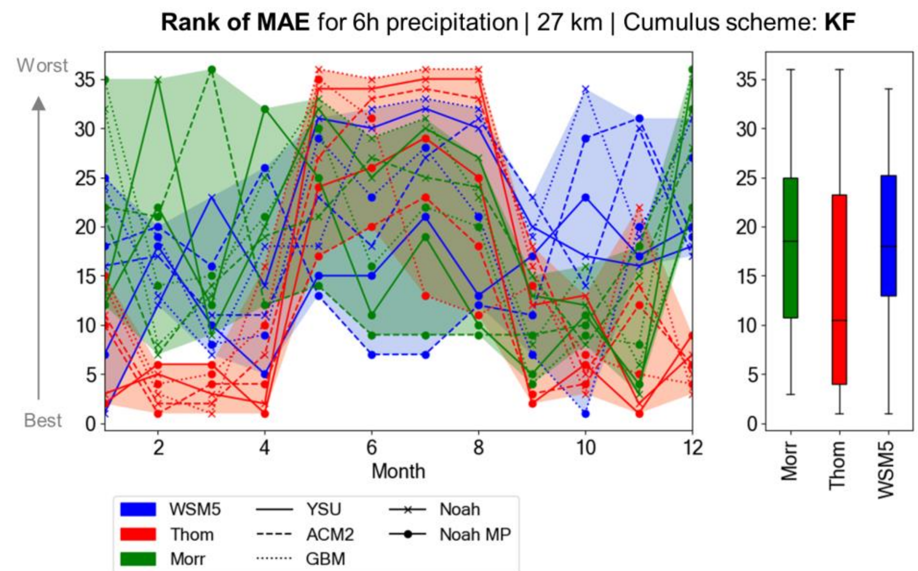
- The bias in the cold/wet season is larger in relative magnitude than in the warm/dry season. Some stations have a very strong wet bias especially at the coarser grid.
- In the cold season central Vancouver Island verifies too dry, the Coast Range verifies too wet, highly populated areas (e.g. metro Vancouver, Fraser Valley, Victoria) have small errors in comparison – Suggests overdone orographic influences.

