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# Unrealistic increases in wind speed explain reduced eastern Pacific heat flux in reanalyses

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## ABSTRACT

Tropical eastern Pacific sea surface temperature plays a pivotal role in mechanisms that determine global mean surface temperature variability. In this study, the surface flux contribution to recent cooling of the tropical eastern Pacific is investigated using data from three atmospheric reanalyses with full assimilation of observations, an observations-based net surface energy flux reconstruction and fifteen atmospheric-only climate model simulations. For the ERA-Interim reanalysis, 78% of the decrease in net surface flux ( $-0.65 \text{ Wm}^{-2}\text{yr}^{-1}$  over 1988-2008) is explained by the latent heat flux variability. Latent heat flux variability differs between datasets and this is investigated using a bulk formula. We find that discrepancies in wind speed change explain contrasting latent heat flux trends across datasets. The significant increase of  $0.26 \text{ ms}^{-1}\text{decade}^{-1}$  in wind speed over the tropical eastern Pacific in the ERA-Interim reanalysis is not reproduced by satellite or buoy observations and atmospheric-only climate model simulations, casting questions on the reliability of reanalysis-based surface fluxes over the tropical eastern Pacific.

### Key points:

- 1) Latent heat flux explains decreasing surface heat flux trend over tropical eastern Pacific area.
- 2) Near surface wind speed change is the main driver of the latent heat flux variability.
- 3) Changes in heat flux over the tropical eastern Pacific depicted by reanalyses estimates are unrealistic

Key words: Global warming slowdown, tropical eastern Pacific cooling, Surface flux contribution, Reliability

## 1. Introduction

Cooling over the Tropical Eastern Pacific (*TEP*) has been identified as an important factor in explaining the mechanisms leading to suppressed global warming at the beginning of the 21<sup>st</sup> century [Easterling and Werner, 2009; Knight *et al.*, 2009; Trenberth and Fasullo, 2013; Huber and Knutti, 2014; Watanabe *et al.*, 2014; Kosaka and Xie, 2013; Meehl *et al.*, 2014; England *et al.*, 2015]. Using both NOAA (National Oceanic and Atmospheric Administration) 20<sup>th</sup> century [Compo *et al.*, 2011] and ECMWF (European Centre for Medium-Range Weather Forecasts) Interim Reanalysis (ERA-Interim) [Dee *et al.*, 2011] atmospheric reanalysis data, as well as model simulations, England *et al.* [2014] found that the cooling is due to the observed pronounced strengthening in Pacific trade winds which enhance the ocean heat uptake and the upwelling of the subsurface cold water over the *TEP* area. Zhou *et al.* [2016] found that the sea surface temperature (*SST*) pattern-induced low cloud increase [Norris and Evan, 2015] over the *TEP* region can enhance the shortwave reflection and modify the Earth's energy budget. This has been linked to changes in atmospheric stability and can explain increases in climate sensitivity relating to the evolution of *SST* patterns in response to radiative forcing [Ceppi and Gregory, 2017; Andrews and Webb, 2017]. The cloud feedback on *SST* changes over the decadal time scale can amplify cooling in *TEP* region where air descends. Brown *et al.* [2014] also showed that cooling may be enhanced in both duration and magnitude by increasing the shortwave reflection (*RSW*) over *TEP* region, where the reduced outgoing longwave radiation (*OLR*) cannot fully compensate the shortwave reflection, due to the relatively cool marine stratiform clouds present [Klein and Hartmann, 1993], reducing the net downward surface energy flux ( $F_s$ ) and cooling the surface.

On one hand, the cooling *TEP* will suppress the longwave radiation and the turbulent energy transfer from ocean to the atmosphere, so the net downward energy flux will be increased over this region, as depicted by the AMIP (Atmospheric Model Intercomparison Project) model simulations

[Liu *et al.*, 2015]. On the other hand, increased winds [England *et al.*, 2014] will cause more evaporation, so more latent heat may be lost to the atmosphere and decrease the net downward energy flux. In order to further understand the mechanisms and driving factors of the *TEP* cooling, different surface flux data from atmospheric reanalyses, observational reconstructions [Liu *et al.*, 2017] and AMIP5 simulations are used to study the surface energy flux contributions to the *TEP* cooling in this study. Considering the imperfect temporal homogeneities in parameterized reanalysis fluxes [Berrisford *et al.* 2011; Balmaseda *et al.* 2013; von Schuckmann *et al.*, 2016], the detailed analysis of the reasons causing the spurious changes is conducted in this study using a bulk formula, so as to investigate the role of meteorological variables in determining latent heat flux changes.

75

## 2. Data and method

The three atmospheric reanalyses used in this study are ECMWF ERA-Interim reanalysis [Dee *et al.*, 2011; Berrisford *et al.*, 2011] (hereinafter referred to as ERAINT). JRA55 (the Japanese 55-year Reanalysis, [Kobayashi *et al.* 2015]) and MERRA2 (Modern Era-Retrospective Analysis for Research and Applications, [Gelaro *et al.*, 2017]). Surface fluxes, including the surface shortwave (*SW*) and longwave (*LW*) radiation fluxes, the latent heat (*LH*) and sensible heat (*SH*) turbulent fluxes, forecasted directly by the reanalyses, are used. The monthly fluxes available for this study are averaged from the forecast every 12 hours for ERAINT, every 6 hours for JRA55 and every hour for MERRA2. A four-dimensional variational analysis is used in ERA-Interim and JRA55 reanalyses, and a three-dimensional variational data assimilation in MERRA2, where data from the full observing system are assimilated. The derived net surface heat fluxes based on the atmospheric energy tendencies and transports of ERAINT and TOA (top of atmosphere) satellite radiation budget data [Allan *et al.*, 2014; Liu *et al.*, 2015, 2017] are also exploited based on results from the DEEPC (Diagnosing Earth's Energy Pathways in the Climate system) project. DEEPC takes advantages of the assimilation of full observations in ERA-Interim and the observed energy budget of the Earth

91 system [Liu *et al.*, 2015], the atmospheric energy transports are mass corrected [Trenberth *et al.*  
 92 1995; Chiodo and Haimberger, 2010; Mayer and Haimberger, 2012] and the land surface fluxes are  
 93 adjusted based on the energy budget conservation [Liu *et al.*, 2017] and has applications in a number  
 94 of previous studies [Williams *et al.*, 2015; Valdivieso *et al.*, 2015; Senior *et al.*, 2016; Roberts *et al.*,  
 95 2017]. The CERES (Clouds and the Earth's Radiant Energy System [Loeb *et al.*, 2012]) surface  
 96 radiation fluxes are used to infer the surface turbulent fluxes from DEEPC net surface flux.

