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1 **Solar radiation estimation in West Africa: impact of dust conditions during**  
2 **2021 dry season**

3

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13

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15 **Abstract**

16 The anticipated increase in solar energy production in West Africa requires high-quality solar  
17 radiation estimates, which is affected by meteorological conditions and in particular the  
18 presence of desert dust aerosols. This study examines the impact of incorporating desert  
19 dust into solar radiation and surface temperature estimations. The research focuses on a  
20 case study of a dust event in March 2021, which is characteristic of the dry season in West  
21 Africa. Significant desert aerosol emissions at the Bodélé depression are associated with a  
22 Harmattan flow that transports the plume westwards. Simulations of this dust event were  
23 conducted using the WRF meteorological model alone, as well as coupled with the  
24 CHIMERE chemistry-transport model, using three different datasets for the dust aerosol  
25 initial and boundary conditions (CAM5, GOCART, MERRA2). Results show that considering  
26 desert dust reduces estimation errors in global horizontal irradiance (GHI) by about 75%.  
27 The dust plume caused an average 18% reduction in surface solar radiation during the  
28 event. Additionally, the simulations indicated a positive bias in aerosol optical depth (AOD)  
29 and PM10 surface concentrations. The choice of dataset for initial and boundary conditions  
30 minimally influenced GHI, surface temperature, and AOD estimates, whereas PM10  
31 concentrations and aerosol size distribution were significantly affected. This study  
32 underscores the importance of incorporating dust aerosols into solar forecasting for better  
33 accuracy.

34

35 **Short summary**

36 Solar energy production in West Africa is set to rise, needing accurate solar radiation  
37 estimates, which is affected by desert dust. This work analyses a March 2021 dust event  
38 using a modelling strategy incorporating desert dust. Results show that considering desert  
39 dust cut errors in solar radiation estimates by 75% and reduces surface solar radiation by  
40 18%. This highlights the importance of incorporating dust aerosols into solar forecasting for  
41 better accuracy.

42

43 **1. Introduction**

44 The West African region is facing significant development challenges due to global change.  
45 One of these challenges is related to access to electricity, particularly through the use of  
46 renewable energy. West African countries have committed to reduce their greenhouse gas  
47 emissions as part of the Paris Agreement (2015). Furthermore, assessments of solar  
48 resources in West Africa demonstrate the region's substantial potential, as shown by  
49 Diabaté et al. (2004), Plain et al. (2019) and Yushchenko al. (2018). The International  
50 Energy Agency (IEA) projects that the installed capacity for photovoltaic (PV) power  
51 generation will increase by almost 20 times from 2020 to 2030 under its Sustainable Africa  
52 Scenario (Africa Energy Outlook, IEA, 2022). PV energy is expected to experience  
53 significant growth due to its competitiveness and low-carbon nature. However, solar  
54 production is highly dependent on weather conditions (Dajuma et al., 2016).

55 The growth of solar energy in West Africa calls for the development of tailored tools to  
56 facilitate its integration into power grids and ensure optimal operational maintenance.  
57 Accurate production forecasts are required by solar power plant operators, spanning various  
58 timescales, ranging from a few hours to several days. This is essential for maximising  
59 production, reducing penalties linked to predicted deliverable energy, and optimising plant  
60 maintenance to minimise production losses. High-quality forecasts are also crucial for  
61 electricity grid operators to maintain supply-demand equilibrium and ensure system stability.  
62 Therefore, the variability of energy production significantly affects them. The key



63 meteorological variables that influence photovoltaic production are the Global Horizontal  
64 Irradiance (GHI) and the air temperature. These factors, which directly impact electricity  
65 production and cell efficiency, often reach high levels in this region as demonstrated by  
66 Dajuma et al. (2016) and Ziane et al. (2021). Their findings indicate that solar radiation is the  
67 primary factor influencing PV production, as the generated current by the photoelectric effect  
68 is proportional to the irradiance. Furthermore, they demonstrate that, at the second order,  
69 the air temperature affects the efficiency of solar cells, as both parameters are inversely  
70 correlated.

71

72 Clauzel et al. (2024) identified desert dust aerosol as a significant source of GHI forecast  
73 errors for the only two solar power plants in the Sahel region of Sococim (Senegal) and  
74 Zagtouli (Burkina Faso), particularly during the dry season. Dust aerosols are a key element  
75 in the West African climate and strongly influence solar farm production through their direct  
76 effect (aerosol-radiation interaction (ARI), Briant et al., 2017) and indirect effects (aerosol-  
77 cloud interaction (ACI), Tuccella et al., 2019) on radiation, and also through their deposition  
78 on solar panels (fouling effect, Diop et al., 2020, Aidara et al., 2023). As mentioned by Kok et  
79 al. (2021), the West African desert aerosol load is the highest in the world and occurs mainly  
80 during the dry season. In fact, North Africa, including the Sahara, is the world's largest  
81 contributor to desert dust emissions (Prospero et al., 2002), and 60% of this dust is  
82 transported to the West African region (D'Almeida, 1986; Kok et al., 2021). Most dust  
83 emissions are associated with synoptic-scale atmospheric dynamics such as the Harmattan  
84 flow during the dry season (Klose et al., 2010). Engelstaedter and Washington (2007)  
85 pointed out the importance of small-scale wind events associated with the large-scale flow,  
86 especially in the Bodele depression, which is a hotspot for dust emissions (Engelstaedter et  
87 al., 2006). Analysing satellite observations, Schepanski et al. (2009) show that 65% of the  
88 activation of the dust source area occurred in the early morning, demonstrating the important  
89 role of the breakdown of the nocturnal low-level jet. Washington and Todd (2005) confirmed  
90 the importance of the Bodele low-level jets during the dry season in initiating dust emissions  
91 that can be transported to the West African coast within a few days. Dust aerosol emissions  
92 are also highly linked to Mesoscale Convective Systems (MCS, Marsham et al., 2008 ;  
93 Bergametti et al., 2017) and to strong near-surface winds in the intertropical discontinuity  
94 zone during the rainy season (Bou Karam et al., 2009).

95

96 Some studies intend to model dust events in West Africa such as Ochiegbu (2021) who  
97 implemented a back-trajectories model to understand the dust event reaching Nigeria. This  
98 work revealed that most of the aerosols coming to Nigeria between 2011 and 2014 were  
99 originating from the Bodele Depression. Menut (2023) focused on dust forecasting during the  
100 Cloud-Atmospheric Dynamics-Dust Interactions in West Africa (CADDIWA) campaign during  
101 summer 2021 (Flamant et al., 2024) using the CHIMERE regional chemistry-transport model  
102 (Menut et al., 2021). The model was coupled online with the Weather Research and  
103 Forecasting (WRF) meteorological model (Briant et al., 2017; Tuccella et al., 2019) to  
104 perform dust aerosol concentration forecasts. The results of this work provide confidence in  
105 the model coupling in the region as the dust forecast quality does not decrease with time  
106 over a few days. In addition, only a limited number of studies have been conducted on the  
107 prediction of GHI in the West African region. Sawadogo et al. (2024) conducted an  
108 evaluation of WRF-solar GHI forecast (Jimenez et al., 2016) in Ghana for the year 2021. In  
109 their work, a version of the model coupled offline with Copernicus Atmosphere Monitoring  
110 Service (CAMS) Aerosol Optical Depth (AOD) forecasts was considered to integrate



111 information on aerosol load. They showed that WRF-Solar outperforms in predicting GHI  
112 under clear sky conditions while its performance under high aerosol levels remains poor, that  
113 was mainly attributed to uncertainties in the input AOD during data assimilation within the  
114 model. Close to the region of interest, for the northern Morocco area, El Alani et al. (2020)  
115 compared the performance of global models (Global Forecast System, Integrated Forecast  
116 System, McClear) and demonstrated their proficiency in capturing GHI hourly temporal  
117 variability.

118

119 As far as our knowledge is concerned, no studies have been conducted to assess online  
120 coupled simulations between a meteorological model and an aerosol life cycle model  
121 representing the emissions, the transport and the deposition in West Africa to estimate solar  
122 radiation. This is despite the significant presence of desert dust, characterised by high  
123 concentrations in the region. Additionally, scarce attention has been given to the significance  
124 of initial and boundary conditions for conducting the aerosol model on the performance of  
125 analysis simulations, and to our knowledge, investigating these aspects would represent a  
126 novel contribution to research in the West African region.

127

128 Within this general context, the objectives of this study are two folds i) to evaluate the ability  
129 to reproduce a dust event using a meteorological and dust life cycle model coupling  
130 configuration, and ii) to investigate whether the performance of the simulations can be  
131 enhanced by modifying the aerosol initial and boundary conditions employed, and to  
132 estimate the uncertainty associated with this dataset selection with regard to the errors made  
133 by the model. Section 2 introduces the case study, the simulation configuration, the data and  
134 models selected for this work. In Section 3, the results are presented, beginning with the  
135 variables of interest for solar production (GHI and surface air temperature), followed by the  
136 variables associated with the desert aerosols (AOD, concentration, size distribution,  
137 emissions). Section 4 gives main conclusions and draws some perspectives for this study.

