WRF Precipitation Performance and Predictability for Systematically Varied Parameterizations over Complex Terrain

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Outline

1. Background and introduction
2. Methodology
3. Results and discussion
4. Summary and conclusions

1. Background and introduction

a. Research site

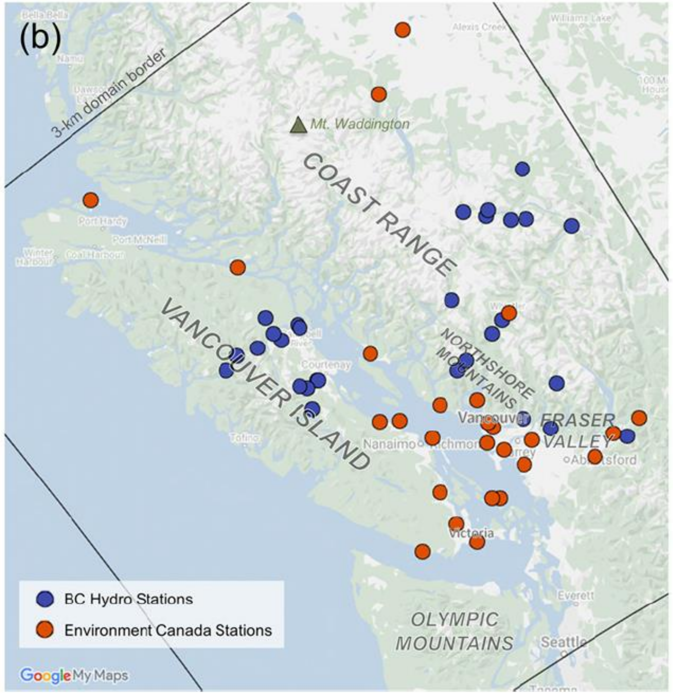
- Southwestern British Columbia (BC), Canada
- Two hydrometeorological seasons:

  1. wet, cool *season (fall, winter, spring)*

  2. dry, warm *season (summer)*

- Enhanced precipitation on windward slopes
- Accurate precipitation forecasts are crucial for

  reservoir and flood management



1. Background and introduction

b. NWP issues in BC area

- **NWP limitations**:

  1. imperfect initial conditions

  2. simplified approximations

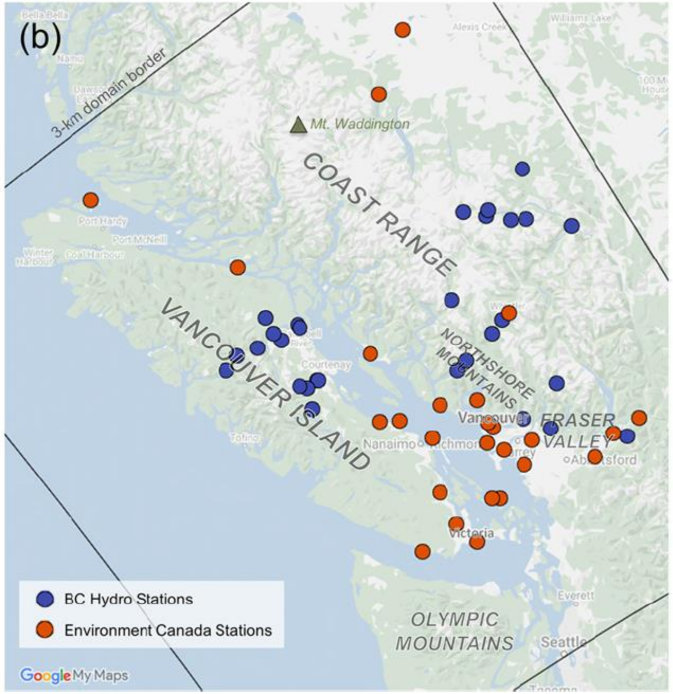
- **Observation limitations**:

  1. radar observations are blocked by terrain

  2. weather station are spatially uneven

- **Mixed-phased** orographic clouds are challenging in NWP models.

- Unresolved **complex terrain** in NWP models can cause false advection and blocking.



1. Background and introduction

c. WRF parameterizations

Microphysics	Represent cloud hydrometeor processes of formation, growth, and fallout.
Cumulus	Represent the effect of unresolved vertical motion
Planetary Boundary Layer (PBL)	Estimate vertical mixing and turbulence fluxes
Land surface model	Estimate heat, moisture , and radiation from the ground to atmosphere

1. Background and introduction

d. Model resolution issues

- Finer resolutions are often expected to improve forecasts by generating more *realistic* precipitation distribution.
- Finer resolutions are prone to temporal and spatial verification "***double-penalty***".
- NWP "***gray zone***" is also important to be aware of.

Finer resolution: Explicitly resolve the process	**Gray Zone** **(4 km)**	**Coarser resolution**: Implicitly describe the process through parameterization

- Scale-aware schemes are developed to bridge the gap between implicitly (parameterization) and explicitly (resolved) represented processes.

1. Background and introduction

e. The goal of this study

- Evaluate WRF precipitation forecasts over the ***complex terrain*** of southwest BC.
- Systematically select different ***parameterization*** scheme (microphysics, cumulus, PBL, and land surface).
- Evaluate the performance of each ***WRF configuration***.
- The 2016 full calendar year is selected for ***verification***, which is more statistically robust than case studies.

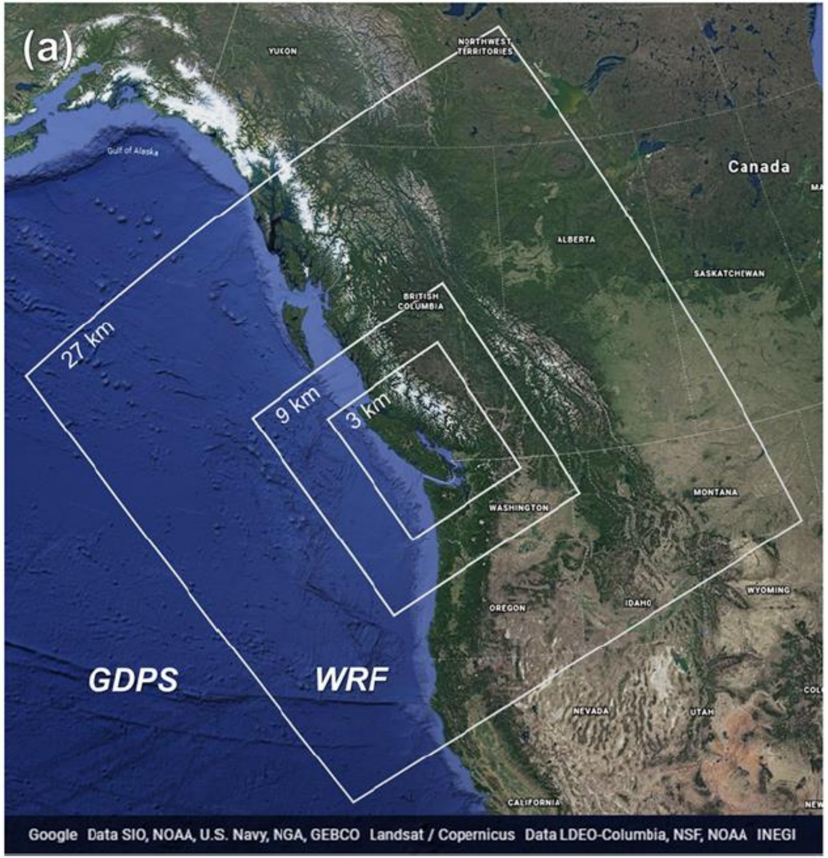
2. Methodology

a. Modeling

- **Model**: WRF 3.8.1
- **Domain**: 27/9/3km two-way nesting
- **Initial/Boundary condition**:

  Global Deterministic Prediction System (GDPS)

  ($0.24° \times 0.24°$, every 3 hours)
- **Daily initialized** at 0000 UTC for year 2016
- **Forecast horizon**: 3 day
- **Model top**: 50 hPa
- **65 sigma levels**



2. Methodology

a. Modeling

- **36 different** model configurations

Physics parameterization scheme	Abbreviation
	Cumulus convection
Kain–Fritsch	KF
Grell–Freitas	GF
	Microphysics
WRF Single-moment 5-class scheme	WSM5
1.5-moment 6-class Thompson	Thom
2-moment 6-class Morrison	Morr
	Planetary boundary layer
Yonsei University scheme	YSU
Asymmetric Convective Model	ACM2
Grenier–Bretherton–McCaa scheme	GBM
	Land surface
Unified Noah land surface model	Noah
Multiphysics Noah land surface model	Noah-MP

- **Longwave radiation**: RRTM
- **Shortwave radiation**: Dudhia
- **For cumulus scheme:**

1. turn on at each domain

2. KF: conventional scheme

3. GF: scale-aware scheme

2. Methodology

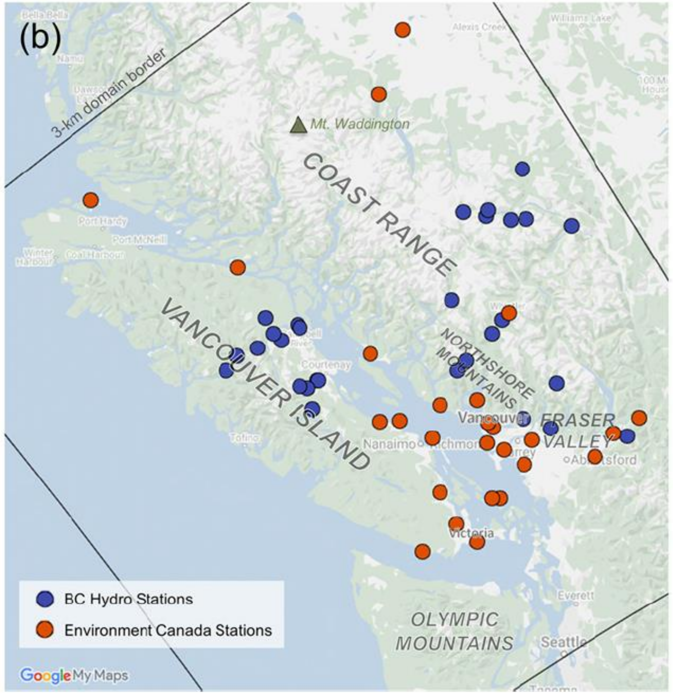
b. Verification

- **55 hourly precipitation observations are used**
- **Nearest-neighbor method is used**
- **Hourly precipitation verification**

→ double-penalty issues

→ extended accumulation windows

→ this study focuses on 6-hour accumulation precipitation



2. Methodology

b. Verification – Continuous metrics

- Mean absolute error (MAE)

$$\boldsymbol{MAE} = \frac{1}{n}\sum_{k=1}^{n}|y_k - o_k|$$

- Mean square difference (MSD)

$$\boldsymbol{MSD} = \frac{1}{n}\sum_{k=1}^{n}(y_k - o_k)^2$$

- Bias

$$\boldsymbol{Bias} = \frac{1}{n}\sum_{k=1}^{n}(y_k - o_k)$$

- Standard deviation (SD) of error

- SD (forecast) / SD (observation)

- Pearson correlation coefficient (CC)

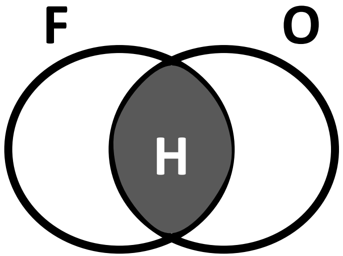
2. Methodology

b. Verification – Categorical metrics

- Choose a precipitation ***threshold***, and then:

Contingency Table		Observation	
		O	X
Forecast	O	(a) Hit	(b) False Alarm
	X	(c) Miss	(d) Correct Rejection

$$\textbf{Accuracy} = \frac{a+d}{a+b+c+d}$$



$$F = a + b$$

$$O = a + c$$

$$H = a$$

$$Frequency\ \textbf{Bias} = \frac{F}{O}$$

$$False\ Alarm\ Ratio\ (\textbf{FAR}) = \frac{F-H}{F}$$

$$Probability\ of\ detection\ (\textbf{POD}) = \frac{H}{O}$$

$$Domain\ point\ number = N$$

$$Random\ Guesses\ (R) = F \times \frac{O}{N}$$

$$Equitable\ Threat\ Score\ (\textbf{ETS}) = \frac{H-R}{F+O-H-R}$$

3. Results and discussion

a. Individual model performance – Continuous metrics

<u>For 9-km grid, 6-hour accumulated precipitation</u>:

- **Noah-MP** is better than **Noah**
- **KF** is better than **GF**
- In postprocessing, bias is easier to be removed than random error

  → Lower $\frac{MSD_{random}}{MSD_{total}}$ and SD_{error} are better

- **Thom-KF** performs the best

MP	CU	PBL	LS	MAE	BIAS	SD(Error)	SD(Fcst) / SD(Obs)	Correlation	MSD	MSD random/total
WSM5	KF	YSU	Noah	1.29	0.106	3.12	1.05	0.474	11.4	0.705
			N MP	1.27	0.0952	3.09	1.04	0.481	11.2	0.705
		ACM2	Noah	1.29	0.109	3.16	1.07	0.476	11.8	0.719
			N MP	1.29	0.0905	3.15	1.06	0.477	11.7	0.712
		GBM	Noah	1.29	0.113	3.16	1.06	0.472	11.7	0.719
			N MP	1.25	0.0909	3.07	1.02	0.47	11.2	0.712
	GF	YSU	Noah	1.31	0.113	3.2	1.09	0.469	12	0.727
			N MP	1.29	0.0922	3.14	1.06	0.477	11.6	0.714
		ACM2	Noah	1.32	0.123	3.25	1.11	0.469	12.4	0.741
			N MP	1.31	0.12	3.23	1.1	0.472	12.3	0.739
		GBM	Noah	1.32	0.115	3.25	1.1	0.462	12.4	0.73
			N MP	1.31	0.109	3.24	1.1	0.467	12.4	0.736
Thom	KF	YSU	Noah	1.28	0.117	3.07	1.02	0.475	11	0.671
			N MP	1.27	0.0988	3.05	1.01	0.475	10.8	0.669
		ACM2	Noah	1.28	0.124	3.1	1.04	0.474	11.1	0.688
			N MP	1.26	0.1	3.04	1.02	0.483	10.8	0.68
		GBM	Noah	1.3	0.123	3.12	1.05	0.47	11.3	0.691
			N MP	1.28	0.106	3.09	1.04	0.478	11.1	0.689
	GF	YSU	Noah	1.29	0.097	3.14	1.06	0.47	11.4	0.694
			N MP	1.27	0.0758	3.09	1.03	0.476	11.2	0.682
		ACM2	Noah	1.31	0.126	3.21	1.1	0.463	11.9	0.716
			N MP	1.3	0.118	3.17	1.08	0.471	11.7	0.715
		GBM	Noah	1.31	0.114	3.19	1.08	0.46	11.7	0.713
			N MP	1.3	0.109	3.19	1.08	0.465	11.7	0.715
Morr	KF	YSU	Noah	1.28	0.107	3.08	1.03	0.474	11	0.688
			N MP	1.28	0.0964	3.08	1.03	0.475	10.9	0.688
		ACM2	Noah	1.29	0.107	3.12	1.05	0.47	11.3	0.701
			N MP	1.28	0.0963	3.11	1.04	0.474	11.3	0.699
		GBM	Noah	1.29	0.102	3.13	1.05	0.469	11.5	0.703
			N MP	1.29	0.0974	3.13	1.05	0.472	11.5	0.707
	GF	YSU	Noah	1.31	0.138	3.17	1.08	0.469	11.5	0.71
			N MP	1.28	0.127	3.1	1.05	0.472	11.2	0.71
		ACM2	Noah	1.32	0.151	3.21	1.1	0.466	11.9	0.731
			N MP	1.32	0.153	3.2	1.1	0.47	11.9	0.732
		GBM	Noah	1.33	0.141	3.24	1.11	0.458	12.1	0.73
			N MP	1.35	0.15	3.27	1.12	0.463	12.4	0.736