97

98 The bulk formula used to calculate the latent heat fluxes at surface is from Singh *et al.* [2005],

$$99 \quad LH = \rho L C_E U (Q_s - Q_a) \quad (1)$$

100 where  $\rho$  is the air density,  $L$  is the latent heat of evaporation,  $C_E$  is bulk transfer coefficient for water  
 101 vapor (also called the Dalton number) and can be estimated using near surface wind speed (Bentamy  
 102 *et al.* 2003),  $U$  is the wind speed at a height of typically 10 m,  $Q_s$  is the saturation specific humidity  
 103 at the surface and can be estimated using *SST* and sea level pressure, and  $Q_a$  is the near-surface  
 104 specific humidity at the atmospheric measurement level and can be empirically estimated from *SST*  
 105 and the total column water vapor content (please see Singh *et al.* [2005] for the detailed  
 106 descriptions). The  $LH$  estimation is specially designed to use satellite observations. The four input  
 107 fields are the total column water vapour content ( $WV$ ), near surface wind speed, *SST* and mean sea  
 108 level pressure (*MSLP*), which are all available as analysis time variables from the reanalyses.  
 109 Considering the good temporal homogeneity of the SSM/I data (Fig. S1), the observed  $WV$  and  $U$   
 110 from SSM/I are employed and the time series is constructed using F08, F11 and F13 datasets. The  
 111 wind speed has a general increasing trend before 2009, but decreases after 2012 (Fig. S1a). The data  
 112 from 15 AMIP5 model simulations are also used, with prescribed observed *SST* and sea ice and  
 113 realistic radiation forcings [Taylor *et al.*, 2012]. The wind speed data from TAO (Tropical  
 114 Atmosphere Ocean) moored buoy array [TAO Project Office, 2000] are also used for comparison. All  
 115 datasets are listed in Table 1 with some brief descriptions.

### 3. Results

#### 3.1 Trends in surface heat flux

The net surface heat flux trends from ERAINT, DEEPC and AMIP5 ensemble mean over 1988-2008 are shown in Fig. 1, together with the ERAINT *SST* trend. The corresponding area mean anomaly time series over *TEP* are also plotted on the right column. The trends of ERAINT *SST* ( $-0.06 \text{ K decade}^{-1}$ ) and net surface flux from DEEPC ( $-0.32 \text{ Wm}^{-2}\text{yr}^{-1}$ ) and ERAINT ( $-0.65 \text{ Wm}^{-2}\text{yr}^{-1}$ ) show a consistent negative trend over *TEP* (Figs. 1a-c). The DEEPC  $F_s$  is based on a combination of satellite data and ERAINT atmospheric energy transports but does not use the simulated surface fluxes. While both datasets display a negative trend in downward net heat flux over *TEP*, the DEEPC trend is smaller in magnitude than that of ERAINT (Figs. 1f and g). The strong negative trend can also be seen from JRA55 data (Fig. S2a), but is weak in MERRA2 data (Fig. S2b) and not present in AMIP5 ensemble mean simulations (Fig. 1d). Both trends from ERAINT and JRA55 (Fig. 1c and Fig. S2a) show similar spatial patterns, with negative trends over central Indian Ocean, western and eastern Pacific, but positive trends in northeastern Pacific. A contrasting pattern is produced by MERRA2: the trend over northeastern Pacific is negative but positive over most of the *TEP* area. Trend patterns in *SST* (Fig. 1a) and AMIP5 ensemble mean simulated  $F_s$  (Fig. 1d) are anti-correlated, indicating that reducing *SST* leads to reduced heat loss to the atmosphere so more surface flux into the ocean (increased  $F_s$ ). While in contrast this is not seen in DEEPC (Fig. 1b) and ERAINT (Fig. 1c). Although the input data used to generate the DEEPC product are not fully coupled, it is considered the best representation of the coupled system available to us. The errors can be introduced from incomplete coverage, biases and model inadequacies during observational input to ERAINT, but it is representative of the coupled system, in which heat fluxes can drive changes in *SST* (e.g. reduced  $F_s$  can cool the ocean and reduce *SST*).

141 The deseasonalized anomaly time series of  $F_s$  and its four components ( $SW$ ,  $LW$ ,  $SH$  and  $LH$ ) over  
 142  $TEP$  are plotted in Figs. 1g-h and Figs. S2c-d; the reference period for the anomaly calculation is  
 143 from 2001-2008. It is clear that the  $LH$  variation dominates the  $F_s$  variability in three atmospheric  
 144 reanalyses and the AMIP5 ensemble mean. The  $LH$  trend follows the corresponding  $F_s$  trend and the  
 145 correlation coefficients ( $r$ ) between  $LH$  and  $F_s$  over 1988-2008 are 0.97, 0.94, 0.90 and 0.96, the  $LH$   
 146 trend magnitudes are 78%, 98%, 169% and 44% of the  $F_s$  trends for ERAINT, JRA55, MERRA2 and  
 147 the AMIP5 ensemble mean, respectively. The turbulent fluxes ( $SH$  and  $LH$ ) are also derived from  
 148 the difference of the DEEPC net surface energy fluxes and the CERES surface radiation fluxes and  
 149 the anomaly time series is plotted in Fig. 1f. The corresponding correlation coefficient between  
 150 turbulent flux and  $F_s$  over 2002-2015 is 0.98. It is apparent that  $SW$  and  $F_s$  variability are also well  
 151 correlated ( $r = 0.69, 0.72, 0.73$  and  $0.56$  for ERAINT, JRA55, MERRA2 and AMIP5 ensemble  
 152 mean, respectively), but the  $SW$  trend is generally smaller than the  $F_s$  trend. The corresponding  $SW$   
 153 trend contribution to the  $F_s$  trend is 22% for ERAINT and 11% for JRA55, and the contribution of  
 154 31% in AMIP5 ensemble mean is relatively strong. The  $SW$  trend in MERRA2 is in opposite sign  
 155 with  $F_s$  trend. All these correlation coefficients are significant based on the two-tailed test using  
 156 Pearson critical values at the level of 5% and the trends (except for the  $LH$  trend of AMIP5) are also  
 157 significant using Mann-Kendall test at a significance level of 0.05 [Hipel and McLeod, 1994], which  
 158 emphasise that the evaporation dominates variabilities and trends in surface fluxes in the equatorial  
 159 eastern Pacific.

160

161 Both ERAINT and JRA55 show strong downward  $F_s$  trends of  $0.65 \text{ Wm}^{-2}\text{yr}^{-1}$  and  $0.50 \text{ Wm}^{-2}\text{yr}^{-1}$   
 162 over 1988-2008, respectively. MERRA2 also shows a weak negative trend in  $F_s$  ( $-0.13 \text{ Wm}^{-2}\text{yr}^{-1}$ ) and  
 163  $LH$  ( $-0.22 \text{ Wm}^{-2}\text{yr}^{-1}$ ). Considering the global changes may include spurious jumps, as a very crude  
 164 adjustment, the global mean  $F_s$  trend over the same period shown in Fig. S2e is removed, and the  
 165 corresponding  $F_s$  trends over  $TEP$  are  $-0.53, -0.29$  and  $-0.35 \text{ Wm}^{-2}\text{yr}^{-1}$  for ERAINT, JRA55 and



DEEPC, respectively. They are all significant using Mann-Kendall test at a significance level of 0.05. Considering the ocean heat capacity of  $4.2 \times 10^6 \text{ J/K/m}^2/\text{m}$ , the mean mixing depth of 100m over eastern Pacific [Roberts *et al.*, 2017] and  $F_s$  is  $3 \text{ Wm}^{-2}$  lower in the 2000s vs the 1990s, the estimated temperature change  $\Delta T \approx -2.3 \text{ K}$  is too large considering the observed ocean temperature change over *TEP* area (Fig. 1e). This suggests that either the trends are unrealistic or changes in ocean heat transport convergence offset these surface heat flux changes. It is noticed that there are discontinuities in global area mean  $F_s$  time series of MERRA2 (Fig. S2e): it has a step change near 1992, a large negative trend between 1992 and 2008 and an anomalous positive trend after 2009. Since the DEEPC global mean net surface flux is well constrained by the TOA satellite observations [Allan *et al.*, 2014] and the zero global atmospheric energy convergence [Liu *et al.*, 2015, 2017], so the global mean  $F_s$  from DEEPC product can be regarded as realistic, and any large trend deviation in the global mean time series from that of DEEPC data can be questioned. It is also noticed both  $F_s$  and  $LH$  trends from MERRA2 over *TEP* differ with the other two atmospheric reanalyses.

