Temperature and precipitation changes in ten cities in Southeast Asia: an analysis based on CMIP6 climate projections

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Abstract:

Climate change influences both average states and extremes in temperatures and precipitation. Southeast Asia, one of the most vulnerable regions worldwide to floods and heatwaves, indicates an escalation of the possibility of severe climate extremes. Extreme precipitation events can bring increasing floods, leading to considerable damage to property and human well-being. Yet, droughts also occur in Southeast Asia due to changing precipitation patterns in different regions. In big cities, such damages and risks are highly influential, given the large population density and the proximity to the coast or rivers.

Global Earth system models predict the average trends and extremes of the climate system, including record-shattering extreme events that have exceeded previous records. I use the recently released Coupled Model Intercomparison Project Phase 6 (CMIP6), a multi-model large ensemble of climate predictions under different scenarios, to investigate changes in climate conditions in ten highly populated cities in Southeast Asia. I first evaluated the CMIP6 simulations in the present day (2005-2014) in the ten cities and found good consistency in temperature and precipitation. I then examine changes in the mean, minimum, and maximum temperature and precipitation on an annual, monthly, and daily basis respectively, under the high-emission SSP5-8.5 scenario. Furthermore, I find that annual maximum temperatures hit more than 40 ℃ in Bangkok, Chiang Mai, and Vientiane in the late century. In addition, cities in our study are projected to experience 5-6 ℃ increases in temperature from November to April, indicating significant changes in the seasonal cycle. Precipitation increases significantly from May to October in most large cities in our study, except for Johor Bahru, Malaysia, where some reductions in precipitation in summer are expected. Yangon, in particular, is projected to increase

more than 4 millimeters per day in July, indicating a very high challenge from flooding as a city facing flood risk every year at present.

In summary, our results indicate significant changes in the mean and extreme states of temperature and precipitations in Southeast Asia. Based on these, I identified major physical risks of climate change among the ten cities. Decision-makers should build resilience to these risks to avoid significant damage. For example, Yukiko Hirabayashi et al. (2013) discovers the risks of floods increase due to the degree of warming. Increasing floods might lead to damage to households and other organisms. Moreover, a greater incidence of climate change, such as droughts, in Southeast Asia is caused by decreasing precipitation in regions (Teerachai Amnuaylojaroen and Pavinee Chanvichit (2019)).

To investigate and explore the future pattern of climate extremes in Southeast Asia particularly, this investigation utilizes CMIP6 model simulations to predict the future climate with reference to historical and present statistics. One of the reasons for choosing CMIP6 to predict near future and future climate extremes is that it performs well in reproducing the climatological spatial distribution of temperature and precipitation, with better performance for temperature than for precipitation (Yang et al. for China). With large-ensemble data for climate extremes, CMIP6 is able to predict more precise climate extremes. And this model is necessary for research about extreme climate, as it addresses the natural variability of the climate system in different regions with different topographic features.

Introduction:

Climate change has been continuously shifting temperature and precipitation patterns, exceeding historical records for climate extremes (E. M. Fischer, S. Sippel & R. Knutti, 2021).

The possibility of severe extremes occurring in Southeast Asia escalates (ADB, 2009). South East Asia has been the main agricultural production base and ecological resource. It is also one of the most populous regions worldwide. As such, it is crucial to understand the risks and vulnerabilities associated with climate change.

This work explores changes in climate conditions and their extremes in major cities in South East Asia. In particular, Yangon in Myanmar, Kuala Lumpur in Malaysia, Bangkok in Thailand, and Ho Chi Minh in Vietnam are included, as they are the capital cities with massive populations and coastal locations. They are also the local or regional economic centers and are therefore the most exposed to climate risks. In addition, other major coastal cities, including Johor Bahru in Malaysia and Nha Trang in Vietnam, are also included due to their high sensitivity to climate change. Meanwhile, major inland cities are also included, including Chiang Mai, the second biggest city in Thailand. In addition, I included Mandalay in Myanmar, Vientiane at the boundary of Thailand and Laos, and Phnom Penh in Cambodia, as they are major cities close to rivers and thus also sensitive to climate change. In summary, cities included in this study represent a comprehensive set of climate conditions, sometimes with contrasting climates across South East Asia.

This work focuses on climate impacts on temperature and precipitation. Overheated temperatures might cause human health problems, such as heat cramps and heat strokes, even resulting in death (CDC, 2022) and reduced labor productivity(EPIC, 2019). Excessive precipitation contributes to floods or even tsunamis, harming humans and ecosystems by including heavy metals, pesticides, and other types of toxic chemicals. It can heavily damage the lives of human beings as these eventually end up in rivers and lands where humans grow food to consume. Despite the physical health aspect, extreme temperatures and precipitation impact the ecosystem to a great extent. Higher temperatures enhance warmer climates in regions and worsen extreme weather events that occur—floods, droughts, etc. For example, climate models have suggested the frequency of occurrence of floods in South East Asia increases by 42% in a warmer climate (Hirabayashi, 2013). More specifically, the flood occurrence shows a high consistency in South East Asia according to the 42% increase, meaning the flood might occur continuously and significantly more flood events might happen. Indeed, South East Asia has been identified as the world's most vulnerable region to climate change by the regional review of the Asian Development Bank (ADB, 2009). Moreover, droughts are likely to occur in mainland South East Asia (Teerachai Amnuaylojaroen and Pavinee Chanvichit, 2019) due to insufficient and inefficient agricultural water use or higher temperatures. Droughts rise with a rise in temperatures, adding more risk of hunger and poverty to human society. In summary, South East Asia is a global hotspot for disasters due to climate extremes. This investigation is designed to fill the gap of some research which is novel to other studies by choosing precise locations in particular for detection while combining CMIP6 as a tool to discover extreme weather in Southeast Asia.

As mentioned above, the location stands this study out from previous studies since it fills the neglect of the city-level, which most studies possibly have not focused on. Cities vary in location but gain similarities in city characteristics; for example, these cities major in the economy of their countries and are located either coastal or inland. Besides, this study offers brand new perspectives, predicting behaviors of extreme climates more accurately and precisely, especially crucial to distinguish different extreme weather in different regions with various topographic and geographical features.

This study applies the climate simulation data in the Climate Model Intercomparison Project - Phase 6 (CMIP6) (Eyring et al., 2016) to analyze patterns in temperature and precipitation under RCP 8.5. CMIP6 includes an ensemble of climate models for future scenarios and experiments. This allows us to analyze the uncertainty of climate extremes in South East Asia. In particular, it addresses the natural variability of the climate responses, interpreting and analyzing the climate situation amid the large uncertainty naturally associated with extremes.

Methodology:

All cities are selected according to the main focus of the investigation—South East Asia—cities in this region, which are Kuala Lumpur, Bangkok, Ho Chi Minh, Yangon, Johor Bahru, Mandal ay, Nha Trang, Chiang Mai, Vientiane, and Phnom Penh, are included in this investigation.

1. CMIP6 data

I obtained CMIP6 data to analyze regional climates (Yang, X., Zhou, B., Xu, Y. et al.,2021). In particular, SSP585 among the CMIP6 future projection scenarios represented a world with high levels of fossil fuel use and weak climate policies, therefore placing the highest challenges in both climate mitigation and adaptation (Riahi, Keywan, et al., 2017). Under this scenario, anthropogenic impacts would lead to 8.5 W/m^2 by the end of the century (Riahi, Keywan, et al., 2017). I thus focused on this scenario, as it is important to understand extremes in climate conditions, as the greatest increases in temperature and the largest percentage-based changes in annual precipitation would be expected (Yuan et al., 2021).

2. ERA-5 data

To validate results from CMIP6 before analyzing its future projections, I obtained the ERA5-land hourly data set and historical reanalysis data (Hersbach et al., 2020). This data set included hourly climate metrics from 1950 to the present, providing good accuracy by the reanalysis combining modeled results with observations (Hersbach et al., 2020). I used the hourly temperature and precipitation data at 0.5 by 0.5 degrees. I then calculated the monthly average for each city in this study. The monthly averages were then compared to modeled results from CMIP6.

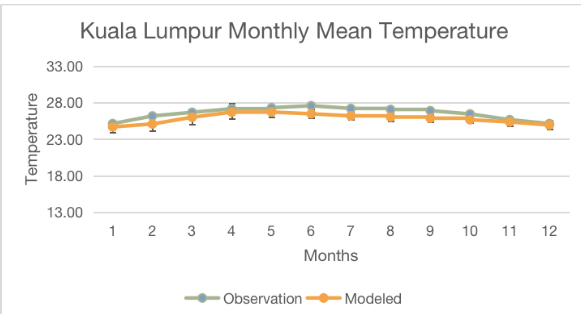
3. Statistical analysis

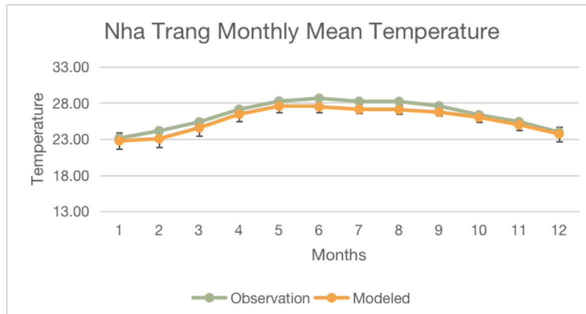
I first analyzed annual climate impacts by looking into four periods, defined as historical (1951-1961), present-day (2005-2014), near-future (2041-2051), and far-future (2090-2100). I calculated the annual average of temperature and precipitation within each period and obtained the minimum and maximum across the years within each period as the uncertainty range. Moreover, I looked into the seasonal impacts of climate change by calculating the mean monthly temperature and precipitation for four seasons, defined as DJF (December-January-February), MAM (March-April-May), JJA (June-July-August), SON(September-October-November). For each season, I compared changes for each city across the four periods above. Statistical analysis on CMIP6 and ERA-5 data was implemented using Python, and the rest analysis and visualization were conducted in Excel and Tableau respectively.

