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Characteristic Scales of Tropical Convection Based on the Japanese Advanced Himawari-8 Imager Observations

Jingchen Pu and Xiaolei Zou *

Joint Center of Data Assimilation for Research and Application, Nanjing University of Information Science and Technology, Nanjing 210044, China; 201883170043@nuist.edu.cn
* Correspondence: xzou@nuist.edu.cn

Abstract: Convective activities play an important role in tropical weather systems. To investigate the characteristic scales of convection, a method combining a principal component (PC) analysis with Fourier decomposition is applied to brightness temperature observations from Advanced Himawari-8 Imager (AHI). Characteristic scales of different modes in tropical convective systems are obtained. The explained variance reduces rapidly from the first to the 60th PC mode by two magnitudes; the horizontal scale decreases from over 2000 km to about 100 km, and the timescale changes from more than 4 days to around 5 h. By a detailed comparison of the first, 20th, 40th, and 60th PC modes, it is found that large-scale (over 2000 km in wavelength) convective activities usually have significant nocturnal enhancement, whereas meso-scale (about 100 km in wavelength) convective activities feature short period and fast change with more intense development in regions of active large-scale convection. This study may be of some importance for the choice of AHI data assimilation cycling interval, the horizontal resolution as well as data thinning for geostationary satellite observations.

Keywords: geostationary satellite; tropical convection; scale analysis; PCA; Fourier decomposition

1. Introduction

Most of the tropical weather phenomena, including precipitation, are closely related to the occurrence and development of convective clouds. In terrestrial areas, the convective systems are usually strong. They tend to be accompanied with thick clouds in different phases, strong vertical movements, and weather like lightning and heavy rain [1]. Such convective activities vary diurnally with large amplitude. The boundary layer instability caused by reinforced land surface radiative heating could strengthen vertical movements in the afternoon, resulting in convective cloud development and enhanced precipitation [2,3]. In marine areas, convective systems are relatively shallow [4]. Clouds over oceans show smaller diurnal variation than over land, with stratocumulus, cumulonimbus, and some other clouds peaking in early morning [2], and precipitation reaching its maximum at night [5]. There were several hypotheses for cloud and precipitation over oceans to have diurnal variations. Kraus (1963) [6] stated that the reduction of temperature at night leads to the enhancement of condensation and causes an increase in cloud cover at night. Xu and Randall (1995) [7] argued that cloud top absorbs solar radiation during daytime, which warms the upper troposphere, increases the stability, and inhibits the daytime convective activities, making the daytime convection relatively weaker than nighttime. Gray and Jacobson (1977) [8] suggested that convection-active regions have thicker clouds at night so that the low-level radiation cooling is weaker than that in the non-convection regions. The baroclinic circulation between the convection-active and nonactive regions, with convergence in convection-active area, enhances the nighttime cumulus activities. Over monsoonal regions, convective activities over land during monsoon-active periods exhibit oceanic characteristics and recovers to continental characteristics during the break periods [1].
Numerous studies have shown impacts of tropical convection on multiple weather systems. For examples, when coupled with wet convection, equatorial waves, such as Kelvin and mixed Rossby-gravity waves, would propagate slower than theoretical values [9]; shallow cumulus systems at the northern boundary of Indian summer monsoon could humidify the mid-tropospheric dry air, favoring north-westward monsoon progression [10,11]; and the eastward shift of tropical deep convection due to El Nino would further weaken the easterlies, strengthening El Nino [12]. Complex interactions exist among convective systems of different scales [13].

Past studies on tropical weather systems mostly focus on large-scale convective systems, such as tropical cyclones and typhoons [14,15]. An understanding of mesoscale convective systems (MCSs) and small-scale convection remains insufficient [16]. In terms of model simulation, Moncrieff et al. (2017) [17] pointed out that the upper bound of model resolution to treat MCSs explicitly is 10 km. Brunet et al. (2015) stated that it remains vital to do further research on the large-scale effects of convective systems in order to improve cumulus parameterization. Observational studies on tropical convection were mainly based on marine and/or land stations [6,8,18], balloon sounding [19], radar observations [20] and Tropical Rainfall Measuring Mission (TRMM) Precipitation Radar (PR) and microwave imager (TMI) observations [5].

