

1       **An Efficient Parameterization for Surface Shortwave**  
2       **3D Radiative Effects in Large-Eddy Simulations of**  
3       **Shallow Cumulus Clouds**

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7       **Key Points:**

- 8       • We correct simulations of shallow cumulus cloud days with 1D radiative transfer  
9       for the 3D radiative effects in a post-processing step  
10      • The probability distributions of diffuse and global radiation closely match the ob-  
11      servations after filtering the surface diffuse radiation  
12      • The filter size can be parameterized as a linear function of one or multiple cloud  
13      variables, resulting in a minimal computational overhead

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**Abstract**

Most atmospheric models consider radiative transfer only in the vertical direction (1D), as 3D radiative transfer calculations are too costly. Thereby, horizontal transfer of radiation is omitted, resulting in incorrect surface radiation fields. The horizontal spreading of diffuse radiation results in darker cloud shadows, whereas it increases the surface radiation in clear sky patches (cloud enhancement). In this study, we developed a simple method to account for the horizontal transfer of diffuse radiation. We spatially filter the surface diffuse radiation field with a Gaussian filter, which is conceptually simple and computationally efficient. We applied the filtering to the results of Large-Eddy Simulations for two summer days in Cabauw, the Netherlands, on which shallow cumulus clouds formed during the day. We obtained the optimal filter size by matching the simulation results with detailed high-quality observations (1Hz). Without the filtering, cloud enhancements are not captured, and the probability distribution of global radiation is unimodal, whereas the observed distribution is bimodal. After filtering, the probability distribution of global radiation is bimodal and cloud enhancements are simulated, in line with the observations. We found that small changes in the filter width do not strongly influence the results. Furthermore, we showed that the width of the filter can be parameterized as a linear function of e.g. the cloud cover. Hence, this work presents a proof-of-concept for our method to come to more realistic surface irradiances by filtering diffuse radiation at the surface.

**Plain Language Summary**

The pattern of radiation at the surface is characterized by the presence of cloud shadows and peaks in the radiation caused by scattering of light by clouds. The amount of solar radiation that reaches the Earth's surface determines how much energy is produced by solar panels and how much heat and moisture is supplied to the clouds, thus it influences how the clouds develop. Existing models neglect the scattering of radiation in the horizontal direction, therefore the high peaks in the radiation are not modelled. In this paper, we show for two days with shallow cumulus clouds how we can include the effect of the horizontal propagation of radiation. We redistribute the radiation at the surface, and we compare our model results with measurements. After the redistribution, the high peaks in radiation are modeled. In general, we get a good match between the observed and modelled radiation distribution. We show that the redistribution can be made a function of the clouds in the model. Hence, this work presents a proof-of-concept for our method to come to more realistic surface radiation, without complex calculations.

**1 Introduction**

The amount of solar energy that reaches the earth surface is strongly influenced by the complex interactions between clouds and radiation. Therefore, solar energy partly reaches the surface directly and partly reaches the surface as diffuse radiation after it is scattered in the atmosphere by gases, aerosols and clouds. The total amount of solar energy reaching the surface, also referred to as surface irradiance or global radiation, governs many processes at the surface. It drives the sensible and latent heat fluxes, which supply moisture and energy to boundary layer clouds and thus determine their development. Apart from the surface fluxes, the surface irradiance also influences plant photosynthesis, as diffuse radiation is taken up by the canopy more efficiently than direct radiation (Kanniah et al., 2012). Furthermore, surface irradiance determines the production of renewable energy by solar panels. It is therefore important to have a good model representation of the surface irradiance and the partitioning between direct and diffuse radiation.

Currently, clouds as well as radiation are usually parameterized in weather and climate models. Existing parameterizations for radiation generally neglect the horizontal

64 transport of radiation. Radiative transfer is considered in 1D and within separate ver-  
65 tical columns (Independent Column Approximation, ICA), to keep calculations afford-  
66 able. Recent methods (Schäfer et al., 2016; Hogan et al., 2016) can account for the hor-  
67 izontal transport of radiation through cloud sides within grid boxes, making it possible  
68 to include the mean 3D effects in general circulation models. Between grid boxes, the  
69 horizontal transport can only be neglected if the grid boxes are large enough such that  
70 a cloud and its shadow fall within the same grid cell (Wapler & Mayer, 2008). As com-  
71 puting capacity increases, so does the model resolution. With that it becomes possible  
72 to resolve individual clouds in limited area models and horizontal transport of radiation  
73 between grid boxes is no longer negligible (Wissmeier et al., 2013). In Large-Eddy Sim-  
74 ulations (LES), clouds and their full 3D structure are resolved explicitly, while the cal-  
75 culation of radiative transfer remains generally 1D. To make a next step in realism, it  
76 becomes increasingly relevant to improve existing parameterizations to account for the  
77 horizontal transport of radiation.

78 There are two major effects of the horizontal transport of radiation that cause the  
79 differences between radiative transfer in 1D and 3D. Firstly, in 1D, the cloud shadow is  
80 located exactly below the cloud. In reality, the cloud shadow is displaced and elongated.  
81 The displacement of the cloud shadow can impact the cloud size (Veerman et al., 2020),  
82 trigger secondary circulations (Gronemeier et al., 2017) and increase the formation of  
83 cloud streets (Jakub & Mayer, 2017). Secondly, the diffuse radiation reaches the surface  
84 exactly under the cloud in 1D. In reality, diffuse radiation is spread out over a larger sur-  
85 face area (Wissmeier et al., 2013; Wapler & Mayer, 2008; Hogan & Shonk, 2013). The  
86 horizontal spreading of the diffuse radiation results in more uniformly dark cloud shad-  
87 ows, whereas it increases the surface radiation in clear sky patches (cloud enhancement).  
88 Recently, Villefranque and Hogan (2021) provided the observational evidence for the 3D  
89 radiative effects. The horizontal spreading of radiation causes the characteristic bimodal  
90 distribution of solar irradiance observed under cloudy conditions (Schmidt et al., 2007,  
91 2009; Gristey et al., 2020b; Kreuwel et al., 2020). Gristey et al. (2020b) showed that the  
92 probability distribution of global radiation of simulations with 1D radiative transfer clearly  
93 differs from the distribution of global radiation of observations and simulations with 3D  
94 radiative transfer. This difference is caused by the lack of horizontal spreading of dif-  
95 fuse radiation. Therefore, the spreading of the diffuse radiation is the focus point of this  
96 study.

97 Different methods exist to include 3D radiative effects or account for them. Ra-  
98 diative transfer can be computed accurately in 3D, for example with a Monte Carlo sim-  
99 ulation (Mayer, 2009), but these calculations are orders of magnitude slower than 1D cal-  
100 culations. A more efficient 3D method is the TenStream solver (Jakub & Mayer, 2015).  
101 However, with the TenStream solver the surface fields of diffuse radiation are not dif-  
102 fused enough (Jakub & Mayer, 2015) and the calculations are still more than an order  
103 of magnitude slower than 1D calculations (Veerman et al., 2020; Jakub & Mayer, 2015).  
104 The probability distribution of the global radiation can also be predicted from cloud field  
105 properties with machine-learning (Gristey et al., 2020a). Alternatively, 1D radiative trans-  
106 fer calculations can be adapted to account for the 3D radiative effects. Such adaptations  
107 include the spatial information that is necessary to study the impact of the 3D effects  
108 on the simulations, which is not possible with the method of Gristey et al. (2020a). Fur-  
109 thermore, such adaptations are computationally more efficient than Monte Carlo sim-  
110 ulations or the TenStream solver. Therefore, adaptations of 1D radiative transfer cal-  
111 culations can potentially be applied to longer time ranges and larger domains.

112 Existing literature shows that the errors in the location and shape of the cloud shadow  
113 can be tackled by using tilted columns (Tilted Independent Column Approximation, TICA)  
114 (e.g., Wissmeier et al., 2013; Wapler & Mayer, 2008; Várnai & Davies, 1999). The spread-  
115 ing of the diffuse radiation can be included by smoothing the 1D diffuse radiation fields  
116 (Nonlocal Independent Column Approximation, NICA, Marshak et al. (1995)). Espe-

117 cially these smoothing methods strongly simplify the actual radiative transfer. It is there-  
 118 fore very important to thoroughly validate the performance of these methods. In pre-  
 119 vious work, the smoothed 1D radiation was validated against 3D simulations for snap-  
 120 shots of cloud fields (Marshak et al., 1995; Zuidema & Evans, 1998; Wapler & Mayer,  
 121 2008; Wissmeier et al., 2013). Instead, we will use observations for the development and  
 122 validation of our smoothing method, which allows us to test our method over a period  
 123 of time. Different options exist to smooth the diffuse radiation. The simplest option is  
 124 to use the area average diffuse radiation for the whole study area (Wapler & Mayer, 2008),  
 125 which works well for small domains sizes with a regular cloud field, but often a more gen-  
 126 erally applicable approach, such as a smoothing filter, is required. Possible filters use a  
 127 gamma distribution (Marshak et al., 1995) or a Gaussian distribution (Zuidema & Evans,  
 128 1998; Wissmeier et al., 2013). The simplest distribution, the Gaussian, requires the de-  
 129 termination of only one parameter, the standard deviation ( $\sigma$ ).  $\sigma$  can be pa-  
 130 rameterized for use in operational models. Wissmeier et al. (2013) proposed a method  
 131 where  $\sigma$  is a function of the solar zenith angle and the distance from the center of  
 132 the surface pixel to the center of the base of the closest cloud. This method requires the  
 133 calculation of many  $\sigma$ s, as  $\sigma$  differs per surface pixel.