3. Results and discussion

a. Individual model performance
– Categorical metrics

<u>**For 0.25mm threshold (precipitation or not)**</u>**:**

- **WSM5-KF**, **WSM5-GF**, and **Thom-GF** perform best
- For **Thom-KF** configuration:

  frequency bias ↑

  false alarm ratio ↑ / accuracy ↓

  POD ↑

MP	CU	PBL	LS	0.25 mm Accuracy	0.25 mm ETS	0.25 mm False Alarm Ratio	0.25 mm Frequency Bias	0.25 mm POD	75^{th} Percentile Accuracy	75^{th} Percentile ETS	75^{th} Percentile False Alarm Ratio	75^{th} Percentile Frequency Bias	75^{th} Percentile POD
WSM5	KF	YSU	Noah	0.813	0.338	0.412	1.17	0.67	0.922	0.218	0.614	1.14	0.415
			N MP	0.82	0.346	0.403	1.14	0.667	0.924	0.227	0.607	1.14	0.426
		ACM2	Noah	0.816	0.34	0.404	1.14	0.659	0.923	0.219	0.615	1.13	0.414
			N MP	0.818	0.343	0.397	1.12	0.656	0.922	0.218	0.613	1.11	0.41
		GBM	Noah	0.816	0.34	0.411	1.16	0.666	0.923	0.22	0.614	1.13	0.416
			N MP	0.817	0.338	0.408	1.14	0.655	0.925	0.216	0.619	1.12	0.406
	GF	YSU	Noah	0.817	0.341	0.396	1.1	0.651	0.92	0.217	0.616	1.14	0.414
			N MP	0.821	0.346	0.39	1.09	0.65	0.922	0.222	0.609	1.14	0.419
		ACM2	Noah	0.82	0.339	0.395	1.09	0.643	0.921	0.217	0.62	1.16	0.417
			N MP	0.821	0.342	0.391	1.08	0.643	0.921	0.221	0.618	1.17	0.426
		GBM	Noah	0.818	0.338	0.396	1.09	0.641	0.921	0.216	0.62	1.15	0.413
			N MP	0.82	0.339	0.393	1.08	0.639	0.922	0.218	0.618	1.14	0.415
Thom	KF	YSU	Noah	0.803	0.329	0.437	1.28	0.702	0.922	0.217	0.609	1.12	0.407
			N MP	0.808	0.336	0.426	1.25	0.697	0.924	0.22	0.601	1.1	0.407
		ACM2	Noah	0.805	0.329	0.433	1.26	0.694	0.923	0.22	0.607	1.12	0.409
			N MP	0.809	0.336	0.424	1.23	0.69	0.924	0.224	0.601	1.11	0.414
		GBM	Noah	0.801	0.324	0.438	1.27	0.695	0.922	0.218	0.61	1.12	0.406
			N MP	0.807	0.334	0.425	1.24	0.691	0.923	0.223	0.602	1.11	0.411
	GF	YSU	Noah	0.816	0.335	0.4	1.11	0.645	0.921	0.218	0.611	1.14	0.413
			N MP	0.818	0.34	0.396	1.1	0.647	0.922	0.221	0.606	1.13	0.414
		ACM2	Noah	0.816	0.332	0.398	1.09	0.637	0.92	0.213	0.623	1.16	0.411
			N MP	0.818	0.336	0.395	1.09	0.638	0.921	0.218	0.618	1.17	0.419
		GBM	Noah	0.814	0.326	0.402	1.08	0.627	0.921	0.213	0.623	1.16	0.41
			N MP	0.815	0.33	0.396	1.07	0.629	0.921	0.218	0.618	1.16	0.417
Morr	KF	YSU	Noah	0.809	0.331	0.423	1.2	0.676	0.922	0.217	0.613	1.13	0.41
			N MP	0.813	0.338	0.415	1.18	0.675	0.922	0.218	0.61	1.12	0.41
		ACM2	Noah	0.812	0.332	0.418	1.18	0.666	0.923	0.216	0.613	1.12	0.408
			N MP	0.813	0.332	0.415	1.16	0.661	0.923	0.216	0.611	1.11	0.407
		GBM	Noah	0.81	0.33	0.421	1.19	0.668	0.922	0.217	0.613	1.12	0.408
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		ACM2	Noah	0.812	0.325	0.414	1.15	0.649	0.921	0.214	0.622	1.18	0.417
			N MP	0.812	0.328	0.412	1.15	0.65	0.921	0.218	0.618	1.18	0.423
		GBM	Noah	0.811	0.322	0.415	1.13	0.641	0.921	0.212	0.623	1.16	0.409
			N MP	0.811	0.325	0.41	1.13	0.644	0.92	0.216	0.618	1.16	0.416

3. Results and discussion

a. Individual model performance
– Categorical metrics

<u>For 75th percentile threshold (significant event)</u>:

- **KF** is better than **GF**
- **Thom-KF** performs best
- **WSM5** has better POD performance
- For **Thom-KF** configuration:

  frequency bias ↓

  false alarm ratio ↓ / accuracy ↑

  POD ↓

				0.25 mm					75th Percentile				
MP	CU	PBL	LS	Accuracy	ETS	False Alarm Ratio	Frequency Bias	POD	Accuracy	ETS	False Alarm Ratio	Frequency Bias	POD
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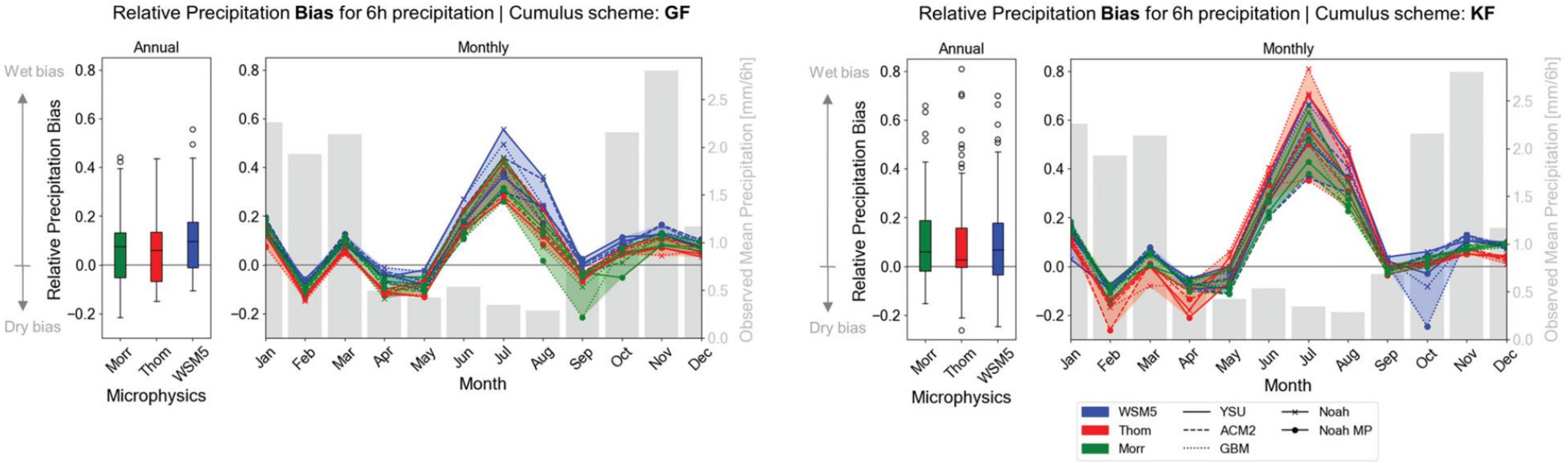
3. Results and discussion

b. Seasonal performance variation – 27km grid



■ **<u>Climatology (gray bars)</u>**:

cool and wet (stratiform)

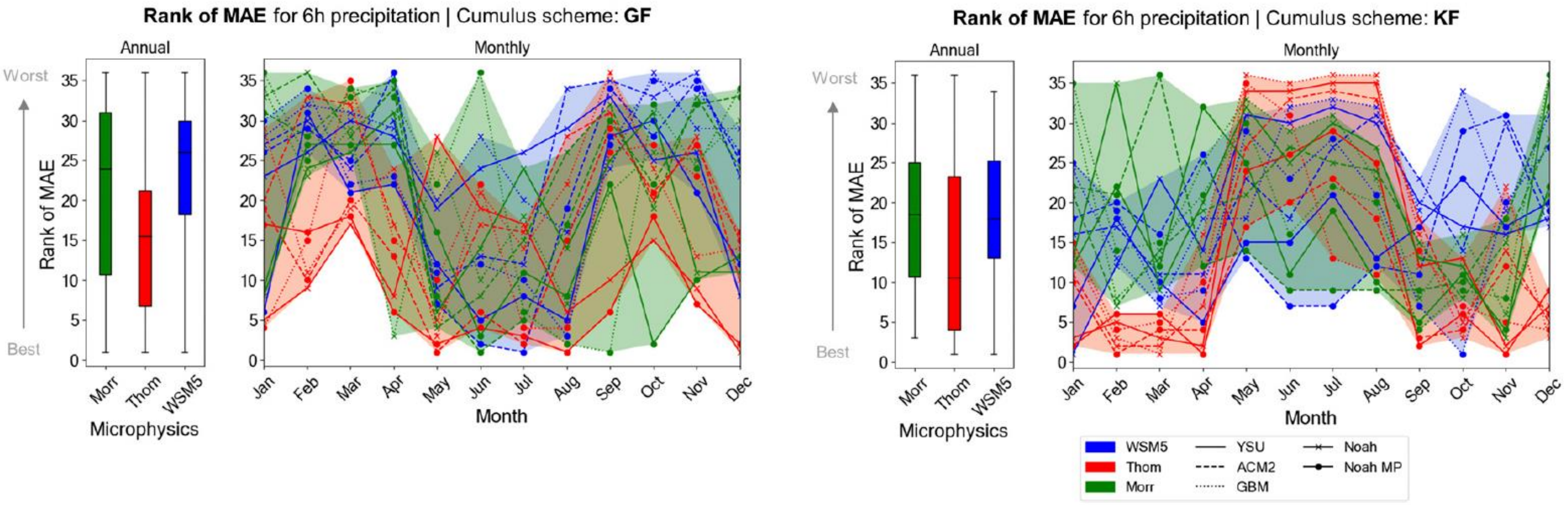
warm and dry (convective)

■ **<u>Warm season</u>**: wet bias (GF better than KF)

■ **<u>Cool season</u>**: neutral to dry bias

3. Results and discussion

b. Seasonal performance variation – 27km grid



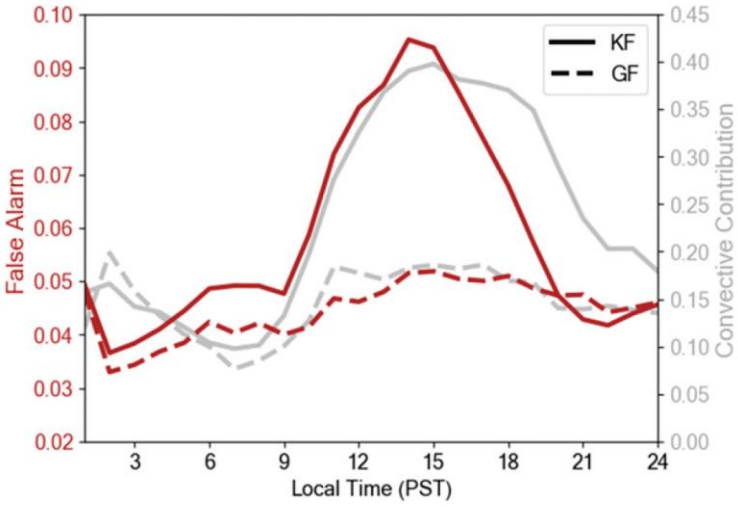
- **Thom-KF** performs well in cool season (stratiform precipitation)
- **Thom-KF** performance has large seasonal variation
- Scale-aware **GF** performs better in warm season (convective precipitation)

3. Results and discussion

b. Seasonal performance variation

<u>For 9km grid forecast in summer (June - August):</u>

- Cumulus scheme has large impact on summer convective precipitation performance
- For **KF** at 1400 LST:
  apparent diurnal pattern (observation not show)
  9.5% false alarm ratio (FAR)
  40% total precipitation contribution
- **GF** performs better than **KF** in warm season



3. Results and discussion

c. Geographical performance patterns

$$\textit{Relative Bias} = \frac{WRF - Obs}{Obs}$$

- **<u>For cool and wet season</u>**:

  1. dry bias on the lee side

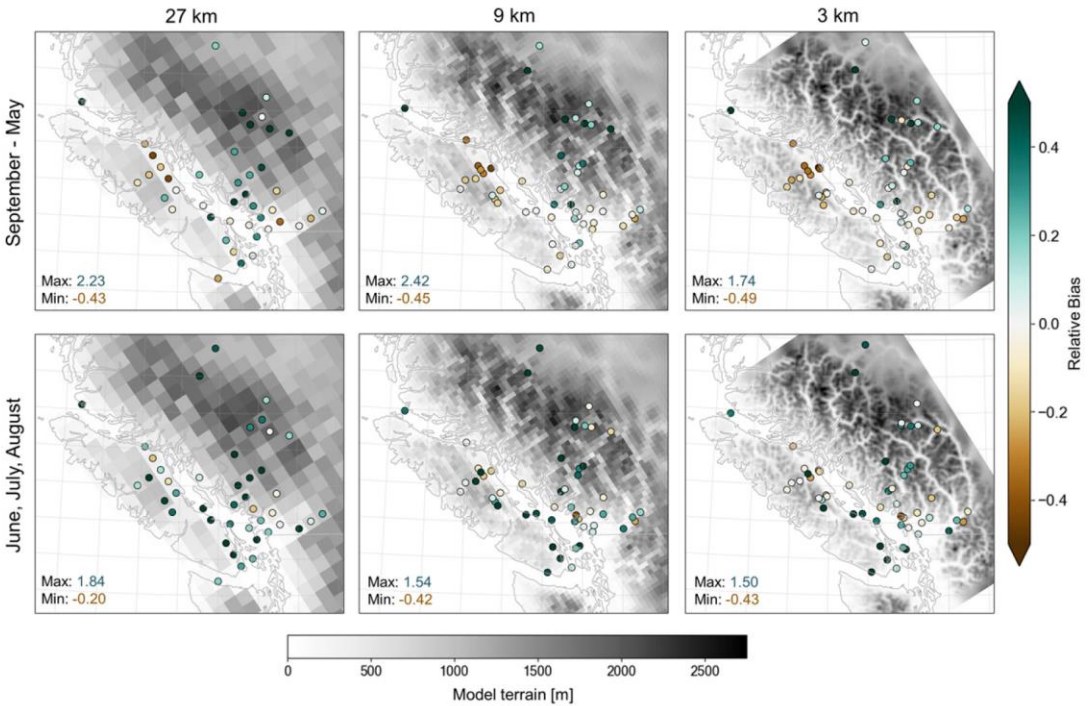
  2. wet bias on wind ward slope

- **<u>For warm and dry season</u>**:

  general wet bias

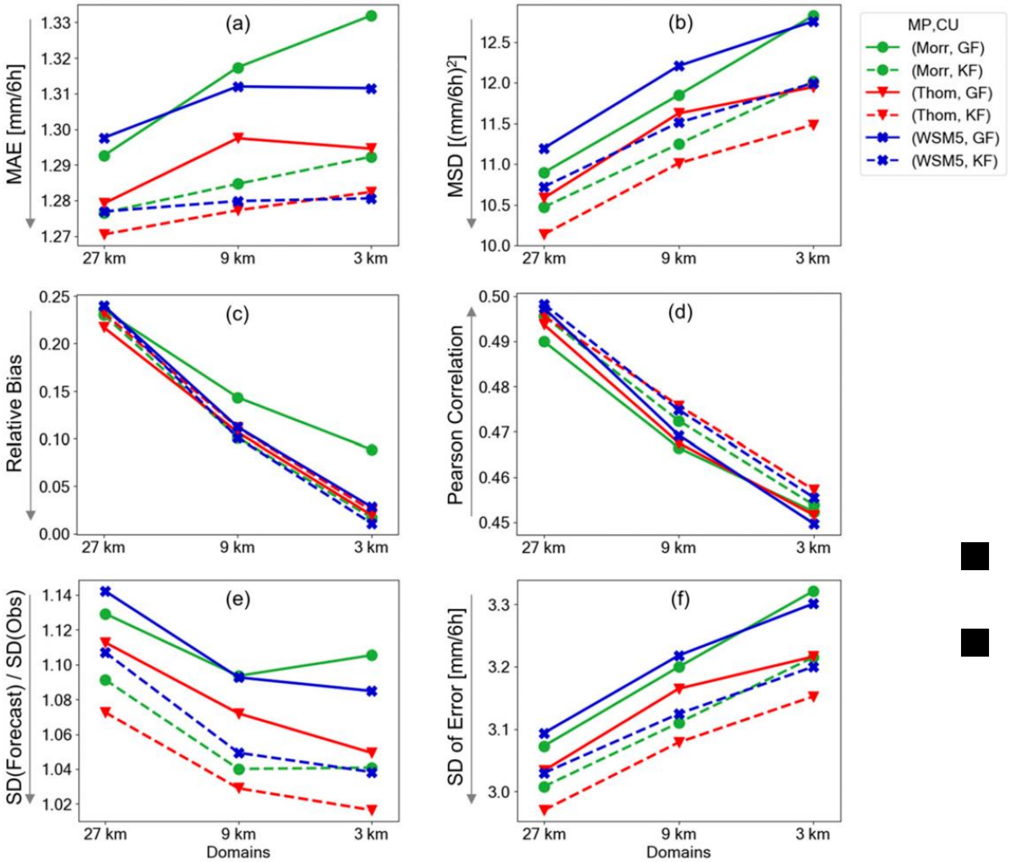
  (without geographical variation)

- Extreme wet bias on windward slope in the model



3. Results and discussion

d. Resolution-dependent performance



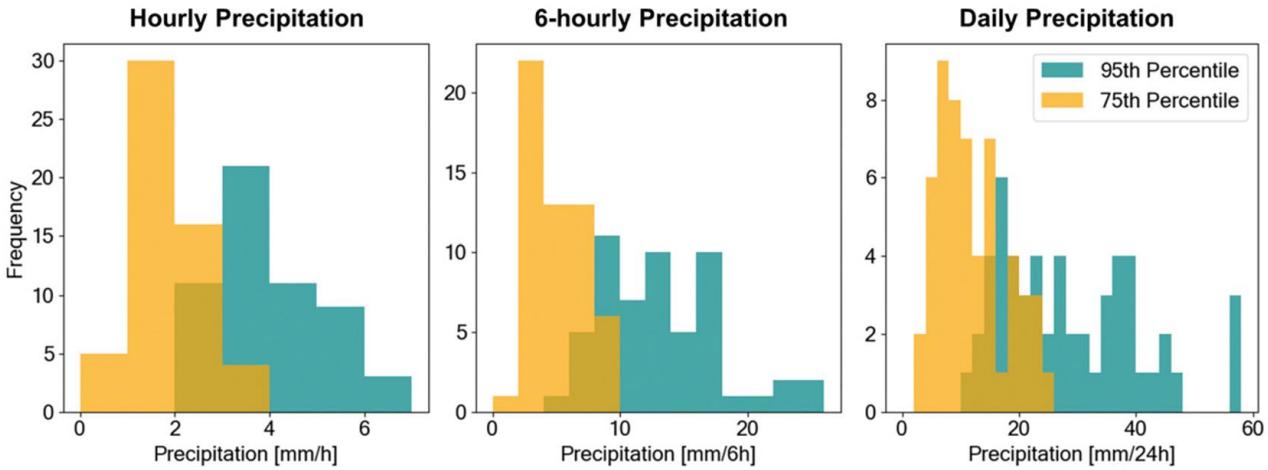
	Coarser (27-km)	Finer (3-km)
(a) MAE	O	
(b) MSD	O	
(c) Bias		O
(d) Correlation	O	
(e) SD ratio		O
(f) Error SD	O	

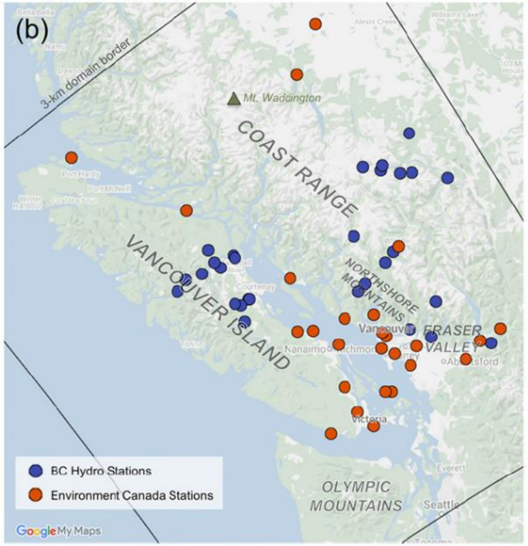
- **KF** performs better than **GF** (surprisingly)
- Finer resolution produces more extreme and localized precipitation → worse MAE, MSD, and SD of error