Results:

1. Comparing CMIP6 results with ERA-5 reanalysis

(A)





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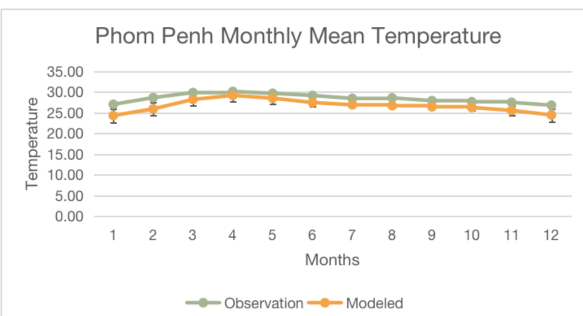

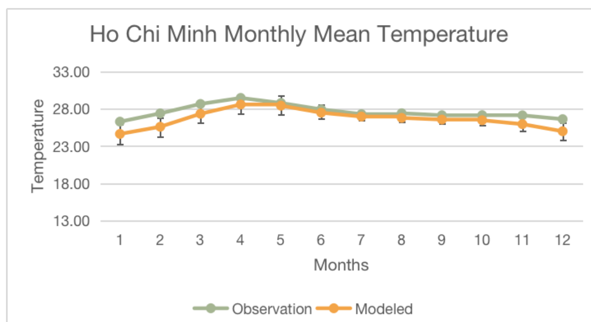

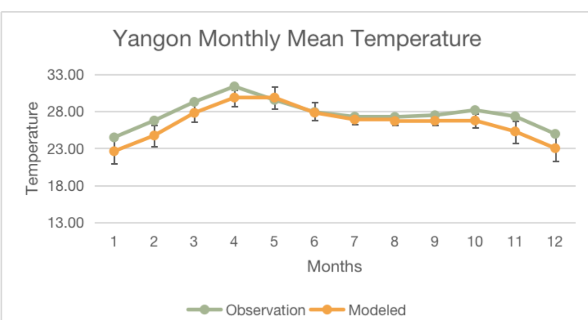

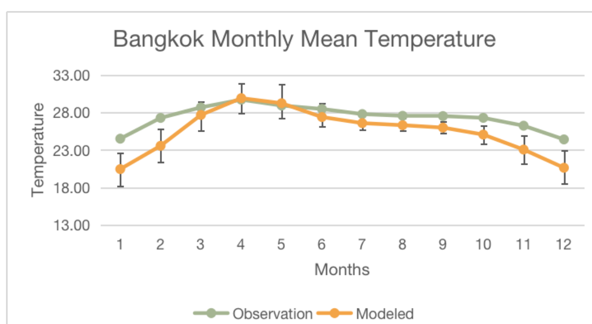

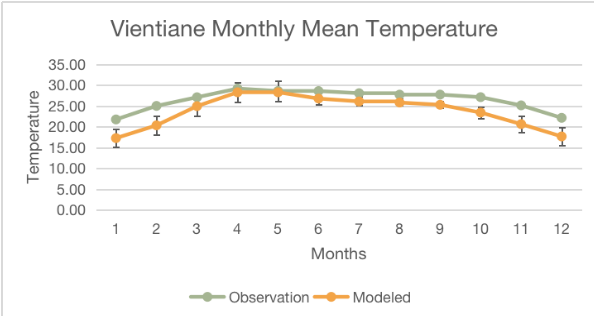

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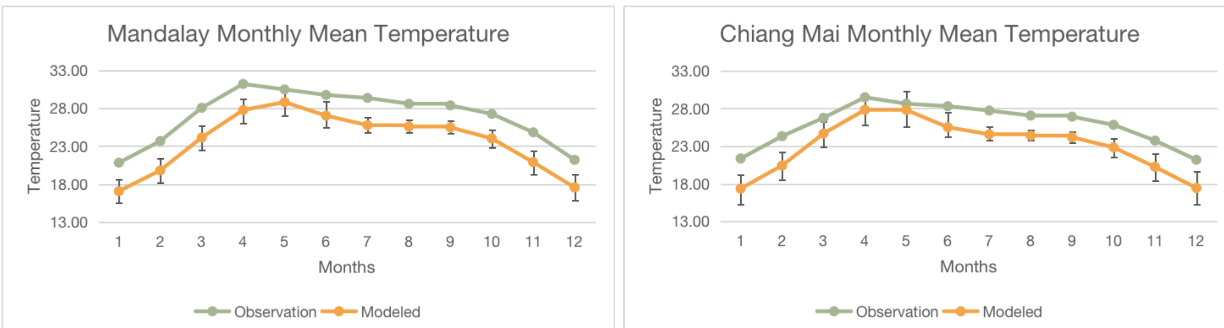

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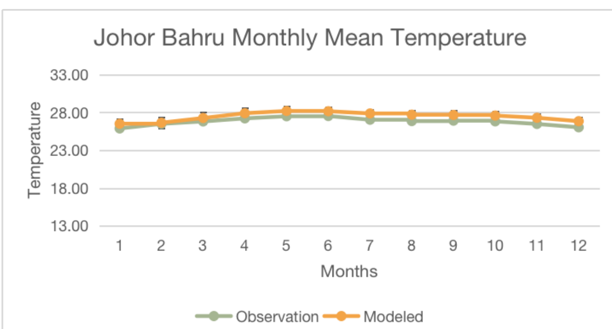


Figure 1: Comparison of monthly mean temperature between CMIP6 modeled results and ERA-5 reanalysis data for the present-day period (2005-2014) for cities in SE Asia. Error bars show the minimum and maximum of modeled results from CMIP6.

Figure 1 displays the differences and similarities between results in the present-day period modeled by CMIP6 and observed by ERA-5, with uncertainties of modeled results shown by the error bars. The results of each city are categorized from their trends and behaviors in mean temperature.

Kuala Lumpur and Nha Trang are categorized as category A because of their similar pattern as well as the subtle differences between observation and modeled data. Generally, modeled results are 1-2℃ lower than observations all over the year. Observation data in Kuala Lumpur hit its greatest monthly mean temperature of 27.6 degrees Celsius (℃) in June. Comparatively, the modeled data displays a similar pattern, but it reaches the greatest temperature of 26.7 ℃ in May. Observation and modeled data in Nha Trang hit the greatest temperatures in June and May, 28.6 and 27.6 ℃, respectively. In the summers of Kuala Lumpur and Nha Trang, the monthly mean temperatures in December and January are around 23 ℃. CMIP6 data in the two cities reflects a similar pattern and values to ERA-5 data, meaning CMIP6 results rather precisely estimate monthly temperature in this situation, regarding cities' characteristics.

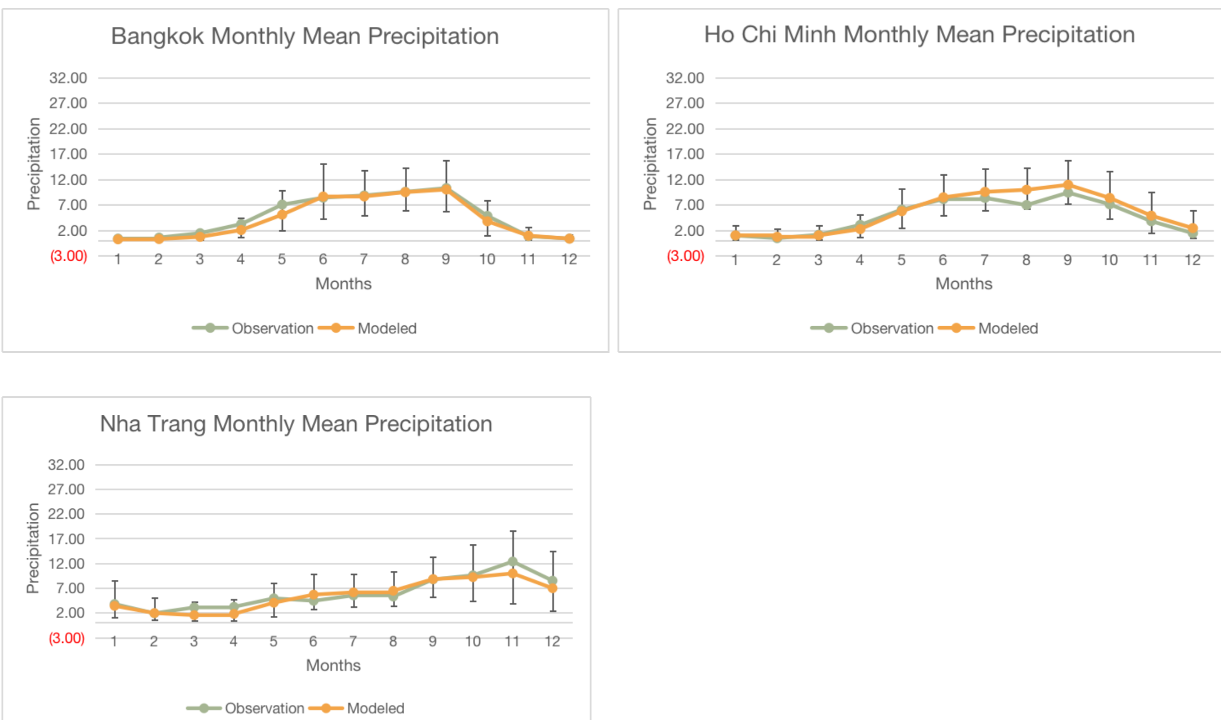
Phnom Penh, Ho Chi Minh, Yangon, Bangkok, and Vientiane are classed into category B. All five cities explicitly perform their greatest temperature around April, then remain stable from June to September, and ultimately hit the lowest temperature in December and January. CMIP6 models mostly capture the seasonal patterns, predicting the cities' highest mean temperature in April. Yet there is still a slight underestimate of temperature in April in Ho Chi Minh and Yangon. In other months, especially in winter, the models tend to underestimate the temperature by 1.6-4.5 ℃. In this sense, CMIP6 obtains a mostly consistent pattern with ERA-5; nonetheless, the model does not reflect the actual data in this situation.

In category C, ERA-5 data is distinctly higher than CMIP 6 data, while uncertainties of modeled data do not cover observation data. Both cities hit their highest temperature in April.

CMIP6 predicted temperature starts around or below 18 ℃ and predicts the highest around 28 ℃. However, Mandalay has its greatest temperature at 31.2 ℃, and Chiang Mai hits 29.5 ℃ of its greatest temperature. As such, there is a general underestimation all over the year, but commendably the models precisely predict the seasonal cycle of the variation in temperature in a year.

CMIP6 perfectly matches ERA-5 data in predicting seasonal variations of temperatures in John Bahru; therefore, the city is classified into a new category. The mean temperature of the city remains above 23 ℃ and rises to around 28 ℃ of its highest temperature.