Seasonal Performance Variation





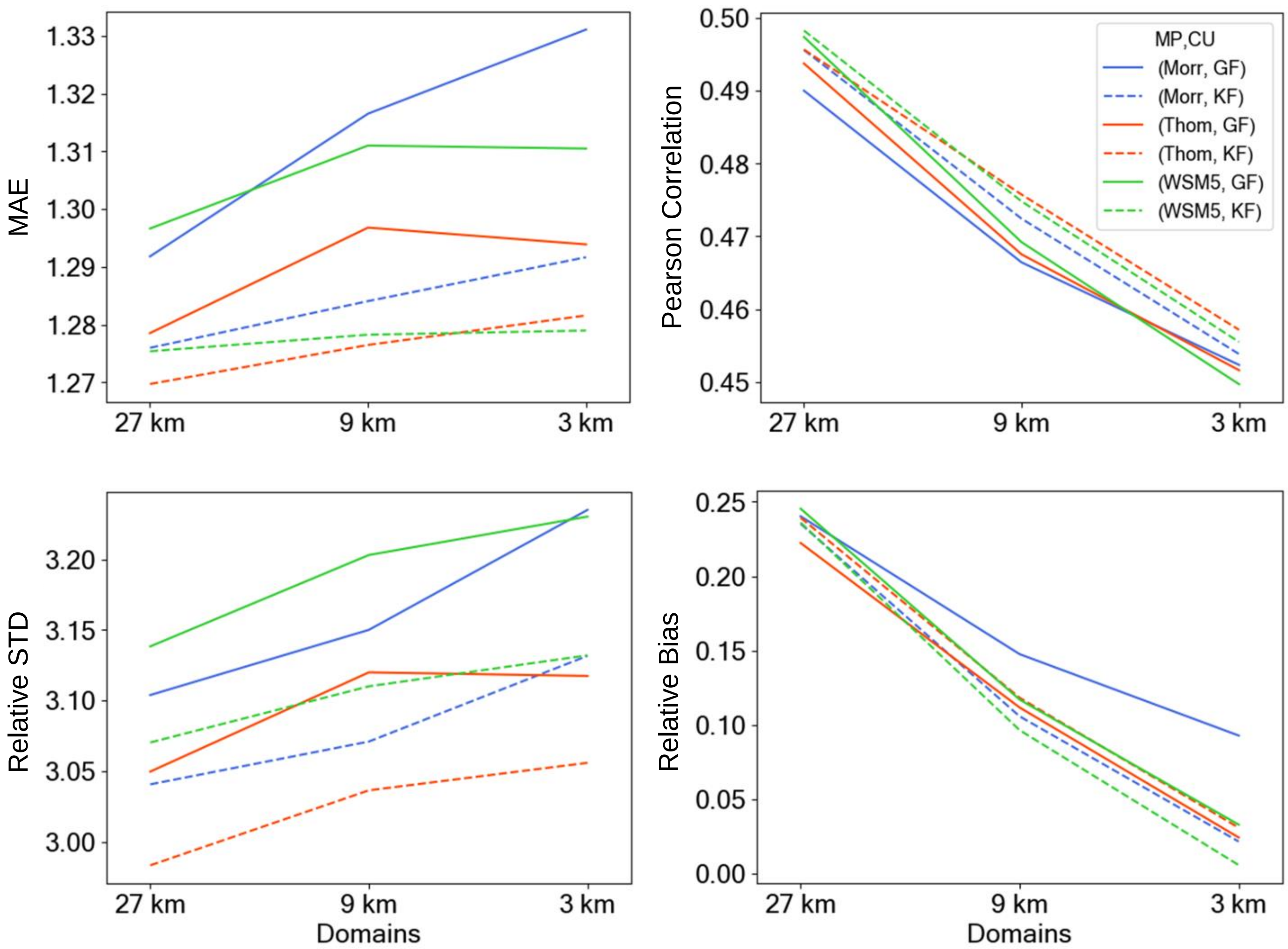




- GF models perform better in the warm and drier season (reduced wet bias compared to KF)
- KF models perform better in the cold and wet season, which contributes the majority of the total precipitation in BC

Resolution dependent Performance

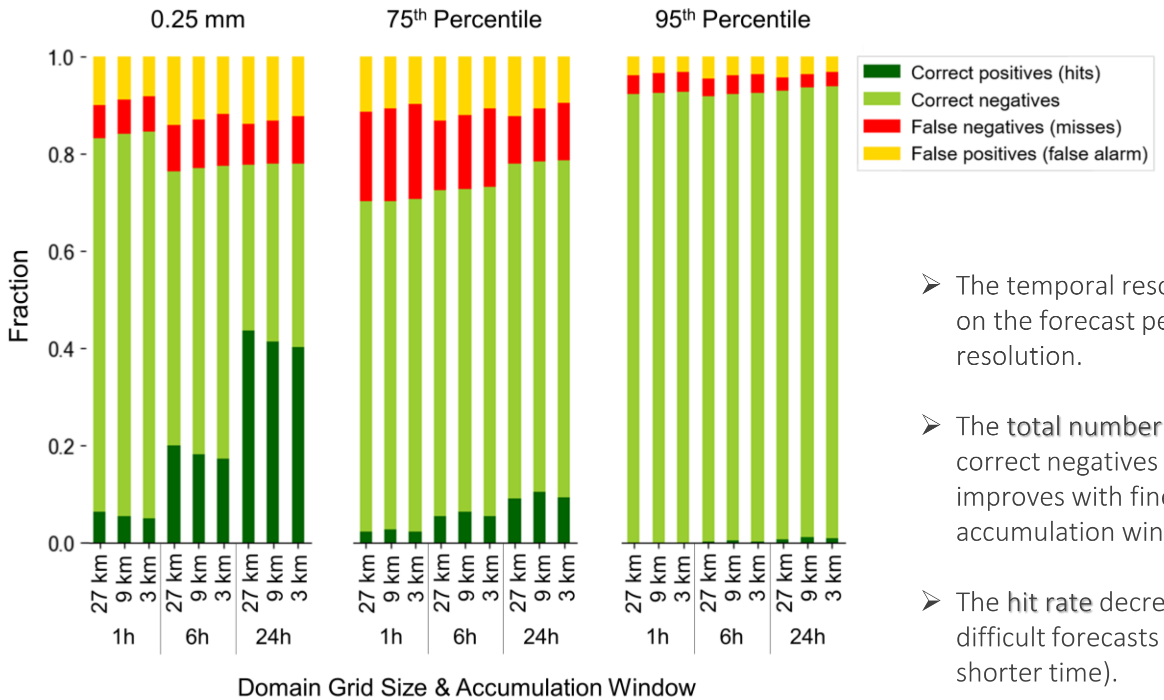
Error metrics for 6-hourly precipitation



- MAEs are worse for finer grids. GF models show a surprisingly large grid dependency.
- Pearson Correlation Coefficients decrease with finer grid spacings. The change with resolution is more significant than the spread between the models.
- The relative Standard Deviation (STD) is larger for finer grids on average (as fine grids can represent more detail and are prone to double penalty), where STDs are more sensitive to model configurations than grid spacings.
- The relative Biases are larger for coarser grids.

