

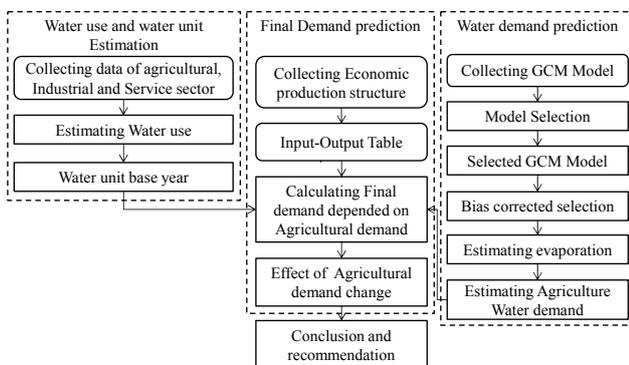
2. OBJECTIVES

This paper aims to estimate water use in each production sector in Rayong province as input in term of water and to estimate future agricultural water demand could be directly impacted by future climate for Input-Output Table calculation. At the end, this paper aims to propose that Input-output table can be used as tool in order to estimate final demand based on future climate situation for Rayong province, Thailand, especially affected on Agriculture, Industrial and Service production sectors.

3. METHODOLOGY

The study was conducted as shown in Figure2 in the following steps; i.e., Water use and water unit Estimation, Water demand prediction and Final Demand prediction

Figure2 Methodology steps



3.1 Water use and water unit Estimation

1) Water use was estimated in each production sector in Rayong province by data collection on agricultural, Industrial and service sectors.

2) The Meteo-Hydrological data and cropping area were collected and were analyzed water use in agricultural sectors in the Rayong province with past data (1975-2011).

3) Industrial water use was calculated by using recorded data of manufacturing production sectors with horse power, number of workers and water use unit modified from the study in the past

(Sucharit K. et.al., 2008).

4) Service water use was estimated with population and water use rates in domestic use and calculated actually water use with recorded tab water data.

5) This paper presents in 3 main production sectors; i.e., Agriculture, Industrial and Service production sectors that have been modified based on Thailand Input-output table by using Input-output table of Rayong province, Thailand studied on 40 sectors (Pawinee, 2011) as shown in Table1. Water unit on base year have been calculated sector by sector by using total input and water use.

Table1 Input-output table of Rayong province, Thailand

Unit: MTB					
Sector	Agriculture	Industry	Service	Total final demand	Total output
Agriculture	438	8,199	230	21,639	30,506
Industry	9,070	1,315,777	76,078	572,665	1,973,590
Service	1,771	83,110	48,327	91,786	224,994
Value added	19,227	566,504	100,359		
Total input	30,506	1,973,590	224,994		

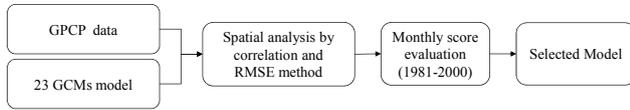
3.2 Water demand prediction

1) For this paper, Global Climate Models (GCMs) were selected by model selection step, as shown in Figure3, with spatial regression analysis on 23 GCMs model data; i.e., *bcc_bcm2*, *cccma_cgcm3_1*, *cccma_cgcm3_1_t63*, *cnrm_cm3*, *csiro_mk3_0*, *csiro_mk3_5*, *gfdl_cm2_0*, *gfdl_cm2_1*, *giss_aom*, *giss_model_e_h*, *giss_model_e_r*, *iap_fgoals1_0_g*, *ingv_echam4*, *inmcm3_0*, *ipsl_cm4*, *k-1*, *miroc3_2_hires*, *miroc3_2_medres*, *miub_echo_g*, *mpi_echam5*, *mri_cgcm2_3_2a*, *ncar_ccsm3_0*, *ncar_pcm*.

All of 23 GCMs model data covered Thailand region are from 95° to 109° east longitude and from 2° to 25° north latitude was perform spatial analysis based on the best correlation and the least root mean square error (RSME) method in following equation

(1) and (2). Duration for GCMs model selection analysis (1981-2000) was selected to be same as coupled Model Inter-comparison Project phase 3 (CMIP3). Since selected GCMs model data can be used to predict runoff corresponded to future precipitation, so GCMs model selection is focused on precipitation parameter with both good spatial correlation (Scorr) and less root mean square error (RSME). Observed global grid (0.25°x0.25°) precipitation dataset were GPCP data from the Asian precipitation-highly resolved observational data integration toward the evaluation of water resources management data for Asia, has been estimated monthly rainfall from 1979 to the present. For GCMs model data, precipitation parameter from 1981 to 2000 can be used to evaluate relationship by spatial correlation (Scorr) and root mean square error (RSME) method.