3. Results and discussion

e. Common versus extreme event performance

- The climatology of 55 stations across the region are disparate
- 75th (common) and 95th (extreme) percentile distributions are different

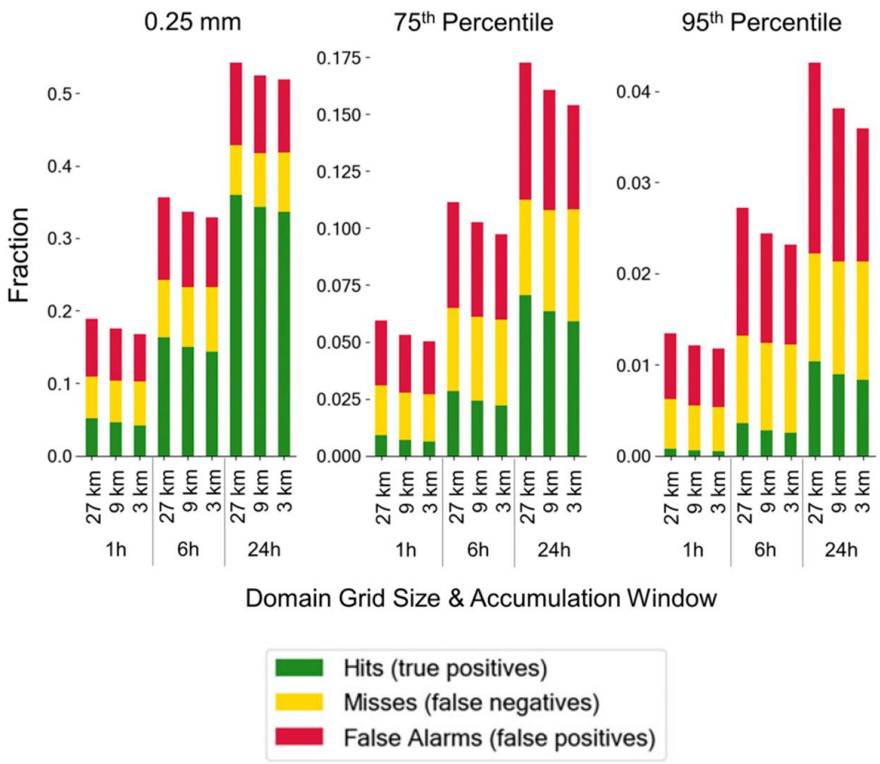




3. Results and discussion

e. Common versus extreme event performance

For the mean of all configurations:

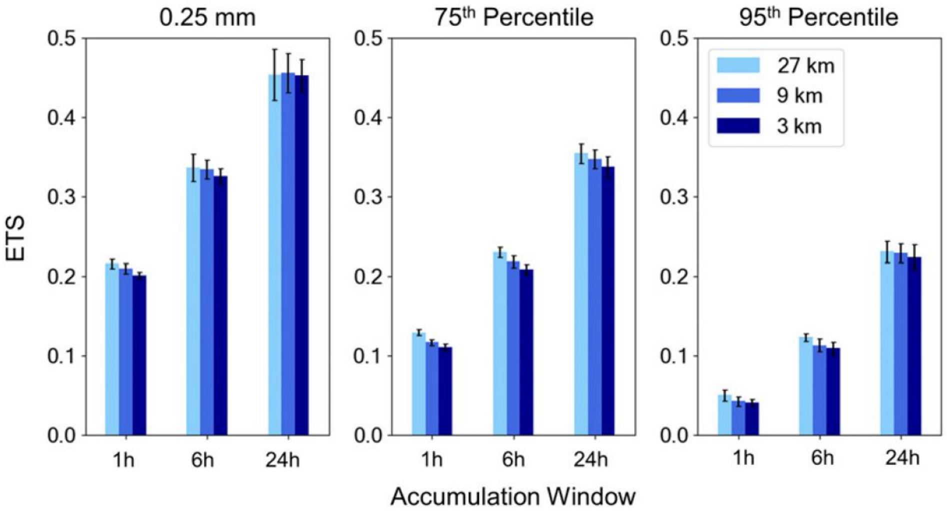


- Temporal resolution impacts more than spatial resolution
- **Hit rate decreases for**:
  1. more extreme events
  2. smaller accumulation time windows
  3. finer grid resolutions
- The "*deterministic limit*" is exceeded for smaller accumulation windows and more extreme events

3. Results and discussion

e. Common versus extreme event performance

<u>For the mean of all configurations:</u>

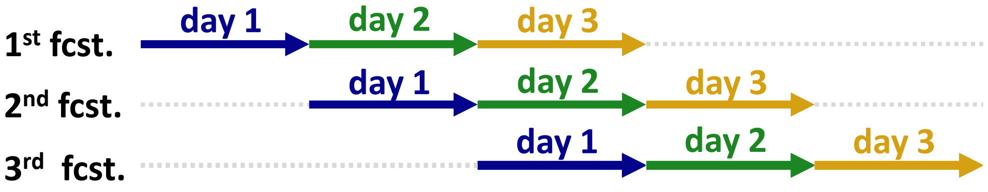


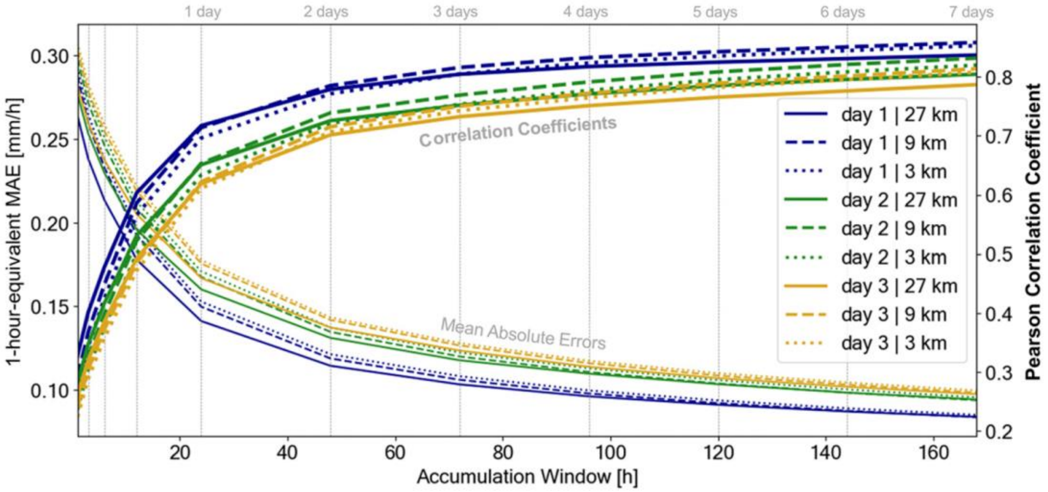
(Error bars represent the spread among individual models)

- Temporal resolution impacts more than spatial resolution
- **<u>Hit rate decreases for</u>**:
  1. more extreme events
  2. smaller accumulation time windows
  3. finer grid resolutions
- The "*<u>deterministic limit</u>*" is exceeded for smaller accumulation windows and more extreme events