134 The aim of this study is to correct 1D radiative transfer calculations for the 3D ra-  
 135 diative effects. We focus on the spreading of the shortwave diffuse radiation at the sur-  
 136 face as this is essential to capture the cloud enhancements and more uniformly dark cloud  
 137 shadows. We will use a spatial filter to smooth the diffuse radiation at the surface. We  
 138 strive to keep the parameterization as simple as possible, thus we will use one filter size  
 139 per time step for the whole domain and we will investigate the possibilities to describe  
 140 this filter size as a linear function of one or a couple of cloud variables. As we aim to in-  
 141 vestigate the potential of the filtering, we will apply the filtering as a post-processing step  
 142 to our LES output. We base our filtering on and validate our filtering against observa-  
 143 tions, as observations are available for long periods of time, for which 3D calculations  
 144 are not feasible anymore. Additionally, the advantage of observations is that they are  
 145 measurements of reality and not influenced by any model parameterization or assump-  
 146 tion. We will study two shallow cumulus cloud days in Cabauw, the Netherlands, for which  
 147 high-resolution observations (1Hz) are available from the Baseline Surface Radiation Net-  
 148 work (BSRN) station.

## 149 2 Data

150 For this study, we selected two summer days (4 July and 15 August 2016) in Cabauw,  
 151 the Netherlands, during which shallow cumulus clouds formed. The 3D radiative effects  
 152 are most pronounced when cloud shadows and regions with cloud enhancements both  
 153 occur frequently, thus we selected days with highly variable surface global radiation. Fur-  
 154 thermore, ice and liquid water impact radiation differently, thus we selected days with-  
 155 out high clouds (which contain ice). Lastly, we are interested in clouds that are surface  
 156 driven, as the formation of these clouds is the result of the local surface irradiance. There-  
 157 fore, we selected days that started and ended with cloud-free skies and had shallow cu-  
 158 mulus clouds during the day.

159 We compared the simulation results (as described in the next section) with obser-  
 160 vations from the Royal Netherlands Meteorological Institute (KNMI) observatory in Cabauw.  
 161 Cabauw is located in the centre of the Netherlands (51.971 °N, 4.927 °E), where the sur-  
 162 roundings are flat and mainly consist of meadows and ditches. At the measurement site,  
 163 basic meteorological variables such as specific humidity, temperature and wind speed are  
 164 measured at 7 levels along a 200 m high tower (KNMI Data Services, 2022b). The cloud  
 165 cover is measured with a NubiScope, which is a scanning infrared radiometer (KNMI Data  
 166 Services, 2022a). These observations all have a 10 min resolution. We used these obser-  
 167 vations to validate the general performance of the LES model. For the main analyses,  
 168 we used the observed shortwave irradiances (global, direct and diffuse) from the Base-

169 line Surface Radiation Network (BSRN) site in Cabauw. At this station, broadband ir-  
 170 radiances are measured at a single location with a high frequency (1 Hz). Details about  
 171 the radiation measurements can be found in Knap (2018).

172 Apart from the observations, the clear sky radiation is available every minute, as  
 173 calculated with the McClear model (Gschwind et al., 2019). The clear sky radiation is  
 174 the amount of radiation that would have reached the surface if there were no clouds present.

## 175 **3 Methods**

### 176 **3.1 Model Simulation**

177 We performed realistic LESs using MicroHH (Van Heerwaarden et al., 2017). Our  
 178 simulations use an interactive land-surface scheme, similar to HTESSEL (Balsamo et al.,  
 179 2009) and our land surface is a homogeneous grassland. The 1D radiative transfer is cal-  
 180 culated every 10 sec with RTE+RRTMGP (Pincus et al., 2019), using delta-scaling of  
 181 the cloud optical properties. We simulate realistic weather conditions by coupling our  
 182 LES to ERA5 with a method similar to the one described by e.g Neggers et al. (2012)  
 183 and Schalkwijk et al. (2015). In short, in this setup, the atmosphere and soil are initialised  
 184 from ERA5. Furthermore, the large scale forcings acting on the LES domain are recon-  
 185 structed from ERA5 and added to the LES as time and height varying external forcings.  
 186 These forcings are the advective tendencies of potential temperature, humidity and wind,  
 187 the subsidence velocity, and geostrophic wind components. The domain mean state of  
 188 the simulations is nudged towards ERA5 at a time scale of 3 hours, to prevent long ex-  
 189 periments from drifting away from reality. For 4 July, the humidity close to the surface  
 190 is much lower in ERA5 compared to the observations, thus we increased the initial hu-  
 191 midity with 10% at the surface, and a linearly decreasing percentage above until roughly  
 192 1000 m (50 model levels). Additionally, we increased the nudging timescale to 12 h in  
 193 the lowest 2 km (82 levels), to prevent the model from going towards the too dry ERA5  
 194 data.

195 Our domain has a size of 25.6 km x 25.6 km x 17 km, with a horizontal resolution  
 196 of 50 m and a vertical grid spacing that increases with height, starting with 20 m grid  
 197 spacing at the surface. Our LES uses double-periodic boundary conditions. We ran the  
 198 simulations from 6 to 18 UTC (8-20 local time) and we saved the domain average statis-  
 199 tics every 5 min. Additionally, we saved, every 10 sec, the results for an individual col-  
 200 umn in the centre of the domain ( $x = y = 12.8$  km) and the horizontal cross sections for  
 201 some key variables: liquid water path (including ice), shortwave downward radiation at  
 202 the surface (both global and direct), cloud base height, cloud top height.

203 We investigated the probability distributions to compare the modeled radiation with  
 204 the observations. We used the Probability Density Functions (PDFs) as used by Gristey  
 205 et al. (2020b). These PDFs show the relative occurrence of the radiation values. There-  
 206 fore, they provide insight into the occurrence and strength of cloud shadows and cloud  
 207 enhancements. Apart from changes in the cloud field, PDFs based on time series include  
 208 the effect of the changing solar zenith angle (SZA). We correct for the changing SZA by  
 209 dividing the radiation values of both the simulation and the observations by  $\cos(\text{SZA})$   
 210 when PDFs are considered. Hereby, the radiation is normalised to a 0 degree solar zenith  
 211 angle or, in other words, it is the radiation value as if the sun was right above the ob-  
 212 server. For all PDFs, we used a binsize of  $20 \text{ W m}^{-2}$  and we resampled the observations  
 213 to 10 sec averages, to match with the model resolution.

### 214 **3.2 Smoothing Diffuse Radiation**

215 We used a Gaussian filter to account for the 3D effects on diffuse radiation. This  
 216 filter convolves the surface diffuse radiation from the 1D radiative transfer model with

217 a Gaussian distribution. This means that the diffuse radiation at one point becomes a  
 218 weighted average of the point itself and its neighbours. In 1D, the weights are described  
 219 by a Gaussian distribution ( $G_{1D}$ ) of the form:

$$220 \quad G_{1D}(x) = \frac{1}{\sqrt{2\pi}\sigma_{\text{filter}}} \exp\left(\frac{-x^2}{2\sigma_{\text{filter}}^2}\right).$$

221 In which  $\sigma_{\text{filter}}$  is the standard deviation of the distribution and  $x$  is the distance  
 222 from the point of interest. The filter includes the neighbours within four times the stan-  
 223 dard deviation ( $\sigma_{\text{filter}}$ ), so  $x$  ranges between  $-4\sigma_{\text{filter}}$  and  $+4\sigma_{\text{filter}}$ . At the borders of the  
 224 domain, the data is wrapped, meaning that data from the opposite side of the domain  
 225 is included in the convolution. This is in line with the periodic boundaries of the sim-  
 226 ulations. To filter in 2D, 1D convolutions are performed in both horizontal directions sub-  
 227 sequently. We tested the filtering for  $\sigma_{\text{filter}}$  between 0 and 1.5 km, in steps of 50 m, to  
 228 determine the optimal sigma ( $\sigma_{\text{opt}}$ ). We determine  $\sigma_{\text{opt}}$  per time step. as we apply the  
 229 Gaussian filter per time step.