The contributions of SW fluxes to the net surface flux trends over *TEP* are significant for the later periods ( $-0.50 \text{ Wm}^{-2}\text{yr}^{-1}$  for 1995-2015 in ERAINT and  $-0.42 \text{ Wm}^{-2}\text{yr}^{-1}$  over 2000-2015 for JRA55), consistent with evidence of increased low cloud cover (*LCC*) [Norris and Evan, 2015; Zhou *et al.*, 2016]. However, for the longer 1988-2008 period,  $LH$  is found to dominate the changes in  $F_s$ .

### 3.2 Sensitivity of latent heat flux to atmospheric variables

Since the  $LH$  change dominates the  $F_s$  variability over *TEP* in three atmospheric reanalyses, observation and AMIP5 simulation ensemble mean, it is necessary to investigate the driver for the  $LH$  change. In order to do this, the bulk formula developed by Singh *et al.* [2005] is employed to compute  $LH$ . This bulk formula is designed for the application of satellite observations so only four meteorological variables are required for input: *SST*, *MSLP*, *WV* and *U* (near surface wind speed,

generally at 10m). For the sensitivity test, climatologies of four fields are applied, and each time-varying individual field is subsequently substituted into the bulk formula to isolate the contribution of the determinant variables. Effects on  $LH$  trend from the different  $SST$  and  $MSLP$  datasets are similar, so are not shown and discussed here. An unrealistic decline in global area mean ERAINT  $WV$  around 1991-1993 compared with SSM/I observations [Allan *et al.* 2014; Allan, 2017] was removed by adjusting values prior to 1993 to force agreement with the global mean SSM/I  $WV$  anomalies over the 1988-1992 period. The influence of water vapour and wind speed changes on  $LH$  variability (downward defined as positive) are estimated for ERAINT, SSM/I and AMIP5 in Fig. 2. For ERAINT (Fig. 2a-e). The generally positive global net downward  $LH$  trend in Fig. 2a is due to the increasing  $WV$  (Fig. 3a) which decreases the surface evaporation, but the effect on the  $LH$  trend over the  $TEP$  region is weak. The estimated influence of changes in  $U$  on surface evaporation is substantial (Fig. 2b). The strong negative trend in downward  $LH$  over the central and eastern Pacific is driven by the wind speed variability. After combining  $U$  and  $WV$ , the trend pattern of  $LH$  is similar to that using  $U$  alone (Fig. 2c). When all four actual fields of ERAINT are used, the trend pattern is still dominated by that using the wind speed alone (Fig. 2d) and the  $LH$  trend of  $-0.20 \text{ W/m}^2/\text{yr}$  over  $TEP$  is still significant (the corresponding global trend of  $-0.02 \text{ W/m}^2/\text{yr}$  is small and insignificant), indicating that the wind speed is the driver of negative  $LH$  trend over  $TEP$  in ERAINT. Compared with the  $LH$  trend from direct model output (Fig. 2e), it can be seen that the model generated  $LH$  trend has more extensive negative trend areas over the whole tropical region, and the  $LH$  trend over  $TEP$  is also stronger ( $-0.51 \text{ W/m}^2/\text{yr}$ , see Fig. 1g). After removing the global  $LH$  trend, the corresponding  $LH$  trend of  $-0.39 \text{ W/m}^2/\text{yr}$  over  $TEP$  area is roughly consistent with  $-0.18 \text{ W/m}^2/\text{yr}$  from the bulk formula, and their correlation coefficient is 0.81 over 1988-2008 (Fig. S3a).

To check the effect of the data type used in this study on the  $LH$  estimation, the results from both the daily and monthly data, from the analysis and forecast fields of  $SST$ ,  $MSLP$ ,  $WV$  and  $U$ , and from

216 the estimated and model output specific humidities were all tested. The estimated *LH* trends over the  
217 *TEP* area from 1988-2008 are -0.23, -0.22 and -0.20 W/m<sup>2</sup>/yr using the daily forecast, monthly  
218 forecast and monthly analysis fields of ERAINT, respectively. Since there is no direct specific  
219 humidity output available for us from ERAINT, the JRA55 data are used for the sensitivity test. The  
220 estimated *LH* trends are -0.35 and -0.46 W/m<sup>2</sup>/yr using the estimated specific humidity from *WV* and  
221 *SST* and the reanalysis specific humidity, respectively. Therefore the impact of these factors on  
222 the *LH* trend over *TEP* area is small, so it is assumed that the discrepancies in spatial structure and  
223 values between *LH* estimates from bulk formula and direct model output are mainly due to different  
224 bulk formula used in the *LH* calculation. The bulk formula of *Singh et al.* [2005] is applied to the  
225 monthly data in this study.

226 Since only *WV* and *U* are available from SSM/I data, the climatologies of four fields from  
227 ERAINT are used at first, then the corresponding climatologies are replaced by SSM/I *WV* (Fig. 2f)  
228 and SSM/I *U* (Fig. 2g), respectively. The spatial pattern of the SSM/I *WV* effect on *LH* trend is  
229 similar to that of ERAINT *WV*. The SSM/I wind speed variability also generates negative downward  
230 *LH* trend over *TEP* region, but it is relatively weak compared with that from ERAINT wind speed  
231 (Figs. 2b and g). When combining SSM/I *WV* and *U* together, the negative trend over *TEP* area is  
232 greatly reduced (Fig. 2h), and it is further smoothed out after the actual fields of *WV* and *U* from  
233 SSM/I and *SST* and *MSLP* from ERAINT are used. This indicates that the SSM/I wind speed  
234 variability is not large enough to produce the strong negative *LH* trend and this will be further  
235 investigated in next section.

236 For the AMIP5 data, the above method is applied to each member and the trends are interpolated  
237 into a common grid of 3°x3°, the ensemble mean results are shown in Figs. 2j-m. The spatial pattern  
238 of the mean effect of *WV* on *LH* trend (Fig. 2j) is similar to those in Figs. 2a and f, implying similar  
239 *WV* trend in three datasets [Allan, 2017]. The wind speed effect is strong in the central Pacific, but  
240 weak over *TEP* area where the *LH* trend is overall positive (reduced evaporative flux). The

combined  $WV$  and  $U$  effect enhances the positive trend over  $TEP$  region, although the spatial patterns over other regions are similar between these three datasets. After all four fields are used (Fig. 2m), the trend over  $TEP$  is very weak ( $\sim -0.02 \text{ W/m}^2/\text{yr}$ ) and insignificant (Fig. S3b). The mean  $LH$  trend from 15 AMIP5 model simulation ensemble mean is in Fig. 2n, which shows similar but stronger spatial pattern compared to that from bulk formula (Fig. 2m) (spatial correlation  $r = 0.61$ ), particularly the  $LH$  trend of  $0.11 \text{ W/m}^2/\text{yr}$  over  $TEP$  area (Fig. 1h) is stronger, but still insignificant (Fig. S3b). This implies that the application of the bulk formula to the monthly data may smooth the  $LH$  calculation, even though the global spatial patterns are still consistent (Figs. 2m and n). Therefore, according to the sensitivity test using bulk formula and direct model output, it is clear that the bulk formula used in this study can reasonably capture aspects of the main features of the corresponding data. Furthermore, these sensitivity tests highlight discrepancies in  $LH$  trends between datasets over  $TEP$  area and the overall sign of the  $LH$  trend depends primarily on the wind speed variability.

