Selection of CMIP6 Global Climate Models for long-term hydrological projections

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CONTENTS

INTRODUCTION

Selection of CMIP6 Global Climate Models for long-term hydrological projections

- ✓ More and **more regions will start feeling the effects of climate change in multiple ways**, drought, flood, fire forest, landslide, heatwave …….

- ✓ The **analyzation and simulation** of the spatio-temporal climate variables variation **for small scale such as regional, local, or basin scale under future climate projection scenarios is a significant necessity** for the water management policies.

- ✓ The Global climate models (GCMs) were released under a series of CMIPs in different phases which **have been considering as powerful resource for Earth science researches**.

- ✓ The CMIP3, CMIP5 consisted 25 GCMs, 40 GCMs, respectively and the CMIP6 which is the most recent have 55 GCMs. However, **the uncertainty in future projections due to differences between GCMs** and the necessity of using a suitable subset of GCMs in the development of climate change scenarios are addressed in many researches.

Therefore, **choosing a suitable subset CMIP6 GCMs play a vital role**, creating a firmly foundation for long-term hydrological projections.

- ✓ Located in **East Asia**, has large climate fluctuation with complicated topography.
- ✓ It have **Western and eastern are bordered by the Yellow Sea**, and **the East Sea, respectively**.
- ✓ Four general regions: an **eastern** region of **high mountain ranges and narrow coastal plains**; a **western** region of **broad coastal plains, river basins, and rolling hills**; a **southwestern** region of **mountains and valleys**; and a **southeastern** region dominated by the broad **basin of the Nakdong River**.
- ✓ Five major river basins: Yeongsan River, Seomjin River, Geum River, Nakdong River, and Han River with 56 weather stations as shown Figure 1.

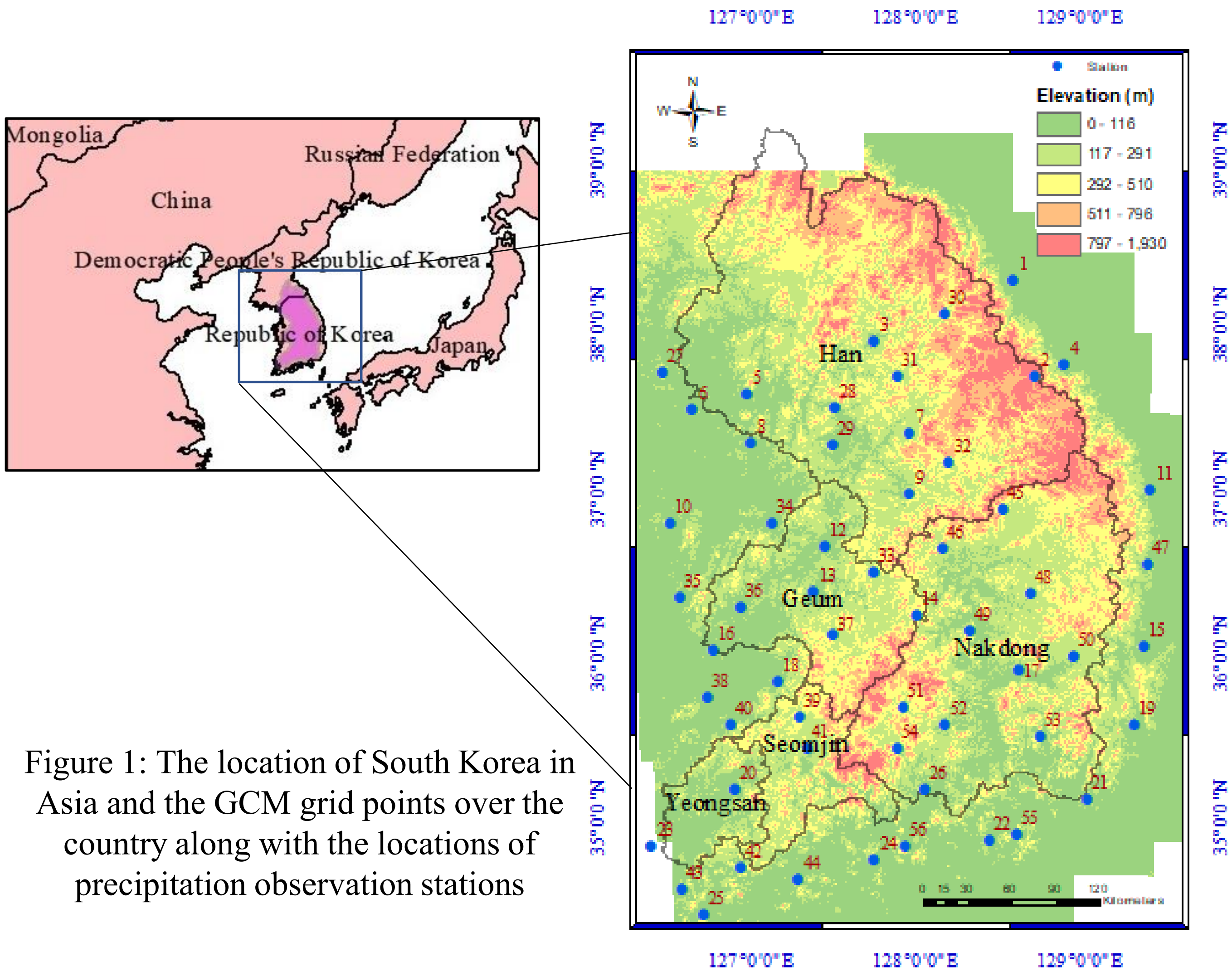


Figure 1: The location of South Korea in Asia and the GCM grid points over the country along with the locations of precipitation observation stations

- ✓ **Monthly precipitation data at 56 weather stations** (Table I) recorded comes from the Korea Meteorological Administration (KMA).