138

## 139 **2. Material and methods**

140

### 2.1. Case study

141

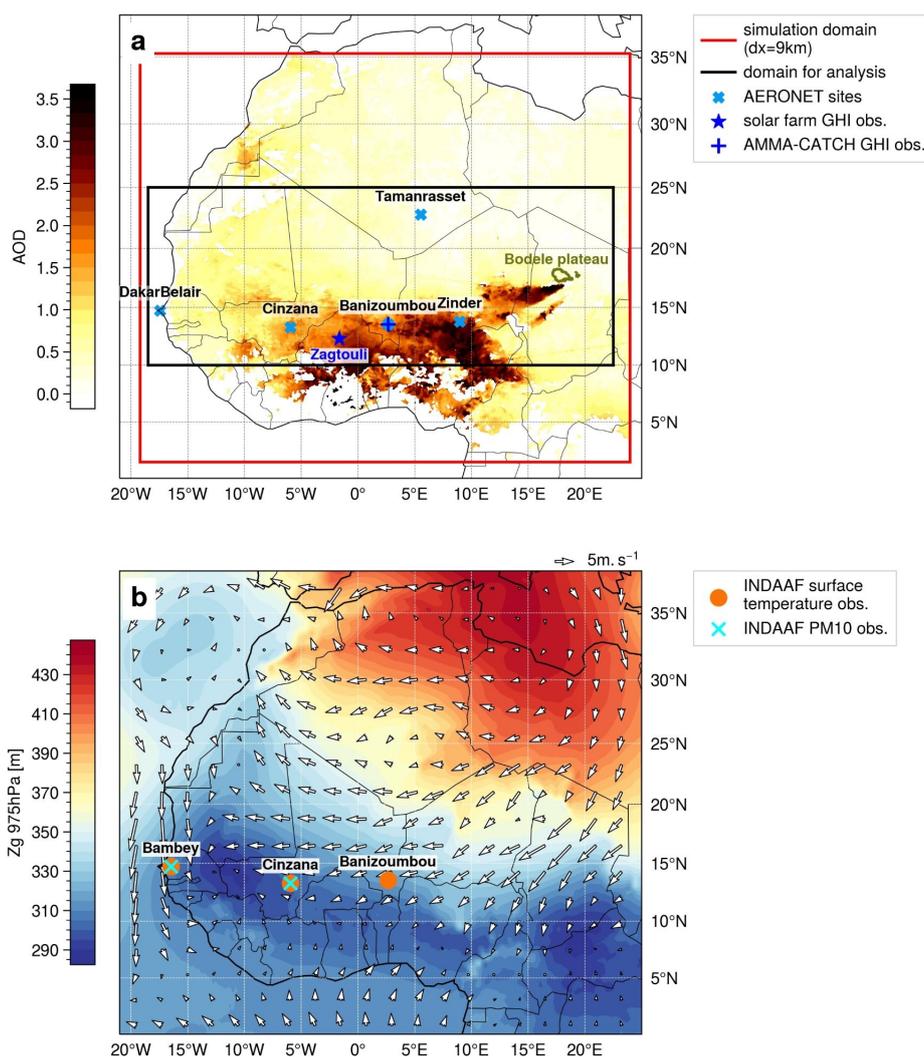
142 The case study is a dust event that occurs in West Africa from March 26<sup>th</sup>-00 UTC to April  
143 2<sup>nd</sup>-00 UTC, 2021, i.e., during the dry season. High dust emissions occur at the Bodélé  
144 Depression (Chad), the plume being then transported westward. The dust plume reached its  
145 maximum intensity in terms of AOD and dust concentration over West Africa, and in  
146 particular over the Zagtouli solar farm (Burkina-Faso, Fig. 1a), on March 30<sup>th</sup>. The event  
147 was also chosen because it was not predicted in the solar forecast currently implemented for  
148 the Zagtouli solar farm, leading to solar forecast errors during the passage of the dust plume  
(Clauzel et al., 2024).

149

150 Figure 1 illustrates that this event is characterised by a strong Harmattan flow, with surface  
151 winds from the South/South-West sweeping across the Bodélé Depression (Chad), where  
152 the potential for desert dust emissions is very high (Prospero et al., 2002; Washington et al.,  
153 2006). Additionally, this event is characterised by a westward flow between Chad and the  
154 Atlantic coast, which facilitates the transportation of the dust plume. Fig. 1a shows  
155 MODerate-resolution Imaging Spectroradiometer (MODIS) satellite observations of the AOD,  
156 identifying the initial dust source area on the Bodélé Depression, as well as the westward  
157 movement of the plume. This event is characteristic of the West African dry season  
158 climatology, with a dominant Harmattan flow as described in the introduction. Figure S1  
159 provides further insight into the dust plume transport during the case study.



159



160  
 161 **Figure 1** - a) Mean aerosol Optical Depth at 550nm from MODIS satellite observations over  
 162 the period 28 March-00 UTC to 02 April-00 UTC 2021. The Global Horizontal Irradiance  
 163 (GHI) observations and AERONET aerosol measurement network, introduced in 2.4, are  
 164 presented, as well as the boundaries of the simulated domain (red rectangle) and the area of  
 165 interest for analysis (black rectangle). b) Mean synoptic conditions of the geopotential height  
 166 (Zg) at 975hPa and the 10m-wind (white arrows - in m/s) over the period 28 March-00 UTC  
 167 to 02 April-00 UTC 2021 from ERA5 reanalysis. The surface temperature and aerosol  
 168 concentration observations from the INDAAF network, introduced in 2.4, are presented.

169

170

## 2.2. Modelling tools

### 2.2.1. WRF model

171



172 The meteorological Weather and Research and Forecasting model (WRF) model version  
 173 3.7.1 is taken for compatibility with the CHIMERE coupling procedure. It is used in its non-  
 174 hydrostatic configuration (Skamarock et al., 2008) and is forced at the boundaries of the  
 175 domain every hour by the meteorological reanalysis data of ERA5 (ECMWF) provided on a  
 176 regular 0.25° x 0.25° grid.

177 The model is run with a 9 km horizontal resolution, a 45s integration time step and 50  
 178 vertical levels, from the surface to 50 hPa. The updated Rapid Radiative Transfer Model  
 179 (RRTMG) radiation scheme (Iacono et al., 2008), which is mandatory for the aerosol optical  
 180 properties feedback, is employed for both long- and short-wave radiations. Additionally, the  
 181 Thompson aerosol-aware microphysics scheme (Thompson and Eidhammer, 2014) is  
 182 applied. The Yonsei University planetary boundary layer's surface layer scheme (Hu et al.,  
 183 2013) is also used, and the cumulus parameterisation is based on the Grell-Freitas scheme  
 184 (Arakawa, 2004). The Revised MM5 surface layer scheme (Jiménez et al., 2012) is  
 185 employed, while the Noah-MP Land Surface Model (Niu et al. 2011) is implemented for the  
 186 land surface physics scheme.

187

### 188 2.2.2. CHIMERE model

189 The chemistry-transport model CHIMERE version v2020r3 (Menut et al., 2021) is used in  
 190 conjunction with the WRF model. Both models have a 9 km horizontal grid. The CHIMERE  
 191 model has 30 pressure-dependent vertical levels from the surface up to 200 hPa, with a first  
 192 layer thickness of 3 hPa. The model is configured for dust-only, with no chemistry and only  
 193 considering dust aerosols (details in section 2.3). The threshold friction velocities for dust  
 194 emission are estimated using the Shao and Lu scheme (2000) and the 6-km spatial  
 195 resolution GARLAP (Global Aeolian Roughness Lengths from ASCAT and PARASOL)  
 196 dataset from Prigent et al. (2012). Mineral dust emission fluxes were calculated employing  
 197 the Alfaro and Gomes (2001) scheme on 10 aerosol size bins ranging from 0.01 to 40 µm.  
 198 The Fécan et al. (1999) parametrization is employed to account for the inhibitory effect of  
 199 soil moisture on dust emission. Dry deposition is treated as described in Zhang et al. (2001).  
 200 Wet scavenging for aerosol is computed following the Willis and Tattelman scheme (1989).  
 201 The CHIMERE model includes the Fast-JX module, version 7.0b (Wild et al., 2000; Bian et  
 202 al., 2002) for the calculation of radiative processes. It considers the radiative properties for  
 203 each aerosol species and each aerosol size bin independently to compute the aerosol  
 204 optical depths, the single scattering albedo and the aerosol asymmetry factor. More details  
 205 on the dust aerosol radiative properties are given in Tables S1 and S2. Finally, we test three  
 206 different initial and boundary condition datasets for mineral dust load (see 2.2.3).

207

208 **Table 1** - Parameterizations used in WRF and CHIMERE

WRF	
microphysics	Thompson aerosol-aware (Thompson and Eidhammer, 2014)
radiation	RRTMG scheme for LW and SW (Iacono et al., 2008)
land surface	Noah-MP land surface scheme (Niu et al., 2011)
planetary boundary layer	Yonsei University scheme



	(Hu et al., 2013)
surface layer	Revised MM5 surface layer scheme (Jimenez et al., 2012)
cumulus	Grell-Freitas scheme (Arakawa, 2004)
<b>CHIMERE</b>	
threshold friction velocities	Shao and Lu (2000) scheme
soil moisture	Fécan et al. (1999) scheme
dust emission fluxes	Alfaro and Gomes (2001) scheme
radiative processes	Fast-JX model, version 7.0b (Wild et al., 2000; Bian et al., 2002)
	0.010 - 0.022
	0.022 - 0.048
	0.048 - 0.107
	0.107 - 0.235
aerosol size distribution bins (diameters in $\mu\text{m}$ )	0.235 - 0.516
	0.516 - 1.136
	1.136 - 2.500
	2.500 - 5.000
	5.000 - 10.00
	10.00 - 40.00

209

210

### 2.2.3. Dust aerosol initial and boundary condition datasets

211 In this study, the uncertainty in the solar estimate associated with the initial and boundary  
212 conditions of the dust aerosol load is evaluated. Three datasets were used: a climatology  
213 derived from the Global Ozone Chemistry Aerosol Radiation and Transport (GOCART,  
214 Ginoux et al., 2001), the Modern-Era Retrospective analysis for Research and Applications  
215 Version 2 (MERRA2) reanalysis (Gelaro et al., 2017) and the CAMS reanalysis (Inness et  
216 al., 2019).

