1. Introduction

Differential phase $\Phi_{DP}$ is a parameter observed by polarimetric weather radar, and this parameter is the difference between the propagation phase shift of horizontally and vertically polarized waves as the waves propagate through precipitation (Bringi and Chandrasekar 2001). Because $\Phi_{DP}$ is insensitive to radar calibration errors and precipitation attenuation, it plays a significant role in meteorological applications.

$\Phi_{DP}$ is a very useful parameter when correcting propagation effects at shorter radar wavelengths, because the propagation effects induce attenuation and differential attenuation throughout the radar echo volume (Bringi et al. 1990; Aydin and Giridhar 1992; May et al. 1999; Carey et al. 2000). The specific differential phase $K_{DP}$ derived from the range derivative of $\Phi_{DP}$ along a radial is closely related to rain intensity and has largely been applied to more accurate estimations of rainfall and raindrop size distribution (Balakrishnan and Zrnić 1990; May et al. 1999; Brandes et al. 2001; Maki et al. 2005; Bringi et al. 2006; Silvestro et al. 2009; Matrosov et al. 2013; Adachi et al. 2015; Boodoo et al. 2015).

Since raindrops are oblate and have a minor axis oriented vertically in the mean, $\Phi_{DP}$ in the rain gener-
ally exhibits a monotonically increasing trend within a particular range. However, $\Phi_{DP}$, which is measured by polarimetric weather radar, is easily contaminated, resulting in both positively and negatively biased $K_{DP}$ values and greatly degrading the usefulness of $\Phi_{DP}$ and $K_{DP}$. Previous studies showed that the contamination of $\Phi_{DP}$ and biases in $K_{DP}$ are commonly manifested as both gate-to-gate fluctuations and perturbations within a distance much greater than a range gate (or on a 10-km scale) along the radial direction. In this study, the former will be referred to as high-frequency range fluctuations and the latter as low-frequency range perturbations. The identification and removal of these high-frequency range fluctuations and low-frequency range perturbations in $\Phi_{DP}$ and $K_{DP}$ remain challenging issues.

High-frequency range fluctuations in $\Phi_{DP}$ originate from the statistical variance of the $\Phi_{DP}$ measurement and are commonly induced by both nonmeteorological echoes and differential backscatter phase $\delta$. Nonmeteorological echoes stem from targets, such as ground clutter, sea clutter, chaff, biological scatter, clear air echoes, and so on. These targets produce highly variable $\Phi_{DP}$ values. Ryzhkov and Zrnić (1998b) found that the combined use of thresholds of the copolar cross-correlation coefficient $\rho_{HV}$ and the standard deviation of $\Phi_{DP}$ can notably remove nonmeteorological noises. Their method for removing nonmeteorological echoes has largely been applied to the quality control of polarimetric radar measurements. Algorithms based on fuzzy logic can also be successfully applied to distinguish between meteorological and nonmeteorological radar echoes (Gourley et al. 2007; Moisseev and Chandrasekar 2009; Chandrasekar et al. 2013; Krause 2016).

On the other hand, $\delta$ is attributed to non-Rayleigh scatter and becomes more significant at shorter radar wavelengths (Bringer and Chandrasekar 2001), which can often induce high-frequency range fluctuations in $\Phi_{DP}$ and greatly affect the accuracies of $\Phi_{DP}$ and $K_{DP}$. An effective method for removing the undesirable effect of $\delta$ was proposed by Hubbert and Bringer (1995), where an iterative filtering technique was employed along the range direction. Recently, Maesaka et al. (2012) and Giangrande et al. (2013) proposed methods with a monotonicity constraint on $\Phi_{DP}$ to remove high-frequency range fluctuations from phase measurements. As indicated by Hubbert and Bringer (1995), $\delta$ can also extend over many range gates, resulting in perturbed $\Phi_{DP}$ and biased $K_{DP}$ within longer distances along the radial direction.

Low-frequency range perturbations in $\Phi_{DP}$ and the effects of these perturbations were described in detail by Ryzhkov and Zrnić (1998a). They revealed evidence from both the modeling and observational investigations that negatively biased $K_{DP}$ can appear on both sides of a rain cell in the range direction if the $\Phi_{DP}$ profile used to estimate the $K_{DP}$ is perturbed by nonuniform beam filling (NBF). Negatively biased $K_{DP}$ on both sides of a rain cell may be accompanied by a positively biased $K_{DP}$ near the center of the cell. The perturbation of $\Phi_{DP}$ induced by NBF was also found by Ryzhkov and Zrnić (1998a) in regions with large cross-beam gradients around strong reflectivity. The perturbed $\Phi_{DP}$ exhibited a spurious oscillatory behavior with a wavelength of approximately 14 km in the range direction. Such a low-frequency range perturbation in $\Phi_{DP}$ resulted in a biased $K_{DP}$ with similar oscillatory behavior, leading to biases in the $K_{DP}$-based rain rate estimates. As indicated by Ryzhkov (2007), enhanced attenuation can also increase the gradient of reflectivity and induce the NBF-related perturbation in $\Phi_{DP}$. Some studies have also investigated the detailed impacts of NBF on the qualities of polarimetric variables, both theoretically and experimentally (Gorgucci et al. 1999; Gosset 2004; Ryzhkov 2007). Gorgucci et al. (1999) revealed that the $K_{DP}$ bias induced by NBF can be both positive and negative, and this bias increases with increased reflectivity variation along the range direction. Simple formulas have been developed to theoretically estimate $\Delta\Phi_{DP}$, which is the perturbation of $\Phi_{DP}$ induced by NBF due to large cross-beam gradients of reflectivity (Ryzhkov 2007; Ryzhkov and Zrnić 2019). The correlation between the radial profiles of $\Phi_{DP}$ and $\Delta\Phi_{DP}$ is high when $\Phi_{DP}$ is perturbed by NBF. As will be presented in Sections 3 and 5 of this study, $\Phi_{DP}$ and $K_{DP}$ contaminated by second-trip echoes also show significant low-frequency range perturbations along the radial direction. Specifically, second-trip echoes can induce spurious $\Phi_{DP}$ and $K_{DP}$ with considerably greater magnitudes than those induced by NBF.

Although several methods have been developed to detect and remove spurious $\Phi_{DP}$ and $K_{DP}$ with high-frequency range fluctuations, few studies have addressed the identification and removal of low-frequency range perturbations in $\Phi_{DP}$ and $K_{DP}$. Particularly, as will be presented in Sections 3 and 5 of this study, the methods developed to handle high-frequency range fluctuations in $\Phi_{DP}$ and $K_{DP}$ may not be suitable for the detection and removal of the spurious $K_{DP}$ resulting from the low-frequency range perturbations of $\Phi_{DP}$.

The purpose of this study was to develop an algorithm to detect low-frequency range perturbations
in the range profiles of $\Phi_{DP}$ and $K_{DP}$ measured in the rain by C-band polarimetric radar. The algorithm, which is applied after the removal of high-frequency range fluctuations in $\Phi_{DP}$, is a threshold filter based on an empirical relationship between $K_{DP}$ and the radar reflectivity factor at horizontal polarization $Z_H$ for raindrops. In Section 2, the data used to construct and validate the algorithm and data preprocessing are described. In Section 3, the features of the spurious low-frequency range perturbations in $\Phi_{DP}$ and $K_{DP}$ are illustrated. Details of the algorithm development are presented in Section 4. In Section 5, the algorithm’s performance is investigated, and finally, a summary and discussion are presented in Section 6.

2. Data and preprocessing

In this study, the data measured by the polarimetric radar on board the research vessel Mirai were used to illustrate the characteristics of spurious $\Phi_{DP}$ and $K_{DP}$ with low-frequency range perturbations. These data were also utilized to develop and validate the algorithm to detect the spurious $\Phi_{DP}$ and $K_{DP}$.

The Mirai polarimetric radar is a C-band weather radar that has been under operation since the summer of 2014 (Katsumata 2014). This radar uses a solid-state transmitter and has been developed by employing advanced semiconductor and pulse compression techniques (Wada et al. 2009; Anraku et al. 2013). The major specifications of the Mirai polarimetric radar are presented in Table 1.

The data used in this study were observed by the Mirai polarimetric radar around 4.067°S, 101.9°E at an elevation of 0.5° from 23 November to 17 December 2015, when a pilot field campaign of the Years of the Maritime Continent (YMCI) project was conducted in the Indian Ocean (Yokoi et al. 2017). As presented in Fig. 1, the observational area is part of a tropical rainy region near Sumatra in Indonesia. The time interval, azimuthal resolution, range resolution, and maximum range of the data used to develop the algorithm were 6 min, 0.7°, 150 m, and 150 km, respectively. The data were obtained by using a pulse of 1-μs width before and 64-μs width after the range of 12 km. At the same time, a dual-pulse repetition frequency (PRF) (667/833 Hz) mode was employed to extend the range of the Nyquist velocity interval. Low-level plan position indicator (PPI) scans were also performed with a low PRF (400 Hz) every 30 min. Data from these low-PRF scans have an unambiguous range greater than 300 km and were used as the supplemental material for the identification of second-trip echoes.