- ✓ **Simulated monthly precipitation of 32 available CMIP6 GCMs** for ensemble run r1i1p1f1 were obtained from website *http://cmip-pcmdi.llnl.gov/cmip6/* for the historical period 1973-2014 **as Table II**.

Sta. No.	Sta. name	Lat. (N)	Lon. (E)
90	Sokcho	128.5814	38.2648
100	Daeqwalyeong	128.7183	37.6772
101	Chuncheon	127.7357	37.9026
105	Gangneung	128.891	37.7515
108	Seoul	126.9658	37.5714
112	Incheon	126.6244	37.4776
114	Wonju	127.9466	37.3376
119	Suwon	126.9856	37.2728
127	Chungju	127.9527	36.9704
129	Seosan	126.4939	36.7766
130	Uljin	129.4128	36.9918
131	Cheongju	127.4407	36.6392
133	Daejeon	127.3721	36.372
135	Chupungryeong	127.9946	36.2202
138	Pohang	129.3796	36.0326
140	Gunsan	126.7613	36.0053
143	Daegu	128.619	35.8852
146	Jeonju	127.155	35.8215
152	Ulsan	129.3203	35.5601
156	Gwangju	126.8916	35.1729
159	Busan	129.032	35.1047
162	Tongyeong	128.4356	34.8455
165	Mokpo	126.3812	34.8169
168	Yeosu	127.7406	34.7393
170	Wan-do	126.7018	34.3959
192	Jinju	128.04	35.1638
201	Ganghwa	126.4463	37.7074
202	Yangpyeong	127.4945	37.4886
203	Icheon	127.4842	37.264
211	Inje	128.1671	38.0599
212	Hongcheon	127.8804	37.6836
221	Jecheon	128.1943	37.1593
226	Boeun	127.7341	36.4876
232	Cheonan	127.1192	36.7767
235	Boryeong	126.5574	36.3272
236	Buyeo	126.9208	36.2724
238	Geumsan	127.4817	36.1056
243	Buan	126.7166	35.7295
244	Imsil	127.2856	35.6123
245	Jeongeup	126.8661	35.5632
247	Namwon	127.333	35.4054
260	Jangheung	126.9195	34.6887
261	Haenam	126.569	34.5536
262	Goheung	127.2757	34.6182
272	Yeongju	128.517	36.8719
273	Mungyeong	128.1488	36.6273
277	Yeongdeok	129.4094	36.5333
278	Uiseong	128.6886	36.3561
279	Gumi	128.3205	36.1306
281	Yeongcheon	128.9514	35.9774
284	Geochang	127.911	35.6712
285	Hapcheon	128.1699	35.565
288	Miryang	128.7441	35.4915
289	Sancheong	127.8791	35.413
294	Geoje	128.6045	34.8882
295	Namhae	127.9264	34.8166

Table I: 56 weather stations

DATA

Selection of CMIP6 Global Climate Models for long-term hydrological projections

No.	Models	Institution	Country	Longtitude (°)	Latitude (°)
1	ACCESS-CM2	CSIRO and ARCCSS	Australia	1.25	1.875
2	ACCESS-ESM1-5	CSIRO and ARCCSS	Australia	1.25	1.875
3	AWI-CM-1-1-MR	Alfred Wegener Institute Bremerhaven	Germany	0.937	0.934
4	AWI-ESM-1-1-LR	Alfred Wegener Institute Bremerhaven	Germany	1.875	1.86
5	BCC-CSM2-MR	Beijing Climate Center	China	1.125	1.121
6	BCC-ESM1	Beijing Climate Center	China	2.812	2.788
7	CAMS-CSM1-0	Chinese Academy of Meteorological Sciences	China	1	1
8	CanESM5	CCCma	Canada	2.812	2.789
9	CAS-ESM2-0	Chinese Academy of Sciences	China	1.406	1.417
10	CESM2-FV2	National Center for Atmospheric Research	USA	1.9	2.5
11	CESM2-WACCM-FV2	National Center for Atmospheric Research	USA	1.9	2.5
12	CESM2-WACCM	National Center for Atmospheric Research	USA	0.9	1.25
13	CESM2	National Center for Atmospheric Research	USA	0.9	1.25
14	CMCC-CM2-HR4	Fondazione Centro Euro-Mediterraneo sui Cambiamenti Climatici	Italy	1	1
15	CMCC-CM2-SR5	Fondazione Centro Euro-Mediterraneo sui Cambiamenti Climatici	Italy	1	1
16	CMCC-ESM2	Fondazione Centro Euro-Mediterraneo sui Cambiamenti Climatici	Italy	1.25	0.942
17	E3SM-1-1-ECA	Lawrence Livermore National Laboratory (LLNL)	USA	1	1
18	E3SM-1-1	Lawrence Livermore National Laboratory (LLNL)	USA	1	1
19	EC-Earth3-AerChem	EC-Earth-Consortium	Europe	0.35	0.35
20	EC-Earth3-CC	EC-Earth-Consortium	Europe	0.35	0.35
21	EC-Earth3-Veg-LR	EC-Earth-Consortium	Europe	0.35	0.35
22	EC-Earth3-Veg	EC-Earth-Consortium	Europe	0.35	0.35
23	EC-Earth3	EC-Earth-Consortium	Europe	0.35	0.35
24	FGOALS-f3-L	Chinese Academy of Sciences	China	1	1
25	FGOALS-g3	Chinese Academy of Sciences	China	2	2
26	FIO-ESM-2-0	First Institute of Oceanography, Ministry of Natural Resources	China	0.9	1.25
27	GFDL-CM4	National Oceanic and Atmospheric Administration	USA	1.25	1
28	GFDL-ESM4	National Oceanic and Atmospheric Administration	USA	1.25	1
29	GISS-E2-1-G-CC	Goddard Institute for Space Studies (NASA-GISS)	USA	1.25	1.25
30	GISS-E2-1-G	Goddard Institute for Space Studies (NASA-GISS)	USA	1.25	1.25
31	GISS-E2-1-H	Goddard Institute for Space Studies (NASA-GISS)	USA	1.25	1.25
32	GISS-E2-2-H	Goddard Institute for Space Studies (NASA-GISS)	USA	1.25	1.25

