Projection of very hot days, hot nights, and cold days in Hong Kong based on CMIP6 Models

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ABSTRACT: The Hong Kong Observatory (HKO) has been conducting climate projection to investigate the plausible changes of hot and cold extremes in Hong Kong using statistical methods since early 2000s. With the United Nations Intergovernmental Panel on Climate Change (IPCC) releasing its Sixth Assessment Report (AR6), HKO updated the projections for the average annual number of very hot days, hot nights and cold days in Hong Kong in the 21st century by statistically downscaling 25 sets of global climate model projection data of the CMIP6 under various emissions scenarios. In this update, two statistical downscaling methods, namely the Quantile-Quantile Mapping (QQM) and the statistical downscaling method adopted in phase 3 of Inter-Sectoral Impact Model Intercomparison Project (ISIMIP3), were adopted to improve the downscaling skills. The updated projections based on IPCC AR6 models reveal that the observed trend in the annual number of very hot days, hot nights and cold days in Hong Kong in the past century will continue in the 21st century with substantial increase in the annual number of very hot days and hot nights and decrease in the annual number of cold days. The projected trends of very hot days, hot nights and cold days obtained in this study in general align with the findings of previous studies in Hong Kong based on IPCC AR4 and AR5 models, reaffirming the projected substantial changes in extreme temperature events in Hong Kong under the foreseeable warming climate.

KEYWORDS: Climate change, Climate projection, Statistical downscaling

1. INTRODUCTION

In the context of climate change, there is a significant rising trend in the global temperature in the past century. According to the World Meteorological Organization (WMO), 2023 was the warmest year on record globally, reaching 1.45oC above the pre-industrial average. The nine years from 2015 to 2023 were also the nine warmest years on record (WMO, 2024). The warming climate also results in increases in the frequency and severity of extreme high temperature events, including heatwaves (e.g. Lee et al., 2011 and Robinson et al., 2021).

Hong Kong, situated at the eastern side of the Pearl River Delta in southern China, has a subtropical climate with hot and humid summer (HKOa, 2024). In line with the global trend, Hong Kong has been warming up in the last century or so. Based on the long-term meteorological observations at the Headquarters of the Hong Kong Observatory (HKO), the increasing rate of the annual mean temperature in Hong Kong was +0.14°C per decade during 1885–2023. The rising temperature also resulted in notable changes in both hot and cold extremes in the city. The annual number of very hot days (daily maximum temperature of 33°C or above at HKO) and hot nights (daily minimum temperature of 28°C or above at HKO) have a significant increasing trend during the concerned period. Meanwhile, the number of cold days (daily minimum temperature of 12°C or below at HKO) dropped significantly (HKOb, 2024). In 2021, there were 61 hot nights and 54 very hot days in Hong Kong, both ranking the highest on record (HKO, 2022).

The Intergovernmental Panel on Climate Change (IPCC) jointly established by WMO and the United Nations Environment Programme (UNEP) released the Working Group I report of its Sixth Assessment Report (AR6) in August 2021. This report summarizes multiple scientific evidence and, for the first time, unequivocally confirms the impact of human activities on global warming (IPCC, 2021). It

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also presents the latest climate model projections from the Coupled Model Intercomparison Project Phase 6 (CMIP6) using a set of Shared Socioeconomic Pathways (SSPs) to generate climate projections for the 21st century, diverging from the previous use of Representative Concentration Pathways (RCPs).

Due to the relatively coarse resolution of global climate models (typically around 100x100 kilometers per grid cell), direct calculations using the original data from the climate models are unable to resolve local climate characteristics well and may not yield satisfactory results for the projection of certain climate metrics such as the number of hot nights, very hot days, and cold days for a specific region/place. Therefore, downscaling methods are often employed to improve the performance of the regional-scale climate change projections. There are two common approaches for the downscaling, namely statistical downscaling and dynamical downscaling. Statistical downscaling involves constructing statistical models using data from past simulation periods within the climate models and local observational data to adjust the future projections from the climate models (e.g. Tang et al., 2016 and Lanzante et al., 2020). On the other hand, dynamical downscaling utilizes the outputs of global climate models as initial and boundary conditions to drive a higher-resolution regional dynamical climate model, achieving the goal of downscaling (e.g. Lu et al., 2019 and Gao, 2020).

