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# A cloud detection algorithm using the downwelling infrared radiance measured by an infrared pyrometer of the ground-based microwave radiometer

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## Abstract

For a better utilization of the ground-based microwave radiometer, it is important to detect the cloud presence in the measured data. Here, we introduce a simple and fast cloud detection algorithm by using the optical characteristics of the clouds in the infrared atmospheric window region. The new algorithm utilizes the brightness temperature ( $T_b$ ) measured by an infrared radiometer installed on top of a microwave radiometer. The two step algorithm consists of a spectral test followed by a temporal test. The measured  $T_b$  is first compared with a predicted clear sky  $T_b$  obtained by an empirical formula as a function of surface air temperature and water vapor pressure. For the temporal test, the temporal variability of the measured  $T_b$  during one minute compares with a dynamic threshold value, representing the variability of the clear sky condition. It is designated as cloud free data only when both the spectral and temporal tests confirm a cloud free data. Overall, most of the thick and uniform clouds are successfully screened out by the spectral test, while the broken and fast-varying clouds are screened out by the temporal test. The algorithm is validated by comparison with the collocated ceilometer data for 6 months, from January 2013 to June 2013. The overall proportion correct is about 88.3 % and the probability of detection is 90.8 %, which are comparable with or better than those of previous similar approaches. Two thirds of failures occur when the new algorithm detects clouds while the ceilometer does not detect, resulting in different values of the probability of detection with different cloud base altitude, 93.8, 90.3, and 82.8 % for low, mid, and high clouds, respectively. Finally, due to the characteristics of the spectral range, the new algorithm is found to be insensitive to the presence of inversion layers.

## 1 Introduction

Ground-based remote sensing instruments such as the microwave sounding radiometer for the acquisition of vertical profiles of temperature and humidity have long been

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considered as candidates to replace conventional observations, offering potential advantages in cost efficiency, temporal resolution, and spatial coverage (Löhnert and Maier, 2012; Li et al., 1997). For better utilization of data from these instruments, not only the acquisition of accurate and reliable measurement data, but also the characterizations of the measurement data are critically important. One of the frequently used methods to characterize the measured brightness temperature ( $T_b$ ) of a ground-based microwave radiometer is to compare it with simulated theoretical values (Liljeberg and Lesht, 1996; Cimini et al., 2003). However, one condition which is neither usually obtained, nor treated correctly either by observation or simulation, and also introduces a significant uncertainty in the theoretical simulation is the cloud conditions. Usually, the presence of clouds with even a small optical depth increases downwelling radiation, and thus introduces significant uncertainties in the comparison results.

The presence of clouds also affects the retrieval accuracy of the vertical profiles of temperature and humidity (Han and Westwater, 1995; Hewison, 2007), cloud liquid water, and precipitable water vapor (Solheim et al., 1998; Turner, 2007; Löhnert et al., 2008). This is mainly due to the disparate cloud effects on the downwelling radiance at the different frequencies, being more prominent at the window bands than at the absorption bands and decreasing with increasing frequency. To mitigate this effect, multi-sensors approaches are commonly used (Crewell and Löhnert, 2003; Turner, 2007; Gaussiat et al., 2007), which take advantage of the differential optical response of clouds with the additional instruments such as the ceilometer and cloud radar (Han and Westwater, 1995; Gaussiat et al., 2007; Löhnert et al., 2008). However, for a certain situation where the additional instruments are not available or the collocation of the multi-sensor data is difficult, there are no other choices than to use only data from a single instrument. Further, when the additional instruments have uncertainties in the calibration, the need for an independent algorithm increases. Indeed, the microwave radiometer used for the current study lacks additional instruments for cloud detection for a large portion of the available data and thus an independent algorithm is highly desired.

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Here, we introduce an algorithm using the downwelling radiance measured by the infrared radiometer (IRT) installed on top of the microwave radiometer (RPG, 2013), together with the surface air temperature ( $T_{\text{sfc}}$ ) and the surface water vapor pressure ( $e$ ) data obtained at 2 m above the ground. The possibility of cloud detection using 5 downwelling infrared radiation has long been demonstrated either by using total irradiance (Brutsaert, 1975; Marty and Philipona, 2000; Dürr and Philipona, 2004), narrow band radiance (Thurairajah and Shaw, 2005; Brocard et al., 2011; Feister et al., 2010; Klebe et al., 2014), or by multi-spectral radiance (Turner and Gero, 2011; Gero and Turner, 2011). Regardless of approach, the background physics for the cloud detection 10 is that the atmospheric emissivity in the infrared window regions is much smaller than that of clouds. Thus, even with optically thin clouds, the downwelling radiation increases significantly and the cloud detection could be relatively straightforward.

However, depending on the approach, there are certain limitations and difficulties. For example, the total irradiance approach is not capable of detecting the high clouds because of the weak sensitivity in the total irradiance to the high clouds (Ohmura, 2001; Dürr and Philipona, 2004). On the other hand, this approach could falsely identify clear sky as a cloudy sky when there is a strong inversion layer at the lower atmosphere (Stutter et al., 2004). The thin cirrus problem in the total irradiance approach also occurs in the narrow band approach, and thus Brocard et al. (2011) use the temporal variability of the measured radiance to overcome this limitation. One of the other issues with the narrow band approach is that the features other than the clouds such as a thick aerosol or haze are falsely detected as a cloud. Thus, a dynamic threshold approach using auxiliary data has been applied for a better cloud detection (Thuraiyah and Shaw, 2005). Even in the case of the multi-spectral radiance, the thin high clouds with the humid atmosphere are known to be difficult to be correctly detected (Turner and Gero, 2011).

Thus, the new algorithm utilizes both the spectral and the temporal characteristics of the clouds captured by the downwelling  $Tb$  at the relatively narrow band in the mid-infrared region. For the spectral test, the measured  $Tb$  is compared with the clear sky

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*Tb* ( $Tb_{clr}$ ) which is dynamically determined as a function of  $T_{sfc}$  and  $e$ . The empirical formula to estimate  $Tb_{clr}$  is prepared by using an extensive calculation of the radiative transfer model with the vertical profiles of temperature and humidity provided by the reanalysis of numerical weather prediction models. For the temporal test, the short-term variability of the measured  $Tb$  is compared with a threshold value which is also determined dynamically as a function of the measured  $Tb$  itself. Section 2 introduces the data used for the current study along with a brief introduction of the instruments. In Sect. 3, we first introduce an empirical formula to estimate the predicted  $Tb_{clr}$  (hereafter called  $Tb_{clr}^P$ ) used for the spectral test, followed by an approach to derive the dynamical threshold value for the temporal test. For the algorithm validation, we use the cloud detection data from the collocated ceilometer, which provides the accurate cloud base altitudes, and the results are given in Sect. 3. The paper is summarized in Sect. 4 with planned future work for further utilization of the current work.

## 2 Data

### 2.1 Radiometer data

Downwelling infrared radiance is measured by IRT installed on top of a ground-based microwave sounding radiometer at the Changwon Weather Station ( $35.23^\circ N$ ,  $128.67^\circ E$  at 86 m above the sea level) of South Korea, which has been operated by the Korea Meteorological Administration (KMA) since April 2010. The microwave radiometer is manufactured by Radiometer Physics GmbH and measures downwelling microwave radiation at seven frequencies in the 22.235 GHz water vapor absorption band (K-band) and at other seven frequencies in the 60 GHz oxygen absorption band (V-band) (RPG, 2013). With the 14 frequency channels, various atmospheric information with a high-temporal resolution (2 or 3 min) are derived (Solheim et al., 1998; Li et al., 1997). Recently, Won et al. (2009) also showed the possibility of deriving rainfall intensity from downwelling microwave radiances.

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On the other hand, the pyrometer IRT manufactured by Heitronics (KT19.85) receives the sky radiance reflected by a gold mirror (Edmund NT32-089). The reflected input radiation passes through the optical lenses and is filtered to the detector (Heitronics pyroelectric detector), which converts the radiant flux to an electrical signal. The overall spectral response function of IRT is determined from the spectral characteristics of the mirror, lenses, filter, and detector and is shown in Fig. 1 (Morris, 2006). Although the spectral coverage spans from 9.4 to 11.8  $\mu\text{m}$ , broad peak responses are concentrated between 10 to 11.5  $\mu\text{m}$ , where it is characterized by weak absorption of greenhouse gases, mainly water vapor, and is away from the ozone and carbon dioxide absorption bands. The output signal is calibrated by the “chopped radiation method” utilizing the frequent observations of internal blackbody (having a pre-defined temperature) radiation between the actual target observation (Morris, 2006). The mechanical blades regularly interrupt incoming radiation from the observation target to stream the blackbody radiation into the detector. At the millisecond chopping cycles, the calibration accuracy is about 0.5 K for different temperature precisions depending on the target temperature (Morris, 2006). The current version of IRT installed on the Changwon radiometer records measurement data every 2 ~ 3 s as the brightness temperature (hereafter called  $Tb_{\text{IRT}}$ ), which is derived by the blackbody calibration. The actual  $Tb_{\text{IRT}}$  in winter can record below  $-70^{\circ}\text{C}$ , although the minimum  $Tb_{\text{IRT}}$  is set to be  $-50^{\circ}\text{C}$  because the accuracy below  $-50^{\circ}\text{C}$  is not practical (RPG, 2013).

