The warmest year 2015 in the instrumental record and its comparison with year 1998

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ABSTRACT
The global annual averaged Surface Air Temperature Anomaly (SATA) in 2015 and its rank in the historical instrumental records are analyzed using the CRU, NASA, and NOAA datasets. All datasets indicate that 2015 is the warmest year, which is 0.74 \degree C warmer than normal years from 1961 to 1990 in the HadCRUT4 data set. The most evident warm anomaly occurs over land, especially at high latitudes. The averaged SATA over land is 1.13 \degree C, which is 0.54 \degree C warmer than that over oceans (0.59 \degree C). Because an El Niño event occurred in 2015 and 1998 and 1998 is also the warmest year in the twentieth century, these two years are compared to explain the formation of the warmest climate. A statistical approach that is known as the Ensemble Empirical Mode Decomposition (EEMD) is employed to isolate the components with different timescales, which range from interannual to centennial and a long-term trend. In 2015 the developing El Niño may have contributed an anomaly of 0.10 \degree C, while this value is 0.18 \degree C for 1998. The contribution of the decadal-multidecadal variability and beyond to 2015 is 0.64 \degree C, which is significantly larger than that of the interannual anomaly components (0.10 \degree C). This indicates that the warmest climate in 2015 occurred in the context of the timescales beyond the interannual.

1. Introduction
During the last century, the global annual averaged Surface Air Temperature Anomaly (SATA) has exhibited a warming trend (Cook et al. 2014). The trend has created a challenge to the environment, society, and economy of many countries and caused greater occurrences of extreme weather and climate events, such as flooding, drought, and heat waves (Hao, AghaKouchak, and Phillips 2013; Cook et al. 2014; Li, Zhang, and Yao 2015). Thus, global warming is a controversial research topic in various fields of the global environment and society.

Global warming has been extensively investigated. During the first ten years of the twenty-first century, the global averaged air temperature did not exhibit an evident warming trend; instead, a neutral trend was observed. People referred to this trend as the hiatus of global warming (Bala 2013). The hiatus has attracted a substantial amount of attention, and various reasons have been proposed. The future evolution of this hiatus is concerning. Particularly, the emergence of the record warmest year 2015 has sparked a debate about the hiatus.

Many media sources reported that 2015 is the warmest year in the instrumental records.\textsuperscript{1, 2, 3} Why the warmest climate emerged in 2015 is not only intriguing for predicting interannual climate anomaly, but also important for projecting the future evolution of the hiatus. If the primary factor for the 2015 anomaly is physical forcing on the interannual timescale, it may provide no indication or implication of the tendency of the hiatus. Conversely, if
the primary factor that is responsible for the 2015 anomaly consists of decadal components and beyond, it may imply that the hiatus is fading away. Thus, understanding the cause of the occurrence of the warmest air temperatures in 2015 is critical.

The year 2015 resembles the year 1998 in two aspects. In addition to the warmer SATA, a developing El Niño event occurred in 2015. Similarly, 1998 is the warmest year in the twentieth century, and the strongest ENSO occurred in winter 1997–1998 (Bell et al. 1999; Lu 2005; Zhang and Li 2015). Previous studies suggest that an El Niño event elevates the global averaged air temperature (Bell et al. 1999; Lean and Rind 2008, 2009) and that the 1997/1998 El Niño event contributed a value of 0.23 °C to the average temperature from June 1997 to November 1997 (Lean and Rind 2008). Thus, we attempt to explain the formation of the anomalously warmer climate in 2015 by comparing it with the climate in 1998. We address the following questions: (1) Is the global averaged SATA in 2015 consistently the strongest anomaly in different observational or reanalysis datasets? Do differences exist in the annual averaged SATA between the oceans and the continents, or in the seasonal averaged SATA between the four seasons? (2) What caused the occurrence of the warmest SATA in 2015? In comparison to year 1998, is the primary influential factor in 2015 different?

2. Datasets and methods

2.1. Datasets

The monthly land SATA data-set and the monthly sea surface temperature anomaly data-set are obtained from the CRUTEM4 (Jones et al. 2012) and HadSST3 data-set (Kennedy et al. 2011), respectively. Both datasets are provided by the Climatic Research Unit (CRU) at the University of East Anglia. The monthly global SATA data-set is obtained from HadCRUT4, which is a collaborative product of Met Office Hadley Centre and CRU combining the CRUTEM4 and HadSST3 datasets (Morice et al. 2012). These anomalies are calculated relative to the 1961–1990 normal, have a horizontal resolution of 5° × 5° and cover the period from 1850 to 2015.

