Anthropogenic influence on long-term surface air temperature trends: Attribution of temperature changes across East Asia

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Research Article

Keywords: Climate change, Detection and attribution, CMIP6, East Asia, Future projections

DOI: https://doi.org/10.21203/rs.3.rs-207433/v1

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Abstract

Global warming/abnormal climate change is an ongoing process impacting ecosystem functions and human health; East Asia (EA) is one of the most vulnerable regions being influenced by such changes. This study examines the long-term variability of surface air temperatures (SATs) across EA using the new Coupled Model Intercomparison Project Phase 6 (CMIP6) datasets. Historical simulations (20\textsuperscript{th} century) and future (21\textsuperscript{st} century) SAT projections were investigated based on multi-model ensemble simulations. We also demonstrate the contribution of external and natural (NAT) forcings to SAT change. This study mainly focuses the effect of human-induced/anthropogenic forcings (ANT) on EA climate for a long period (1850-2100). Our simulations show that SAT in EA increased by 0.014 °C/decade during the period 1850–2014 owing to combined ANT and NAT (‘ALL=ANT+NAT’) forcings, while an increase of 0.082 °C/decade can be attributed to greenhouse gas (GHG) emissions. The ANT forcing rapidly increased after the third industrial revolution (after 1969). Consequently, SAT change accelerated to 0.255 °C/decade and 0.268 °C/decade owing to ALL and GHG forcings, respectively. Human-induced GHG emissions, carbon dioxide concentrations, and land use were the dominant factors driving SAT warming during the study period, and will contribute to substantial future warming trends. Furthermore, optimal fingerprinting method demonstrates the significance of ANT influences on climate change in EA. ANT forcing was clearly detected and distinct from NAT forcing in a two-signal analysis. In a three-signal analysis, GHG emissions were strongly detected and classified as distinct from other ANT and NAT forcings. The shared socioeconomic pathway emission scenarios (SSP1–2.6, SSP2–4.5, and SSP5–8.5) showed future projections (warming trends) from 2015–2100. This analysis suggests that climate change could be mitigated by restricting anthropogenic factors/activities in EA.

1. Introduction

The world faces the major challenge of on-going global warming/abnormal climate change, which greatly impacts socioeconomic and human activities as well as human health (IPCC 2013; Stocker et al. 2014). For example, during the 20\textsuperscript{th} century, average surface air temperatures (SATs) have increased by 0.6 °C worldwide (IPCC 2013; Stocker et al. 2014). Many authors have investigated the effects of external forcing on mean temperatures at global and regional scales, with increases primarily attributed to anthropogenic greenhouse gas (GHG) emissions alongside other human forcings (Stott et al. 2010; Bindoff et al. 2013; Jones et al. 2013). Meehl et al. (2004) explored a combination of natural and anthropogenic forcing using a parallel climate model, finding that natural (solar) forcing dominated warming during the early 20\textsuperscript{th} century and anthropogenic forcing (GHG emissions) dominated the late 21\textsuperscript{st}-century warming. Egorova et al. (2018) also reported an annual mean global warming rate of 0.3 K during the early 20\textsuperscript{th} century (1910–1940), with approximately half of this warming attributed to CO\textsubscript{2}, CH\textsubscript{4}, and N\textsubscript{2}O (well-mixed GHGs), and approximately one-third attributed to solar irradiance.

East Asia (EA) is one of the regions most vulnerable to climate change. It is one of the most densely populated regions, containing several major industrial and agricultural centers including high-altitude
areas such as the Tibetan Plateau. Thus, the EA region is sensitive to climate change that impacts the global climate as well. Therefore, understanding and assessing climate change across EA is important for estimating and predicting global climate change (Zhou et al. 2004). Increasing SAT trends in EA have been linked to extreme weather events (Xuejie et al. 2002; Li et al. 2018) including heatwaves (Yoon et al. 2018) and intense precipitation (Paik et al. 2020). In 2019, EA experienced extreme heat during the summer monsoon season, while in 2020, a long monsoon was associated with heavy rains and landslides, as a result of climate change (Korea Meteorological Administration; Japan Meteorological Agency; China Meteorological Administration).