Figure 2 shows a few examples of the time series of  $Tb_{\text{IRT}}$ . The time series shows the large variability of  $Tb_{\text{IRT}}$  embedded within the slowly-varying seasonal trend, in line with the variation of atmospheric temperature and humidity. The high-frequency variability is associated with the fast varying sky conditions, mostly caused by the clouds and water vapor. The usefulness and limitation of the  $Tb_{\text{IRT}}$  data for cloud detection are well explained by Fig. 2. For example, when a cloud, even with a small optical depth, is present within the IRT field of view (FOV),  $Tb_{\text{IRT}}$  increases significantly from that of the background clear sky. Thus, it could be fairly straightforward to detect the cloud presence (Thurairajah and Shaw, 2005; Brocard et. al., 2011) and even to estimate

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the cloud base altitude with high accuracy (Morris et al., 2006). On the other hand, as the clear sky  $Tb_{IRT}$  has seasonal (clearly shown in Fig. 2a) and sometimes diurnal variations (as shown in Fig. 2b and c), a fixed threshold for the cloud detection will introduce the error. For this, an objective approach to determine the threshold value taking into consideration of the fast varying atmospheric conditions is required.

## 2.2 Temperature and humidity data

The best approach to take into account of varying atmospheric conditions in the cloud detection would be an estimation of instantaneous  $Tb_{clr}$  which is compared directly with the measured  $Tb$ . However, as the necessary information for the estimation, the vertical profiles of temperature and humidity, are not available in most cases,  $Tb_{clr}^P$  is prepared by using other available data. Here, we utilize the real time  $T_{sfc}$  and  $e$  along with an empirical formula. Although the radiometer is equipped with temperature and humidity sensors, the surface weather data obtained by an automatic weather station (AWS) at the Changwon Weather Station are used, mainly due to the malfunctioning of the humidity sensor of the radiometer during the study period. The AWS data are in the form of temperature and relative humidity and are recorded every minute after the real time collection, quality control, and archival processes at the KMA headquarters.

## 2.3 Theoretical clear sky $Tb$

To prepare the empirical formula for  $Tb_{clr}^P$ , we use the theoretical  $Tb_{clr}$  using a radiative transfer model (RTM) with the input data of various atmospheric conditions. Here, the RTM simulation is done by the Modtran 5.1.2 (Berk et al., 2011) with the input vertical profiles of temperature and humidity from a high resolution reanalysis data using the KLAPS (Korea Local Analysis and Prediction System) which provides hourly vertical profiles. The high resolution ( $1 \text{ cm}^{-1}$ ) spectral radiance from the RTM simulation is converted to the simulated  $Tb$  through the convolution with the IRT spectral response functions (Fig. 1) and then by the inverse of the Planck function. To have an enough

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number of atmospheric profiles, we use 8760 vertical profiles corresponding to a one year time period which includes the atmospheric variability for the four different seasons. One thing to note here is that we assume that all profiles are cloudy free and thus we may include profiles that are from the extremely wet atmospheric conditions.

## 5 2.4 Validation data

For the algorithm validation, we use a lidar ceilometer CL31 (Vaisala, 2004) for the quantitative assessment along with the high-resolution satellite data for a qualitative comparison. The ceilometer produces the cloud fraction from 0 to 8 denoting clear and overcast, respectively, and the cloud base altitudes at three different layers (Vaisala,

10 2004). As the cloud fraction is estimated using the accumulated data for a certain time period, here 20 min, it is not suitable for current study which requires an instantaneous estimate. Thus, instead of the cloud fraction, we use an instantaneous cloud presence derived by checking cloud base altitudes, determining it as clear if all three cloud bases are recorded as 7.62 km (a situation that represents a clear condition). Here, it should be noted that the detection limit of 7.62 km is variable depending on the atmospheric conditions such as the lower atmospheric turbidity, fog, density (Clothiaux et al., 2000). The instrument is installed at a distance of 15 m southwest from the radiometer. The ceilometer data is available with the temporal resolution of 1 min and the vertical resolution of 10 m, although it is available only after 27 September 2012.

## 20 2.5 Pre-processing

For the algorithm development, we first derive one minute averaged  $Tb_{IRT}$  and its standard deviation obtained from the original data having 2 ~ 3 s resolution, providing enough number of data points to have a reliable statistic. The archived AWS data are in the form of  $T_{sfc}$  and relative humidity (RH) which is converted to the surface air vapor pressure  $e$  in mb using;

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$$e = 0.01 \times \text{RH} \times e_s \quad (1)$$

where,  $e_s$  is the saturation vapor pressure corresponding to  $T_{\text{sfc}}$ . An empirical formula valid for  $-30^\circ\text{C}$  to  $50^\circ\text{C}$  is used to calculate  $e_s$  for the current study (Buck, 1981);

$$e_s = 6.1121 \exp \left( \frac{17.502 \times T_{\text{sfc}}}{T_{\text{sfc}} + 240.97} \right) \quad (2)$$

The hourly vertical profiles of temperature and humidity from the re-analysis data is provided in 5 km spatial resolution. For the current study, we select the nearest grid point to the Changwon Weather Station and retrieved data from 1 January 2012 to

31 December 2012. The model vertical grids are reformatted to be used in the RTM simulation. For the algorithm development, the one minute data of AWS and IRT data are averaged for 30 min to match with the model re-analysis data. For the validation, we use the minute data of IRT, AWS, and ceilometer from 1 January 2013 to 30 June 2013 when both the ceilometer and radiometer data are available. The total number of data points are 237 963.

### 3 Algorithm

We first establish the relationship between the theoretical  $Tb_{\text{clr}}$  and other readily available data, here  $T_{\text{sfc}}$  and  $e$ , through the extensive RTM simulation. We, then, relate the theoretical  $Tb_{\text{clr}}$  with the actually observed  $Tb_{\text{IRT}}$  to finalize the formula for the  $Tb_{\text{clr}}^P$ .

Although the comparison between the measured  $Tb_{\text{IRT}}$  and  $Tb_{\text{clr}}^P$  could detect most of the clouds, there are situations when the comparison does not work properly. For this, the temporal variability of the  $Tb_{\text{IRT}}$  data compares with a threshold value which represents the clear sky condition. As the threshold also varies with the atmospheric conditions, especially with  $Tb_{\text{IRT}}$ , an empirically derived formula is used to derive the instantaneous threshold value.

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### 3.1 Predicted clear sky $Tb$ ( $Tb_{\text{clr}}^{\text{P}}$ )

Figure 3 shows the time series of the simulated hourly downwelling  $Tb$  with the reanalysis data (hereafter called  $Tb_{KLAPS}$ ) along with  $T_{sfc}$  and  $e$ . Figure 3 reveals several important characteristics of  $Tb_{KLAPS}$ , representing theoretical  $Tb_{clr}$ . First, even though the cloud layer is not included in the RTM simulation,  $Tb_{KLAPS}$  varies significantly with the different atmospheric conditions, similar to the actual  $Tb_{IRT}$ . The value can be as cold as 160 K during the cold and dry winter period, while it could go up to 260 K during the summer period, resulting in about 100 K difference between the two extremes. A significant variation of  $Tb_{KLAPS}$  is also evident even during a short time period within the same season, especially during the cold season. For example,  $Tb_{KLAPS}$  varies more than 40 K during mid January, mainly due to the sudden changes in  $e$  along with  $T_{sfc}$ .

On the other hand, the variations of  $Tb_{KLAPS}$ ,  $T_{sfc}$ , and  $e$  are well correlated. Although the amplitudes are quite different, the three time series vary with the same phase. Although it is not shown, it is also true that the differences between  $Tb_{KLAPS}$  and  $T_{sfc}$  are well correlated with  $e$  and the correlation further improves when  $e$  is divided by  $T_{sfc}$ . Consequently, similar to the previous studies (Brutsaert, 1975; Idso, 1981; Marty and Philipona, 2000; Durr and Philipona, 2004; Zhnag et al., 2007; Long and Turner, 2008; Carmona et al., 2014), an empirical formula which relates the downwelling infrared radiation to the surface weather data could be derived. Depending on the spectral range and interested variable, such as the radiance measured in the narrow window region vs. the irradiance representing the integrated flux in the whole infrared region, a slightly different formula (such as given by Idso, 1981; Liu et al., 2013) is required.