Figure3 GCMs model selection step



$$Scorr = \frac{\sum_{i=1}^n (X_{obs,i} - \overline{X_{obs}}) \cdot (X_{model,i} - \overline{X_{model}})}{\sqrt{\sum_{i=1}^n (X_{obs,i} - \overline{X_{obs}})^2 \cdot \sum_{i=1}^n (X_{model,i} - \overline{X_{model}})^2}} \quad (1)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (X_{obs,i} - X_{model,i})^2}{n}} \quad (2)$$

Both monthly correlation and monthly RMSE were compared with each average value of monthly precipitation parameter as score for model selection by using followed equation:

Monthly Scorr. avg. monthly Scorr., index is 1

Monthly Scorr. < avg. monthly Scorr., index is 0

Monthly RMSE ≥ avg. monthly RMSE, index is 0

Monthly RMSE < avg. monthly RMSE, index is 1 and then

If index of Scorr = 1 and index of RMSE = 1 then score = 1

If index of Scorr = 1 and index of RMSE = 0 then score = 0

If index of Scorr = 0 and index of RMSE = 1 then score = 0

If index of Scorr = 0 and index of RMSE = 0 then score = -1 (3)

Monthly temperature parameter of selected GCMs model was bias corrected with pattern of observed monthly mean temperature data in past year at observed meteorological station, covers Rayong province, Thailand region as shown in Figure4. Monthly CGDF function of selected GCMs model data mapping to monthly CGDF of observed data followed this equation:

$$T_{cor} = CDF_p^{-1}(T_p; \alpha_{obs}, \beta_{obs}) \quad (4)$$

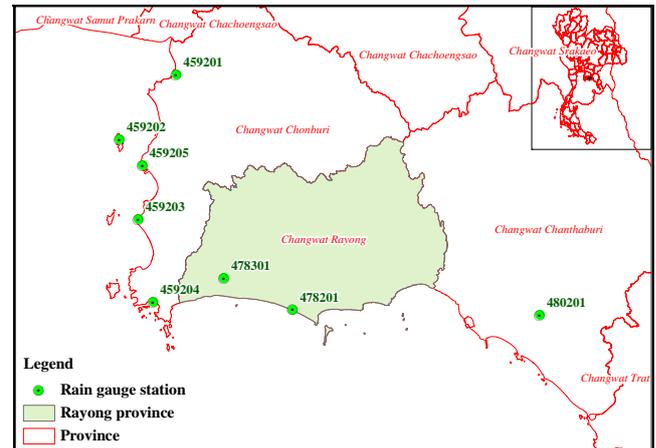
Where

T_{cor} = Corrected temperature parameter

T_p = GCMs temperature parameter in past year

CDF_p^{-1} = Inverse cumulative gamma distribution function (CGDF) on past temperature parameter of selected GCMs model with α_{obs} and β_{obs} .

Figure4 Observed meteorological station



1) Future representative time period of Climate Temperature parameter was determined in 2046-2065 by using SRESA1B global circulation model with good correlation on monthly pattern in past year. For future temperature prediction, monthly CGDF of future GCMs model data mapping to monthly CGDF of corrected GCMs model data

followed this equation:

$$T_{pre} = CDF_f^{-1}(T_f; \alpha_{cor}, \beta_{cor}) \quad (5)$$

Where

T_{pre} = Predicted temperature parameter

T_f = GCMs temperature parameter in future year

CDF_f^{-1} = Inverse cumulative gamma distribution function (CGDF) on future temperature parameter of selected GCMs model with α_{cor} and β_{cor}

2) Future temperature parameter of selected GCMs model was bias corrected with past pattern of temperature parameter covered Rayong province region, Thailand region

3) Future agricultural water demand was estimated with reference evapotranspiration (ET_o) that was calculated from future temperature parameter by Blaney–Criddle equation (FAO) and cropping area on base year (2003). Reference evapotranspiration (ET_o) is estimated from the FAO followed this equation:

$$ET_o = p (0.46T + 8) \quad (6)$$

Where

ET_p = reference crop evapotranspiration (mm/d)

p = mean daily percentage of total annual daytime hours

T = mean daily air temperature (°C)

$$ET_p = K * ET_o \quad (7)$$

K = adjusted factor = 1.15.