HKO has been conducting climate projections based on the global climate model data of IPCC assessment reports since early 2000s (e.g. Leung et al., 2004; Leung et al., 2007 and Lee et al., 2011). Considering that statistical downscaling methods require fewer computational resources compared to dynamical downscaling, previously HKO adopted statistical downscaling techniques for the climate projections of Hong Kong based on global climate model projection data of the Fourth Assessment Report (AR4) and the Fifth Assessment Repots (AR5) of IPCC. In these past studies, a wide range of forecast predictors and observational data were utilized to establish statistical relationships for climate projections (Lee et al., 2011, Chan et al., 2014). With the release of the IPCC AR6 model projection data and in light of the innovative statistical methods employed in the IPCC AR6, specifically the trend-preserving bias adjustment and statistical downscaling method adopted in phase 3 of Inter-Sectoral Impact Model Intercomparison Project (ISIMIP3) (Lange, 2019) for calculating high-temperature thresholds, this study is undertaken to use the new statistical methods from IPCC AR6 to project the annual number of hot nights, very hot days, and cold days in Hong Kong in the 21st century. Additionally, the Observatory also explores the use of quantile mapping to compare the results for these three metrics. The climate data and statistical downscaling methods used in this study are described in Section 2. The verification and projection results are respectively presented in Sections 3 and 4. Section 5 contains the discussion and conclusion of the study.

2. DATA AND METHOD

In this study, HKO has utilized four Shared Socioeconomic Pathways (SSPs) from the IPCC AR6 report, namely SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5. These pathways correspond to low, intermediate, high, and very high greenhouse gas emission scenarios, respectively. The Observatory has referenced 25 CMIP6 global climate models selected in the IPCC Atlas of Interactive Maps (Gutiérrez et al., 2021 and Iturbide et al., 2021) (Table 1) to establish a comprehensive set of climate projections for Hong Kong.

HKO has been conducting various meteorological observations (e.g. temperatures, rainfall, pressure, relative humidity, etc.) at its headquarters since 1884 (Lee, 2016). The HKO headquarters was also accredited by the WMO as one of the first batch of centennial observing stations (HKO, 2017) and the long-term observational data collected from this station are highly suitable for local climate research. Therefore, for this study, the primary source of observational data is the weather station at the Hong Kong Observatory's headquarters.

To estimate the number of very hot days, hot nights and cold days, simulated data from global climate models need to be extracted. This data includes daily maximum temperature, daily mean temperature, and daily minimum temperature near the surface. Since different climate models have varying horizontal resolutions, each model needs to undergo re-gridding to achieve a consistent resolution. The output values for the grid cells closest to Hong Kong are then obtained.

For statistical downscaling, this study utilizes two different methods to downscale the above-mentioned daily temperature data from global model to Hong Kong and then estimate the number of very hot days, hot nights and cold days in Hong Kong. These two methods are the ISIMIP3 approach and quantile mapping. Further details of these two statistical downscaling methods are depicted in the sub-sections 2.1 and 2.2. By using these two methods, the study aims to provide more accurate estimation of the number of very hot days, hot nights and cold days in Hong Kong.

Table 1 The CMIP6 global climate models utilized in this downscaling study. (Gray cells indicate that the model does not provide data for that scenario.)

Models \ Scenario	SSP1-2.6	SSP2-4.5	SSP3-7.0	SSP5-8.5
ACCESS-CM2	✓	✓	✓	✓
ACCESS-ESM1-5	✓	✓	✓	✓
AWI-CM-1-1-MR	✓	✓	✓	✓
BCC-CSM2-MR	✓	✓	✓	✓
CanESM5	✓	✓	✓	✓
CNRM-CM6-1	✓	✓	✓	✓
CNRM-CM6-1-HR	✓			✓
CNRM-ESM2-1	✓	✓	✓	✓
EC-Earth3	✓	✓	✓	✓
EC-Earth3-Veg	✓	✓	✓	✓
EC-Earth3-Veg-LR		✓	✓	
FGOALS-g3	✓	✓	✓	✓
GFDL-CM4		✓		✓
GFDL-ESM4	✓	✓	✓	✓
HadGEM3-GC31-LL	✓	✓		✓
IPSL-CM6A-LR	✓	✓	✓	✓
KACE-1-0-G	✓	✓	✓	✓
MIROC-ES2L	✓	✓	✓	✓
MIROC6	✓	✓	✓	✓
MPI-ESM1-2-HR	✓	✓	✓	✓
MPI-ESM1-2-LR	✓	✓	✓	✓
MRI-ESM2-0	✓	✓	✓	✓
NESM3	✓	✓		✓
NorESM2-MM	✓	✓	✓	✓
UKESM1-0-LL	✓	✓	✓	✓

2.1 ISIMIP3

The ISIMIP3 method is a statistical approach used to improve climate projections and involves constructing statistical models based on historical climate data and observational records to adjust future projections from global climate models (Lange, 2019). A study (Piani et al., 2010) suggests that individually correcting the daily maximum temperature, daily mean temperature, and daily minimum temperature near the surface may result in larger errors in diurnal temperature range. Therefore, it is necessary to transform the daily maximum temperature and daily minimum temperature into the daily temperature range and temperature skewness. The equations for the variable transformation are as follows:

$$tasrange = tasmax - tasmin$$

$$tasskew = \frac{(tas - tasmin)}{tasrange}$$

where "tasrange" is daily temperature range, "tasmax" is daily maximum temperature, "tasmin" is daily minimum temperature, "tas" is daily average temperature, "tasskew" is Temperature skewness.

$$Q_{obs}^{Fut}(p) = Q_{obs}^{Hist}(p) + [\, Q_{sim}^{Fut}(p) - Q_{sim}^{Hist}(p) \,]$$

where Q_{obs}^{Hist} is quantile function derived from observed data for a specific variable during a historical period. Q_{sim}^{Hist} is quantile function derived from simulated data for a specific variable during the historical period. Q_{sim}^{Fut} is quantile function derived from simulated data for a specific variable during the future period. Q_{obs}^{Fut} is quantile function derived from observed data for a specific variable during the future period. "p" is cumulative probability.