Table II. 32 available CMIP6 GCMs for ensemble run r1i1p1f1

Selection of CMIP6 Global Climate Models for long-term hydrological projections

Step 1	All the GCMs and the observed were **linearly interpolated to** a same spatial grid having **0.125° resolution** to facilitate comparison.
Step 2	Compare between monthly precipitation of observed and simulated precipitation of 32 CMIP6 GCMs at all grid points using four spatial metrics, Cramer's V, SPAEF, KGE, and FSS.
Step 3	The GCMs were ranked separately according to the value of each metrics in their monthly precipitation reconstruct skill.
Step 4	The overall ranking of 32 GCMs were determined by comprehensive Rating Metrics (RMs) values to identify the best subset GCMs.
Step 5	Evaluation performance of the selected GCMs based on their bias of precipitation simulation ability.

Figure 2. Research process

Machine learning models and statistical metrics have been applied to evaluate and select the best performing GCMs by various researchers such as:

- ✓ Information entropy, Probability distribution function, Bayesian approach, Correlation, Clustering, Hierarchical ANOVA models, symmetrical uncertainty, and recursive feature elimination.
- ✓ With standard deviation (σ), skill score (SS), deterministic coefficient (DC), correlation coefficient (CC), relative error (RE), root mean square error (RMSE) , average absolute relative error (AARE), normalized root mean square error (NRMSE), absolute normalized mean bias error (ANMBE).

However, literature review as aforementioned are mostly ignores explicit evaluation of spatial performance, but only focused on the temporal performance which is equally important in procedure of choosing GCM.

Four spatial performance indicators:

✓ The SPAtial EFficiency metric (SPAEF) [Demirel et al., 2018b]

✓ Kling–Gupta efficiency (KGE) [Gupta et al., 2009]

✓ Cramer's V [Cram´er, 1999]

✓ Fractions skill score (FSS) [Roberts and Lean, 2008]

1. Cramer’s V

- ✓ a statistical test base on Pearson’s chi-squared statistic and was first published in 1946 by Harald Cram´er.
- ✓ It is used to know the strength of the relationship between two categorical variables.
- ✓ ranges 0-1 without any negative values, where a value close to 0 indicates no relationship and 1 means perfect association.
- ✓ Here, the study used Cramer’s V to evaluate spatial agreement of precipitation between observational and GCMs output data [Ahmed et al., 2019] [Iqbal et al., 2021] with the Equation (1) as below:

$$V = \sqrt{\frac{x^2/n}{min(c-1, r-1)}} \qquad (1)$$

where: x^2 is chi-square value, n is total of observations, c and r respectively being the number of columns and row of dataset, c=2 (observational and simulated precipitation), r = 511056 (the number of rows of data).

2. SPAtial EFficiency metric (SPAEF):

- ✓ A multiple-component spatial performance metric, is proposed by [Demirel et al., 2018a].
- ✓ Can be used to compare spatial patterns in two raster maps base on considering three distinct and complementary components of (1) coefficient of variation, (2) correlation, and (3) histogram overlap.
- ✓ Between −∞-1, where a value closer to 1 refer to a higher agreement between observations and simulations data.
- ✓ In this research, the SPAEF values between observed precipitation and GCMs-simulated precipitation were implemented by Equation (2)

$$SPAEF = 1 - \sqrt{(\alpha - 1)^2 + (\beta - 1)^2 + (\gamma - 1)^2} \quad (2)$$

where:

***α represents the Pearson correlation coefficient between the observational (obs) and GCMs simulate (sim) precipitation, is calculated by Equation (3)

$$\alpha = \rho(obs, sim) \qquad (3)$$

***β is coefficient of variation (CV) that represents spatial variability, is calculated by Equation (4)

$$\beta = CV = \frac{\left(\frac{\sigma_G}{\mu_G}\right)}{\left(\frac{\sigma_O}{\mu_O}\right)} \qquad (4)$$

with σ_G, σ_O are standard deviation of GCM-simulated and observed precipitation, and μ_O, μ_G are the means of GCM-simulated and observed precipitation, respectively.

***γ represents histogram overlap, is calculated by Equation (5)

$$\gamma = \frac{\sum_{j=1}^{b} min(H_j, L_j)}{\sum_{j=1}^{b} H_j} \qquad (5)$$

with H, L, and b represent histogram values of observations pattern, histogram values of simulated pattern, and the number of bins in a histogram, respectively

3. Fractions skill score (FSS):

✓ FSS also is a good statistical measure of the spatial accuracy of simulated and observed precipitation, developed by [Roberts and Lean, 2008].