To compare with the time series calculated from the CRU datasets, the time series from both the GISTEMP dataset (Hansen et al. 2010) produced by the Goddard Institute of Space Studies (GISS) at the National Aeronautics and Space Administration (NASA, with the base period: 1951–1980) and the MLOST data-set (Smith et al. 2008) provided by the National Climatic Data Center (NCDC) at National Oceanic and Atmospheric Administration (NOAA, with the base period: 1901–2000) are also used. The Extended Reconstructed Sea Surface Temperature V3b data-set (Smith et al. 2008), which has a horizontal resolution of 2° × 2°, covers the period from 1854 to 2015 and comes from NOAA, is also utilized to calculate the time series of annual averaged SATA with the base period from 1961 to 1990.

2.2. Ensemble empirical mode decomposition

To separate the components with different timescales consisting of the observed SATA series, the Ensemble empirical mode decomposition (EEMD) method is used (Wu and Huang 2009). The decomposition processes of the EEMD method are as follows:

1. Add a white noise series to the targeted data, \( X(t) \),

\[
X_j(t) = X(t) + W_j(t),
\]

where \( X(t) \) is the initial data, \( W_j(t) \) is the \( j \)th realization of the white noise series, and \( X_j(t) \) is the noise-added series and is utilized for the \( j \)th decomposition.

2. Decompose the data with added white noise into different components, which are referred to as the intrinsic mode functions (IMFs). The total number of IMFs of \( X(t) \) is close to \( \log_2 Y \), where \( Y \) is the length of \( X(t) \),

\[
X_j(t) = \sum_{k=1}^{n} c_{jk} + r_{jn},
\]

where \( c_{jk} \) and \( r_{jn} \) is the \( k \)th and the \( n \)th (the residue) component, respectively, in the \( j \)th decomposition.

3. Repeat step 1 and step 2 again and again, but with different white noise series added each time.

4. Obtain the ensemble means of corresponding IMFs of the decompositions as the final result,

\[
\bar{c}_j(t) = \lim_{x \to \infty} \frac{1}{N} \sum_{k=1}^{N} [c_{jk}(t)],
\]

where \( N \) is the ensemble size.

The IMFs are extracted level by level: first the highest-frequency local oscillations riding on the corresponding lower-frequency part of the data are extracted; second, the next level highest-frequency local oscillations of the residual of the data are extracted. This process continues until no complete oscillation can be identified in the residual. In short, the EEMD is an adaptive method that will decompose data, \( X(t) \), into several series components with different timescales from interannual, decadal, multidecadal, and centennial, \( c_j \), and a long-term trend, \( r_j \), i.e.
Define the residual component, $r_n$, as the overall adaptive trend ($R$), and consider the sum of $R$ and the components, which pass the 0.01 significance test based on the a posteriori test method proposed by Wu and Huang (2004), as the multidecadal trend (Wu and Huang 2004; Wu et al. 2007). During the process of decomposition, the white noise with a standard deviation of 0.2 was added in each EEMD ensemble member and an ensemble size of 1000 was utilized.

3. The spatial-temporal distribution of surface air temperature anomalies

The time series of the annual averaged SATA in the different datasets are shown in Figure 1. The global averaged SATA in 2015 is 0.74 °C warmer than the climatological mean for the 1961–1990 base period in the HadCRUT4 data-set (Figure 1(a)). It is the warmest year in the analysis period and is warmer than year 1998, which is the warmest year in the twentieth century. The averaged SATA over land and oceans in 2015 is 1.13 and 0.59 °C in the CRUTEM4 and HadSST data-set, respectively, both ranking the 1st warmest year. The datasets from NASA and NOAA reveal similar results (Figure 1).

The seasonal averaged SATA over the globe, land, and oceans from the HadCRUT4, CRUTEM4, and HadSST3 data-set, respectively, are shown in Figure 2. The global averaged SATA for the four seasons from winter 2014–2015 (i.e. December 2014 to February 2015) to autumn 2015 is 0.64, 0.68, 0.72, and 0.80 °C, respectively. All SATAs are ranked first. Compared with 1998, the global averaged SATA for the four seasons from winter to autumn is 0.09, 0.09, 0.1, and 0.44 °C cooler, respectively.

The magnitude of SATA over land is greater than that over oceans. The summer and autumn seasonal SATA over land in 2015 both rank first with an anomaly of 0.97 and 1.15 °C, whereas the winter and spring seasonal SATA both rank second with an anomaly of 1.14 and 1.03 °C, respectively. Over oceans, with the exception of winter 2014–2015, which ranks the third warmest year with an anomaly of 0.43 °C, the averaged SATAs during the three remaining seasons all rank first with an anomaly of 0.52, 0.63, and 0.71 °C, which may be related to the ongoing El Niño event.

