Indo-Pacific warm pool present warming attribution and future projection constraint

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Abstract
The Indo-Pacific warm pool (IPWP) has warmed and expanded substantially over the past decades, which has significantly affected the hydrological cycle and global climate system. It is unclear how the IPWP will change in the future under anthropogenic (ANT) forcing. Here, we quantify the human contribution to the observed IPWP warming/expansion and adjust the projected IPWP changes using an optimal fingerprinting method based on Coupled Model Intercomparison Project phase 6 (CMIP6) simulations. We find that more than 95% rapid warming and 85% expansion of the observed IPWP are detected and attributable to human influence. Furthermore, human activities affect IPWP warming through both greenhouse gases and ANT aerosols. The multiple model ensemble mean can capture the ANT warming trend and tends to underestimate the ANT warming trend. After using the observation constraint, the IPWP warming is projected to increase faster than that of the ensemble mean in the 21st Century, and the Indian Ocean warm pool is projected to expand more than previously expected. The rapid warming and expansion of IPWP over the rest of the 21st century will impact the climate system and the life of human beings.

1. Introduction
The Indo-Pacific warm pool (IPWP) is the largest tropical warm water mass in the world (de Deckker 2016). The IPWP is often defined as the region where sea surface temperatures (SSTs) are warmer than 28 °C (Wyrtki 1989, Picaut et al 1996, Clement et al 2005, Kim et al 2012), which is the threshold temperature for atmospheric deep convection (Fu et al 1994). The IPWP plays a vital role in supplying heat and water vapor flux through deep convection (Visser et al 2003, Duan et al 2008). Since saturation vapor pressure is an exponential function of SST (Graham and Barnett 1987, Fu et al 1994), the intensity of deep convection is very sensitive to IPWP SST changes. Small changes in the IPWP SST can exert a significant influence on regional to global climates by modulating Hadley–Walker circulations (Lindzen and Nigam 1987, Numaguti 1995, Feng et al 2018) and the El Niño-Southern Oscillation (Brijker et al 2007, Marathe et al 2021). The global mean SST has increased by 0.88 °C (0.68 °C–1.01 °C) since the early 20th century, and SSTs will likely continue to increase in nearly the entire ocean except the North Atlantic (IPCC 2021). The Indo-Pacific Ocean is undergoing rapid climate change under global warming. For example, warming in the tropical Indian Ocean is twice to three times as fast as that in the tropical Pacific (Luo et al 2012, Rao et al 2012). During recent decades, the warm pool has been significantly warmed and expanded (Cravatte et al 2009, Williams and Funk 2011,
The area of the IPWP was twofold larger in 1981–2018 than in 1900–1980, with the largest warming occurring in the western Pacific (Roxy et al 2019). The observed IPWP warming and expansion are attributed to either internal climate variability (Lin et al 2013) or external forcings, such as the greenhouse gas (GHG) forcing (Weller et al 2016, Watanabe et al 2021). Recent studies suggest that a human-induced greenhouse forcing since the 1950s accounts for the warming and expansion of the warm pool (Rao et al 2012, Dong and Zhou 2014, Weller et al 2016, Hayashi et al 2021) while internal variability, such as the Pacific decadal oscillation, plays a smaller but significant role (Weller et al 2016).

Although GHG-induced warming and expansion have been the primary causes of IPWP changes since the 1950s (Weller et al 2016), the extent to which historical anthropogenic (ANT) effects increase warming and expansion, and how the IPWP will change in the future under ANT forcing, remain unclear. In this study, we sought to quantitatively assess the contributions of different external forcings to the observed warming and expansion trends on the IPWP, with a focus on two questions: (a) whether and to what extent the observed IPWP warming and expansion can be attributable to human activities, and (b) how the IPWP is projected to change in the future based on the optimal constraint. We used an optimal fingerprinting method similar to that in the study by Weller et al (2016) but with newly released simulations from the Coupled Model Intercomparison Project phase 6 (CMIP6). In addition, we evaluated the contributions of two competing forcings, GHGs and anthropogenic aerosols (AAs), quantified the human contribution to the IPWP warming and expansion, and conducted corrected projections of the warm pool intensity and extension for the 21st century, which is quite different from Weller et al (2016).

