

Using simulated data to investigate 10-11 μ m BTD for volcanic ash detection in the tropics and compare instrument sensitivity

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Abstract

Volcanic ash clouds produced during eruptions pose a hazard to aviation and human health, motivating research on improved volcanic ash detection. This study compares the use of different channels for the brightness difference method (BTD) of volcanic ash detection. The 10-11 μ m channels could lead to better detection in the humid climates than the more typical 11-12 μ m. A secondary aim is to find and compare the ash detection limits of instruments which measure in the thermal infrared range based on the ash input parameters.

BTDs are calculated for a large set of simulated spectra generated using the Scattering Reference Forward Model (SRFM) for instruments AHI, ABI, and VIIRS. The probability of measuring the BTDs to be positive based on instrument resolution is also calculated. Contour plots of the BTDs and their associated probability variables show dependence on ash input parameters. Results appear consistent with Dr. Andrew Prata's, though further work must be done to verify this. Findings also suggest that ABI can detect the largest variety of ash. A larger set of ash parameter values and removal of other input variables would be required to extend this study.

1 Introduction

Around 50–70 volcanic eruptions occur per year, with resulting volcanic ash (VA) presenting hazards to human health [1], infrastructure [2], and aviation [3]. For example, the eruption of Eyjafjallajökull in 2010 led to a closure of European airspace for six days due to the dangers and economic consequences of flying through VA. As a result, 108,000 commercial flights were cancelled, causing travel disruptions for 10.5 million passengers, blockage of movement of goods, delays in transplant donations, and a USD 1.7 billion total loss in revenue [4]. The impact of this eruption highlighted the need for improved detection methods, which would allow better hazard assessments for aviation, public health, and air quality [5].

Data obtained from satellite remote sensing is commonly used for VA detection using the reverse absorption effect [6]. This effect describes how the silicates in VA absorb more as wavelengths go from 12 μ m to 10 μ m, opposite to H₂O. This opposing behaviour led to the brightness temperature difference (BTD) method for VA detection [7, 8]. The method typically uses brightness temperatures (BTs) calculated for satellite instrument channels centred around 11 μ m and 12 μ m and takes the difference between them. This BTD is typically negative for an ash cloud and positive for a water cloud, meaning they can be distinguished for instruments which have channels in this region. This method of ash detection will be further discussed in section 2.2.

The BTD detection method often breaks down

when humidity is higher, such as in the tropics, due to the masking effect of the H₂O. When there is a large quantity of H₂O in the atmosphere, the signal from any VA present may be overpowered, leading to an overall positive BTD. High humidity introduces difficulty in providing accurate VA tracking to such areas, thus presenting more significant hazards. Previous studies have tried to correct for this using methods such as BTD with water vapour correction (WVC) [9] and the robust satellite technique ash plume detection (RST_{ASH}) technique [10]. Dr. Andrew Prata is investigating the use of 10 μ m and 11 μ m channels for the tropics, with results thus far indicating larger absolute BTDs than the typical 11-12 BTDs [11].

Certainty in VA detection methods is often established using simulated spectral data. This allows for a wider range of atmospheric input parameters – where the parameter values are known with certainty – than could be found from observations. Spectra resulting from such simulated atmospheric conditions may be computed using radiative transfer models, such as those developed by Wen & Rose [8] and Yu et. al. [12].

In this project, a large set of simulated data is used to test how effective the 10-11 μ m BTD method is compared to 11-12 μ m for VA detection in the tropics. Results from this comparison could contribute to the development of a better method for detecting VA in humid climates.

The spectral dataset contains a variety of ash cloud property combinations, which will also be studied to identify how BTD varies with each pa-

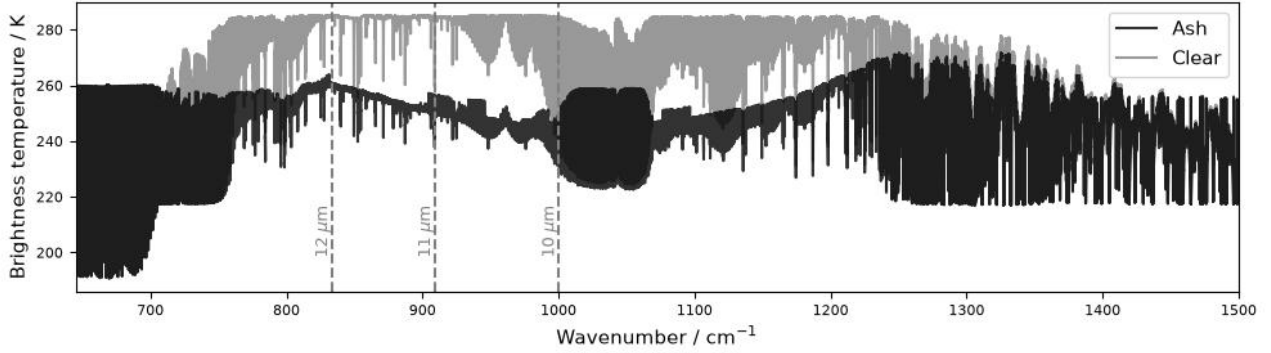


Figure 1: Spectra generated by SRFM for cases where there is a clear sky (grey) or an ash cloud present (black). The ash cloud example uses a mass loading of 5gm^{-2} , particle radius of $0.8\mu\text{m}$, and central altitude of 10km . Vertical lines indicate where the wavelengths of interest in this study, 10, 11, and $12\mu\text{m}$, are situated.

rometer. BTDs will be calculated for satellite instruments which measure in the thermal infrared (TIR) and have channels centred near 10, 11, and $12\mu\text{m}$. Hence, the VA detection limits for each instrument will be found and compared.

In section 2, the data and its generation, VA detection methods, and analysis methods used are described. The results obtained using these methods are presented in section 3, with a comparison between detection methods for the tropics found in section 3.1 and instrument detection limits shown in section 3.2. A discussion of these results are found in section 4, and a summary of the findings and potential future work are shown in section 5.

2 Methods

In this section, the spectral data and methods used in this project are explained. First, the method for generating the data and the inputs used to generate it are shown. Second, the BTD method is discussed in more detail, with the method for computing BTD explicitly laid out and the potential relevance of $T_{10} - T_{11}$ outlined. Finally, a variable which is used to compare the suitability of instruments for detecting volcanic ash (VA) is introduced.