Tropical convections occur at different scales. Due to limited resolution, traditional observations could not capture structural features of micro-scale and meso-scale systems, and some important signals may be treated as errors [21]. They are hardly effective for researches involving tropical convections at different scales. Geostationary satellites provide imager observations with high temporal and horizontal resolutions over the tropical areas. Therefore, satellite observations can better capture small-scale structures and rapid evolutions of mesoscale convective systems in the tropics. In this paper, spatial and temporal characteristics of tropical convections are investigated by applying a spatial and temporal scale analysis on Japanese Advanced Himawari-8 Imager (AHI) observations. Such a study has a potential value for determining the data assimilation cycling interval and horizontal resolution of geostationary satellite data assimilation. Although 6 h are usually selected [22], a data assimilation cycling interval that was chosen based on the actual time scale of physical variables could better preserve observation information and improve assimilation results [23]. Kain et al. (2008) [24] found that simply improving spatial resolution could not significantly improve the model prediction skills. Arakawa (2004) [25] pointed out that sub-grid scale systems that cannot be simulated explicitly can cause large errors in numerical models. These past studies suggest the importance of scale analysis on convective systems to improve simulation and assimilation of observations within these systems. When selecting the horizontal resolution and data assimilation cycling interval of forecast and assimilation systems, major scales of the tropical atmosphere should be considered.

This paper contains the following sections: Section 2 illustrates the characteristics of Himawari-8 satellite data and the method used for scale separation and analysis. Section 3 gives overall features of the first 60 principal component (PC) modes, which explain most of the data variances. Section 4 discusses in detail the spatial and temporal scales along with the changes of intensity in first, 20th, 40th, and 60th PC modes. Summary and conclusion are provided in Section 5.

2. Materials and Methods

2.1. AHI Observations

Himawari-8 is the first in the new generation of Japanese geostationary meteorological satellites. It was launched on 7 October 2014, and put into operation in July 2015. Himawari-8 satellite belongs to Japanese new generation of geostationary meteorological satellites. It is fixed at 140.7°E above the equator. The AHI imager onboard Himawari-8 has three visible, three near infrared, and 10 infrared channels. Compared with Multifunctional Transport Satellite (MTSAT) imager onboard the previous generation of Japanese geostationary
meteorological satellites, AHI features higher temporal and spatial resolution [26]. The three key technologies for AHI data assimilation: bias characteristic [27], cloud mask [28], and cloud detection [29], as well as impact of AHI data assimilation for short-term quantitative precipitation forecast [30] were studied.

AHI channel 13 is a window channel [26]. Its central wavelength is 10.45 µm. Observations of this channel over cloudy sky reflect the cloud top brightness temperature, and is often used to illustrate the convective cloud systems. With a spatial resolution of 2 km and a temporal resolution of 10 min at sub-satellite point and slightly larger away from the sub-satellite point, channel 13 provides sufficiently high-resolution observations for an investigation of the characteristic scales of tropical convection systems.

To illustrate the relationship between channel 13 observations and the actual convective activities, CLAVR-x is used to obtain the cloud products based on AHI observation field [31,32]. Figure 1 shows the cloud type and cloud mask generated by CLAVR-x, along with the brightness temperature of channel 13 and the albedo of channel 3. It is clear that channel-13 brightness temperature observations are sensitive to actual convection. The lower brightness temperatures (Figure 1a) correspond spatially to the area of higher albedo in channel 3 observation (Figure 1b), convective cloud (Figure 1c), and cloudy area (Figure 1d). Thus, brightness temperature observations of channel 13 captures the actual convective activities, and can be used for studying tropical convection.

This paper employs the AHI channel 13 observations from 0000 UTC 10 May 2021 to 2350 UTC 17 May 2021. This time period is arbitrarily chosen during which convection at different scales occurred (Figure 2). With a 10 min interval, there are a total of 1135 full-disk (no data at 0240 and 1400 every day, and there is a missing at 1800 UTC 17 May). Since this study focuses on tropical areas, we limit our study for the observations within an analysis region from 90°E to 170°W and from 20°S to 20°N (see the white box in Figure 1a). In order to facilitate analysis and calculation, the nearest neighboring method is applied to interpolate the brightness temperature observations at pixel points into the grid points at 0.1° × 0.1° resolutions. There are $M \times N$ ($M = 401$, $N = 1001$) grid points in the analysis region.