The above equations represent the steps involved in the ISIMIP3 approach. It first calculates the climate change signal for each quantile in the climate model based on daily data on a monthly basis. This signal is then added to the quantile function derived from observed data, resulting in an adjusted quantile function for the future period Q_{obs}^{Fut}.

However, since some variables have constraints, simply overlaying the climate change signal onto the observed data may lead to unrealistic adjustments, such as negative diurnal temperature changes. To address this issue, the ISIMIP3 approach utilizes a parameterized quantile mapping method for further adjustments. Further details are available from the study by Lange (2019).

2.2 Quantile-Quantile Mapping

Generally speaking, quantile mapping, is a statistical technique used to adjust model outputs to match the observed distribution of a particular variable. It helps in correcting biases and improving the reliability of climate projections (Lader et al., 2017, Putra et al., 2020). Quantile-Quantile mapping, also known as quantile-to-quantile transformation, is a common model post-processing method for quantile mapping. The general approach involves adjusting the cumulative distribution function (CDF) of predicted values based on the CDF of observed values. However, in the context of this study, which focuses on the changes in simulated data between the historical and future periods, a specific threshold based on observed data is used to identify the corresponding threshold in the simulated data.

The process involves finding the simulated data threshold that corresponds to a specific observed data threshold (such as "very hot day"). This allows for the adjustment and alignment of the simulated data to the observed data, considering the changes observed between the historical and future periods. The equations for Quantile-Quantile mapping are as follows:

$$x_{sim}^{Hist} = F_{sim}^{Hist-1}\left(F_{obs}^{Hist}\left(x_{obs}^{Hist}\right)\right)$$

$$f_{sim}^{Fut} = F_{sim}^{Fut}\left(x_{sim}^{Hist}\right)$$

where F_{obs}^{Hist} is CDF derived from observed data during the historical period. F_{sim}^{Hist} is CDF derived from simulated data during the historical period. F_{sim}^{Hist-1} is inverse function of F_{sim}^{Hist}. x_{obs}^{Hist} is threshold value based on observed data during the historical period. x_{sim}^{Hist} is threshold value corresponding to a certain quantile of simulated data during the historical period. f_{sim}^{Fut} is cumulative frequency of simulated data in the future period.