(E)



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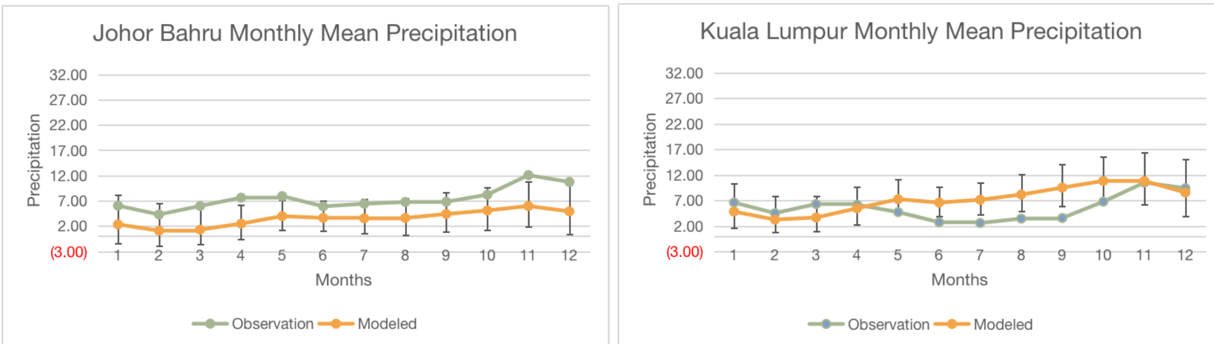
Johor Bahru Monthly Mean Precipitation
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Months
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Kuala Lumpur Monthly Mean Precipitation
Precipitation
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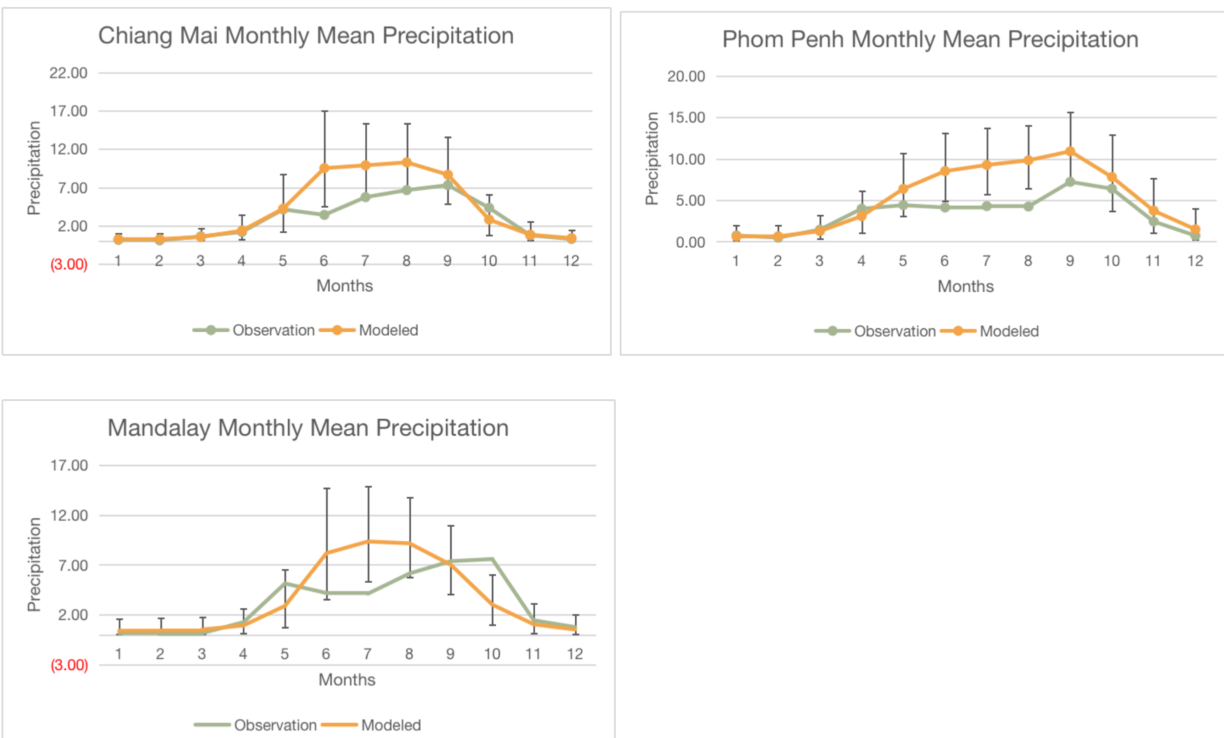
Chiang Mai Monthly Mean Precipitation
Precipitation
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1 2 3 4 5 6 7 8 9 10 11 12
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Phom Penh Monthly Mean Precipitation
Precipitation
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Mandalay Monthly Mean Precipitation
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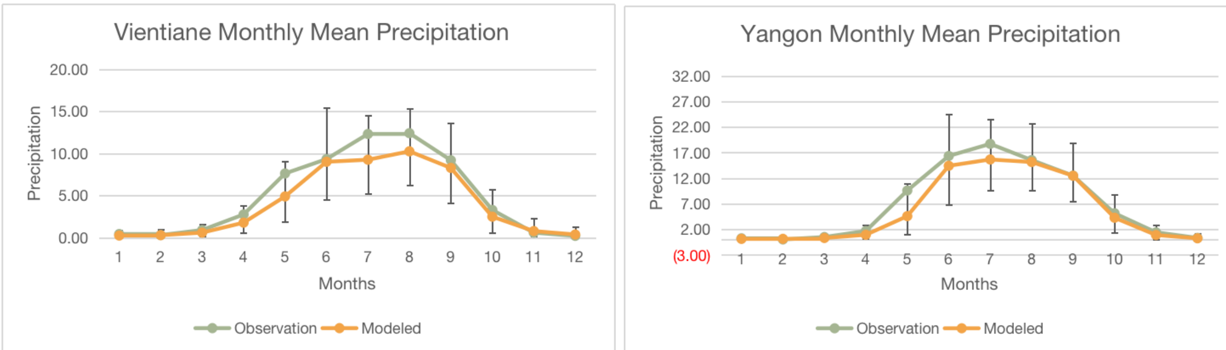

Figure 2: Comparison of monthly mean precipitation between CMIP6 modeled results and ERA-5 reanalysis data for the present-day period (2005-2014) for cities in SE Asia. Error bars show the minimum and maximum of modeled results from CMIP6.

Figure 2 presents correspondence and differences in CMIP6 and ERA-5, with uncertainties of the modeled results shown for comparison. In general, cities in SE Asia show two typical seasonal patterns for precipitation. In most cities, heavy precipitation mainly concentrates in the summer and autumn seasons (May to October) and barely occurs in spring and winter. Additionally, in Nha Trang, Johor Bahru, and Kuala Lumpur, there is no apparent raining season, such that precipitation is more averaged each month, slightly higher at the end of the year (November and December).

Based on the modeled results from CMIP6, Bangkok, Ho Chi Minh, and Nha Trang are categorized into one group because of the high similarities between modeled data and observation data, suggesting CMIP6 highly reflects the actual precipitation in these cities. Concentrated precipitation from June to September occurs in Bangkok and Ho Chi Minh but occurs in Nha Trang from September to December.

In group F, Johor Bahru and Kuala Lumpur have a relatively similar pattern of even precipitation year around. Interestingly, error bars on modeled data are mostly able to cover observation data, although there is a slight underestimation of precipitation in Johor Bahru around the year and a slight overestimation from May to October in Kuala Lumpur. In general, CMIP6 predicts a relatively precise precipitation volume in two cities.

Precipitation of Chiang Mai, Phnom Penh, and Mandalay shows a similar trend in observations, showing a raining season from May to October. Precipitation peaks in September in Chiang Mai and Phnom Penh, while Mandalay has a slightly later peak in precipitation in October. Generally, the modeled data do not fully synchronize with the original. In particular, CMIP6 models tend to underestimate precipitation in the raining season in Chiang Mai (May to September) and Phnom Penh (April to November) by up to 6 mm/day. In Mandalay, in particular, the CMIP6 models estimate a seasonal cycle reaching the highest precipitation in June to August, without fully reflecting the fact that precipitation peaks later in the year in October. Notwithstanding the differences between the two data sets, their uncertainties effectively include the observation data in it, therefore still proving the general accuracy of using CMIP6 for climate predictions.

Apparently, Vientiane and Yangon share a similar pattern for both observation and modeled data. Vientiane has high precipitation during summer, which is the same as Yangon. The precipitation rises rapidly from April to June for both cities and decreases drastically from September to October. CMIP6 modeled results readily capture the seasonal patterns in these cities.

2. Temperature impacts

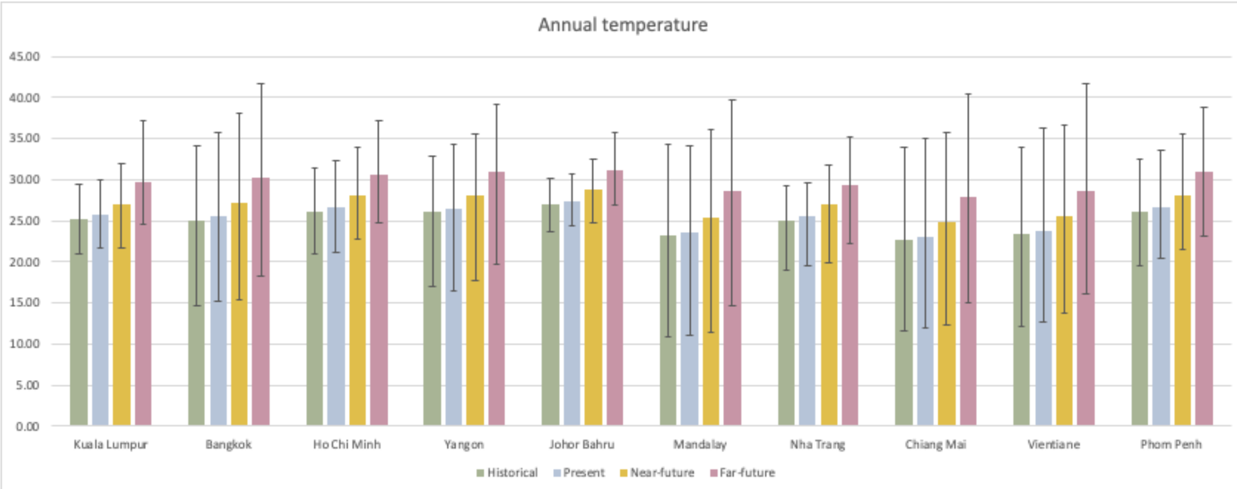

Figure 3: Annual temperature changes in historical, present, near-future, and far-future periods in 10 cities in SE Asia. Error bars represent the minimum and maximum annual temperature.

In temperature observations, the monthly temperatures of chosen cities are under comparison. Error bars are added to each value, meaning the value of annual temperature actually fluctuates in this range. Based on the data collected, the mean temperature for all selected cities, from historical to far-future time, has increased by around 5 ℃. What I can see from the maximum temperature, for example, the historical temperature for most cities is above 30 ℃, such as Bangkok, Ho Chi Minh, and Yangon. And historical temperatures of all these cities are around 30 to 35 ℃. But for the far-future annual temperatures, most cities have temperatures around 40 ℃ or over. Especially in Bangkok, this behavior is obvious. Previously, it has been mentioned that Bangkok is the capital city and the economic center in Thailand, containing a large population. Due to its geographical location, near the equator, the possibility of health damage because of exposure to extreme heat increases. In another city, Vientiane, Laos, because of the demographic size, demand for energy is high, meaning more factories operate and release emissions. This further causes a higher temperature as more greenhouse gasses are released into the atmosphere. The minimum temperature, from historical temperature to far-future, is around 3 ℃. This minimal increase in minimum temperature might be caused by agriculture, that greenhouse gasses increase. Furthermore, in the late century, annual maximum temperatures hit more than 40 ℃ in Bangkok, Chiang Mai, and Vientiane. In addition, cities in our study are projected to experience 5-6 ℃ increases in temperature from November to April, indicating significant changes in the seasonal cycle.