Thus, with the several different types of the scatter plot between the different variables, such as shown in Fig. 4, which shows the relationship between  $Tb_{\text{KLAPS}} / T_{\text{sfc}}$  and  $e / T_{\text{sfc}}$ , several different formulas including linear, logarithmic, and quadratic relationships, have been tested. Based on the correlation characteristics and error statistics (the first two moments) for each tested variable and formula, a quadratic relation between the logarithm of  $Tb_{\text{KLAPS}} / T_{\text{sfc}}$  and  $e / T_{\text{sfc}}$  was found to best fit the data, as

shown in Eq. (3);

$$\log \left( \frac{Tb_{KLAPS}}{T_{sfc}} \right) = a_0 + a_1 \left( \frac{e}{T_{sfc}} \right) + a_2 \left( \frac{e}{T_{sfc}} \right)^2 \quad (3)$$

where  $a_0$ ,  $a_1$ , and  $a_2$  are the empirical coefficients. With the derived coefficients, the best fit  $Tb_{KLAPS}^E$  is given as;

$$Tb_{KLAPS}^E = T_{sfc} \exp \left( -0.5422 + 6.727 \times \left( \frac{e}{T_{sfc}} \right) - 26.53 \times \left( \frac{e}{T_{sfc}} \right)^2 \right) \quad (4)$$

The overall performance of  $Tb_{KLAPS}^E$  is tested by the comparison with the collocated  $Tb_{KLAPS}$ , as shown in Fig. 5. The scatter plot shows that most of data are well aligned

to the one-to-one line, although there are a few outliers. The accuracy estimated by the difference between  $Tb_{KLAPS}^E$  and  $Tb_{KLAPS}$  is estimated to be about 6.3 K (one standard deviation) with the correlation coefficient of 0.98. The difference between  $Tb_{KLAPS}^E$  and  $Tb_{KLAPS}$  shows no significant variation with independent variables such as  $Tb_{KLAPS}$ ,  $T_{sfc}$  and  $e$ , or time. Here, it should be noted that the uncertainty and the correlation coefficient represent the fitting accuracy of the Eq. (4), not the accuracy of  $Tb_{clr}^P$ . Nevertheless, the uncertainty is fairly small compared to the  $Tb$  change due to the cloud presence (see demonstrated in Fig. 7 and also by Gero and Turner, 2011; Turner, 2007).

To correctly use  $Tb_{KLAPS}^E$  for the cloud detection, a relationship between the theoretical  $Tb_{KLAPS}$  and the measured  $Tb_{IRT}$  should be established. This is important because the two  $Tb$  values could be different, either due to the overall uncertainty in the calculation of  $Tb_{KLAPS}$  or due to the uncertainty associated with the instrument calibration. For the comparison with the hourly theoretical data, the high resolution  $Tb_{IRT}$  data are degraded by taking a half-hour averaged value and the results are shown in Fig. 6. As shown in Fig. 6a, the relationship shows a large spread and irregular distribution. However, it seems that all the points fall into three different groups, two groups with heavily

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packed-points and one group with widely distributed points in between the two groups. A close inspection of these points leads to the conclusion that the different groups correspond to the different sky conditions. The upper group represents the overcast condition with an appreciable addition to the downwelling radiances, while the lower group is for the clear sky where the measured and estimated  $Tb$  values are similar. The widespread points in between represent the broken or fast-varying cloud conditions and the measured  $Tb$  vary with the degree of cloud contamination.

Thus, to establish a relationship between  $Tb_{KLAPS}$  and the measured  $Tb_{IRT}$ , we select only data points having a small temporal variability (see the Sect. 3.2 for details). Figure 6b shows the resultant two groups, removing most of the points in between the two groups, clearly separated from each other. The slopes between  $Tb_{IRT}$  and  $Tb_{KLAPS}$  for the cloudy and the clear condition are different and the difference represents the differential cloud effects on the downwelling radiance. As the cloud effect on the downwelling radiance is more prominent for the cold and dry atmosphere (Morris, 2006; also see Fig. 7), the difference between the cloudy and clear radiance increases with decreasing  $Tb_{IRT}$ . Another interesting relation between the  $Tb_{IRT}$  and  $Tb_{KLAPS}$  is that they are not linear (seemingly quadratic) and the slope is not one, even for the clear sky condition. It is interesting to note that the spreadness of  $Tb_{IRT}$  increases at the lower  $Tb_{IRT}$ , which is thought to be related to the absolute calibration of IRT. For example, an imperfect reflector (possibly due to the degradation) and its uncertainty will give a larger uncertainty at lower  $Tb_{IRT}$ . For a quantitative assessment, further investigation is required, but this is beyond the scope of the current study.

With the limitations of the uncertainties introduced above, relationship between  $Tb_{KLAPS}$  and the measured  $Tb_{IRT}$  for the clear sky condition is established by using the lower portions of the data points in Fig. 6b. In order to do that, a simple threshold is applied to Fig. 6b and the remaining data points are best fitted by a quadratic formula. As  $Tb_{KLAPS}$  is obtained by assuming a clear sky condition, the resulting relationship between  $Tb_{KLAPS}$  and  $Tb_{IRT}$  can be considered as the relationship between  $Tb_{clr}^P$  and  $Tb_{KLAPS}^E$ . Thus, the empirical formula for the predicted clear sky brightness

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temperature,  $Tb_{\text{clr}}^P$ , to be used for the clear sky detection, is given by;

$$Tb_{\text{clr}}^P = 4.39 + 0.865 \times Tb_{\text{KLAPS}}^E + 0.0032 \times (Tb_{\text{KLAPS}}^E)^2 \quad (5)$$

where, the fitting uncertainty is estimated to be 3.13 K.

### 5 3.2 Temporal variability

A small variation of the cloud parameters, such as the cloud optical depth, the cloud fraction, and the cloud base temperature, can introduce a significant variation in the measured  $Tb_{\text{IRT}}$ . For example, as shown in Fig. 7, even with the same cloud base altitude and composition, the measured  $Tb$  differs as much as 30 K due to the different atmospheric condition. Thus the downwelling radiance in the cloudy condition has much larger spatial and temporal variability than that of the clear sky condition (Brockard et al., 2011). However, it should be noted that when a uniform cloud, such as a thick stratus or fog, are present, the variations are much smaller. As the ground-based IRT represents only one space dimension, i.e. the vertical space, temporal variability is used to check for both spatial and temporal variabilities. To derive a threshold value for the variability check, we first need an optimal time span to derive the temporal variability. Here, we choose one minute for three reasons: first, validation data (the ceilometer data) and auxiliary surface weather data (the AWS data) are available every minute; second, the number of available  $Tb_{\text{IRT}}$  for one minute is about 25 to 30, which provides enough statistical confidence in obtaining reliable temporal variability information; and lastly, high temporal resolution data is to be maintained as much as possible.

Figure 8 shows the time series of the averaged  $Tb_{\text{IRT}}$  over one minute and its standard deviation ( $\sigma_{1\text{min}}$ ) for 48 h for the summer, fall, and winter seasons. Indeed, the temporal variability ( $\sigma_{1\text{min}}$ ) clearly indicates cloud presence, showing a larger  $\sigma_{1\text{min}}$  for the cloudy conditions, which are also characterized by the highly variable and relatively warm  $Tb_{\text{IRT}}$ . On the other hand, the seemingly clear periods with a uniform and relatively cold  $Tb_{\text{IRT}}$  are characterized by the much smaller  $\sigma_{1\text{min}}$ . From careful inspection

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of other time periods (that are not shown in Fig. 8), we conclude that temporal variability can be used for cloud discrimination, as suggested by others (Morris et al., 2006; Durr and Philipona; 2004; Brocard et al., 2011). However, we also found that the threshold value which separates the cloudy sky from the clear sky should be carefully selected.

Especially, when we compare the  $\sigma_{1\min}$  for the clear sky condition among the three different seasons, the compactness and its magnitude depend significantly on the season. As can be seen in Fig. 8,  $\sigma_{1\min}$  for the clear data during the summer (such as during 4 August) shows a smaller and less variable distribution compared that during the winter (such as during 6 November).