3. Results and discussion

f. Predictability with forecast horizon and accumulation window

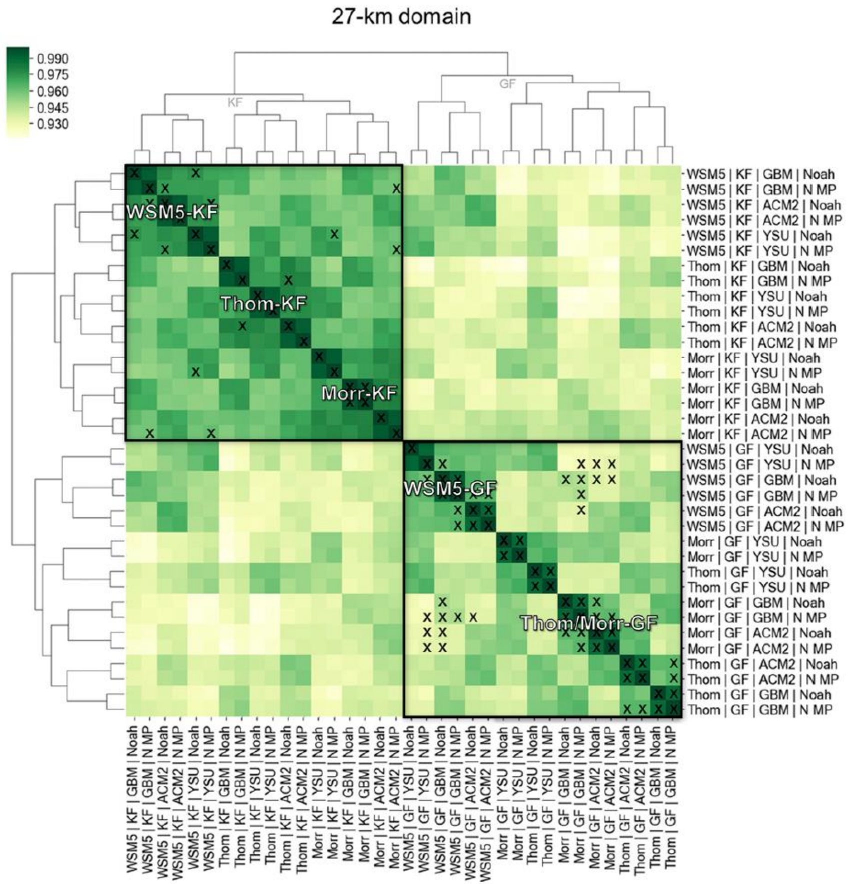




- **<u>Forecast quality will diminish with</u>**:
  - *1.* longer forecast horizons
  - *2.* shorter accumulation windows
- The difference between day 1 and day 2 is larger than day 2 and day 3
- **<u>MAE</u>**: 3-km performs the worst
- **<u>Correlation</u>**:
  - 27-km performs well in the 1st day
  - 9-km performs well after the 2nd day

3. Results and discussion

g. Model interdependence – hierarchical clustering



- Based on Pearson correlation coefficients
- Correlation are generally large (>0.9)

<u>1st hierarchy: cumulus scheme</u>

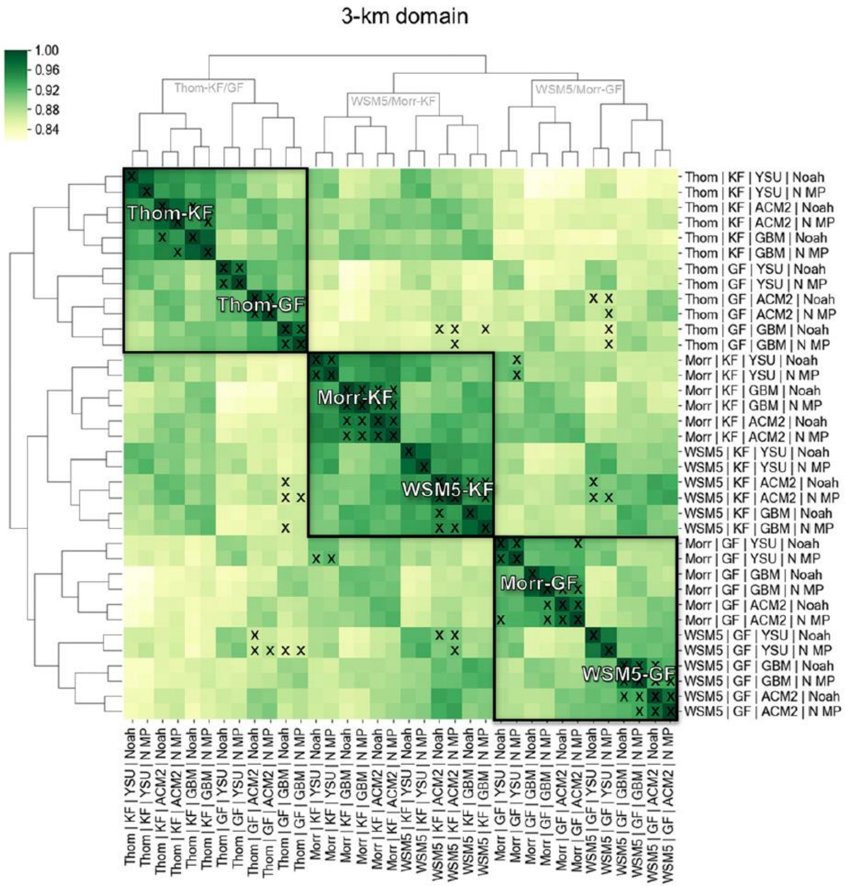
- **KF** configurations are more correlated in precipitation than **GF**

<u>2nd hierarchy: microphysics scheme</u>

- **Thom** and **Morr** are better correlated
- **WSM5** has its own group

3. Results and discussion

g. Model interdependence – hierarchical clustering



- Based on Pearson correlation coefficients
- Correlation are less correlated (>0.8)

<u>1st hierarchy: cumulus-microphysics mixing</u>

- **Thom-KF** and **Thom-GF**
- **WSM5-KF** and **Morr-KF**
- **Morr-GF** and **WSM5-GF**

<u>2nd hierarchy: PBL scheme</u>

- **ACM2** and **GBM** often group together
- **YSU** has its own group

4. Summary and conclusions

- **Cumulus** and **microphysics** are confirmed the primary parameterization to determine the precipitation forecast performance.
- <u>**For microphysical scheme**</u>:

  WSM5 and **Thom** both perform well, but **WSM5** is less expensive .
- <u>**For cumulus scheme**</u>:

  1. **GF** performs well in summer convective precipitation.

  2. **KF** performs well in wintertime precipitation, which is the majority of annual rainfall.

  3. Scale-aware **GF** scheme does not outperform conventional **KF** scheme at finer resolutions.

4. Summary and conclusions

- The best-performing configuration is ***unique to each area*** and application.
- **In southwest BC, the following 5 configuration perform better**:

1. WSM5-KF-YSU-NoahMP

2. WSM5-KF-GBM-NoahMP

3. Thom-KF-YSU-NoahMP

4. Thom-KF-ACM2-NoahMP

5. Thom-GF-YSU-NoahMP

4. Summary and conclusions

For spatial resolution issues:

- Higher spatial resolutions can produce more realistic spread of precipitation, while they have higher random errors and are prone to *"double-penalty"* issues.
- Coarser spatial resolutions have less random errors while the bias are larger.
- Configurations with finer grids diverge more, so the choice of cumulus and microphysics parameterization combinations become increasingly important.