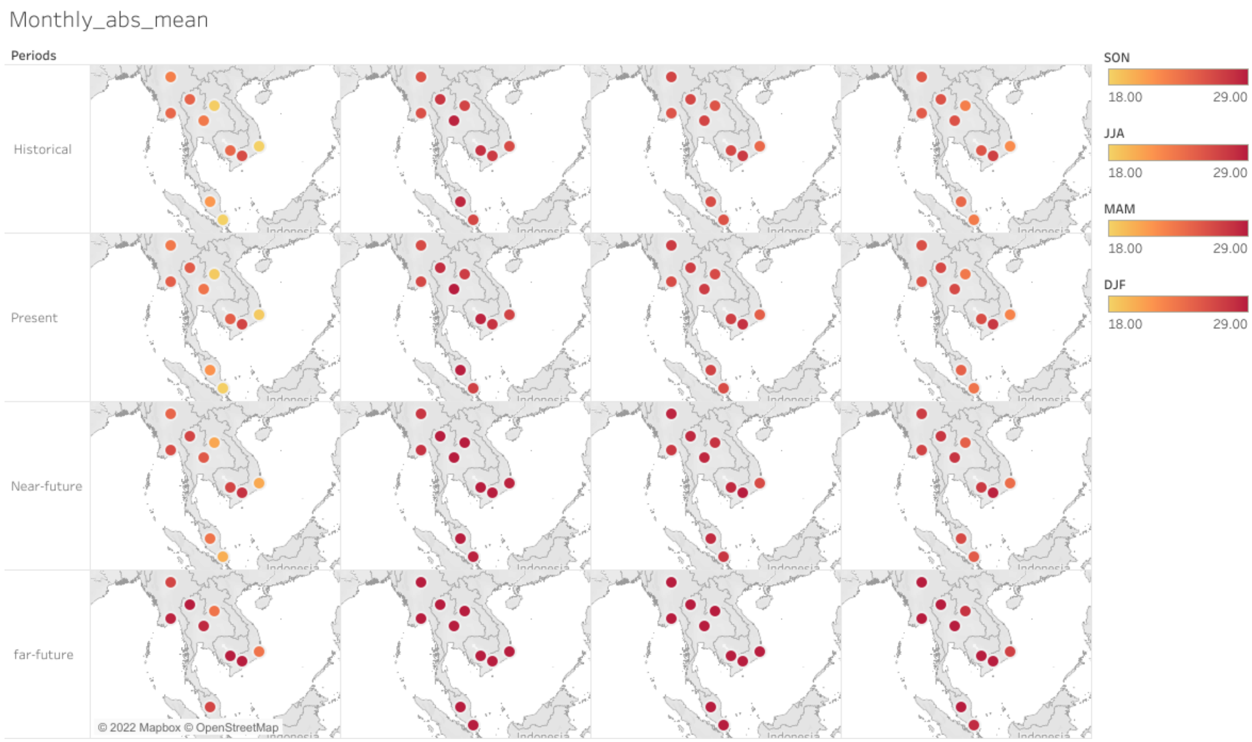

Figure 4: Monthly mean temperature changes in historical, present, near-future, and far-future periods in 10 cities in SE Asia.

This graph represents the seasonal pattern for all cities. The left column represents spring, and the rest columns represent summer, autumn, and winter in order. From the first column, it is apparent that the monthly mean temperature in spring from the historical to far-future period is predicted to increase. For instance, in Nha Trang, the color turns from yellow to orange, meaning the temperature in spring increases with time. For the summer and autumn seasons, the colors are dark orange and red, showing the temperature in these seasons gets extremely high, and this situation becomes worse when the time shifts to the far future. Moreover, in winter, the average temperature for cities increases with time passing. The graph displays that the color turns from orange to deep red for most cities in the far future. This indicates that the risks of droughts and illness-related problems might increase.

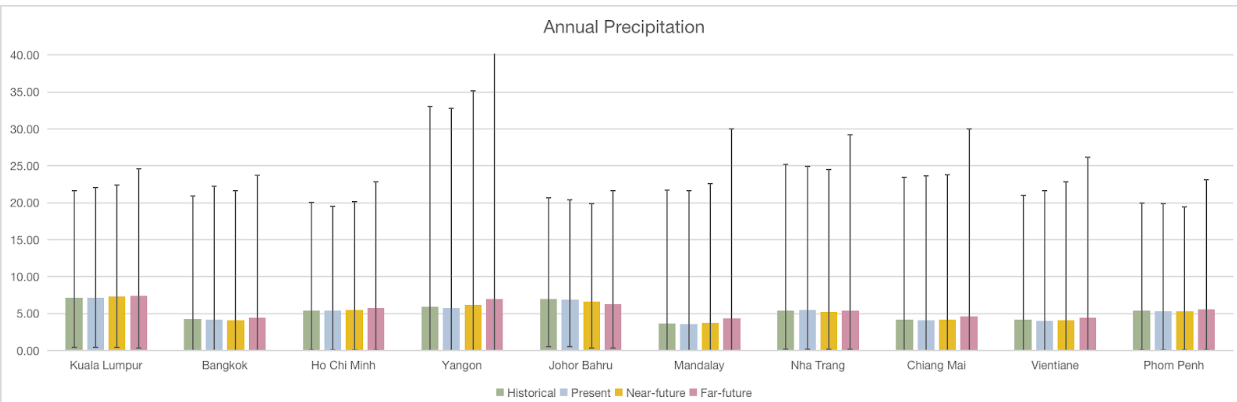

Figure 5: Annual precipitation changes in historical, present, near-future, and far-future periods in 10 cities in SE Asia. Error bars represent the minimum and maximum of annual precipitation.

For precipitation, from the figure above, most cities have mild increases around 0-2 millimeters per day, except for Johor Bahru, which has a slight difference of a decrease of 1 to 2 millimeters per day in its annual precipitation. All cities have a 1-2 millimeters increase per day in maximum precipitation from historical to far-future, such as Yangon and Chiang Mai. Despite mild changes in the present day and near future, precipitation accelerates in the late century and toward extremes. Yangon has a maximum of over 40 millimeters per day, and Chiang Mai has around 30 mm per day. In the case of Yangon, since it's over 40mm per day, this challenges the city's resilience. Due to the large population of Yangon, the capital city of Myanmar, higher risks of extreme weather are added, and the weather possibly gets moister because of greater precipitation. Precipitation increases significantly from May to October in most large cities in our study, except for Johor Bahru, Malaysia, where some reductions in precipitation in summer are expected. Yangon, in particular, is projected to increase more than 4 millimeters per day in July, indicating a very high challenge from flooding as a city facing flood risk every year at present.

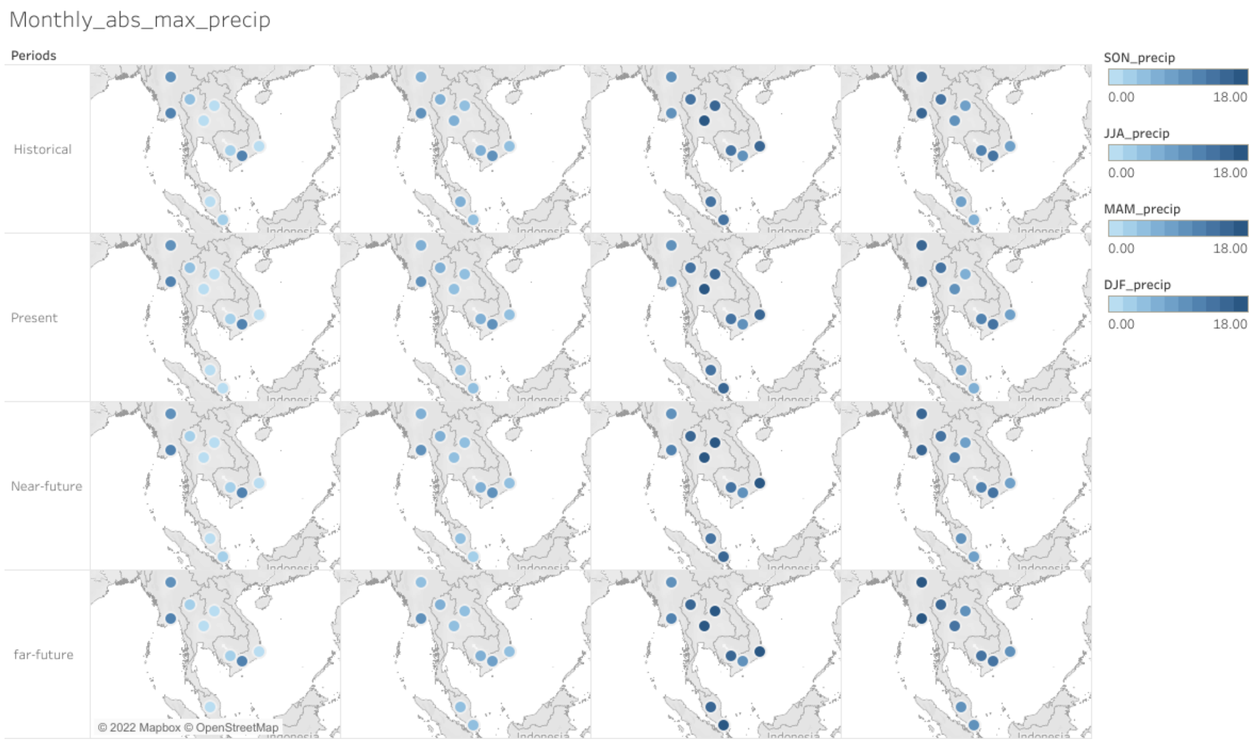

Figure 6: Monthly maximum precipitation changes in historical, present, near-future, and far-future periods in 10 cities in SE Asia.

This graph exhibits the monthly maximum precipitation among cities. It can be seen from the spring, in the left column, that the colors do not shift much from historical to far-future, meaning the precipitation volume in spring might stay the same. This scenario happens in summer as well; the level of precipitation does not vary hugely. In autumn, a few cities, such as

Yangon, have higher precipitation compared to the historical and far-future. In general, all cities stay in the same pattern, the same as these in winter.

Discussion:

Generally, our validation of CMIP6 results with observations shows good consistency in the ten cities in this study. Temperature estimates show superior accuracy in both absolute levels and seasonal patterns than precipitation. As such, I have high confidence in the temperature projections and good confidence in the precipitation projections.

From all of our results above, I may claim that the extreme temperature and precipitation add risks of floods and droughts to these SE Asian cities. Because of the large population of cities in SE Asia, the cities are expected to prioritize building preparedness for natural disasters. Also, the poorer a community is, the higher the vulnerability for it to be exposed to natural hazards (The World Bank, 2022). Therefore, it is important for the cities to simultaneously develop the economy and build resilience against climate extremes. Since most cities define themselves as developing countries, the World Bank funded 85 countries, including developing countries (The World Bank, 2022), in disaster risk reduction. As such, SE Asian cities have some resources and capabilities to strengthen preparedness for climate risks.

In order to increase resilience to climate conditions, natural resources need to be protected, including forests, watersheds, wetlands, etc. Nature-based solutions stand out in the situation for SE Asia. For example, wetlands effectively reduce flood risks by holding excess water. However, based on a World Bank report (The World Bank, 2022), the holding capacity of Colombo's wetlands dropped by 40% over a decade due to the lack of protections. SE Asia is traditionally rich in natural resources; therefore, the climate solutions should emphasize the protection of natural resources and places where species live and populate.