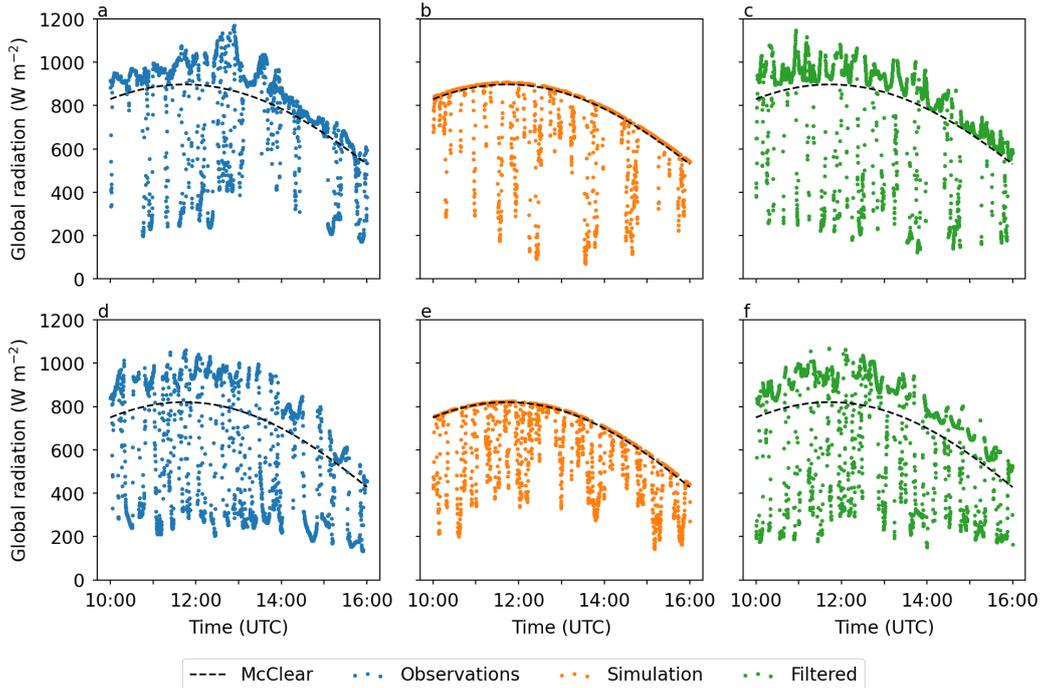
### 230 3.3 Determining the Optimal Filter Size

231 We determine  $\sigma_{\text{opt}}$  by comparing the simulation with the observations. The sim-  
 232 plest way to do this is to compare the standard deviation of the observations with the  
 233 standard deviation of the simulated field. From the simulation, we used the standard de-  
 234 viation of the diffuse radiation PDF after filtering ( $\text{std}_{\text{smooth}}$ ). This means that  $\text{std}_{\text{smooth}}$   
 235 is calculated over a smoothed field normalised by  $\cos(\text{SZA})$ . Thus,  $\text{std}_{\text{smooth}}$  is calculated  
 236 per time step. The standard deviation of the observations ( $\text{std}_{\text{obs}}$ ) is calculated from the  
 237 time series between 10 and 16 UTC, normalised by  $\cos(\text{SZA})$ . Therefore,  $\text{std}_{\text{obs}}$  is con-  
 238 stant. We consider the filtered distribution optimal if  $\text{std}_{\text{smooth}}$  is as close as possible to  
 239  $\text{std}_{\text{obs}}$ . The impact of using the standard deviation as the optimization criterion is dis-  
 240 cussed in section 5, as well as the impact of using  $\text{std}_{\text{obs}}$  for all time steps.

### 241 3.4 Parameterization for the Filter Size

242 The optimal filter size ( $\sigma_{\text{opt}}$ ) is a characteristic of the distribution of diffuse radi-  
 243 ation, thus it is related to the cloud field. Therefore,  $\sigma_{\text{filter}}$  might be calculated as a func-  
 244 tion of properties of this cloud field. A possible parameterization was proposed by Wissmeier  
 245 et al. (2013). Their parameterization involves the calculation of  $\sigma_{\text{filter}}$  per grid cell per  
 246 time step. We investigated the possibilities to have a parameterization with less differ-  
 247 ent values of  $\sigma_{\text{filter}}$  by using one  $\sigma_{\text{filter}}$  per time step for the whole domain. We tested  
 248 parameterizations of the simple form:  $\sigma_{\text{filter}} = cv$ , in which  $c$  is a constant and  $v$  a vari-  
 249 able related to the cloud field. In section 5, we will discuss further how well one filter  
 250 size can be used for the entire domain.

251 From existing literature, it is expected that  $\sigma_{\text{filter}}$  is related to the cloud base height  
 252 and/or the solar zenith angle (Wissmeier et al., 2013; Wapler & Mayer, 2008). On top  
 253 of that, we hypothesize that  $\sigma_{\text{filter}}$  is related to the sizes of the individual clouds, as the  
 254 effect of small clouds can be filtered away with a narrow filter, whereas the effect of large  
 255 clouds needs a wider filter to be filtered out. We used the maximum cloud size as a mea-  
 256 sure for the cloud sizes present in the cloud field. The maximum cloud size is determined  
 257 using a cloud tracking algorithm, as described by Heus and Seifert (2013). In short, all  
 258 columns with a Liquid Water Path (LWP) larger than  $0 \text{ g m}^{-2}$  that are connected to each  
 259 other are considered to form one cloud. The cloud size is then simply the square root  
 260 of the area of the cloud. Apart from the maximum cloud size, we consider the cloud thick-  
 261 ness and cloud cover for the parameterization of  $\sigma_{\text{filter}}$  as these variables are related to  
 262 the maximum cloud size (Van Laar et al., 2019). In summary, we considered cloud thick-  
 263 ness, cloud cover, cloud base height, solar zenith angle, and maximum cloud size to de-  
 264 termine the best parameterization for  $\sigma_{\text{filter}}$ .



**Figure 1.** Timeseries of global radiation as (a) observed, (b) simulated and (c) filtered for 4 July. (d), (e) and (f) are as (a), (b) and (c), but for 15 August. For the simulations, the time series are taken at the centre point of the domain.

265 In addition to the single variable parameterizations, we investigate the improve-  
 266 ment that can be obtained by using multiple linear regression. We start from the sin-  
 267 gular variable parameterization that gives the best match (the highest correlation coeffi-  
 268 cient) with our  $\sigma_{\text{opt}}$ . We add one variable at a time and determine which combination  
 269 gives the highest correlation with  $\sigma_{\text{opt}}$ .

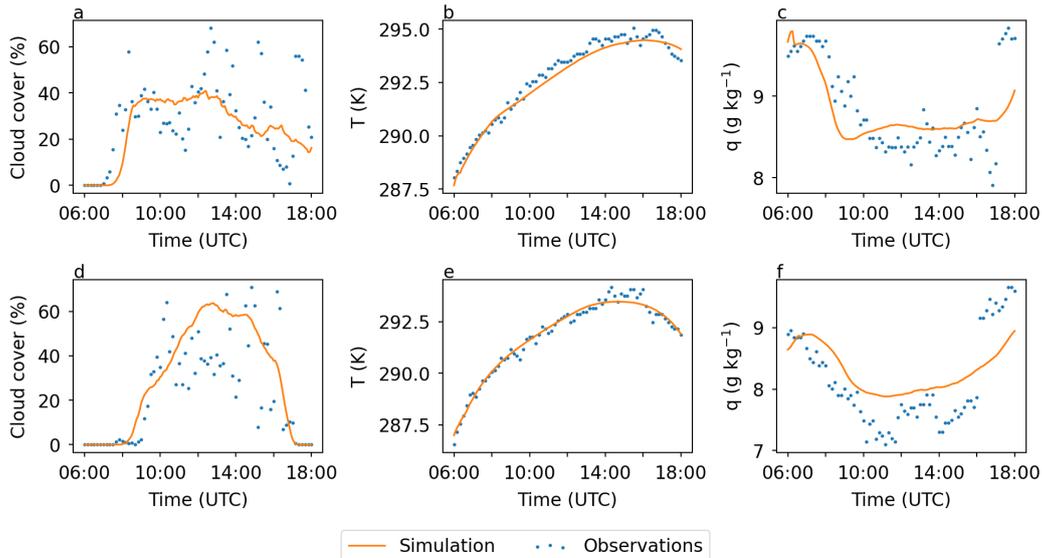
## 270 4 Results

271 We will first show the general development of the simulations and compare it to  
 272 the observations. Then, we will discuss the distribution of the radiation in detail, fol-  
 273 lowed by the filtering of the radiation and the possible parameterizations for this filter.