Before analyzing the spurious $\Phi_{DP}$ and $K_{DP}$ with low-frequency range perturbations and developing the algorithm to detect the perturbations, the observed parameters were processed as follows. The initial $\Phi_{DP}$ measurements were performed to remove the system offsets and correct aliased data using the method of Wang and Chandrasekar (2009). Similar to previous studies (e.g., Ryzhkov and Zrnić 1998b), nonmeteorological echoes, such as ground and sea clutter, were detected and removed based on thresholds of $\rho_{HV}$ and the areal standard deviation of $\Phi_{DP}$, and these thresholds were set to 0.65° and 40°, respectively. These values were determined experimentally by analyzing the observed data for various precipitation events. The standard deviation of $\Phi_{DP}$ was computed in a box consisting of three pixels in the azimuthal direction and nine pixels in the range direction. Similar to previous
studies (e.g., Katsumata et al. 2008; Boodoo et al. 2015), echoes with low values of the signal quality index (SQI) have also been removed. The SQI threshold used in this study was set to 0.3. Some second-trip echoes can be removed by applying the thresholds of \(\rho_{HV}\) and SQI. However, as will be shown in Sections 3 and 5 of this study, considerable second-trip echoes still remained undetected. The dual-PRF technique used to reduce second-trip echoes (e.g., Katsumata et al. 2005) has not been employed in this study.

Occasionally, radar observables were contaminated with the presence of other ships. Those ship-contaminated data have been identified and removed manually. The contribution of \(\delta\) within \(\Phi_{DP}\) was then removed by applying the iterative finite impulse response (FIR) filtering technique of Hubbert and Bringi (1995). The FIR filtering process was repeated 10 times by using the same coefficients of the FIR as those of Hubbert and Bringi (1995).

After removing the high-frequency range fluctuations induced by nonmeteorological echoes and \(\delta\) from \(\Phi_{DP}\), \(K_{DP}\) was calculated based on the slope of a least-squares fit of the filtered profile of \(\Phi_{DP}\) over a range interval of 1.5 km. The range interval utilized here corresponds to a light filter for the estimation of \(K_{DP}\) (Ryzhkov and Zrnić 1996; Wang and Chandrasekar 2009). Notably, although the light filter for the \(K_{DP}\) estimation is useful for high spatial resolution, the light filter may induce larger standard errors in \(K_{DP}\) if there are errors in the estimation of \(\Phi_{DP}\).

The high-frequency range fluctuations in \(\rho_{HV}\) and \(Z_{H}\) were then removed using the same filter as that of Hubbert and Bringi (1995). Next, \(\rho_{HV}\) was corrected for noise using the signal-to-noise ratio (Schuur et al. 2003). The attenuation of \(Z_{H}\) was corrected using \(\Phi_{DP}\). The linear \(\Phi_{DP}\) method was applied owing to its simplicity (e.g., Bringi et al. 1990). An attenuation correction coefficient of 0.072 dB per degree was utilized, which was experimentally determined by applying the correcting method of Carey et al. (2000) to the observed data. To reduce the undesirable effect of the contaminated \(\Phi_{DP}\), the attenuation correction of \(Z_{H}\) was repeated three times with the detection and removal of spurious \(\Phi_{DP}\). The impact of attenuation on the algorithm developed in this study has been examined. Before the application of attenuation correction, some relatively high \(K_{DP}\) values may be misjudged as spurious data in areas where enhanced attenuation of \(Z_{H}\) occurred. Such a defect has been resolved by performing the above attenuation correction process (not shown). The range derivatives of \(K_{DP}\) and \(Z_{H}\), which have been used in the algorithm developed in this study, were also calculated based on the slope of the least-squares fit of their profiles over a range interval of 1.5 km.

The \(\Delta \Phi_{DP}\) value was calculated based on Eq. (6.73) of Ryzhkov and Zrnić (2019):

\[
\Delta \Phi_{DP} = 0.02\theta_{i}^{2} \left( \frac{d \Phi_{DP}}{d \theta} \frac{d Z_{H}}{d \theta} + \frac{d \Phi_{DP}}{d \varphi} \frac{d Z_{H}}{d \varphi} \right),
\]

where \(\theta_{i}\) is the 3-dB beamwidth, \(\theta\) is the elevation, and \(\varphi\) is the azimuth. In Eq. (1), \(\Delta \Phi_{DP}\), \(\theta\), and \(\varphi\) are in degrees, whereas \(Z_{H}\) is in dBZ. The calculation of \(\Delta \Phi_{DP}\) was performed using the data from a PPI scan, assuming that there were no vertical gradients. The azimuthal gradient of \(\Phi_{DP}\) or \(Z_{H}\) at a grid was calculated utilizing the data on each side of the grid. Although \(\Delta \Phi_{DP}\) calculated in this way may underestimate the magnitude of intrinsic perturbations in \(\Phi_{DP}\), this method could be used to qualitatively ascertain the impact of NBF.

Although the Mirai radar antenna is operated by compensating for the attitude angles of the ship so that data can be obtained at a ground-relative elevation and azimuth of designation, the effects of ship movement on the polarization plane remained uncorrected. However, Thurai et al. (2014) found that the effects of ship movement are tolerable if the canting angle of the drop’s symmetry axis relative to the polarization plane is less than 10–15°. In fact, the sea was calm when the data used in this study were obtained, with the maximum and mean canting angles of the data being 3.43° and 0.37°, respectively. More than 99% of the total data have canting angles below 1.5°, which is much smaller than the tolerable canting angle revealed by Thurai et al. (2014). Therefore, the polarization plane remained as observed, and the correction method of Thurai et al. (2014) for ship movement has not been applied in this study.

3. Features of spurious \(\Phi_{DP}\) and \(K_{DP}\) with low-frequency perturbations

An analysis of the observed data revealed that the low-frequency range perturbations of \(\Phi_{DP}\) and \(K_{DP}\) exhibit distinct signatures. These signatures will be illustrated in this section based on a low-elevation scan from the Mirai polarimetric radar.

As an example, Fig. 2 presents the horizontal distributions of \(Z_{H}\) and \(K_{DP}\) observed at a 0.5° elevation angle for 1930 UTC 25 November 2015. The precipitation system presented in Fig. 2 was generally of intermediate intensity. In some regions, a \(Z_{H}\) value greater than 44 dBZ and a \(K_{DP}\) value greater than
1° km$^{-1}$ were observed. As indicated by the light purple color in Fig. 2b, prominent features in the $K_{DP}$ field were the dozen pockets of large negative $K_{DP}$ values recognized on the west and northwest sides of the radar.

The characteristics of spurious $\Phi_{DP}$ and $K_{DP}$ can be seen more clearly in Fig. 3, which presents the range profiles of the radar observables in three directions, along lines A1, A2, and A3, as depicted in Fig. 2. Notably, for the data used in Fig. 3, the high-frequency range fluctuations in $\Phi_{DP}$ have already been removed, and then, the $K_{DP}$ has been derived. Most of the low-frequency range perturbations in $\Phi_{DP}$ can be attributed to the effect of second-trip echoes or NBF. The arrows in the top panels of Fig. 3 indicate some of these perturbations in $\Phi_{DP}$.

Figure 3a presents the range profiles along line A1. A 20° jump in $\Phi_{DP}$ is evident in the range of approximately 50 km to 55 km. Then, $\Phi_{DP}$ returns to nearly the value before the jump and begins a generally monotonic increase from a range of 60 km. Corresponding to the jump and resumption of $\Phi_{DP}$, $K_{DP}$ exhibited a maximum (greater than 2° km$^{-1}$) and a minimum (less than −3° km$^{-1}$) before a range of 60 km. The values of the maximum and minimum $K_{DP}$ appear to be unrealistic and inconsistent with the intensity of the $Z_H$ (below 22 dBZ) observed in the same segment. Consequently, the $\Phi_{DP}$ jump is spurious and results in an unrealistic $K_{DP}$.

The $\Phi_{DP}$ jump from its local mean trend occurred where relatively weak echoes below 22 dBZ were observed (Fig. 3a). There was no such jump in the $\Phi_{DP}$ profile obtained from the low-PRF scan during the nearest time. These facts suggest that the jump and resumption of $\Phi_{DP}$ could be attributed to the contamination of second-trip echoes from rain located beyond the maximum range of 150 km (Fig. 2c). Because the $\Phi_{DP}$ measured by the polarimetric radar is cumulated along the range direction, the jump of $\Phi_{DP}$ as shown above could be attributed to the fact that second-trip echoes originate from rain outside the unambiguous range, which possesses higher $\Phi_{DP}$ than that related to rain within the unambiguous range.

A sharp drop and restoration in the SQI and $\rho_{HV}$ were observed in the segment contaminated by the second-trip echoes (Fig. 3a). The values of the SQI and $\rho_{HV}$ dropped as low as 0.3 and 0.86, respectively, near the range of 55 km, where second-trip contaminated $\Phi_{DP}$ reached its maximum value. However, it is evident that the spurious $\Phi_{DP}$ and $K_{DP}$ induced by the second-trip echoes in the range of approximately 50 to 60 km could also be accompanied by relatively high intensity of $Z_H$ (below 22 dBZ).
SQI and $\rho_{HV}$ values. Second-trip echoes with high SQI and $\rho_{HV}$ values were also observed in other studies (e.g., Park et al. 2016). Thus, using only SQI and $\rho_{HV}$ thresholds may not be effective for the elimination of the second-trip contamination from $\Phi_{DP}$ and $K_{DP}$.