✓ FSS ranges between 0-1 where the value closer to 1 is a perfect match between simulated and observed precipitation.

$$FSS = 1 - \frac{MSE_n}{MSE_{n(wc)}} \quad (6)$$

✓ This study calculated FSS values according to below Equation (6)

- MSE_n is the mean squared error between the observational and simulated fractions.
- MSE is normalized with the worst case $MSE_{n(wc)}$ which means zero agreement about the spatial patterns.
- N_x, N_y respectively are number of columns and rows in the observational or simulated map.
- $ref_{(n)ij}$, $scen_{(n)ij}$ are observed and GCMs output fraction, respectively.

$$MSE_n = \frac{1}{N_{xy}} \sum_{y=1}^{N_x} \cdot \sum_{j=1}^{N_y} [ref_{(n)ij} - scen_{(n)ij}]^2 \quad (7)$$

$$MSE_{n(wc)} = \frac{1}{N_{xy}} \left[\sum_{y=1}^{N_x} \sum_{j=1}^{N_y} ref^2_{(n)ij} + \sum_{y=1}^{N_x} \sum_{j=1}^{N_y} scen^2_{(n)ij} \right] \quad (8)$$

4. Kling–Gupta efficiency (KGE):

✓ A useful spatial performance assessment index, developed by [Gupta et al., 2009].

✓ Three main involved components:

- Pearson correlation coefficient,
- The ratio between the mean of the simulated precipitation and the mean of the observed precipitation,
- The ratio between the CV (coefficient of variation) of the simulated precipitation and the CV of the observed precipitation.

✓ KGE values with three equally weighted components are computed as Equation (9)

$$KGE = 1 - \sqrt{(\alpha_P - 1)^2 + (\beta_P - 1)^2 + (\gamma_{RP} - 1)^2} \quad (9)$$

***α represents the Pearson correlation coefficient between the observational (obs) and GCMs simulated (sim) precipitation, is calculated by Equation (10)

$$\alpha = \rho(obs, sim) \qquad (10)$$

***β_P relative variability based on the ratio of standard deviation in simulated and observed precipitation, is calculated by Equation (11)

$$\beta_P = \frac{\mu_G}{\mu_O} \qquad (11)$$

with μ_G, μ_O are the means of GCM-simulated and observed precipitation, respectively.
***γ_{RP} represents the bias term which is normalized by the standard deviation of the observed precipitation, is calculated by Equation (12)

$$\gamma_{RP} = \frac{CV_G}{CV_O} = \frac{\left(\frac{\sigma_G}{\mu_G}\right)}{\left(\frac{\sigma_O}{\mu_O}\right)} \qquad (12)$$

KGE varies between 0-1, where a value closer to 1 refer to a higher agreement between observed and simulations data.

The GCMs has a difference rank for difference evaluation index. How can we over ranking GCMs?

We used the information aggregation approach - A comprehensive rating metric that should combine obtained results to total ranking to find the top group of GCMs. Comprehensive rating metric for four indices using Equation (13):

$$RM = 1 - \frac{1}{mn}\sum_{i=1}^{n} rank_i \qquad (13)$$

- n and m respectively represent the number of the metrics and the number of models.
- $rank_i$ indicates the rank of GCM based on index i^{th}.

1. Assessment of spatial pattern of mean annual precipitation data
2. The value of spatial indicators and ranking of GCMs
3. Comprehensive rating metric to total ranking GCMs
4. The bias of the selected GCMs subset

1. Assessment of spatial pattern of mean annual precipitation data

- ✓ Observation data shows precipitation in the study area in the range of 1000-1800mm.
- ✓ Highest precipitation (1600-1800mm) occurs in the eastern of Han River basin.
- ✓ Relative higher precipitation (1300-1500mm) comes in the south of Nakdong and Seomjin basin.
- ✓ Lowest precipitation (1000-1100mm) occurs in the central and north of Nakdong basin.

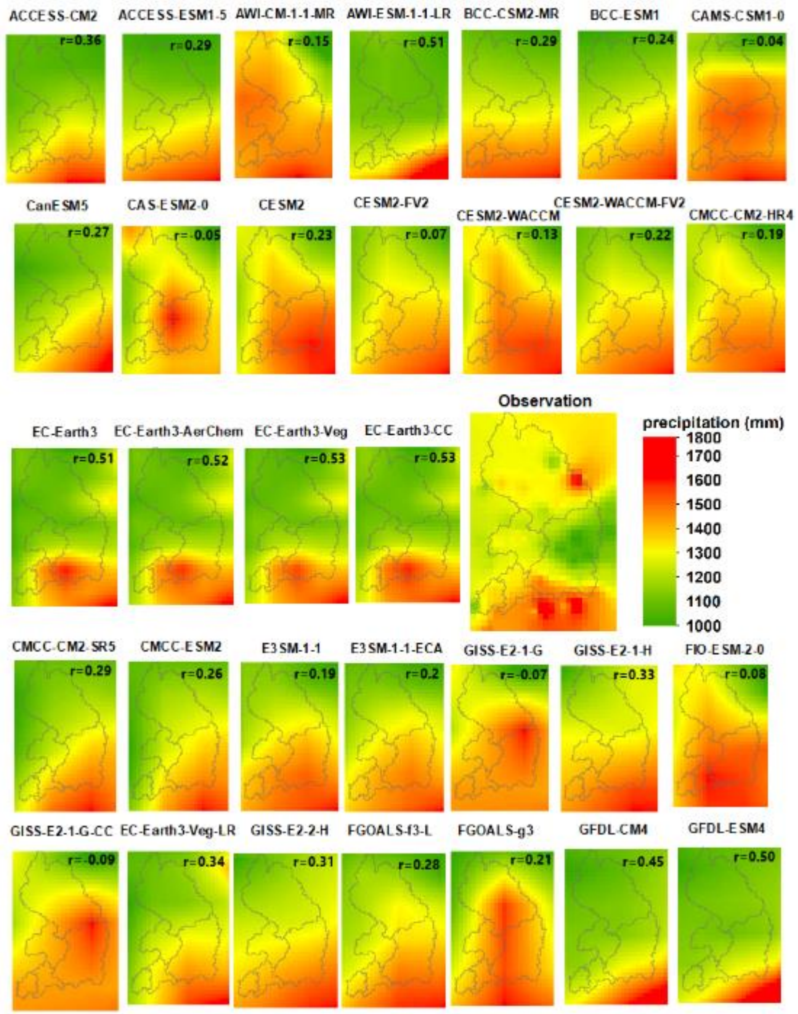


Fig. 2. Spatial distribution of mean annual precipitation (1973-2014) of observational data and 32 GCMs outputs