2.1 Simulated data generation

In this project, top of atmosphere (TOA) spectral data is generated using the Scattering Reference Forward Model (SRFM) [13]. The SRFM solves the radiative transfer problem using Mie theory for particle scattering calculations. Here, radiative transfer refers to how radiation is absorbed, emitted, and scattered as it passes through a medium, and Mie theory described the scattering of radi-

ation by spherical particles with size comparable the wavelength of the radiation. To generate spectra, the SRFM uses 1D atmospheric simulations with no horizontal variation which the user inputs through a driver table. This allows for a range of atmospheric conditions and compositions. Two existing radiative transfer codes are implemented within the SRFM – the Reference Forward Model (RFM) [14] and the Discrete Ordinate Radiative Transfer (DISORT) [15]. An example of spectra for atmospheres with a clear sky and a VA cloud are shown in figure 1.

The dataset used in this project was generated using an equatorial atmospheric profile [16] and a combination of ice, water, and VA clouds. Each cloud can be present or not present, with the ice and water clouds having fixed parameters if present, shown in table 1, and the ash cloud having a variety of possible properties, shown in table 2.

The definitions for the cloud properties are:

- Mass loading: The mass of a substance (e.g., VA or H_2O) in a column of atmosphere, measured in grams per square metre.
- Particle radius: Median radius of number distribution, measured in micrometres.
- Central altitude: The height of the middle of the cloud in kilometres.
- Cloud thickness: The distance between the bottom and top of the cloud in kilometres.

For each parameter, typical and limiting case values were included.

Note that each cloud is modelled as a slab in the SRFM, with no overlap possible between different clouds.

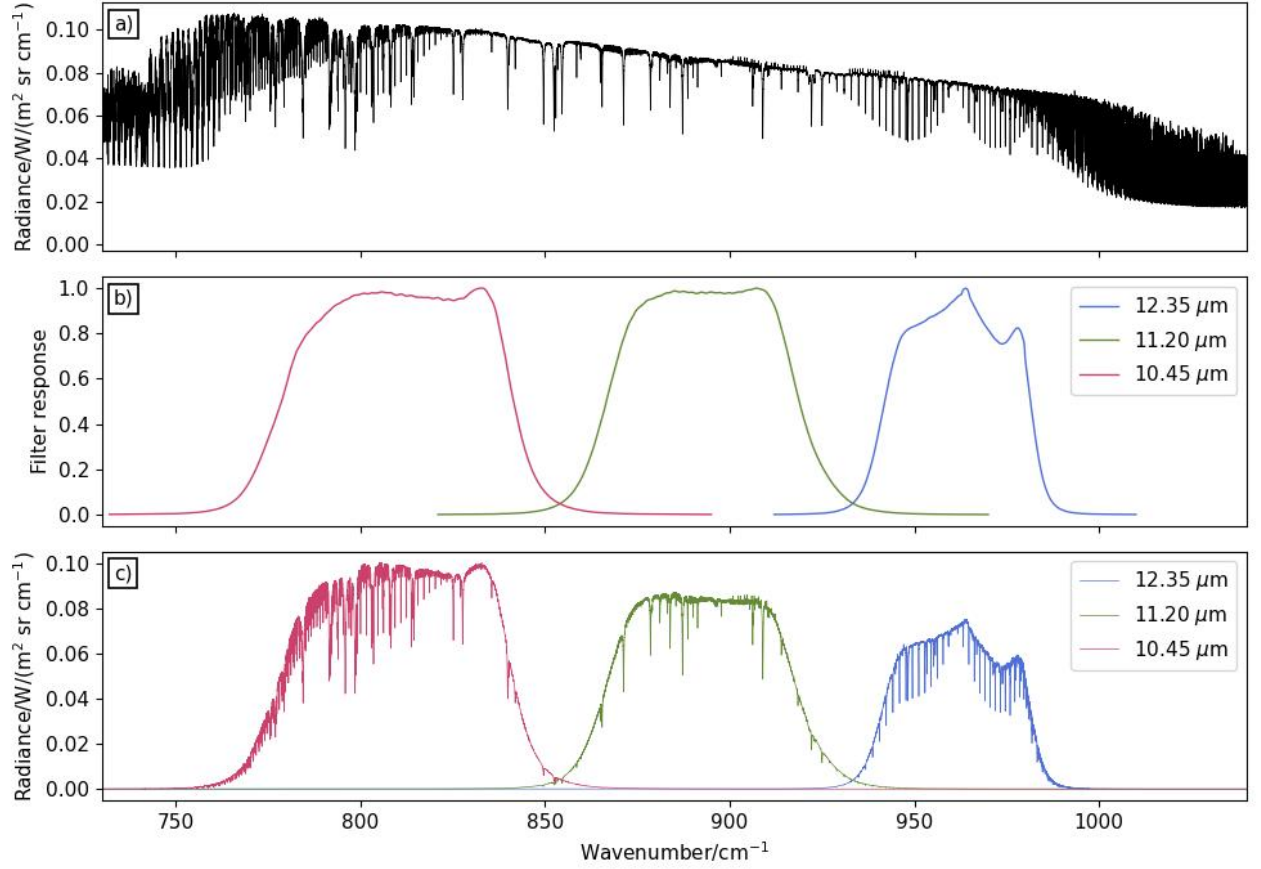


Figure 2: Simulation of HIMAWARI 9 AHI measurement, with (a) signal incident on satellite, (b) signal response functions for channels centred on 10.45, 11.20, and 12.35 μm , and (c) the signal after being filtered through these channels. The simulation uses an ash scattering layer with cloud central altitude 22 km, cloud thickness 1.5 km, ash mass loading 0.1 g m^{-2} , and ash particle radius 0.8 μm .

H ₂ O cloud property	Possible values	
	Water	Ice
Mass loading / g m^{-2}	1.0	0.1
Particle radius / μm	15	15
Central altitude / km	3.0	7.5
Cloud thickness / km	1.0	0.5

Table 1: Water and ice cloud input parameter values used to generate spectral data for this study.

Ash cloud property	Possible values
Mass loading / g m^{-2}	0.1, 0.5, 1, 2, 5, 15, 40, 65, 90
Particle radius / μm	0.1, 0.4, 0.8, 1.5, 3, 5, 7, 10
Central altitude / km	6, 12, 17, 22
Cloud thickness / km	0.1, 0.5, 1.0, 1.5, 1.9

Table 2: Ash input parameter values used to generate spectral data for this study. Each spectrum with an ash cloud present will have a combination of these values.

2.2 Brightness temperature difference

In 1989, Prata used the reverse absorption effect [6] to develop the brightness temperature difference (BTD) method [7] for detecting VA. This method involves calculating the brightness temperatures (BTs) measured by channels typically centred near 11 μm (T_{11}) and 12 μm (T_{12}) and subtracting them to obtain $\text{BTD} = T_{11} - T_{12}$. Generally, BTD is negative if there is only VA or positive if there is only water/ice clouds. This is due to the absorbing properties of the silicates in VA.