### 3.3 Evaluation of water vapor and wind speed trends

To understand the influence of  $WV$  and  $U$  variability on  $LH$  and surface heat flux trend patterns, the trends of  $WV$  and  $U$  from ERAINT, SSM/I and the AMIP5 ensemble mean over 1988-2008 are investigated (Fig. 3). For  $WV$  trends (Figs. 3a-c), the spatial patterns from the three datasets are similar; the trend pattern from ERAINT  $WV$  is in close agreement with SSM/I which is unsurprising since this is assimilated by ERAINT over the ice-free oceans. Both JRA55 and MERRA2 show strong positive trends in the central and eastern tropical Pacific (Figs. S4a-b). The similarity of the  $WV$  trend across datasets can also be clearly seen from the area mean anomaly time series over  $TEP$  (Fig. 3g and Fig. S4e). The  $WV$  trends from the AMIP5 ensemble mean (Fig. 3c) and fifteen members (Fig. S5) are also similar. The  $LH$  trend spatial pattern in Figs. 2a,f,j and the  $WV$  trend

265 spatial pattern in Figs. 3a-c are similar, confirming that the higher *WV* in the atmosphere column will  
266 suppress local evaporation.

267 The wind speed trends contrast across datasets. Both ERAINT (Fig. 3d) and JRA55 (Fig. S4c)  
268 show strong positive wind speed trends over the central and eastern Pacific, but positive trends from  
269 both SSM/I and MERRA2 are much weaker (Fig. 3e and Fig. S4d). This can also be clearly seen  
270 from the area mean wind speed anomaly time series over *TEP* as shown in Fig. 3h and Fig. S4f  
271 (good agreement between 1995 and 2008 is due to the selection of the reference period of 2001-  
272 2008). The trends over 1988-2008 are both 0.26 m/s/decade for ERAINT and JRA55, larger than  
273 those from SSM/I (0.10 m/s/decade, Fig. 3e) and the AMIP5 ensemble mean (0.07 m/s/decade, Fig.  
274 3f). Although the trends are different, variability is similar (Fig. 3h and Fig. S4f). All AMIP5  
275 members show strong wind speed trends in the central Pacific, but weak trends over *TEP* (Fig. S6).

276 In order to see if the *MSLP* drives the wind changes, the *MSLP* trend over 1988-2008 and the  
277 multiannual mean were compared (Fig. S7). The similarity of the trend structure in ERAINT (Fig.  
278 S7a) and JRA55 (Fig. S7b) in the meridional direction indicates similar gradient changes of *MSLP*  
279 between subtropics and equator, which may explain the agreement of wind speed trend structure  
280 between them. The relatively weak trend of the subtropical high south of the *TEP* in MERRA2 (Fig.  
281 S7c) and AMIP5 (Fig. S7d) indicates weak gradient changes of *MSLP* between the south subtropics  
282 and equator, which may explain the weak wind speed trend over *TEP* area. Therefore, although the  
283 *MSLP* change over *TEP* area has very small direct effect on the *LH* trend estimation, their spatial  
284 structure difference can affect the gradient and further change the wind speed. In addition, Boisséson  
285 *et al.* [2014] found good agreement for zonal wind speed trends over the tropical Pacific between  
286 ERAINT and observations. However they noted that the discontinuities between different satellite  
287 products are not taken into account, such as the big jumps between ERS2 (European Remote Sensing  
288 satellite) and QSCAT (Quick Scatterometer) near 2000 in their Fig. 2a and between ERS2 and

289 ENVISAT satellite near 2003 in their Fig. 2b. Different conclusions may be obtained if these  
290 discontinuities are considered.

291

### 292 **3.4 Comparison with buoy observations**

293 The large discrepancies in wind speed changes over *TEP* cast doubt on the reliability of the wind  
294 speed in these datasets. To further check the wind speed quality, data from TAO moored buoy array  
295 (220-255°E, 9°N-8°S) are used in this study for comparison [*TAO Project Office*, 2000]. There are 27  
296 buoys working in this area; they are all calibrated before deployment and there is no post-deployment  
297 calibration involved. Data quality control information can be found at  
298 [http://tao.ndbc.noaa.gov/proj\\_overview/qc\\_ndbc.shtml](http://tao.ndbc.noaa.gov/proj_overview/qc_ndbc.shtml). The locations of the buoys are plotted in Fig.  
299 4a (colored dots represents the wind speed trend from the buoy), which is an enlargement of Fig. 3d  
300 showing the ERAINT wind speed trend. From January 1990 to December 2015, there are 312  
301 months; the minimum coverage period from start month to end month over all stations is 202  
302 months at station 8N110W (Fig. S8a), so all buoy records span at least 65% of the record length.  
303 However, there are considerable gaps in the buoy timeseries: the minimum fraction of the data  
304 coverage over 1990-2015 is about 30% at station 5N125W (Fig. S8b) and the mean fraction is 50%.  
305 At each station, the anomaly is calculated by removing the monthly mean (over 2001-2008) which is  
306 calculated if the total number of months is  $\geq 2$ . The wind speed anomaly time series is plotted in Fig.  
307 S9, but the actual number of valid buoy data points is not well reflected due to the smoothing of six  
308 month running mean. The wind speed trends from individual buoy records (Table S1) are generally  
309 insignificant: only 9 out of 27 display significant trends and 8 of these are positive (see also Fig. S9)  
310 while the composite trend of -0.05 m/s/decade is small and insignificant. 21 out of 27 wind speed  
311 trends calculated from ERAINT grid points nearest to the corresponding buoy stations (bottom right  
312 matrix of Table S1) are positive and significant, and the composite trend of 0.28 m/s/decade is also  
313 significant. When the ERAINT grid box time series are sampled to mimic the intermittent buoy time

314 series (bottom middle matrix of Table S1), 16 out of 27 of the trends remain positive and significant  
315 and the composite trend of 0.25 m/s/decade is significant. Therefore, although intermittent data  
316 coverage reduces the significance of trends, there are more robust positive trends in the ERA-Interim  
317 data when sampled to mimic the buoy spatial and temporal coverage.

318 Mean wind speed variability in the *TEP* for 1990-2008 is displayed in Fig. 4b for ERAINT using a  
319 variety of spatial and temporal sampling strategies and the composite of the buoy measurements. The  
320 fraction of valid buoy data in each month increases steadily from about 1990 to 2000 and then  
321 becomes stable afterwards while there is a drop between 2011 and 2015 (Fig. S8c). Variability in  
322 mean ERAINT wind speed over the *TEP* (Fig. 4b, thick red line) is similar to when only grid boxes  
323 corresponding to the buoy locations are sampled (cyan line). This indicates that the area mean from  
324 the buoy spatial coverage is representative of the wider, completely sampled region; trends over the  
325 1990-2015 period are significant (based on the Mann-Kendall test at significance level of 0.05) and  
326 positive for both although is larger for the *TEP* region (0.34 m/s/decade) than for the buoy grid  
327 points (0.28 m/s/decade). The composite wind speed time series from buoys (Fig. 4b, thick black  
328 line) displays an insignificant negative trend of -0.05 m/s/decade over 1990-2008. Sampling  
329 ERAINT to also match the temporal coverage of the buoys (magenta line) alters the timeseries  
330 substantially demonstrating the substantial effect of incomplete observational coverage. Agreement  
331 between ERAINT buoy spatial and temporal sampling (magenta line) and the buoy time series  
332 variability is markedly improved ( $r = 0.92$ ), indicating successful assimilation of the observational  
333 variability by ERAINT. However, the ERAINT composite (magenta line) trend remains positive  
334 (0.25 m/s/decade) and substantially larger than the corresponding trend from the buoy data. The  
335 corresponding plot for *LH*, similar to Fig. 4b, is shown in Fig. S8d for reference.