**Figure 1.** Cont.
Figure 1. (a) Brightness temperature observations of AHI channel 13 (10.45 µm), the white box indicates the data analysis region; (b) albedo observations of AHI visible channel 3 (0.65 µm); (c) AHI-derived cloud types, including clear (clr, cyan), fog (yellow), water (light green), supercooled water (scwt, green), opaque ice (op_ice, forest green), cirrus (orange), overlapping (overlap, blue), and overshooting (oversht, red); and (d) AHI-derived clear (clr), probably clear (prob_clr), probably cloudy (prob_cldy), and cloudy (cldy) pixels at 0000 UTC 13 September 2021. Black cross indicates the sub-satellite position.

2.2. PCA Method

Principal component analysis (PCA) [33] is a popular and useful method for decomposing complex data into orthonormal modes of different contribution to variations in data. For examples, it was applied in monitoring Madden Julian Oscillation (MJO) [34], and used for mitigating striping noise in Advanced Technology Microwave Sounder (ATMS) observations [35]. Since convection of different scales contribute differently to variations of AHI channel 13 observations, we use PCA method to extract the dominant variabilities in tropical convective systems.

Figure 2. Cont.
The data matrix is constructed as:

\[
A = \begin{pmatrix}
T_{b}^{obs}(1, 1) & \cdots & T_{b}^{obs}(1, T) \\
\vdots & \ddots & \vdots \\
T_{b}^{obs}(M \times N, 1) & \cdots & T_{b}^{obs}(M \times N, T)
\end{pmatrix}
\]  

where \( T_{b}^{obs}(k + M(j - 1), t) \) \((k = 1, 2, \ldots, M; j = 1, 2, \ldots, N; t = 1, 2, \ldots, T)\) represents the AHI observations of brightness temperature at the grid point \((k, j)\) and time \(t\), \(M\), and \(N\) are the total numbers of grid point in the south–north and west–east directions, respectively, \(T\) is the total number of observation times. Thus, \(K = M \times N\) is the total number of grid points at an observation time \(t\).

A \(K \times K\) squared symmetric data matrix \(S\) can be created based on matrix \(A\):

\[
S = AA^T
\]

The eigenvalues \((\lambda_i)\) and eigenvectors \((\vec{e}_i)\) \((i = 1, 2, \ldots, K)\) of matrix \(S\) can be calculated as follows:

\[
S \vec{e}_i = \lambda_i \vec{e}_i \quad (i = 1, 2, \ldots, K)
\]
where \( \vec{e}_i = (e_{1,i}, e_{2,i}, \ldots, e_{K,i})^T \) is the \( i \)th PC mode, \( \lambda_i \) is the explained data variance by \( \vec{e}_i \).

Equation (3) can be written in matrix form:

\[
SE = EA
\]

where

\[
\Lambda = \begin{pmatrix}
\lambda_1 & 0 & \cdots & 0 \\
0 & \lambda_2 & \cdots & 0 \\
\vdots & \vdots & \ddots & \vdots \\
0 & 0 & \cdots & \lambda_K
\end{pmatrix},
E = (\vec{e}_1, \vec{e}_2, \ldots, \vec{e}_K).
\]

Since \( \vec{e}_i \) \( (i = 1, 2, \ldots, K) \) are orthonormal with each other, we can get \( E^{-1} = E^T \). Thus Equation (4) can be written as:

\[
S = E\Lambda E^T
\]

By defining the PC coefficient matrix (U) as

\[
U = E^T \Lambda = \begin{pmatrix}
u_{1,1} & u_{1,2} & \cdots & u_{1,T} \\
u_{2,1} & u_{2,2} & \cdots & u_{2,T} \\
\vdots & \vdots & \ddots & \vdots \\
u_{K,1} & u_{K,2} & \cdots & u_{K,T}
\end{pmatrix} \triangleq \begin{pmatrix}
\vec{u}_1^T \\
\vec{u}_2^T \\
\vdots \\
\vec{u}_K^T
\end{pmatrix},
\]

we obtain the following expression for reconstructing the original data matrix from the eigenvectors \( \vec{e}_i \) and the PC coefficients \( \vec{u}_i \):

\[
A = EU = \sum_{i=1}^{K} \vec{e}_i \vec{u}_i^T.
\]