In response to these challenges, many studies have described the characteristics of SAT changes in EA countries. In China, Tang et al. (2010) reported that SAT increased by 0.78 ± 0.27 °C between 1906 and 2005, and Xu et al. (2015) observed a warming of 0.25 °C/decade and 0.17 °C/decade between 1961 and 2005 as a result of GHG emissions and other anthropogenic factors, respectively. The same authors reported that the emission of GHGs is the dominant factor forcing impacting climate change in China. Qian and Qin (2006) analyzed the spatiotemporal characteristics of temperature trends across China using data from 486 meteorological stations, reporting increases of 0.2–0.3 °C/decade and < 0.1 °C/decade in northern and southern China, respectively, between 1960 and 2000. The same authors report that the greatest increases occurred in winter temperatures (0.5–0.7 °C/decade and 0.2–0.3 °C/decade in northern and southern China, respectively). Mean annual temperature changes in China between 1961 and 2005 were attributed to the combined effect of GHG emissions and sulfate aerosol forcing (Xu et al. 2015). Across the Korean Peninsula, extreme heatwave events have also been associated with climate change (Yoon et al. 2020). In North Korea, Om et al. (2019) observed a temperature change of 0.21 °C/decade from 1918 to 2015, which is higher than the changes reported for mainland China and the global average. Coastal areas were found to experience lower warming trends than inland regions in North Korea. Similarly, Jung et al. (2002) observed that mean annual SATs in South Korea increased at a rate of 0.23 °C/decade between 1954 and 1999, with a higher warming rate during winter. Across the entire Korean Peninsula, Chung and Yoon (2000) reported that the annual mean temperature increased by 0.42 °C/decade between 1974 and 1997 in association with GHG emissions, with larger cities experiencing faster warming trends than rural areas and small cities. Wang et al. (2016) also reported a 0.35 °C/decade warming in northeast China and a 0.2 °C/decade warming in Hokkaido, Japan, between 1951 and 2000. They also observed that extreme high- and low-temperature events were significantly positively correlated between these two regions, with variations in warming recorded between region and countries with different rates of development. Moreover, in Japan, Fujibe (2009) observed that SATs in regions with population densities of over 100 and 3,000 persons km⁻² increased at a rate of 0.03–0.05 °C/decade and 0.1 °C/decade, respectively, between 1979 and 2006.

Detection and attribution analysis is a versatile tool that can be used to identify the drivers of climate change (Allen and Tett 1999; Allen and Stott 2003; Ribes and Terray 2013; Ribes et al. 2013; Wang et al. 2018). Several researchers have used this method to examine temperature increases from regional to global scales, with anthropogenic forcing being identified as the dominant factor in most cases (e.g.,
Lu et al. 2016; Weller et al. 2016; Wang et al. 2018; Paik and Min 2020). Detection and attribution analyses have been performed using the Coupled Model Intercomparison Project Phase 3 (CMIP3; Santer et al. 2009), Phase 5 (CMIP5; Xu et al. 2015; Yin et al. 2017; Zhang et al. 2019), and the new Phase 6 (CMIP6) model simulations (Paik and Min 2020; Paik et al. 2020) to assess the relative contributions of various external forcings to climate change. Xu et al. (2015) used an optimal detection technique to identify distinct GHG- and anthropogenic (ANT)-associated temperature changes in China from between 1961 and 2005; Yin et al. (2017) used multimodal CMIP5 simulations for the period 1958–2012 to detect ANT forcing of both extreme cold and warm temperatures in China; and Paik et al. (2020) reported that anthropogenic GHG emissions are the major contributor to extreme precipitation events across a range of climatic settings. As an attribution technique, the optimal fingerprinting method detects both anthropogenic and natural forcings (referred to as 'ALL' forcing) and ANT forcing (Wang et al. 2018). Applying this approach to China, Wang et al. (2018) showed that warming in western China can be attributed to anthropogenic forcing, and also projected the future warming trends of this region.

Most of the studies mentioned above focused on climate change in China and few studies have focused on Korea or Japan. Furthermore, most studies have considered the period 1950–2010 and employed CMIP3 and CMIP5 model simulations. To the best of our knowledge, CMIP6 datasets have not yet been used to examine EA climate trends during the historical period from 1850 to 2014 nor have future projections (2015–2100) been provided at this scale. There are also no detection and attribution studies of climate change across the whole of EA. To address this gap, here we focus on SAT changes in EA between the second half of the 19th century and the 21st century based on the new state-of-the-art multimodel CMIP6 simulations. This allows us to describe the contributions of external/internal and natural forcings on climate change in this region. Based on our analysis, we also describe the relative contributions of each forcing in each EA country as well as across the EA as a whole. The main focus of the study is to examine the effect of human-induced/anthropogenic forcings on climate change over EA using CMIP6 simulations. We also provide future projections of each EA country and the entire EA region based on three different scenarios.

The rest of the paper is structured as follows. Section 2 describes the data and methodology and Section 3 provides a discussion of our results including observed and simulated temperature trends in response to the different forcing factors, the detection and attribution results, and the observation-constrained future projections. Finally, a summary of our findings and our conclusions are presented in Section 4.

2. Data And Methodology

We used the CRU (resolution = 1° × 1°) and HadCRUT4 (resolution = 5° × 5°) observational datasets for the period 1901–2018 and 1850–2019, respectively; the HadCRUT4 dataset was primarily used to cover the period not considered by the CRU dataset (1850–1900). Land and ocean data were separated, and the former was used for this study. The state-of-the-art global multimodal simulations of CMIP6 (Eyring et al. 2016), supported by the World Climate Research Program, were used to estimate the influence of different external forcings. Some of the CMIP6 models are more biased when compared to observational
datasets (Eyring et al. 2016). Therefore, we used multimodal ensemble mean values to mitigate any bias and obtain the most accurate values possible. The various CMIP6 models (Table 1) were re-gridded using bilinear interpolation to achieve a uniform resolution of 1° × 1°. The 20th century historical and 21st century future shared socioeconomic pathway (SSP) scenarios were used to define historical and future temperature trends, respectively. The historical datasets with all (ALL), anthropogenic aerosol (AER), natural (NAT), GHG, solar irradiance (SOL), carbon dioxide (CO2), and land use (LU) forcings were used to define their influence on the temperature trends. The low SSP1–2.6 and SSP2–4.5 scenarios and high SSP5–8.5 scenarios were used for the future projections (2015–2100). Initially, the monthly anomalies of the historical (considered land data and discarded ocean data) datasets (ALL, AER, NAT, GHG, SOL, CO2, and LU) and future scenarios (SSP1–2.6, SSP2–4.5, and SSP5–8.5) were collected from CMIP6. Initially, the 1° × 1° gridded data were averaged for their respective models and any missing data were masked. The multi-model ensemble mean was then estimated as the weighted arithmetic mean of all model datasets. Finally, the yearly and decadal anomalies were evaluated for each EA country (the area-weighted mean of each country) as well as the entire EA region.