336 The ERAINT minus buoy wind speed difference using consistent spatiotemporal sampling (Fig.  
337 4c) depicts an increasing trend (0.14 m/s/decade over 1990-2015) which contributes about 50% to  
338 the overall trend of ERAINT wind speed over *TEP*. Thus, the discrepancy between the buoy and

ERAINT wind speed trends cannot easily be explained by the variable buoy coverage. It is not currently clear how the assimilation of data from an evolving observing system simply explains this discrepancy and further investigation is merited. The remaining difference is apparently associated with the fact the influence of the assimilation declines rapidly with distance from the buoy as pointed out by *Josey et al.* [2014]. Based on the comparison and analysis, the area mean from the limited buoy spatial coverage (cyan line in Fig. 4b) is representative of that over the wider, completely sampled *TEP* area (red line in Fig. 4b), and the intermittent buoy wind speed variability is well assimilated into the ERA-Interim model. However, increases in the ERAINT minus buoy wind speed, when consistently sampled in space and time, indicate that increases in wind speed and therefore also surface latent heat flux are unrealistic and so the large decreases in net downward energy flux into the tropical eastern Pacific are questionable.

350

#### 351      **4. Conclusions**

Cooling of the surface ocean over the tropical eastern Pacific influences the global mean rate of surface temperature change [*Kosaka and Xie*, 2013; *Trenberth and Fasullo*, 2013; *England et al.*, 2015]. In order to understand the mechanism of the cooling, numerous studies have been conducted [*Meehl et al.*, 2011; *Hansen et al.*, 2011; *Guemas et al.*, 2013; *Katsman and van Oldenborgh*, 2011; *Solomon et al.*, 2010, 2011; *Kaufmann et al.*, 2011; *Norris and Evan*, 2015; *Brown et al.* 2014; *Zhou et al.*, 2016]. Motivated by a discrepancy between observations-based estimates of surface heat flux changes and simulations from atmosphere-only models over the *TEP* [*Liu et al.* 2015], an investigation of the causes of the surface energy flux is conducted using data from three atmospheric reanalyses, fifteen AMIP5 model simulations and the DEEPC observations-based reconstruction. It is found that the net downward surface flux change over *TEP* is dominated by the *LH* variability and the trend is significantly negative in ERAINT, JRA55 and DEEPC data. The negative trend over *TEP* from DEEPC is not as strong as that from ERAINT (Figs. 1f and g) due to the contrasting



364 methodologies. In contrast, the  $F_s$  and  $LH$  trends in AMIP5 ensemble mean show positive trend over  
365  $TEP$  region, and the spatial pattern is closely related to the  $SST$  pattern, indicating that  $SST$  changes  
366 are driving heat flux changes in the AMIP5 model simulations. Since the atmosphere simulations do  
367 not permit a coupled response to the surface fluxes, it is possible that they are missing an important  
368 mechanism yet the negative trends depicted by the reanalysis-based estimates appear unrealistically  
369 large.

370 To investigate the realism and cause of the implied changes in surface heat flux, sensitivity tests  
371 using turbulent heat flux bulk formula are applied. These indicate that the  $LH$  changes depicted by  
372 ERAINT are dominated by wind speed changes, which show increasing trends over the eastern  
373 Pacific. This wind speed trend is very weak in SSM/I satellite observations and is absent in AMIP5  
374 ensemble mean simulations. After further comparison with buoy observations, it is found that few  
375 buoy stations show significant positive wind speed trends, although the corresponding composite  
376 trends from ERAINT grid points nearest to the stations are significantly positive. The variable spatial  
377 coverage of the buoy wind speed is assimilated by ERA-Interim and the buoy coverage is shown to  
378 reasonably represent the  $TEP$  area mean wind speed (cyan line in Fig. 4b). However, an increase in  
379 ERAINT minus buoy wind speed, when consistently sampled in space and time, suggest that the  
380 increases in wind speed depicted by ERAINT are overestimated. This further implies that increased  
381 evaporative fluxes and reduced downward heat flux trends depicted by ERAINT and other datasets  
382 may be unrealistic. The discrepancies between different datasets cast questions on the reliability of  
383 the reanalysed surface fluxes over the tropical eastern Pacific area. In AMIP5 simulations, models  
384 are forced by  $SST$ , so the  $SST$  decrease over  $TEP$  suppresses the evaporation and reduce the upward  
385  $LH$  flux, enhancing the downward net surface flux. In the atmospheric reanalysis, such as the  
386 ERAINT the dominant contribution of strong wind speed trend to the  $LH$  flux changes is evident.  
387 The strong ERAINT  $LH$  trend is unrealistic considering the observed temperature changes over  $TEP$   
388 region (based upon energy budget arguments) and comparison with buoy data when accounting for

389 sampling. This will indirectly affect the budget-based DEEPC product since erroneous wind speeds  
390 will influence the energy transports used in the calculation of surface fluxes; the precise influence is  
391 uncertain but has implications for budget-based indirect estimates of surface energy fluxes [*Liu et al.*  
392 2017; *Trenberth et al.* 1995; *Chiodo and Haimberger*, 2010; *Mayer and Haimberger*, 2012;  
393 *Trenberth and Fasullo*, 2017]. *Josey et al.* [2014] found that assimilation of TAO mooring  
394 contributed to unrealistic near surface humidity and wind speed anomalies in ERAINT. The impact  
395 of these unrealistic anomalies on the latent heat flux in the tropical Pacific may play a role in the  
396 unrealistic *LH* trend. However, these results do not appear to contradict the mechanisms invoked to  
397 explain *TEP* cooling discussed by *England et al.* [2014] since this key region of wind enhancement  
398 centres on the central pacific where satellite data and simulations broadly agree on recent changes.  
399 Nevertheless, the TEP is a key region in determining global climate variability and time-varying  
400 climate sensitivity [*Ceppi and Gregory*, 2017; *Andrews and Webb*, 2017] so understanding the role  
401 of surface fluxes in this region is crucial. While AMIP5 simulations are temporally homogeneous,  
402 they do not represent the key atmospheric feedbacks on ocean temperature so additional in-depth  
403 investigation is necessary to elucidate the mechanisms of decadal variability in ocean temperature,  
404 including using data from the ocean reanalysis and ECMWF ERA5 for further comparisons and  
405 coupled reanalysis for feedback mechanism studies.