Water requirement for agriculture water demand in the future based on the relationship between cropping pattern and bias corrected climate data was calculated from these equations:

$$ET = K_c \times ET_p \quad (8)$$

$$WD = (ET + P - Re) * Area / Eff$$

Where

WD = Agricultural water demand, MCM

ET = water consumption of plant

P = percolation in paddy field

Re = effective rainfall (mm)

K_c = water demand coefficient

ET_p = reference crop evapotranspiration (mm/d)

Eff = effective of irrigation water demand

4) In this paper, Industrial and Service water demand are based on assumption that equals to industrial water use and Service water use on present year.

5) The final result leads to evaluate impact of future climate change in term of water affected to final demand in term of economic.

$$WD = U_w * (I-A)^{-1} * FD$$

(7)

$$WD = C * FD$$

$$FD = C^{-1} * WD \quad (9)$$

Where

WD = Water demand (MCM/year)

U_w = Water unit (MCM/THBHT)

(I-A)⁻¹ = Leontief Inverse Matrix

FD = Final demand (THBHT)

6) Summarize and conclude the result in term of direct and indirect impact on economic.

4. RESULTS AND DISCUSSION

4.1 Water use and water unit Estimation

Water use and water unit were calculated based on production sectors of Thailand Input-output table. Water use in agricultural sectors, industrial sectors and services were estimated about 315.8, 341.0 and 21.6 MCM respectively as shown in Table2. For water unit calculation, water unit of agricultural sectors, industrial sectors and services were calculated about 0.01035, 0.00017 and 0.00010 MCM/MTHB respectively as shown in Table3. It means that these water units have been used to calculate final demand in future.

4.2 Water demand prediction

For future water demand prediction, we started to select GCMs model suitable to Thailand region. The

selected GCMs model was considered base on comparing sum score of each model greater than the 3st quartile of sum score of all GCMs model.

Table2 Water use in sectors group (Unit: mm/year)

Economics	Types	Water use
<u>315.8</u>	Agricultural	
	Crops	19.7
	Forestry	0.3
	Livestock	6.4
	Cassava	44.0
	Vegetables and Fruits	218.1
	Sugarcane	6.7
	Oil Palm	14.7
	Rubber	0.9
	Fishery	5.1
<u>341.0</u>	Industrial Sectors	
	Mining and Quarrying	6.8
	Petroleum	0.0
	Food Manufacturing	6.4
	Coconut and Palm Oil	0.0
	Sugar Refineries	0.0
	Beverages and Tobacco	0.0
	Clothes, fur, paper	12.7
	Basic Chemical Products	122.0
	Fertilizer and Pesticides	8.8
	Other Chemical Products	112.9
	Ceramic, Concrete	4.3
	Petroleum Refineries	33.6
	Basic Metal	25.0
	Motor Vehicles	0.0
	Repairing of Motor	0.6
	Construction	0.1
	Electricity	6.8
	Pipe Line	0.9
	<u>21.6</u>	Service
Water Works and Supply		17.5
Retail Trade, Wholesale		2.0
Restaurants		0.2
Hotels		0.0
Land Transport Supporting		0.2
Water Transport Services		0.0
Post and		0.7
Transportation		0.0
Banking and Insurance		0.1
Other Services		0.7
Education		0.0
Hospital	0.1	
Personal Services	0.1	