In addition, the second-trip contamination induced an inconsistent variation between $K_{DP}$ and $Z_H$ along the range direction. The change in $K_{DP}$ measured in the rain is positively correlated with that of $Z_H$. However, Figure 3a shows that overall, the rapid increase in $K_{DP}$ in ranges from approximately 45 to 53 km occurred with a decrease in $Z_H$, whereas the sharp decrease in $K_{DP}$ in ranges from approximately 53 to 58 km was associated with an increase in $Z_H$. Notably, values of spurious $K_{DP}$ were close to $0^\circ$ km$^{-1}$ near the range of 55 km, where relatively weak echoes below 20 dBZ were observed.

Another perturbation in the $\Phi_{DP}$ profile along line A1 was found at distances over 135 km (Fig. 3a). The perturbation of $\Phi_{DP}$ resulted in negatively biased $K_{DP}$ in ranges from approximately 135 to 145 km. $K_{DP}$ exhibited a minimum (less than $-1^\circ$ km$^{-1}$) near the range of 140 km, where $Z_H$ was close to 35 dBZ. As seen from Fig. 2, line A1 passed through the periphery of a reflectivity core stretching approximately along the radar beam at far distances from the radar. Consequently, relatively large cross-beam gradients of reflectivity could exist along line A1. Figure 3a shows that the magnitude of $\Delta\Phi_{DP}$ increased from approximately 120 km. An increase or a decrease in $\Phi_{DP}$ was generally in agreement with that in $\Delta\Phi_{DP}$ at far distances from the radar. As seen from Fig. 3a, a noticeable decrease in $\rho_{HV}$ occurred from the range of 120 km. These facts suggest that the perturbation in $\Phi_{DP}$ and unrealistic $K_{DP}$ at distances over 135 km could be attributed to NBF due to large cross-beam gradients of reflectivity (e.g., Ryzhkov 2007).

The range profiles along line A2 are presented in

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**Fig. 3.** Range profiles (from left to right) along lines (a) A1, (b) A2, and (c) A3, as presented in Figs. 2a and 2b, for $\Phi_{DP}$ (top panels, black curves), $\Delta\Phi_{DP}$ (upper middle panels), $K_{DP}$ (middle panels), $Z_H$ (lower middle panels, black curves), $\rho_{HV}$ (black curves), and SQI (green curves) (bottom panels). In the top and lower middle panels, the range profiles of $\Phi_{DP}$ and $Z_H$ (chartreuse curves) from the low-PRF scan presented in Fig. 2c are supplemented. The arrows in the top panels designate some regions where spurious perturbations of $\Phi_{DP}$ were observed.
Fig. 3b. Line A2 passed through a reflectivity core centered at a distance of 110 km. In ranges from approximately 100 km to 116 km, perturbations in $\Phi_{\text{DP}}$ induced $K_{\text{DP}}$ to have a negative minimum in front of and behind the reflectivity core, respectively, which is consistent with the results of Ryzhkov and Zrnić (1998a) and could be attributed to the NBF effects. Figure 3b shows that NBF can also induce an inconsistent variation between $K_{\text{DP}}$ and $Z_{\text{H}}$ along the range direction. In fact, the decrease in $K_{\text{DP}}$ in ranges from approximately 100 to 102 km occurred with the increase in $Z_{\text{H}}$. In contrast, the increase in $K_{\text{DP}}$ in ranges from approximately 116 km to 120 km occurred with the decrease in $Z_{\text{H}}$.

The perturbation of $\Phi_{\text{DP}}$ along line A2 also occurred in ranges from approximately 120 km to 130 km, which induced both positive (as high as $1.5^\circ$ km$^{-1}$) and negative (as low as $-1.5^\circ$ km$^{-1}$) biased $K_{\text{DP}}$ in areas of $Z_{\text{H}}$ at approximately 30 dBZ. Notably, line A2 passed through the periphery of another reflectivity core, and the magnitude of $\Delta \Phi_{\text{DP}}$ increased in ranges between 120 and 130 km (Figs. 2a, 3b), which indicates that the $\Phi_{\text{DP}}$ perturbation and the associated spurious $K_{\text{DP}}$ along line A2 at far distances from the radar could also be attributed to NBF (e.g., Ryzhkov 2007).

Figure 3c presents the range profiles along line A3. Perturbations in $\Phi_{\text{DP}}$ occurred before the range of 75 km. Such perturbations were not found in the $\Phi_{\text{DP}}$ profile obtained from the low-PRF scan during the nearest time, which suggests that the $\Phi_{\text{DP}}$ perturbations before the range of 75 km could be attributed to the contamination of second-trip echoes from rain located beyond the maximum range of 150 km (Fig. 2c). Similar to the second-trip contamination presented in Fig. 3a, spurious jumps of $\Phi_{\text{DP}}$ from the local mean trend and pairs of unrealistically positive and negative $K_{\text{DP}}$ are evident in Fig. 3c before the range of 75 km. In the segment contaminated by the second-trip echoes, $K_{\text{DP}}$ showed spurious maximum values of more than $3^\circ$ km$^{-1}$ and spurious minimum values of less than $-1.5^\circ$ km$^{-1}$ in areas with a $Z_{\text{H}}$ intensity of below 15 dBZ. The spurious $\Phi_{\text{DP}}$ and $K_{\text{DP}}$ induced by the second-trip echoes were also associated with a sharp drop in but relatively high values of SQI and $\rho_{\text{HV}}$.

The $K_{\text{DP}}$ biases were further statistically investigated. Figure 4 presents the scatterplot of $K_{\text{DP}}$ versus $Z_{\text{H}}$ from the low-level scan, as presented in Figs. 2a and 2b. The dashed curve in Fig. 4 is generated by a best fit to $\log(K_{\text{DP}})$ and $Z_{\text{H}}$ based on a linear regression analysis. Figure 4 reveals that $K_{\text{DP}}$ and $Z_{\text{H}}$ were clustered around the best fitting curve. In areas with $Z_{\text{H}}$ values below 40 dBZ, some data significantly deviated and were outside the major cluster, which could be attributed to the $K_{\text{DP}}$ biases of both signs, as seen from Fig. 3. In contrast, Fig. 4 also reveals that in areas with $Z_{\text{H}}$ values above 40 dBZ, the $K_{\text{DP}}$ and $Z_{\text{H}}$ were clustered more tightly around the best fitting curve, with a much smaller deviation from the major cluster. This fact suggests that $K_{\text{DP}}$ is less noisy in the high-$Z_{\text{H}}$ areas. The observational results in Fig. 4 are consistent with the conclusion of Ryzhkov and Zrnić (1996), indicating that deviations due to processing noise prevail in the low-$Z_{\text{H}}$ areas, whereas meteorological variability, such as the variability of drop size distribution (DSD), dominates scatter in the high-$Z_{\text{H}}$ areas.

In summary, the analyses presented above reveal that after the removal of high-frequency range fluctuations in $\Phi_{\text{DP}}$, the low-frequency range perturbations of $\Phi_{\text{DP}}$ can remain. Second-trip echoes and NBF could be two sources of low-frequency range perturbations in $\Phi_{\text{DP}}$. The low-frequency range perturbations in $\Phi_{\text{DP}}$ can induce spurious $K_{\text{DP}}$ that may show significantly positive and negative biases on the best fitting curve between $\log(K_{\text{DP}})$ and $Z_{\text{H}}$. Moreover, the spurious $K_{\text{DP}}$ may also have a range variation inconsistent with that of $Z_{\text{H}}$. These signatures facilitate the development of an algorithm to identify both spurious $\Phi_{\text{DP}}$ and unrealistic $K_{\text{DP}}$.

4. Algorithm development

4.1 Grand design

As presented in Fig. 4, $K_{\text{DP}}$ may increase logarithmically with $Z_{\text{H}}$, as measured in the rain by the Mirai C-band polarimetric radar. Such an empirical relationship between the $K_{\text{DP}}$ and $Z_{\text{H}}$ has also been previously noted via observational studies and scattering simulations for C-band polarimetric radar (Aydin and Giridhar 1992; Carey et al. 2000; Bringi et al. 2001). According to Aydin and Giridhar (1992), the empirical relationship between $K_{\text{DP}}$ and $Z_{\text{H}}$ in the rain can be expressed as follows:

$$ Z_{\text{H}} = a \times \log(K_{\text{DP}}) + b, $$

(2)

where $Z_{\text{H}}$ is in dBZ and $K_{\text{DP}}$ is in $^\circ$ km$^{-1}$. Two coefficients, $a$ and $b$, can be obtained using the least-squares method.

Ryzhkov and Zrnić (1996) have suggested that the spurious values of $K_{\text{DP}}$ can be recognized by examining the scattergrams of $K_{\text{DP}}$ versus $Z_{\text{H}}$. They noted that “bad” data points are outside “good” data points in the scattergrams of $K_{\text{DP}}$ versus $Z_{\text{H}}$, which was also observed in this study (Fig. 4). Based on their sugges-
an objective function is used to identify spurious \( \Phi_{DP} \) and \( K_{DP} \).

The algorithm developed in this study processes radar observables on an individual radial basis. To obtain the objective function, Eq. (2) is changed into an exponential form:

\[
K_{DP} = 10^{-a K_{DP}^{b} Z_H}
\]  

(3)

The member on the right-hand side of Eq. (3) can be considered as the empirical \( K_{DP} \) estimated from \( Z_H \). In addition, the range derivative of Eq. (2) is obtained, which results in the following:

\[
K_{DP} \frac{\partial K_{DP}}{\partial r} = K_{DP} \frac{\partial Z_H}{\partial r},
\]  

(4)

where \( r \) is in km.