Figure 3 shows a comparison of the spatial distributions of the year-averaged and seasonal-averaged SATAs of 2015 and 1998. In addition to a greater anomaly value over land than over ocean, the warmth at the higher latitudes is greater than the lower latitudes in 2015, especially north of 50°N, where the zonal mean of SATA exceeds 1.5 °C during the entire year, which is significantly higher than that of 1998. Regarding the different regions, the most prominent regions with warm anomalies include the central-western Eurasian continent, the western North America continent, the central-eastern tropical Pacific and the north-eastern Pacific with anomalies that range from 0.5 to 3.5 °C. Seasonally, the warm anomalies over the Eurasian continent and western North America are most evident during winter 2014–2015 and weaken in the subsequent seasons. Over oceans, warm anomalies are also observed in the central-eastern tropical Pacific and the north-eastern Pacific in spring 2015 and became enhanced and are spatially extended in the subsequent summer and autumn.

In comparison, the 1998 SATA over land is substantially warmer over the North American continent, especially during winter 1997–1998 and spring 1998, and significantly

$$X(t) = \sum_{j=1}^{n} c_j + r_n.$$ (4)
After the EEMD, seven components were isolated; their periodicities and the explained variance rates for the three time series are listed in Table 1. C1 and C2, which have visual periodicities in the range of 2–7 years, should reflect the ENSO signal, whereas C3 with a periodicity of approximately 11 years should reflect the solar cycle. Only C4–C6 reflect the variability from the decadal component to the multidecadal component (Wu et al. 2007; Qian et al. 2009; Wu and Huang 2009; Qian et al. 2011). A statistical test suggests that the fourth (C4), the fifth (C5), and the last (R) components, which were isolated from the time series of the annual averaged SATA over the globe and oceans, and the C5 and R, which were isolated from the time series of the annual averaged SATA over land, were at a 99% confidence level (Table 1). This finding suggests the importance of multidecadal and beyond components.

Thus, the several terms reflecting the different timescales, including a linear trend, the decadal (represented with a 9-yr running average), the overall adaptive trend (R in EEMD) and the multidecadal trend (the sum of R and the components that pass the 0.01 significance test) are plotted in Figure 4(a)–(d). A total of three terms (1850–1878, 1910–1944, and 1975–2015) with a warming tendency and two terms (1879–1909 and 1945–1974) with a cooling tendency are observed. When overlapped with the overall cooler over the northern Eurasian continent, especially during winter 1997–1998 and spring and autumn 1998 than the same seasons in 2015. Over oceans, significant warmth occurred in the central-eastern Pacific during winter 1997–1998 and weakened in the subsequent seasons, which differs from the warmth in 2015. The negative SATAs that occurred over the northern Pacific persisted during the four seasons of 1998, which is consistent with the anomalies in 2015.

4. Possible causes

In the above analysis, we discovered that the annual averaged SATA over the globe, land and oceans in 2015 were the warmest SATAs in the instrumental record. These three time series are analyzed to explain why 2015 is the warmest year. The EEMD method is employed to decompose one series into several series components with different timescales – interannual, decadal, multidecadal, centennial and a long-term trend – which are reflected in different terms ($C_i$: the $i$th component after EEMD) in Equation (4). Because the variations with different timescales can be traced to different physical reasons, this timescale decomposition may indicate the formation of the 2015 warmest anomaly.
patterns, which indicate cyclical variability on a shorter timescale than the overall adaptive trend, are observed (Wu et al. 2007). When the components from the decadal to centennial and the long-term trend are removed, the remaining SATAs in 2015 are not the warmest, which indicates a substantial contribution from the decadal to centennial components and beyond. The decadal background along with the global warming trend may both play important roles for the formation of the warmest SATA in 2015.

Figure 3. Comparison of the spatial distribution of the annual mean (the top row) and the seasonal mean of the SATA in four different seasons (from the second to the last row) in 2015 (left column) and 1998 (right column). The black curves in the right subpanel indicate the zonal mean. Units: °C.
Then, the magnitude of the SATA in 2015 was compared with the interannual noise based on the idea of signal-to-noise ratio. The noise is estimated as the standard deviation of the residual series when the components with the timescales beyond the interannual (including the decadal, multidecadal, centennial, and the overall adaptive trend) are removed. The results suggest that the magnitudes of the remaining SATAs in 2015 and 1998 that exceed one

Table 1. The periodicity (noted as 'P', units: year) and the explained variance rate ('Var', units: %) of the individual components derived by the EEMD method from the time series of the annual mean SATA over the globe ('Globe'), land ('Land'), and oceans ('Ocean').

| Components | Globe | Land | Ocean |
|------------|-------|------|-------|
|            | P     | Var  | P     | Var  | P     | Var  |
| C1         | 3.2   | 4.83 | 3.0   | 7.21 | 3.3   | 4.76 |
| C2         | 6.4   | 1.83 | 5.9   | 2.08 | 6.6   | 1.9  |
| C3         | 11.9  | 1.22 | 11.4  | 0.83 | 11.9  | 1.85 |
| C4         | 35.4  | 1.86 | 30.5  | 1.27 | 49.2  | 3.19 |
| C5         | 79.8  | 3.97 | 64.7  | 4.44 | 81.5  | 6.7  |
| C6         | 168.2 | 0.24 | 81.0  | 0.13 | 167.8 | 0.19 |
| R          | –     | 86.05| –     | 84.04| –     | 81.41|

Notes: The values in black bold text with none, single and double asterisks at the top-right corner indicate the significance of the component at a 99%, 95%, and 90% confidence level, respectively.