2. Data and methods

2.1. Observational SST datasets

We use three monthly mean SST datasets, including the Hadley Centre Sea Ice and SST (HadISST, Rayner et al 2003) v1.1 dataset, Extended Reconstruction SST v3 (ERSST, Smith et al 2008), and Centennial In Situ Observation Based Estimates SST v2 (COBE SST, Hirahara et al 2014). To reduce uncertainties, we use the average of HadISST, ERSST, and COBE SSTs as the best observational SST estimate (referred to as “observation”).

2.2. CMIP6 models and simulations

Outputs from a total of 607 simulations are used in this study, including 336 historical (referred to as the ALL forcing) from 30 models of the CMIP6 (Eyring et al 2016), 90 GHGs only, 81 AA only, and 100 natural only (NAT only) experiments from 11 models of the detection and attribution model intercomparison project (Gillett et al 2016). We estimate the ANT forcing as the difference between ALL and NAT under the assumption of linear additives from available simulations. A total of 20 160 years of preindustrial control (CTL) simulations from all available models are used to estimate internal variability (table S1 available online at stacks.iop.org/ERL/17/054026/mmedia). Furthermore, SST projections in the 21st Century under the shared socioeconomic pathway SSP2-4.5 and SSP5-8.5 scenarios from 24 CMIP6 models are used to derive observationally constrained projections (table S1). In addition, we use CMIP5 models (Taylor et al 2012) to discuss the differences between the CMIP5 (table S2) and CMIP6 simulations.

The observational and historical simulations include the monthly means from 1953 to 2012. All data are first regridded to a standard resolution of 1° by 1° through bilinear interpolation. In the detection and attribution analyses, ensemble means are first calculated for individual models. Then, the multimodel means are acquired by taking the arithmetic averages of the ensemble means, giving equal weight to each model when calculating the ensemble mean.

2.3. Metrics for the warm pool properties

The IPWP is defined as the oceanic region between 30° S–30° N and 40° E–135° W with an SST of no less than 28 °C, and the IPWP is divided into Indian and Pacific parts by the 120° E meridian. The warm pool intensity is defined by the averaged SST value in the region within the SST 28 °C isotherms. The warm pool area is defined by the area size enclosed by the 28 °C isotherm. The mean seasonal cycle of intensity and area calculated for 1953–2012 is removed to calculate monthly intensity and area anomalies. Annual mean anomalies are constructed from monthly anomalies for analysis and comparison with model simulations.

2.4. Detection method

We employ the optimal fingerprinting method based on generalized linear regression (Allen and Tett 1999, Allen and Stott 2003, Ribes et al 2013, Ribes and Terray 2013) to conduct the detection and attribution analysis. Total least squares regression is used in this study, which can be expressed as $Y = (X - \nu) \beta + \mu$. Here, vector $Y$ represents the observed variations, matrix $X$ denotes the multimodel ensemble mean response to external forcings, $\beta$ is the scaling factor that can adjust the signal magnitude to optimally match the observation, $\nu$ indicates the sampling noise resulting from a finite model ensemble, and $\mu$ shows the internal variability in the climate system that the
external forcing cannot explain. Here, the matrix $X$ would be one vector for the single-signal analysis (e.g. ALL), two vectors for the two-signal analysis (e.g. ANT and NAT), and three vectors for the three-signal analysis (e.g. GHG, AA, and NAT); hence, the number of elements for scaling factor $\beta$ would be 1, 2, and 3, respectively. The CTL simulations from CMIP6 models are employed to extract the internal variability (noise covariance). We divide 60 years chunks of CTL simulations into two sets (168 chunks each) for the optimal fingerprinting method. One set is for optimization, and the other is for testing. To improve the signal-to-noise ratio, we use the 5 years nonoverlapping means for intensity and area anomalies. We test the consistency between the model-simulated noise estimates $\sigma$ and regression residual $\mu$ using the standard residual consistency test (Allen and Tett 1999) to confirm the reliability of the attribution results. In addition, we conducted analyses with doubled noise estimates (Zhou and Zhang 2021).