Brightness temperatures are calculated by:

1. Convolve a spectrum with satellite instrument spectral response functions (SRFs) for the channels of interest. A filtered spectrum corresponding to each SRF is obtained from this, with an example shown in figure 2.
2. Integrating over the filtered spectrum to obtain the channel radiance.
3. Converting the channel radiance to BT using the Maxwell-Boltzmann distribution.

Satellite	Instrument	Channel centres/ μm	NEDT/K	Resolution/km
GOES 16–19	ABI	10.3, 11.2, 12.3	0.1, 0.1, 0.1	2
HIMAWARI 9 & 10	AHI	10.45, 11.20, 12.35	0.1, 0.1, 0.1	2
SNPP & NOAA 20	VIIRS	10.763, 11.450, 12.013	0.07, 1.5, 0.07	0.375

Table 3: Satellite instruments used in this study, with the satellite name in the first column; the instrument of interest in the second; the channels used in the third column; the corresponding NEDTs in the fourth column; and the spatial resolution of the channels in the fifth column.

For this study, SRFs for all instruments which had channels centred near 10, 11, and 12 μm were used. The instruments which matched this criteria are the advanced baseline imager (ABI) on the 16–19th generation geostationary operational environmental satellites (GOES); the advanced Himawari imager (AHI) on the 8th and 9th generation HIMAWARI satellites; and the visible infrared imager radiometer suite (VIIRS) on the partnered Suomi National Polar-orbiting Partnership (SNPP) and 20th generation national oceanic and atmospheric administration satellite (NOAA-20). Table 3 summarises these instruments, including the noise equivalent delta temperatures (NEDTs) of the relevant channels, a quantity which is defined in section 2.3. The orbits of GOES and HIMAWARI are geostationary, whereas those of SNPP and NOAA 20 are polar. Hence, the latter satellites can achieve better spatial resolution, as they orbit closer to the Earth.

Following Prata’s initial conception of the BTD method, further development was made by Wen & Rose [8] and Yu, Rose & Prata [12]. The former introduced an algorithm for computing effective particle size, cloud optical depth, and total mass of fine ash in VA clouds based on satellite data, and influenced future radiative transfer model development [8]. The latter developed a scheme to reduce the number of false negative VA detections in humid climates [12]. Such false negatives occur in more humid climates as the signal from the H_2O in the atmosphere overpowers that of the VA, leading to an overall positive BTD. This was one of the first papers which developed methods for reducing the effects of humidity when using the BTD method.

More recently, Dr. Andrew Prata (distinct from Dr. Alfredo Prata) has been investigating the efficacy of using $\text{BTd} = T_{10} - T_{11}$ for VA detection in the tropics, where humidity is relatively high [11]. Results thus far have indicated larger absolute BTDs are found for VA clouds in the absence of water clouds, alongside a smaller background BTd. This makes VA clouds more prominent when using the 10 and 11 μm channels instead of the 11 and 12 μm . However, $T_{10} - T_{11}$ has been

observed to change sign from negative to positive when VA effective radius is great than around 5 μm . This study aims to further investigate the $T_{10} - T_{11}$ method to verify and build upon Dr. Prata’s results.

2.3 Probability of $\text{BTd} > 0$

When an instrument measures a BT, there will be some uncertainty in the resulting BTd due to the noise of the channels. The main source of uncertainty arises from the noise of the instrument, which may be measured to deduce the noise equivalent delta temperature (NEDT). This is the temperature which would be required to produce a signal equal to the noise.

Assuming the BTs of interest are independent and of Gaussian form, the uncertainty may be calculated for the BTd:

$$\sigma_{\text{BTd}} = \sqrt{\text{NEDT}_{\lambda_1}^2 + \text{NEDT}_{\lambda_2}^2} \quad (1)$$

where σ_{BTd} is the uncertainty in $\text{BTd} = T_{\lambda_1} - T_{\lambda_2}$ and NEDT_{λ} is for a channel centred on wavelength λ . This noise leads to a non-binary probability of measuring the BTd to be either positive or negative. I.e., a source with an actual BTd slightly below zero has a finite probability of being measured as being positive due to the instrument noise. This probability in measuring some BTd to be positive may be written analytically:

$$P(\text{BTd} > 0) = \Phi\left(\frac{\text{BTd}}{\sigma_{\text{BTd}}}\right) \quad (2)$$

where $\Phi(z)$ is a cumulative distribution function.

From this probability, conditions in which BTd is measured to be negative (i.e. VA is detected) with a certainty surpassing 3σ may be found. This certainty would correspond to $P(\text{BTd} < 0) > 0.99865$, or:

$$P(\text{BTd} > 0) = 1 - P(\text{BTd} < 0) < 0.00135 \quad (3)$$

This limit will be used to deduce and compare the limits of VA detection for different instruments in this study.

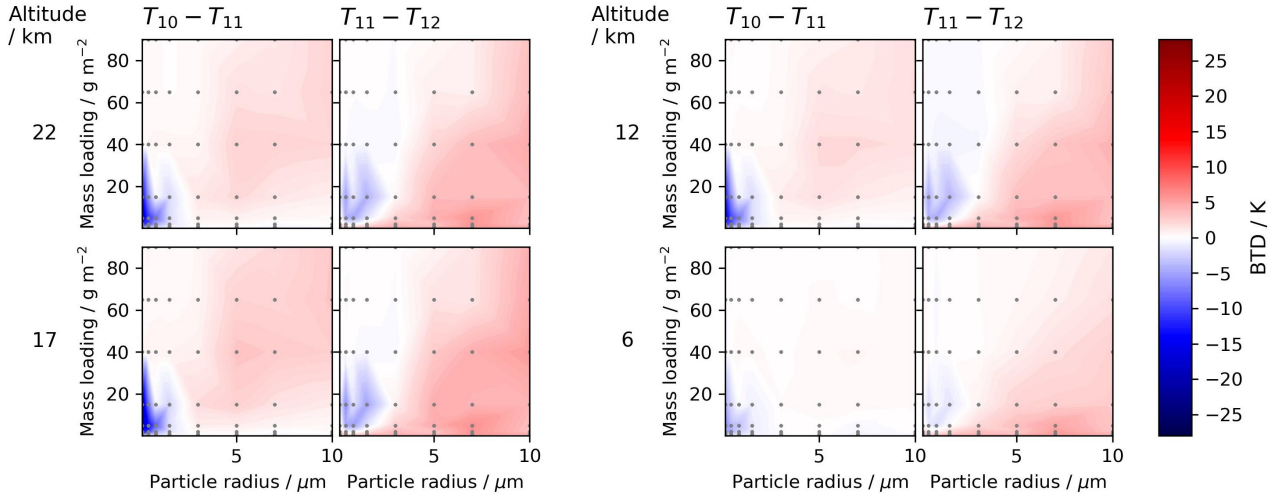


Figure 3: Contour plots showing dependence of $T_{10}-T_{11}$ (left columns) and $T_{11}-T_{12}$ (right columns) on ash mass loading (y-axis) and particle radius (x-axis) at fixed altitudes, indicated to the left of each row. BTs are calculated for HIMAWARI 9 AHI with an ash cloud thickness of 1km. The grey dots indicate points found in the dataset. The variable BTD is linearly interpolated between these points to obtain the contour plots.