RESULTS AND DISCUSSION

Selection of CMIP6 Global Climate Models for long-term hydrological projections

1. **Assessment of spatial pattern of mean annual precipitation (prec.) data**

- ✓ **EC-Earth3-AerChem, EC-Earth3-Veg, and EC-Earth3-CC have the highest correlation coefficient** (0.51, 0.52, 0.53, and 0.53, respectively) relatively well simulated the prec. occurs in the Nakdong and Seomjin basin
- ✓ while several GCMs such as CAS-ESM2-0, GISS-E2-1-G, GISS-E2-1-G-CC, and CAMS-CSM1-0 showed opposite result to observed prec. that the high prec. in Nakdong basin.
- ✓ AWI-ESM-1-1-LR have the high correlation coefficient (0.51) showed suitable simulated result for the prec. in the Nakdong basin.
- ✓ However, almost of GCMs **can not capture the precipitation in the eastern of Han basin**, underestimated the prec. occurs in the Han and Geum basin.
- ✓ **This is reason why we proposed combining the spatial performance metrics for accurate evaluating and choosing CMIP6 GCMs** over the major River basin of South Korea.

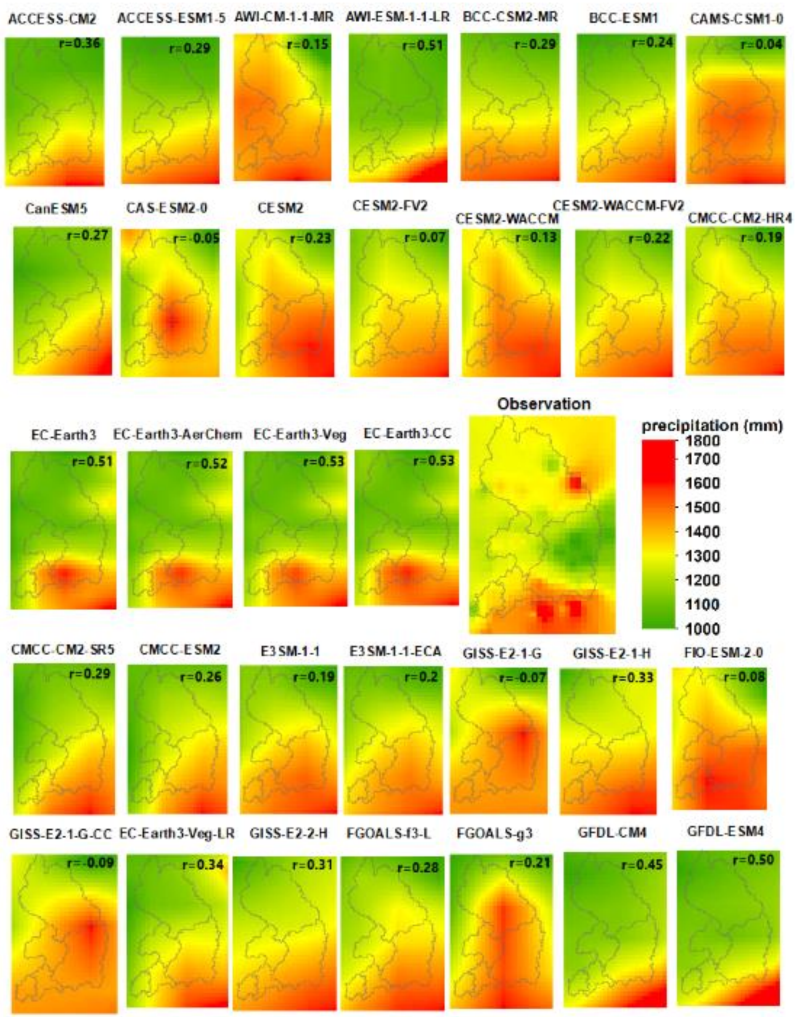
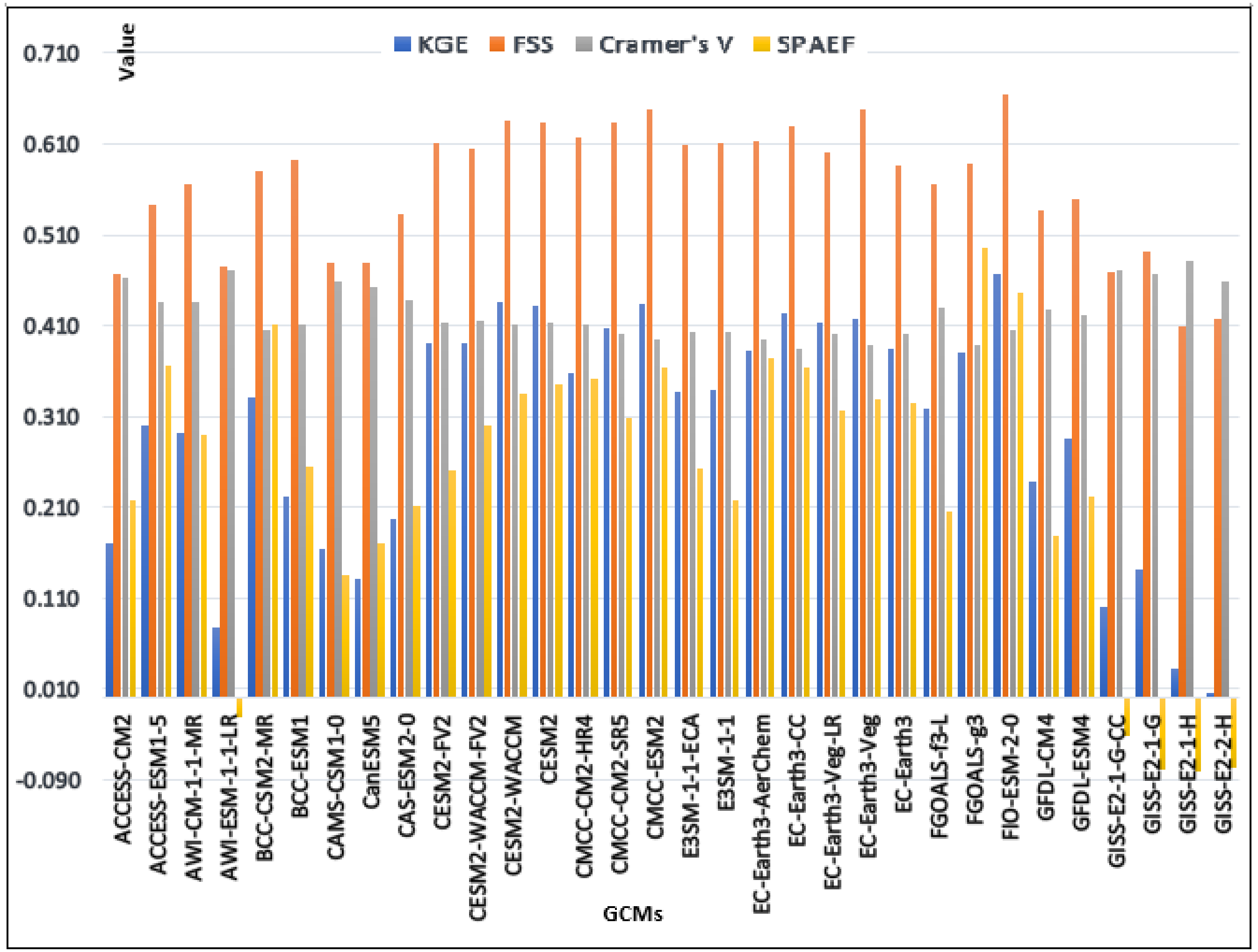