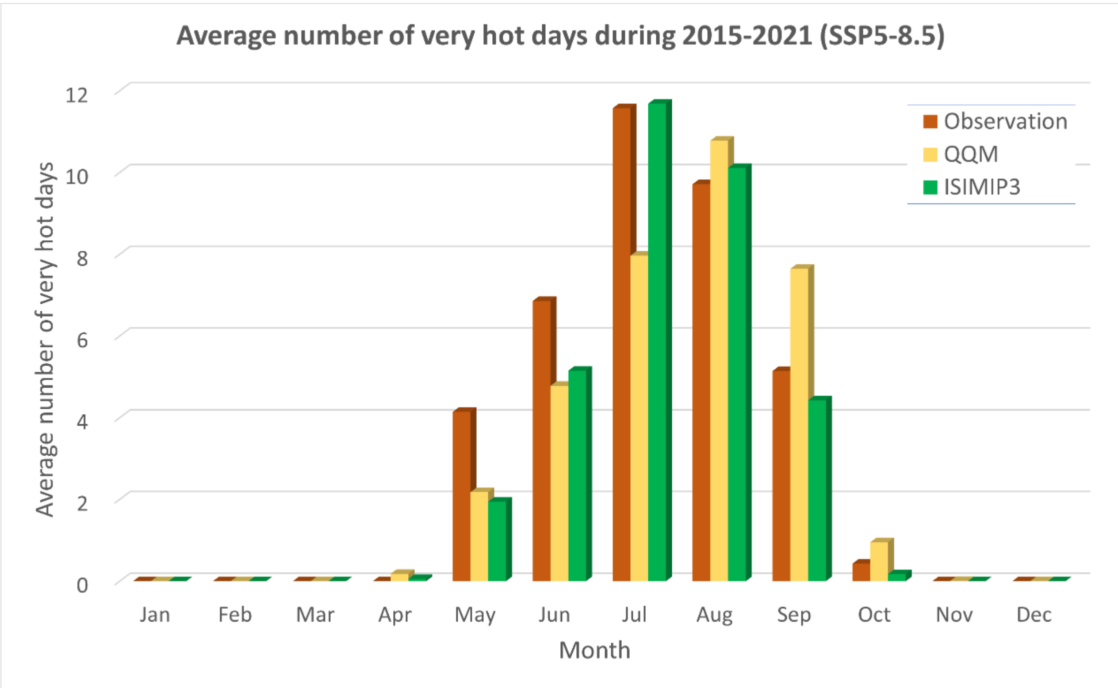

Figure 1 shows the observed (orange) average monthly number of very hot days from 2015 to 2021 and the corresponding projections by QQM (yellow) and ISIMIP3 (green) under SSP5-8.5

3.VERIFICATION

In this study, statistical models are constructed using data from different time periods as the training set. With a view to assessing the performance of the statistical model and the sensitivity of them to the choice of time period of training dataset, four different time periods as training sets, including 1965-1994 (30 years), 1985-2014 (30 years), 1995-2014 (20 years), and 2005-2014 (10 years), were verified. The validation period is set from 2015 to 2021.

Figures 1, 2 and 3 respectively showed the comparison between the observed and projected average number of very hot days (NVHD), hot nights (NHN), and cold days (NCD) in different months for 2015-2021 using ISIMIP3 and QQM with 1965-1994 as the training set period for reference. Both the ISIMIP3 and QQM can reasonably depict the seasonal variations of NVHD, NHN and NCD with some biases in individual month. Overall, ISIMIP3 demonstrates better simulation accuracy for projecting the monthly variations of the number of very hot days and hot nights, especially from July to September. Conversely, QQM tends to overestimate the number of hot nights from July to September. However, ISIMIP3 has a tendency to overestimate the average number of cold days, particularly in February and March. These observations reflect the varying strengths and biases of ISIMIP3 and QQM in capturing inter-seasonal variations, hinting the possibility of enhancing the overall quality of downscaled climate projections by combining these two methods.

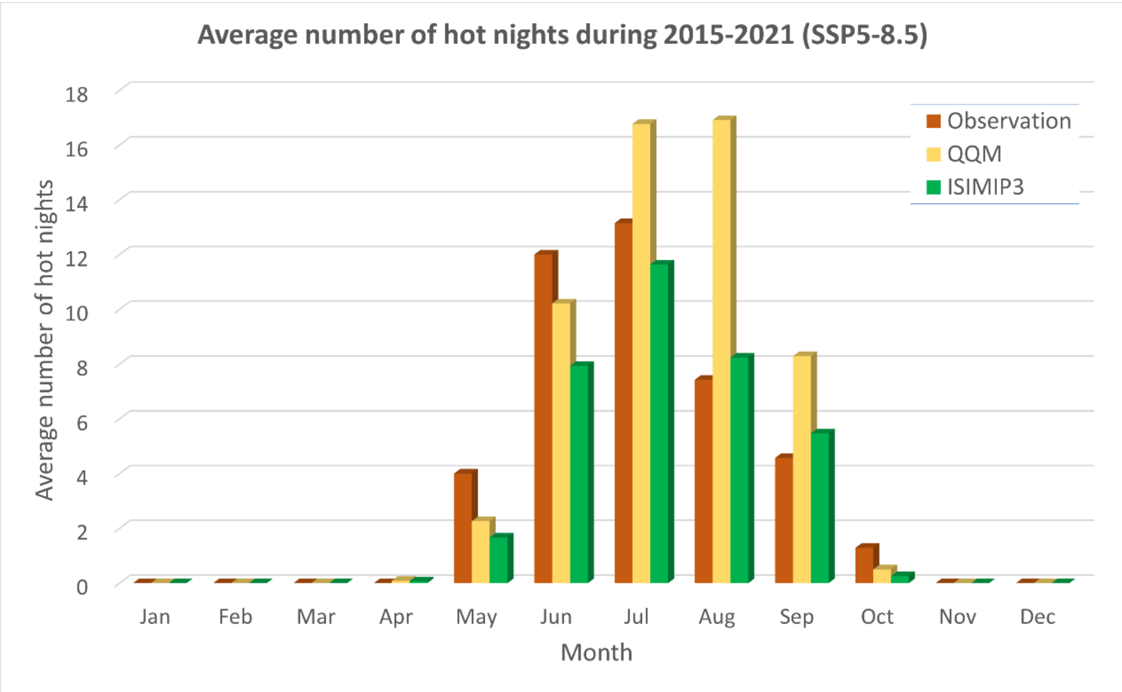

Figure 2 shows the observed (orange) average monthly number of hot nights from 2015 to 2021 and the corresponding projections by QQM (yellow), and ISIMIP3 (green) under SSP5-8.5

To evaluate the model's performance quantitatively, the errors between the projected and observed values of NHN, NVHD, and NCD, cannot be simply aggregated. Therefore, these three parameters are combined into a vector, and the Euclidean distance (ED) between the predicted and observed values is calculated as an objective indicator. By using the ED, the study quantifies the discrepancy between the predicted and observed data, allowing for an objective assessment of the model's performance in capturing the variation of NHN, NVHD, and NCD during the validation period. The equation is as follows:

$$\mathrm{ED} = \sqrt{(NCD_{proj} - NCD_{obs})^2 + (NHN_{proj} - NHN_{obs})^2 + (NVHD_{proj} - NVHD_{obs})^2}$$

A smaller value of ED indicates that the statistical model's predictions have a smaller error.