3 Results

In this section, the BTD method described in section 2.2 is used on the data explained in section 2.1. The dependence of BTD on the ash parameters is shown first in section 3.1, and a comparison between $P(\text{BTD} > 0)$ calculations for AHI, ABI, and VIIRS are shown in section 3.2.

3.1 Dependence of BTD on ash parameters

Four ash parameters are varied in this study to identify regimes where the BTD method is effective for detecting VA. These parameters are mass loading (g m^{-2}), particle radius (μm), central altitude (km), and cloud thickness (km). For a specified set of ash parameters, there are up to 9 different BTD values due to the scattering layer possibilities (ash, ash + water, ash + ice) and the three zenith angles.

Thickness is excluded because little variation was seen when this parameter was varied (see figures 5 and 6 in appendix A). This is to be expected as, for the same mass loading, a different thickness of cloud will vary the ash concentration.

Figure 3 shows the dependence of $T_{10} - T_{11}$ and $T_{11} - T_{12}$ on mass loading and particle radius at specific central altitude values. For both $T_{10} - T_{11}$ and $T_{11} - T_{12}$, BTD is negative (VA is detected) when particle radius is relatively low (radius $\lesssim 2 - 2.5$ and $2.5 - 3$ respectively) and mass loading is less than $\sim 40 \text{ g m}^{-2}$. The minimum BTD is lower for $T_{10} - T_{11}$ than for $T_{11} - T_{12}$, as are the positive BTD values.

Similar plots but with a row per mass loading or particle radius value are shown in figures 7 and 8 in appendix A.

3.2 Comparison between ABI, AHI, and VIIRS for VA detection

The probabilities laid out in section 2.3 are used to compare the detection limits for the satellite instruments shown in table 3. Each instrument has been launched on more than one generation of the same satellite. It was found that results were almost identical between satellite generations as the instruments were made to be as similar as possible to those on previous generations. Hence, only results from the most recent generation of each instrument (i.e. GOES 19 ABI, HIMAWARI 9 AHI, and NOAA 20 VIIRS) will be shown.

Figure 4 shows the contour plots of $P(\text{BTD} > 0)$ against mass loading and particle radius (y-axis and x-axis) for constant central altitude values (row) for the three instruments. Areas which are white indicated $P(\text{BTD} > 0) \approx 0$, so these are the areas where VA would be detected by each instrument with high certainty. Correspondingly, black areas indicated $P(\text{BTD} > 0) \approx 1$, so it's highly improbable VA with such properties would be detected.

For ABI and AHI (figure 4a and 4b), $P(T_{11} - T_{12} > 0)$ are very similar due to their similar 11 and 12 μm channels. These plots indicate high probability of VA detection for mass loading bigger than $\sim 0.5 \text{ g m}^{-2}$ and particle radius smaller than $\sim 2 - 3 \mu\text{m}$. Smaller areas where VA would