Fig. 2. Spatial distribution of mean annual precipitation (1973-2014) of observational data and 32 GCMs outputs

2. The value of spatial indicators

No	Models	KGE	FSS	Cramer's V	SPAEF
1	ACCESS-CM2	0.17128	0.46714	0.46262	0.217554
2	ACCESS-ESM1-5	0.30074	0.54367	0.43558	0.36584
3	AWI-CM-1-1-MR	0.29211	0.56544	0.43595	0.290508
4	AWI-ESM-1-1-LR	0.07769	0.47433	0.4714	-0.02193
5	BCC-CSM2-MR	0.33062	0.57953	0.40516	0.410874
6	BCC-ESM1	0.22237	0.59206	0.41026	0.254638
7	CAMS-CSM1-0	0.16447	0.47813	0.45812	0.13482
8	CanESM5	0.13227	0.47886	0.45268	0.170805
9	CAS-ESM2-0	0.19698	0.53295	0.43704	0.212458
10	CESM2-FV2	0.39099	0.61154	0.4139	0.250647
11	CESM2-WACCM-FV2	0.39108	0.60397	0.41467	0.301088
12	CESM2-WACCM	0.43517	0.6348	0.41047	0.334286
13	CESM2	0.43224	0.63364	0.41422	0.345541
14	CMCC-CM2-HR4	0.35679	0.61764	0.4117	0.35218
15	CMCC-CM2-SR5	0.40682	0.63438	0.40085	0.307954
16	CMCC-ESM2	0.4349	0.6489	0.39513	0.363564
17	E3SM-1-1-ECA	0.33777	0.60952	0.40401	0.252735
18	E3SM-1-1	0.33849	0.61028	0.40231	0.218366
19	EC-Earth3-AerChem	0.38238	0.61382	0.39375	0.374549
20	EC-Earth3-CC	0.4243	0.62882	0.38449	0.36452
21	EC-Earth3-Veg-LR	0.41345	0.60007	0.40091	0.317309
22	EC-Earth3-Veg	0.4178	0.64744	0.38878	0.329185
23	EC-Earth3	0.38504	0.58552	0.40143	0.324136
24	FGOALS-f3-L	0.31955	0.56554	0.4295	0.206315
25	FGOALS-g3	0.37962	0.58817	0.38802	0.495254
26	FIO-ESM-2-0	0.46618	0.66474	0.40578	0.445845
27	GFDL-CM4	0.23916	0.53771	0.42799	0.179353
28	GFDL-ESM4	0.28563	0.54983	0.42137	0.222205
29	GISS-E2-1-G-CC	0.10008	0.46983	0.47151	-0.04169
30	GISS-E2-1-G	0.14255	0.49219	0.46656	-0.07863
31	GISS-E2-1-H	0.03353	0.40816	0.48221	-0.08099
32	GISS-E2-2-H	0.00579	0.41738	0.45831	-0.07715

Table 3. The ranking of each GCMs based on each metrics



The barplot of the value of four spatial metrics for each GCMs

3. Comprehensive rating metric

The range of the RM values in the three categories:

- ✓ high values: (0.72–0.84) with FIO-ESM-2-0, CESM2-WACCM, CESM2, and CMCC-ESM2 models;
- ✓ low values: (0.26–0.39) with AWI-ESM-1-1-LR, GISS-E2-1-G-CC, GISS-E2-1-H, GISS-E2-2-H models;
- ✓ and medium values: (0.41–0.66) with the remain GCMs.