Regularized optimal fingerprinting (ROF) was used for detection and attribution analysis based on the different forcings (Ribes et al. 2013). This approach can assess the contribution of external forcings based on the scaling factors in a linear regression model (Allen and Tett 1999; Ribes et al. 2013). ROF is similar to classical optimal fingerprinting except that a regularized covariance matrix is used for the optimization and estimation of the null-distribution used for the residual consistency test. ROF is based on the space-time evolution of SAT trends and is more accurate than the classical optimal detection method (Ribes et al. 2013; Zhang et al. 2019), overcoming the limitation of empirical orthogonal function truncations. ANT was estimated by subtracting NAT from ALL (ANT = ALL − NAT). We also used a set of 225 110-year-segment pre-industrial control (CTL) simulations (segment length equal to the 1905–2014 period used for the detection analysis) to estimate internal climate variability to increase the independent noise data; this reduces the sampling uncertainty in covariance estimations (Ribes et al. 2013).

We conducted one-signal, two-signal, and three-signal analyses over the last hundred years (1905–2014) for each EA country and EA overall. In the one-signal analysis (Eq. 1), the observations were regressed onto each fingerprint (ALL, GHG, ANT, NAT, and AER) separately to detect their relative influence on the observed change. In the two-signal analysis (Eq. 2), the observations were regressed simultaneously into the ANT and NAT fingerprints to isolate their separate contributions. In the three-signal analysis (Eq. 4), the observations were regressed onto the response patterns from the GHG, ANTnoGHG (i.e., ANT − GHG), and NAT simulations simultaneously to clearly detect and isolate the GHG forcing effect.
\[ Y_{\text{OBS}} = \beta_M X_M + \epsilon \] (1)

\[ Y_{\text{OBS}} = \beta_{\text{ANT}} X_{\text{ANT}} + \beta_{\text{NAT}} X_{\text{NAT}} + \epsilon \] (2)

\[ X_{\text{ALL}} = X_{\text{ANT}} + X_{\text{NAT}} \] (3)

\[ Y_{\text{OBS}} = \beta_{\text{GHG}} X_{\text{GHG}} + \beta_{\text{ANTnoGHG}} X_{\text{ANTnoGHG}} + \beta_{\text{NAT}} X_{\text{NAT}} + \epsilon \] (4)

\[ X_{\text{ALL}} = X_{\text{GHG}} + X_{\text{ANTnoGHG}} + X_{\text{NAT}} \] (5)

where \( Y_{\text{OBS}} \) represents the observations; \( X \) indicates the model simulations; \( M \) is the fingerprints of ALL, GHG, ANT, ANTnoGHG, AER, and NAT; \( \beta \) is the unknown regression coefficient or scaling factor; \( \epsilon \) is the regression residual term; \( X_{\text{ALL}}, X_{\text{GHG}}, X_{\text{ANT}}, X_{\text{ANTnoGHG}}, \) and \( X_{\text{NAT}} \) are the model simulation responses to the ALL, GHG, ANT, ANTnoGHG, and NAT forcings, respectively; and \( \beta_{\text{GHG}}, \beta_{\text{ANT}}, \beta_{\text{ANTnoGHG}}, \) and \( \beta_{\text{NAT}} \) are scaling factors corresponding to the GHG, ANT, ANTnoGHG, and NAT forcings, respectively.

### 3. Results And Discussion

#### 3.1 Observed and model simulation trends

Figures 1a and 1b show the annual mean temperatures from 1901 to 2014 estimated from CRU and CMIP6 (ALL forcings), respectively. The mean temperature varied between \(-15^\circ C\) and \(30^\circ C\) throughout EA. Southeast China showed the highest mean temperature (approximately \(25^\circ C\)), while Tibet and northwest Mongolia showed the lowest (< 0 \(^\circ C\)). In Korea and Japan, the mean temperature varied from 4 to 16 \(^\circ C\). The performance of the CMIP6 model simulations was validated in comparison with the CRU observations. The bias (CMIP6 – CRU) in all EA countries is shown in Figure 1c., and the 25% and 75% quartiles indicate a bias of < 1.8 \(^\circ C\). Overall, the mean bias for EA was \(\leq 0.5^\circ C\), indicating that the performance of the CMIP6 simulations was satisfactory. Figures 1a and 1b also show that the mean temperature values of CRU and CMIP6 outputs are consistent. The Student’s t test also showed no significant differences between the observations and model estimations at the selected time period (significance level < 0.05). Further, we compared the trends of the simulations and observations (see Figure 3 and the following paragraphs), which showed good agreement.