### 274 4.1 Case Description and Model Validation

275 The timeseries of observed global radiation (Fig. 1a, d) show that the global ra-  
 276 diation is either higher or lower than under clear sky conditions. The global radiation  
 277 is lower than the clear sky value in a cloud shadow. When there is no cloud shadow, the  
 278 radiation is enhanced by diffuse radiation scattered by a nearby cloud. In the simula-  
 279 tion with 1D radiative transfer (Fig. 1b, e), the global radiation is either lower than or  
 280 equal to the radiation under clear-sky conditions, meaning that cloud shadows occur, but  
 281 cloud enhancements are not simulated. The rightmost panels in Fig. 1 show the time-  
 282 series after we filtered the diffuse radiation. These will be discussed in section 4.3.

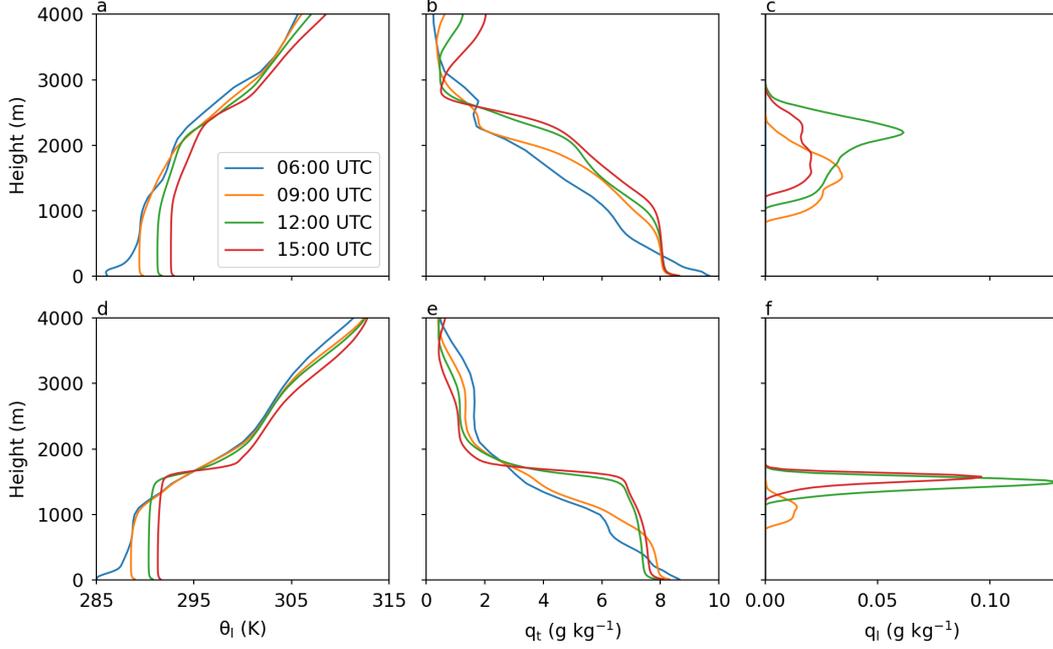
283 Fig. 2 shows the timeseries of cloud cover, temperature and humidity. Comparing  
 284 the model simulations with the observations shows that the simulations accurately cap-



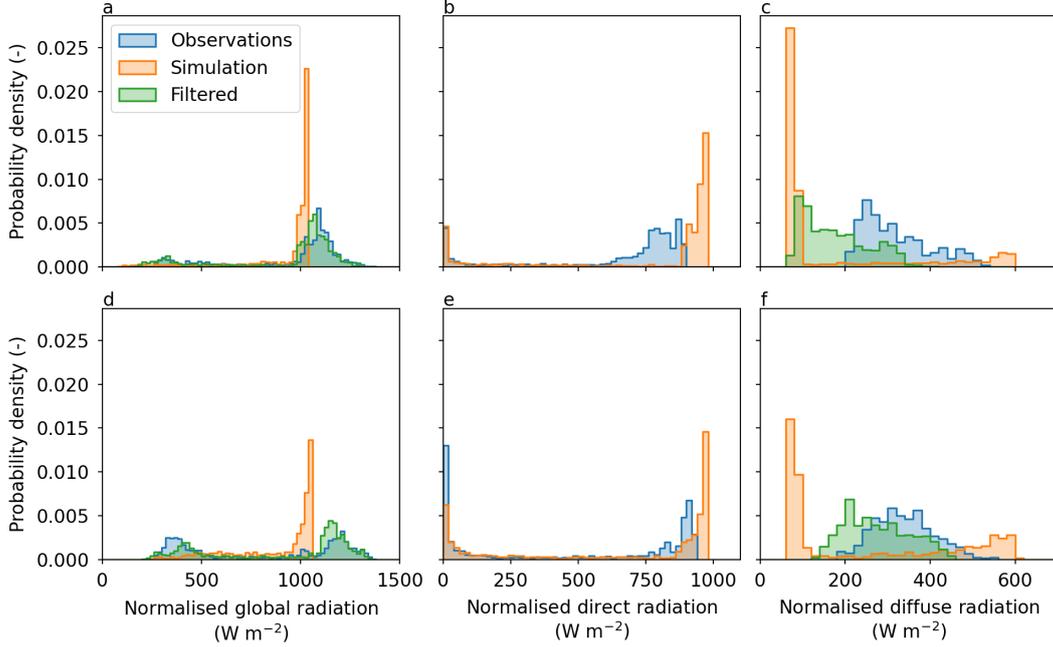
**Figure 2.** Time series of (a) cloud cover, (b) temperature and (c) specific humidity for 4 July. (d), (e) and (f) are as (a), (b) and (c), but for 15 August. Temperature and humidity are at 10m height.

285      ture realistic weather conditions. The simulation results are more smooth, because they  
 286      are average values over the model domain, whereas the observations are at one location.  
 287      For 4 July, the simulated cloud onset is about half an hour later than in the observations,  
 288      whereas for 15 August it is about half an hour earlier. Although the modelled cloud struc-  
 289      tures will never be exactly as observed, the average cloud cover is well simulated for both  
 290      days. Veerman et al. (2022) showed for the case of 15 August 2016 that a similar cloud  
 291      cover is modelled when 3D radiative transfer calculations are used.