First, we perform a single-signal analysis, with the observed intensity and area anomalies regressed onto the model-simulated anomaly response to the ALL, ANT, GHG, AA, and NAT forcings. A scaling factor $\beta$ and a confidence interval significantly larger than zero indicate that the corresponding influence of external forcing can be detected. A scaling factor $\beta$ equal to unity suggests that the model response can capture the observed change well. If the best estimate of $\beta$ is above (below) unity, then the models underestimate (overestimate) the forced signal in observations. Then, we conduct a two-signal analysis, with the observed intensity and area anomalies simultaneously regressed onto model-simulated responses to ANT-NAT (or GHG-AA) to examine whether ANT-NAT (or GHG-AA) can be jointly detected and whether the influence of ANT (GHG) can be separated from that of NAT (AA). If the origin $(0, 0)$ is outside the 95% joint confidence regions for ANT-NAT (or GHG-AA), then the combined influence of ANT-NAT (or GHG-AA) can be detected. Specifically, if ANT (GHG) scaling factors are larger than zero and NAT (AA) scaling factors include zero, the ANT (GHG) influence can be detected and separated from the NAT (AA) influence. Finally, we perform a three-signal analysis using GHG, AA, and NAT signals to estimate the relative contributions of the individual external forcings.

To account for the models’ uncertainties in the responses to ANT forcings, we use the attribution result to constrain the future projections of ANT warming. Observation-constrained future projections are imposed by multiplying the multimodel ensemble mean projections under the SSP2-4.5 and SSP5-8.5 scenarios with the scaling factor of the ANT forcing from the two-signal analyses, as in previous studies (Sun et al 2014, Zhou and Zhang 2021).

3. Results

3.1. Indo-Pacific warm pool (IPWP) trends

The warming of the Indo-Pacific exhibits distinct spatial differences in observations (figure 1(a)). In particular, the tropical Indian Ocean has warmed faster than the tropical Pacific Ocean (Du and Xie 2008, Rao et al 2012, Weller et al 2016). The warming trend in SST in the tropical Indian Ocean is not uniform throughout the basin, and the maxima are located south of the equator (Rao et al 2012). The warming centers of the tropical Pacific Ocean are located in the western Pacific and south of the equator (Cravatte et al 2009). The ALL forcing simulations reproduce the observation well (figure 1(b)), although with greater warming in the central to eastern tropical Pacific, a region affected by the equatorial Pacific cold tongue bias (Li and Xie 2014). The ALL forcing simulation presents a meridionally narrower and zonally elongated IPWP compared with the observation. The ALL forcing warming is mainly dominated by the ANT forcing (figure 1(c)). The contribution from the NAT forcing is negligible (figure 1(f)). In particular, the warming pattern in the ANT forcing simulation is due to the GHG forcing (figure 1(d)), with a more robust warming pattern. The AA forcing simulation has a negative effect on the ANT warming (figure 1(e)). It is noteworthy that the same results are obtained when using CMIP5 models, but the warm pool area in the present-day climate is better represented in CMIP5 than CMIP6 due to overestimation of the climate mean IPWP area in the off-equatorial Pacific and the tropical in CMIP6 (figures 1 and S1).

