Global and Planetary Change 100 (2013) 234–244

Contents lists available at SciVerse ScienceDirect

Global and Planetary Change

journal homepage: www.elsevier.com/locate/gloplacha

Thermal variability of the Indo-Pacific warm pool

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ARTICLE INFO

Article history:
Received 16 August 2012
Accepted 29 October 2012
Available online 2 November 2012

Keywords:
Indo-Pacific warm pool
trend
heat storage
Pacific Decadal Oscillation
Ensemble Empirical Mode Decomposition

ABSTRACT

The Indo-Pacific warm pool (IPWP) over the Indian Ocean and the Pacific Ocean is the largest warm pool in the global oceans. Its thermal variability and trend between 1982 and 2011 are extracted from the Ensemble Empirical Mode Decomposition method. Time–frequency energy distributions using the Hilbert–Huang transform are computed to evaluate the thermal spectrum-energy. From the SST variability and the heat storage anomaly, we find that the thermal variability is strongly influenced by the Pacific Decadal Oscillation (PDO). The size, increasing trend in the IPWP, calculated from the SST data is $(0.18\pm0.01)\times10^6$ km^2/decade. Besides, the magnitude of increasing rate during the positive phase of the PDO is couple times higher than that during the negative phase. Furthermore, the SST trend is also associated with 1999/2000 climate shift. The heat increases in the IPWP from 1993 to 2011 implied an average warming rate of 1.41 Wm^{-2}. The thermal variations in the IPWP are controlled by interannual to decadal variabilities mostly related to the PDO in the Pacific Ocean sector and by annual variability in the Indian Ocean sector.

1. Introduction

There is an alternation of warm period and cold period in the climate oscillation of the Earth's circulation. Since Industrial Revolution, the climate system is affected by anthropogenic, especially the increasing concentrations of the greenhouse gasses. The global warming events due to greenhouse effects have focused on previous studies. The estimated increase of observed global ocean heat content between the 1950s and 1990s is at least one order magnitude larger than the increase in heat content of any other period (Levitus et al., 2001). During 1955–2003, the mean temperature from surface through 300-meter depth in the global oceans increased about 0.171 °C. The increases of mean temperature were 0.188 °C and 0.159 °C for the oceans of northern hemisphere and southern hemisphere, respectively (Levitus et al., 2005). Casey and Cornillon (2001) calculate global sea surface temperature (SST) trends in the data-rich period between 1960 and 1990 from the Comprehensive Ocean–atmosphere Data Set (COADS) to be 0.10 ± 0.03°C. Because of the high density and specific heat of seawater, water can store and transport large amounts of heat. The atmosphere and polar areas can also gain large amount of heat from the oceans. Measuring the thermal variability is thus important for studies and predications of climate change.

The global heat budget is strongly influenced by the tropical ocean. The Indo-Pacific Warm Pool (IPWP) in the tropical ocean has the warmest SST and the widest warm water mass in the global oceans. However, warm pool conventionally defined by the area where the SST≥28°C or 28.5 °C (Yan et al., 1992; Cravatte et al., 2009) has attracted more attention recently, because it is a large area of heat accumulation in the global oceans and is related to the development of El Niño-Southern Oscillation (ENSO) events (Ho et al., 1995; Yan et al., 1997; Kim et al., 2012). Most of the investigations focused on the Pacific sector of the warm pool. However, some studies looked into the Indian Ocean warm pool (IOWP) indicated the atmosphere–ocean interaction between IPWP and IOWP (Vinayachandran and Shetye, 1991; Kim et al., 2012). In the study, we separate the IPWP into a Pacific sector and an Indian Ocean sector to contrast and examine their decadal variability.

Yan et al. (1992) tracked the variability of temperature and size of the Western Pacific Warm Pool (WPWP). They found that solar irradiance variability, ENSO events, and global warming possibly cause the SST and the size of the pool fluctuated. Ho et al. (1995), using Advanced Very High Resolution Radiometer (AVHRR) derived SST data, demonstrated that the movement of the centroid of WPWP traces an ellipse-like trajectory during a year and moves counterclockwise in most years from 1982 to 1991. Model simulations also suggested that the alteration of the SST patterns of the warm water in WPWP plays an important role in the onset of El Niño event (Cane, 1983). Kim et al. (2012) examined the size, SSTs, and central position in the IPWP and suggested that the interannual variability is more vigorous in the Pacific Ocean than in the Indian Ocean. Fasullo and Webster (1999) also found that the warm pool in the Indian sector has a stronger annual cycle than in the Pacific sector. Wang and Mehta (2008)

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http://dx.doi.org/10.1016/j.gloplacha.2012.10.022

investigated the warming of the IPWP in recent decades and suggested to be capable of regulating decadal variability in the Hadley and Walker circulations.

The tropical Pacific Ocean plays a key role on the global oceanic heat budget and it strongly influenced the development of ENSO phenomenon. During the warm phase of ENSO, warm SST, low sea level pressure, low outgoing radiation, and shallow thermocline in the eastern equatorial Pacific. The intensity of the westward South Equatorial Current and the North Equatorial Current also decreases during El Niño events (McPhaden et al., 1998; Wang et al., 1999; Wang and McPhaden, 2000). Measuring variations in heating of the tropical Pacific can thus be important for studies and predictions of climate in other parts of the world (Chambers et al., 1998). One of the principal goals of global climate research is the prediction of long-period changes in the Earth's climate. Of the many parameters which influence long-term climate change, one of the most important and most poorly measured is the variation in heat budget in the oceans. Traditionally, stored heat is computed from ocean temperature changes, such as those made by expendable bathythermographs (XBTs). In present study, we can compute heat storage anomalies directly from satellite altimeter measurements of sea level change. Yan et al. (1995) documented seasonal heat storage in the North Pacific. Average across the entire basin, the difference between the average monthly heat storage rate derived from XBT dataset and the average monthly heat flux derived from COADS dataset is 3.76 Wm^{-2}.