Here PC mode \( \vec{e}_i \) \( (i = 1, 2, \ldots, K) \) gives the spatial structure of the brightness temperature observations, PC coefficient \( \vec{u}_i \) \( (i = 1, 2, \ldots, K) \) represents the temporal structure of the observations, and \( \vec{e}_i \vec{u}_i^T \) is regarded as the \( i \)th PCA component. Subscript \( i \) are given according to the descending order of the eigenvalue \( \lambda_i \). The eigenvector/eigenvalue Equation (3) is solved with the Jacobi method [36,37].

2.3. Fourier Transform

Fourier transform is often used for decomposing original data into waves of different wavelengths and amplitudes. By doing so, complex observations can be separated into fluctuations of different scales and intensities, which makes it possible for the analysis of scales in the original observations. In our study, this method is applied for analyzing the temporal (one-dimensional) and spatial (two-dimensional) scale characteristics in different PCA components.

The discrete Fourier transform (DFT) for one-dimensional data \( x(j), (1 \leq j \leq N) \) is:

\[
F(k) = \frac{1}{N} \sum_{j=1}^{N} x(j)e^{-2\pi i jk},
\]

where \( i \) represents the imaginary unit, \( k \) is wavenumber. If \( N \) is odd, \( k \) would be \(-\frac{N-1}{2N}, -\frac{N-3}{2N}, \ldots, -\frac{1}{2}, 0, \frac{1}{2}, \ldots, \frac{N-3}{2N}, \frac{N-1}{2N}\) [38]. According to the orthogonality of trigonometric function, the inverse DFT (IDFT) for \( F(k) \) is expressed as:

\[
x(j) = \sum_{k=-\frac{N-1}{2N}}^{\frac{N-1}{2N}} F(k)e^{2\pi i jk}.
\]
The absolute value $|F(k)|$ is the amplitude of the wave with wavenumber $k$. Based on Equations (8) and (9), we obtain the spectrum of the original data $x(j)$. If $x(j)$ is real, $F(k)$ and $F(-k)$ are a conjugate pair, $|F(k)| = |F(-k)|$, and the imaginary part of the data is zero after the IDFT.

The DFT for two-dimensional data $x(m, n)$, $(1 ≤ m ≤ M, 1 ≤ n ≤ N)$ is expressed as:

$$F(k, l) = \frac{1}{MN} \sum_{n=1}^{N} \sum_{m=1}^{M} x(m, n)e^{-2\pi i(km+ln)}, \quad (10)$$

where $i$ is the imaginary unit, $k$ is the wavenumber in the west–east direction, and $l$ is the wavenumber in the south–north direction. The total numbers of grid points $M$ and $N$ in our study are odd numbers, $k = -\frac{M-1}{2M}, -\frac{M-3}{2M}, \ldots, -\frac{1}{M}, 0, \frac{1}{M}, \ldots, \frac{M-3}{2M}, \frac{M-1}{2M}$, and $l = -\frac{N-1}{2N}, -\frac{N-3}{2N}, \ldots, -\frac{1}{N}, 0, \frac{1}{N}, \ldots, \frac{N-3}{2N}, \frac{N-1}{2N}$. The coefficient $F(0,0)$ is kept in the center of the 2-D frequency plane by a periodic shift [38]. As a result, the wavenumber at the center of the frequency plane is 0 and gradually increases outward, which corresponds to an infinity wavelength at the center and gradually decreasing wavelengths going outward from the center. The IDFT is expressed as:

$$x(m, n) = \sum_{k=-\frac{M-1}{2M}}^{\frac{M-1}{2M}} \sum_{l=-\frac{N-1}{2N}}^{\frac{N-1}{2N}} F(k, l)e^{2\pi i(km+ln)}, \quad (11)$$

where $|F(k, l)|$ is the amplitude of the wave with wavenumbers $k$ and $l$. For real $x(m, n)$, $F(k, l)$ is conjugate with $F(-k, -l)$, and the imaginary part after IDFT is zero. In other words, $|F(k, l)|$ is centrosymmetric about $(0, 0)$ [38].