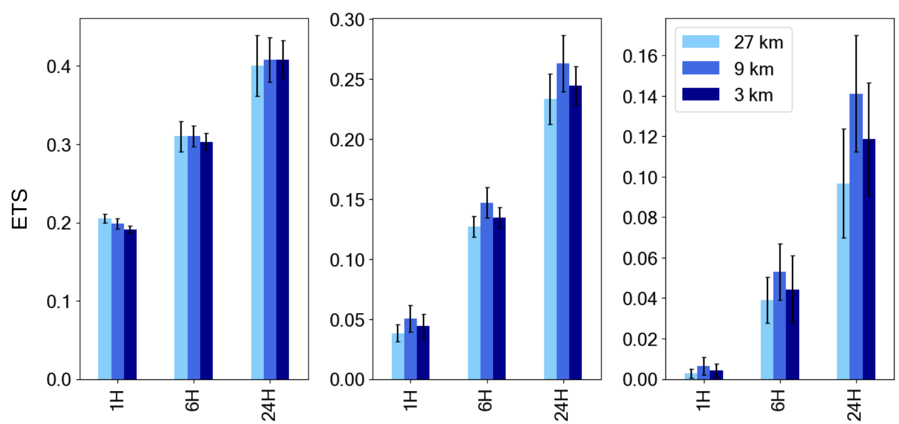
Performance for Common vs Extreme Events

Contingency Table Variables:



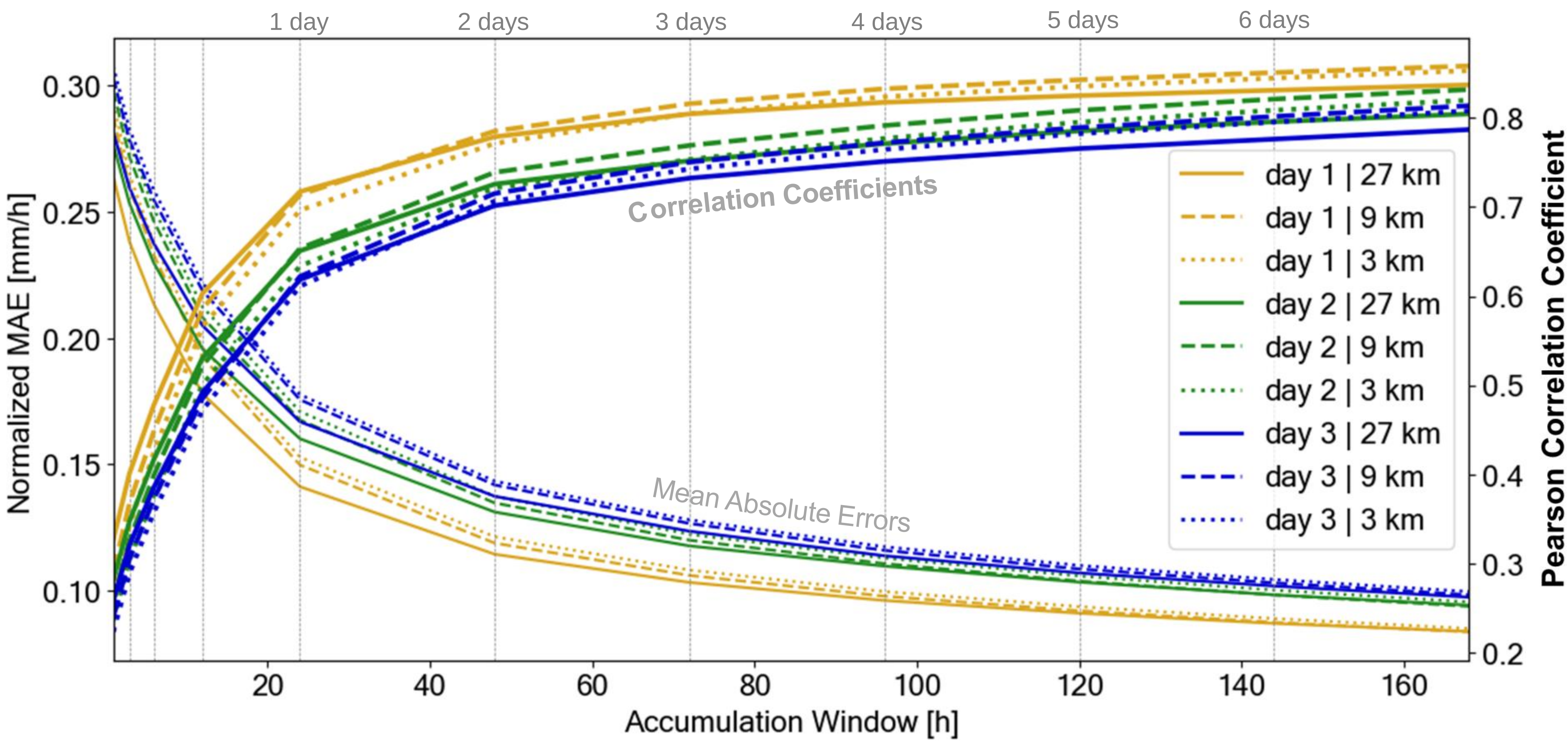
Equitable Threat Score (ETS):