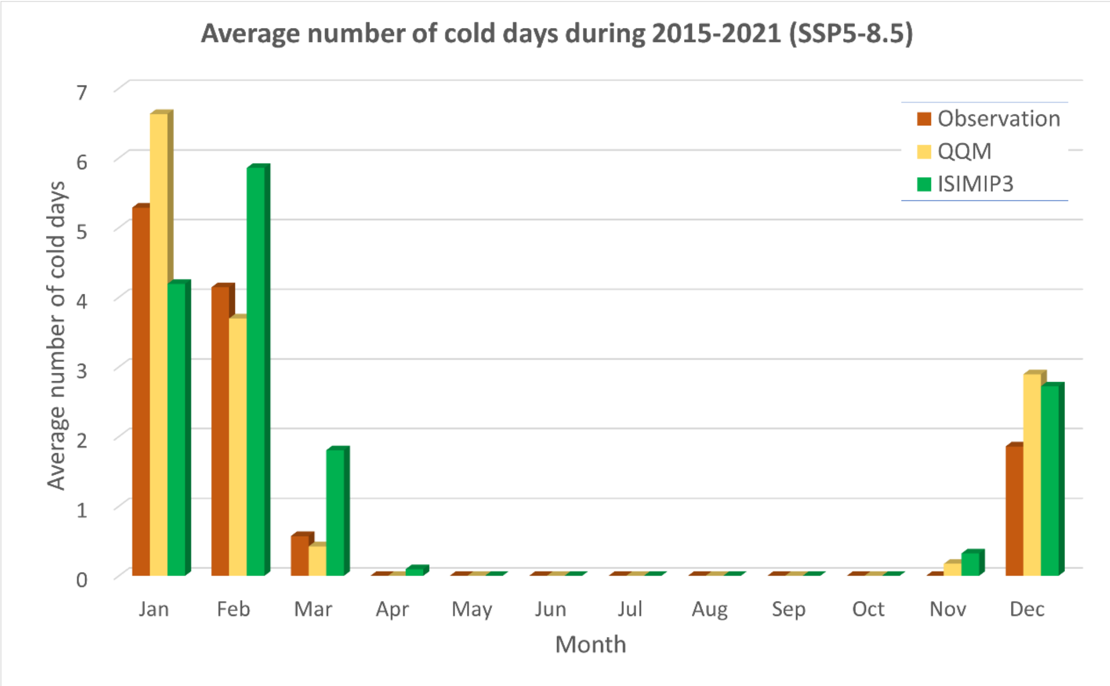

Figure 3 shows the observed (orange) average monthly number of cold days from 2015 to 2021and the corresponding projections by QQM (yellow) and ISIMIP3 (green) under SSP5-8.5

Table 2 The validation results of the statistical models established using data from different time periods (Obs: observation, QQM: Quantile-Quantile mapping, AVG: average value of ISIMIP3 and QQM).

Verification: 2015 - 2021 (SSP5-8.5)					
Method	**Training periods**	**NCD**	**NHN**	**NVHD**	**ED**
Obs		11.9	42.4	37.9	NA
ISIMIP3	1965-1994 (30-year)	15	35	34	8.9
QQM		14	55	35	13.1
AVG		14	45	34	5.1
ISIMIP3	1985-2014 (30-year)	12	32	24	17.4
QQM		12	47	25	13.7
AVG		12	40	24	14.1
ISIMIP3	1995-2014 (20-year)	12	28	23	20.7
QQM		13	43	24	14.0
AVG		13	35	34	15.8
ISIMIP3	2005-2014 (10-year)	18	27	28	19.3
QQM		18	40	30	10.3
AVG		18	33	29	14.3

The validation results for the period from 2015 to 2021 using ISIMIP3 and QQM and the four training set periods are shown in Table 2. It is noted that the ED values using the 1965-1994 (30 years) period are relatively lower than other three training set periods. Moreover, the ED is further reduced by using the ensemble of the two statistical methods. This indicates that using the 1965-1994 as the training set period and combining the two statistical methods could improve the performance of the downscaling approach.

Table 3a Projected average annual number of very hot days (days with a maximum temperature of 33°C or above) in Hong Kong under different greenhouse gas emissions scenarios.