217 The GOCART climatology is provided with the distribution of the CHIMERE model. It is a  
218 monthly climatology on a coarse horizontal grid ( $2^\circ \times 2.5^\circ$ ), which is corrected by applying a  
219 factor of 0.3 as in Vautard et al. (2005).

220 The MERRA2 reanalysis combines the Goddard Earth Observing System (GEOS) and  
221 GOCART models, which are online coupled and implemented with a data assimilation  
222 system. It has a 3-hour temporal resolution and is presented on a  $0.5^\circ \times 0.635^\circ$  horizontal  
223 grid. The observational data considered in the data assimilation process are AOD satellite  
224 observations from MODIS, Advanced Very High Resolution Spectroradiometer (AVHRR),  
225 Multi-angle Imaging SpectroRadiometer (MISR) and ground observations from the AEROSOL  
226 RObotic NETwork (AERONET).

227 The CAMS reanalysis was constructed using 4DVar data assimilation in ECMWF's  
228 Integrated Forecast System (IFS). It has a temporal resolution of 3 hours and is computed  
229 on a regular  $0.75^\circ$  horizontal grid. The AOD data from the Visible Infrared Imaging



230 Radiometer Suite (VIIRS), the MODIS and the Infrared Atmospheric Sounding Interferometer  
231 (IASI) satellite observations are used as observational information in the data assimilation  
232 process.

233 These three dust aerosol initial and boundary datasets differ in type (climatological or  
234 reanalysis), in horizontal, vertical and temporal resolution, and in the resolution and range of  
235 their aerosol size distribution. While GOCART has the highest number of aerosol classes  
236 with 7 bins, CAMS covers a wider size spectrum despite a lower size resolution with only 3  
237 classes. MERRA2 has an intermediate resolution with 5 classes, but covers a smaller  
238 particle size spectrum than CAMS. The CHIMERE model pre-processes these dust aerosol  
239 size distributions by applying a transfer coefficient  $\delta$  to compute the dust aerosol  
240 concentration on the 10 aerosol size bin defined for the simulations :

$$c_j = \sum_i \delta_{i,j} \times c_i \quad (1)$$

241 where  $c_i$  is the dust aerosol concentration of the  $i^{\text{th}}$  size bin from the initial and boundary  
242 condition dataset considered,  $c_j$  is the dust aerosol concentration of the  $j^{\text{th}}$  size bin in the  
243 CHIMERE simulation, and  $\delta_{i,j}$  is the transfer coefficient. This transfer coefficient is derived  
244 as :

- 245 -  $\delta_{i,j} = 0$  if the  $i^{\text{th}}$  size bin from the initial and boundary condition dataset is found to be  
246 wholly outside the  $j^{\text{th}}$  size bin in the CHIMERE simulation;
- 247 -  $\delta_{i,j} = 1$  if the  $i^{\text{th}}$  size bin from the initial and boundary condition dataset is wholly  
248 encompassed by the  $j^{\text{th}}$  size bin in the CHIMERE simulation;
- 249 -  $\delta_{i,j} = \frac{\log(r_{j,max}) - \log(r_{j,min})}{\log(R_{i,max}) - \log(R_{i,min})}$  if the  $i^{\text{th}}$  size bin from the initial and boundary condition  
250 dataset wholly encompasses the  $j^{\text{th}}$  size bin in the CHIMERE simulation;
- 251 -  $\delta_{i,j} = \frac{\log(R_{i,max}) - \log(r_{j,min})}{\log(R_{i,max}) - \log(R_{i,min})}$  if the  $i^{\text{th}}$  size bin from the initial and boundary condition  
252 dataset partially overlaps the  $j^{\text{th}}$  size bin in the CHIMERE simulation, but extends  
253 below the start of this size bin;
- 254 -  $\delta_{i,j} = \frac{\log(r_{j,max}) - \log(R_{i,min})}{\log(R_{i,max}) - \log(R_{i,min})}$  if the  $i^{\text{th}}$  size bin from the initial and boundary condition  
255 dataset partially overlaps the  $j^{\text{th}}$  size bin in the CHIMERE simulation, but extends  
256 beyond the end of this size bin;

257 where  $R_{i,min}$  and  $R_{i,max}$  are respectively the radius of the lower and upper limit of the  $i^{\text{th}}$  size  
258 bin from the initial and boundary condition dataset, and  $r_{j,min}$  and  $r_{j,max}$  are respectively the  
259 radius of the lower and upper limit of the  $j^{\text{th}}$  size bin in the CHIMERE simulation.

260

261 For the sake of simplicity, throughout this article, we will refer to the WRF-CHIMERE  
262 simulations runned with the GOCART, the MERRA2, and the CAMS dust aerosol initial and  
263 boundary conditions as *wrf\_chimere-G*, *wrf\_chimere-M*, and *wrf\_chimere-C* simulations  
264 respectively.

265 Table 2 summarises the characteristics of the three dust aerosol datasets and their  
266 associated size distributions.

267



268 **Table 2.** Summary of the characteristics of the dust initial and boundary condition products.

	<b>GOCART</b>	<b>MERRA2</b>	<b>CAMS</b>
type	climatology	reanalysis	reanalysis
temporal resolution	monthly	3h	3h
vertical levels	20	72	60
horizontal resolution (lat x lon)	2°x2.5°	0.5°x0.635°	0.75°x0.75°
aerosol size distribution (radius in µm)	0.20 - 0.36 µm	0.1 - 1.0 µm	0.03 - 0.55 µm
	0.36 - 0.60 µm	1.0 - 1.8 µm	0.55 - 0.90 µm
	0.60 - 1.20 µm	1.8 - 3.0 µm	0.90 - 20.00 µm
	1.20 - 2.00 µm	3.0 - 6.0 µm	
	2.00 - 3.60 µm	6.0 - 10.0 µm	
	3.60 - 6.00 µm		
	6.00 - 12.00 µm		

269

270

### 2.3. Modelling strategy

271

The domain of simulation extends from 2° to 35°N and from 19°W to 24°E, as illustrated by the red box in Figure 1b. The domain is large enough to represent the primary atmospheric flows, including the Harmattan North/North-West flow and the monsoon South flow, as well as the transport of the emitted aerosol plumes. A horizontal resolution of 9 km has been selected in order to ensure that the grid ratio is approximately 3 with the ERA5 meteorological forcing. This choice is also motivated by the a priori intention to achieve a resolution higher than that of previous CHIMERE simulations performed in this region and compared to the operational solar forecast model used for the Zagtouli solar farm, which are based on global forecast models (see 2.4.1). The CHIMERE model is configured in a “dust only” model, which models only the mineral dust type. This hypothesis is supported for this dust case study by Fig. S2, as desert dust is the dominant aerosol during the event, particularly above 10°N. It is notable that biomass burning, which represents the other principal aerosol source in this region, is no longer a significant contributor to aerosol levels at that time of the year (Evans et al., 2018).

285

The WRF and CHIMERE models are coupled online through the OASIS3 MCT coupler. A two-way coupling strategy is selected, in which WRF sends meteorological variables to CHIMERE which in turn exchanges aerosol information such as AOD, Single Scattering Albedo (SSA) and Asymmetry Factor. This coupling strategy imposes most of the WRF parameterisations. The exchange frequency is set to 15 minutes. The WRF model computes fields on 50 levels, which are linearly interpolated over the 30 CHIMERE vertical levels via the OASIS coupler. The coupling includes the feedbacks of aerosol-radiation interactions (ARI, direct aerosol effect) and aerosol-cloud interactions (ACI, indirect aerosol effects) simultaneously.

293



294 The simulation starts on March 14th-00 UTC and ends on April 2nd-00 UTC, 2021. The first  
295 two weeks served as the spin-up period. The simulation outputs are analysed for the period  
296 of March 28th-00 UTC to April 2nd-00 UTC, which corresponds to the passage of the  
297 dust plume in the Sahel region, in particular around the Zagtouli solar farm in Burkina Faso.  
298 Four simulations were conducted: a meteorological simulation using WRF model alone, and  
299 dust simulations with the coupled WRF-CHIMERE models using as initial and boundary  
300 conditions the GOCART climatology, the MERRA2 reanalysis and the CAMS reanalysis. The  
301 simulation using only WRF allows for the evaluation of the impact of taking into account dust  
302 aerosols in estimating solar radiation. This is compared to the other three simulations, which  
303 are also used to evaluate the uncertainties associated with the choice of the aerosol initial  
304 and boundary condition dataset. A domain of interest, spanning 10°N to 25°N (Fig. 1a), was  
305 selected for analysis and comparisons. This choice was guided by the dust plume trajectory  
306 (Fig. S1) and the “dust only” hypothesis (Fig. S2).

307

#### 308 **2.4. Evaluation datasets**

309 This section presents the local and regional data that are employed in the evaluation of the  
310 simulations.

311

##### 311 **2.4.1. GHI**

312 The Global Horizontal Irradiance (GHI) is the total shortwave irradiance from the Sun on a  
313 horizontal surface on Earth. It is the sum of direct irradiance, which takes into account the  
314 solar zenith angle, and diffuse horizontal irradiance. It is measured in  $W.m^{-2}$  for the  
315 wavelength range 0.3 - 3.0  $\mu m$ .

316

317 The national electricity company of Burkina-Faso, Sonabel, operates a solar farm in Zagtouli  
318 (12.31°N;1.64°W; Fig. 1a), approximately 15 km west of the capital, Ouagadougou. It has an  
319 installed capacity of 34 MWp and contributes up to 4% of Burkina Faso's annual electricity  
320 production. Ground GHI measurements from pyranometers are available at a temporal  
321 resolution of 15 minutes for the Zagtouli solar plant and undergo pre-processing to ensure  
322 quality control. This involves removing outliers and days with missing data, visually checking  
323 the consistency of the measured values and selecting data corresponding to production  
324 hours (positive values for solar radiation at the top of the atmosphere). Operational GHI  
325 forecasts for this solar farm are computed by the French company Steadysun. These  
326 forecasts are based on a multi-model, multi-member and multi-mesh grid aggregation, which  
327 is derived from the NCEP Global Ensemble Forecast System and the ECMWF Integrated  
328 Forecast System (Clauzel et al., 2024).