For temporal resolution issues:

- The length of accumulation windows have large impact on verification.

Thanks for listening.

	IC/BC	cumulus scheme	microphysics scheme	MAE	MSE	BIAS	STD_error	STD_ratio	CC
E01	NCEP FNL	Kain-Fritsch	WDM 6-class	39.99	3203.73	-14.03	54.84	0.77	0.30
E02	NCEP FNL	Kain-Fritsch	Goddard	36.48	2848.72	-21.70	48.76	0.68	0.41
E03	NCEP FNL	Kain-Fritsch	Thompson	40.46	3165.17	-22.37	51.62	0.60	0.29
E04	NCEP FNL	Kain-Fritsch	Morrison	32.17	2370.68	-22.15	43.36	0.65	0.54
E05	NCEP FNL	Betts-Miller-Janjic	WDM 6-class	37.60	2894.23	-17.57	50.85	0.78	0.40
E06	NCEP FNL	Betts-Miller-Janjic	Goddard	38.66	2997.20	-15.95	52.37	0.84	0.40
E07	NCEP FNL	Betts-Miller-Janjic	Thompson	34.89	2340.04	-8.33	47.65	0.77	0.47
E08	NCEP FNL	Betts-Miller-Janjic	Morrison	38.91	2723.02	-10.95	51.02	0.77	0.39
E09	NCEP FNL	Grell 3D ensemble	WDM 6-class	35.06	2637.50	-17.54	48.27	0.83	0.49
E10	NCEP FNL	Grell 3D ensemble	Goddard	38.19	2891.51	-13.77	51.98	0.90	0.43
E11	NCEP FNL	Grell 3D ensemble	Thompson	43.38	3557.61	-14.69	57.81	0.89	0.29
E12	NCEP FNL	Grell 3D ensemble	Morrison	33.06	2410.29	-20.39	44.66	0.75	0.54
E13	NCEP FNL	Grell-Devenyi ensemble	WDM 6-class	39.98	3299.41	-18.85	54.26	0.93	0.40
E14	NCEP FNL	Grell-Devenyi ensemble	Goddard	37.70	2872.21	-16.28	51.06	0.82	0.42
E15	NCEP FNL	Grell-Devenyi ensemble	Thompson	44.90	3785.54	-15.86	59.45	0.85	0.22
E16	NCEP FNL	Grell-Devenyi ensemble	Morrison	33.97	2466.23	-20.29	45.33	0.74	0.52
E17	EC ERA5	Kain-Fritsch	WDM 6-class	37.74	2743.46	-9.05	51.59	0.89	0.44
E18	EC ERA5	Kain-Fritsch	Goddard	43.56	3681.04	-1.25	60.66	0.98	0.29
E19	EC ERA5	Kain-Fritsch	Thompson	41.34	3308.54	-2.60	57.46	0.94	0.33
E20	EC ERA5	Kain-Fritsch	Morrison	35.55	2607.72	-4.19	50.89	1.02	0.52
E21	EC ERA5	Betts-Miller-Janjic	WDM 6-class	38.78	2991.42	-23.05	49.60	0.58	0.35
E22	EC ERA5	Betts-Miller-Janjic	Goddard	38.98	2943.88	-21.82	49.68	0.51	0.32
E23	EC ERA5	Betts-Miller-Janjic	Thompson	55.42	5402.37	-10.78	72.71	0.92	-0.09
E24	EC ERA5	Betts-Miller-Janjic	Morrison	38.82	2906.98	-6.92	53.47	0.90	0.40
E25	EC ERA5	Grell 3D ensemble	WDM 6-class	42.61	3349.79	-13.40	56.30	0.80	0.27
E26	EC ERA5	Grell 3D ensemble	Goddard	42.69	3680.89	-8.75	60.04	0.96	0.29
E27	EC ERA5	Grell 3D ensemble	Thompson	46.87	3913.19	-11.69	61.45	0.85	0.17
E28	EC ERA5	Grell 3D ensemble	Morrison	36.26	2623.80	-13.32	49.46	0.74	0.42
E29	EC ERA5	Grell-Devenyi ensemble	WDM 6-class	44.17	3461.02	-17.96	56.02	0.72	0.22
E30	EC ERA5	Grell-Devenyi ensemble	Goddard	39.12	3190.67	-7.37	56.00	0.98	0.39
E31	EC ERA5	Grell-Devenyi ensemble	Thompson	47.65	3880.28	-9.02	61.63	0.84	0.15
E32	EC ERA5	Grell-Devenyi ensemble	Morrison	34.94	2617.87	-13.82	49.26	0.91	0.50

	IC/BC	cumulus scheme	microphysics scheme	TS	ETS	BIAS	FAR	POD	Accuracy
E01	NCEP FNL	Kain-Fritsch	WDM 6-class	0.13	0.08	0.37	0.57	0.16	0.79
E02			Goddard	0.13	0.09	0.23	0.39	0.14	0.81
E03			Thompson	0.03	0.01	0.10	0.70	0.03	0.79
E04			Morrison	0.18	0.14	0.22	0.15	0.19	0.83
E05		Betts-Miller-Janjic	WDM 6-class	0.17	0.11	0.45	0.53	0.21	0.79
E06			Goddard	0.21	0.13	0.53	0.51	0.26	0.80
E07			Thompson	0.26	0.19	0.56	0.42	0.32	0.82
E08			Morrison	0.08	0.02	0.41	0.74	0.11	0.76
E09		Grell 3D ensemble	WDM 6-class	0.29	0.23	0.47	0.28	0.33	0.84
E10			Goddard	0.27	0.19	0.65	0.46	0.35	0.81
E11			Thompson	0.20	0.12	0.60	0.56	0.27	0.79
E12			Morrison	0.18	0.13	0.36	0.41	0.21	0.81
E13		Grell-Devenyi ensemble	WDM 6-class	0.24	0.18	0.44	0.37	0.28	0.82
E14			Goddard	0.21	0.14	0.49	0.48	0.26	0.80
E15			Thompson	0.15	0.08	0.56	0.63	0.21	0.77
E16			Morrison	0.22	0.16	0.40	0.36	0.25	0.82
E17	EC ERA5	Kain-Fritsch	WDM 6-class	0.20	0.11	0.71	0.60	0.28	0.77
E18			Goddard	0.21	0.11	0.89	0.63	0.33	0.75
E19			Thompson	0.22	0.12	0.83	0.60	0.33	0.76
E20			Morrison	0.37	0.28	0.90	0.43	0.52	0.82
E21		Betts-Miller-Janjic	WDM 6-class	0.04	0.02	0.16	0.68	0.05	0.79
E22			Goddard	0.00	0.00	0.06	1.00	0.00	0.79
E23			Thompson	0.01	0.00	0.55	0.97	0.02	0.70
E24			Morrison	0.14	0.05	0.64	0.69	0.20	0.75
E25		Grell 3D ensemble	WDM 6-class	0.09	0.02	0.51	0.76	0.12	0.75
E26			Goddard	0.17	0.09	0.61	0.62	0.23	0.77
E27			Thompson	0.10	0.03	0.48	0.72	0.13	0.76
E28			Morrison	0.07	0.02	0.29	0.72	0.08	0.77
E29		Grell-Devenyi ensemble	WDM 6-class	0.07	0.01	0.38	0.76	0.09	0.76
E30			Goddard	0.23	0.14	0.70	0.54	0.32	0.79
E31			Thompson	0.12	0.04	0.60	0.71	0.18	0.75
E32			Morrison	0.29	0.21	0.57	0.39	0.35	0.83