406

407

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**Table 1.** Datasets

Dataset	Period (in this study)	Resolution	References
Reconstruct (DEEPC)			
Surface net flux: $F_s$	1985-2015	$0.7^\circ \times 0.7^\circ$	<i>Liu et al.</i> [2015, 2017]
CERES	2001-2016	$1.0^\circ \times 1.0^\circ$	<i>Loeb et al.</i> [2012]
SSM/I			
F08	1987-2016	$0.25^\circ \times 0.25^\circ$	<i>Wentz and Spencer</i> [1998]
F11			<i>Vila et al.</i> [2010]
F13			
Atmospheric reanalyses			
ERA-Interim (ERAINT)	1985-2015	$0.7^\circ \times 0.7^\circ$	<i>Dee et al.</i> [2011]
JRA55	1985-2014	$0.56^\circ \times 0.56^\circ$	<i>Kobayashi et al.</i> [2015]
MERRA2	1985-2016	$0.5^\circ \times 0.625^\circ$	<i>Gelaro et al.</i> , [2017]
TAO buoy	1990-2017		<i>TAO Project Office</i> , [2000]
AMIP5 models	1985-2008		
ACCESS1-0		$1.25^\circ \times 1.875^\circ$	<i>Bi et al.</i> [2013]
CanAM4		$2.79^\circ \times 2.81^\circ$	<i>Arora et al.</i> [2011]
CCSM4		$0.94^\circ \times 1.25^\circ$	<i>Gent et al.</i> [2011]
CMCC-CM		$0.75^\circ \times 0.75^\circ$	<i>Scoccimarro et al.</i> [2011]
CNRM-CM5		$1.40^\circ \times 1.41^\circ$	<i>Voldoire et al.</i> [2012]
FGOALS-g2		$3.0^\circ \times 2.81^\circ$	<i>Li et al.</i> [2013]
GFDL-CM3		$2.0^\circ \times 2.5^\circ$	<i>Delworth et al.</i> [2006]
GISS-E2-R		$2.0^\circ \times 2.5^\circ$	<i>Schmidt et al.</i> [2014]
HadGEM2-A		$1.25^\circ \times 1.875^\circ$	<i>Collins et al.</i> [2011]
INM-CM4		$1.5^\circ \times 2.0^\circ$	<i>Volodin et al.</i> [2010]
IPSL-CM5A-LR		$1.89^\circ \times 3.75^\circ$	<i>Dufresne et al.</i> [2013]
MIROC5		$1.39^\circ \times 1.41^\circ$	<i>Watanabe et al.</i> [2011]
MPI-ESM-LR		$1.85^\circ \times 1.875^\circ$	<i>Raddatz et al.</i> [2007]
MRI-CGCM3		$1.11^\circ \times 1.13^\circ$	<i>Yukimoto et al.</i> [2012]
NorESM1-M		$1.89^\circ \times 2.5^\circ$	<i>Zhang et al.</i> [2012]

592

593 **Figure captions**

594

595 **Fig. 1.** Left column is the trend of (a) *SST* and (b-d) net surface flux over 1988-2008. Right column  
596 is the corresponding area mean anomaly time series over tropical eastern Pacific (marked area: from  
597 20°N–20°S and 210°E to the west coast of Central America). Four components of  $F_s$  are also plotted  
598 in g and h, and the *SW* and *LW* from CERES are plotted in f, together with the turbulent flux derived  
599 from the difference between DEEPC net surface flux and CERES radiation fluxes. The reference  
600 period is 2001-2008. The datasets are from ERAINT, DEEPC and AMIP5 15 member ensemble. All  
601 fluxes are downward positive. All lines are six month running means and some linear trends are also  
602 displayed.

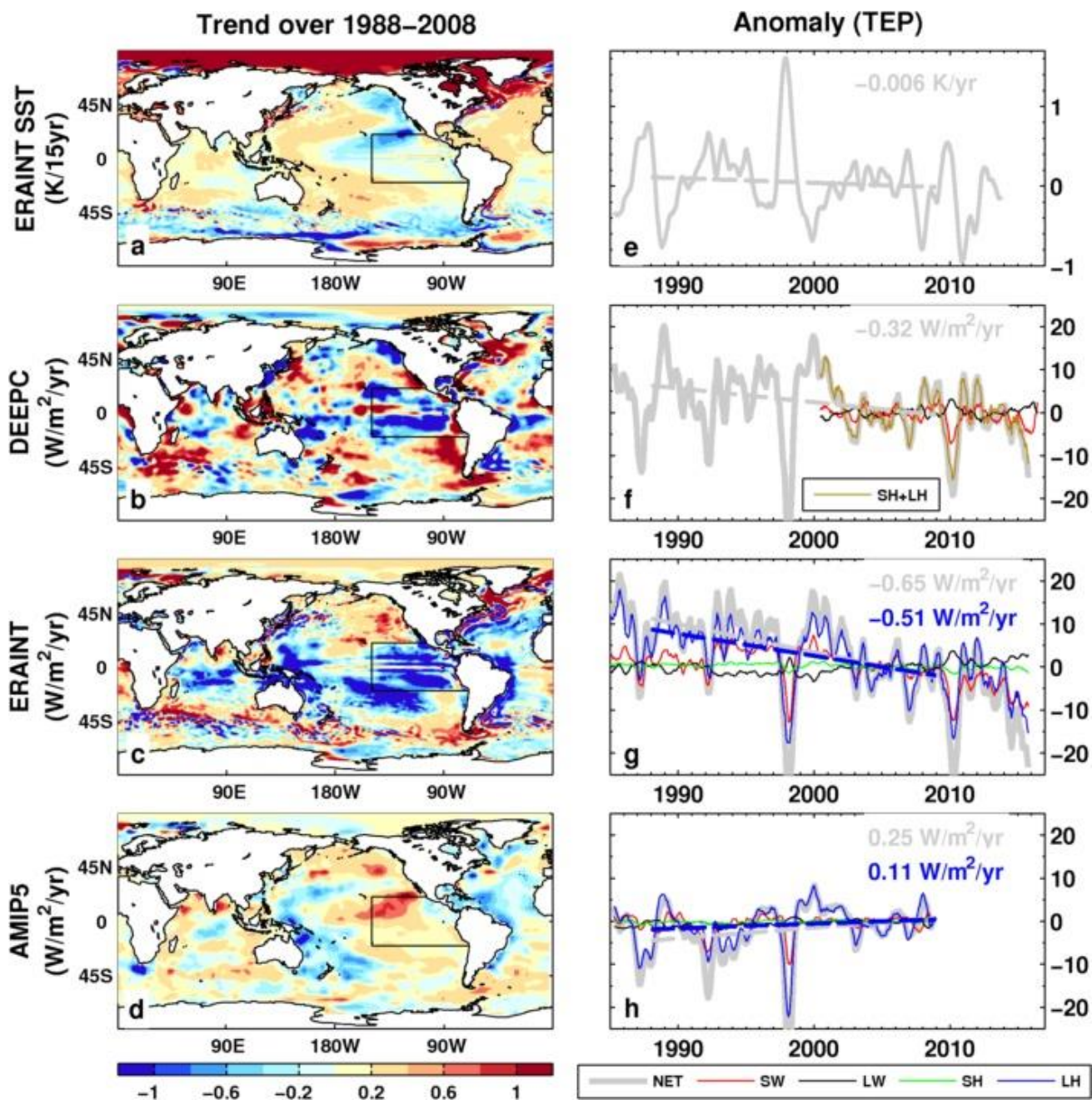
603

604 **Fig. 2.** Sensitivity test of *LH* trend using bulk formula over 1988-2008. The climatologies of *SST*,  
605 *MSLP*, *WV* and wind speed from ERAINT are used at first, then the corresponding climatologies are  
606 replaced by (a) ERAINT *WV*, (b) ERAINT wind speed, (c) ERAINT *WV* and wind speed, (d) all  
607 four fields from ERAINT, (f) SSM/I *WV*, (g) SSM/I wind speed, (h) SSM/I *WV* and wind speed and  
608 (i) *WV* and wind speed from SSM/I, *SST* and *MSLP* from ERAINT. The *LH* trend from directly  
609 ERAINT reanalysis is in (e). The same method is applied to each of 15 AMIP5 models, and the  
610 ensemble means are plotted in (j-m). The mean *LH* trend from 15 AMIP5 model simulations is in  
611 (n).