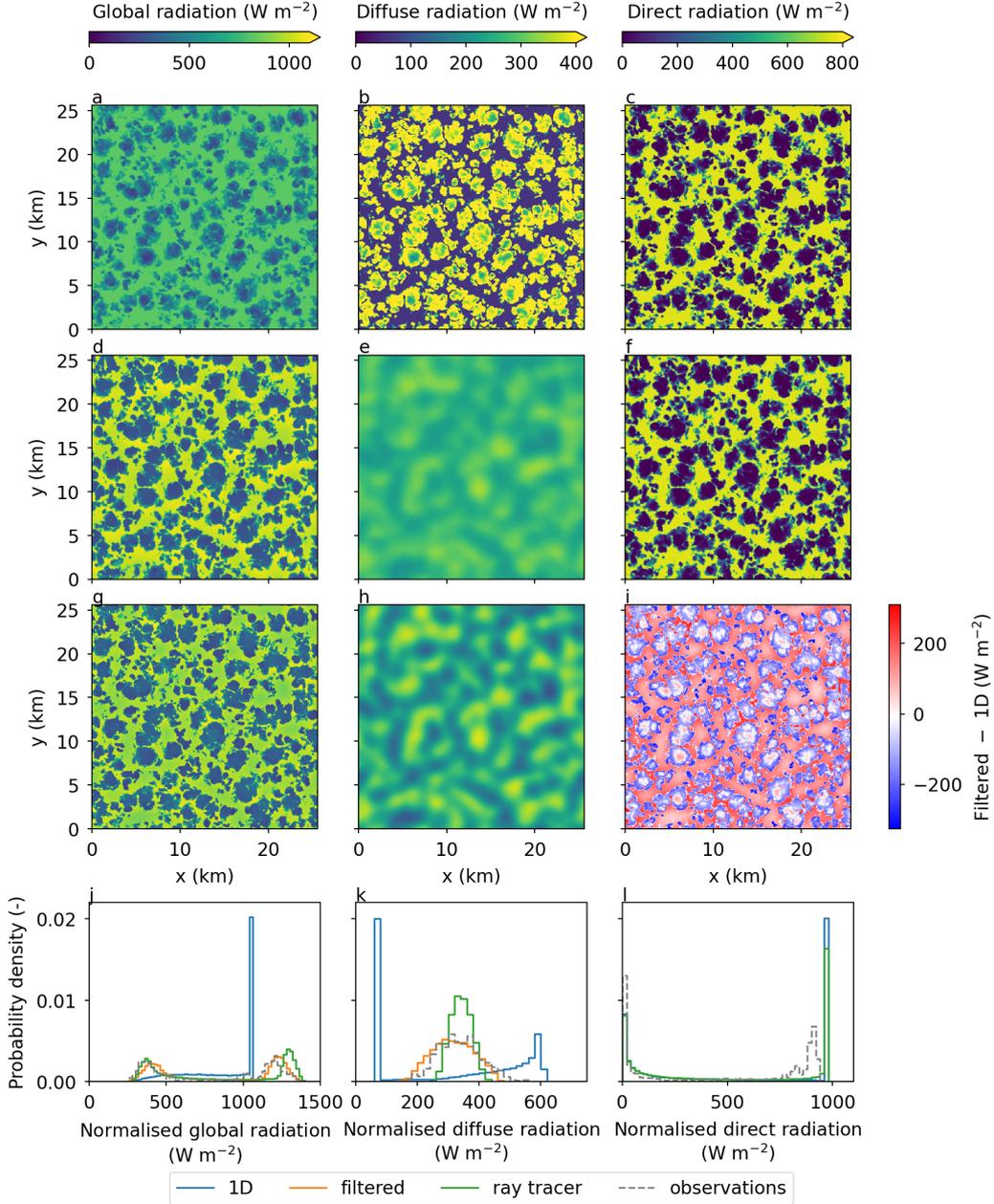
292      The simulated vertical profiles (Fig. 3) show that, in both cases, a stable bound-  
 293      ary layer was present at the beginning of the day, at 6 UTC. The addition of sensible  
 294      heat caused the boundary layer to grow and heat up. In the afternoon, the boundary  
 295      layer was well mixed. On 4 July, the humidity above the boundary layer increases over  
 296      time, but the changes are only small close to the boundary layer top. In general, only  
 297      small changes in the profiles occur above the boundary layer, indicating that large scale  
 298      advection plays a minor role. On both days, the local surface fluxes determine the devel-  
 299      opment of the profiles during the day, which makes these days suitable case studies.  
 300      The profiles of liquid water show that clouds are formed under the inversion (Fig. 3c,  
 301      f). On the 15<sup>th</sup> of August, a strong inversion ( 7 K) was present at the top of the bound-  
 302      ary layer (Fig. 3d, e). The clouds spread out horizontally under the inversion, as the in-  
 303      version prevents the clouds from growing in the vertical. This causes relatively thin clouds  
 304      and a high cloud cover (Fig. 2d) for a case with shallow cumulus clouds. The clouds on  
 305      both days clearly differ in their thickness and liquid water content. Thus, we can get an  
 306      indication of how well our method works for shallow cumulus conditions, by testing our  
 307      filtering method for these two days. In the remainder of this paper, we will focus on the  
 308      hours between 10 UTC and 16 UTC when clouds are observed and simulated on both  
 309      days.



**Figure 3.** Domain-average vertical profiles of (a) liquid water potential temperature, (b) specific humidity, (c) liquid water specific humidity for 4 July. (d), (e) and (f) are as (a), (b) and (c), but for 15 August.



**Figure 4.** PDFs of (a) global radiation, (b) direct radiation, (c) diffuse radiation for the observations, the original simulation and the simulation after filtering for 4 July. (d), (e) and (f) are as (a), (b) and (c), but for 15 August. For these PDF, the time series from 10 to 16 UTC are used. For the simulation, the time series is taken at the centre point of the domain. All values are normalised by  $\cos(\text{SZA})$ .



**Figure 5.** Surface fields at 15 August 12 UTC. The first row shows the original fields of (a) global radiation, (b) diffuse radiation, and (c) direct radiation. The second row shows the fields obtained with Monte Carlo ray tracing of (d) global radiation, (e) diffuse radiation and (f) direct radiation. The third row shows the fields after filtering the diffuse radiation of (g) global radiation and (h) diffuse radiation. (i) shows the difference in radiation between the original and filtered simulation. Note that we did not change the direct radiation. Therefore, the difference in (f) is the difference in diffuse radiation (b vs e) as well as the difference in global radiation (a vs d). The SZA is  $37.9^\circ$ . The fourth row shows the PDFs of (j) global radiation, (k) diffuse radiation, and (l) direct radiation corresponding to the fields in (a) until (h). For the PDFs of the observations, the time series between 10 and 16 UTC are used.

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## 4.2 1D Radiative Transfer

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In this section, we examine the surface irradiance from the simulation with 1D radiative transfer by looking at PDFs of global, direct and diffuse radiation (Fig. 4) and an example of the surface radiation fields in the simulation (Fig. 5, top row). We will first discuss the differences between the observations and the simulation with 1D radiative transfer. The PDFs and surface fields of the simulation after filtering will be discussed in the next section.

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The simulated distribution of global radiation does not resemble the observed distribution (Fig. 4a, d). This is in line with the results of Gristey et al. (2020b) and Schmidt et al. (2007). The differences between the observations and the simulation can be explained by considering the direct and diffuse radiation separately (Fig. 4) and from the spatial patterns (Fig. 5, top row).

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The direct radiation is close to zero in the cloud shadows and around  $800 \text{ W m}^{-2}$  in other areas (Fig. 5c). The simulated diffuse radiation is highest under the clouds (Fig. 5b). This partly compensates for the reduced direct radiation. Under the clouds, the diffuse radiation is highest, up to  $500 \text{ W m}^{-2}$ , in areas with a low LWP. In areas with a high LWP, the diffuse radiation is reduced as more radiation is absorbed and more radiation is scattered back upwards. In simulations with 1D radiative transfer, the cloud shadows are located exactly below the clouds (Fig. 5c). From simple geometry, it is clear that the shadow of a cloud is not directly below a cloud, unless the sun is right above the cloud. Additionally, the cloud shadows are too small in simulations with 1D radiative transfer, as only the top of the cloud intercepts radiation. In reality, the radiation falls on the cloud under an angle, thus part of the cloud sides also intercepts radiation, causing a larger cloud shadow. Previous studies showed that the, more complex, Tilted Independent Column Approximation (TICA) can be used to simulate the cloud shadows correctly in terms of both size and location (Wapler & Mayer, 2008; Várnai & Davies, 1999).

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The spatial radiation patterns result in the PDFs shown in Fig. 4. The PDFs of the direct radiation show peaks around zero and between  $800$  and  $1000 \text{ W m}^{-2}$ , for both observations and simulations (Fig. 4b, e). The high values of simulated direct radiation are higher than the maximum observed direct radiation. On 4 July, the simulated values are up to  $74 \text{ W m}^{-2}$  more than the maximum observed, on 15 August up to  $37 \text{ W m}^{-2}$ . In line with this overestimation, the average diffuse radiation is underestimated (Fig. 4c, f). This is also observed for the clear sky radiation, indicating that the difference might be the effect of aerosols, which are not included in the radiation calculations. The impact hereof is discussed in section 5. The simulated diffuse radiation PDF is dominated by amounts of diffuse radiation around  $50 \text{ W m}^{-2}$ , that occur under clear sky conditions. This diffuse radiation is the result of scattering by gases. The large peak in the PDF is clearly not in line with the observed PDF (Fig. 4c, f). Thus, for the days and times shown in fig. 4, we find that the differences in the smoothness of the global radiation field and thereby the shape of the global radiation PDF are primarily caused by differences in the diffuse radiation, which is in line with the findings of Gristey et al. (2020b). Hence, we will focus on accounting for the horizontal transport of diffuse radiation to get the PDF correct.