Other than wetlands, the rainforest in SE Asia is a crucial natural resource whose preservation is key to climate resilience. Specifically, the volume of water retained by rainforests depends on characteristics including forest cover area, the length of vegetation growing season, tree composition, and tree density, as well as the age and the number of layers of vegetation cover (EEA, 2015). Rainforest retains water by increasing and maintaining the infiltration and storage capacity of the soil and eventually affects the amount and timing of the water delivered to streams and groundwater. This becomes a key factor for flooding. Forests can soak up excess rainwater, preventing run-offs and damage from flooding. Moreover, by releasing water in the dry season, forests can also help provide clean water and mitigate the effects of droughts.

Furthermore, natural solutions should be largely integrated into the development of cities. Natural-based solution refers to using methods to protect, sustainably manage, and restore natural ecosystems that are in danger (International Union for Conservation of Nature, 2022). For example, setting green roofs and rain gardens on rooftops of buildings, or constructing wetlands can minimize damaging runoff by absorbing stormwater, thus reducing flood risks and safeguarding freshwater ecosystems (World Wildlife Fund, 2020). Urbanization often impedes environmental protection and nature preservation, as more space and resources are acquired for modern buildings, roads, city space, etc. Based on the World Bank's estimation, natural solutions will be able to provide 37% of the mitigation needed by 2030 to achieve the 2 ℃ targets of the Paris Agreement (The World Bank, 2022). In rapid urbanization, more issues arise such as insufficient water acquirement and water pollution, which would require even more efforts to mitigate. This means that dynamically, SE Asian cities undergoing rapid urbanization need to target more than 37% of natural-based solutions. For example, to alleviate water pollution and to access more drinkable water, nature-based solutions such as climate-smart farming, and restoration of wetlands, and degraded forests should be largely applied in SE Asian cities (The World Bank, 2022).

Conclusion:

Based on the projections of CMIP6, I estimated the changes in temperature and precipitation in 10 cities in SE Asia in both the near-future and far-future. I first showed that modeled results in CMIP6 have a good consistency with historical records for temperature and precipitation in these cities. Based on the projections, significant changes are projected to occur in the mean and extremes of temperature and precipitation. The mean temperature for SE Asia cities could reach around 40 ℃ for the summer and autumn seasons, a 5 ℃- increase in the far-future from the present day. Precipitation generally shows increases between 0 to 2 millimeters per day on average in most SE Asia cities, except that Johor Bahru is projected to have a decrease. Moreover, maximum precipitation in most cities is also projected to rise by 1-2 millimeters per day on average. As such, precipitation changes likely accelerate the occurrence of extreme climate events; therefore, more floods and droughts might take place in the future. These extreme climate events can be especially harmful in Mandalay, Yangon, and Chiang Mai, the three near-river cities with large populations. Based on the climate projections, the flood risks can become increasingly threatening physical risks across the 10 cities. To effectively prevent severe climate extremes from harming living organisms and cities, decision-makers should consider building resilience to avoid significant damage in the future.

Acknowledgment

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Reference:

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1. Comparing CMIP6 results with ERA-5 reanalysis

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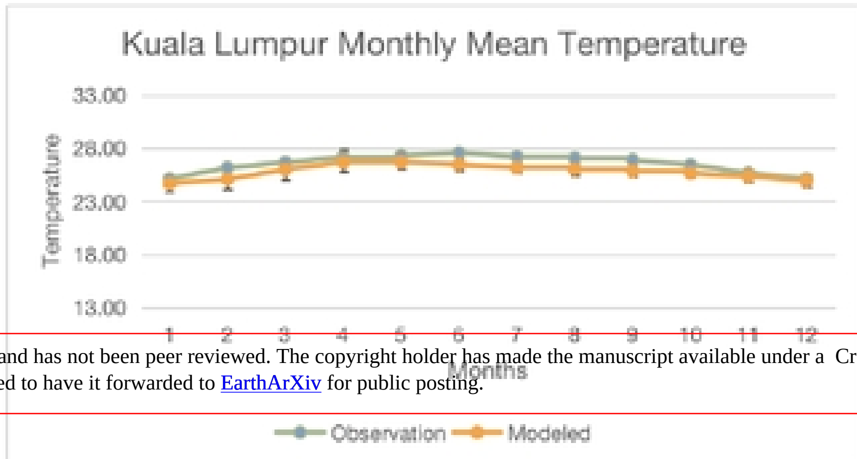

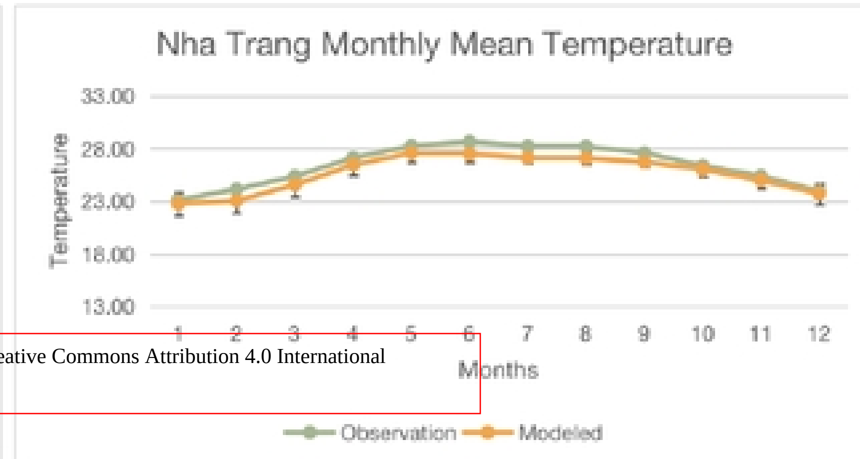

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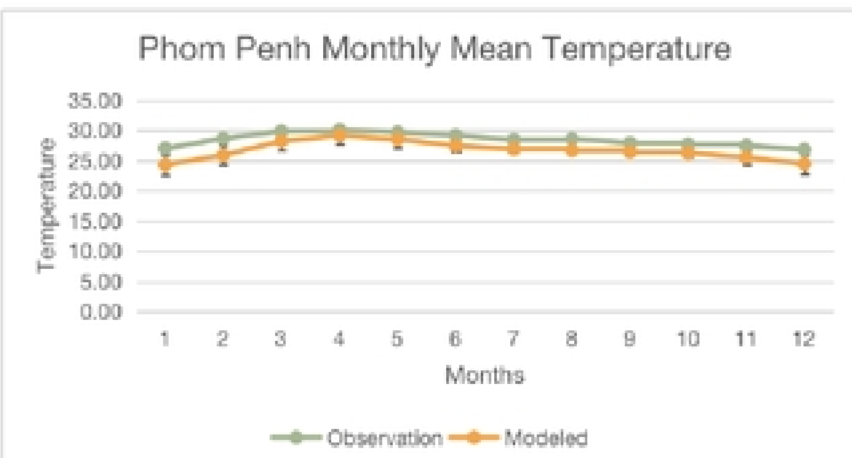
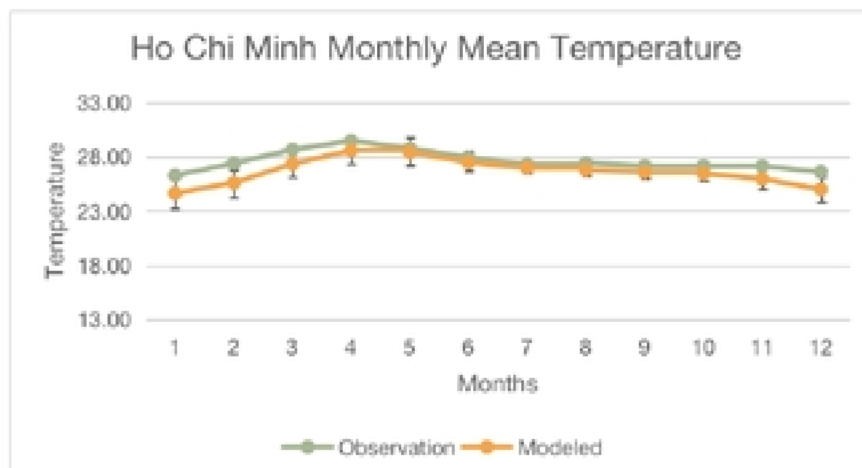
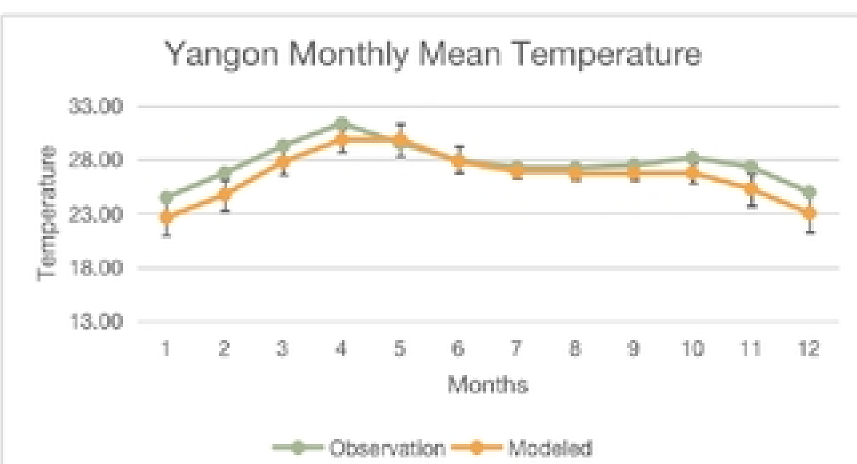
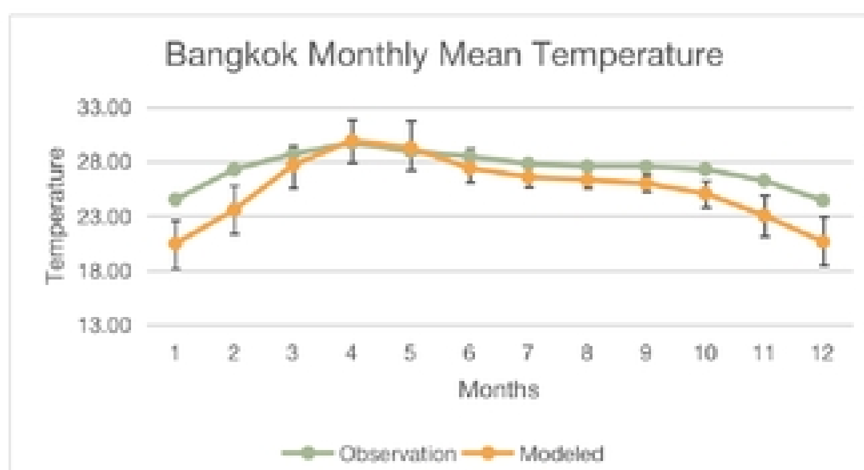
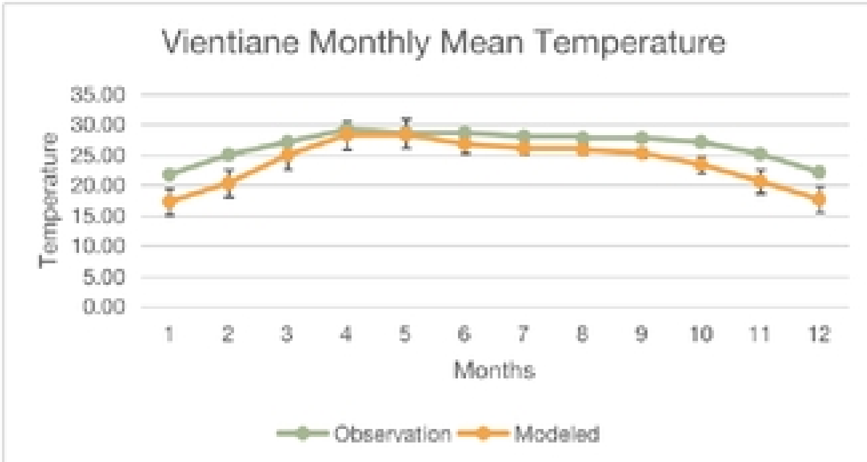