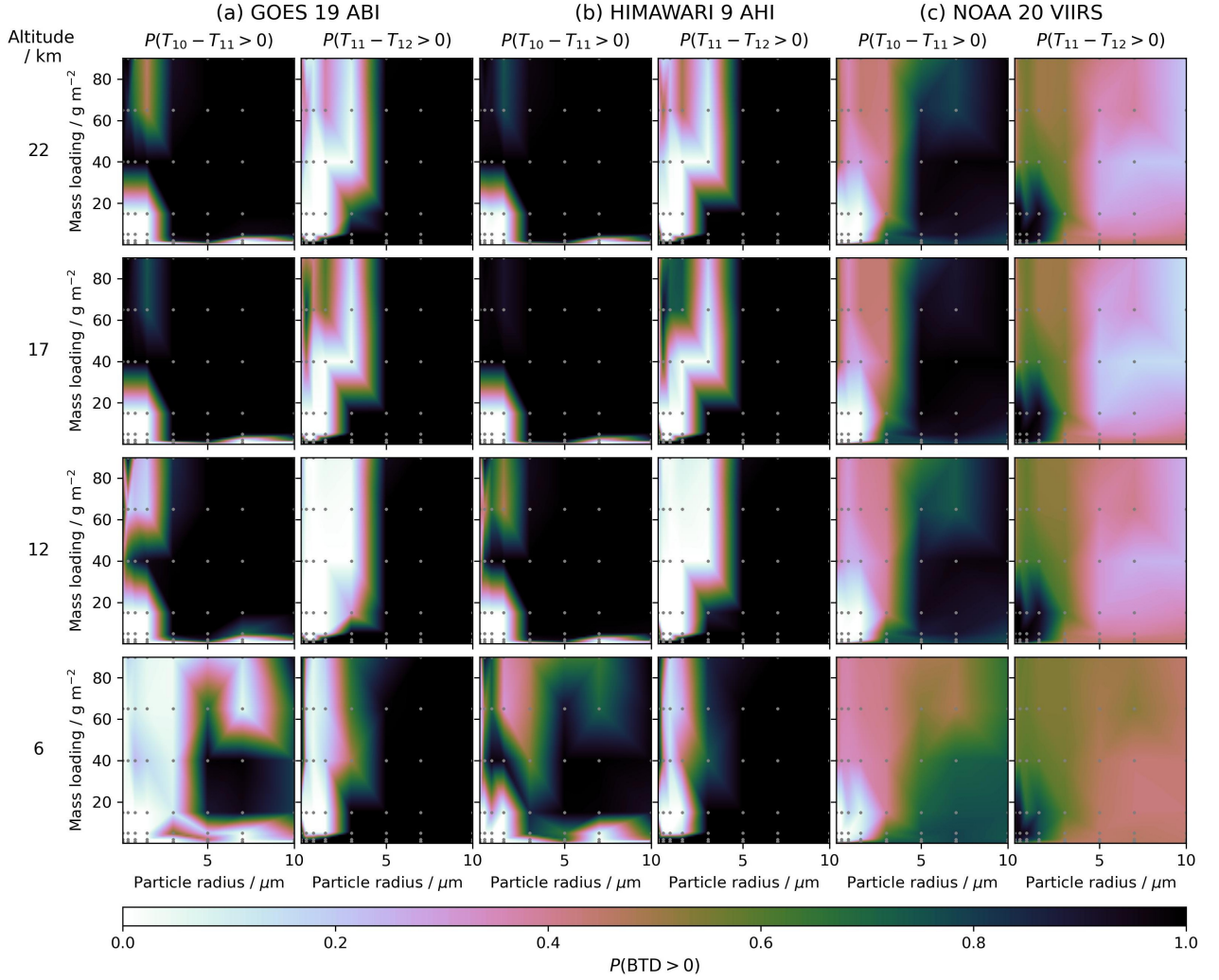


Figure 4: Probability of detecting $T_{10} - T_{11}$ (left column for each instrument) and $T_{11} - T_{12}$ (right column for each instrument) to be positive for instruments (a) GOES 19 ABI, (b) HIMAWARI 9 AHI, and (c) NOAA 20 VIIRS. The grey dots indicate points found in the dataset. The variable $P(\text{BTD} > 0)$ is linearly interpolated between these points to obtain the contour plots.

Altitude / km	Percentage of area where $P(\text{BTD} > 0) < 0.00135$ / %					
	GOES 19 ABI		Himawari 9 AHI		NOAA 20 VIIRS	
	10 – 11	11 – 12	10 – 11	11 – 12	10 – 11	11 – 12
22	2.92	3.44	2.01	1.99	1.18	0.00
17	3.03	1.95	2.72	1.68	1.35	0.00
12	3.11	6.45	2.77	4.85	1.09	0.00
6	3.79	1.50	1.95	0.90	0.46	0.00

Table 4: Percentage of interpolated $P(\text{BTD} > 0)$ values which are less than 0.00135. Percentages are placed in the same arrangement as in figure 4, where each instrument has two columns – one for $\text{BTD} = T_{10} - T_{11}$ (left) and one for $\text{BTD} = T_{11} - T_{12}$ – and each percentage is calculated at a specified altitude value, indicated on the first column.

be detected exist for $P(T_{10} - T_{11} > 0)$. In this case, high probability of detection is observed for mass loading less than $\sim 20 \text{ g m}^{-2}$ and particle radius less than $\sim 2 \mu\text{m}$ when the central altitude is $> 6 \text{ km}$ (i.e. the VA cloud is the highest cloud). When the central altitude is 6 km, larger areas where the probability is neither 0 or 1 are seen. This is because, in the spectra where an ice cloud are present, the VA cloud is no longer the highest

cloud, so the signal from the VA is weakened.

The patterns shown for VIIRS (figure 4c) are quite different to those of ABI and AHI. This is due to the difference between channel central wavelengths. The $11.45 \mu\text{m}$ channel also has a relatively high NEDT of 1.5K, compared to 0.1K for the ABI and AHI channels. This high NEDT leads to large areas where the probability is non-binary.

A simplistic way to compare the VA detection

capabilities of these three instruments is to calculate the area where $P(\text{BTD} > 0) < 0.00135$ (see equation 3), i.e. where VA is detected with certainty surpassing 3σ . The fraction of the total interpolated area where this condition is met is shown in table 4. The percentages shown are highest for ABI.

4 Discussion

The results shown in section 3 begin to indicate the strengths of the $T_{10} - T_{11}$ and $T_{11} - T_{12}$ methods for detecting VA in the tropics, where humidity is relatively high. However, the study is limited by the data – increasing the number of values of each ash input parameter would increase the reliability of the interpolated contour plots found in figures 3 and 4. This is computationally expensive, as the SRFM is a line-by-line program, and each addition to the input parameters greatly increases the number of spectra generated. However, this can be done with more time.

Despite the coarse grid, some dependence of BTD on the ash parameters may be deduced from figure 3. Firstly, the minimum of $T_{10} - T_{11}$ is approximately double that of $T_{11} - T_{12}$, which is consistent with Prata’s finding that the 10–11 μm channels give stronger signals. The reduction in positive BTD for the 10–11 μm channels is also consistent, indicating that these channels may be effective at removing some of the masking effect of the atmospheric water. However, $T_{10} - T_{11}$ becomes positive at lower particle radii than $T_{11} - T_{12}$, which may also be consistent with Prata’s finding that the VA BTD signal becomes positive for effective radii above $\sim 5\mu\text{m}$. As this study uses particle radius rather than effective radius, a direct comparison cannot be made. Adding effective radius as an output in the data generation code would help establish whether this finding is consistent with Prata’s.

A comparison with Prata’s results would also be clearer if the spectra with water or ice clouds were excluded from the analysis, as he focussed on a case where there was only a ash cloud. This would be a better starting point for looking at the dependence of $T_{10} - T_{11}$ and $T_{11} - T_{12}$ on VA parameters, and the effect of adding in H_2O clouds could be observed more clearly. Furthermore, the relationship between BTD and altitude would be made clearer if just VA was present, as the ice cloud at 7.5km disproportionately affects the calculations made in this study when the VA cloud

central altitude is 6km.

According to figures 3 and 4, VA is detectable for:

$$0.1 \lesssim m \lesssim 40 \text{ g m}^{-2}, \quad (4)$$

$$0 < r \lesssim \begin{cases} 1.5 \mu\text{m} & \text{for BTD} = T_{10} - T_{11}, \\ 2\text{--}3 \mu\text{m} & \text{for BTD} = T_{11} - T_{12}. \end{cases} \quad (5)$$

where m is mass loading and r is particle radius. The values in equation 4 appear sensible, as BTD is expected to tend to zero as mass loading gets large. In this case, the view gets saturated with VA and no BT contrast may be observed, and similarly for a mass loading of zero. Previous studies have found that $T_{11} - T_{12}$ is negative for ice-free ash clouds with mean particle radius less than $3\mu\text{m}$ [6, 7]. Hence, the results in equation 5 also appear sensible.

Figure 3 indicates that the BTD minima are lowest when central altitude is close to 17km. This is expected, as the tropopause – where BT contrast between the cloud and the ground would be largest – in the tropics is situated at around 17km. However, the percentages in table 4 indicate VA detection occurs for the widest range of radius and mass loading values at an altitude of 12km. The author is unsure why VA with, for example, a mass loading of $\sim 60 \text{ g m}^{-2}$ would be detected at 12km but not 17km in a tropical atmosphere. This could be further investigated.