We also evaluated the spatial distributions of the annual mean SAT response trends to the different forcings for the period 1850–2014. Figures 2a–e correspond to the temperature trends associated with the ALL, AER, NAT, GHG, and SOL forcings. The \(CO_2\) and LU datasets were only available for very few models and did not cover all the EA regions (Table 2) owing to their low spatial resolutions. Therefore, the distributions for \(CO_2\) and LU are not presented here. The lowest increases in temperature owing to ALL and GHG occurred in southeast China, while the highest increases were observed in Tibet and southern Mongolia. As the third industrial revolution began in 1969, we also estimated the
temperature changes over the last 40 years (1971–2014; Table 2). The SAT response to ALL forcings clearly shows a positive trend throughout EA during the study period, with an increase of approximately 0.0145 °C/decade between 1850 and 2014 (Period 1 = P1) and 0.255 °C/decade between 1971 and 2014 (P2). Overall, Mongolia showed the highest rate of increase at 0.041 °C/decade in P1 and 0.379 °C/decade in P2, and Japan the lowest at 0.009 °C/decade in P1 and 0.231 °C/decade in P2. AER showed a negative and the lowest temperature trend in all the EA countries (Figure 2b and Table 2). Thus, it is determined that AER cools SAT and slows the warming rate. Across EA, the overall AER cooling trend was −0.076 °C/decade during P1 and −0.023 °C/decade in P2. Interestingly, in P2, Mongolia showed a positive/increasing trend in association with the highest degree of warming observed in this region.

Figure 2c shows that the SAT values were less influenced by NAT forcing, and Table 2 shows slightly negative NAT values for P1 in all the EA countries compared to positive trends during P2, except for North Korea. Consequently, SATs in EA remained relatively stable during P1 (−0.003 °C/decade) in P1 and P2 (0.019 °C/decade) in response to NAT forcing. The increasing trends during P2 can be attributed to the third industrial revolution (Tett et al. 2002). GHG forcing produced the strongest warmest trend among all the forcings (Figure 2d) corresponding to 0.082 °C/decade across all of EA during P1 and 0.268 °C/decade during P2. Mongolia, North Korea, and China showed higher warming rates as a result of GHG forcing than in other countries (Table 2). A significant increase in GHG forcing effects can be seen for P2, again indicating the impact of industrialization during this period. The SOL forcing effects (Figure 2e) show mostly stable trends during P1 and slightly negative trends in P2, with values of 0.002 and −0.001 °C/decade for the entire EA region, respectively. The average temperature trends in response to CO₂ and LU forcing are shown in Table 2 for each EA region, both associated with warming trends. Across all of EA, CO₂ increased SATs by 0.045 and 0.145 °C/decade and LU by 0.084 and 0.239 °C/decade during P1 and P2, respectively. These trends further indicate an enhanced warming rate after industrialization (P2).

The multimodal ensemble mean of each forcing was averaged for each EA country as well as for the whole of EA. The annual temperature anomalies for each forcing were calculated relative to the 1850–2019 period; anomalies were also estimated for 1850–2014, which was the period for which ALL forcing simulations were available. Figure 3 shows the temperature anomalies of ALL forcings as well as ground observations, CRU (1901–2018), and HadCRUT4 (1850–2019) for all of EA and each country. Based on these results, the SAT trends associated with ALL forcings were consistent with the observed trends. The SATs in the HadCRUT4 and ALL datasets were mostly stable between 1850 and 1900, after which SAT dropped. This may have been caused by the cooling effect of AER, as discussed in the following text. From 1901 to 1970, the observations (CRU and HadCRUT4) and the ALL data anomalies show slow increasing SAT trends. However, from 1970 to 2014/2019, SAT increased rapidly owing to the third industrial revolution. Across all of EA, SAT had increased by 1.5 °C by 2019, with trends in each country being broadly similar. Specifically, under the ALL forcings, all the East Asian countries experienced smaller increments of change between 1900 and 1969 compared to a higher rate of increase between 1970 and 2014. By 2019, the SATs in China, Japan, and Taiwan had increased by ≥ 1 °C, while in Korea and Mongolia, the increase had reached ≥ 1.5 °C. The SAT anomaly response to GHG forcing is shown in Figure 4 for the period 1850–2019, with observational and simulated SAT datasets showing a similar
increasing trend. A slow increase in GHG forcing is observed until 1969, after which SATs begin to increase very rapidly. Indeed, GHG forcing has been the dominant contributor to the observed SAT warming in each country as well as across the whole of EA. For example, GHG forcing increased SATs by approximately 1.9 °C throughout EA and China by 2019, with even higher degrees of warming (≥ 2 °C) in Mongolia and North Korea. In Taiwan, Japan, and South Korea, the equivalent temperature increase was ≤ 2 °C. Figure 5 shows that in response to CO₂ forcing, SATs have increased, as reflected in the CRU/HadCRUT4 observations. However, the warming attributed to CO₂ is less than that attributed to GHG forcing overall. In response to LU forcing, SAT warming rates closely match the CRU/HadCRUT4 observations (Figure 6). The temperature trend response to AER forcing was negative throughout EA and in each country (Figure 7), indicating that the cooling effect of AER forcing partially counteracts the warming caused by other forcings. AER forcing was initially high during the first few decades of the study period and then decreased. The high/positive AER forcing values present for the 1850–1900 period, while the warming rate (caused by other forcings) is low. On the other hand, weaker/negative AER values present from 1901-2014 contrastingly the warming rate is high. The SAT changes in response to the NAT and SOL forcings are shown in Figures 8 and 9, respectively, which remained broadly stable in all the EA regions indicating minimal forcing effects.