We calculate the annual means for intensity and area anomalies, defined in section 2.3, to examine long-term IPWP changes. The IPWP has warmed and expanded steadily in both observations and historical simulations (figure S2). In the observations, the IPWP exhibited evident warming and expansion trends of 0.38 °C/60a and 30.3%/60a, respectively, over 1953–2012 at the 95% confidence level (figure 2 and table 1). The observed overall warming and expansion trends are reproduced well in ALL, with significant warming and expansion trends of 0.33 °C/60a and 25.5%/60a, respectively. However, the NAT simulations show no significant long-term trends and fail to reproduce the observed warming and expansion trends. This finding suggests that the ANT forcings dominate the warming and expansion trends in the ALL simulations. The warming trend in the ANT forcing simulation is mainly from the GHG forcing and partly offset by the AA forcing. In contrast, the expansion trends in the ANT and GHG forcings are comparable. The observed warming and expansion trends exceed the internal variability in the CTL simulations. The results show no significant intensity differences in the Indo-Pacific, Indian, and...
Pacific warm pools, while the expansion in the Indian warm pool is underestimated. The Indian warm pool expands at a rate of up to three times larger than the Pacific warm pool in the observation; trends are comparable in response to external forcings (figure 2 and table 1).

The above results are consistent with Weller et al. (2016) regarding the long-term intensity and area changes in the IPWP obtained from the CMIP5 models. Although their definition of the IPWP, the baseline for calculating anomalies, and model members are different from what we used here, we find that biases in the IPWP warming and expansion trends are all better in the CMIP6 than CMIP5 models compared with the same observation from HadISST (figure S3). For example, the biases in the IPWP warming trends simulated by the ALL forcings are 0.05 °C/60a and 0.01 °C/60a in CMIP5 and CMIP6, respectively, which show significant improvement in CMIP6 relative to CMIP5. In general, CMIP6 results are closer to observations than CMIP5, but it is worth noting that the simulation ability of CMIP5 for the Indian Ocean warm pool area is much better than that of CMIP6 (figure S4).

3.2. Detection of human influence

We use an optimal fingerprinting method (Allen and Tett 1999, Allen and Stott 2003) to detect and quantify the relative contributions from individual external forcings to long-term IPWP intensity and area changes (figure 3). Single-signal analyses show that external ANT responses combined with NAT or ANT forcings, or the GHG forcing alone, can be detected. In most cases, the models’ ALL and ANT responses can capture the observed warming and expanding magnitude well. The models somewhat underestimate the ALL and ANT responses for the Indian warm pool. For the Pacific warm pool, the
models overestimate the ALL and ANT responses. Except for the Indian warm pool area, the models somewhat overestimate the GHG response. The influences of AA and NAT could not be detected in any analyses. Most single-signal analyses pass the residual consistency test, indicating that the regression observational residual $\mu$ is consistent with the model-simulated internal variability $\nu$. The results show no significant difference when the modeled internal variability is doubled. Our single-signal results are consistent with Weller et al (2016), and the CMIP6 multimodel mean tends to overestimate the ALL responses of warm pool intensities for the IPWP and Pacific warm pool. Further, except for the Indian Ocean warm pool area, the scaling factors for ALL and ANT for CMIP6 are closer to 1 compared to that in CMIP5, indicating that the models’ ALL and ANT responses can better capture the observed warming and expanding magnitude in CMIP6 (figure S5).

In the two-signal analyses, the combined influence of ANT-NAT can be detected. Specifically, the ANT influence can be detected and separated from the NAT influence. The combined effect of GHG-AA can be detected except in the Pacific warm pool area. Only the GHG influence in intensity cases can be detected and separated from the AA influence.
Additionally, the scaling factors for GHG and AA are correlated due to the strongly tilted joint confidence ellipses for GHG-AA. Negative contributions from AA could offset the IPWP warming caused by GHGs. The three-signal analyses further confirmed the attribution to the GHG forcing with clear separations from AA and NAT in the intensity cases (figure S6). The two-signal results of ANT-NAT are consistent with Weller et al (2016), but we further evaluated the competing effects of GHG and AA.