	Low SSP1-2.6		**Intermediate SSP2-4.5**		**High SSP3-7.0**		**Very high SSP5-8.5**	
	Mean	Likely range	Mean	Likely range	Mean	Likely range	Mean	Likely range
2041-2060	58	34 - 82	65	42 - 100	68	44 - 101	81	53 - 121
2081-2100	60	27 - 90	95	58 - 137	124	86 - 176	152	104 - 202

Table 3b Projected average annual number of hot nights (days with a minimum temperature of 28°C or above) in Hong Kong under different greenhouse gas emissions scenarios.

	Low SSP1-2.6		**Intermediate SSP2-4.5**		**High SSP3-7.0**		**Very high SSP5-8.5**	
	Mean	Likely range	Mean	Likely range	Mean	Likely range	Mean	Likely range
2041-2060	78	47 – 120	87	54 - 128	90	56 - 135	104	68 - 143
2081-2100	81	40 – 128	117	78 - 153	145	108 - 177	167	130 - 201

Table 3c Projected average annual number of cold days (days with a minimum temperature of 12°C or below) in Hong Kong under different greenhouse gas emissions scenarios.

	Low SSP1-2.6		**Intermediate SSP2-4.5**		**High SSP3-7.0**		**Very high SSP5-8.5**	
	Mean	Likely range	Mean	Likely range	Mean	Likely range	Mean	Likely range
2041-2060	9	6 – 12	9	4 – 13	9	5 – 13	7	3 – 10
2081-2100	9	5 – 13	6	3 – 9	4	1 – 6	2	0 – 5

4. PROJECTION OF HOT NIGHTS, VERY HOT DAYS AND COLD DAYS IN HONG KONG

4.1 Very hot days and hot nights

Based on the method depicted in Sections 2 and 3, the projected values and likely ranges of the two-decade average of annual number of very hot days and hot nights in the mid (2041-2060) and end (2081-2100) of the 21st century for all four greenhouse gas emission scenarios are tabulated in Table 3a and 3b respectively. Figures 4 and 5 also respectively showed the projected trend of the two-decade average of annual number of very hot days and hot nights in the 21st century for SSP2-4.5 and SSP5-8.5. The shaded area in the figure represents the range of climate projections based on the 5th and 95th percentiles of the climate model simulations.

The projections reveal a significant increasing trend for both annual number of very hot days and hot nights in Hong Kong in the future when compared to the observed average annual number of 14 very hot days and 21 hot nights during the period of 1995-2014. Under the very high greenhouse gas emission scenario (SSP5-8.5), the average annual number of very hot days and hot nights in the last two decades of this century (2081-2100) will exceed 150 days and exceed 160 days respectively. Even under an intermediate greenhouse gas emission scenario (SSP2-4.5), the average number of very hot days and hot nights throughout the year in the last two decades of the 21st century will reach around 100 days [likely range: 58 – 137 days] and 120 days [likely range: 78 – 153 days] respectively.