The objective function, \( F \), is determined to contain three variables, which can be expressed as follows:

\[
F = \frac{R_a + R_e}{N}
\]  

(5)
In Eq. (5), the variable $R_A$ is used to regulate the magnitude of $F$ for all measured data. The variable $R_K$ is designed to further regulate the magnitude of $F$ in a distinct $K_{DP}$ area, where spurious $K_{DP}$ cannot be sufficiently detected by $R_A$. The values of $R_A$ and $R_K$ are set to 0 if the measured $K_{DP}$ and $Z_{HI}$ are positioned along both empirical curves defined by Eqs. (3) and (4). The values of $R_A$ and $R_K$ are augmented for possibly spurious $K_{DP}$ deviating significantly from either of the empirical curves defined by Eqs. (3) and (4). $N$ represents a normalization factor with respect to $Z_{HI}$. $F$ is designed as a dimensionless quality. The dimensionless $F$ is obtained simply by dividing each of the variables used in $F$ by 1 with an identical unit, which will not be shown explicitly in this study.

$F$ has been determined experimentally according to the signatures of the spurious $\Phi_{DP}$ and $K_{DP}$ revealed in Section 3. A threshold of $F$ is then used to detect spurious $K_{DP}$. As shown in Fig. 3, the correlation between the low-frequency perturbations of $\Phi_{DP}$ and the spurious values of $K_{DP}$ was high. As a result, spurious $\Phi_{DP}$ can be detected simultaneously with the detection of spurious $K_{DP}$.

4.2 Objective function design

a. Definition of $R_A$

$R_A$ is used to evaluate deviations for all measured data and is defined as follows:

$$R_A = \left(1 + \frac{D_1}{\rho_{HV}}\right)^{1.5} \times \left(1 + \frac{D_2}{\rho_{HV}}\right) \times \left(1 + \frac{D_3}{\rho_{HV}}\right) - 1. \quad (6)$$

$R_A$ has utilized the multiplication of $D_1-\overline{D}_3$. As shown below, $D_1-\overline{D}_3$ are the measured $K_{DP}$ and $Z_{HI}$ deviations from the empirical curve defined by Eq. (3) or Eq. (4). The magnitude of $R_A$ is also inversely correlated with that of the squared $\rho_{HV}$ based on the observation that the values of $\rho_{HV}$ often decrease in the region associated with spurious $\Phi_{DP}$ and $K_{DP}$ (Fig. 3).

1) $D_1$

$D_1$ is calculated according to the formula

$$D_1 = \left[K_{DP} - 10^{\frac{Z_{HI} - a}{a}}\right]. \quad (7)$$

$D_1$ is the measured $K_{DP}$ and $Z_{HI}$ deviation from the empirical curve defined by Eq. (3), which facilitates the identification of the spurious $K_{DP}$ deviating from the empirical $K_{DP}$ as estimated from $Z_{HI}$. The effectiveness and limitation of $D_1$ in detecting spurious $K_{DP}$ have been examined. As presented in Figs. 4a and 4b, a lower threshold of $F$ is required for using only $D_1$ to detect spurious $K_{DP}$ values in low-$Z_{HI}$ areas. On the other hand, the lower threshold of $F$ results in overdetection of spurious data in the high-$Z_{HI}$ areas. Therefore, $D_2$ is designed to facilitate in the identification of spurious $K_{DP}$ values in the low-$Z_{HI}$ areas while retaining quality measures of $K_{DP}$ in the high-$Z_{HI}$ areas.

2) $D_2$

$D_2$ is calculated according to the formula

$$D_2 = \left[\frac{D_2}{\rho_{HV}}\right]^{a/b}. \quad (8)$$

$D_2$ utilizes the ratio of $D_1$ to the empirical $K_{DP}$ estimated from $Z_{HI}$, which allows the magnitude of $D_2$ to increase with a decrease in $Z_{HI}$. This ratio also varies in accordance with $a$ and $b$, with the ratio value tending to be larger with smaller $a$ and larger $b$ for the $K_{DP}$ measured at the same $Z_{HI}$. Such variation can be compensated for by using an exponent $a/b$ in Eq. (8). Figure 4c shows that after the supplement of $D_2$, the spurious values of $K_{DP}$ in low-$Z_{HI}$ areas can be detected effectively. However, some spuriously small or negative $K_{DP}$ values in the high-$Z_{HI}$ areas still remained undetected.

3) $D_3$

Figure 3a shows that spurious $\Phi_{DP}$ around the range of 55 km can induce spurious $K_{DP}$ close to 0° km⁻¹ in regions with relatively weak echoes. Such spuriously small $K_{DP}$ associated with weak echoes can hardly be identified using only $D_1$ and $D_2$ (Fig. 5a), because it is located near the empirical curve defined by Eq. (3), with values of $D_1$ and $D_2$ close to 0.

$D_3$ is designed to overcome the above restriction, which is calculated according to the formula

$$D_3 = \left[\rho_{AI} \times \frac{\partial K_{DP}}{\partial r} - |K_{DP}| \times \frac{\partial Z_{HI}}{\partial r} \right]^{0.5} \times \left[\frac{1 + \left|\frac{\partial K_{DP}}{\partial r}\right|}{1 + a \times D_1 \times 10^{0.5 a}} + \frac{1 + \left|\frac{\partial K_{DP}}{\partial r}\right|}{1 + a \times D_2 \times 10^{0.5 a}}\right]. \quad (9)$$

The design of $D_3$ has utilized the observational fact seen from Fig. 3, which shows that spurious $K_{DP}$ may have a range variation inconsistent with that of $Z_{HI}$. On the right-hand side of Eq. (9), the absolute value represents the deviation of the measured range derivatives of $K_{DP}$ and $Z_{HI}$ from the empirical curve defined.
by Eq. (4). As indicated by the numerator within the parentheses on the right-hand side of Eq. (9), $D_3$ is designed to be proportional to the magnitude of the range derivative of $K_{DP}$. Such a design is based on the observational fact seen from Fig. 5a, which shows that the spurious $\Phi_{DP}$ and $K_{DP}$, which are shown in red, was tested by setting $D_1$ and $R_k$ to 0 and the threshold of $F$ to 8. The arrows indicate the region where the spurious $\Phi_{DP}$ and $K_{DP}$ remained undetected. (b) Same as (a), but for setting $R_k$ to 0 and the threshold of $F$ to 8 and using $D_3$, as expressed by Eq. (9). (c) Scatter-plot of $K_{DP}$ versus $Z_H$ at an elevation of 0.5° for 1624 UTC 28 November 2015. The dashed curve was obtained by a least-squares fit to log($K_{DP}$) and $Z_H$. The identification of the spurious $K_{DP}$, which is shown in red, was tested by setting $N$ to 1 and the threshold of $F$ to 8. Horizontal distributions of $Z_H$ and $K_{DP}$ are presented in Figs. 7b and 8b, respectively. (d) Same as (c), but for setting the threshold of $F$ to 8 and using $N$, as expressed by Eq. (11).

Fig. 5. (a) A segment of range profiles along line A1 presented in Figs. 2a and 2b for $\Phi_{DP}$ (top panels) and $K_{DP}$ (bottom panels). The detection of the spurious $\Phi_{DP}$ and $K_{DP}$, which are shown in red, was tested by setting $D_1$ and $R_k$ to 0 and the threshold of $F$ to 8. The arrows indicate the region where the spurious $\Phi_{DP}$ and $K_{DP}$ remained undetected. (b) Same as (a), but for setting $R_k$ to 0 and the threshold of $F$ to 8 and using $D_3$, as expressed by Eq. (9). (c) Scatter-plot of $K_{DP}$ versus $Z_H$ at an elevation of 0.5° for 1624 UTC 28 November 2015. The dashed curve was obtained by a least-squares fit to log($K_{DP}$) and $Z_H$. The identification of the spurious $K_{DP}$, which is shown in red, was tested by setting $N$ to 1 and the threshold of $F$ to 8. Horizontal distributions of $Z_H$ and $K_{DP}$ are presented in Figs. 7b and 8b, respectively. (d) Same as (c), but for setting the threshold of $F$ to 8 and using $N$, as expressed by Eq. (11).

by Eq. (4). As indicated by the numerator within the parentheses on the right-hand side of Eq. (9), $D_3$ is designed to be proportional to the magnitude of the range derivative of $K_{DP}$. Such a design is based on the observational fact seen from Fig. 5a, which shows that the spurious $K_{DP}$ remaining undetected by applying only $D_1$ and $D_2$ may vary rapidly in the range direction.

Since $D_3$ is used to further facilitate the identification of spuriously small $K_{DP}$ values located close to the empirical curve defined by Eq. (3), it is designed to be inversely proportional to the magnitudes of $D_1$, $D_2$, and $K_{DP}$, as expressed by the denominators within the parentheses on the right-hand side of Eq. (9). As a result, the magnitude of $D_3$ decreases when the magnitudes of $D_1$, $D_2$, and $K_{DP}$ increase, allowing $D_3$ to have a smaller effect on the realistic, large $K_{DP}$ values deviating from the empirical curve defined by Eq. (3). Figures 5a and 5b indicate that with the supplement of $D_3$, the remaining spurious $\Phi_{DP}$ and $K_{DP}$ after applying only $D_1$ and $D_2$ can be detected effectively.
b. Definition of $R_K$

As presented in Fig. 4c, if only $R_a$ which utilized the multiplication of $D_1-D_3$, is applied to the detection of spurious $K_{dp}$, some spuriously small or negative $K_{dp}$ values in the high-$Z_{hi}$ areas remain undetected. $R_K$ is designed to overcome this restriction, and $R_K$ is defined as follows:

$$R_K = 0,$$

for $K_{dp} \geq 10^{(Z_d-h)/a}$,

$$R_K = \left[ 1 + \frac{D_1}{(1+D_2) \times p_{iv}} \times 10^{-\min(0.1-K_{dp})/5} \right] - 1,$$

for $K_{dp} < 10^{(Z_d-h)/a}$.