3. Numerical Results

Different PCA components are generated from AHI channel-13 observations of brightness temperature. The explained variance is 99.54% by the first PC mode, decreases rapidly with increasing number of eigenvector/eigenvalue, and is 0.001% by the 60th PC mode. PCA components with larger values of explained variance contribute more greatly to spatial and temporal variations in the original observations, and usually capture the dominant characteristic features in AHI data [36]. The PCA components with small explained variance might contain random errors. Meanwhile, based on the atmospheric scale definition by Orlanski [39], macro-scale motion often has large spatial scales (over 2000 km), long time duration (over a few days), and significant impacts on physical variables in the atmosphere; meso-scale motion usually has small spatial scales (2–2000 km) and short time duration (a few hours to a few days); and micro-scale motion features smaller spatial scales (less than 2 km) and time duration (less than an hour) with randomness in its occurrence and development. Accordingly, it can be inferred that PCA components with high explained variances correspond to macro-scale convective activities, while those with small explained variance correspond to meso-scale or even small-scale convective activities.

In this study, we focus mainly on the first 60 PCA components, which 99.94% of the total variance, to understand scale characteristics in AHI data. The sum of these PCA components ($\sum_{i=1}^{60} \vec{e}_{i} \vec{u}_{i}$) and its differences from the original observations are shown in Figure 3, which can be compared with the original observations of brightness temperature shown in Figure 2a. The first 60 PCA components capture most features of convective variabilities in AHI data. The sum of the first 60 PCA components has larger-scale variations, and well preserves the structure of convection. The differences (Figure 3b) between the sum of the first 60 PCA components (Figure 3a) and the original data (Figure 2a) are an order of magnitude smaller than the sum, and are of a random distribution over convective active regions.
In order to examine quantitatively the scale changes of PCA components 1–60, we generate their characteristic scales based on the two-dimensional waves using the Fourier transform described in Section 2.3. Wave components with large amplitudes represent the scales of PCA components. The large-amplitude first few PCA components in turn represent dominant characteristics of the original data. The so-called harmonic mean of wavelengths is used to reflect the characteristic scales, which is defined as:

$$L^* = \frac{1}{N} \sum_{A > \sigma A_{\text{max}}} f_A,$$

where $L^*$ is the characteristic scale, $A$ represents wave amplitude, $A_{\text{max}}$ is the maximum amplitude of all waves, $f_A$ represents the wavenumber with amplitude of $A$, $\sigma$ is an empirical parameter whose value is between 0 and 1, and $N$ is the number of waves with amplitudes $A > \sigma A_{\text{max}}$. The summation in (12) is carried out for the wavenumbers of all waves whose amplitudes are greater than $\sigma A_{\text{max}}$. This characteristic scale $L^*$ synthesizes features of multiply significant fluctuations, and is used to quantitatively describe the scale of a particular PCA component. If $L^*$ is generated with waves in a certain direction instead of all the waves in the spectrum, it can also be applied to analyzing features of scales in that direction. Of course, the choice of $\sigma$ is important.

The value of parameter $\sigma$ is chosen in such a way to ensure that $f_{A > \sigma A_{\text{max}}}$ are representative of most variations in the first 60 PCA components. To choose a proper value of $\sigma$, the standard deviations of $f_{A > \sigma A_{\text{max}}}$ for all fields of PCA components 1–60 are first calculated and then averaged. As is shown in Figure 4, the standard deviations of all PCA components and the average STD decrease most rapidly as $\sigma$ increases from zero to 0.1. The higher the PCA mode number, the larger the standard deviations are. When $\sigma > 0.2$, the variations

\[\text{Figure 3. Horizontal distributions of (a) the sum of the PCA components 1–60 and (b) differences between the sum and the original brightness temperature observations at 1500 UTC 10 May 2021. The local time at the corresponding longitude is indicated at the top of the figure panel. (c) The sum and (d) the difference along 3°N (the black line in (a,b)).}\]
of both the standard deviations and the gradient of the average STD with respect to \( \sigma \) are slow. The threshold of \( \sigma \) is chosen in such a way that not only wavenumbers with too low amplitudes are excluded to prevent noise, but also enough wavenumbers are included to avoid inadequate wave samples. Therefore, we choose \( \sigma = 0.2 \). The corresponding standard deviation is \( 14.47 \times 10^{-4} \text{ km}^{-1} \). Once the value of parameter \( \sigma \) is chosen, the characteristic scales \( L^* \) of all PCA components 1–60 can be generated according to (12).