Table 3 shows the correlations between the SAT trends of the observed data (CRU) and the response to different forcings based on the CMIP6 historical models. The SAT response to LU is strongly correlated with the CRU SAT data, and ALL, GHG, and CO₂ also show positive correlations. In contrast, AER is negatively correlated with the CRU data, and NAT and SOL show very weak/no correlation. These correlations clearly demonstrate the direction (i.e., warming or cooling) and relative strength of the contributions of the different forcing factors to SAT changes over the entire study period. Specifically, ALL, GHG, CO₂, and LU forcings are associated with SAT increases; AER forcing produced a cooling effect; and NAT and SOL forcings had very weak or no impact on the warming rate.

3.2 Detection and attribution analysis

We conducted detection and attribution analysis based on the ROF method for the annual mean temperature in EA over the last 110 years (1905–2014). The scaling factors, with 90% confidence intervals, of the one-, two-, and three-signal analyses are presented in Figure 10. One-signal analyses were performed on the individual forcings of ALL, GHG, ANT, AER, and NAT, as shown in Figure 10a. The 90% confidence intervals of ALL, GHG, and ANT are all above zero, indicating that these forcings are robustly detected in EA. Furthermore, the best estimates of ALL, GHG, and ANT are close to unity, indicating good agreement with the observed changes. However, AER and NAT showed 90% confidence intervals below or including zero, indicating that these forcings are not detected in EA. The two-signal analyses were performed on the ANT and NAT forcings, the scaling factors of which are shown in Figure 10b with 90% confidence intervals. ANT is robustly detected in EA, with a 90% confidence interval above zero; the best estimate is close to unity and is also comparable with ANT in the one-signal analysis, implying good agreement with the observed changes. In comparison, the lower bound of the NAT forcing is below zero,
indicating that this forcing is undetected in EA. Therefore, ANT is separated from NAT, signifying that the observed variations are mainly explained by ANT forcing.

We conducted the three-signal analyses using GHG, ANTnoGHG, and NAT to determine the major contributors among the anthropogenic forcings or other factors causing changes in the observations. This analysis also explored the influence of GHG forcing on SAT variations. Figure 10c shows the scaling factors for GHG, ANTnoGHG, and NAT. GHG is robustly detected in EA, with a 90% confidence interval above zero and a best estimate close to unity and comparable to the one-signal analysis, which implies good agreement with the observations. In contrast, the lower bounds of the ANTnoGHG and NAT forcing include zero indicate that these are not detected in EA. Therefore, GHG forcing can be separated from ANTnoGHG and NAT forcing, and is considered the dominant anthropogenic factor forcing for the observed temperature changes in the study region.

3.3 Observation-constrained future projections

The single-signal analysis shown in Figure 10a demonstrates that the best estimate of ALL forcings is 1.16 (above 1), indicating an underestimation of the CMIP6 historical simulations. This historical underestimation could continue in future projections, requiring appropriate adjustment/correction to ensure the accurate estimation of future scenarios. Therefore, the multi-model ensemble mean future projections under the low SSP1–2.6 and SSP2–4.5, and high SSP5–8.5, scenarios were multiplied by the best estimate of the ALL forcing scaling factor obtained in the single-signal analysis. Figure 11a shows the resulting historic (1850–2014) and future scenarios (2015–2100) for EA. These observation-constrained future projections show higher warming rates than the raw simulations. The adjusted/best estimate of the future projections show temperature increases of 2.23 °C (SSP1–206), 2.46 °C (SSP2–4.5), and 3.11 °C (SSP5–8.5) by 2050 compared to 1.92 °C, 2.12 °C, and 2.68 °C based on the unadjusted simulations, respectively; by 2070, the best estimate temperature increases under SSP1–2.6, SSP2–4.5, and SSP5–8.5 are 2.64 °C, 3.07 °C, and 4.59 °C, respectively, compared to 2.28 °C, 2.64 °C, and 3.95 °C based on the original simulations; and by 2100, the best estimates under the same three scenarios are 2.52 °C, 3.66 °C, and 7.19 °C compared to 2.17 °C, 3.15 °C, and 6.19 °C based on the original simulations, respectively. We also estimated the best values for the ALL forcing scaling factors for each EA country and generated projections for each EA country. The best estimates for the ALL forcing scaling factors, with 90% confidence intervals, for each EA country are shown in Table 4. The country-scale future projections under each of the scenarios were adjusted based on their respective ALL forcing best estimates, as shown in Figures 11b–g. The resulting observation-constrained future projections in all the EA countries (except North Korea) show higher warming rates relative to the raw simulation data, and warming is projected to increase over time.