(10)

As seen from Eq. (10), $R_K$ is applied only to those $K_{dp}$ values that are less than the empirical $K_{dp}$ estimated from $Z_d$. $R_K$ has utilized the ratio of $D_1$ to $1+D_2$ based on the fact that the magnitude of $D_1$ increases with a decrease in $Z_d$. As a result, $R_K$ can effectively identify the spurious $K_{dp}$ in the high-$Z_{hi}$ areas that cannot be detected using only $R_a$, whereas $R_K$ has a smaller effect on the low-$Z_{hi}$ areas (Figs. 4c, d). Since $R_K$ is used to further facilitate in the identification of spuriously small and negative $K_{dp}$, the exponential expression of Eq. (10) is designed to allow the magnitude of $R_K$ to decrease with an increase in $K_{dp}$ above 1.0° km⁻¹. As a result, $R_K$ has a smaller effect on the realistic, large $K_{dp}$ in the high-$Z_{hi}$ areas. The effectiveness of the supplement of $R_K$ in detecting spurious $K_{dp}$ can be seen by comparing Fig. 4c with Fig. 4d.

The algorithm designed in this study is intended for retaining the negative $K_{dp}$ that may be statistically significant. Ryzhkov and Zrnić (1996) noted that after the removal of high-frequency fluctuations in $\Phi_{dp}$, negative $K_{dp}$ can stem from statistical noise at low rain rates or from low-frequency perturbations of $\Phi_{dp}$. They emphasized that these negative $K_{dp}$ values need to be treated differently. Negative $K_{dp}$ associated with spurious $\Phi_{dp}$ should be removed. However, to avoid bias at low rain rates, a statistically significant negative $K_{dp}$ is necessary for $K_{dp}$-based rainfall estimates. The magnitudes of statistically significant negative $K_{dp}$ values are small. Ryzhkov and Zrnić (1998a) suggested the removal of negative $K_{dp}$ values if the values are below $-1°$ km⁻¹. As presented in Fig. 4d, the algorithm developed in this study can effectively identify and remove negative $K_{dp}$ values below $-1°$ km⁻¹.

c. Definition of $N$

$N$ normalizes $F$ with respect to $Z_{hi}$ and is defined as follows:

$$N = 1 + \left( \frac{Z_d-h}{10} \right)^2.$$  

(11)

Figure 4 shows that $K_{dp}$ becomes less noisy with increases in $Z_{hi}$. As noted by Ryzhkov and Zrnić (1996), meteorological variability, such as the variability in drop size distribution, dominates scatter in the high-$Z_{hi}$ areas. Figure 5c shows that if $F$ is not normalized with respect to $Z_{hi}$ (i.e., $N = 1$), it means that there were large amounts of quality measures of $K_{dp}$ misjudged as spurious data in the high-$Z_{hi}$ areas. The normalization factor $N$ is experimentally designed to allow for $K_{dp}$ and $Z_{hi}$ scatter due to meteorological variability in the high-$Z_{hi}$ areas remaining unaffected as much as possible. As expressed on the right-hand side of Eq. (11), the magnitude of $N$ is designed to vary in accordance with the second power of the empirical $K_{dp}$ estimated from $Z_{hi}$. The effectiveness of $N$ in retaining variations and quality measures of $K_{dp}$ in the high-$Z_{hi}$ area can be seen by comparing Fig. 5c with Fig. 5d.

4.3 Procedures for applying the algorithm

Coefficients $a$ and $b$, as presented in Eq. (2), are first obtained via a linear least-squares fit to log($K_{dp}$) and $Z_{hi}$. Data from a PPI scan are used for the above statistical process. Notably, both $a$ and $b$ contain implicit information on the microphysics of rain, which varies with time. To reflect such variations, $a$ and $b$ are statistically calculated from each PPI scan.

An adequate number of radar observables in the high-$Z_{hi}$ areas are necessary for $a$ and $b$ to be properly retrieved. The minimum number of data points required for the statistical calculation of $a$ and $b$ in the high-$Z_{hi}$ areas has been tested by utilizing the observed data. Coefficients $a$ and $b$ can be properly retrieved if the number of data with $Z_{hi}$ values greater than 45 dBZ is greater than 5000. For a PPI scan with fewer data points in the high-$Z_{hi}$ areas, pseudo-data were added between 45 and 65 dBZ, utilizing the $a$ and $b$ that were retrieved from the latest PPI scan with a sufficient number of data points in the high-$Z_{hi}$ areas. As will be presented in Section 5, by using such a pseudo-data approach, the algorithm can efficiently detect and remove spurious $\Phi_{dp}$ and $K_{dp}$ values observed from weak precipitation.

After the coefficients $a$ and $b$ have been determined, $F$ is calculated according to Eq. (5), and spurious $\Phi_{dp}$ and $K_{dp}$ values are then identified using a threshold of $F$. However, unlike $a$ and $b$, the threshold of $F$ appears to be independent of precipitation system types. In this study, the threshold of $F$ is set as 8.0. By using such a threshold of $F$, spurious data can be detected,
whereas quality data, especially those with high $Z_{H}$ values, remain unaffected as far as possible (Fig. 6a). A detailed validation of the algorithm’s performance will be presented in Section 5.

The threshold of $F$ used in this study was determined by comparing the scatterplots and range profiles of the polarimetric radar variables before and after the applications of the algorithm. At first, the threshold of $F$ was determined approximately by examining the scatterplots of $K_{DP}$ versus $Z_{H}$ (Fig. 6). One of the decisive factors in determining the threshold of $F$ is that quality measures of $K_{DP}$ need to be less affected by applying the algorithm. Figure 6c indicates that a lower threshold of $F$ results in overdetection of spurious data. As stated previously, $K_{DP}$ is less noisy in the high-$Z_{H}$ areas, where meteorological variability dominates (Ryzhkov and Zrnić 1996). Quality measures of $K_{DP}$ prevail in areas with $Z_{H}$ values above 40 dBZ, and the selected threshold of $F$ ought to retain these quality data as much as possible. Another decisive factor in determining the threshold of $F$ is that an acceptable accuracy for $K_{DP}$ observed in light rain or low-$Z_{H}$ areas, where meteorological variability is less dominant and $K_{DP}$ becomes very noisy (Ryzhkov and Zrnić 1996), needs to be obtained after the application of the algorithm.

The statistical accuracy of $K_{DP}$ can be evaluated using the standard deviation of $K_{DP}$, which has been calculated based on the expression of Balakrishnan and Zrnić (1990) and Carey et al. (2000)

$$SD(K_{DP}) = \frac{\sqrt{3}SD(\Phi_{DP})}{n^\frac{1}{2}}\Delta,$$

(12)

where $SD(K_{DP})$ and $SD(\Phi_{DP})$ are the standard deviations of the $K_{DP}$ and $\Phi_{DP}$ at each range gate, respectively, $n$ is the number of range gates used to calculate $K_{DP}$ (10 in this study), and $\Delta$ is the range gate spacing (0.15 km in this study). The standard deviation of $\Phi_{DP}$ was computed using a range interval of 1.5 km.

As discussed by Bringi and Chandrasekar (2001), the acceptable value of $SD(\Phi_{DP})$ for accurate $K_{DP}$ estimation is around 2°, or lower. Based on Eq. (12), if $SD(\Phi_{DP}) = 2°$, then $SD(K_{DP}) = 0.73°$ km$^{-1}$. Accordingly, it is determined that the selected threshold of $F$ ought to reduce the values of $SD(K_{DP})$ to less than 0.73° km$^{-1}$ for light rain with $Z_{H}$ values below 30 dBZ. As presented in Figs. 6e and 6f, a higher threshold of $F$ results in both underdetection of spurious $K_{DP}$ and an increase in $SD(K_{DP})$ in the low-$Z_{H}$ areas. By using the selected threshold of $F$, the values of $SD(K_{DP})$ in the low-$Z_{H}$ areas have been improved (Fig. 6b). An improvement of $SD(K_{DP})$ for all the observed data can be seen from Fig. 19b.

A final decision on the threshold of $F$ was made with the supplementary examination of range profiles of the polarimetric radar variables. As presented in Figs. 3, 5a, and 5b, the range variation of spurious $\Phi_{DP}$ often deviates from the mean trend of genuine $\Phi_{DP}$, whereas spurious $K_{DP}$ may have a range variation inconsistent with that of $Z_{H}$. These signatures make it easier to discriminate between spurious and genuine $\Phi_{DP}$ and $K_{DP}$. Therefore, the performance of the selected threshold of $F$ can be evaluated more precisely through the examination of range profiles of the observed data.

5. Validation

In this section, the algorithm’s performance will be investigated through the application of the algorithm to the observed data used in this study, and the observed data contain information for a variety of precipitation systems (Yokoi et al. 2017). Detailed examinations were conducted for three selected precipitation events, which cover the major modes of convective organization in the observational area. These events were observed on 28 November, 11 December and 15 December 2015. A validation using all the observed data was also conducted.