Note: 21.6 this format is the total water use in a sector group

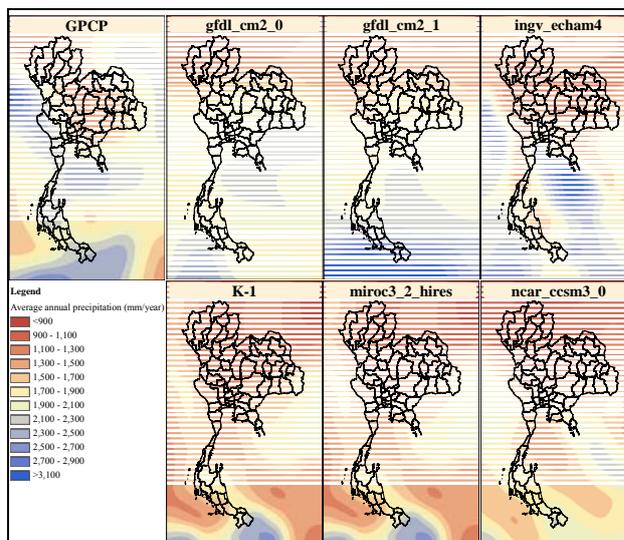
Table3 Water use in sectors group

Sector	Agriculture	Industry	Service
Water use : MCM	315.8	341.0	21.6
Total input : MTHB	30,506	1,973,59	224,994
Water unit : MCM/ MTHB	0.01035	0.00017	0.00010

It shows that monthly spatial correlation score of GCMs model are in Table4. Monthly spatial RMSE of GCMs model are shown in Table5.

The selected GCMs model suitable to Thailand region are shown in Table 6; *i.e.*, *gfdl_cm2_0*, *gfdl_cm2_1*, *ingv_echam4*, *inmcm3_0*, *k-1*, *miroc3_2_hires* and *ncar_ccsm3_0*. For these 6 selected GCMs model suitable to Thailand region, the average annual precipitation data (mm/year) are plotted Figure4.

Figure4 Selected GCMs model for Thailand



There are two major rainfall phenomena in June-July and August-October that make rainfall to the region. The average annual rainfall over Thailand region is around 1,500 mm/year. Average monthly rainfall also generally released a large scale of average monthly runoff in September.

Figure5 Bias correction of mean temperature parameter for 6 selected GCMs model.

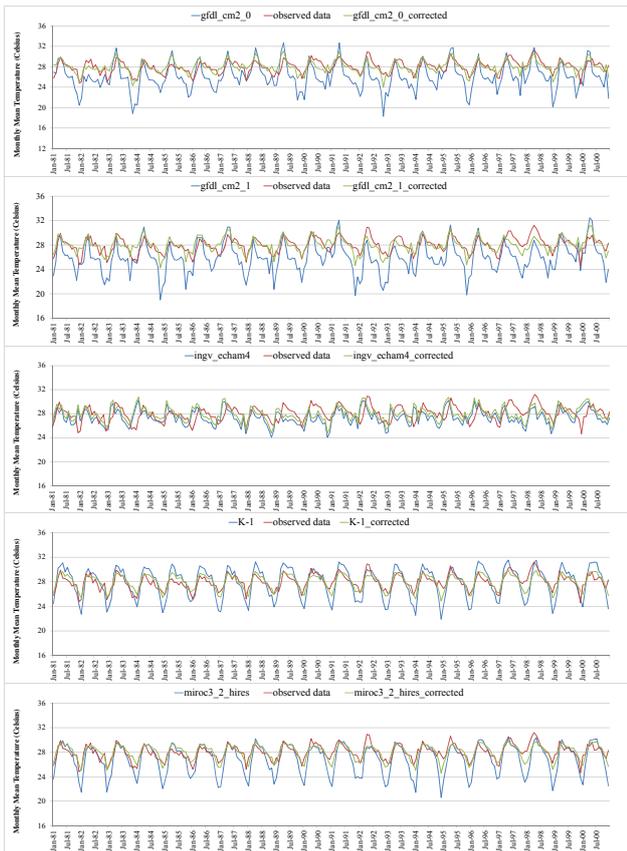
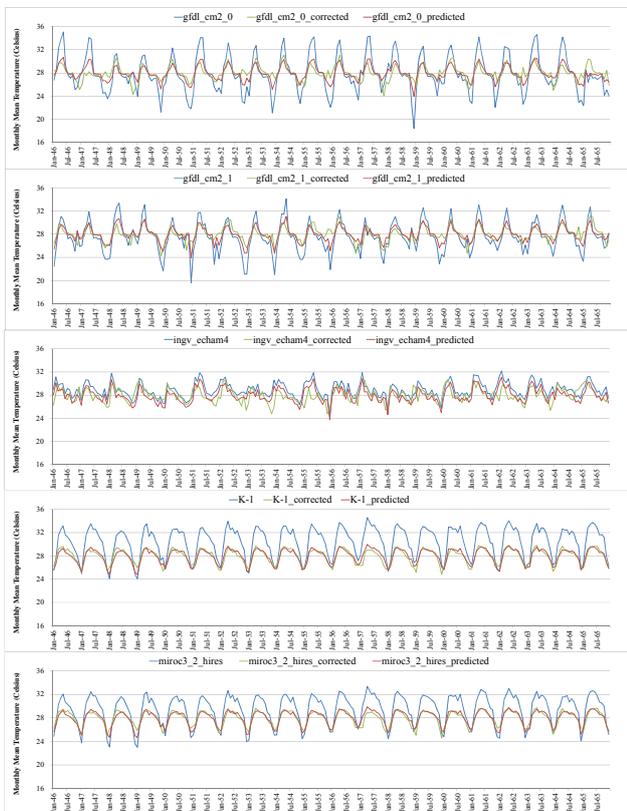