Figure 4. Variations of standard deviations (STDs) of wavenumbers whose amplitudes are greater than \( \sigma A_{\text{max}} \) with respect to \( \sigma \) for each of PCA components 1–60 (thin solid colored curves), the average variation of the 60 STDs (thick solid black curve), and the gradient of the averaged STD (thick dotted black curve). The STD curve of the first, 20th, 40th, and 60th PCA component is indicated by the thick red, magenta, orange, and cyan curve, respectively. The chosen value of threshold at 0.2 (thin dotted black line) is also indicated.

Variations given by two-dimensional Fourier decomposition in each PCA component are shown in Figure 5. Variations of wave amplitudes with regard to wavelength in PCA components 1–60 are given in west–east direction (Figure 5a), 45° direction (Figure 5b), south–north direction (Figure 5c), and the azimuth average (Figure 5d). The directions of waves are selected in 2-D frequency plane, and the azimuth averaged wavelength is calculated as \( L = L_x L_y / \sqrt{L_x^2 + L_y^2} \), where \( L_x \) is meridional wavelength, \( L_y \) is latitudinal wavelength. Quadratic mean is applied for the amplitudes of waves with the same wavelength (\( L \)) but in different directions. Comparison among Figure 5a–d reveals that from the first to the 60th PCA component, the wavelengths of waves with large amplitude gradually decrease. This suggests that the dominant wavelengths in PCA components reduces as the PCA number increases, and thus the corresponding convective motion scales are also reduced. The averaged spectrum in Figure 5d seems smoother than that in one direction because it contains waves in all directions.
Figure 5. Variations of the spectrum of PCA components 1–60 ($\vec{e}_i, \vec{u}_i, i = 1, \ldots, 60$) in (a) zonal direction, (b) $45^\circ$ direction, (c) meridional direction, as well as (d) the azimuthally averaged spectrum at 1500 UTC 10 May 2021 (color shading). The amplitude is divided by the maximum amplitude in the same PCA component. Also shown are the characteristic scales (black solid curve) and explained variances (dashed curve) of each of the 60 PCA components.

The characteristic scales and the explained variances of the first 60 PCA components are also given in Figure 5. They are generated with waves in certain directions (Figure 5a–c) and all the waves (Figure 5d) in the PCA components. It is clear that from the first to the 60th PCA component, the characteristic scales tend to decrease gradually from over 2000 km (macro scale according to Orlanski) to nearly 100 km (meso scale). The decrease rate is in general similar to that of the explained variance. Moreover, there are some distinguishable differences of the characteristic scales of waves among different directions. For example, characteristic scales in the zonal direction are greater than those in the meridional direction for most PCA components. In conclusion, there are obvious differences in the scales of different PCA components. The PCA components of large explained variances correspond to macro-scale convective activities, while these of small explained variances correspond to
meso-scale convective activities. Convective activities have the largest characteristic scales in the zonal direction.

4. Temporal and Spatial Scales of the First, 20th, 40th, and 60th PCA Components

In this section, we further illustrate the data features in more details by examining the first, 20th, 40th, and 60th PCA components, whose characteristic scales are 2386, 560, 224, and 167 km, respectively.

The spatial distributions of the first, 20th, 40th, and 60th PC modes are shown in Figure 6. Values of the first PC mode (Figure 6a) along 5°N and south of 10°S between 150°E–170°W are significantly lower than that in the extra-equatorial area beyond 10°N or 10°S between 90°–150°E. This indicates that macro-scale convective activities develop vigorously along 5°N and south of 10°S between 150°E–170°W, which is an obvious characteristic of intertropical convergence zone (ITCZ) and south Pacific convergence zone (SPCZ). In addition, the convection scales gradually decrease from mode 20, 40, to 60. In these three PC modes, the changes of values in ITCZ and SPCZ are much more intense than those in other regions. This reveals that meso-scale features of convective systems are more active over the regions of macro-scale convective activities. This is similar to the results of Salby et al. (1991) [40]. They have pointed out that the standard deviation of brightness temperature observations in ITCZ is larger than other areas, indicating that convective systems there are more active.