Figure 4. Left column: a comparison of the time series (black solid line) of the annual mean SATA over the (a) globe, (b) land, and (c) oceans and their various trends (red: the linear trend; green: the overall adaptive trend; blue: the multidecadal trend; and red: the 9-year running mean). Right column: the residual with the linear trend removed (red), the residual with the overall adaptive trend removed (green), and the residual with the multidecadal trend removed (blue). A value of 0.25 °C is added or subtracted to the red solid lines and blue solid lines, respectively, to improve the readability of the lines.
standard deviation can be treated as a signal, implying that the interannual components are also important.

El Niño typically contributes to an elevated global mean SATA (Lean and Rind 2008, 2009). In the EEMD, C1 and C2 reflect the ENSO-related signals. The sum of C1 and C2 was 0.10 °C in 2015, which suggests that the developing El Niño may contribute 0.10 °C to the global annual SATA in 2015. The value of 0.18 °C in 1998 indicates a substantial contribution from the strong El Niño event. A similar contribution value (0.2 °C) has been obtained in a previous study (Lean and Rind 2008). C3 represents the contribution from the 11-year periodic solar cycle of 0.04 and 0.01 °C in 2015 and 1998, respectively. In 2015, the components with the multidecadal timescales (C4–C6 with periodicities from 30.0 to 168.2 years) and the overall adaptive trend contribute a value of 0.09 and 0.32 °C. In 1998, the values are 0.03 and 0.32 °C, which are significantly smaller than the values in 2015, suggest that the multidecadal components have contributed a greater fraction to 2015 than 1998; the opposite situation occurs for the interannual components.

5. Summary

In the study, we confirmed that 2015 is the warmest year using several datasets. The annual SATA over the globe, land, and oceans were analyzed based on the CRU datasets; the results were compared with the results for 1998. Considering that the observed SATA consists of components with different timescales and may originate from various physical processes, the EEMD method was employed to decompose the SATA series and discuss the potential causes. The primary conclusions are summarized as follows:

(1) The global annual averaged SATA in 2015 is 0.74 °C warmer than the 1961–1990 base period. It is not only the warmest, but also 0.2 °C warmer than year 1998. In 2015, the annual averaged SATA is greater over high latitudes than low latitudes, over land than over oceans. Strong warmer SATAs occurred on the central Eurasian continent, the western North American continent, the central-eastern tropical Pacific Ocean, and the north-eastern Pacific Ocean.

(2) The roles of the different timescale components in 2015 are not the same as in 1998. The decadal and trend background may have played a more important role in 2015 than in 1998. The interannual components have contributed an anomaly value of 0.10 and 0.18 °C to the global annual SATA in 2015 and 1998, respectively. The decadal variability and beyond have contributed an anomaly value of 0.64 °C in year 2015, whereas the value was 0.36 °C in 1998.

(3) These results have important meaning for not only understanding the formation of the SATA in 2015, but also projecting the future trend of the warming hiatus in the beginning decade of the century because the contribution of the decadal-multidecadal variability and beyond to 2015 is much greater than that of the interannual components. This indicates that the developing El Niño is important to the formation of the warmest climate in 2015; however, it is not the primary factor. This evidence also suggests that the substantial importance of the decadal-multidecadal variability and beyond, and the potentially lower possibility of interannual external forcing, implying that substantial warming in years such as 2015 may occur more frequently and the ‘warming hiatus’ may be fading away.

The EEMD method was developed as a data-adaptive filter for nonlinear and nonstationary time series analysis (Wu and Huang 2009; Qian et al. 2011). It improves the efficiency of representing signals in data. However, it also has an ‘end effect’, which occurs near the ends where cubic spline fitting can have large swings and eventually propagate inward (Huang et al. 1998). Due to the ‘end effect’, the conclusions based on the EEMD method may require further validation.

Notes

1. http://www.climatecentral.org/news/2015-warmest-year-more-certain-19548.
2. http://www.thedailybeast.com/articles/2015/05/16/2015-is-the-hottest-year-on-record.html.
3. http://www.aljazeera.com/news/2015/11/2015-set-hottest-year-record-151125154306485.html.

Disclosure statement

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