612

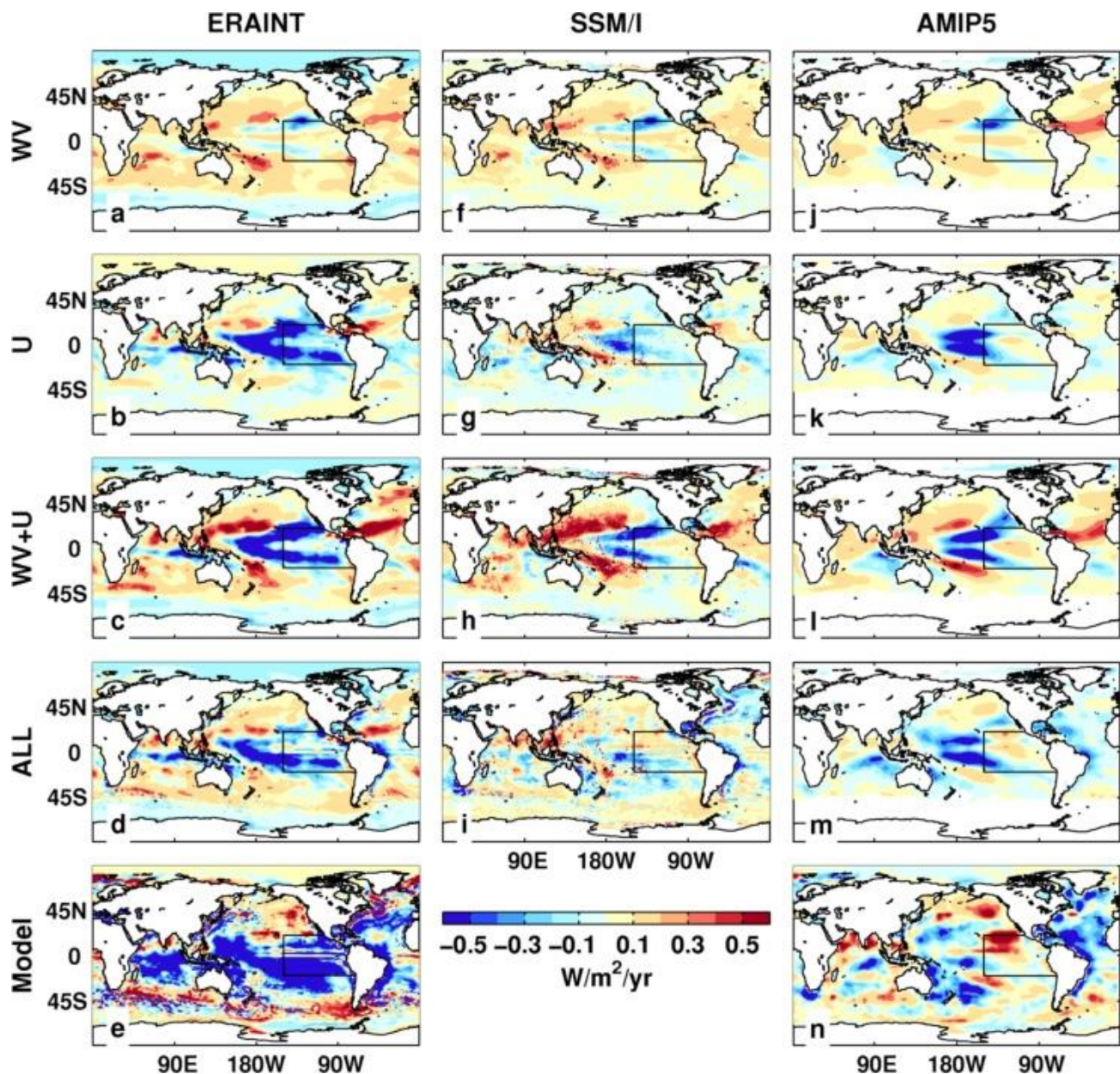
613 **Fig. 3.** (a-f) Trends of *WV* and wind speed over 1988-2008 from ERAINT, SSM/I and AMIP5  
614 ensemble mean. (g-h) Corresponding deseasonalized time series of area mean *WV* and wind speed  
615 over *TEP*. The shaded areas of AMIP5 are 15-member ensemble mean (solid black line)  $\pm 1$  standard  
616 deviation. The reference period is 2001-2008 for anomaly calculation. The wind speed trends over  
617 1988-2008 are also displayed in (h).

618 **Fig. 4.** (a) Wind speed trend from ERAINT (enlargement of Fig. 4d). Colored dots indicate 27 TAO  
619 buoy locations and wind speed trends. (b) Deseasonalized wind speed anomaly (relative to 2001–  
620 2008 period) time series from buoy stations (composite, thick black line), ERAINT area weighted  
621 mean over *TEP* (thick red line), ERAINT mean from grid points nearest to buoy stations including  
622 all data points (thick cyan line, no area weighting) and the ERAINT mean including data points  
623 where the buoy station has the valid data (magenta line, no area weighting). All lines are 12 month  
624 running mean. (c) The time series of mean wind speed bias between ERAINT and buoy data using  
625 consistent spatiotemporal sampling. The trend of 0.14/m/s/decade over 1990-2015 is also displayed.  
626  
627