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## 4.3 Smoothing Diffuse Radiation

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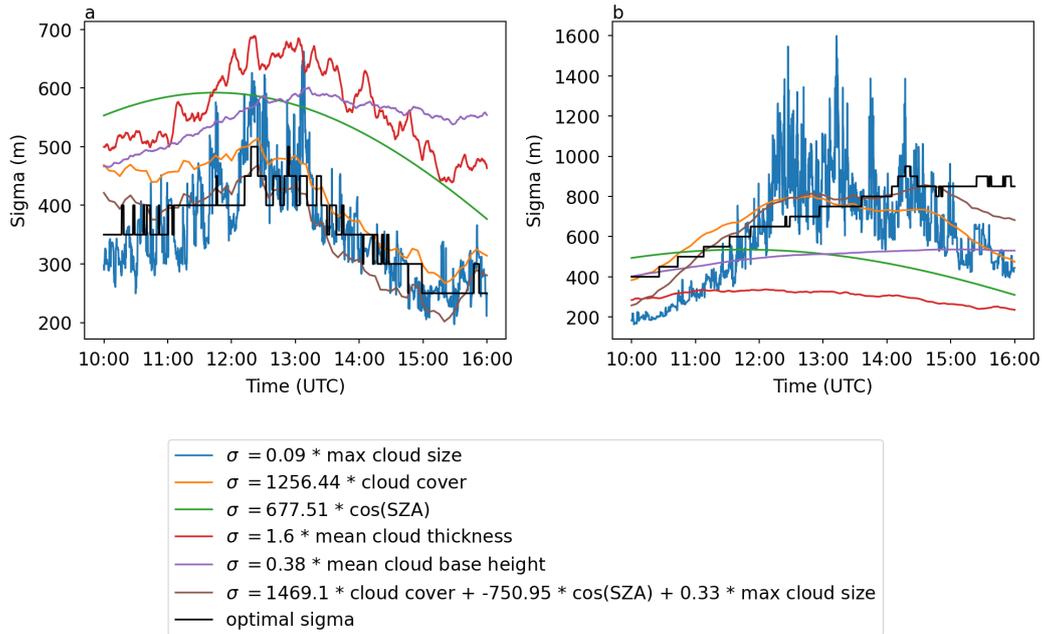
We applied a spatial filter, to account for the horizontal spreading of diffuse radiation. Then, we combined the filtered diffuse radiation with the original direct radiation, to obtain the new global radiation. This means that we introduced the horizontal spreading of the diffuse radiation, but not the 3D effect on the direct radiation. Fig. 5g, h shows an example of the resulting surface radiation fields. The difference between the original and filtered fields is shown in Fig. 5i. The difference in Fig. 5i is the difference in diffuse radiation as well as the difference in global radiation, as we did not change the di-

361 rect radiation. The difference plot makes clear how the filtering influences the radiation.  
 362 Diffuse radiation is reduced in the regions where it was originally the highest, thus un-  
 363 der the clouds. Diffuse radiation is increased in the regions where it was originally low,  
 364 thus in the clear sky patches and in the centres of the clouds. In the example cross sec-  
 365 tions of diffuse radiation at the surface in Fig. 5b, h, diffuse radiation under the clouds  
 366 is reduced with a maximum reduction of  $327 \text{ W m}^{-2}$  and in clear sky patches it is increased  
 367 with a maximum of  $310 \text{ W m}^{-2}$ . The cross section in Fig. 5h shows that the highest amounts  
 368 of diffuse radiation still occur below the clouds, but the areas around the clouds also re-  
 369 ceive diffuse radiation. This is in line with the results of Wissmeier et al. (2013), who  
 370 showed that filtering the diffuse radiation can greatly improve the surface radiation fields.  
 371 Combining the filtered diffuse radiation field (Fig. 5e) with the original direct radiation  
 372 field (Fig. 5c) results in the global radiation field shown in Fig. 5d. This global radia-  
 373 tion field shows cloud enhancements in addition to the cloud shadows and clear sky patches.

374 For comparison, we performed a 3D radiative transfer calculation for this time step.  
 375 To this end, we took the cloud field from our simulation with 1D radiative transfer and  
 376 performed Monte Carlo ray tracing, as described in Veerman et al. (2022) but with delta-  
 377 scaled cloud optical properties. The surface irradiance fields obtained with the ray trac-  
 378 ing are shown in Fig. 5d, e, f. Fig. 5 j, k and l show the PDFs corresponding to the fields  
 379 in Fig. 5a until h. In the direct radiation fields, we see that with 3D radiative transfer,  
 380 the cloud shadows are shifted northwards compared to the 1D simulation. The diffuse  
 381 radiation field is much more smooth with 3D radiative transfer compared to 1D radi-  
 382 ative transfer. The ray tracer, as well as the filtered 1D simulation, shows a single peak  
 383 in the diffuse radiation PDF, in contrast with the two peaks of the 1D simulation. Also  
 384 compared to our filtered diffuse radiation field, the 3D radiative transfer calculations give  
 385 a more smooth diffuse radiation field. This results in a narrower distribution for the ray  
 386 tracer compared to the filtered 1D simulation. As a result of the more smooth diffuse  
 387 field, the cloud enhancements are larger in the 3D simulation, compared to our filtered  
 388 simulation. This is visible both in the surface fields and in the PDFs. In Fig. 5 j, k and  
 389 l, the distribution of the observations is also shown. The simulated distributions should  
 390 be compared with the observations with care, as the observations are at one location over  
 391 6 hours, and the simulations are a field at one time. It is clear that by filtering the 1D  
 392 simulations, a close match with the observations is obtained in this time step. This in  
 393 line with our expectations, as our filter size is chosen such that we match the observa-  
 394 tions as good as possible.

395 The impact of the filtering is also clearly visible in the timeseries (Fig. 1c, f) and  
 396 corresponding PDFs (Fig. 4). The shape of the simulated diffuse radiation PDFs closely  
 397 matches the shape of the observed PDF, when the diffuse radiation is filtered with the  
 398 optimal filter width ( $\sigma_{\text{opt}}$ ). The PDFs of global radiation are now bimodal. There is one  
 399 peak below  $500 \text{ W m}^{-2}$ , showing that the cloud shadows became more uniformly dark.  
 400 The second peak is at higher irradiance values than the original peak, showing that the  
 401 irradiance in regions other than the cloud shadows is increased. The bimodal PDFs of  
 402 global radiation can also be obtained directly from the characteristics of the cloud field  
 403 by using machine learning as shown by Gristey et al. (2020a). By filtering the diffuse ra-  
 404 diation, we provide not only the global radiation statistics, but also the partitioning be-  
 405 tween direct and diffuse radiation, as well as an indication of how the radiation is dis-  
 406 tributed spatially. This spatial information is essential to couple a parameterization for  
 407 the 3D radiative effects to an LES in the future.

408 The cloud enhancements are also clearly visible in the timeseries (Fig. 1c, f). Be-  
 409 fore filtering, the McClear value was simulated in the clear sky periods. After filtering,  
 410 the cloud enhancements are simulated and their magnitude is in line with the peaks in  
 411 the observations. Furthermore, before filtering, some cloud shadows were much darker  
 412 than others. After filtering, the cloud shadows are more similar, which is also in line with



**Figure 6.** Time series of  $\sigma_{\text{filter}}$  for (a) 4 July and (b) 15 August (b).  $\sigma_{\text{opt}}$  and  $\sigma_{\text{filter}}$  as a linear function of the individual cloud variables, as well as the combination of cloud cover,  $\cos(\text{SZA})$  and mean cloud base height.

413 the observations. Together, Fig. 4 and Fig. 1 show that our filtering method greatly im-  
 414 proves the model results.

#### 415 4.4 Sigma Parameterization

416 Next, we want to parameterize  $\sigma_{\text{filter}}$  as a function of the cloud properties in the  
 417 simulation, to be able to filter the diffuse radiation in a simulation. Therefore, we inves-  
 418 tigated how well  $\sigma_{\text{opt}}$  can be described as a function of cloud thickness, cloud cover, cloud  
 419 base height, solar zenith angle, and maximum cloud size. The time series of  $\sigma_{\text{opt}}$  are shown  
 420 in Fig. 6. Note that for 15 August, the range of  $\sigma$  shown is larger than for 4 July. On  
 421 the 15<sup>th</sup> of August,  $\sigma_{\text{opt}}$  increases during most of the period and is fairly constant at the  
 422 end. On the 4<sup>th</sup> of July,  $\sigma_{\text{opt}}$  increases a bit in the first three hours and decreases after-  
 423 wards. The average  $\sigma_{\text{opt}}$  on 15 August is 700 m, which is close to the 625 m found by  
 424 Wissmeier et al. (2013) for their case with cumulus mediocris. For 4 July, we find a smaller  
 425 average  $\sigma_{\text{opt}}$  of 360 m.

426 The optimal filter size ( $\sigma_{\text{opt}}$ ) can be parameterized by relating it to the cloud field.  
 427 Fig. 6 shows simple approximations of  $\sigma_{\text{opt}}$ . Regarding the trends, the maximum cloud  
 428 size, cloud cover,  $\cos(\text{SZA})$  and mean cloud thickness all show an increase in the begin-  
 429 ning of the period and a decrease later on. For 4 July, this is exactly what we also ob-  
 430 serve for  $\sigma_{\text{opt}}$ . For 15 August, we do not find a decrease in  $\sigma_{\text{opt}}$  at the end of the period,  
 431 which is best captured by the approximation based on the cloud base height. Regarding  
 432 the values, we find that using  $\cos(\text{SZA})$ , mean cloud thickness or mean cloud base  
 433 height gives an overestimation of the filter size on 4 July and an underestimation of the  
 434 filter size on 15 August. The estimates based on the maximum cloud size and cloud cover  
 435 capture the trends more closely. However, especially near the end of the period on 15  
 436 August, the estimates based on cloud cover and maximum cloud size also underestimate

**Table 1.** Correlation coefficient ( $r$ ) showing the correlation between  $\sigma_{opt}$  and possible parameterizations of  $\sigma_{filter}$  using different (combinations of) variables.