Error bars show spread between individual models



- The temporal resolution has a larger impact on the forecast performance than the spatial resolution.
- The total number of correct forecasts (where correct negatives are often the majority) improves with finer grids and shorter accumulation windows.
- The hit rate decreases significantly for more difficult forecasts (extreme events and shorter time).
- The best hit rate is achieved by the coarsest grid for events > 0.25mm, whereas 75th- and 95th-percentile events have the highest hit rate at the mid-size domain.
- The ETS for 75th and 95th percentiles are best at the 9-km grid, followed by 3-km grid; it is worst at the 27-km grid.
- The false-alarm rate often exceeds the miss rate: WRF overpredicts precipitation frequencies.

Predictability with Forecast Horizon and Accumulation Window

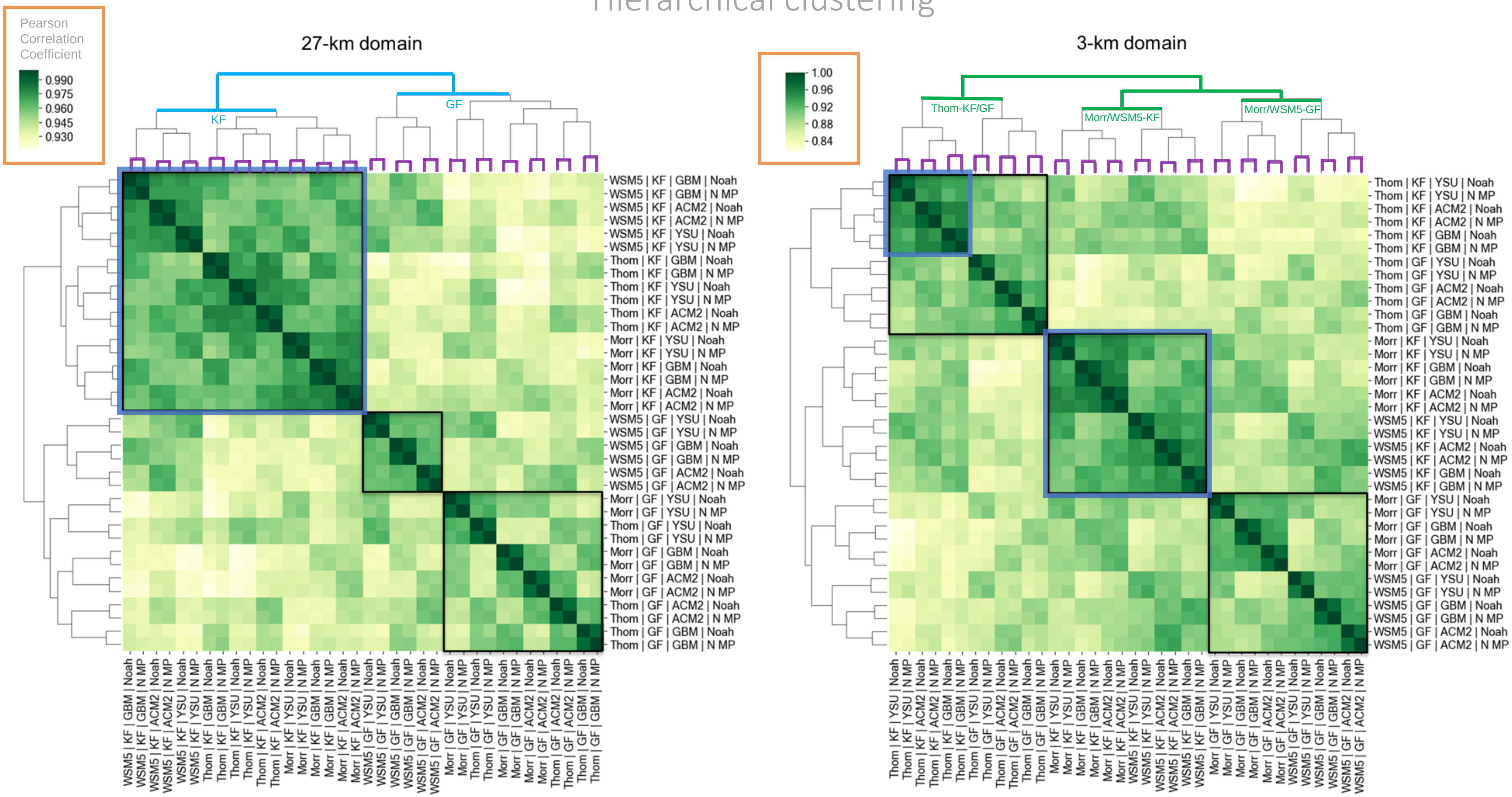


- Ensemble-mean MAE’s and correlation coefficients improve asymptotically with extended accumulation windows. The improvement is rapid within the first day and levels out after about 2 or 3 days of accumulation.
- Correlation coefficients are only best at the coarsest grid for accumulation periods up to 1 day, then the finer grids become better.

Longer accumulation windows are more likely to capture the entirety of a rain event and compensate for potential temporal offsets between forecasted and observed rainfall. On the other hand, important information about variable precipitation rates at time scales shorter than a given accumulation window are averaged out and poorly represented.

Model interdependence

Hierarchical clustering



- All models are highly correlated with one another (27-km more than 3-km due to dynamical downscaling).
- The cumulus scheme is most important for precipitation at coarser resolutions (especially models that use KF produce very similar precipitation); the combination of cumulus with microphysics becomes more important as resolution increases.
- PBL schemes have a minor, and the choice of land surface scheme has the lowest impact on precipitation forecasts.

Summary & Conclusions

1 year of numerical weather prediction data from over 100 WRF configurations reveals:

- Cumulus and microphysics together are most important for total model precipitation.

- WSM5 yields competitive verification scores when compared to more sophisticated and computationally expensive microphysics. (Model runs with Thom and Morr take on average ~20% longer than with WSM5.)

- In contradiction to what one might expect for a scale-aware cumulus scheme, GF did not outperform the conventional KF scheme at finer resolutions. Although GF performed better for convective precipitation in summer, KF was better across all scales for cold-season frontal precipitation, which contributes the majority of the annual rainfall in southwest BC.

- Using Noah MP yields slight yet consistent improvements (compared to the older Noah land surface model).

- Coarser grids had smaller random errors, smaller MAEs, and higher correlation coefficients compared to finer grids. Categorical forecasts on finer grids resulted in better frequency biases, ETS's, and accuracies, which means that they had the largest fraction of correct forecasts (although most of the total correct forecasts are correct rejections). The midsize domain (9-km) had the highest hit rate and ETS for 75^{th} and 95^{th}-percentile precipitation.

- Extended accumulation windows can greatly improve precipitation verification scores. Temporal resolution has shown a larger impact on the forecast performance than the spatial model resolution.

Predictability of Precipitation in Complex Terrain using the WRF Model with Varying Physics Parameterizations

Julia Jeworrek, Gregory West, Roland Stull
Contact: jjeworrek@eoas.ubc.ca

J. Jeworrek et al. (2020): WRF Precipitation Performance and Predictability with Systematically Varying Parameterizations over Complex Terrain. *In Preparation.*