5.1 The 28 November 2015 event

Figure 7 presents the horizontal distributions of $Z_{H}$ observed at a 0.5° elevation angle on 28 November 2015. On this day, synoptic-scale disturbances were not observed. Precipitation had been initiated over land in the afternoon (LST = UTC + 7 h) and propagated westward away from the coast. At 1154 UTC (Fig. 7a), a rainband nearly parallel to the coast was observed by the Mirai radar over the offshore regions. The rainband propagated further westward and evaporated by 1624 UTC into a loosely organized precipitation system over the ocean (Fig. 7b).

The horizontal distributions of $K_{DP}$ measured at a 0.5° elevation angle simultaneously with $Z_{H}$ are presented in Fig. 8. Before the application of the algorithm (Figs. 8a, b), large negative values of $K_{DP}$, which are indicated by the light purple color, can be recognized on the west and northwest sides of the radar. The horizontal distributions of $K_{DP}$ after the application of the algorithm are presented in Figs. 8c and 8d, which indicate that the spurious $K_{DP}$ seen from Figs. 8a and 8b can be identified and removed, whereas the genuine $K_{DP}$ is less affected.

The ability and accuracy of the algorithm can be
Fig. 6. (a–b) Scatterplots of $K_{DP}$ versus $Z_{\theta}$ (left panel) and $SD(K_{DP})$ versus $Z_{\theta}$ (right panel) at an elevation of 0.5° for 1930 UTC 25 November 2015. The dashed curve was obtained by a least-squares fit to log ($K_{DP}$) and $Z_{\theta}$. The spurious $K_{DP}$, which is shown in red, was detected by the algorithm presented in this study by setting the threshold of $F$ to 8. (c–d) Same as (a–b), but for setting the threshold of $F$ to 3. (e–f) Same as (a–b), but for setting the threshold of $F$ to 20.
verified in detail in Fig. 9, which shows the range profiles along lines B1–B3, as illustrated in Figs. 7 and 8. In Fig. 9, the spurious $\Phi_{DP}$ and $K_{DP}$ values detected by the algorithm are shown in red.

The profiles of $\Phi_{DP}$ and $K_{DP}$ along line B1 are presented in Fig. 9a. By comparing the $\Phi_{DP}$ profile with that from the low-PRF scan during the nearest time, the $\Phi_{DP}$ profile could have been contaminated by second-trip echoes before the range of 95 km. The second-trip echoes originated from precipitation in the far northwest, as presented in Fig. 7c. The jumps and resumptions of $\Phi_{DP}$ due to the second-trip echoes were much more apparent in ranges from approximately 20 km to 35 km and from approximately 45 km to 65 km, respectively. Each jump in $\Phi_{DP}$ was accompanied by a sharp drop in SQI and $\rho_{HV}$. The second-trip echoes induced both positively and negatively biased $K_{DP}$, reaching as high as $4.5^\circ \text{km}^{-1}$ and as low as $-4.5^\circ \text{km}^{-1}$, respectively. Clearly, these spurious $\Phi_{DP}$ and $K_{DP}$ values have been successfully identified by the algorithm.

As presented in Fig. 9a, the algorithm also detected the $\Phi_{DP}$ perturbation and positively and negatively biased $K_{DP}$ along line B1 from the range of 120 km, where line B1 passed between two reflectivity cores (Fig. 7a). These spurious $\Phi_{DP}$ and $K_{DP}$ values could be associated with NBF (e.g., Ryzhkov 2007), as $\Delta\Phi_{DP}$ increased in magnitude and exhibited a range varia-
tion consistent with the $\Phi_{DP}$ perturbation in the same segment (Fig. 9a).

Figure 9b presents the range profiles along line B2. A contamination of second-trip echoes appears to have occurred close to the radar. The second-trip contamination near the radar can be identified by a comparison between the $\Phi_{DP}$ profiles, which were obtained by using different PRFs. The second-trip echoes resulted from precipitation beyond the range of 150 km (Fig. 7d). The algorithm has identified a positively biased $K_{DP}$ occurring from a range of 12 km. The biased $K_{DP}$ was apparently induced by the spurious jump in $\Phi_{DP}$, which was also identified by the algorithm. The spurious $\Phi_{DP}$ and $K_{DP}$ values near the range of 12 km occurred in the regions where $Z_{H}$ was close to 45 dBZ, SQI was close to 0.85, and $\rho_{HV}$ was close to 0.97. This fact implies that the contamination of $\Phi_{DP}$ and $K_{DP}$ by second-trip echoes may occur despite the $Z_{H}$, SQI, and $\rho_{HV}$ showing negligible influences of the second-trip echoes.

Figure 9b shows that in addition to the second-trip contamination, the algorithm has also successfully identified spurious $\Phi_{DP}$ and $K_{DP}$ values beyond the range of 110 km, where relatively large cross-beam gradients of reflectivity could exist along line B2 (Fig. 7b). These spurious $\Phi_{DP}$ and $K_{DP}$ values could have been induced by NBF, as evidenced by the fact that $\Delta \Phi_{DP}$ increased in magnitude and exhibited a range...
variation generally consistent with that of $\Phi_{DP}$ beyond the range of 110 km (e.g., Ryzhkov 2007).

The range profiles along line B3 are presented in Fig. 9c. The algorithm detected the spurious perturbations of $\Phi_{DP}$ and the associated negative values of $K_{DP}$ before the range of 90 km. Notably, these spurious $\Phi_{DP}$ and $K_{DP}$ values occurred in front of or behind reflectivity cores, which suggests that these values could have been induced by NBF (e.g., Ryzhkov and Zrnić 1998a). Figure 9c shows that $\Delta \Phi_{DP}$ increased in magnitude and had a range variation consistent with that of $\Phi_{DP}$ beyond the range of 90 km, indicating that the spurious $\Phi_{DP}$ and biased $K_{DP}$ values of both signs detected by the algorithm at far distances from the radar could have also been induced by NBF. Notably, the increase in $\Delta \Phi_{DP}$ occurred behind intense reflectivity cores and in regions with relatively weak echoes. This fact suggests that the NBF-related perturbation in $\Phi_{DP}$ could have been enhanced by the attenuation of radar reflectivity (e.g., Ryzhkov 2007).

The ability of the algorithm can be further supported by Figs. 10a and 10b, which shows the scatterplots of the $K_{DP}$ versus $Z_H$ observed on 28 November. In Figs. 10a and 10b, the spurious $K_{DP}$ detected by the algorithm has also been shown in red. Evidently, the algorithm can efficiently detect not only the negatively biased $K_{DP}$ but also the positively biased $K_{DP}$. Although the biased $K_{DP}$ prevailed in areas with relatively low $Z_H$, there were also small amounts of biased $K_{DP}$ in regions with $Z_H$ values above 45 dBZ.

In addition to the qualitative verification shown above, a quantitative statistical evaluation was further conducted using $SD(K_{DP})$. The scatterplots of the $SD(K_{DP})$ versus $Z_H$ observed on 28 November 2015,
are presented in Figs. 10c and 10d. In areas with \( Z_H \) values below 40 dBZ, the magnitude of \( SD(K_{DP}) \) was substantially reduced after the application of the algorithm. Specifically, the maximum values of \( SD(K_{DP}) \) have been reduced to less than 0.5° km\(^{-1} \) for \( Z_H \) values below 30 dBZ and less than 0.25° km\(^{-1} \) for \( Z_H \) values below 20 dBZ. This result indicates that the application of the algorithm has led to the improvement of the \( K_{DP} \) estimation.

5.2 The 11 December 2015 event

On 11 December 2015, precipitation was initiated over land in the afternoon and moved offshore (Fig. 11), as was the case in the 28 November event. Radar echoes were also organized into a rainband parallel to the coast and propagated westward. However, in contrast to the 28 November event, precipitation on this day was enhanced by a synoptic-scale, westward-moving disturbance (not shown). The rainband developed strongly and lasted for a long time.

Figure 12 presents the horizontal distributions of the \( K_{DP} \) at a 0.5° elevation angle before and after applications of the algorithm. Relatively high \( K_{DP} \) values were observed in the intensified precipitation region. Before the application of the algorithm, artifacts, such as large negative \( K_{DP} \) values, were found along the rainband (Figs. 12a, b). These artifacts have been successfully detected and removed using the algo-
algorithm (Figs. 12c, d). Similar to the previous event, the distribution of genuine $K_{dp}$ values was less affected by the application of the algorithm.

The range profiles of $\Phi_{dp}$ and $K_{dp}$ along line C1 are presented in Fig. 13a. Perturbations in $\Phi_{dp}$ and positively and negatively biased $K_{dp}$ values were observed before the range of 75 km. A jump and resumption of $\Phi_{dp}$ were much more apparent in ranges from approximately 60 to 75 km, which were not found in the $\Phi_{dp}$ profile obtained from the low-PRF scan during the nearest time. Relatively steep decreases in SQI and $\rho_{hv}$ were associated with the $\Phi_{dp}$ perturbations. These facts indicate that the $\Phi_{dp}$ profile before the range of 75 km could have been contaminated by second-trip echoes from the rain located beyond the maximum range of 150 km, as found in the low-PRF scan (Fig. 11c). From the range of 75 km, line C1 passed through strong echoes. Three reflectivity cores with $Z_{H}$ values above 40 dBZ were found around the ranges of 90, 120, and 145 km, respectively. Negatively biased $K_{dp}$ values were observed in front of and behind these reflectivity cores. These results indicate that the $\Phi_{dp}$ perturbations and associated spurious $K_{dp}$ values beyond the range of 75 km could be attributed to the NBF effects (e.g., Ryzhkov and Zrnić 1998a).