In this study, we use satellite altimeter data and SST data to produce IPWP estimates of upper ocean thermal variability. In order to find out dominant period components and the relationship of energy-frequency distribution without being influenced by nonlinear and nonstationary signals, the Hilbert–Huang transform applying to Ensemble Empirical Mode Decomposition mode is suitable for solving interdecadal time series (Huang et al., 1998). The purpose of this study expects to use satellite data to analyze the trend, size fluctuations, and heat storage variability in the IPWP and realize the thermal variations of the tropical Pacific and Indian oceans.

2. Data and methods

2.1. Altimeter data

The sea level anomaly data used in this study is the Ssalto/duacs multi-mission products provided by Archiving Validation and Interpretation of Satellite Data in Oceanography (AVISO) with a 1/3° spatial resolution and 1-month temporal interval. The data span is from January 1993 to July 2011. Over the data span, the sea level products were chiefly based on TOPEX/POSEIDON, Jason-1, Jason-2, ERS-1, ERS-2, and Envisat. The data had been corrected by environmental corrections, including effects of wet and dry troposphere influence, ionosphere bias, electromagnetic bias, inverse barometer and tides (Chambers et al., 1997). This provides an extended continuous time series of high-accuracy measurements of the ocean surface topography from which scientists can detect the climate change. The accuracy of sea level anomaly is as high as 2.5 cm or better (Willis et al., 2003). More details on the corrections applied to sea level data and most updated geophysical and environmental improvements have been applied to previous studies (Tapley et al., 1996; Chambers et al., 1997; Le Traon and Ogor, 1998; Willis et al., 2003).

2.2. Reynolds and Smith SST dataset

In order to understand the processes involved in climate change, many different scientific measurements are necessary. SST variability is an important indicator of oceanic variable of changes in the Earth's climate system. Because the accuracy of satellite derived SST used to be affected by cloud cover and atmospheric aerosol. To overcome the shortcomings of the satellite derived SST, the Reynolds and Smith SST dataset uses both in-situ SSTs and satellite derived SSTs from the National Oceanic and Atmospheric Administration (NOAA) AVHRR (Reynolds and Smith, 1994). The satellite derived SSTs are from the multi-channel SST products that have been constructed operationally from the AVHRR sensor on the polar orbiting weather satellite. SSTs derived from ships and buoys are applying to Reynolds and Smith SST dataset. The multi-satellite and in-situ SST dataset is weekly and monthly averaged global product on a 1° by 1° grid. The data span used to study the thermal variability of IPWP is from January 1982 to December 2011.

2.3. Heat storage

In fact, changes in heat storage will also cause the changes in the sea surface topography, since heat variations are associated with density changes. Thus, we can calculate heat storage anomaly (HSA) directly from sea level change (Chambers et al., 1997) as:

$$\Delta H = \frac{\rho C_P}{\alpha}\Delta\eta, \tag{1}$$

where ΔH is HSA derived from altimetry in J m^{-2}, ρ is the density of seawater, C_p is the specific heat of sea water and is assumed constant, $\Delta\eta$ is the sea level anomaly from measured by satellite altimetry in meter and α is the thermal expansion coefficient of sea water in K^{-1}, where K is the unit of absolute temperature ($K = -273.15 + °C$). The constants of Eq. (1) are given as follows: $C_p = 4000$ J kg^{-1} K^{-1} and $\rho = 1027$ kg m^{-3}. To generate the thermal expansion coefficient for each grid, we fit a liner polynomial to α versus sea temperature, using data from Table A3.1 of Gill (1982), and assuming that salinity is equal to 35 psu. However $\Delta\eta$ is the change in sea level due only to heating, but the sea level measured by altimetry contains oceanic dynamical process effects. Chambers et al. (1997) and Chambers et al. (1998) suggested that these effects are generally smaller than the thermal effects. To examine long-term heat storage changes, heat storage rates for each grid are calculated by:

$$\frac{\Delta H}{\Delta t} = \frac{\rho C_P}{\alpha}\frac{\Delta\eta}{\Delta t}, \tag{2}$$

where Δt is time interval. Considering the accuracy of sea surface height anomaly and the coefficients of ρ, C_p and α, the error in heat storage computed from Eq. (1) is between 20×10^7 and 30×10^7 J m^{-2} (Chambers et al., 1997). Chambers et al. (1998) further compared heat storage changes in the equatorial Pacific by TOPEX altimeter and TAO dataset. The average root mean square of the differences between altimeter and TAO data is about 48×10^7 J m^{-2}. White and Tai (1995) found that good agreement is between global patterns of TOPEX altimetry height and XBT HSAs from approximately 30°S to 60°N for 2-year period from 1993 to 1994. And basin-wide averages of heat storage rates can be inferred from TOPEX altimetry with an accuracy of about 2 Wm^{-2}.

2.4. Ensemble Empirical Mode Decomposition and Hilbert–Huang transform

Generally, the time series analysis is supposed that the data must be linear, periodic, or stationary, since most real time series dataset do not exactly follow the rules. In order to conquer the difficulties of searching for a small amplitude signal embedded in noisy data, we employed the Ensemble Empirical Mode Decomposition (EEMD) method developed by Huang et al. (1998) and Wu and Huang (2009), which can deal with nonlinear, non-periodic and non-stationary data. Edge effects have caused problems to all known data analysis methods in the calculation process and Wu and Huang (2009) get ensemble approach to reduce edge effects. EEMD method is empirical because the local characteristic time scales of data itself are used to decompose the time