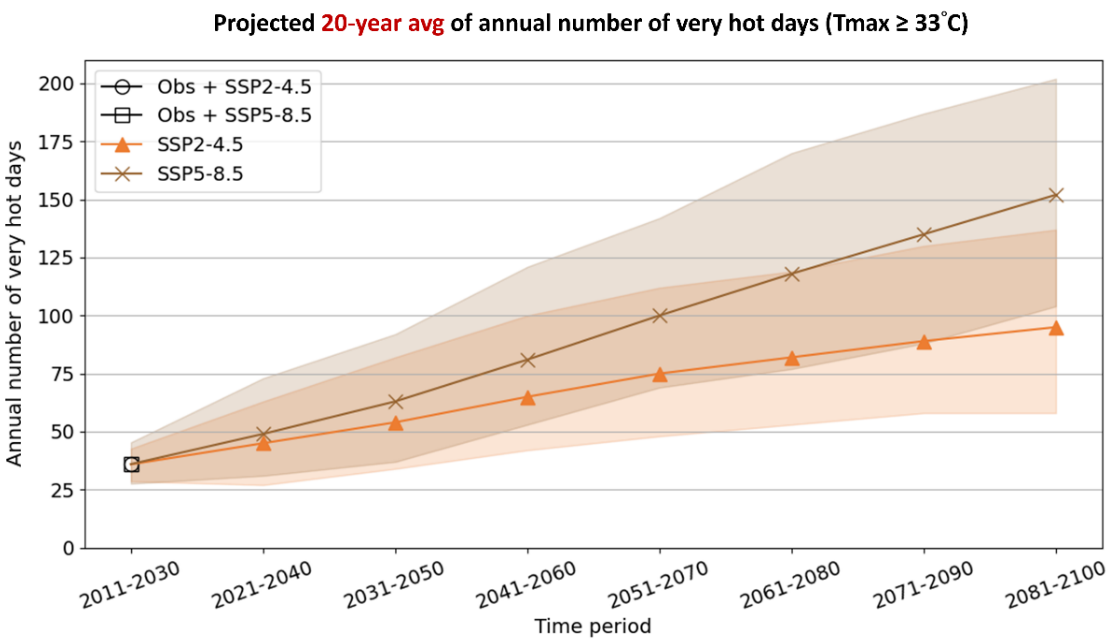

Figure 4 shows the projected two-decade average of annual number of very hot days in the 21st century under the scenario of intermediate and very high greenhouse gas emission. The shaded area represents the range of climate projections based on the 5th and 95th percentiles of the climate model simulations. (note: The average value for the 1st two-decade (2011-2030) is obtained by combining data observed at HKO Headquarters from 2011 to 2021 and the projected values from 2022 to 2030.)

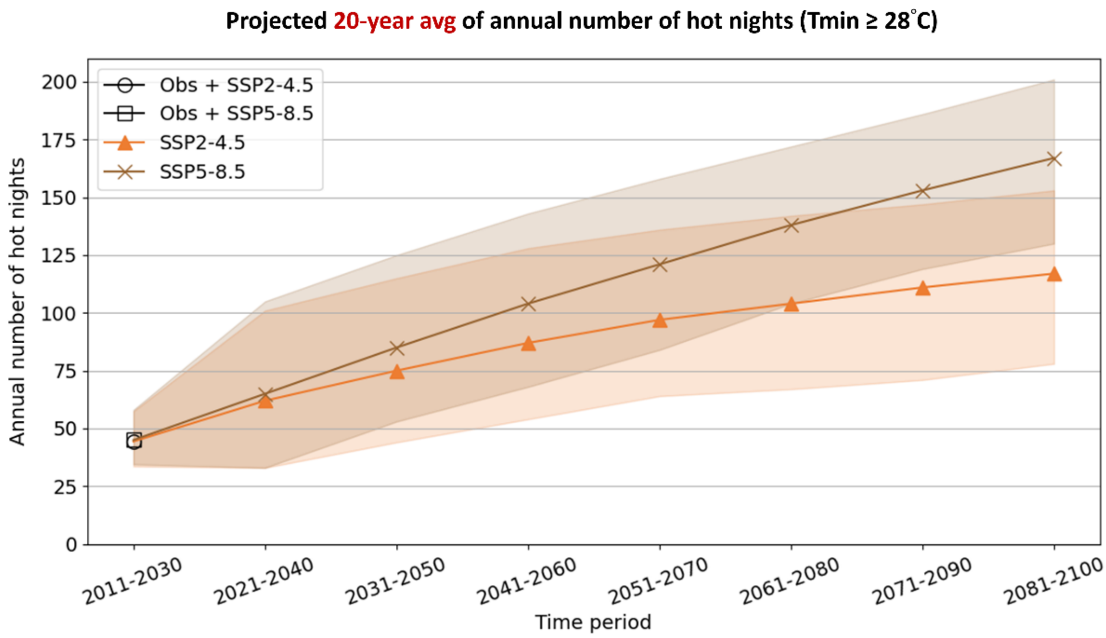

Figure 5 shows the projected two-decade average of annual number of hot nights under the scenario of intermediate and very high greenhouse gas emission. The shaded area represents the range of climate projections based on the 5th and 95th percentiles of the climate model simulations. (note: The average value for the 1st two-decade (2011-2030) is obtained by combining data observed at HKO Headquarters from 2011 to 2021 and the projected values from 2022 to 2030.)