Thus, to check any seasonal dependence of  $\sigma_{1\min}$  for the clear sky condition, the variability of  $\sigma_{1\min}$  during one year is investigated. To select enough number of data and ensure that only the clear sky data are selected, we estimate an hourly average of  $\sigma_{1\min}$  and its standard deviation ( $\sigma_{1h}$ ) and then select data having a small  $\sigma_{1h}$ . Figure 9 shows the relationship between the hourly average of  $\sigma_{1\min}$  as a function of the hourly averaged  $Tb_{IRT}$  for the cases having  $\sigma_{1h}$  value of less than 0.03 (this value is empirically selected, although the resulting coefficients in Eq. (6) are not very sensitive to the threshold value used). The hourly averaged  $\sigma_{1\min}$  decreases with increasing  $Tb_{IRT}$ , which is consistent with Fig. 8, which shows a smaller  $\sigma_{1\min}$  for the summer period (a higher  $Tb_{IRT}$ ) and vice versa. Thus, the seasonal dependence of the  $\sigma_{1\min}$  is mainly due to the variations of the measured  $Tb_{IRT}$ . One of plausible cause of this dependence is the difference in instrument precision (or noise performance), which is reported to be 1.1 and 0.45 K at 223 and 293 K, respectively (Morris, 2006).

Based on Fig. 9, the relationship between  $Tb_{IRT}$  and the  $\sigma_{1\min}$  for clear sky ( $\sigma_{clr}^E$ ) could be best fit with a quadratic formula;

$$25 \quad \sigma_{clr}^E = 0.087 - 7.68 \times 10^{-3} \times Tb_{IRT} + 1.08 \times 10^{-5} \times Tb_{IRT}^2 \quad (6)$$

Here, the  $Tb_{IRT}$  is the one minute averaged value in Celsius and the fitting uncertainty with the hourly averaged variability is about 0.008 °C.

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### 3.3 Overall flow chart

With the spectral and temporal characteristics described in the previous sections, the overall flow for the detection algorithm is schematically summarized in Fig. 10. The algorithm applies to data for every minute just after a collection of one-minute worth of

5 IRT data and surface weather data. For the spectral test,  $Tb_{clr}^P$  is prepared by using  $T_{sfc}$  and  $e$  from the AWS using Eq. (4), followed by Eq. (5). If the difference between  $Tb_{IRT}$  and  $Tb_{clr}^P$  is larger than the threshold value, it is considered as cloud contaminated. For the temporal test, one-minute IRT data are averaged to give the averaged  $Tb_{IRT}$  and  $\sigma_{1\min}$ . The measured  $\sigma_{1\min}$  is then compared with  $\sigma_{clr}^E$  obtained by Eq. (6). If the 10 difference is larger than the threshold value, it is considered as cloudy data. Finally, the data are determined as cloud free, only when both the spectral and temporal tests identify the measured  $Tb_{IRT}$  as clear sky data.

Here, the final question about the algorithm is “how do we choose the threshold values?” For the spectral test, the uncertainty associated with the  $Tb_{clr}^P$  preparation could 15 be used as the criterion. It is estimated by the combination of the uncertainties in the derivation of  $Tb_{KLAPS}^E$  (Eq. 4; considered as the random uncertainty) and in the connection between  $Tb_{clr}^P$  and  $Tb_{KLAPS}^E$  (Eq. 5; considered as the systematic uncertainty). As the two processes are considered as independent, the overall uncertainty (one standard level) in the determination of  $Tb_{clr}^P$  is estimated to be  $\sqrt{6.3^2 + 3.13^2} = 7.0$  K. Thus, 20 for the spectral test, we apply twice the standard deviation value as the threshold based on two factors: the cloudy data show much higher  $Tb_{IRT}$  than the clear data and the cases giving the less prominent signal could be filtered out by the temporal test. On the other hand, the uncertainty associated with the temporal variability is relatively straightforward, which is obtained from the fitting process. As the estimated variability is fairly 25 small, about 0.06 K (0.008 times square root of 60), we use 0.18 K (three times the one sigma value) as our threshold value.

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### 3.4 Validation

Figure 11 shows the original time series of  $Tb_{IRT}$ ,  $Tb_{clr}^P$  and  $\sigma_{1\min}$  and the algorithm results. The time period is selected to present the characteristics of the algorithm when cloud detection is more problematic due to increased clear sky  $Tb_{IRT}$ . Overall,  $Tb_{clr}^P$  is in good agreement with the clear sky  $Tb_{IRT}$ , which corresponds to the data measured between 15:10 to about 16:10 UTC (clear sky is confirmed by another observation data such as ceilometer and satellite images, not shown). In the current case,  $Tb_{clr}^P$  is slightly cooler than the clear sky  $Tb_{IRT}$  by about 7 K, which is much smaller than the threshold value used for the clear sky detection. Also, the temporal variability is in good agreement with the overall feature of  $Tb_{IRT}$ , i.e. increases with increasing  $Tb_{IRT}$ . The detection results are also as expected. For example, as can be seen for the time period from 17:40 to 18:30 UTC, the data are determined as cloud contaminated by both spectral and temporal tests, while the data from about 18:30 to 19:00 UTC are determined as cloudy by the spectral test alone. On the other hand, during a few occasions such as at around 16:20 UTC and the time period between 16:50 and 17:30 UTC, the cloud presence is detected by temporal variability only (except a few occasions when both tests detect). Thus, most thick and uniform clouds are identified by the spectral test, while the highly variable broken clouds are mostly identified by the temporal test. On the other hand, the edges of the advancing thick clouds are detected by both the spectral and temporal tests as exemplified by the time period between 17:40 and 18:30 UTC.

For an objective validation, the collocated ceilometer data from 1 January 2013 to 30 June 2013 are directly compared with the IRT results, with the consideration of several factors for a direct comparison. For example, the two instruments are not looking at the exact same target at the same time. This is due to two factors. First of all, IRT field of view is much larger than that of ceilometer, 1.0 vs. 0.064°, which implies the higher possibility of the cloud contamination. Secondly, the two instruments are not located exactly at the same location, the distance between ceilometer and IRT is about 15 m. Thus, the two causes introduce a target off-set issue which will be important for

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the fast-moving clouds with the broken sky conditions. Another important characteristic that should be kept in mind is that there is well known detection limit of ceilometer. The current version of the CL-31 has the known limit of 7.62 km. Thus, for the high clouds it would be quite normal that IRT detects clouds while ceilometer does not. The example case will be given later.

The comparison results are summarized in the contingency table as shown in Table 1 which is prepared with the total of 237 963 pair of 1 min IRT and ceilometer data. The estimated detection accuracy (ratio of the hit and the corrective negative to the total case) is 88.3 %, which is quite comparable with or better than the results from other similar infrared instrumentations. For example, Feister et al. (2010) showed that cloud detection from a sky scanner coincides with the result from a whole sky imager for about 90 % of cases. They also showed that the comparison is better for low clouds than for high clouds (92.2 vs. 85 % accuracy) and attributed the difference to the difference in the detection method. On the other hand, a better validation parameter might be the probability of detection (POD) in view of the limitation that ceilometer has. From the Table 1, the estimated POD for all cases is 90.8 %, which is much better than a previous result (Sutter et al., 2004). They compared the results derived from infrared irradiance along with the surface temperature and humidity to the synoptic observation and found 80 % of the probability of detection. As attributed by the authors, the misses are mainly due to the presence of strong inversions, thin high clouds, and dry haze which are not a significant sources of error for current approach.

Also, as shown in Table 1, more than 2/3 of failures (misses and false alarm) are due to the false alarm. A close inspection of the comparison results reveals two representative types of failures as shown in Fig. 12: one type is due to a highly variable sky condition along with the instrument configuration, and another type is due to the presence of high clouds. Figure 12a shows the time series of  $Tb_{IRT}$  (2 October 2012) and the cloud base altitude (for the lowest cloud) obtained from the ceilometer showing the different comparison results. In this specific case, there seems to be a time lag between the ceilometer measurement and the IRT measurement (IRT leading the

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ceilometer by one minute). For example, at about 04:02 UTC (red triangle), the  $Tb_{IRT}$  time series (and the standard deviation, not shown) indicates a cloudy condition, while the cloud base altitude is estimated to be 7.62 km (clear condition), resulting in the false alarm. On the other hand, at about 04:40 UTC when the  $Tb_{IRT}$  time series clearly indicates a clear sky condition, the cloud based altitude is estimated to be about 2 km, resulting in the misses. Thus, during the time period given by the two cases, all data seems to be shifted by one minute. This kind of discrepancy between the two instruments could be generated by the aforementioned differences such as the differences in field of view and the distance between the two instruments.