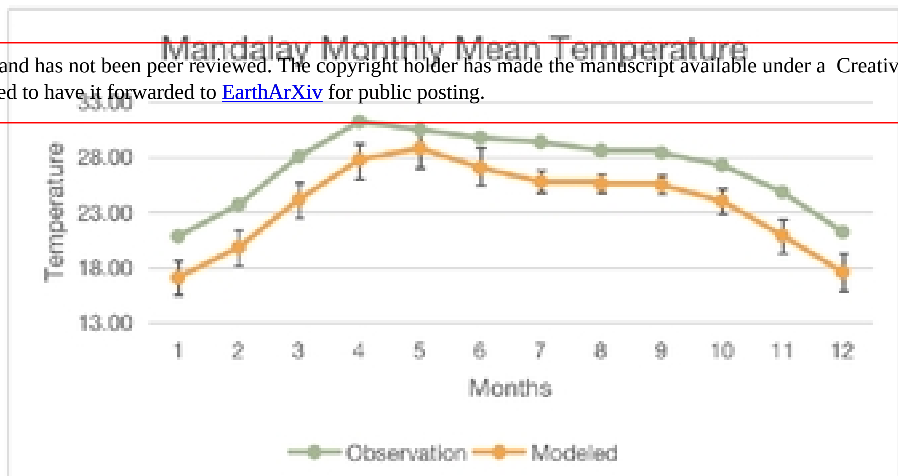


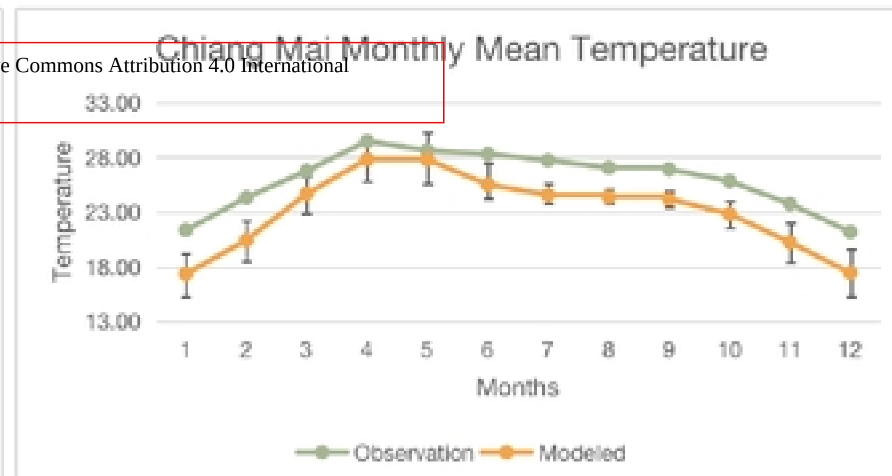






(C)





(D)

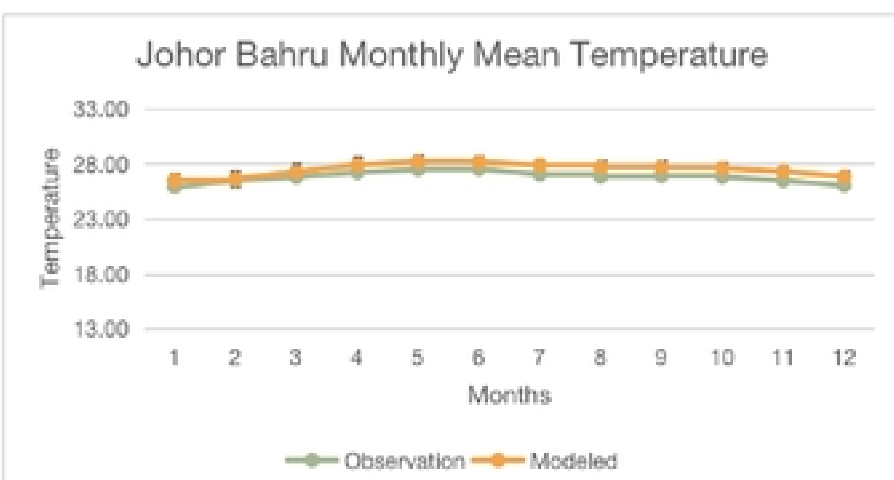
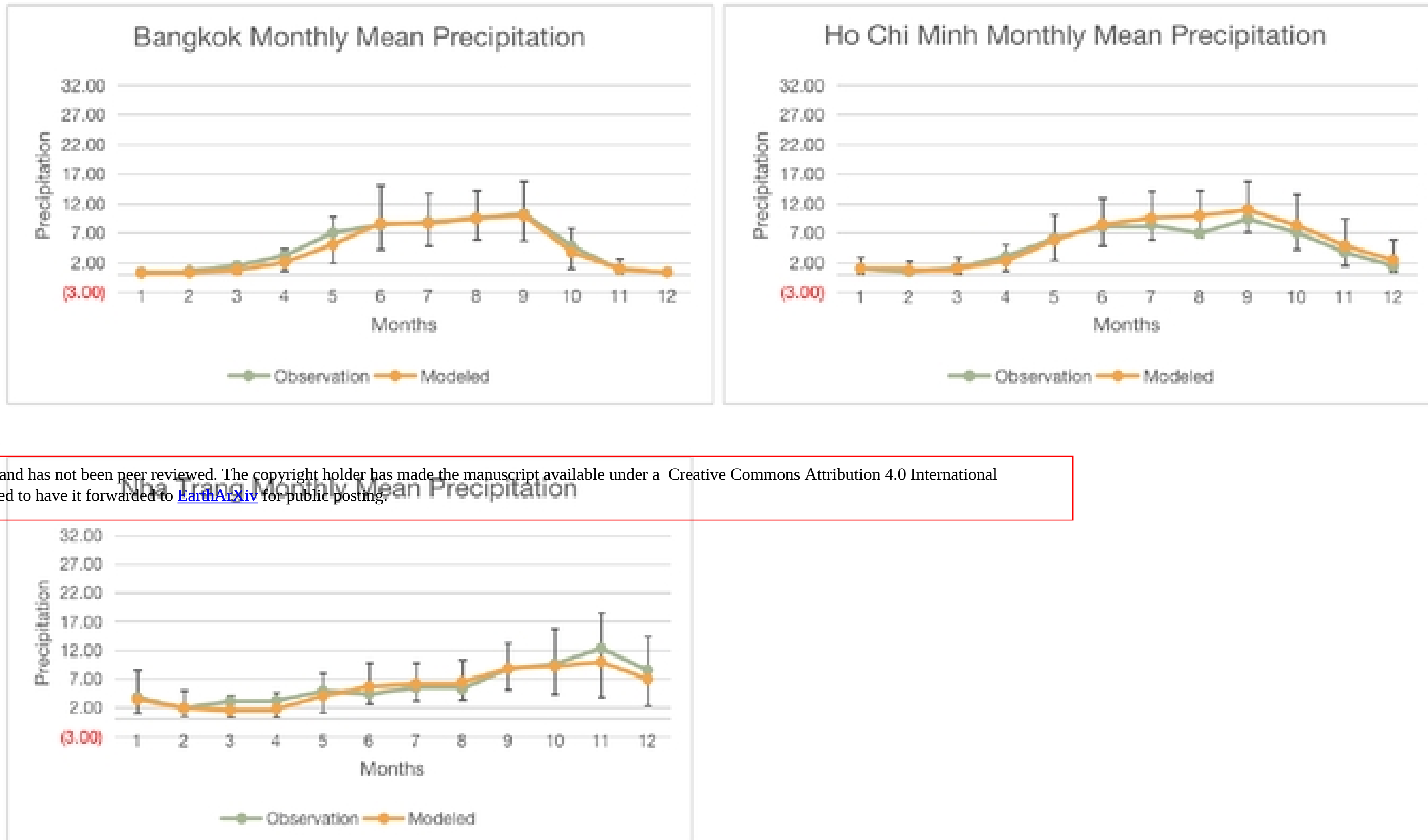
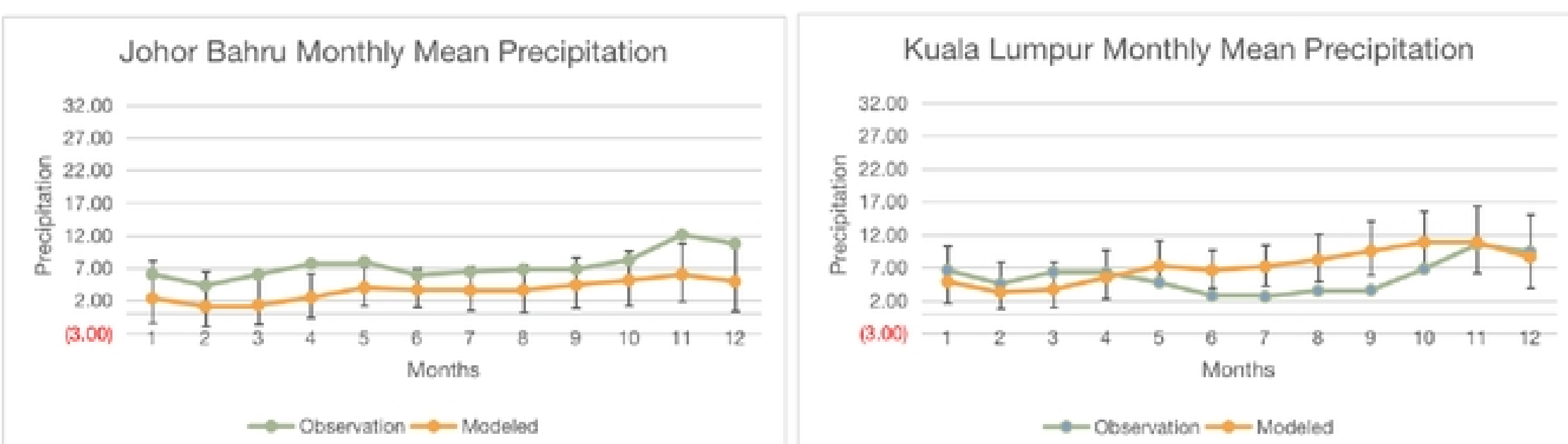


Figure 1: Comparison of monthly mean temperature between CMIP6 modeled results and ERA-5 reanalysis data for the present-day period (2005-2014) for cities in SE Asia. Error bars show the minimum and maximum of modeled results from CMIP6.