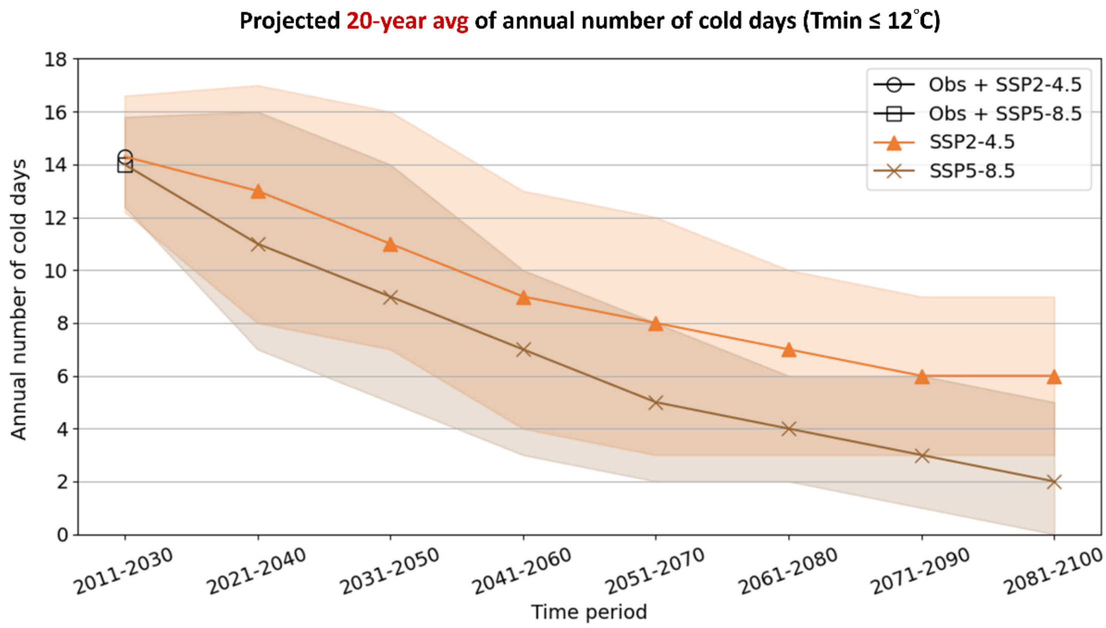

Figure 6 shows the projected two-decade average of annual number of cold days under the scenario of intermediate and very high greenhouse gas emission. The shaded area represents the range of climate projections based on the 5th and 95th percentiles of the climate model simulations. (note: The average value for the 1st two-decade (2011-2030) is obtained by combining data observed at HKO Headquarters from 2011 to 2021 and the projected values from 2022 to 2030.)

4.2 Cold days

The projected values and likely ranges of the two-decade average of annual number of cold days in the mid and end of the 21st century for all four greenhouse gas emission scenarios are tabulated in Table 3c. Figure 6 showed the projected trend of cold days in the 21st century for SSP2-4.5 and SSP5-8.5. The shaded are in the figure represents the range of climate projections based on the 5th and 95th percentiles of the climate model simulations.

The projections indicate that the annual number of cold days in Hong Kong is expected to decrease in the future when compared to the observed average annual number 17 cold days during the period of 1995-2014. Under the very high greenhouse gas emission scenario (SSP5-8.5), the average annual number of cold days in the last two decades of the 21st century (2081-2100) will drop to 2 days [likely range: 0 – 5 days] with the lower bound of the likely range reaching 0 days. Even under an intermediate greenhouse gas emission scenario (SSP2-4.5). the average number of cold days throughout the year in the last two decades of the 21st century will decrease to 6 days [likely range: 3 – 9 days].

5. CONCLUSION AND DISCUSSION

Previous research studies indicated that climate warming and changes in the frequency of extreme temperature events could have significant impacts on the society, especially on public health and energy consumption (Lee et al., 2010, Cheung et al., 2016, Lee et al., 2016, Wang et al., 2019, Lee et al., 2022 and Wang et al., 2022). Since early 2000s, HKO has been conducting climate projections in Hong Kong using statistical methods, including the investigation of the plausible changes of hot and cold extremes. This study updated the projections for the average annual number of very hot days, hot nights and cold days in Hong Kong in the 21st century by statistically downscaling 25 sets of global climate model projection data of the CMIP6. To further improve the downscaling skills, two statistical downscaling methods, namely ISIMIP3 and QQM, were adopted and reviewed in this study. The validation results revealed that both the ISIMIP3 and QQM methods have acceptable skill in reproducing the past statistics of the very hot days, hot nights and cold days in Hong Kong. Moreover, the use of the 30-year training set period from 1965-1994 and the ensemble of the ISIMIP3 and QQM method could further improve the performance of the downscaling.

For the projections under various SSP scenarios, the significant trend in the annual number of very hot days, hot nights and cold days that observed in Hong Kong in the past century will continue in the 21st century with substantial increase in the number of very hot days and hot nights and decrease in the number of cold days. Towards the end of the 21st century, the two-decade average annual number of very hot days (hot nights) are expected to increase from 14 days (21 days) in 1995-2014 to 152 days (167 days) in 2081-2100 under SSP5-8.5 scenario. On the other hand, the annual average number of cold days is expected to decrease from the 1995-2014 average of 17 days to 2 days in 2081-2100 under SSP5-8.5 scenario. The projected trends of very hot days, hot nights and cold days obtained in this study in general align with the findings of previous studies in Hong Kong based on IPCC AR4 and AR5 models (Lee et al., 2011; HKO, 2015), reaffirming the projected substantial changes in extreme temperature events under the warming climate and highlighting the need for relevant climate change adaptation and mitigation measures with a view to avoiding the serious impacts of future climate change (HKSARG, 2021).

Similar to other climate projection studies, there are some limitations in our study and point-to-note in interpreting the projection data. Both QQM method and ISIMIP3 bias-correction give similar results on the projected annual number of very hot days and cold days. However, ISIMIP3 tends to underestimate the annual number of hot nights, regardless of the size and selection of training periods, while QQM slightly overestimates the annual number of hot nights. Therefore, it is essential to explore different statistical projection methods to further enhance the local climate projections in support of climate adaptation and resilience.

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