329 In-situ measurements of GHI from pyranometers (Fig. 1a) are also available at a 15-minutes  
330 temporal resolution for the Banizoumbou (Niger) surface station, installed as part of the  
331 AMMA-CATCH observatory (Analyse Multidisciplinaire de la Mousson Africaine - Couplage  
332 de l'Atmosphère Tropicale et du Cycle Hydrologique, AMMA-CATCH (2005)).

333 The two measurement sites were selected because they are the only locations where GHI  
334 observations have been made available along the dust plume transport for the case study,  
335 with the Zagtouli power station being one of the first large solar farms in West Africa and the  
336 AMMA-CATCH observatory being the only one to offer continuous GHI measurements for  
337 the region and period of interest.

338

339 The CAMS gridded solar radiation dataset (CAMS solar radiation services v4.6, Schroedter-  
340 Homscheidt et al., 2022), based on the Heliosat-4 method (Qu et al., 2017), provides several  
341 variables related to solar radiation, such as clear-sky and all-sky GHI. It has a horizontal



342 resolution of  $0.1^\circ \times 0.1^\circ$  and provides data every 15 minutes. The clear sky model includes  
343 aerosols through the CAMS chemical transport model (Inness et al., 2019), which integrates  
344 data assimilation of AOD and is coupled online to a numerical weather prediction model.  
345 Cloud information for the all-sky model is derived from MeteoSat Second Generation (MSG)  
346 satellite observations using the AVHRR Processing scheme Over cLOUDs, Land and Ocean  
347 (APOLLO) Next Generation cloud processing scheme (Klüser et al., 2015). The dataset was  
348 selected for comparison with the simulations as it integrates a description of aerosol  
349 processes. While Yang and Bright (2020) show that it is the best performing product for  
350 estimating surface solar radiation in the West African region among several satellite-based  
351 gridded irradiance products, this dataset still has a negative bias of about 10% at desert  
352 stations in North Africa (CAMS solar radiation regular validation report, 2020).

353

354

#### 2.4.2. Surface temperature

355 In-situ surface temperature measurements are available for three stations of the  
356 International Network to study Deposition and Atmospheric composition in Africa (INDAAF) :  
357 Banizoumbou (Niger,  $13.54^\circ$  N,  $2.66^\circ$  E, 6.2m above surface; Rajot et al, 2010a; Marticorena  
358 et al, 2010; Kaly et al., 2015), Cinzana (Mali,  $13.28^\circ$  N,  $5.93^\circ$  W, 2m above surface; Rajot et  
359 al, 2010b; Marticorena et al, 2010; Kaly et al., 2015) and Bambey (Senegal,  $14.70^\circ$  N,  
360  $16.47^\circ$  W, 5.2m above surface; Marticorena et al, 2021a) (Fig. 1b). The measurement sites  
361 were selected since they are almost aligned around  $13\text{-}15^\circ$  North, which represents the main  
362 pathway of Saharan and Sahelian dust towards the Atlantic Ocean during the case study.  
363 The ERA5 atmospheric reanalysis (Hersbach et al., 2020) provides spatially continuous  
364 hourly values of surface temperature at 2 metres and has a horizontal resolution of  $0.25^\circ \times$   
365  $0.25^\circ$ .

366

367

#### 2.4.3. Aerosol

368 The INDAAF network also provides data on aerosol concentration through ground  
369 measurements of  $PM_{10}$ , i.e. the concentration of atmospheric particles having an  
370 aerodynamic diameter less than  $10\ \mu\text{m}$ . For this case study, hourly  $PM_{10}$  measurements are  
371 available for two stations (Fig. 1b): Cinzana (Rajot et al, 2010c; Marticorena et al, 2021; Kaly  
372 et al, 2015) and Bambey (Marticorena et al, 2021b).

373 The CAMS atmospheric reanalysis (Inness et al., 2019) is also used to evaluate regional  
374 surface  $PM_{10}$  concentration and AOD. It provides 3-hourly data with a horizontal resolution of  
375  $0.75^\circ \times 0.75^\circ$ , with a surface layer thickness of 2.4 hPa.

376

377 Local ground measurements of AOD are retrieved from the AErosol RObotic NETwork level  
378 1.5 dataset (AERONET, Holben et al., 1998; Giles et al., 2019). AOD is calculated from sun  
379 photometer recordings, along with Ångström Exponent, and is only available during clear sky  
380 conditions in daylight hours, with a resolution of 1 minute. The AOD at 400 nm simulated  
381 with the WRF-CHIMERE model is converted to 440 nm for comparison with AERONET,  
382 using the Ångström formula :

$$\frac{AOD_\lambda}{AOD_{\lambda_0}} = \left( \frac{\lambda}{\lambda_0} \right)^{-\alpha} \quad (2)$$

383 where  $AOD_\lambda$  is the AOD at the desired wavelength,  $\lambda = 440\ \text{nm}$  here ;  $AOD_{\lambda_0}$  is the AOD at  
384 the wavelength simulated in the model,  $\lambda_0 = 400\ \text{nm}$  here ;  $\alpha$  is the Ångström exponent,



385 derived from the simulated AOD at different wavelengths and here given for the range from  
386 400 nm to 600 nm.

387 AERONET provides an aerosol size distribution dataset estimated through inversion of the  
388 photometers data, as described in Dubovik and King (2000). The algorithm for inversion  
389 provides a volume particle size distribution for 22 bins, which are logarithmically distributed  
390 for radii between 0.05  $\mu\text{m}$  and 15  $\mu\text{m}$ .

391 The locations of the five AERONET sites used for comparison in this study are illustrated in  
392 Figure 1a.

393

394 The spatially continuous AOD is also derived from level 2 aerosol products of MODIS Terra  
395 and Aqua satellites (combined Dark Target, Deep Blue AOD at 0.55 micron, Collection 6.1,  
396 Platnick et al., 2015). It provides a measure of the AOD at 550 nm during daytime for clear  
397 sky conditions, with a spatial resolution of 10 km. To compare simulated AOD from WRF-  
398 CHIMERE models with AOD from MODIS, the former is converted from 600 nm to 550 nm.  
399 The conversion is performed using the Ångström formula (eq. 2).

400

401 Table 3 provides a general overview of the data used to evaluate the simulations in this  
402 study.

403

404 **Table 3** - Summary of data used to evaluate the simulations.

	product	type	resolution
<b>GHI</b>	Zagtouli solar farm monitoring system	pyranometer GHI measurement	local
	AMMA-CATCH observational network	pyranometer GHI measurement	local
<b>temperature</b>	CAMS gridded solar radiation	atmospheric reanalysis	0.01°x0.01°
	INDAAF network	ground measurements	local
<b>PM<sub>10</sub></b>	ERA5	atmospheric reanalysis	0.25°x0.25°
	INDAAF network	ground measurements	local
<b>Aerosol Size Distribution</b>	CAMS (EAC4)	atmospheric reanalysis	0.75°x0.75°
	AERONET network	inversion product	local
<b>Aerosol Optical Depth</b>	AERONET network	sunphotometer ground measurements	local
	MODIS	satellite observations	10km

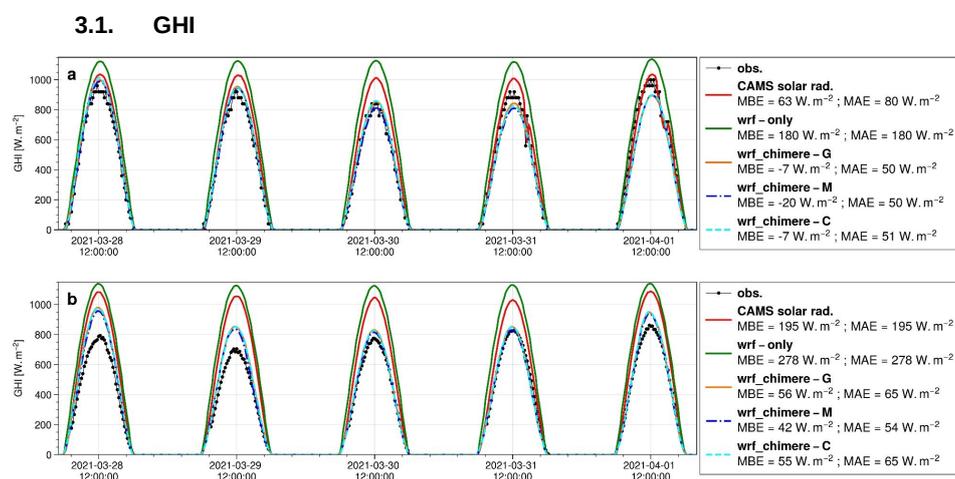
405

406 **3. Results**



407 The analysis starts by assessing the errors and uncertainties associated with the dust  
 408 aerosol initial and boundary condition dataset employed to estimate the variables of interest  
 409 for solar production, i.e. GHI and surface temperature. Subsequently, we investigate the  
 410 potential causes of these uncertainties by evaluating the AOD, aerosol size distribution, and  
 411 surface aerosol concentration (PM<sub>10</sub>), as well as by examining mineral dust emissions and  
 412 the flux of these aerosols at the boundaries of the domain. The metrics used to assess the  
 413 quality of the simulations are described in Supplementary Materials.