The results in section 3.2 allow for comparison in VA detection capabilities of the three satellite instruments which have channels near 10, 11, and 12 μm - ABI, AHI, and VIIRS. By calculating the percentage of interpolated $P(\text{BTD} > 0)$ values which are less than 0.00135 (VA detected with certainty surpassing 3σ), an overall comparison can be made. As ABI has the highest percentage for almost all altitudes, this study suggests that ABI is the best instrument of the three as it detects VA with high certainty for the largest range of properties. However, this suggestion is tentative as the percentage calculations are based off a linear interpolation over a coarse grid. Here, a larger dataset would, again, be highly beneficial.

A more detailed study would be beneficial to analyse how the detection limits vary for each instrument in terms of specific ash parameters, zenith angles, latitude of view, and presence of other clouds. Creating such an overview of detection limits would provide future studies with

a good source for identifying areas of uncertainty and limitations.

The results for VIIRS (figure 3.2c) are notably different to ABI and AHI. Some further work could confirm whether this is due to the difference in central channel wavelengths. It may be expected that a plot of $P(T_{10} - T_{12} > 0)$ would be similar to the ABI and AHI plots of $P(T_{11} - T_{12} > 0)$, as the $10.7\mu\text{m}$ channel is often used to calculate T_{11} in other studies using the BTD method (e.g. Beckett et. al. 2017 [17]). One might also expect the VIIRS plots to look more similar to the ABI/AHI plots if the $11.45\mu\text{m}$ channel NEDT was set to 0.1K . Overall, figure 3.2c indicates VIIRS would be a poor instrument to use for VA detection due to the large areas of uncertainty.

The conclusions made about these instruments are based on measurements which would be made of a 1D atmosphere and do not take into account the horizontal resolution of each instrument. Due to the polar orbit of SNNP and NOAA 20, the relevant channels of VIIRS have a resolution of 375m . The corresponding channels of AHI and ABI have a 2km resolution. The fine spatial resolution of VIIRS is advantageous in VA detection. To compare the advantages and disadvantages between these three instruments, a study using observational data could be done.

VA is not the only compound found in volcanic plumes. Substances such as sulphuric acid and sulphur dioxide are also ejected during volcanic eruptions. Further work could investigate the effect of these components on the results found in this study. This would indicate further difficulties satellites would have in detecting VA in real measurements.

5 Conclusions

The brightness temperature difference (BDT) method for volcanic ash (VA) detection typically calculates $T_{11} - T_{12}$ to distinguish between VA and H_2O clouds, but the method breaks down in humid climates. In this study, the $T_{10} - T_{11}$ method is applied to a large set of simulated spectral data with the aim of establishing its merits as a volcanic ash (VA) detection method in the tropics, where humidity is relatively high. This investigation was influenced by Dr. Andrew Prata’s findings that the $T_{10} - T_{11}$ method results in a smaller BDT for H_2O , thus reducing the masking effect. This could make it a preferable method for VA detection in the tropics.

The findings in this study appear consistent with Prata’s findings that (i) $T_{10} - T_{11}$ is generally lower than $T_{11} - T_{12}$ for a given spectrum, and (ii) $T_{10} - T_{11}$ becomes positive at a lower particle radius than $T_{11} - T_{12}$. However, further work should be done to increase confidence in these findings. Firstly, a larger set of ash input parameter values are needed to increase confidence in the contour plots, which are linearly interpolated. Secondly, the spectra should be generated for the case where only a VA cloud is present with the zenith angle kept constant to simplify analysis and improve comparison with Prata’s results.

The results also suggest that ABI is the best instrument for VA detection as, for almost all altitudes studied, it detects VA with certainty surpassing 3σ for the largest range of ash property values. Confidence in this result would, again, benefit from a larger set of ash input parameter values as the result is based on linearly interpolated plots.