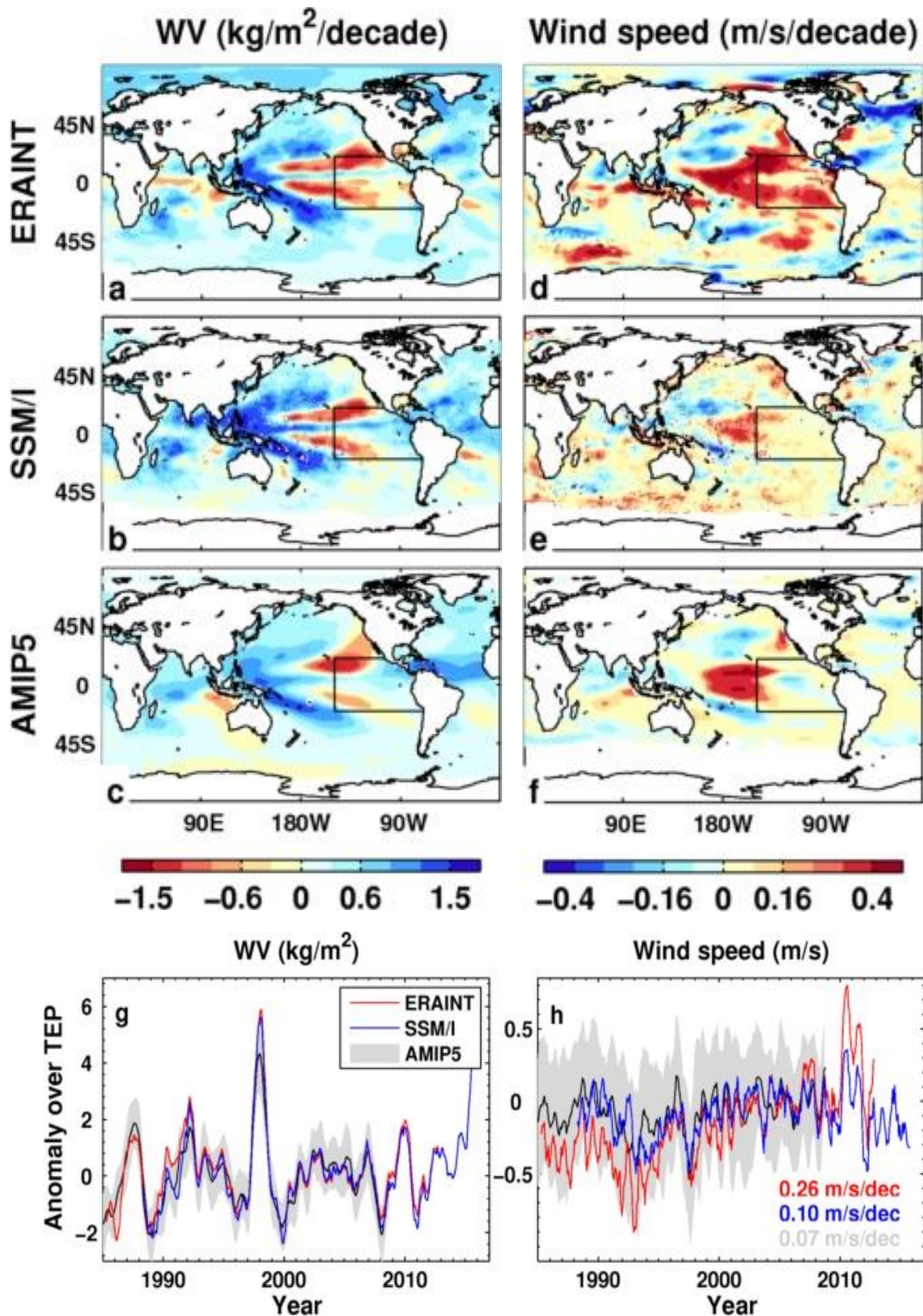
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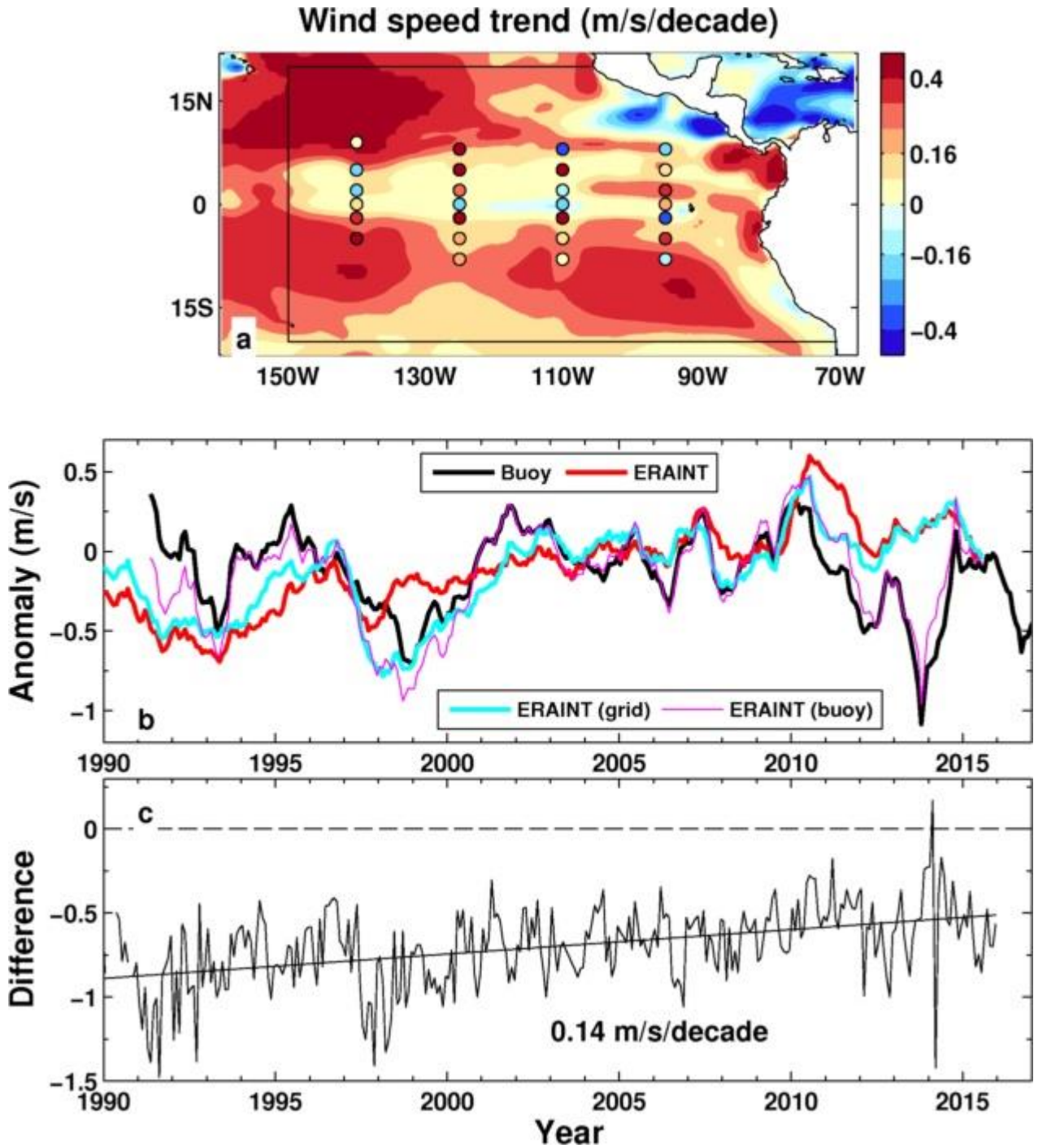
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**Fig. 3.** (a-f) Trends of *WV* and wind speed over 1988-2008 from ERAINT, SSM/I and AMIP5 ensemble mean. (g-h) Corresponding deseasonalized time series of area mean *WV* and wind speed over *TEP*. The shaded areas of AMIP5 are 15-member ensemble mean (solid black line)  $\pm 1$  standard deviation. The reference period is 2001-2008 for anomaly calculation. The wind speed trends over 1988-2008 are also displayed in (h).





**Fig. 4.** (a) Wind speed trend from ERAINT (enlargement of Fig. 4d). Colored dots indicate 27 TAO buoy locations and wind speed trends. (b) Deseasonalized wind speed anomaly (relative to 2001–2008 period) time series from buoy stations (composite, thick black line), ERAINT area weighted mean over *TEP* (thick red line), ERAINT mean from grid points nearest to buoy stations including all data points (thick cyan line, no area weighting) and the ERAINT mean including data points where the buoy station has the valid data (magenta line, no area weighting). All lines are 12 month running mean. (c) The time series of mean wind speed bias between ERAINT and buoy data using consistent spatiotemporal sampling. The trend of 0.14/m/s/decade over 1990–2015 is also displayed.