Figure6 Bias correction of mean temperature parameter for 6 selected GCMs model.

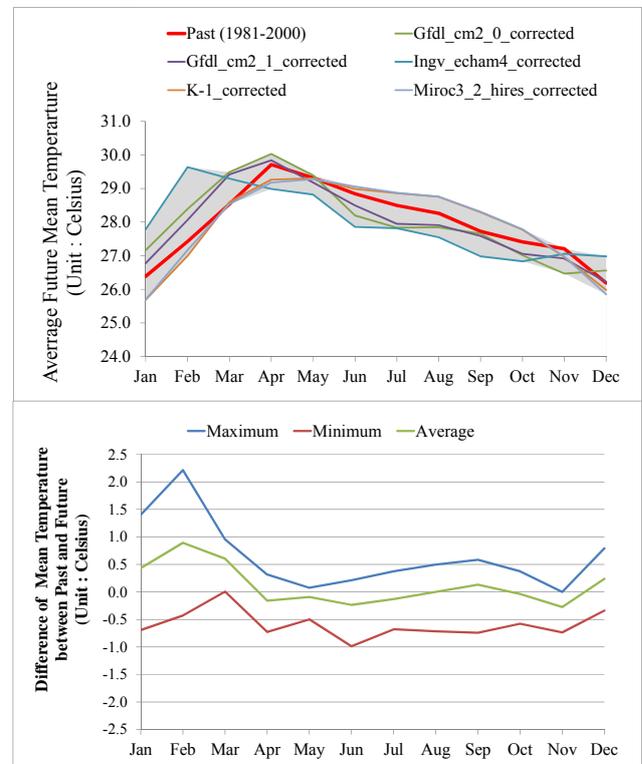


These 6 selected GCMs model were used to analysis and bias correct mean temperature parameter with past temperature data (1981-2000) from observed

meteorological station by cumulative gamma distribution function, however mean temperature parameters is available on only 5 GCMs models; *i.e.*, *gfdl_cm2_0*, *gfdl_cm2_1*, *ingv_echam4*, *inmcm3_0_k-1* and *miroc3_2_hires*. Bias corrected mean temperature parameter is shown in Figure5. Future (2046-2065) mean temperature parameter was also predicted based on mean temperature parameter past pattern as shown in Figure6.

In future (2046-2065), average of mean temperature is increasing in two periods. There are in range of 0.24 to 0.89 Celsius from December to March and in range of 0.00 to 0.13 Celsius from August to September. Average of Mean temperature is also decreasing in two periods. There are in range of 0.09 to 0.24 Celsius from April to July and in range of 0.04 to 0.27 Celsius from October to November as shown in Figure7.

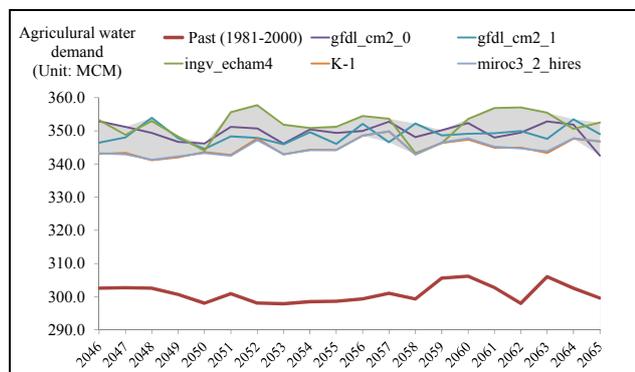
Figure7 Average mean temperature and difference of mean temperature in Celsius



Agricultural water use is in range of 297.9-306.2 MCM/year in past year (1981-2000). Agricultural water demand is going to be in range of 341.1-357.7

MCM/year in future year (2046-2065) as shown in Figure8.