The best selected GCMs are FIO-ESM-2-0, CESM2-WACCM, CESM2, and CMCC-ESM2.

No.	Models	kge	fss	cramerv	spaef	Over rank	RM
1	FIO-ESM-2-0	1	1	21	2	1	0.84
2	CESM2-WACCM	2	4	19	10	2	0.76
3	CESM2	4	6	16	9	3	0.76
4	CMCC-ESM2	3	2	28	7	4	0.72
5	CMCC-CM2-HR4	14	8	18	8	5	0.66
6	EC-Earth3-Veg	6	3	30	11	6	0.64
7	EC-Earth3-CC	5	7	32	6	7	0.64
8	CESM2-WACCM-FV2	9	13	15	15	8	0.63
9	EC-Earth3-AerChem	12	9	29	4	9	0.61
10	CMCC-CM2-SR5	8	5	27	14	10	0.61
11	CESM2-FV2	10	10	17	19	11	0.59
12	ACCESS-ESM1-5	19	22	11	5	12	0.59
13	EC-Earth3-Veg-LR	7	14	26	13	13	0.56
14	BCC-CSM2-MR	17	18	22	3	14	0.56
15	FGOALS-g3	13	16	31	1	15	0.55
16	EC-Earth3	11	17	25	12	16	0.52
17	AWI-CM-1-1-MR	20	20	10	16	17	0.52
18	E3SM-1-1-ECA	16	12	23	18	18	0.49
19	E3SM-1-1	15	11	24	21	19	0.48
20	FGOALS-f3-L	18	19	12	24	20	0.46
21	BCC-ESM1	23	15	20	17	21	0.45
22	GFDL-ESM4	21	21	14	20	22	0.44
23	CAS-ESM2-0	24	24	9	23	23	0.41
24	ACCESS-CM2	25	30	5	22	24	0.39
25	GFDL-CM4	22	23	13	25	25	0.38
26	CAMS-CSM1-0	26	27	7	27	26	0.35
27	GISS-E2-1-G	27	25	4	31	27	0.35
28	CanESM5	28	26	8	26	28	0.34
29	AWI-ESM-1-1-LR	30	28	3	28	29	0.34
30	GISS-E2-1-G-CC	29	29	2	29	30	0.34
31	GISS-E2-1-H	31	32	1	32	31	0.28
32	GISS-E2-2-H	32	31	6	30	32	0.26

Table 4. The total ranking of each GCMs based on each metrics

4. Evaluation the bias of the selected GCMs subset

Compare the historical moonsoon precipitation (late June to late July) simulating skill:

- ✓ Between observed models with the four top-ranked GCMs;
- ✓ Between observed models with those models such as EC-Earth3, EC-Earth3-AerChem, EC-Earth3-Veg, and EC-Earth3-CC models have the highest correlation coefficient shown as Figure 2

The results showed:

- ✓ EC-Earth3, EC-Earth3-AerChem, EC-Earth3-Veg, and EC-Earth3-CC models underestimate precipitation at the large basins such as Han basin and Nakdong basin.
- ✓ The four top-ranked GCMs overestimate the precipitation over South Korea with the bias 100-150/600 mm (25%) at Nakdong basin; 50-100/600 mm (10-15%) at Han basin, 100-150/600 mm (15-25%) at Geum, Yeongsan River, Seomji basins.

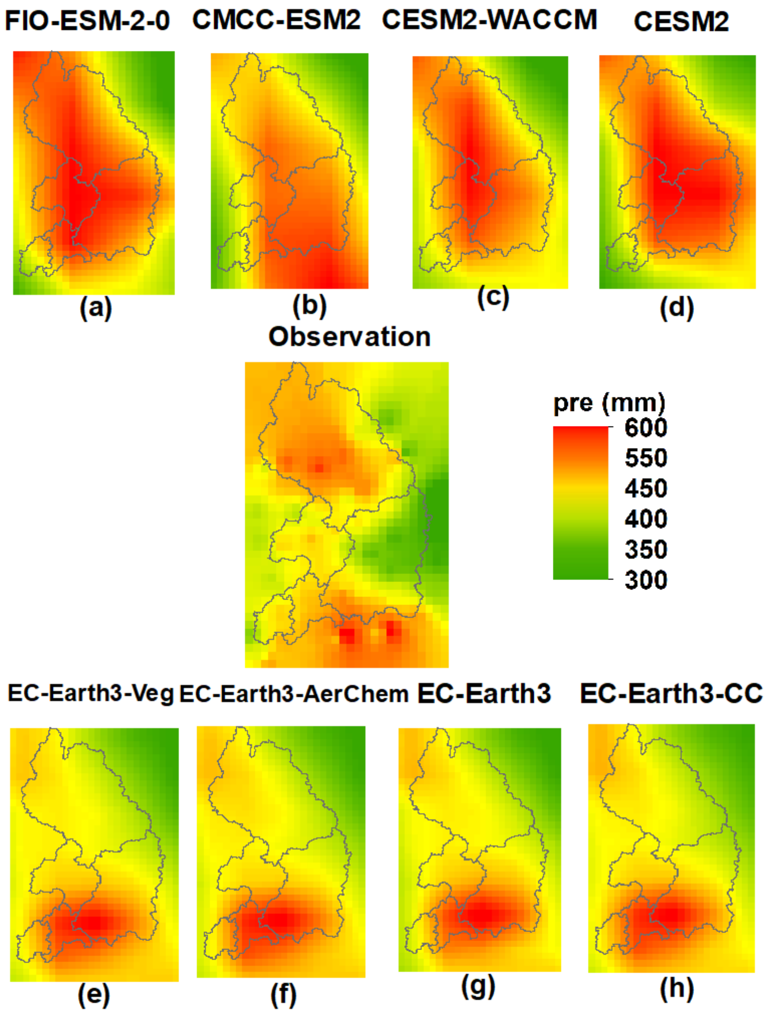


Fig. 3. Spatial patterns of mean moonsoon precipitation (1973-2014) of observed data, the good GCMs using monthly prec over time (e-h) and GCMs ranked 1-4 (a-d)

4. Evaluation the bias of the selected GCMs subset

- ✓ The spatial patterns of monsoon precipitation simulated by the GCMs ranked 1-4 and 29-32 were compared with the spatial patterns of observed precipitation.