414  
 415



416

417 **Figure 2** - Local comparison of CAMS gridded solar radiation product and simulated GHI  
 418 against a) the Zagtoui solar farm observations and b) the Banizoumbou AMMA-CATCH  
 419 observations. *wrf\_chimere-G*, *wrf\_chimere-M* and *wrf\_chimere-C* refer to the WRF-  
 420 CHIMERE simulations using GOCART, MERRA2 and CAMS as dust aerosol initial and  
 421 boundary condition dataset respectively.

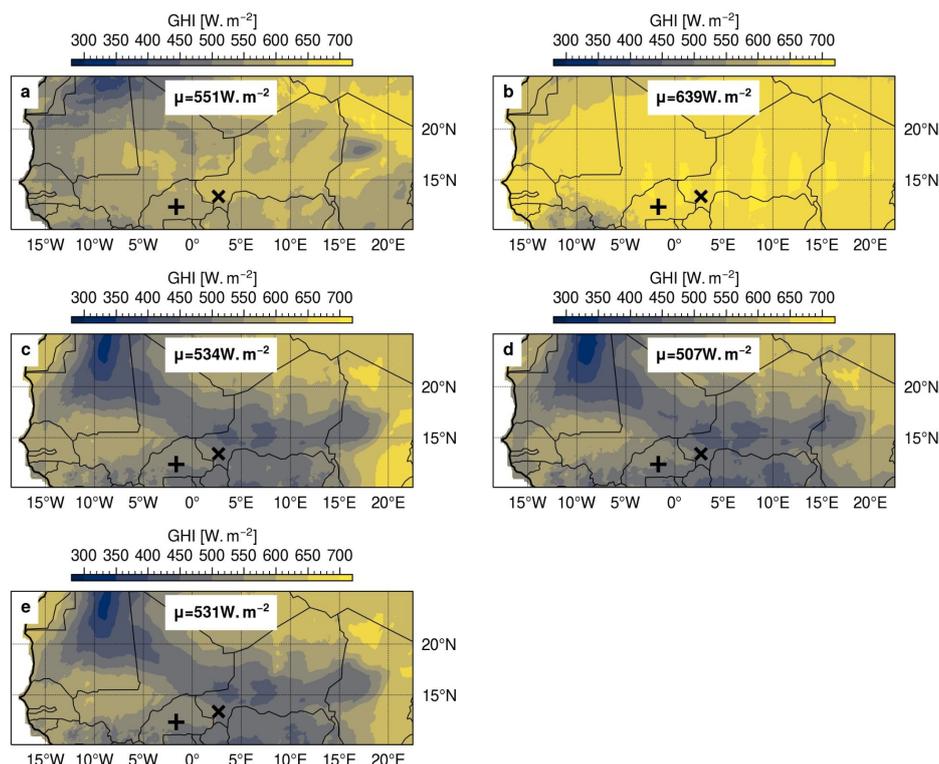
422

423 In Fig. 2, the local evaluation demonstrates the effect of taking into account dust aerosol for  
 424 GHI estimation with the WRF-CHIMERE coupling over the WRF meteorological model  
 425 alone. The coupling reduces the MAE by a factor of 3.6 at Zagtoui and by a factor of 4.6 at  
 426 Banizoumbou on average. The simulations accurately represent the reduction in GHI  
 427 intensity caused by the dust plume at both stations. However, the reduction persists  
 428 compared to the observations at Zagtoui. At Banizoumbou, the simulations overestimate  
 429 GHI at the beginning and end of the case study.

430 Figure 2 also indicates that the CAMS gridded solar radiation product fails to fully reproduce  
 431 the dust event, with only a small reduction in GHI during the passage of the dust plume and  
 432 an intermediate MAE between the WRF only and the WRF-CHIMERE simulations. This point  
 433 serves to highlight the advantages of using a regional model in comparison to a global  
 434 product for the simulation of dust conditions and the estimation of solar radiation.

435 Furthermore, the uncertainty in GHI estimation related to the choice of the dust aerosol initial  
 436 and boundary condition dataset is limited, particularly when compared to the errors. This is  
 437 evidenced by the fact that the mean standard deviation between the three WRF simulations  
 438 is only 7% of the average MAE of these simulations at Zagtoui, and only 5% at  
 439 Banizoumbou.

440



441

442 **Figure 3** - Mean day-time GHI during the period of 28 March-00 UTC to 02 April-00 UTC  
 443 2021 as estimated by a) the CAMS gridded solar radiation dataset, b) the WRF only  
 444 simulation, and the WRF-CHIMERE simulations with c) GOCART, d) MERRA2 and e)  
 445 CAMS as dust aerosol initial and boundary condition dataset; + is the Zagtoui solar farm  
 446 and x is the Banizoumbou site.  $\mu$  is the mean GHI estimates over the domain.

447

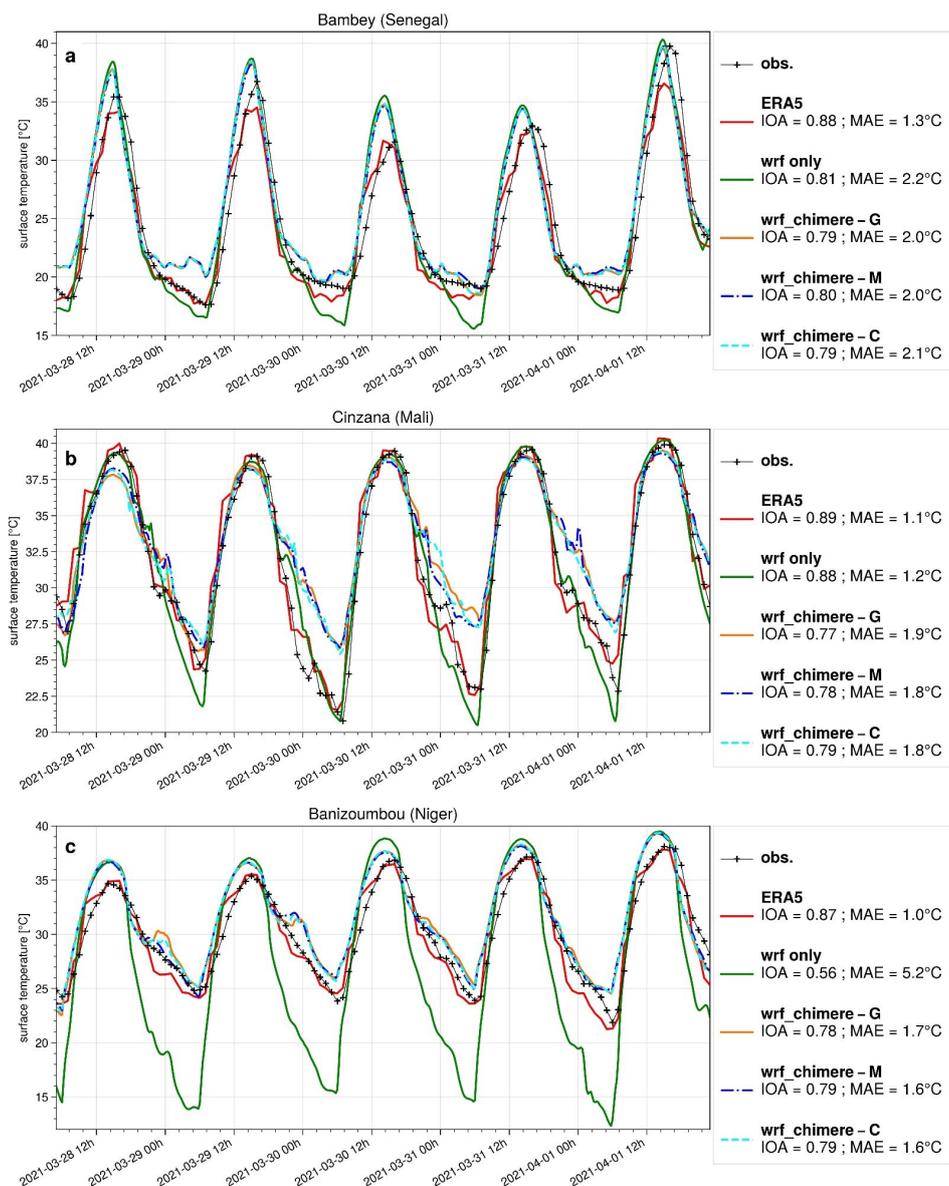
448 The regional comparison presented in Fig. 3 provides more insight into the impact of  
 449 incorporating dust on GHI estimation with the WRF-CHIMERE coupling, when compared to  
 450 the WRF meteorological model alone. As anticipated the WRF-only simulation has the  
 451 highest GHI estimates. The WRF-CHIMERE simulations indicate that dust aerosols reduce  
 452 the mean GHI estimation by approximately  $115 W.m^{-2}$  (-18%), while the CAMS gridded  
 453 solar radiation global product shows a reduction of  $88 W.m^{-2}$  (-14%). The three WRF-  
 454 CHIMERE simulations exhibit identical regional patterns, with lower mean GHI values  
 455 observed on the dust plume trajectory from the Bodélé Depression to the West, and also in  
 456 the South Atlas region. In contrast, the CAMS gridded solar radiation dataset does not show  
 457 this regional pattern, which may indicate that this global product does not fully capture the  
 458 dust event.

459 Furthermore, the uncertainty in GHI estimation associated with the choice of the dust aerosol  
 460 initial and boundary conditions dataset is limited, particularly when compared to the changes  
 461 brought by the taking of dust aerosol into account. Indeed, the standard deviation between  
 462 the three WRF-CHIMERE simulations represents only 5% of the mean difference between  
 463 these three simulations and the WRF-only simulation without dust.