The second representative type exemplified by Fig. 12b is for the case when high clouds are present. This is the main causes of the relatively large number of false alarms and is due mainly to the detection limit of ceilometer. To make sure that this is indeed the case, we check high resolution satellite images obtained by COMS (communication, oceanography and meteorological satellite) as shown in Fig. 13. In comparison with Fig. 12b, the satellite images confirms understandings on the characteristics of the IRT and ceilometer measurements. First of all, during the time period between about 05:00 to 09:30 UTC, except for the short period between about 07:50 and 08:20 UTC, the ceilometer reports no appreciable clouds other than two small bumps, while the satellite images and IRT show clear signs of a significant amount of clouds. For example, at 06:00 UTC when high clouds begin to cover the site, the composite image shows a white/gray patch (interpreted as cold and high clouds based on the visible and water vapor images) over the site, which is detected at IRT with the increase of the measured  $Tb_{IRT}$  (about 5 °C which result in a cloud detection the temporal variability). More clearly, at 07:30 UTC, the site is clearly covered with clouds and the measured  $Tb_{IRT}$  shows an appreciably higher value (about 15 °C) compared to the –36 °C of the clear sky value recorded a few hours earlier. On the other hand, from 08:00 to 08:18 UTC, the ceilometer detects high clouds as low as about 6.5 km, as confirmed by IRT and the satellite image. Although it is not a definite, the satellite image taken at 08:15 UTC shows a bit more whitish cloud, which is located over the

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site, implying increased thickness and lowered cloud altitude, which are also detected by the ceilometer. After 09:15 UTC, all three data reports no appreciable amount of clouds.

Through the comparison with the satellite images, it seems that the IRT measurement is more effective than the ceilometer for high cloud detection. To make sure that the quantitative validation results are indeed altitude-dependent, the probability of detection is estimated based on the different cloud base altitude of ceilometer. For the low clouds (base altitude from 0 to 3 km), the probability of detection is 93.8 % (59 187/(59 187+3897)), while it reduces to 90.3 % for the mid clouds (base altitude ranging 3 to 5 km), and it is further reduced to 82.8 % for the high clouds (base altitude higher than 5 km). This altitude dependence is quite similar to the previous study done by Feister et al. (2010).

Finally, the algorithm performance is checked for the cases of strong thermal inversion. The cases are found from the vertical profiles of temperature and humidity, obtained by rawinsonde launched at the Changwon station. As the rawinsonde is launched for the research purposes, data availability is not regular or continuous. Nevertheless, we could identify cases with a strong inversion and could select cases that were free from cloud influence. Figure 14 shows such a case with a skew-T log-P diagram on 6 March 2013, along with the time series of  $Tb_{IRT}$  similar to that in Fig. 11 and the satellite images taken around the time of radiosonde observation. From the ceilometer data, satellite image, and synoptic observation (not shown), there is no significant cloud presence near the site. Similarly, the  $Tb_{IRT}$  time series clearly indicates a clear sky during the radiosonde observation period with a few occasional cloud presences, probably due to the effect of clouds that had passed north of the observation station as shown in the satellite images. Although the measured  $Tb_{IRT}$  increases slightly after around 00:00 UTC, it is not significant and the value is quite close to  $Tb_{clr}^P$ . Thus, overall, the new algorithm is not sensitive to the strong inversion layer, at even near the ground. This is mainly due to the spectral range that IRT uses, as anticipated from the results of the theoretical radiative transfer calculation.

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## 4 Summary

The detection of the cloud signal in the measured downwelling radiance of the ground-based instrument is an important task for the characterization of the measured radiance and for further utilization of the radiance data. Here, we introduce a simple algorithm 5 to detect cloud presence in the field of view of a ground-based microwave sounding radiometer, which could be used for the real time applications. The algorithm requires the measured downwelling radiance obtained from an infrared pyrometer installed on top of the radiometer, along with the real time surface weather data including surface air temperature and humidity data. The necessary empirical formulas and relationship 10 among the variables and threshold values for the tests are obtained from the combination of theoretical simulation and observation data obtained over a year.

The algorithm is based on the spectral and temporal characteristics of the cloud signal in the downwelling infrared radiation. As the clear sky downwelling radiance at the atmospheric window region is so small, the cloud signal from most clouds are easily 15 discernible. However, as the background clear sky radiance varies significantly with the atmospheric temperature and humidity, a measure to account for the variation has been developed. Here, we use the theoretically calculated downwelling radiance along with the surface air temperature and water vapor pressure to derive an empirical relationship between these variables. With one year worth of data, the fitting accuracy 20 between the expected and calculated clear sky brightness temperatures is to be about 6.3 K, which is a quite small compared to the typical cloud signal in the measured radiance. The theoretically estimated brightness temperature is further compared with actual measurement to check any discrepancies between the two and ultimately to derive an empirical formula to account for the difference with a high confidence level. 25 For the second test, the temporal variability of the measured downwelling radiance is tested (as the radiometer views only one direction, the spatial variability is reflected in the temporal variability). To derive a temporal variability data for the background uniform scenes such as a clear sky or uniform overcast cloud, we use the hourly averaged

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temporal variability, which is given by the standard deviation of one-minute averaged data. From the hourly averaged data, we found that the background temporal variability varies with the measured brightness temperature and derived an empirical formula relating the two variables. The two-step algorithm applies to the one-minute averaged brightness temperature with appropriate threshold values. The measured data are determined to be free only when both steps identify the data as a clear data.

The algorithm performance is validated against collocated ceilometer data producing three cloud base altitudes every minute along with the high resolution satellite data. Overall, the accuracy determined by the proportion correct (probability of detection) is about 89 % (90.8 %), which is comparable with or better than previous studies. Among the failures (IRT results are not the same as the ceilometer results), 2/3 of them are caused by over-detection of clouds by IRT. By a closer inspection of IRT and ceilometer data with high resolution satellite images, the over-detection could be represented by two cases. One case is due to the highly variable cloud condition, caused by the different measurement methods and the distance between the two instruments. Another one is when the altitude of the cloud is beyond the detection limit of the ceilometer, while the cloud signal is strong enough to be detected by IRT, as verified by high resolution satellite data. To make sure that the IRT measurement is not affected by the inversion layer, we also check the available rawinsonde profiles and demonstrate the insensitivity of the new algorithm to the presence of inversion layers.

Overall, the new cloud detection algorithm performs well even with only a limited amount of information available. The results are comparable with the lidar ceilometer and indicate a possibility of better performance for certain situations. However, it still has room for improvement in areas such as the prediction of clear sky radiance and refinement of the threshold value of the temporal test. With better theoretical clear sky radiance, we may improve the estimates of the cloud base altitude. Also, as indicated in the comparison between theoretical and measured radiances, a detailed investigation of calibration accuracy of IRT is necessary, especially paying attention

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to any degradation or variation of the reflectivity of the reflector. Finally, cloud cleared radiance data could be used for further characterization of the microwave radiometer.

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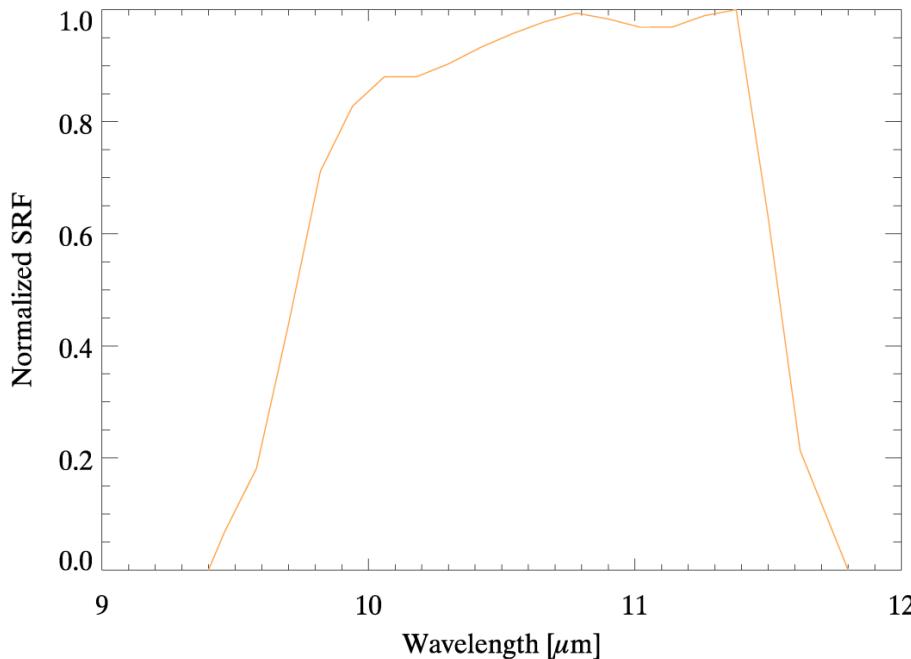
**Table 1.** Contingency table for cloud detection by the infrared pyrometer (IRT) and ceilometer. The estimated proportion correct is 88.3 % and the probability of detection is 90.8 %.