According to the preceding analysis, the warming and expansion trends attributable to different individual external forcings are estimated by multiplying the multimodel mean trends in different forcings with scaling factors of the single-signal and two-signal ALL forcing. Among them, GHG-attributable and AA-attributable expansion trends are not shown here because the GHG and AA influences in area cases are not robustly detected in two-signal and three-signal analyses. For 1953–2012, of the observed 0.38 °C warming and 30.3% expansion, 0.32 °C warming and 22.4% expansion can be attributed to the ALL forcing. According to the best estimate, ANT-attributable trends are the closest to the observed IPWP changes compared with other external forcings, with approximately 0.37 °C warming and 26.7% expansion from 1953 to 2012. The contribution of the human influence is estimated by the relative percentage of the ANT-related warming/expansion trend to the observed warming expansion.
Figure 4. Annual mean intensity (a) and area (b) anomalies (relative to 1981–2010 climatology) over the Indo-Pacific (top), Indian (center), and Pacific (bottom) warm pools from 1953–2099 in the CMIP6 multimodel historical simulations (black lines) and future projections under SSP2-4.5 (purple and blue lines) and SSP5-8.5 (yellow and red lines). The purple and yellow lines and the corresponding shadings indicate the multimodel means and the 5%–95% model intervals derived from the raw projections. The blue and red lines denote the constrained projections by multiplying the ensemble mean projections with the best estimated scaling factors of two-signal ANT forcing. The blue and red shadings indicate the 5%–95% uncertainties of constrained projections estimated based on the uncertainties in scaling factors from the ANT forcing. The intensity and area anomalies are applied with a 5-year smooth-running model. Warming and expansion by the end of the 21st century (2080–2099) from multimodel means and a 5%–95% range for raw (purple and yellow dots with solid bars) and constrained projections (blue and red dots with solid bars) are displayed on the right.

3.3. Implications for future projections

The best estimates of the scaling factors for the ANT forcings are slightly greater than those in the single-signal case (also in the two-signal analyses except for the Pacific warm pool area), indicating that the model-simulated responses to the ANT forcings tend to underestimate the observed IPWP changes. This finding implies that the multimodel ensemble means of CMIP6 may underestimate the future ANT warming and expansion of the IPWP. To correct the bias, we use the attribution results as a constraint on future projections by multiplying the multimodel ensemble mean projection under the SSP2-4.5 and SSP5-8.5 emission scenarios with the best estimate of the scaling factors for the ANT forcing from the two-signal analyses. Note that this constraint assumes that the scaling factors based on historical observations and historical ANT forcings remain appropriate for the future. However, AAs are expected to become less critical in the future (Sun et al., 2014, Zhou and Zhang, 2021). The best estimates of the observation-constrained projections are more robust than those projected by the raw simulations except for the Pacific warm pool area (figure 4). The Indian warm pool would warm and expand by 2.48 °C (1.35 °C) and 142.0% (89.8%) at the end of the 21st century (2080–2099) by the best constraint estimate under the SSP5-8.5 (SSP2-4.5) scenario, which was 2.23 °C (1.22 °C) and 77.1% (48.7%) in the raw simulations (table 2). This result indicates that the tropical Indian Ocean would be filled with a warm water mass with an SST higher than 28 °C at the end of the 21st century under the SSP5-8.5 scenario. The Pacific warm pool would expand by 45.6% (29.7%) at the end of the 21st century by the best constraint estimate, which is 26.1% (17.0%) less expansion than the raw projections. The IPWP shows slight differences under the best constraint estimate as the range of uncertainties shrinks.
Table 2. Comparison of warm pool intensity and area anomaly changes between raw projections and observation-constrained projections (in square brackets) from different reference periods under the SSP2-45 and SSP5-85 scenarios.

| CMIP6               | Intensity (°C) | Area (%) |
|---------------------|----------------|----------|
|                     | Indo-Pacific | Indian   | Pacific |
| SSP245              |               |          |         |
| Middle of the 21st century (2040–2059) | 0.80 (0.81) | 0.80 (0.89) | 0.79 (0.80) |
| End of the 21st century (2080–2099) | 1.19 (1.20) | 1.22 (1.35) | 1.17 (1.19) |
| 1.5 °C threshold (2030–2052) (IPCC 2018) | 0.69 (0.70) | 0.69 (0.76) | 0.68 (0.69) |
| SSP585              |               |          |         |
| Middle of the 21st century (2040–2059) | 1.00 (1.01) | 1.02 (1.13) | 0.99 (1.01) |
| End of the 21st century (2080–2099) | 2.18 (2.20) | 2.23 (2.48) | 2.14 (2.18) |
| 1.5 °C threshold (2030–2052) (IPCC 2018) | 0.81 (0.82) | 0.82 (0.90) | 0.80 (0.81) |