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### 3.2. Temperature



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**Figure 4** - Local comparison of ERA5 and simulated surface temperature with the INDAAF observations for a) Bambey (Senegal), b) Cinzana (Mali) and c) Banizoumbou (Niger) measurement sites. *wrf\_chimere-G*, *wrf\_chimere-M* and *wrf\_chimere-C* refer to the WRF-CHIMERE simulations using GOCART, MERRA2 and CAMS as dust aerosol initial and boundary condition dataset respectively. *IOA* is the Indicator of Agreement and *MAE* is the Mean Absolute Error.



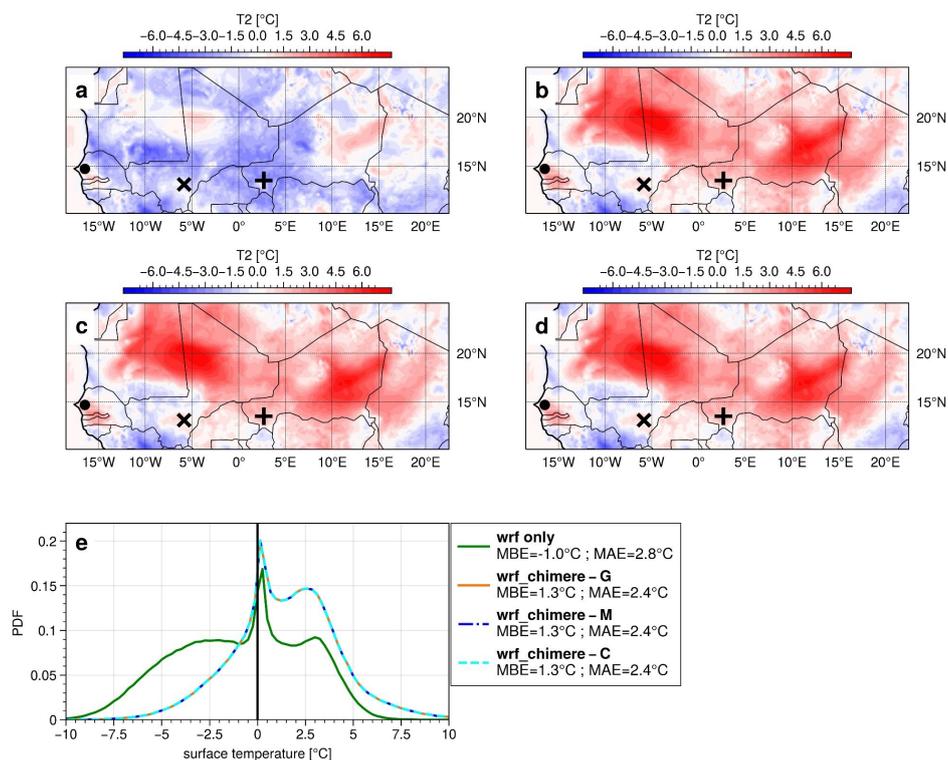
474 Figure 4 illustrates the contrasting outcomes of taking into account dust aerosols into the  
475 WRF-CHIMERE coupling in comparison to the WRF meteorological model alone for the  
476 estimation of surface temperature. At Bambey (Fig. 4a), which is far from the dust source  
477 areas, the coupling has no effect on daytime temperatures but does affect night-time  
478 temperatures. The WRF-CHIMERE and WRF-only simulations have IOA and MAE of the  
479 same order of magnitude. At Cinzana (Fig. 4b), the WRF-only simulation performed better,  
480 with a MAE 0.6°C lower than the coupled simulations, especially for night-time temperatures  
481 but also for estimating the daily temperature peak. Finally, at Banizoumbou (Fig. 4c), which  
482 is near the dust source areas, the coupling leads to a significant improvement in surface  
483 temperature estimation, with an IOA of approximately 0.79 compared to 0.56 for the WRF-  
484 only simulation and a MAE reduced by around 3.6°C. The impact of dust aerosols on  
485 temperature is particularly pronounced at night-time. However, dust also affects the daily  
486 temperature peak, with a reduction of 1.1°C of the daily maximum temperature observed on  
487 the 30th of March.

488 Depending on the position of the measurement station, the results show a contrast, with a  
489 significant improvement with the model coupling close to the source zones at Banizoumbou.  
490 However, this improvement is reversed with increasing distance at Cinzana. This suggests  
491 errors in the simulation of the transport of the dust plume from the source zones (Bodélé  
492 Depression) towards the West. Overall, the main differences between WRF only and WRF-  
493 CHIMERE coupled simulations occur at night time when there is no solar production. These  
494 differences highlight the warming effect due to the dust aerosol interaction with the longwave  
495 earth radiation.

496 In general, the uncertainty associated with the choice of the dust aerosol initial and boundary  
497 condition dataset for the WRF-CHIMERE simulations is negligible compared to the errors in  
498 temperature estimation or the difference with the WRF-only simulation.

499 The value of the ERA5 reanalysis for surface temperature evaluation is also reinforced in  
500 Fig. 4, since it shows the lowest MAE and highest IOA. This dataset can therefore be  
501 considered reliable for a regional evaluation of surface temperature.

502



503

504 **Figure 5** - Mean difference in surface temperature as compared to the ERA5 reanalysis for  
 505 a) the WRF only simulation, the WRF-CHIMERE simulations with b) GOCART, c) MERRA2  
 506 and d) CAMS as dust aerosol initial and boundary condition dataset, during the period of 28  
 507 March-00 UTC to 02 April-00 UTC 2021; the black point is the Bambey, x is the Cinzana and  
 508 + is the Banizoumbou INDAAF sites. e) Probability Density Function for the differences in  
 509 surface temperature between simulations and the ERA5 reanalysis.

510

511 The regional surface temperature evaluation in Fig. 5 also reveals a contrast benefit of the  
 512 coupling approach for the surface temperature estimation. While the WRF alone simulation  
 513 (Fig. 5a) underestimates the surface temperature all over the domain, WRF-CHIMERE  
 514 simulations are overestimating surface temperature in the dusty areas (Saharan region, Fig.  
 515 5bcd). Overall, taking into account dust aerosol in the estimation of surface temperature  
 516 reduces the MAE by 14% (Fig. 5e) when comparing the surface temperature estimates from  
 517 simulations with the ERA5 reanalysis.

518

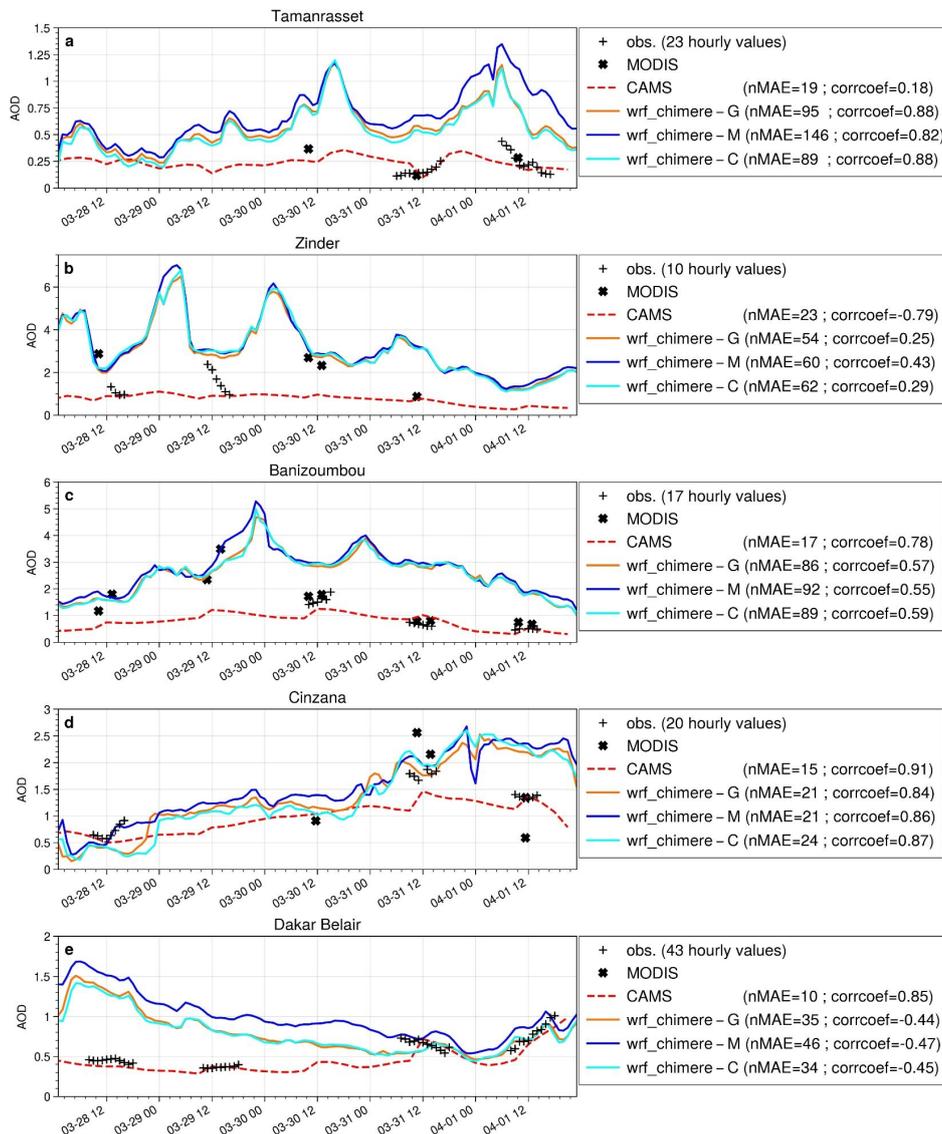
519 Furthermore, the uncertainty associated with the choice of the dust aerosol initial and  
 520 boundary conditions dataset is limited. This is demonstrated by the fact that the standard  
 521 deviation between the three WRF-CHIMERE simulations averaged over the period of  
 522 analysis is 12% of the mean bias of those three simulations in comparison to ERA5  
 523 reanalysis, and only 7% of the difference between the coupled simulations and the WRF-  
 524 only simulation without dust.