		Ceilometer result	
		Cloud	Clear
IRT result	Cloud	Hit (82 772)	False alarm (19 551)
	Clear	Misses (8373)	Correct negative (127 267)

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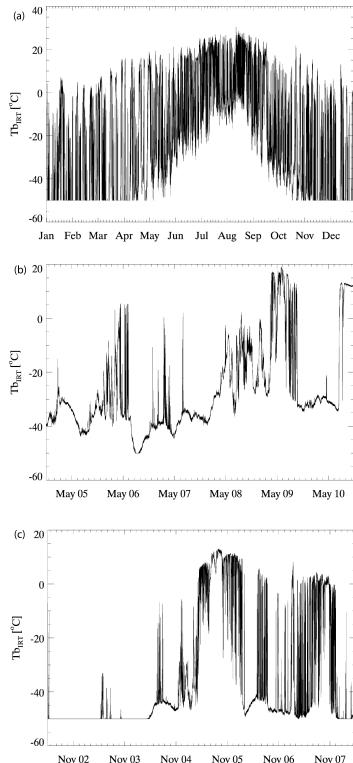


**Figure 1.** The spectral response function of the infrared radiometer installed on top of the ground-based microwave radiometer, at the range of 9.4 ~ 11.8  $\mu\text{m}$  (Morris, 2006). The estimated center wavelength for the given spectral response function is about 10.6  $\mu\text{m}$ .

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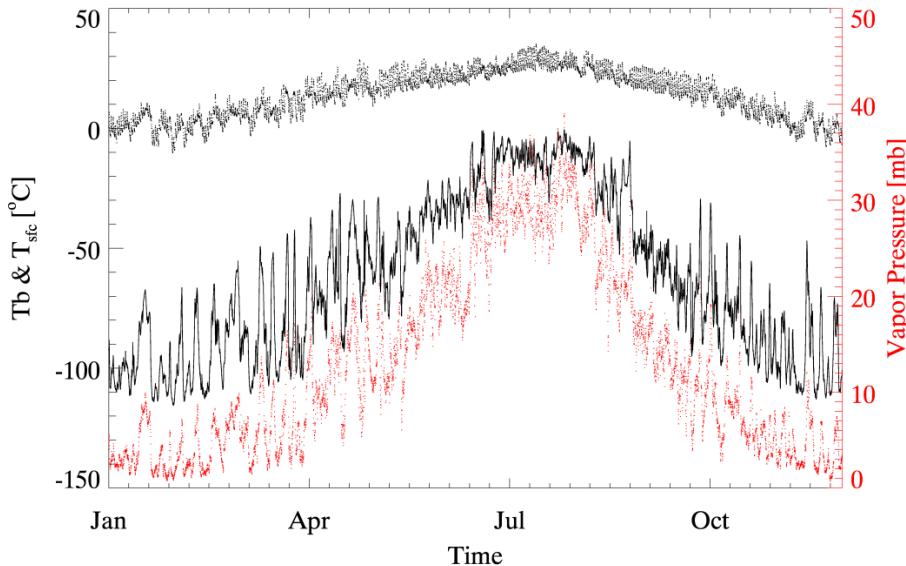


**Figure 2.** Time series of the measured brightness temperature of infrared radiometer ( $T_{\text{IRT}}$ ) for a period of one year (a), and five days during the summer (b), and winter time periods (c) obtained at the Changwon Weather Station. The current version of IRT is set to have a lower limit of detection at  $-50^{\circ}\text{C}$ , which is evident from the data obtained during the winter period.

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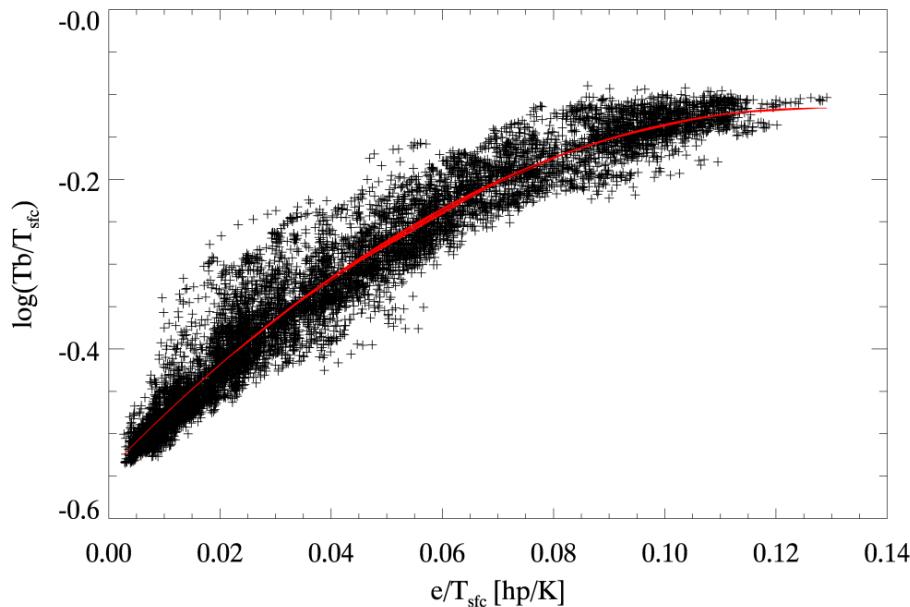


**Figure 3.** Time series of the simulated  $Tb$  (black solid line) along with  $T_{sfc}$  (the surface air temperature; black dotted line, both temperature scales is on the left) and  $e$  (the surface water vapor pressure; red dotted line with the scale is on the right) from 1 January to 31 December 2012. The  $T_{sfc}$  and  $e$  are the values at the lowest levels of the vertical profiles of temperature and humidity used for the radiative transfer calculations.

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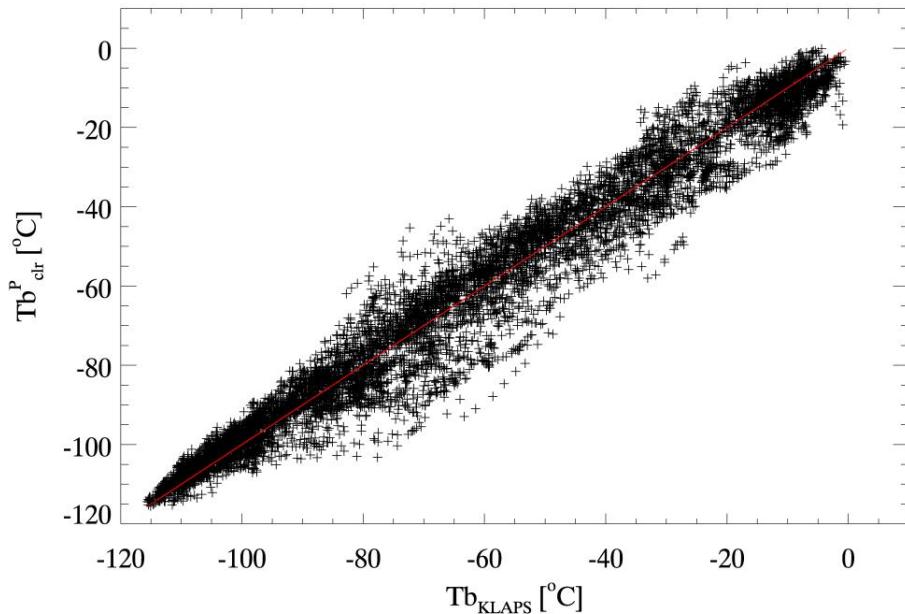


**Figure 4.** Simulated relationship between the ratios of brightness temperature to the surface air temperature ( $Tb / T_{sfc}$ ) and the ratio of water vapor pressure to the surface air temperature ( $e / T_{sfc}$ ). The numbers of data points are 8760 (hourly data for one year). The  $Tb / T_{sfc}$  value increases rapidly with the increase of  $e / T_{sfc}$  due to the increased contribution of surface air in the downwelling radiation. When the  $e / T_{sfc}$  value reaches about 0.09, the  $Tb / T_{sfc}$  value does not vary significantly because the wavelength region is the atmospheric window region (contribution from upper air is always there).