Line C2 passed through strong echoes before the range of 100 km (Fig. 13b). Four reflectivity cores with $Z_{H}$ values above 45 dBZ were found around the ranges of 25, 45, 70, and 85 km, respectively. The NBF effects (e.g., Ryzhkov and Zrnić 1998a) could account for the negatively biased $K_{dp}$ values observed in front of and behind these reflectivity cores. Line
C2 was also located near the edge of the strong reflectivity beyond the range of 100 km (Fig. 11b), and both positively and negatively biased $K_{dp}$ values were observed along line C2 at far distances from the radar (Fig. 13b). These facts indicate that the perturbations of $\Phi_{dp}$ and associated spurious $K_{dp}$ along line C2 beyond the range of 100 km could also be attributed to the NBF effects (e.g., Ryzhkov 2007).

Along line C3 (Fig. 13c), the $\Phi_{dp}$ profile exhibited repeated jumps and resumptions beyond the range of 29 km, which were not observed in the $\Phi_{dp}$ profile obtained from the low-PRF scan during the nearest time. Therefore, the $\Phi_{dp}$ perturbations and associated positively and negatively biased $K_{dp}$ values along line C3 could be attributed to second-trip echoes (Fig. 11d).

As clearly seen from Fig. 13, NBF and second-trip contaminated $\Phi_{dp}$ and $K_{dp}$ values have been successfully detected by the algorithm. Figure 13 further supports the ability of the algorithm to detect and remove spurious $\Phi_{dp}$ and $K_{dp}$.

Figures 14a and 14b present the scatterplots of the $K_{dp}$ versus $Z_{H}$ observed on 11 December. Similar to the previous event, the algorithm detected a number of positively and negatively biased $K_{dp}$ values. This event was associated with an intense rainband. Strong attenuation of radar reflectivity occurred over a larger area (not shown). The validation results of this event indicate that the algorithm can detect and remove spurious $\Phi_{dp}$ and $K_{dp}$ for intense precipitation. An improvement in data quality with the application of the algorithm can be seen from the scatterplots of the
$SD(K_{DP})$ versus $Z_{hh}$ observed on 11 December (Figs. 14c, d). Similar to the previous event, larger $SD(K_{DP})$ values in the low-$Z_{hh}$ areas were removed after the application of the algorithm.

5.3 The 15 December 2015 event

Unlike the previous events, precipitation on 15 December was not triggered over the land. Instead, the precipitation accompanying the convectively active phase of the Madden–Julian Oscillation (MJO, Madden and Julian 1972) was observed over a wide area of the ocean (Yokoi et al. 2017). On this day, a precipitation system associated with the MJO was observed by the Mirai radar over the ocean (Fig. 15). Notably, the precipitation system propagated eastward toward land, which is the opposite of the propagation direction in the previously shown cases. The precipitation system associated with the MJO was organized with leading convective echoes and wide trailing stratiform echoes.

The horizontal distributions of the $K_{DP}$ measured on 15 December are presented in Fig. 16. Compared with the previous events (Figs. 8, 12), relatively low values of $K_{DP}$ were observed. Artifactitious $K_{DP}$ values, manifested as large negative $K_{DP}$ values, were concentrated around the leading convective regions (Figs. 16a, b). Once again, the algorithm correctly detected the artifactitious $K_{DP}$ and showed little influence on the distribution of the genuine $K_{DP}$ (Figs. 16c, d). Additionally, as seen from Fig. 16, the algorithm is capable of identifying spurious $K_{DP}$ observed in both convective and stratiform precipitation.

The range profiles presented in Fig. 17 were analyzed to validate the ability and accuracy of the algorithm. The algorithm correctly detected the spurious $\Phi_{DP}$ and $K_{DP}$ before the range of 60 km along line D1 (Fig. 17a) and before the range of 45 km along line D3 (Fig. 17c), respectively. These spurious data were associated with the jumps and resumptions of $\Phi_{DP}$ which were not observed in the $\Phi_{DP}$ profiles obtained.
from the low-PRF scan during the nearest time (Figs. 15c, d). Accordingly, the $\Phi_{DP}$ perturbations in these regions could have been induced by the second-trip echoes originating from the wide trailing stratiform precipitation.

Simultaneously, the algorithm has also successfully identified both the positively and negatively biased values of $K_{DP}$ along line D1 beyond the range of 100 km (Fig. 17a) and along line D2 beyond the range of 90 km (Fig. 17b). In these regions, lines D1 and D2 passed through either reflectivity cores or the edges of intense reflectivity with strong horizontal gradients of reflectivity (Figs. 15a, b). These results indicate that the $\Phi_{DP}$ perturbations and associated biased $K_{DP}$ along lines D1 and D2 at far distances from the radar could have been induced by NBF (e.g., Ryzhkov and Zrnič 1998a; Ryzhkov 2007).

The scatterplots of $K_{DP}$ versus $Z_H$ and $SD(K_{DP})$ versus $Z_H$ observed on 15 December are presented in Fig. 18. Figure 18 reveals that the algorithm can identify and remove the biased $K_{DP}$ values of both signs very well. In this event, data with $Z_H$ values above 45 dBZ were very few. The validation results of this event reveal that the algorithm is also able to detect and remove spurious $\Phi_{DP}$ and $K_{DP}$ for weak precipitation.

5.4 Validation using all the observed data

In total, data from 5998 low-level PPI scans were available during the observational period from 23 November to 17 December 2015, in the tropical rainy regions near Sumatra (Fig. 1). These data covered a
A variety of precipitation systems, which were initiated either over land or over ocean and evolved under a variety of larger-scale environmental conditions, such as MJO and synoptic-scale disturbances.

The improved quality of $K_{DP}$ for all the observed data is presented in Fig. 19a in the scatterplot of $K_{DP}$ versus $Z_H$. Figure 19a reveals that the algorithm can detect both positively and negatively biased $K_{DP}$ values observed from various precipitation systems. The improvement of the $K_{DP}$ statistical accuracy after the application of the algorithm for all the observed data is also achieved, as seen from the scatterplot of $SD(K_{DP})$ versus $Z_H$ (Fig. 19b). It is evident that after the application of the algorithm, the magnitude of $SD(K_{DP})$ was reduced. The reduction in the magnitude of $SD(K_{DP})$ was much more significant in the low-$Z_H$ areas, with a maximum $SD(K_{DP})$ as low as 0.73° km$^{-1}$ for all the observed data with $Z_H$ values below 30 dBZ.

As indicated by Ryzhkov and Zrnić (1996) and Wang and Chandrasekar (2009), the estimation of rainfall by using $K_{DP}$ is highly susceptible to a large variance in the $K_{DP}$ measured in light and moderate rain. To reduce the variation in $K_{DP}$ and facilitate the rainfall estimation, the researchers applied a longer averaging interval (greater than 3 km) to estimate the $K_{DP}$ observed in the low-$Z_H$ areas. In this study, $K_{DP}$ was estimated over a range interval of 1.5 km. The result presented in Fig. 19b reveals that even with a shorter averaging interval, the algorithm presented in this study enables suppression of the $K_{DP}$ variation in the low-$Z_H$ areas. Therefore, the algorithm facilitates

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Fig. 15. Same as Fig. 7, but for (a) 0630 UTC, (b) 1100 UTC, (c) 0629 UTC, and (d) 1059 UTC 15 December 2015. The solid lines of D1–D3 depict the locations of the range profiles presented in Fig. 17.
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As stated previously, spurious $K_{\text{DP}}$ has a considerable influence on the accuracy of $K_{\text{DP}}$-based rainfall estimations. To verify the impact of the algorithm on the improvement of $K_{\text{DP}}$-based rainfall estimation, Fig. 19c presents the scatterplot of the rain rate derived from $K_{\text{DP}} [R(K_{\text{DP}})]$ versus that from $Z_{\text{H}} [R(Z_{\text{H}})]$. The relations given by Keenan et al. (2000) were used to estimate the radar rainfalls, which can be expressed as follows:

$$R(Z_{\text{H}}) = 0.0072 \times 10^{Z_{\text{H}}/10} \times 0.82,$$  \hspace{1cm} (13)

and

$$R(K_{\text{DP}}) = 34.5 \times |K_{\text{DP}}|^{0.899} \times \text{sign}(K_{\text{DP}}).$$  \hspace{1cm} (14)

Two changes were made to use the formulas of Keenan et al. (2000) (see their Eqs. 2, 3). First, the unit of $Z_{\text{H}}$ in $R(Z_{\text{H}})$ was changed to dBZ. Second, the $R(K_{\text{DP}})$ formula was changed to be able to handle negative $K_{\text{DP}}$ values.