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A Contour plots of BTD

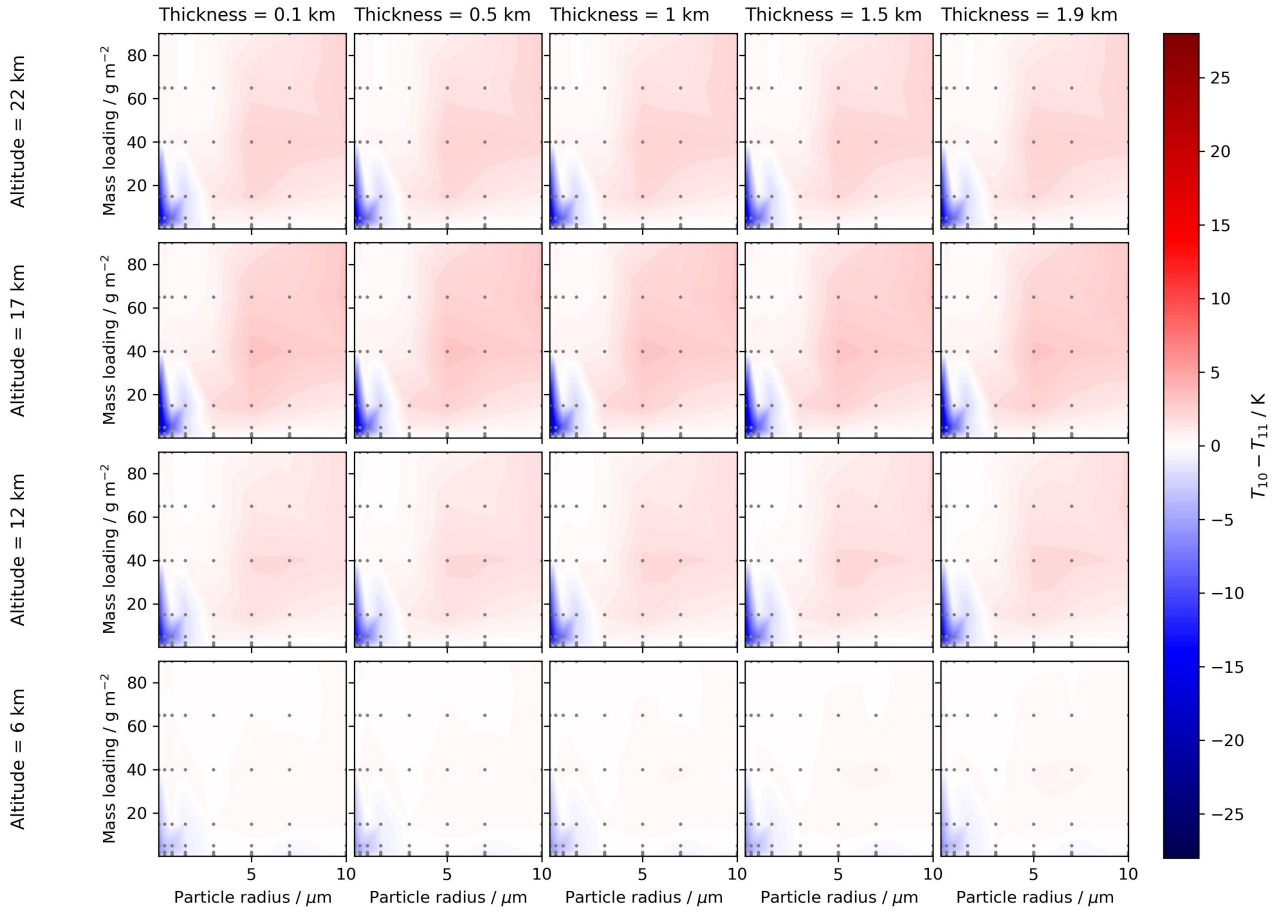


Figure 5: Contour plots showing dependence of $T_{10} - T_{11}$ on particle radius (x-axis) and mass loading (y-axis) at constant ash cloud thickness (column) and central altitude (row) values. BTs are calculated for HIMAWARI 9 AHI.

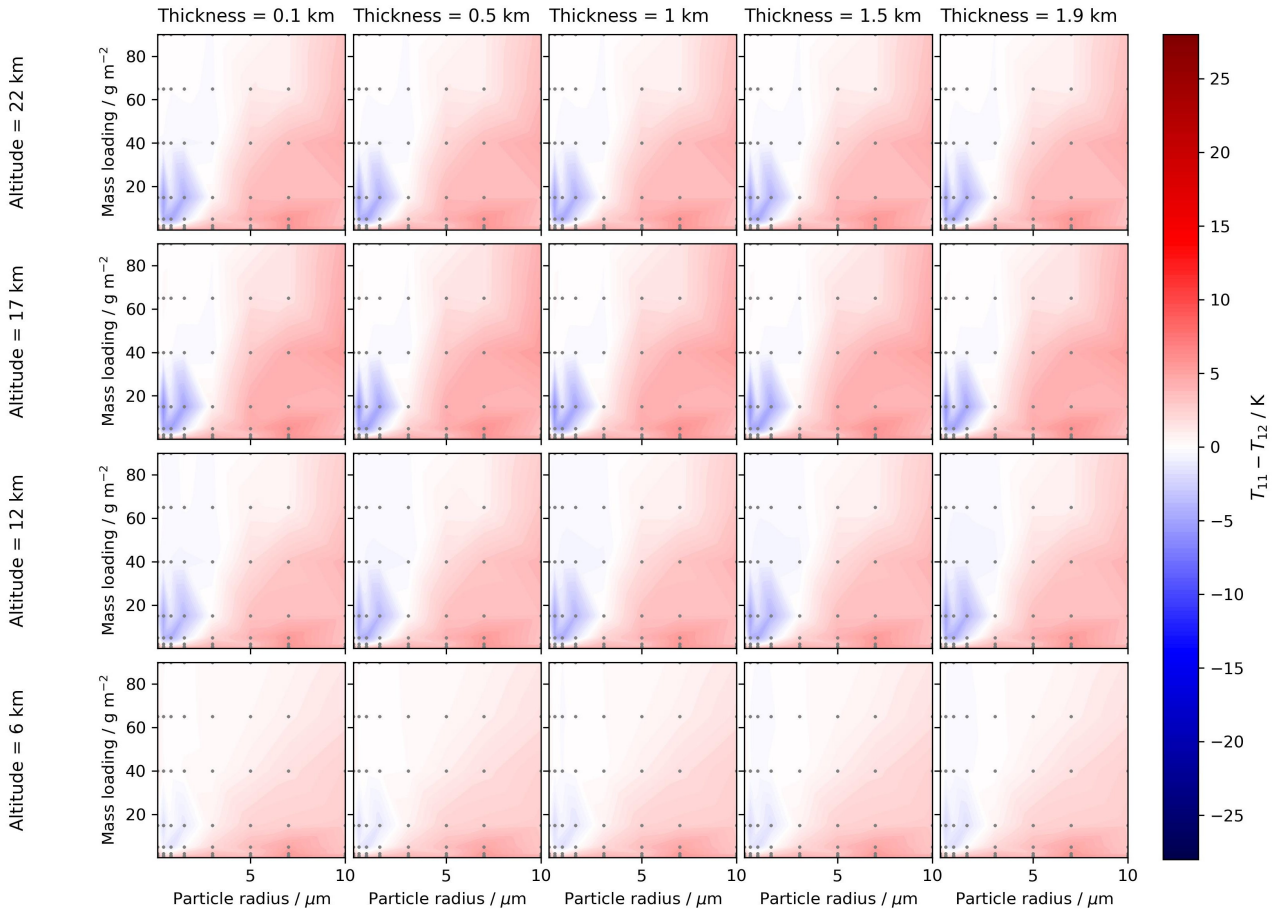


Figure 6: As in figure 5, but for $T_{11} - T_{12}$.