4. Conclusions

The IPWP has been experiencing warming and expansion since the 1950s. Understanding why the IPWP changes and projecting the likelihood of future changes is of vital importance. This study conducted detection and attribution analyses of intensity and area changes from 1953 to 2012 over the IPWP using an optimal fingerprinting method, which compares observations with state-of-art climate coupled model simulations. We find that external forcings have played a substantial role in driving the observed warming and expansion trends over the IPWP. Specifically, more than 95% of the observed rapid warming and 85% expansion of the IPWP are detected and attributed to human influence by an optimal fingerprinting method. The effect of human influence on the IPWP intensity is dominated by GHG and slightly offset by AAs. NAT forcings are relatively small compared with external forcings. The influence of the ANT forcings on the observed warming and expansion can be detected in all seasons (not shown). However, the seasonal difference is underestimated in the models. Specifically, models tend to underestimate the warming trend in summer and the expanding trend in winter over the Indian Ocean warm pool, which is different from the annual mean results. However, the reasons for these differences are still unknown.

We quantify the human influence on the observed IPWP warming and expansion to understand the causes of the past changes and future projections. We show that the constrained projections suggest a faster warming rate for warm pool intensities and a larger expansion rate for the Indian warm pool area than the multimodel ensemble mean. The difference between the constrained and raw multimodel projections for the Indian warm pool is larger than those for the IPWP and Pacific warm pool. The constrained projections suggest a 2.48 °C (1.35 °C) and 142.0% (89.8%) warming and expansion of the Indian warm pool, respectively, under the SSP5-8.5 (SSP2-4.5) scenario at the end of the 21st century (2080–2099) based on observation datasets, which is 0.24 °C (0.13 °C) and 64.9% (41.1%) larger than the raw projections, respectively. In addition, according to the IPCC Special Report on Global Warming of 1.5 °C (IPCC 2018), global warming is likely to reach 1.5 °C between 2030 and 2052 at the current rate. At that time, the Indian warm pool would warm and expand by 0.90 °C (0.76 °C) and 56.6% (46.2%), respectively, under the SSP5-8.5 (SSP2-4.5) scenario by the best constraint estimate.

Rapid warming and expansion of warm pool over the rest of the 21st century imply profound influences on regional to global climate change (Cane and Clement 1999, Feng et al 2018, Wang et al 2019). For instance, the changes in IPWP have implications for tropical cyclones (Wu et al 2022), the marine heat waves (Zhang et al 2021), the Hadley and Walker circulations (Kim et al 2020), and rainfall (Wang and Mehta 2008, Williams and Funk 2011, Weller et al 2016). As the constrained IPWP warming and Indian Ocean warm pool expansion are projected to increase faster than those of the ensemble mean in the 21st century, local positive SST anomalies tend to add a positive frequency of TC occurrences (Murakami et al 2012) to marine heat waves (IPCC 2021), and strengthen the upward branch of Hadley and Walker circulation (Kim et al 2020). Besides, rapid warming and expansion of the Indian Ocean makes the Indian summer monsoon stronger than normal (Kim et al 2012), and tends to increase rainfall over the western Indian Ocean (Weller et al 2016).
Data availability statements

The HadISST dataset is available from [www.metoffice.gov.uk/hadobs/](http://www.metoffice.gov.uk/hadobs/). The COBESSST and ERSSTv5 datasets can be accessed at [www.esrl.noaa.gov/psd/data/gridded/](http://www.esrl.noaa.gov/psd/data/gridded/).

The CMIP5/CMIP6 model data that support the findings of this study are openly available at the following URL/DOI: [https://esgf-node.llnl.gov/projects/esgf-llnl/](https://esgf-node.llnl.gov/projects/esgf-llnl/).

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