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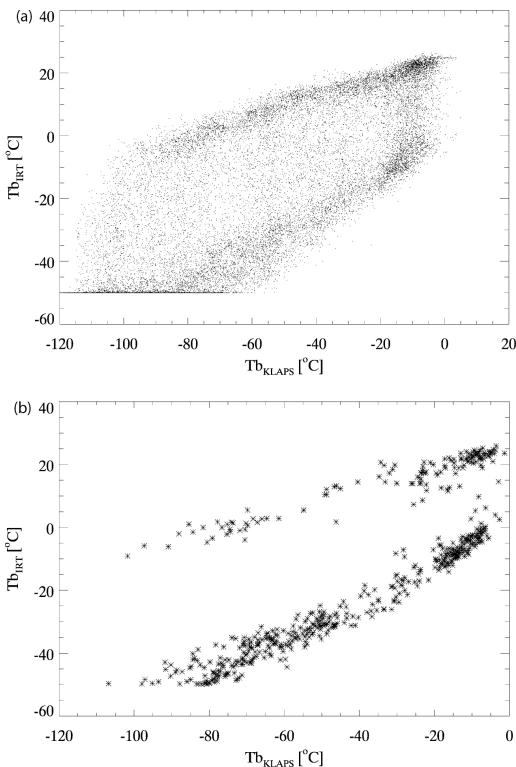


**Figure 5.** Scatter diagram for the estimated clear sky  $Tb$  obtained by using the surface air temperature and water vapor pressure vs. the clear sky  $Tb$  by the radiative transfer calculation (red line is the one to one line). The root mean square difference is 6.3 K and the correlation coefficient is 0.98.

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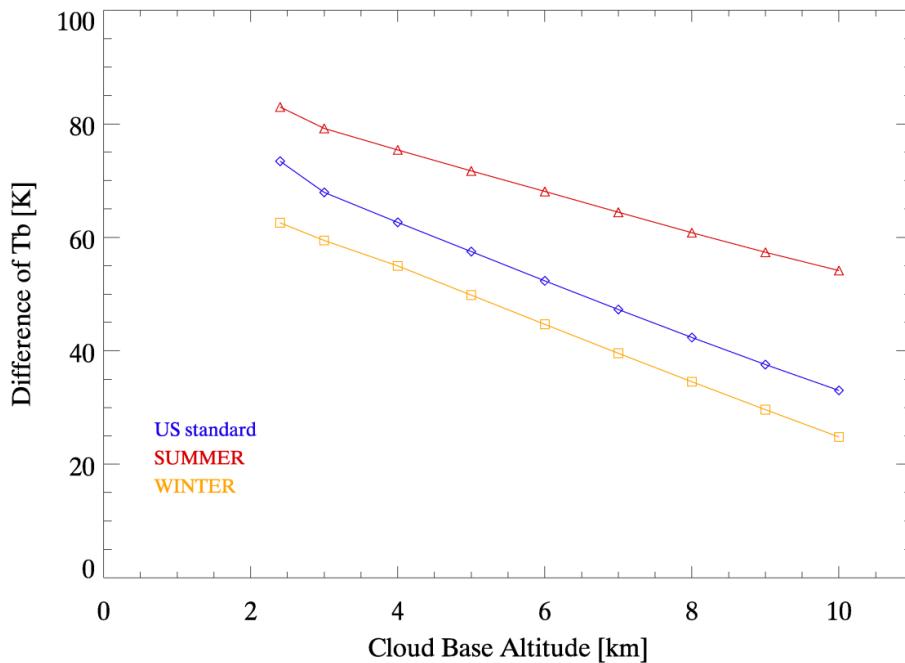


**Figure 6.** The relationship between the simulated clear sky  $Tb$  ( $Tb_{KLAPS}$ ) and the measured  $Tb_{IRT}$  for all conditions for one year **(a)**, and the selected cases with the  $Tb_{IRT}$  values having a small temporal variation **(b)**, representing overcast and clear sky conditions (see text for details).

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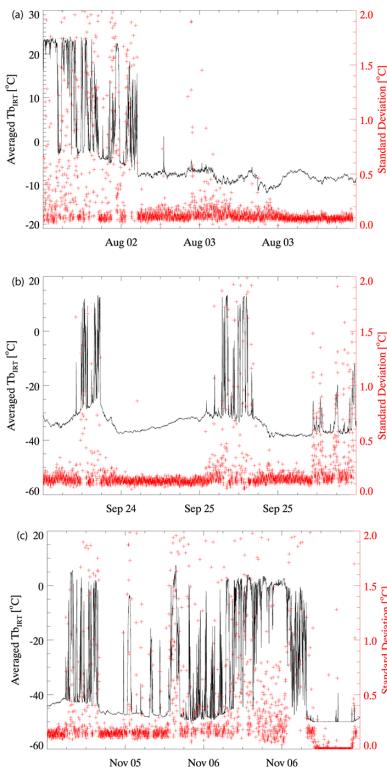


**Figure 7.** The simulated cloud effects to the downwelling radiance (brightness temperature difference between cloud and clear cases) as a function of the different cloud altitudes with different atmospheric profiles. Used cloud type is altocumulus given in Modtran 5.2 with the thickness of 600 m. The high resolution spectral data are convolved with the spectral response function to give the band averaged contribution value and brightness temperature.

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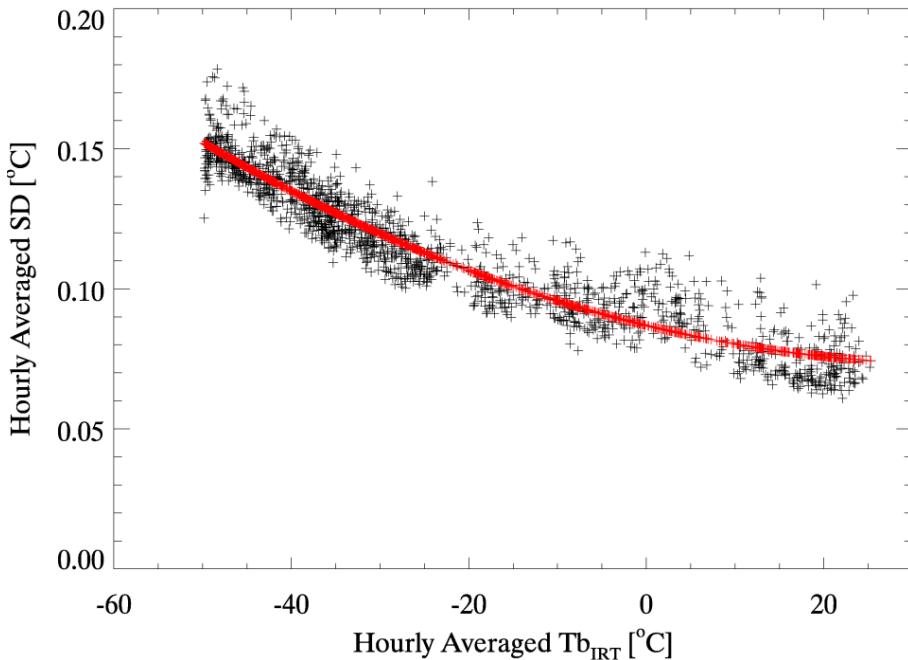


**Figure 8.** Time series of one-minute averaged  $Tb_{IRT}$  (black solid line, reference scale on the left) and its standard deviation (red cross, reference scale is on the right) for 48 h during the summer time **(a)**, the fall time **(b)** and the winter time **(c)** periods. Time duration with relatively cold and homogeneous  $Tb_{IRT}$  is well represented by the relatively smaller and stable value of the standard deviation.

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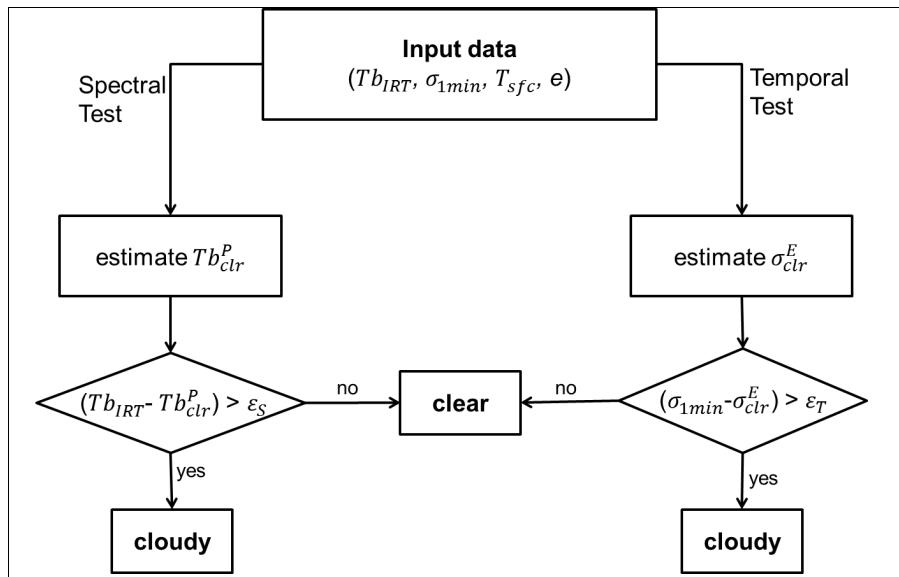


**Figure 9.** The relationship between the hourly averaged standard deviation and the hourly averaged  $Tb_{IRT}$ . The red crosses are the relationship representing the best fit quadratic equation.