![Figure 6. Horizontal distributions of (a) the first, (b) the 20th, (c) the 40th, and (d) the 60th PC modes (i.e., \( \vec{e}_1 \), \( \vec{e}_{20} \), \( \vec{e}_{40} \), and \( \vec{e}_{60} \)) of the AHI brightness temperature observations.](image)

The first, 20th, 40th, and 60th PC coefficients (\( \vec{u}_1 \), \( \vec{u}_{20} \), \( \vec{u}_{40} \), and \( \vec{u}_{60} \)), and their one-dimensional Fourier transform results are shown in Figure 7. Since the average of original brightness temperature observation is not 0, the magnitude of the first PC coefficient is large. There are eight small peaks in the first PC coefficient capturing the diurnal variation of convective activities. It is noted that values of the first PC coefficient are lower during the night hours, indicating that brightness temperature observations are lower at night, and macro-scale convection features an obvious nocturnal enhancement. Meanwhile, the
amplitudes of the 20th, 40th, to 60th PC coefficients decrease while their frequency increase significantly.

Figure 7. The first (black), 20th (blue), 40th (green), and 60th (red) PC coefficients and their spectra. (a) shows the values of PC coefficients, where $\vec{u}_1$ corresponds to the right axis, others correspond to the left axis, and the horizontal axis represents 0000 local time of the corresponding date in May at 135°E; and (b) shows the spectra of these PC coefficients.

These characteristic frequencies can be more obviously seen in terms of power spectrum density (PSD) (Figure 7b). Despite the low-frequency component with a period of over 100 h (four days), the spectrum of the first PC coefficient also has an obvious peak near the period of 24 h. Moreover, frequency at which the PSD reaches the maximum value increases from the first to the 60th PC coefficient, corresponding to a reduction in time period from more than 100 h (four days) to about 5 h. This indicates that major components in these four PC coefficients have increased frequency, which is consistent with the temporal oscillations shown in Figure 7a.

Since the PCA method decomposes the original observation into two parts: PC coefficients $\vec{u}_i$ and PC modes $\vec{e}_j$, their physical meanings are not intuitive. Therefore, we restore each PCA component ($\vec{e}_j \vec{u}_i^T$) based on these PC coefficients and modes. The brightness temperature of each PCA component at different times and their two-dimensional DFT results will also be shown.

We select 0100 and 1200 local times on 11 May 2021 for showing these PCA components. The selected times are shown in Figure 8. It is noted that values of the first PC coefficient at 0100 are relatively small due to the diurnal variation. The AHI observations of brightness
temperature and their first, 20th, 40th, and 60th PCA components at the two selected times are shown in Figure 9. Their two-dimensional spectra are shown in Figure 10 with zero-wavenumber coefficient $F(0, 0)$ at the center. These figures shall illustrate more clearly the temporal and spatial variations of different PCA components.

![Figure 8. Variation of PC coefficients 1 (black), 20 (blue), 40 (green), 60 (red) with time and the selected times (black dotted line). $u_1$ corresponds to the right axis, others correspond to the left axis. The horizontal axis represents the local time at 135°E on 11 May 2021. The black dotted lines represent the time used in the following PCA component diagrams (Figures 9 and 10).](image)

The observed brightness temperatures can vary from lower than 200 to more than 300 K (Figure 9a,f). The horizontal distributions of the first PCA component are smoother than observations, and its variation range is about 50 K (Figure 9b,g), which is much less than that of the observations. Although the differences between the first PCA component at 0100 and 1200 local times are relatively small, it is obvious that the first PCA component of brightness temperature is lower at night. However, the 20th, 40th, and 60th PCA components at 0100 local time (Figure 9c–e) differ significantly from those at 1200 local time (Figure 9g–i). Meanwhile, disturbances in horizontal distributions of the 20th, 40th, and 60th PCA components show decreasing scales.