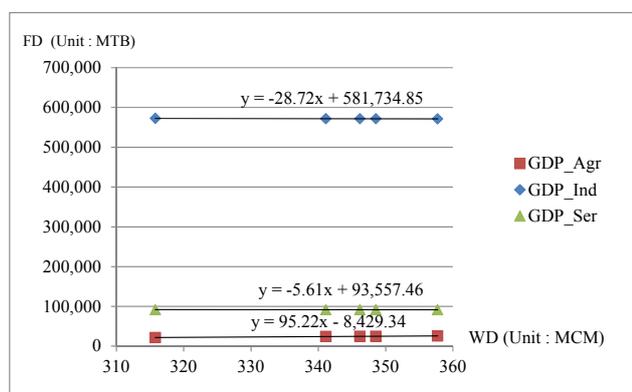
Figure8 Future agricultural water demand



4.3 Final Demand prediction

For future water demand prediction, since future agricultural water demand are maximum increasing about 13.3% (42 MCM) of past year, it could make GDP of agricultural sectors also directly increasing about 18.4% (3,993MTB) of past year. It means that GDP of industrial and service are being indirectly increased about 0.2% and 0.3% of past year (1,204 and 235 MTB respectively). The relationship between water demand and final demand are represented by linear as shown in Figure9.

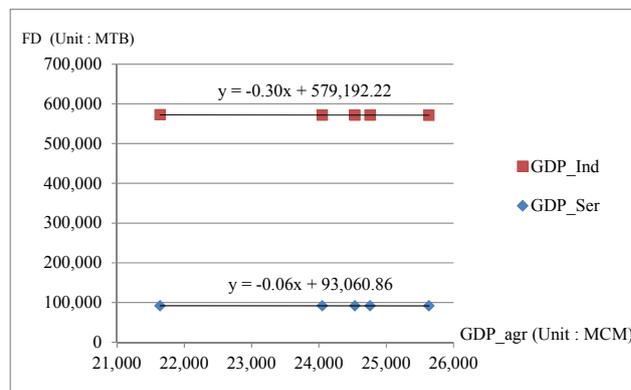
Figure9 The relationship between water demand and final demand (FD)



GDP of industrial and service sector are indirectly affected by increasing GDP of agricultural sector about 30% and 6% of GDP of agricultural sector respectively). The relationship between GDP of

industrial and service sector and GDP of agricultural sector are represented by linear as shown in Figure10.

Figure10 The relationship between GDP (FD) of industrial and service sector and GDP (FD) of agricultural sector



CONCLUSION

Input-Output can be used as tool to estimate impact of agriculture water demand change both direct and indirect effect as well. This paper has been done by using Input-Output table calculation only climate change scenario. However Input-Output can be used to predict final demand (GDP) based on other future water demand scenarios of Industrial and Service sectors change. Input-Output table should be used carefully for GDP prediction in far future because at that time production structures would change and would be different from present.

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Table4 Monthly spatial correlation between GCMs model and observed data