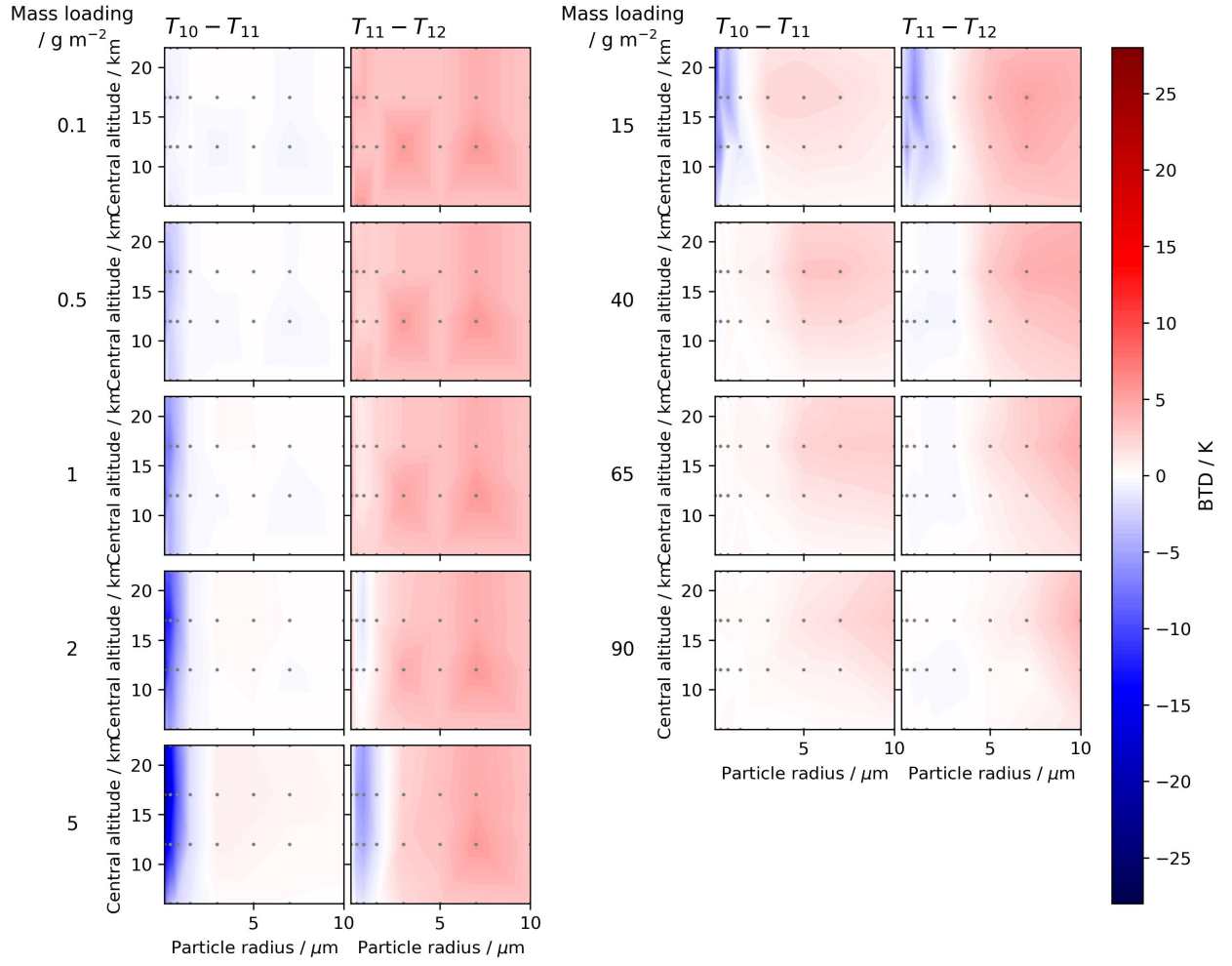


Figure 7: As in figure 3, but with particle radius on x-axis, altitude on y-axis, and each row corresponding to fixed mass loading.

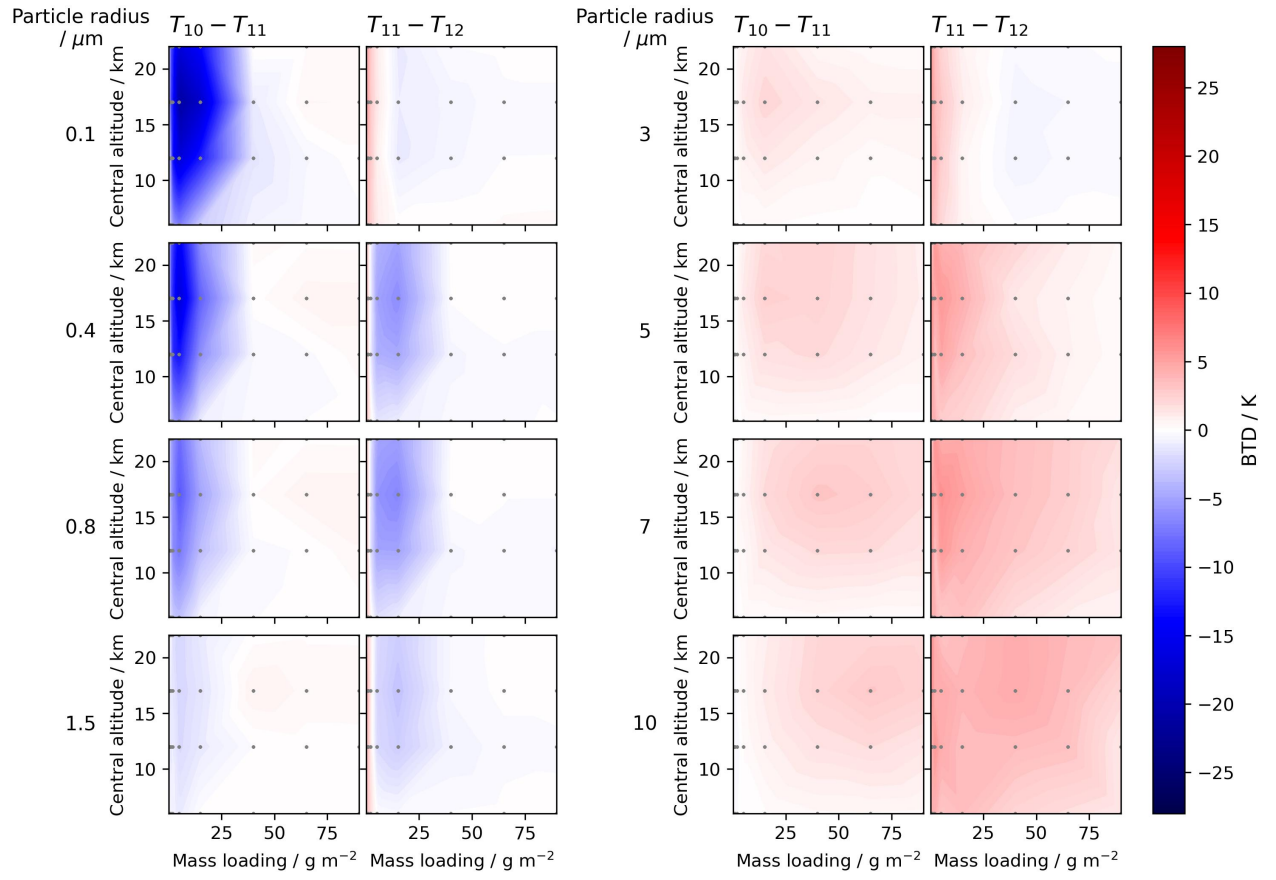


Figure 8: As in figure 7, but with mass loading on x-axis and row corresponding to fixed radius.