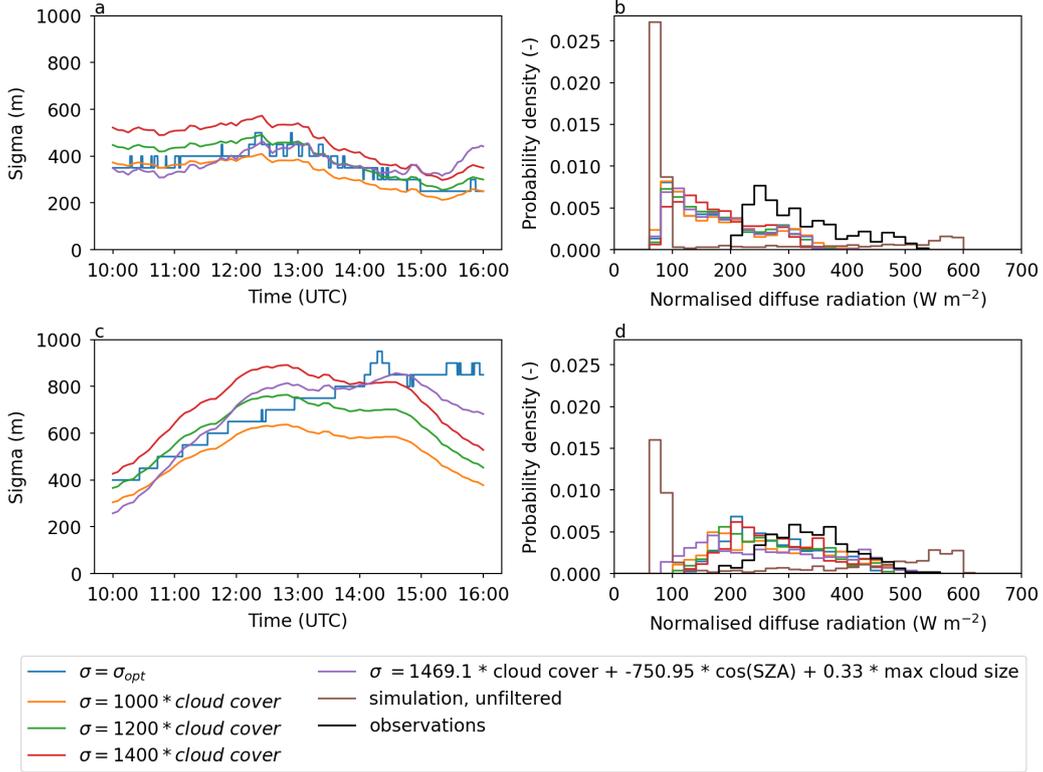
variable(s)	$r$
cloud cover	0.830
cos(SZA)	-0.473
maximum cloud size	0.728
mean cloud thickness	-0.736
mean cloud base	-0.113
cloud cover, cos(SZA)	0.874
cloud cover, maximum cloud size	0.833
cloud cover, mean cloud thickness	0.854
cloud cover, mean cloud base	0.829
cloud cover, cos(SZA), maximum cloud size	0.874
cloud cover, cos(SZA), mean cloud thickness	0.884
cloud cover, cos(SZA), mean cloud base	0.937
cloud cover, cos(SZA), mean cloud base, maximum cloud size	0.941
cloud cover, cos(SZA), mean cloud base, mean cloud thickness	0.943
cloud cover, cos(SZA), mean cloud base, mean cloud thickness, maximum cloud size	0.944

437 the optimal filter size by up to a factor two. The advantage of the cloud cover is that  
 438 it is readily available in the model, whereas the maximum cloud size has to be obtained  
 439 with a cloud tracking algorithm (Heus & Seifert, 2013), and hence induces additional com-  
 440 putational cost.

441 Table 1 shows the correlation coefficients between  $\sigma_{opt}$  and approximations based  
 442 on different variables. First, the correlation coefficients for the single variable approx-  
 443 imations are shown. The highest correlation is obtained when we use the cloud cover.  
 444 We also performed multiple linear regressions. As we obtained the highest correlation  
 445 with a single variable when using the cloud cover, we did multiple linear regression with  
 446 two variables: the cloud cover and one of maximum cloud size, cos(SZA), mean cloud  
 447 thickness and mean cloud base height. The correlation increases most when cos(SZA)  
 448 is added. We continued adding variables to the combination with the highest correla-  
 449 tion coefficient until a multi linear regression with all variables. Adding the cos(SZA)  
 450 and mean cloud base height increased the correlation from 0.83 to 0.94. Adding than also  
 451 the mean cloud thickness and maximum cloud size resulted in an increase in correlation  
 452 of less than 0.01.

453 To fully capture the development of  $\sigma_{opt}$  more complex methods, such as machine  
 454 learning, can potentially be used. For example, Gristey et al. (2020a) used machine learn-  
 455 ing to directly predict the PDFs of global radiation from a set of cloud field properties.

456 During the two days that we studied, especially the cloud cover and maximum cloud  
 457 size are clearly correlated with each other ( $r > 0.8$ ). It is possible that this correlation,  
 458 which is undesired if both variables are used in a multiple linear regression, is specific  
 459 to the chosen shallow cumulus cases. To carefully check whether the parameters included  
 460 are independent of each other, a larger dataset is required. In addition, given the lim-  
 461 ited size of our dataset, there is also a chance that a multiple linear regression overfits  
 462 when using too many variables. We will therefore continue by using the simple approx-  
 463 imations of the filter size based on cloud cover only and cloud cover, cos(SZA), and mean  
 464 cloud base height. Hereby, we can investigate how sensitive the resulting diffuse radia-  
 465 tion PDF is to the used filter size.



**Figure 7.** (a) timeseries of  $\sigma_{opt}$  and approximations of  $\sigma_{filter}$  as a function of the cloud cover. (b) PDFs of the diffuse radiation for the observations, original 1D simulation and filtered simulation. For these PDF, the time series from 10 to 16 UTC are used. For the simulation, the time series is taken at the centre point of the domain. All values are normalised by  $\cos(SZA)$ . For the filtering, the  $\sigma$ 's from (a) are used. (c) and (d) are as (a) and (b), but for 15 August.

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#### 4.5 Sigma Sensitivity

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It is important to know how sensitive the resulting PDFs are to a change in  $\sigma_{filter}$ , as  $\sigma_{filter}$  differs depending on which parameterization is used. We defined three possible approximations of  $\sigma_{opt}$  as a function of the cloud cover, with the constant being 1000, 1200 and 1400 (Fig. 7a, c). For most of the times, all three approximations are close to  $\sigma_{opt}$ . Only for the last part of 15 August, the parameterizations deviate strongly from  $\sigma_{opt}$ . In addition, 7 a, c shows  $\sigma_{filter}$  based on the cloud cover,  $\cos(SZA)$  and mean cloud base height. Fig. 7b and d show the PDFs of diffuse radiation that are obtained when using the different approximations of  $\sigma_{filter}$ . The differences between the three possible approximations based only on the cloud cover are small, as well as the differences between the approximations based only on cloud cover, the approximation based on three variables and  $\sigma_{opt}$ . By eye, it is not possible to tell which one of these PDFs matches the PDFs of the observations best. This shows that with a rough approximation of  $\sigma_{filter}$  we can reach a clear improvement, compared to the original 1D radiative transfer calculations.

## 5 Discussion

In this section, we reflect on the assumptions made while comparing the observations to the simulations.

First, we assumed that one value for  $\text{std}_{\text{obs}}$  is representative for the hours between 10 and 16 UTC. Calculating  $\text{std}_{\text{obs}}$  over different, shorter periods results in different values for  $\text{std}_{\text{obs}}$ , which would have resulted in different values for  $\sigma_{\text{opt}}$ . Ideally, the timespan over which  $\text{std}_{\text{obs}}$  is calculated is related to the changes in the cloud field. If the cloud field changes, the standard deviation should change accordingly. However, the averaging period should also be long enough to have a statistically reasonable estimate for  $\text{std}_{\text{obs}}$ . Furthermore,  $\text{std}_{\text{obs}}$  depends on the clouds that pass over the sensor and the size of these clouds in the direction of the wind. A better representation of the cloud field in all directions can be obtained by performing measurements in a grid. Gristey et al. (2020b) used observations from 10 locations to study the relation between the cloud fraction and the cloud radiative effect. Their results indicate that the observation density should be at least one order of magnitude larger to be able to detect the relationships found in model simulations. Alternatively, one could base  $\sigma_{\text{opt}}$  on a 3D simulation instead of observations, as was done before by e.g. Wissmeier et al. (2013) and Zuidema and Evans (1998).