GCMs Model	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
BCC_BCM2	0.90	0.98	0.97	0.96	0.87	0.64	0.43	0.02	0.34	0.87	0.93	0.89
CCCMA_CGCM3_1	0.94	0.91	0.90	0.77	-0.01	0.67	0.66	0.65	0.66	0.60	0.63	0.71
CCCMA_CGCM3_1_T63	0.93	0.94	0.89	0.42	-0.02	0.74	0.69	0.77	0.74	0.58	0.73	0.69
CNRM_CM3	0.92	0.96	0.92	0.80	0.26	0.42	0.55	0.40	0.10	0.59	0.73	0.85
CSIRO_MK3_0	0.56	0.42	0.44	0.30	0.61	0.86	0.86	0.89	0.87	0.81	0.77	0.66
CSIRO_MK3_5	0.56	0.23	0.18	0.36	0.79	0.85	0.86	0.88	0.87	0.74	0.73	0.63
GFDL_CM2_0	0.86	0.75	0.75	0.37	0.83	0.93	0.94	0.92	0.84	0.74	0.83	0.82
GFDL_CM2_1	0.90	0.92	0.95	0.90	0.45	0.71	0.74	0.71	0.68	0.64	0.87	0.89
GISS_AOM	0.88	0.88	0.91	0.87	0.44	-0.20	0.20	0.24	0.10	0.71	0.86	0.88
GISS_MODEL_E_H	0.82	0.86	0.66	0.30	0.06	0.56	0.76	0.67	0.62	0.53	0.80	0.83
GISS_MODEL_E_R	0.78	0.82	0.60	0.31	0.16	0.56	0.69	0.58	0.53	0.48	0.73	0.82
IAP_FGOALS1_0_G	0.89	0.96	0.95	0.90	0.18	-0.48	-0.18	0.63	0.68	0.72	0.87	0.84
INGV_ECHAM4	0.93	0.92	0.81	0.50	0.79	0.93	0.81	0.85	0.91	0.74	0.83	0.82
INMCM3_0	0.87	0.78	0.67	0.47	0.81	0.83	0.86	0.73	0.58	0.57	0.65	0.48
IPSL_CM4	0.86	0.84	0.88	0.83	-0.13	-0.09	0.69	0.74	0.42	0.57	0.77	0.76
K-1	0.91	0.97	0.97	0.93	0.56	0.80	0.77	0.81	0.78	0.76	0.91	0.88
MIROC3_2_HIRES	0.91	0.97	0.97	0.93	0.56	0.80	0.77	0.81	0.78	0.76	0.91	0.88
MIROC3_2_MEDRES	0.85	0.91	0.94	0.95	0.52	0.50	0.53	0.36	0.31	0.75	0.88	0.82
MIUB_ECHO_G	0.71	0.88	0.74	0.44	0.02	0.81	0.75	0.72	0.66	0.36	0.54	0.63
MPI_ECHAM5	0.88	0.83	0.75	0.69	0.83	0.78	0.73	0.76	0.74	0.61	0.76	0.80
MRI_CGCM2_3_2A	0.77	0.82	0.84	0.66	0.77	0.70	0.59	0.62	0.74	0.75	0.72	0.62
NCAR_CCSM3_0	0.75	0.75	0.80	0.78	0.91	0.92	0.92	0.88	0.85	0.74	0.89	0.78
NCAR_PCM1	0.88	0.26	0.87	0.96	0.82	0.73	0.73	0.73	0.83	0.83	0.80	0.73
Average	0.84	0.81	0.80	0.67	0.48	0.61	0.67	0.67	0.64	0.67	0.79	0.77