- ✓ The results showed that the GCMs that ranked 1-4 (the best-performing GCMs) have spatial patterns more or less similar to those of situ precipitation. On the other hand, GCMs ranked 29-32 (the worst-performing GCMs) showed large differences compared to the spatial patterns of observed precipitation. Besides, Figure 4 clearly shows that GCMs which ranked 31-32 underestimate the precipitation over a large region in the study area.

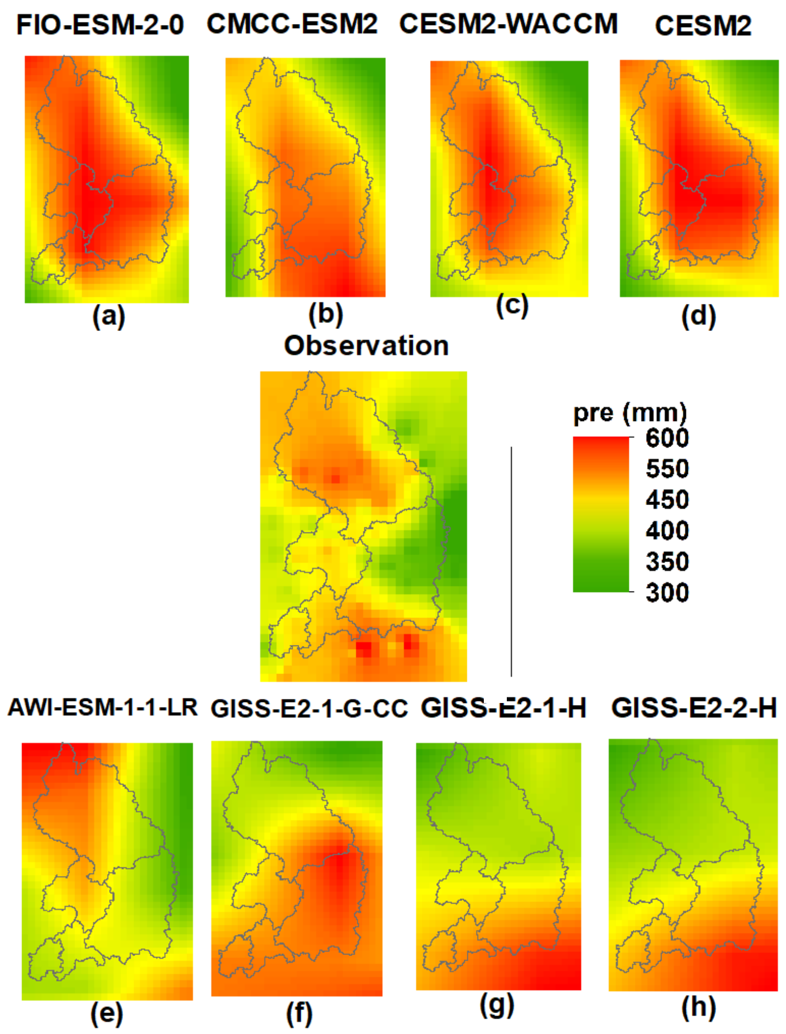


Fig. 4. Spatial patterns of mean moonsoon precipitation (1973-2014) of observational data, the good GCMs using monthly precipitation over time (e-h) and GCMs ranked 29-32 (a-d)

Selection of CMIP6 Global Climate Models for long-term hydrological projections

Conclusion:

1. According to four criteria of Feenstra et al., 1998, this study could be **achieved in choosing of a suitable set of GCMs**: (1). vintage - **CMIP6 GCMs which is the latest generation**; (2). spatial resolution is **0.125 degree that is high grid resolution**; (3). validity - **performance of CMIP6 GCMs were considered**; (4) **representativeness of them was also considered**.

2. **FIO-ESM-2-0, CESM2-WACCM, CESM2, and CMCC-ESM2** were identified as the best-performing GCMs in this study is significant different with the result of [Kim et al., 2020a] where selected EC-Earth3, EC-Earth3-Veg, SAM0-UNICON, KACE-1-0-G, and UKESM-1-0-LL for the top five appreciate CMIP6 GCMs. This revealed **the performance of the GCMs depend on the selecting of climate variables** [Rajuand Kumar, 2020]. Therefore, depending on the objective of the study, we can select difference climate variables (precipitation, temperature, or combining both of them).

3. **Using of spatial metrics** based on the comparison between **monthly precipitation at all grid points for the historical period** of the observed model and each GCMs **indicated more accurate results** than the comparing the spatial correlation between observation and GCM are only **based on the average annual precipitation over time**.

4. **The bias-corrected precipitation results** for this best-performing GCMs is expected **should be able to use to project the spatiotemporal precipitation changes over South Korea in the future**. Calculating the MME of that GCMs subset also is a proposal which we have been interesting and effort to implement in future researches.

5. [Raju and Kumar, 2020] revealed that **the selection of an appreciate GCMs subset depends on** many factors, such as: **climate variables, number of GCMs from the repository with difference generation, data collection, and evaluation metrics identification**. Therefore, we hope this study should be used to compare with the results of the current and future studies, providing useful information in choosing the optimal climate change model subset for the South Korea and neighboring areas.

THANK YOU FOR YOUR WATCHING !!!