Second, we assumed that  $\sigma_{\text{filter}}$  is optimal if the resulting standard deviation of the diffuse radiation field is as close as possible to the standard deviation of the observed diffuse radiation. A matching standard deviation does not guarantee that the PDFs also have a similar shape. To determine the impact hereof, we determined  $\sigma_{\text{opt}}$  also from the shapes of the PDFs of diffuse radiation. To this end, we described the shape of the observed PDF by fitting a gamma distribution through it. Then, we determined  $\sigma_{\text{opt}}$  by minimizing the Euclidean distance between the filtered PDF and the fitted gamma-distribution. There was no clear improvement in the PDFs, although the obtained  $\sigma_{\text{opt}}$  based on the shape is in general a bit larger. We therefore argue that the simple matching of the standard deviations functions well enough.

Third, a matching standard deviation also does not guarantee that the PDFs have a similar mean. From Fig. 4c, f, it became clear that the diffuse radiation is on average too low in our simulations. This underestimation has three possible causes. The modelled and observed clouds might be slightly different. Although the cloud cover is similar in the observations and simulations, the cloud structures might be different. Furthermore, clouds and radiation interact differently in 1D compared to reality. In reality, a fraction of the photons leaves the clouds on the sides after only a few scattering events. Therefore, statistically, these photons are likely to be scattered forward, thus towards the surface. In 1D calculations, these photons do not leave the clouds, so they are likely scattered again. As these photons are scattered multiple times, the chances increase that these photons are scattered back upwards, reducing the amount of diffuse radiation that reaches the surface. However, we also find an underestimation of the clear-sky diffuse radiation, which cannot be related to differences in the cloud field. This underestimation is likely caused by the absence of aerosols in the radiation computations. The underestimation is larger on 4 July (maximum  $70 \text{ W m}^{-2}$ ) than on 15 August (maximum  $50 \text{ W m}^{-2}$ ), which is in line with the larger aerosol optical depth on 4 July compared to 15 August. (We compared the aerosol optical depths from the McClear model (Gschwind et al., 2019), not shown.) For broken cloud conditions, Schmidt et al. (2009) and Gristey et al. (2022) showed that aerosols reduce the irradiance in the gaps between the clouds, by scattering radiation to the cloudy regions. In 1D simulations, the radiation scattered by aerosols cannot propagate horizontally to the cloudy regions, thus it will reach the surface in the gaps between the clouds. Thus in our PDFs, the diffuse radiation in the gaps between the clouds will increase. How the PDF will change exactly depends on the properties of the aerosols. As the optical depth of the aerosols is much smaller than the optical depth of the cumulus clouds, there will still be a large difference in diffuse radi-

534 ation between the cloudy regions and the gaps between the clouds. Therefore, we argue  
 535 that filtering the diffuse radiation can still be used to mimic the effect of the horizon-  
 536 tal propagation of diffuse radiation. As the initial distribution of diffuse radiation is dif-  
 537 ferent when aerosols are included, the optimal filter size will also be different. This means  
 538 that the possible parameterizations in Fig. 6 and Fig. 7 are designed for very clean con-  
 539 ditions and have to be updated when aerosols are included. Aerosols do not only scat-  
 540 ter radiation (direct effect of aerosols), but aerosols also interact with nearby clouds (in-  
 541 direct effect of aerosols). The relative importance of these effects is uncertain as it de-  
 542 pends on characteristics of both the clouds and the aerosols (Boucher et al., 2013).

543 Fourth, we assumed that one  $\sigma_{\text{filter}}$  can be used for the whole domain. On the two  
 544 selected days, the cloud properties were homogeneous in space over an area larger than  
 545 our domain size. For these cases, our results show that we can greatly improve the ra-  
 546 diation field with one filter size. With that we show that  $\sigma_{\text{filter}}$  can be related to the sta-  
 547 tistical properties of the cloud field. Thus, the filter size does not have to vary on the  
 548 scale of a single cloud, which is the case in Wissmeier et al. (2013), where they use the  
 549 distance from the center of the surface pixel to the center of the base of the closest cloud.  
 550 Instead, the filter size can vary on the scales on which the statistical properties of the  
 551 cloud fields vary. This does mean that when the domain is larger and/or the cloud prop-  
 552 erties are not statistically the same in the whole domain, more than one  $\sigma_{\text{filter}}$  will be  
 553 required.

## 554 6 Conclusion

555 In this work, we described a simple approach to correct the unrealistic surface solar  
 556 irradiance fields that arise from LES with 1D radiative transfer. Horizontal trans-  
 557 fer of radiation is omitted in 1D, resulting in a misplacement of the cloud shadows and  
 558 a lack of horizontal spreading of diffuse radiation. We approximated the horizontal spread-  
 559 ing of the diffuse radiation by filtering the diffuse radiation at the surface with a Gaus-  
 560 sian filter. We determined the optimal width of the Gaussian filter by comparing our sim-  
 561 ulations to observations. We applied this approach to two case studies with shallow cum-  
 562 ulus clouds. For these cases, filtering the diffuse radiation resulted in a PDF of global  
 563 radiation that closely matches the observations. The time series of global radiation af-  
 564 ter filtering show the characteristic cloud enhancements that were not simulated with  
 565 the 1D radiative transfer model. The width of our filter can be approximated with a lin-  
 566 ear function of only one cloud variable. For the two shallow cumulus cloud cases that  
 567 we analyzed, we found that the best approximation of the filter width with one variable  
 568 is  $\sigma_{\text{filter}} \approx 1250 \text{ cloud cover}$ . Changing the fitting constant to 1000 or 1400, or adding  
 569 additional variables does not result in a visually worse result.

570 The results show that the used approach has the potential to correct for the 3D  
 571 radiative effect by adding minimal changes to existing methods. This assures that the  
 572 impact on computational times is small. First tests showed that the filtering increases  
 573 the total runtime of the model with less than 1%. Therefore, this method has the po-  
 574 tential to be applied to many more days and different locations in the future.

575 Our results suggest that our method could be further improved by including aerosols,  
 576 especially on days with a high aerosol optical depth, as this should reduce the overes-  
 577 timation of direct radiation and accompanying underestimation of diffuse radiation. In  
 578 addition, the filtering of the diffuse radiation can be combined with the tilted column  
 579 approach, that can correct the direct radiation for the 3D radiative effects. Furthermore,  
 580 one can consider extending the filtering to the longwave spectral range.

581 Extending to many more days will allow for further generalization to different cloud  
 582 regimes and will give more insight in the usability of a single variable parameterization  
 583 and the added value of a multiple variable parameterization. A larger dataset will al-

584 low to split the dataset in a training and test dataset, which would give insight in the  
585 robustness of our parameterization.

586 In short, we have shown that filtering the surface diffuse radiation has the poten-  
587 tial to give more realistic surface irradiances with minimal additional computational cost.  
588 We applied the filtering as a post-processing step, which directly improves model results  
589 regarding the surface, for example when studying the impact of radiation on renewable  
590 energy production by solar panels or the impact on surface processes such as photosyn-  
591 thesis. Additionally, coupling the filter to the LES can potentially contribute to a bet-  
592 ter representation of the surface fluxes and with that a better representation of the cloud  
593 dynamics.

## 594 7 Open Research

595 The observations of temperature, humidity and cloudcover at the measurement sta-  
596 tion in Cabauw are openly available from the KNMI Data Platform ([https://datapatform](https://datapatform.knmi.nl/dataset/cesar-tower-meteo-lc1-t10-v1-0)  
597 [.knmi.nl/dataset/cesar-tower-meteo-lc1-t10-v1-0](https://datapatform.knmi.nl/dataset/cesar-tower-meteo-lc1-t10-v1-0) and [https://datapatform](https://datapatform.knmi.nl/dataset/cesar-nubiscope-cldcov-la1-t10-v1-0)  
598 [.knmi.nl/dataset/cesar-nubiscope-cldcov-la1-t10-v1-0](https://datapatform.knmi.nl/dataset/cesar-nubiscope-cldcov-la1-t10-v1-0), last accessed 16 Septem-  
599 ber 2022). The observations of radiation are available in Knap and Mol (2022) and Mol  
600 et al. (2022). The model simulations are performed with MicroHH (Van Heerwaarden  
601 et al., 2017) and the used version is available at [https://github.com/microhh/microhh/](https://github.com/microhh/microhh/tree/develop)  
602 [tree/develop](https://github.com/microhh/microhh/tree/develop). All other data and scripts used to conduct this research are added for  
603 peer review in the folder data&scripts.zip. This information will be made available in  
604 a repository once the manuscript is accepted.

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