Scale features can be seen more clearly in the spectra of the fields shown in Figure 9 using Fourier transform. The spectra of original observations at 0100 and 1200 local times are shown in Figure 10a,f, respectively. In these two spectra, the amplitude reduces from more than 100 at zero wavenumber to about 0.01 at wavelength 23 km near the boundary of the frequency plane. In the spectra of the first PCA component, the amplitude reduces to nearly 0.001 when the wavelength becomes shorter than 100 km, which is why the first PCA component in Figure 9b,g are much smoother than observations in Figure 9a,f. For the first PCA component, large amplitudes are concentrated in the low-frequency region near the center of spectrum, revealing that the dominant waves in the first PCA component have wavelengths around and longer than 2000 km. Thus, the first PCA component represents the macro-scale features of convection. Differences of the spectra of the first PCA component between 0100 and 1200 local times are small. However, there are differences in the spectra of the 20th, 40th, and 60th PCA components between the two times (Figure 10c–e,h–j), which is consistent with the features in Figure 9. In these three PCA components, wavelengths of larger amplitude gradually decrease. In the 20th PCA component, the waves of the maximum amplitude being greater than 0.1 K have wavelengths around 1000 km (Figure 10h). In the 60th PCA component, the maximum amplitude of the waves is about 0.01 K, and the corresponding wavelengths are around 100 km (Figure 10j). In conclusions, the first PCA component mainly reflect the macro-scale features of convection, characterized by large amplitudes in spatial distributions and slow changes in time. The 20th, 40th, and 60th PCA components illustrate the meso-scale convective features with small amplitudes and fast variations.
Figure 9. (a,f) The AHI observations of brightness temperature, (b,g) the first, (c,h) the 20th, (d,i) the 40th, and (e,j) the 60th PCA components ($\hat{\mathbf{e}}^i, \hat{\mu}^i, i = 1, 20, 40, \text{and } 60$) at 1600 UTC 10 May 2021 (left panels) and 0300 UTC 11 May 2021 (right panels). The local time at the corresponding longitude is indicated at the top of the figure.
Figure 10. The two-dimensional spectra of (a,f) the AHI observations of brightness temperature, (b,g) the first, (c,h) the 20th, (d,i) the 40th, and (e,j) the 60th PCA components ($\hat{e}_i^T$, $i = 1, 20, 40, \text{and} 60$) at 1600 UTC 10 May 2021 (left panels) and 0300 UTC 11 May 2021 (right panels).
5. Summary and Conclusions

We use first the PCA method to decompose the tropical convective systems captured by AHI observations of brightness temperature into eigenvector modes of different spatial scales, and then the Fourier transform to generate the characteristic scales of the first 60 PCA components. AHI observations of brightness temperature during an eight-day period at 10-min interval are employed in this study. The result shows that the first 60 PCA components capture not only the macro-scale but also the meso-scale features of convective activities. The explained variances are large (small) for the macro-scale (meso-scale) PCA components. The spatial and temporal scales decrease from more than 2000 km and four days for the first PCA component to about 100 km and five hours for the 60th PCA component. Moreover, a comparison of the first, 20th, 40th, and 60th PCA components shows that the macro-scale convective activities usually have significant nocturnal enhancement of convection; whereas meso-scale convective activities tend to coexist with active macro-scale convection such as ITCZ and/or SPCZ.

The study on the scales of tropical convective systems is important and has potential value for AHI data assimilation. We will assess how the scale analysis impacts the data assimilation system in the future. Depending on the resolutions of data assimilation experiments, fast-changing, high-frequency components of the tropical convective systems may be treated as noise in data assimilation systems. Considering that most tropical disturbances have a fast rate of initiation, development, and disappearance, future work will also (1) develop an optimal data thinning method for AHI data assimilation; (2) take advantage of the nearly time continuous observations to study convective initiation, hurricane genesis and organization of convection; and (3) compare all-sky radiative transfer model simulations of brightness temperature based on input numerical weather prediction model forecasts with AHI observations to see if the characteristic scales of model forecasted convective activities are consistent with those in AHI observations.

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