It should be noted that the scales of the abscissa and ordinate of Fig. 19c were different: the abscissa ranged from $-380$ to $380$ mm h$^{-1}$, whereas the ordinate ranged from $0$ to $380$ mm h$^{-1}$. Figure 19c indicates that before the application of the algorithm, the scatters of $R(K_{\text{DP}})$ and $R(Z_{\text{H}})$ were large, especially in areas below a $Z_{\text{H}}$-based rain rate of $60$ mm h$^{-1}$. Consistent with the existence of both positive and negative biases...
in $K_{DP}$ (Fig. 19a), $R(K_{DP})$ could also be positively and negatively biased against $R(Z_{H})$. After the detection and removal of the biased $K_{DP}$ via the algorithm, both the positively and negatively biased $R(K_{DP})$ values were significantly reduced, and the scatters of $R(K_{DP})$ and $R(Z_{H})$ were much tighter than before. As a result, the variation in $R(K_{DP})$ became more comparable with that of $R(Z_{H})$ at both the low and high rain rates. These results imply that the physical consistency of $R(K_{DP})$ and $R(Z_{H})$ can be improved with the application of the algorithm.

The performance of the algorithm depends on the retrieval of coefficients $a$ and $b$ on the right-hand side of Eq. (2). Figure 19d presents the scatterplot of $a$ versus $b$ derived from the observed data. There is a pronounced variation in both $a$ and $b$. The values of $a$ and $b$ varied from approximately 9.0 to 16.5 and 35.2 to 45.4, respectively. In general, the variation in $a$ was inversely correlated with that in $b$. The variation in $a$ and $b$ would be associated with that in precipitation systems. It is evident from Figs. 19a and 19b that by incorporating the variation of $a$ and $b$, the algorithm developed in this study is suitable for the identification of spurious $\Phi_{DP}$ and $K_{DP}$ observed from various types of precipitation systems.

Figure 20 presents the time series of the number of data points observed from a PPI scan for positive and negative $K_{DP}$, respectively, in areas with $Z_{H}$ above 10 dBZ. There were a considerable number of data attended with negative $K_{DP}$ values. On average, the number of the negative $K_{DP}$ data accounted for approximately 40% of the total number of the observed data. As presented in Fig. 20 and Table 2, the number of the spurious data identified by the algorithm and its fraction to the total number of the observed data have been examined. The average fractions of the spurious data detected by the algorithm were 6.39% and 9.86% for positive and negative $K_{DP}$, respectively. Table 2 shows that relatively large fractions of the spurious data occurred where weak echoes below 20 dBZ were
observed. This result can be attributed to the fact that there were large amounts of noisy $K_{DP}$ and second-trip echoes in areas with weaker reflectivity. The faction of the spurious data decreased with the increase in $Z_H$. The spurious data detected by the algorithm accounted for just a few percent of the observed data in areas with $Z_H$ above 30 dBZ, consistent with the fact that $K_{DP}$ became less noisy in the high-$Z_H$ areas. It is evident from Fig. 19 that the removal of these spurious data has led to the improvement of the $K_{DP}$ estimation.

6. Summary and discussion

The differential phase $\Phi_{DP}$ is easily contaminated, manifesting as both gate-to-gate fluctuations (i.e., high-frequency range fluctuations) and perturbations within a distance much greater than a range gate along the radial direction (i.e., low-frequency range perturbations). Several previous studies have addressed the removal of high-frequency range fluctuations in $\Phi_{DP}$, which is typically induced by nonmeteorological echoes and differential backscatter phases. However, low-frequency range perturbations in $\Phi_{DP}$ often remain, inducing considerably biased specific differential phase $K_{DP}$ values of both signs. Second-trip echoes and nonuniform beam filling (NBF) could be two significant sources of the low-frequency range perturbations in $\Phi_{DP}$ and the associated biased values of $K_{DP}$.

In this study, an algorithm was developed to detect low-frequency range perturbations in $\Phi_{DP}$ and associated spurious $K_{DP}$ in the rain, as observed by the C-band polarimetric radar on board the research
vessel Mirai. The algorithm is designed to be applied after the removal of the high-frequency range fluctuations in $\Phi_{DP}$. An objective function is formed based on a combination of several formulas developed via the empirical relationship between $K_{DP}$ and the radar reflectivity factor at horizontal polarization $Z_{H}$ in the rain. A threshold of the objective function is then used to simultaneously detect spurious $\Phi_{DP}$ and $K_{DP}$.

The development and validation of the algorithm were conducted using the observed data during a pilot field campaign of the Years of the Maritime Continent (YMC) project in the tropical rainy regions around Sumatra in Indonesia from 23 November to 17 December 2015. These data included a variety of precipitation systems, which were organized with distinct environmental conditions and evolved either over land or over ocean.

The ability and accuracy of the algorithm were examined in detail by comparing the horizontal distributions, range profiles, and scatterplots of the polarimetric radar variables before and after the applications of the algorithm. Low-frequency range perturbations of $\Phi_{DP}$ and associated spurious values of $K_{DP}$ can be efficiently detected by the algorithm, whereas realistic $\Phi_{DP}$ and $K_{DP}$ values are less affected after the application of the algorithm. Both positively and negatively

![Scatterplots](image-url)

**Fig. 19.** Scatterplots of (a) $K_{DP}$ versus $Z_{H}$, (b) $SD(K_{DP})$ versus $Z_{H}$, (c) the rain rate estimated from $K_{DP}$ versus that from $Z_{H}$, and (d) coefficient $a$ versus coefficient $b$ at an elevation of 0.5° for all 5998 scans from 23 November to 17 December 2015. The data associated with the spurious $K_{DP}$ detected by the algorithm presented in this study are shown in red. The vertical dashed line in (b) indicates the location where $SD(K_{DP}) = 0.73°$ km$^{-1}$. 

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biased $K_{dp}$ can be ascertained by the algorithm. After the removal of positively and negatively biased $K_{dp}$ in both the low-$Z_{H}$ and high-$Z_{H}$ areas, the rain rate estimated from the $K_{dp}$ was greatly improved. The performance of the algorithm was further evaluated by using statistics from $K_{dp}$. The standard deviation of $K_{dp}$ is significantly reduced in the low-$Z_{H}$ areas after the spurious $\Phi_{dp}$ identified by the algorithm was removed, which implies that the quality of $\Phi_{dp}$ and $K_{dp}$ can be improved by applying the algorithm.

The data from the YMC project were observed not only in the open ocean but also in coastal areas of the Maritime Continent. Precipitation systems in these regions are usually tall and huge due to both large-scale and orographic lift forces. Second-trip echoes from these precipitation systems are complicated and severely reduce the quality of radar data. The results shown in previous sections indicate that the algorithm developed in this study has good performances in the identification and removal of second-trip echoes not only in the open ocean but also in coastal areas of the Maritime Continent. Therefore, the algorithm can efficiently manage the quality of the data observed during the YMC project.

The empirical relationship between the $K_{dp}$ and $Z_{H}$, as expressed by Eq. (2), is essential to the algorithm. Notably, such an empirical relationship is also reported for S-band (Balakrishnan and Zrnić 1990; Bringi et al. 1991; Ryzhkov and Zrnić 1996) and X-band (Anagnostou et al. 2004; Park et al. 2005; Schneebeli and Berne 2012) polarimetric radars. The application of the algorithm developed in this study with S-band and X-band polarimetric radars will be investigated in detail in the future.

Notably, the algorithm developed in this study is based on the empirical relationship between the $K_{dp}$ and $Z_{H}$, which is valid primarily for liquid precipitation. As indicated by Balakrishnan and Zrnić (1990) and Aydin and Giridhar (1992), hydrometeors other than raindrops can significantly deviate from the empirical relationship, as expressed by Eq. (2). Therefore, caution should be exercised in applying the algorithm for mixed-phase or ice-phase precipitation. Modifying the algorithm so that hydrometeors other than raindrops can also be treated by the algorithm is a challenging issue.

The $K_{dp}$ and $Z_{H}$ scatter about the empirical curve of Eq. (2) due to meteorological variability is not currently clear and can only be determined experimentally, rather than quantitatively, in the algorithm developed.

### Table 2. Mean fraction of the spurious data detected by the algorithm.

| $Z_{H}$ | positive $K_{dp}$ | negative $K_{dp}$ |
|---------|------------------|-------------------|
| $Z_{H} > 10$ dBZ | 6.39 % | 9.86 % |
| $10$ dBZ $< Z_{H} \leq 15$ dBZ | 22.54 % | 26.20 % |
| $15$ dBZ $< Z_{H} \leq 20$ dBZ | 11.90 % | 16.54 % |
| $20$ dBZ $< Z_{H} \leq 25$ dBZ | 5.18 % | 8.86 % |
| $25$ dBZ $< Z_{H} \leq 30$ dBZ | 2.52 % | 5.38 % |
| $30$ dBZ $< Z_{H} \leq 35$ dBZ | 1.64 % | 4.95 % |
| $35$ dBZ $< Z_{H} \leq 40$ dBZ | 1.34 % | 5.94 % |
| $Z_{H} > 40$ dBZ | 3.53 % | 2.84 % |
in this study. In the future, the intention is to investigate the characteristics and processes of the spreads of $K_{dp}$ and $Z_{H}$ about the empirical curve due to meteorological variation alone for various precipitation types. Such work is essential to distinguish between meteorological variability-induced and contaminator-induced scatters about the empirical curve, thus facilitating the establishment of a more robust and quantitative algorithm for quality control of $\Phi_{dp}$ and $K_{dp}$.

Acknowledgments

The authors would like to express their sincere thanks to the entire crew of the research vessel Mirai and the technical staff of Global Ocean Development Inc. for their great support in conducting radar observations and data archiving. The authors also want to thank two anonymous reviewers for their thorough reviews and constructive suggestions that were of great help in the improvement of the manuscript. This study was supported partly by the Japanese Aerospace Exploration Agency (JAXA) Precipitation Measuring Mission (PMM) project.

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