4. Summary And Conclusions

This study describes long-term SAT changes in EA using the new state-of-the-art CMIP6 multi-model simulations. These model simulations were validated in comparison with CRU/HadCRUT4
observational measurements. The SAT variation responses to various external and natural forcings (ALL, AER, NAT, GHG, SOL, CO₂, and LU) were examined between 1850 and 2014/2019. Throughout EA, southeast China has experienced the highest mean temperatures (approximately 25 °C) compared to the lowest on the Tibetan Plateau (approximately −12 °C). SATs during the study period were increased due to GHG, CO₂, and LU forcings and decreased due to the AER forcing. In contrast, NAT and SOL had little impact on SAT changes. GHG forcing was the dominant factor in the observed temperature increase. Overall, the SAT in EA increased by 0.082 °C/decade in response to the GHG forcing, compared to 0.014 °C/decade under ALL forcings from 1850–2014. After the third industrial revolution, SATs increased very rapidly, by 0.268 and 0.255 °C/decade in response to the GHG and ALL forcings, respectively, between 1970 and 2014 (Tett et al. 2002). By 2019, the GHG forcing had increased the SAT across the EA by approximately 1.9 °C, and all countries in EA had also experienced increasing SAT trends as a result of anthropogenic forcings (GHG, CO₂, and LU).

Overall, Mongolia experienced faster rates of temperature rise than other EA countries; however, throughout EA, the highest and lowest amounts of warming occurred in Tibet and southeast China, respectively. The strongest cooling response to AER forcing occurred in southeast China, while across EA, the overall cooling rate associated with AER forcing was approximately −0.076 °C/decade between 1850 and 2014. Interestingly, in Mongolia, AER showed a warming rather than cooling influence during the 1971–2014 period, which might partially explain the high degree of warming in this region. Across EA, CO₂ and LU increased the temperature by 0.045 °C and 0.084 °C, respectively, between 1850 and 2014, while NAT and SOL forcings had a minimal effect overall. Based on these observations, anthropogenic forcing has significantly influenced the climate of EA, associated with distinct warming trends. Furthermore, we present future SAT projections up to 2100 based on the low SSP1–2.5 and SSP2–4.5, and high SSP5–8.5, scenarios.

We applied the ROF detection and attribution technique to CMIP6 simulations to describe climate change in EA resulting from anthropogenic influences. The ALL, GHG, and ANT forcings were robustly detected from the one-signal analyses for the period 1905–2014; in the two-signal analysis, ANT and NAT influences could be separated, and the ANT forcing was clearly detected as a factor including the increase in SATs; and in the three-signal analysis, GHG forcing was separated from ANTnoGHG and NAT forcings and was strongly detected, indicating that GHG forcing was the dominant factor driving climate change in EA. Finally, we generated adjusted/corrected future warming trends by multiplying the raw simulation data with the ALL forcing best estimates, which produced higher projected temperature values under the SSP1–2.5, SSP2–4.5, and SSP5–8.5 scenarios. Overall, we conclude that the climate (SAT) changes observed in EA are the result of anthropogenic forcings, primarily GHG, CO₂, and LU. This implies that efforts to mitigate future climate change in this region should focus on these anthropogenic forcing factors.

Declarations
Acknowledgments

This work was supported by the Korea Institute of Civil Engineering and Building Technology Strategic Research Project (Establishment of 3D Fine Dust Information Based on AI Image Analysis). We acknowledge the World Climate Research Program for making the CMIP6 dataset available for global- and regional-scale climate research. The authors would like to thank the National Climate Center, Research, for providing the CRU dataset.