524



525 Finally, the incorporation of dust aerosol into the estimation of GHI appears to be a crucial  
526 element in this case study. However, the value of this approach is more debatable in the  
527 context of surface temperature estimation. Furthermore, the uncertainty related to the dust  
528 aerosol initial and boundary condition dataset selection is limited, particularly when  
529 compared to the simulation errors, and to the differences between including dust in the  
530 simulation and not including it. The following sections will examine the simulated dust  
531 aerosol condition during the case study in order to explain the discrepancies observed in  
532 GHI and surface temperature, which are key parameters for solar production.  
533  
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### 3.3. Aerosol Optical Depth



535

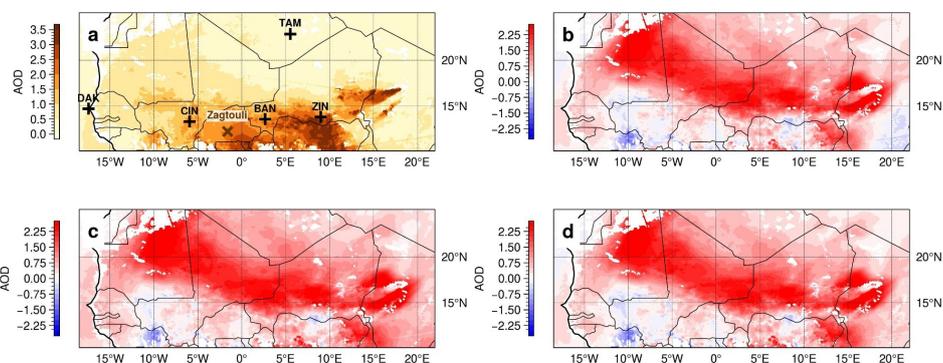


536 **Figure 6** - Local comparison of simulated AOD with AERONET in-situ measurements at 440  
 537 nm for a) Tamanrasset, b) Zinder, c) Banizoumbou, d) Cinzana and e) Dakar Belair stations.  
 538 *wrf\_chimere-G*, *wrf\_chimere-M* and *wrf\_chimere-C* refer to the WRF-CHIMERE simulations  
 539 using GOCART, MERRA2 and CAMS as dust aerosol initial and boundary condition dataset  
 540 respectively; *MODIS* and *CAMS* refer to the AOD at 440 nm from the MODIS satellite  
 541 observations and the CAMS atmospheric reanalysis respectively. *nMAE* is the normalised  
 542 mean absolute error in % and *corrcoef* is the Person correlation coefficient, both derived  
 543 with AERONET measurements as the reference.

544 The local evaluations presented in Figure 6 reveal an overestimation of the AOD for stations  
 545 close to dust sources such as Tamanrasset ( Fig. 6a), Zinder ( Fig. 6b) and Banizoumbou  
 546 ( Fig. 6c). This overestimation is more limited with increasing distance from the dust source  
 547 at Cinzana (Fig. 6d) and Dakar (Fig. 6e). The order of magnitude of the dispersion between  
 548 the three simulations is small when compared to the errors of the simulation in representing  
 549 the observed AOD. As a consequence, the uncertainty associated with the choice of the dust  
 550 aerosol initial and boundary condition dataset is limited. Overall, the AERONET AOD  
 551 measurements appear to be very scarce, particularly close to the dust aerosol sources  
 552 (Zinder, Tamanrasset, Banizoumbou, Cinzana). The AOD measurements are performed by  
 553 sun photometers which give recording by pointing at the sun. Thus these recordings are only  
 554 available during daytime and with clear sky conditions. In some cases of intense dust  
 555 plumes with very high concentration, leading to strong solar radiation absorption, the sun  
 556 photometers are technically limited and cannot produce any record or, sometimes, the  
 557 AERONET quality control system removes them. This may be the reason for the scarcity of  
 558 observations in this case study, which focuses on an intense dust event, increasing the  
 559 perceived overestimation of the simulations. To compensate for this, the AOD estimates  
 560 from MODIS satellite observations have been added to Figure 6 to complete the data.

561 Furthermore, the CAMS reanalysis appears to be a reliable dataset for dust AOD estimation,  
 562 as it has no overestimation and has the lowest *nMAE* for all sites. Although it does not  
 563 reproduce the AOD dynamics close to the dust source at Tamanrasset and Zinder, it has the  
 564 highest correlation coefficient for the other sites.

565



566

567 **Figure 7** - a) Mean from March 28th-00 UTC to April 2nd-00 UTC 2021 of MODIS AOD at  
 568 550 nm satellite observations; x is the Zagtoui solar farm and + corresponds to AERONET  
 569 stations. For panels b, c and d, AOD at 550 nm mean differences from March 28th-00 UTC  
 570 to April 2nd-00 UTC 2021 between each of the WRF-CHIMERE simulations driven by  
 571 GOCART, MERRA2 and CAMS, respectively, and the MODIS satellite observations.



572

573 The AOD differences shown in Fig. 7bcd show that the simulations significantly overestimate  
574 the AOD as compared to the MODIS satellite observations, particularly in the Saharan and  
575 North Sahelian zones and in the South Atlas, with an average overestimation of +1.25  
576 between 15°N and 20°N. It is important to note that this overestimation is localised close to  
577 the desert aerosol source zones. The simulated AOD error in the Sahel zone, particularly  
578 around the Zagtouli solar power plant, is more limited with an average of +0.51 between  
579 10°N and 15°N. The mean standard deviation between the three WRF-CHIMERE  
580 simulations is only 10% of the mean error and 5% of the mean simulated AOD.  
581 Consequently the uncertainty in the AOD estimate associated with the selection of the dust  
582 aerosol initial and boundary condition dataset is small.

583 The observed overestimation of AOD by the WRF-CHIMERE simulations could be due to an  
584 overestimation of the aerosol concentration, or to an inaccurate estimation of the size  
585 distribution of the dust plume, or to excessive aerosol emissions within the domain, or to an  
586 excessive inflow of desert aerosols at the domain boundaries. These hypotheses are  
587 investigated below. Another potential explanation may also be the uncertainties in the  
588 radiative properties of the dust aerosol incorporated in the CHIMERE model, or an  
589 underestimation of the aerosol deposition flux; these aspects are not investigated here.

590

### 591 3.4. Aerosol size distribution

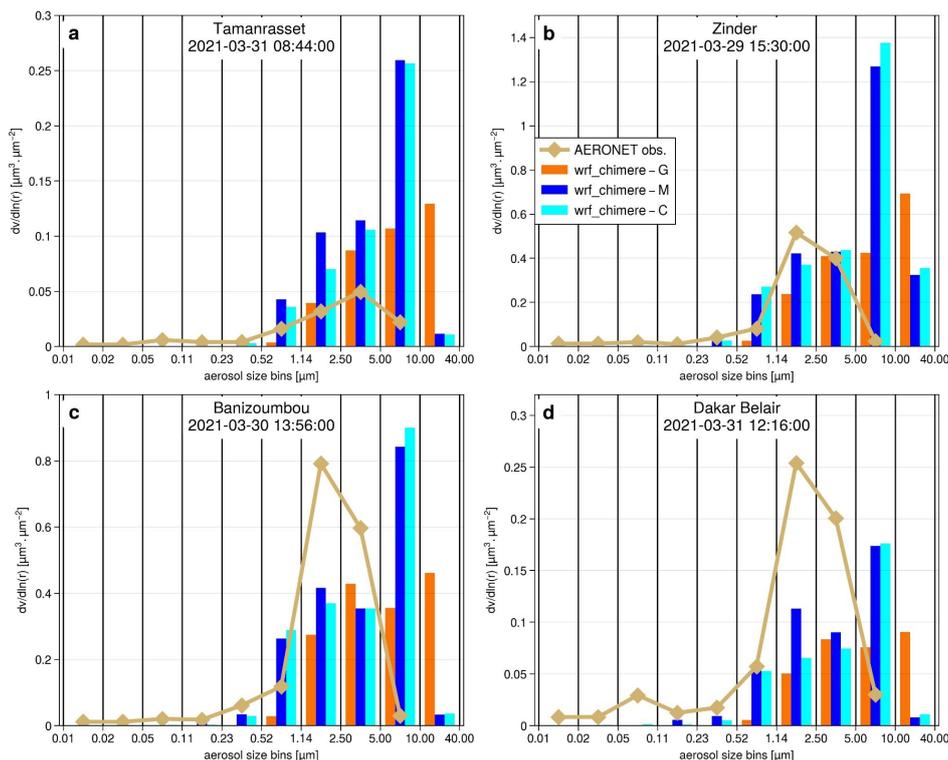
592 As presented in section 2, the AERONET inversion products provide aerosol size distribution  
593 for 22 bins logarithmically distributed ranging from 0.05 to 15 µm. For comparison with the  
594 modelled aerosol size distribution, this distribution is interpolated on the CHIMERE  
595 simulations aerosol size distribution which is composed of 10 bins ranging from 0.01 µm to  
596 40.00 µm in diameter (see Table 1). Given that the last bin (10.00-40.00 µm) is at the limit of  
597 the capabilities of the inversion method, with a maximum wavelength at which the AOD is  
598 measured of 875 nm, it is not shown for the AERONET dataset. Consequently, only  
599 comparisons between the three simulations can be made for the bigger size section. The  
600 column aerosol volume size distribution simulated by the model is calculated for each bin "i"  
601 as in Menut et al. (2016) :

$$\frac{dV(r_i)}{d \ln(r_i)} = \sum_{k=1}^{n_{levels}} \frac{m_{k,r_i} \times \Delta z_k}{\rho_{dust} \times \ln(r_{i,max}/r_{i,min})} \quad (3)$$

602 where  $r_i$  is the mean mass median radius (in µm) and  $r_{i,min}$  and  $r_{i,max}$  the boundaries of the  
603  $i^{th}$  bin.  $m_{k,r_i}$  is the dust aerosol mass concentration (the mass of aerosol in one cubic metre  
604 of air, in  $\mu g \cdot m^{-3}$ ).  $\rho_{dust}$  is the dust aerosol density (the mass of the particle in its own volume,  
605  $\rho_{dust} = 2300 \text{ kg} \cdot m^{-3}$ ).  $\Delta z_k$  is the model layer thickness (in metres), for a total of n levels (here  
606 30 vertical levels).