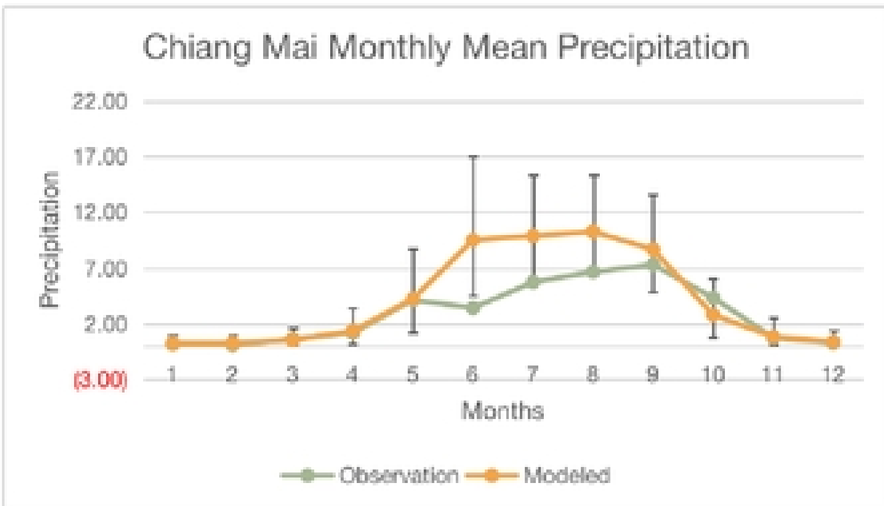
(E)

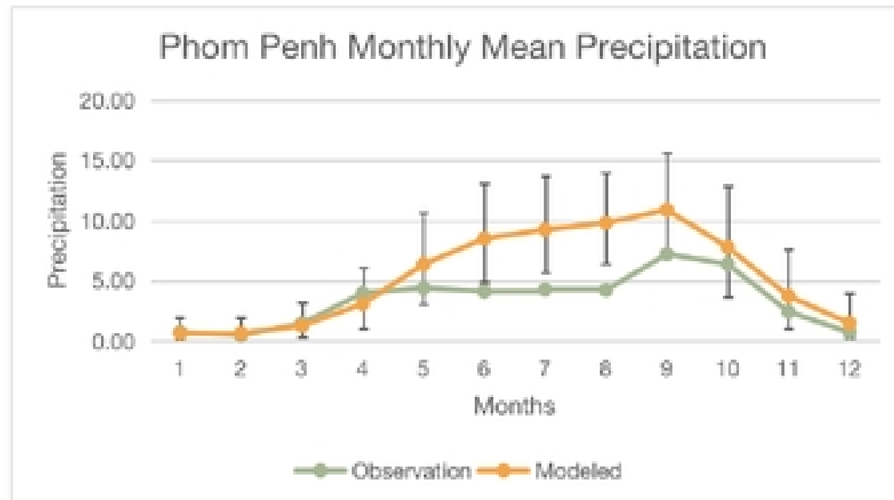

Bangkok Monthly Mean Precipitation
Ho Chi Minh Monthly Mean Precipitation
Nha Trang Monthly Mean Precipitation
Precipitation
32.00
27.00
22.00
17.00
12.00
7.00
2.00
(3.00)
1 2 3 4 5 6 7 8 9 10 11 12
Months
Observation
Modeled

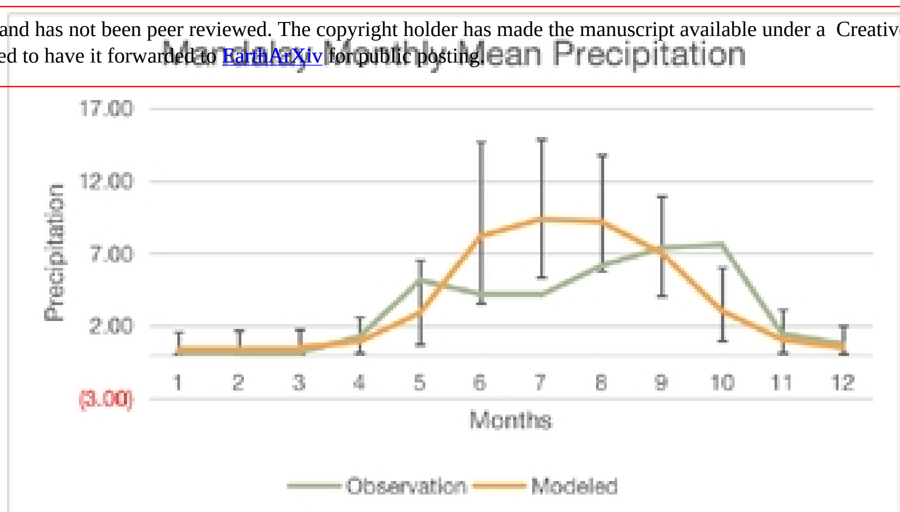
(F)


Johor Bahru Monthly Mean Precipitation
Kuala Lumpur Monthly Mean Precipitation
Precipitation
32.00
27.00
22.00
17.00
12.00
7.00
2.00
(3.00)
1 2 3 4 5 6 7 8 9 10 11 12
Months
Observation
Modeled

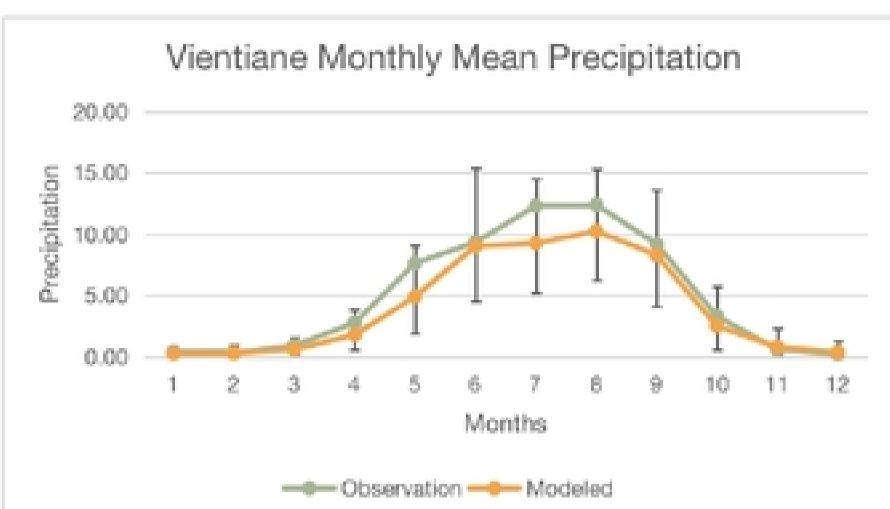
(G)







(H)



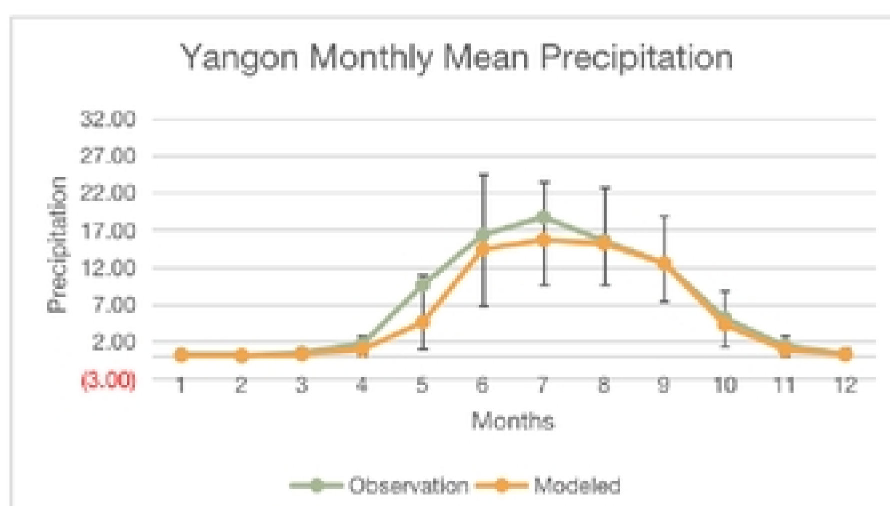


Figure 2: Comparison of monthly mean precipitation between CMIP6 modeled results and ERA-5 reanalysis data for the present-day period (2005-2014) for cities in SE Asia. Error bars show the minimum and maximum of modeled results from CMIP6.

2. Temperature impacts

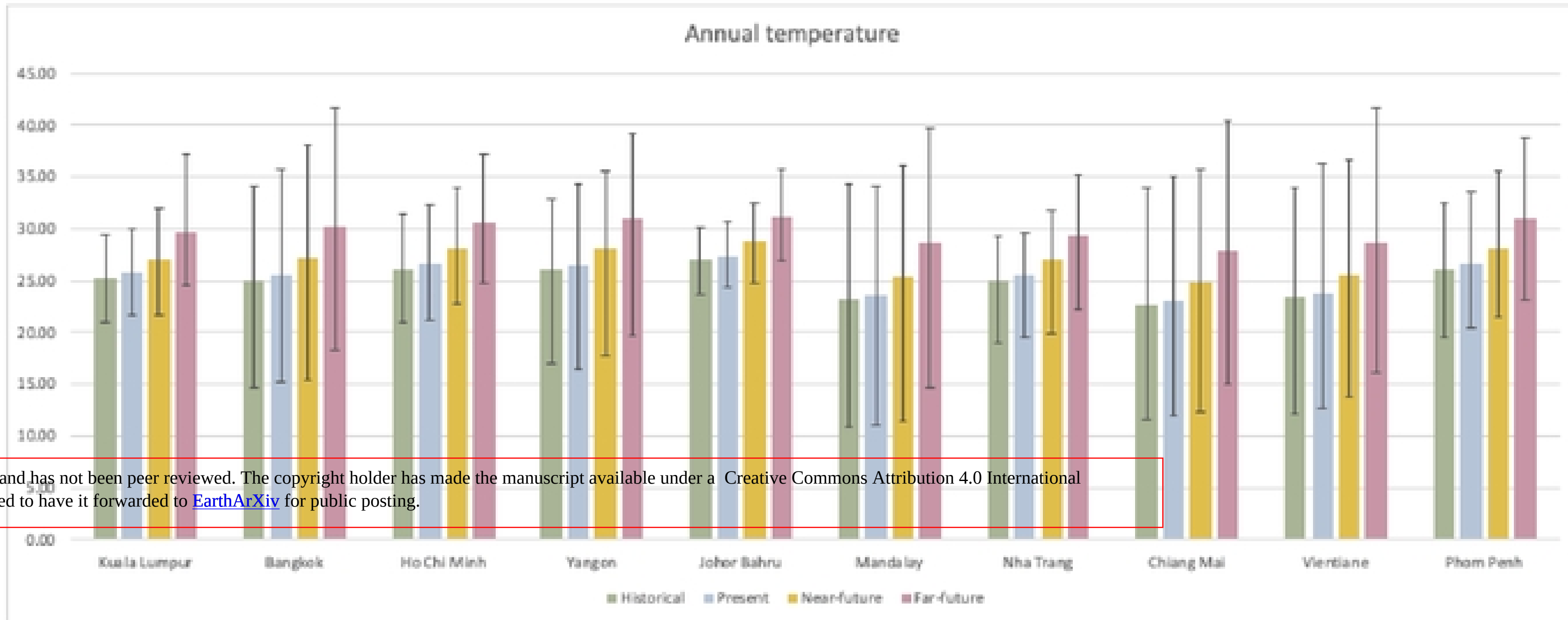


Figure 3: Annual temperature changes in historical, present, near-future, and far-future periods in 10 cities in SE Asia. Error bars represent the minimum and maximum annual temperature.