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Tables

Table 1. Models used in the study for historical and future projections (Y = ‘yes’ and ‘N’ = no). The numbers in parenthesis represent the ensemble sizes of the corresponding models.
| Model name           | Historical forcing (1850–2014) | Future projection (2014–2100) |
|----------------------|--------------------------------|--------------------------------|
|                      | ALL  | AER  | NAT  | GHG  | SOL  | CO₂  | LU  | SSP1-2.6 | SSP2-4.5 | SSP5-8.5 |
| CNRM-CM6-1-HR        | Y (1) | N    | N    | N    | N    | N    | N   | Y (1)    | Y (1)    | Y (1)    |
| CESM2-WACCM          | Y (4) | N    | N    | Y (3) | N    | N    | Y   | Y (1)    | Y (4)    | Y (3)    |
| E3SM-1-0             | Y (5) | N    | N    | N    | N    | N    | N   | N        | N        | N        |
| BCC-CSM2-MR          | Y (3) | Y (3) | Y (3) | Y (3) | N    | N    | N   | N        | N        | N        |
| MRI-ESM2-0           | Y (5) | Y (5) | Y (5) | Y (5) | Y (4) | N    | N   | Y (1)    | Y (5)    | Y (1)    |
| CIESM                | Y (3) | N    | N    | N    | N    | N    | N   | N        | N        | N        |
| CAMS-CSM1-0          | Y (3) | N    | N    | N    | N    | N    | N   | N        | N        | N        |
| INM-CM4-8            | Y (1) | N    | N    | N    | N    | N    | N   | Y (1)    | Y (1)    | Y (1)    |
| FIO-ESM-2-0          | Y (3) | N    | N    | N    | N    | N    | N   | N        | N        | N        |
| CMCC-CM2             | Y (3) | N    | N    | N    | N    | N    | N   | N        | N        | N        |
| HADGEM3-GC31-MM      | Y (6) | N    | N    | N    | N    | N    | N   | Y (1)    | N        | Y (4)    |
| MIROC6               | Y (9) | Y (4) | Y (7) | Y (3) | Y (3) | Y (3) | Y   | Y (9)    | N        | Y (9)    |
| GISS-E2-1-G          | Y (8) | Y (6) | Y (5) | Y (5) | Y (6) | N    | Y   | Y (5)    | Y (6)    | Y (2)    |
| CNRM-CM6-1           | Y (6) | N    | Y (4) | Y (9) | N    | N    | Y   | Y (1)    | Y (4)    | Y (5)    | Y (5)    |
| IPSL-CM6A-LR         | Y (4) | Y (9) | Y (9) | Y (4) | N    | N    | Y   | Y (1)    | Y (3)    | N        | Y (6)    |
| CNRM-ESM2-1          | Y (3) | Y (2) | N    | N    | N    | N    | N   | Y (1)    | Y (4)    | Y (5)    | Y (4)    |
| ACCESS-CM2           | Y (3) | N    | N    | N    | N    | N    | N   | Y (3)    | Y (3)    | Y (3)    |
| ACCESS-ESM1-5        | Y (6) | Y (3) | Y (3) | Y (3) | N    | N    | N   | Y (5)    | Y (6)    | Y (3)    |
| HadGEM3-GC31-LL      | Y (4) | Y (4) | Y (4) | Y (4) | N    | N    | N   | Y (1)    | Y (4)    | Y (4)    |
| UKESM1-0-LL          | Y (6) | N    | N    | N    | N    | N    | N   | Y (4)    | Y (6)    | Y (3)    |
| CanESM5              | Y (5) | Y (9) | Y (5) | Y (6) | Y    | Y    | N   | Y (3)    | Y (5)    | Y (4)    |
|               | (9) | (9) |
|---------------|-----|-----|
| GFDL-ESM4     | N   | Y (1) | Y (3) | Y (1) |
|               | N   | N   | N   | N   |
|               | N   | N   | N   | Y (1) |
| CMCC-ESM2     | N   | N   | N   | N   |
|               | N   | N   | N   | Y (1) |
|               | N   | N   | N   | N   |
| MPI-ESM1-2-LR | N   | N   | N   | N   |
|               | N   | N   | N   | Y (2) |
|               | N   | Y (5) | Y (4) | Y (3) |
| CESM2         | N   | N   | N   | N   |
|               | N   | N   | N   | Y (3) |
|               | N   | Y (3) | Y (3) | Y (3) |
| FGOALS-f3-L   | N   | N   | N   | N   |
|               | N   | N   | N   | Y (1) |
|               | N   | N   | Y (1) | N   |
| NESM3         | N   | N   | N   | N   |
|               | N   | N   | N   | Y (2) |
|               | N   | Y (2) | N   | N   |
| KACE-1-0-G    | N   | N   | N   | N   |
|               | N   | N   | N   | Y (3) |
|               | N   | Y (3) | N   | N   |
| **Total**     | 21  | 10  | 10  | 11  |
|               | 4   | 2   | 8   | 17  |
|               | 17  | 18  | 17  | 17  |
|               | (91)| (46)| (48)| (46)|
|               | (22)| (13)| (54)| (67)|
|               | (59)| (59)| (59)| (59)|

Table 2. Annual mean surface air temperature trend (°C/decade) responses to different forcings in each East Asian country and the entire EA region for the period 1850–2014 (P1) and 1971–2014 (P2, after third industrial revolution, shown in parenthesis). **ALL** = all, **AER** = anthropogenic aerosol, **NAT** = natural, **GHG** = greenhouse gas, **SOL** = solar irradiance, **CO₂** = carbon dioxide, and **LU** = land use forcings.
| 1850–2014 (1971–2014) | East Asia | China | Taiwan | Mongolia | Japan | N. Korea | S. Korea |
|------------------------|-----------|-------|--------|----------|-------|----------|---------|
| ALL                    | 0.0145    | 0.0134| 0.020  | 0.041    | 0.009 | 0.025    | 0.019   |
|                        | (0.255)   | (0.223)| (0.174)| (0.379)  | (0.231)| (0.292)  | (0.242) |
| AER                    | -0.076    | -0.080| -0.067 | -0.081   | -0.067| -0.080   | -0.081  |
|                        | (-0.023)  | (-0.051)| (-0.040)| (0.067) | (-0.027)| (-0.048)| (-0.078) |
| NAT                    | -0.003    | -0.003| -0.001 | -0.002   | -0.002| -0.005   | -0.001  |
|                        | (0.019)   | (0.010)| (0.015)| (0.028)  | (0.018)| (-0.002)| (0.033) |
| GHG                    | 0.082     | 0.083 | 0.0715 | 0.116    | 0.062 | 0.088    | 0.075   |
|                        | (0.268)   | (0.268)| (0.208)| (0.334)  | (0.240)| (0.265)  | (0.257) |
| SOL                    | 0.002     | 0.002 | 0.001  | 0.004    | 0.002 | 0.005    | 0.003   |
|                        | (-0.011)  | (-0.014)| (-0.018)| (-0.021)| (-0.009)| (-0.001)| (-0.001) |
| CO₂                    | 0.045     | 0.045 | 0.041  | 0.049    | 0.037 | 0.051    | 0.044   |
|                        | (0.145)   | (0.126)| (0.112)| (0.200)  | (0.110)| (0.186)  | (0.146) |
| LU                     | 0.084     | 0.069 | 0.085  | 0.079    | 0.077 | 0.100    | 0.092   |
|                        | (0.239)   | (0.235)| (0.237)| (0.327)  | (0.200)| (0.216)  | (0.221) |