Table5 Monthly spatial RMSE between GCMs model and observed data

GCMs Model	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
BCC BCM2	3.50	1.84	1.84	1.67	1.84	3.23	3.21	3.97	2.95	2.16	2.02	3.23
CCCMA CGCM3 1	1.24	1.48	1.44	1.60	3.35	3.82	3.82	4.21	3.73	3.20	3.26	3.02
CCCMA CGCM3 1 T63	1.17	0.99	1.29	2.42	3.61	3.16	3.46	3.60	3.62	3.53	2.80	2.80
CNRM CM3	2.05	1.45	1.88	2.55	3.04	2.92	2.75	3.48	3.22	2.78	2.97	2.51
CSIRO MK3 0	1.44	1.29	1.31	1.99	3.78	3.65	3.84	3.65	3.36	3.29	2.88	2.54
CSIRO MK3 5	1.37	1.32	1.57	2.30	3.32	4.19	4.17	4.10	4.20	4.29	3.33	2.79
GFDL CM2 0	0.96	1.22	1.19	1.97	2.40	2.64	2.49	2.92	4.10	3.77	2.51	1.96
GFDL CM2 1	1.90	1.60	1.20	1.35	1.97	3.22	3.44	3.69	3.72	4.08	2.43	2.21
GISS AOM	2.88	2.81	2.30	2.22	2.80	4.58	4.19	4.13	3.10	2.21	2.20	2.57
GISS MODEL E H	4.62	4.28	5.84	8.65	9.76	7.82	4.53	4.07	4.88	4.71	3.57	4.13
GISS MODEL E R	4.52	4.19	5.79	8.32	10.13	7.40	5.19	4.02	4.30	3.94	3.68	3.74
IAP FGOALS1 0 G	2.20	1.29	1.37	1.73	3.62	5.41	4.02	3.17	2.33	2.74	2.16	2.68
INGV ECHAM4	1.08	1.01	1.45	1.90	2.09	2.85	3.93	3.65	2.27	2.81	2.35	2.26
INMCM3 0	1.16	1.25	1.43	1.68	2.33	4.34	4.25	5.41	4.98	4.30	3.23	2.68
IPSL CM4	2.46	2.66	2.25	2.56	3.52	5.69	3.68	3.47	3.82	3.19	3.34	4.03
K-1	1.73	1.03	0.92	1.49	2.11	3.09	3.16	2.98	2.43	2.28	1.50	2.06
MIROC3 2 HIRES	1.73	1.03	0.92	1.49	2.11	3.09	3.16	2.98	2.43	2.28	1.50	2.06
MIROC3 2 MEDRES	3.28	2.59	1.97	1.52	2.51	3.97	2.79	3.14	2.68	2.15	2.19	3.30
MIUB ECHO G	3.43	2.20	2.81	2.95	2.75	4.29	4.54	5.03	3.23	3.16	3.37	3.64
MPI ECHAM5	0.93	0.98	1.02	1.45	2.74	4.30	4.84	4.87	4.24	4.08	2.73	1.97
MRI CGCM2 3 2A	1.62	1.25	1.25	2.20	3.23	4.31	5.05	5.25	3.89	3.34	3.25	3.00
NCAR CCSM3 0	1.57	1.39	1.31	1.48	1.98	2.88	2.52	3.34	3.41	3.40	2.07	2.32
NCAR PCM1	0.51	1.92	5.11	1.98	3.49	3.23	5.18	5.28	3.91	3.36	3.28	3.02
Average	2.06	1.79	2.06	2.50	3.41	4.09	3.84	3.93	3.51	3.26	2.72	2.81

Table6 Selected GCMs model with score selection

GCMs Model	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Sum	Selection
BCC BCM2	0	0	1	1	1	1	0	-1	0	1	1	0	5	Not OK
CCCMA_CGCM3_1	1	1	1	1	0	1	0	-1	0	0	-1	-1	2	Not OK
CCCMA_CGCM3_1_T63	1	1	1	0	-1	1	1	1	0	-1	-1	0	3	Not OK
CNRM_CM3	1	1	1	0	0	0	0	0	0	0	-1	1	3	Not OK
CSIRO_MK3_0	0	0	0	0	0	1	0	1	1	0	-1	0	2	Not OK
CSIRO_MK3_5	0	0	0	0	1	0	0	0	0	0	-1	0	0	Not OK
GFDL_CM2_0	1	0	0	0	1	1	1	1	0	0	1	1	7	OK
GFDL_CM2_1	1	1	1	1	0	1	1	1	0	-1	1	1	8	OK
GISS_AOM	0	0	0	1	0	-1	-1	-1	0	1	1	1	1	Not OK
GISS_MODEL_E_H	-1	0	-1	-1	-1	-1	0	-1	-1	-1	0	0	-8	Not OK
GISS_MODEL_E_R	-1	0	-1	-1	-1	-1	0	-1	-1	-1	-1	0	-9	Not OK
IAP_FGOALS1_0_G	0	1	1	1	-1	-1	-1	0	1	1	1	1	4	Not OK
INGV_ECHAM4	1	1	1	0	1	1	0	1	1	1	1	1	10	OK
INMCM3_0	1	0	0	0	1	0	0	0	-1	-1	-1	0	-1	Not OK
IPSL_CM4	0	0	0	0	-1	-1	1	1	-1	0	-1	-1	-3	Not OK
K-1	1	1	1	12	OK									
MIROC3_2_HIRES	1	1	1	12	OK									
MIROC3_2_MEDRES	0	0	1	1	1	0	0	0	0	1	1	0	5	Not OK
MIUB_ECHO_G	-1	0	-1	-1	0	0	0	0	1	0	-1	-1	-4	Not OK
MPI_ECHAM5	1	1	0	1	1	0	0	0	0	-1	-1	1	3	Not OK
MRI_CGCM2_3_2A	0	1	1	0	1	0	-1	-1	0	0	-1	-1	-1	Not OK
NCAR_CCSM3_0	0	0	1	0	1	1	9	OK						
NCAR_PCM1	1	-1	0	1	0	1	0	0	0	0	0	-1	1	Not OK