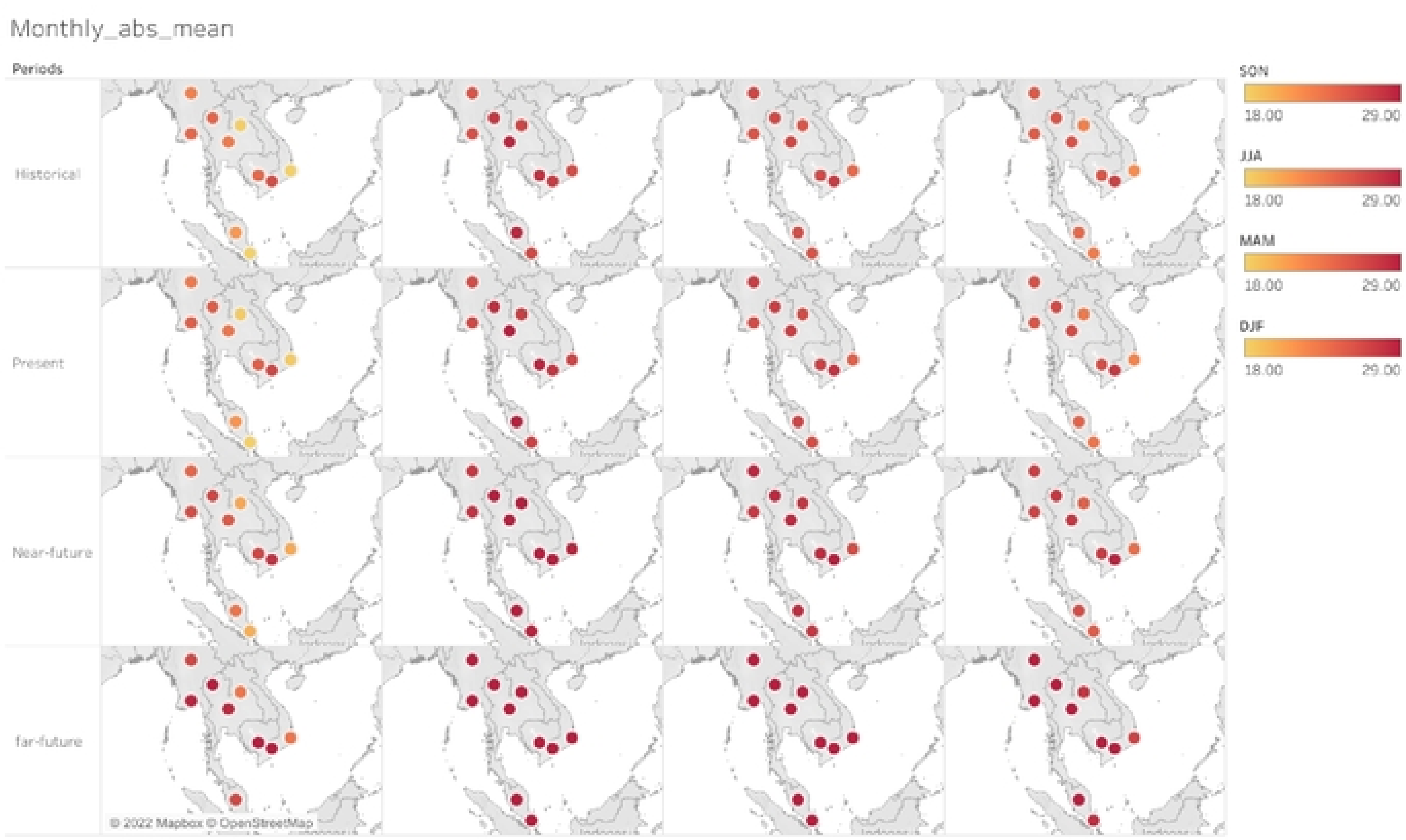


Figure 4: Monthly mean temperature changes in historical, present, near-future, and far-future periods in 10 cities in SE Asia.

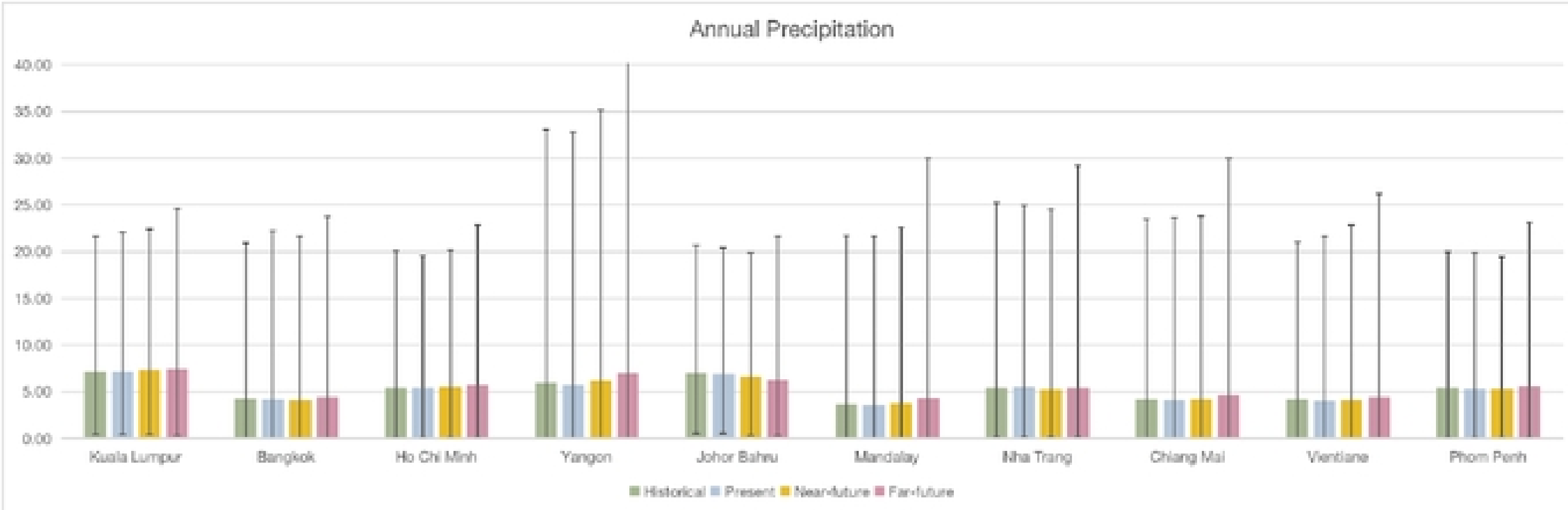


Figure 5: Annual precipitation changes in historical, present, near-future, and far-future periods in 10 cities in SE Asia. Error bars represent the minimum and maximum of annual precipitation.

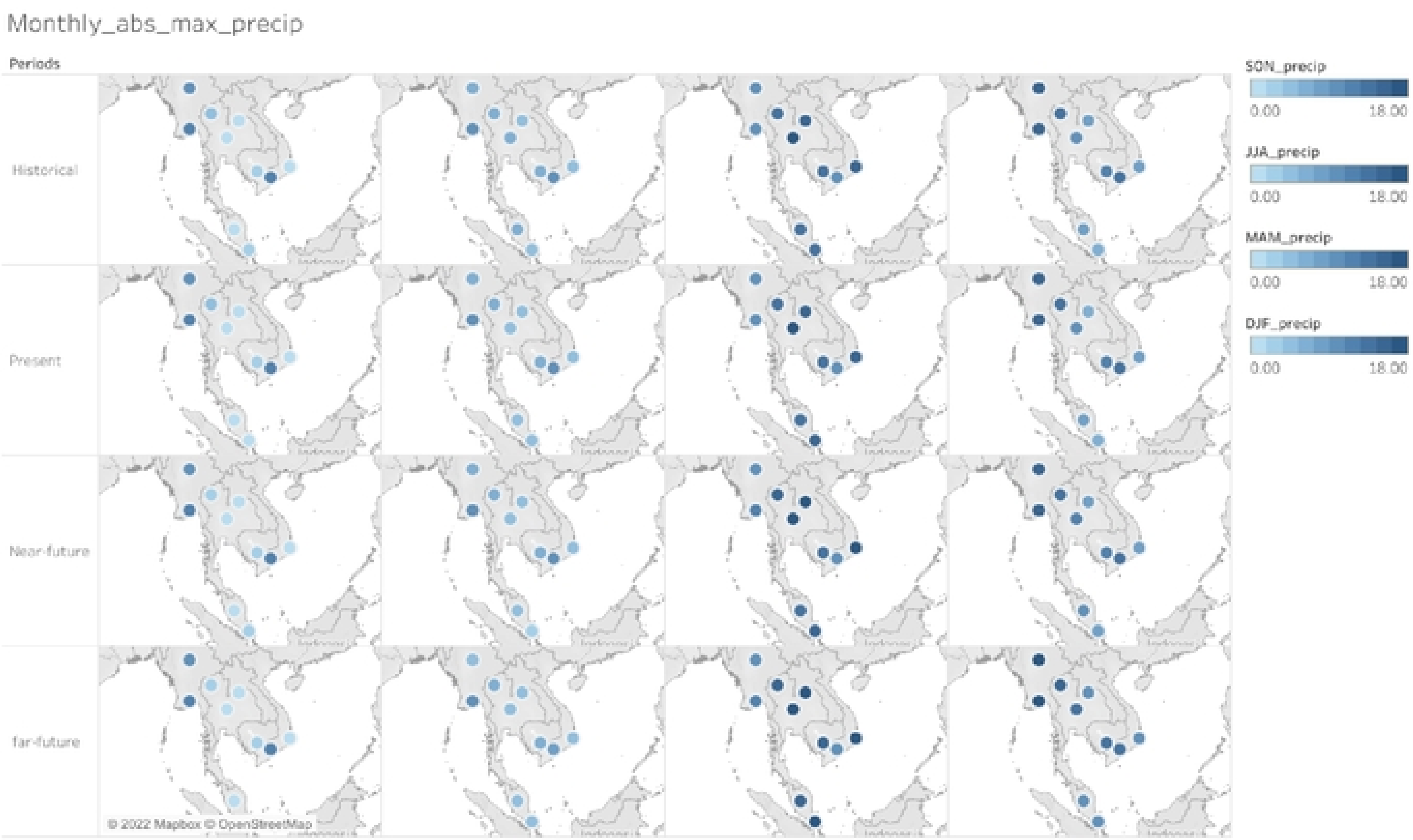


Figure 6: Monthly maximum precipitation changes in historical, present, near-future, and far-future periods in 10 cities in SE Asia.