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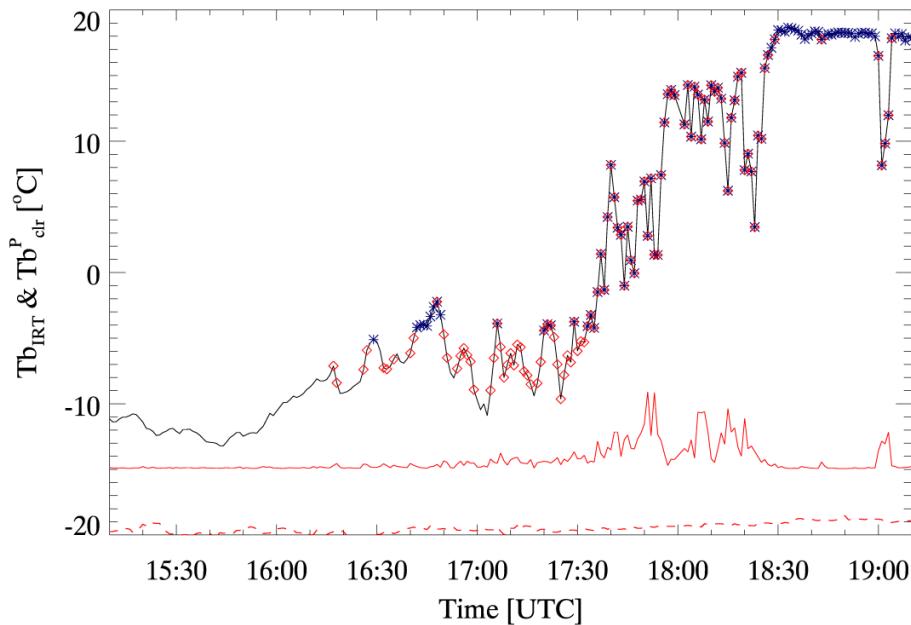
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**Figure 10.** Flow chart of the cloud detection algorithm using the measured  $Tb_{IRT}$  along with the  $T_{sfc}$  and  $e$  from the automatic weather station for every minute. The estimated clear sky  $Tb$  ( $Tb_{clr}^P$ ) and temporal variability ( $\sigma_{clr}^E$ ) are obtained by the Eqs. (5) and (6), respectively. The threshold values of  $\varepsilon_S$  (for spectral test) and  $\varepsilon_T$  (for temporal test) are set to 14 K and 0.18 K, respectively.

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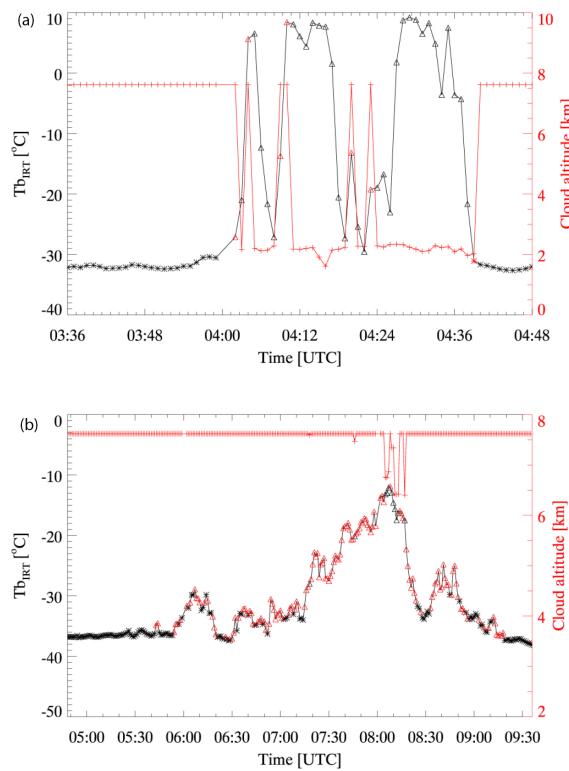


**Figure 11.** Time series of  $Tb_{IRT}$  (black solid line) along with the predicted clear sky  $Tb$  ( $Tb_{clr}^P$ , red dashed line) and  $\sigma_{1\min}$  (red solid line; for clarity value  $-15\text{ K}$  is added to the original value), for about 3 h of 27 June 2013. Symbols blue \* and red  $\diamond$  denote data points classified as cloudy data determined by the spectral test and temporal test, respectively. Data points having both \* and  $\diamond$  are the points detected as cloudy by both tests.

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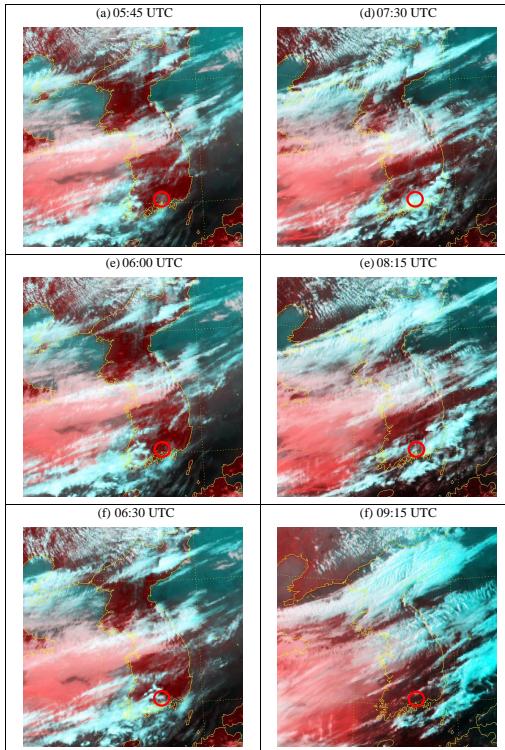
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**Figure 12.** Two representative cases for the characterization of the comparison of cloud detection and cloud base altitude (red crosses) between IRT and ceilometer. The red symbols indicate the failure cases (star and triangle represent misses and false alarm, respectively). On the other hand, the black stars and triangles represent the successful cases. **(a)** represents the highly variable sky condition on 2 October 2012 and **(b)** exemplifies the uniform high clouds condition obtained on 28 March 2013.

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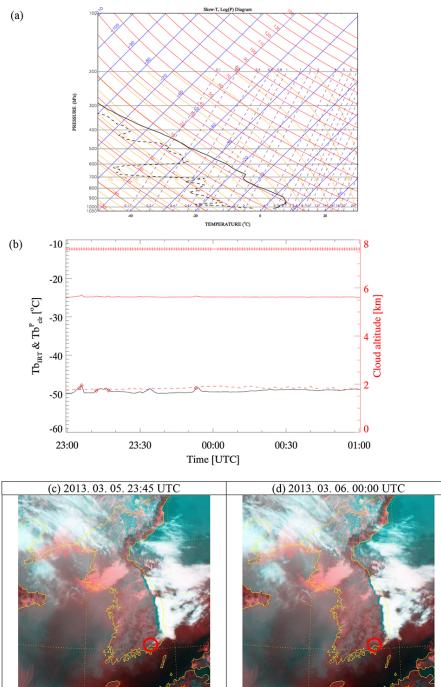


**Figure 13.** False color composite (using visible, infrared window, and water vapor images) image for the time used in the closer comparison of IRT and ceilometer. The time sequence images clearly show the approaching high clouds and a glimpse of thickening clouds over the observation station (located around the center of the red circle).

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**Figure 14.** Vertical profiles of temperature (black solid line) and dew point temperature (black dashed line) on 6 March 2013 **(a)** showing a strong inversion layer from the ground to about 950 hpa, time series of  $Tb_{\text{IRT}}$  (black solid line), predicted clear sky  $Tb$  (red dashed line),  $\sigma_{1,\text{min}}$  (red solid line; for clarity value  $-25^{\circ}\text{C}$  is added to the original value), and cloud base altitude (+; scale is on right) from the ceilometer **(b)**, and color composite satellite images for 23:45 UTC on 5 March 2013 **(c)** and 00:00 UTC on 6 March 2013 **(d)** showing passing of the cloud edge through the north of observation station.

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