Table 3. Correlations between surface air temperature (SAT) in observed data (CRU) and SAT responses to different forcings in CMIP historical models. ALL = all, AER = anthropogenic aerosol, NAT = natural, GHG = greenhouse gas, SOL = solar irradiance, CO₂ = carbon dioxide, and LU = land use forcings.
|          | East Asia (CRU) | China (CRU) | Taiwan (CRU) | Mongolia (CRU) | Japan (CRU) | N. Korea (CRU) | S. Korea (CRU) |
|----------|-----------------|-------------|--------------|----------------|-------------|----------------|----------------|
| ALL      | 0.69            | 0.76        | 0.67         | 0.62           | 0.70        | 0.52           | 0.54           |
| AER      | −0.68           | −0.66       | −0.70        | −0.55          | −0.70       | −0.51          | −0.60          |
| NAT      | 0.03            | 0.05        | 0.07         | −0.03          | 0.01        | 0.01           | 0.11           |
| GHG      | 0.77            | 0.77        | 0.69         | 0.70           | 0.75        | 0.64           | 0.66           |
| SOL      | 0.08            | 0.10        | 0.03         | 0.006          | 0.09        | 0.10           | −0.005         |
| CO₂      | 0.49            | 0.51        | 0.33         | 0.29           | 0.57        | 0.26           | 0.35           |
| LU       | 0.96            | 0.97        | 0.96         | 0.97           | 0.95        | 0.95           | 0.98           |

Table 4. Best-estimate scaling factors and 90% confidence intervals (shown in parenthesis) of ALL (anthropogenic and natural) forcing, estimated from one-signal analysis, in East Asian countries for the period 1905–2014.

| 1905–2014 | East Asia (90%) | China (90%) | Taiwan (90%) | Mongolia (90%) | Japan (90%) | N. Korea (90%) | S. Korea (90%) |
|-----------|-----------------|-------------|--------------|----------------|-------------|----------------|----------------|
| ALL       | 1.16            | 1.11        | 1.34         | 1.22           | 1.19        | 0.9            | 1.26           |
|           | (0.85–1.47)     | (0.85–1.38) | (0.99–1.71)  | (1.01–1.44)    | (0.86–1.51) | (0.50–1.31)    | (0.93–1.59)    |

Figures
Figure 1

Annual mean temperatures from 1901 to 2014. (a) CRU, (b) Multi-model ensemble mean of surface air temperature responses to ALL (anthropogenic and natural) forcing obtained from CMIP6. (c) Bias boxplots between CRU and CMIP6 (CMIP6 − CRU) showing 5%, 25%, mean (diamond), 75%, and 95% values. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.
Figure 2

Spatial distribution of trends in annual mean surface air temperature responses to different forcings (°C/decade) for the historical period 1850–2014. (a) all (ALL), (b) anthropogenic aerosol (AER), (c) natural (NAT), (d) greenhouse gas (GHG), and (e) solar irradiance (SOL) forcings. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.
Figure 3

Temporal variation of annual mean temperature anomaly responses to ALL (all forcings) averaged across East Asia and individual countries from observations (CRU and HadCRUT4) and multi-model mean simulations (CMIP6) for the period 1850–2014 (CRU: 1901–2018, HadCRUT4: 1850–2019). Shaded bands are multi-model ranges. (a) East Asia, (b) China, (c) Taiwan, (d) Mongolia, (e) Japan, (f) North Korea, and (g) South Korea.
Figure 4

As for Figure 3 but showing temperature anomaly responses to GHG forcing.
Figure 5

As for Figure 3 but showing temperature anomaly responses to CO2 forcing.
Figure 6

As for Figure 3 but showing temperature anomaly responses to land use (LU) forcing.
Figure 7

As for Figure 3 but showing temperature anomaly responses to aerosol (AER) forcing.
Figure 8

As for Figure 3 but showing temperature anomaly responses to natural (NAT) forcing.
Figure 9

As for Figure 3 but showing temperature anomaly responses to solar (SOL) forcing.
Figure 10

Best estimates of the scaling factors using the regularized optimal fingerprinting method with 90% confidence intervals over EA for the period 1905–2014. (a) One-signal analysis of all (ALL), greenhouse gas (GHG), anthropogenic aerosols (ANT), aerosols (AER), and natural (NAT) forcings, (b) two-signal analysis of ANT and NAT forcings, (c) three-signal analysis of ANTnoGHG, GHG, and NAT.
Figure 11

Temporal variations in annual SAT anomalies (relative to 1995–2014) during the period 1850–2100. Shaded bands are the multi-model ranges. Future projections are based on the multi-model ensemble means under SSP1–2.6 (gold line), SSP2–4.5 (green line), and SSP5–8.5 (magenta line). The dashed lines indicate best-estimate observation-constrained future temperature projections for (a) East Asia, (b) China, (c) Taiwan, (d) Mongolia, (e) Japan, (f) North Korea, and (g) South Korea.