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**Figure 8** - Aerosol volume size distribution for the AERONET station located in a) Tamanrasset, b) Zinder, c) Banizoumbou and d) DakarBelair. The time indicated corresponds to the time of the AERONET inversion product used for the comparison with the simulated aerosol size distribution. *wrf\_chimere-G*, *wrf\_chimere-M* and *wrf\_chimere-C* refer to the WRF-CHIMERE simulations using GOCART, MERRA2 and CAMS as dust aerosol initial and boundary condition dataset respectively.

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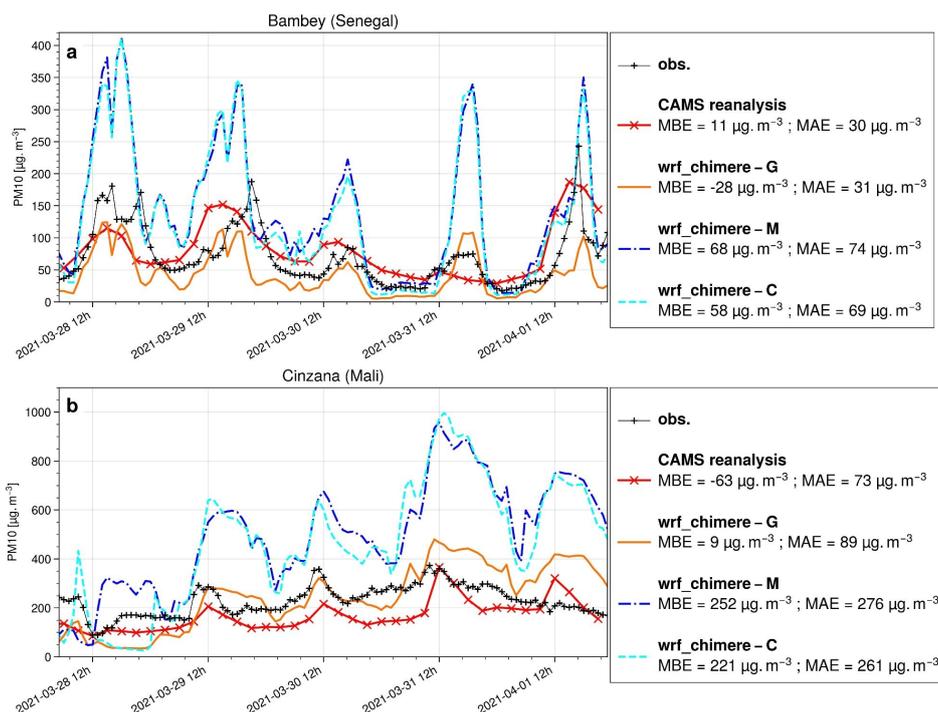
The evaluation of the aerosol size distribution in Fig. 8 shows that the simulations generally have a dominant aerosol size mode shifted towards coarser sizes compared to the AERONET inversion product. The ground-based size distribution has a strong peak between 1.14 µm and 5.00 µm, whereas the size distributions estimated by the WRF-CHIMERE simulations peak for coarser aerosol. For the Dakar Belair station (Fig. 8d), the AERONET inversion product indicates a first peak of lower intensity between 0.05 and 0.11 µm, which suggests the presence of aerosols other than desert dust. These aerosols may be of anthropogenic origin, given the proximity of the measurement site to the Senegalese capital. When comparing the size distributions between the three simulations with different dust aerosol initial and boundary condition dataset, it can be seen that the simulations driven with CAMS and MERRA2 reanalysis are relatively close and well separated from the one driven with the GOCART climatology. Notably, the dominant size bin in the simulation using GOCART dataset is consistently the largest particles, whereas with the aerosol from reanalyses, it is the aerosols between 5 µm and 10 µm. Consequently, the uncertainty associated with the selection of the dust aerosol initial and boundary condition dataset is high when examining the aerosol size distribution, particularly for particles exceeding 5.00



633  $\mu\text{m}$  in diameter. The aforementioned uncertainties in the aerosol size distribution, which are  
 634 linked to the choice of the dust aerosol initial and boundary conditions dataset, may be  
 635 attributed to differences in the flow of desert dust entering the domain, as well as  
 636 uncertainties in the transfer method carried out by the CHIMERE model to match the aerosol  
 637 classes of these datasets to its own size distribution, described in section 2.2.3.  
 638 As a result, the shift in the WRF-CHIMERE size distribution towards coarser particles  
 639 compared to AERONET observations would result in a simulated AOD smaller than  
 640 AERONET measurements. However, the opposite is observed (section 3.3). This suggests a  
 641 positive bias in the simulated aerosol concentration, which would explain the positive bias in  
 642 the AOD, while the coarser size distribution would tend to compensate.

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### 3.5. Aerosol concentrations



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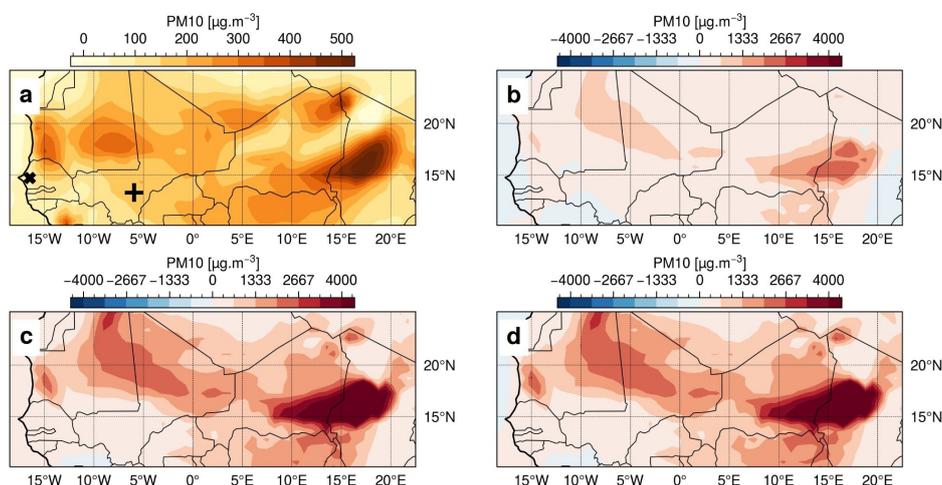
646 **Figure 9** - Local comparison of CAMS reanalysis and simulated  $\text{PM}_{10}$  surface concentrations  
 647 with INDAAF network observations for a) Cinzana and b) Bambey stations. *wrf\_chimere-G*,  
 648 *wrf\_chimere-M* and *wrf\_chimere-C* refer to the WRF-CHIMERE simulations using GOCART,  
 649 MERRA2 and CAMS as dust aerosol initial and boundary condition dataset respectively.  
 650 MBE is the mean bias error and MAE refers to the mean absolute error.

651

652 The three simulations properly capture the dynamics of the  $\text{PM}_{10}$  surface concentration with  
 653 respect to the INDAAF ground measurement (Fig. 9) as correlation coefficients are around  
 654 0.6 at Cinzana and close to 0.7 at Bambey. The WRF-CHIMERE simulations driven with  
 655 MERRA2 and CAMS dust aerosol datasets overestimate the surface  $\text{PM}_{10}$  concentration  
 656 peaks for Bambey (Fig. 9a) and Cinzana (Fig. 9b), with high positive bias values of around  
 657 63  $\text{g.m}^{-3}$  at Bambey and 247  $\text{g.m}^{-3}$  at Cinzana. The latter station is closer to the dust



658 aerosol sources. In contrast, the simulation using the GOCART dust aerosol dataset  
 659 demonstrates superior performance in representing this variable, with an MAE that is  
 660 approximately 60% and 70% lower than the two other simulations at Bambey and Cinzana,  
 661 respectively.  
 662 Furthermore, the uncertainty associated with the selection of initial and boundary condition  
 663 dataset for dust aerosols is of a comparable magnitude to the simulation errors observed for  
 664 surface PM<sub>10</sub> concentrations. Section 3.4 partly explains these discrepancies in surface PM<sub>10</sub>  
 665 concentration estimates between the simulation driven with the GOCART climatology and  
 666 those driven with CAMS or MERRA2 reanalysis in terms of aerosol size distribution. These  
 667 differences may also be attributed to variations in the size distribution of dust aerosol  
 668 emissions or in the inflow of dust into the simulation domain and its aerosol size distribution.  
 669 Furthermore, Fig. 9 indicates that the CAMS reanalysis provides reliable estimates of  
 670 surface PM<sub>10</sub> concentration, as evidenced by the fact it has the lowest MAE values.  
 671 However, the Bambey and Cinzana ground measurements, which are the only two available  
 672 for the case study, are situated at a considerable distance from the dust sources, limiting our  
 673 ability to assess the accuracy of the CAMS reanalysis in capturing the dust event. Moreover,  
 674 the CAMS reanalysis exhibits a negative bias at Cinzana, which is the closest site to the dust  
 675 sources.  
 676



677  
 678 **Figure 10** - a) Mean from March 28th-00 UTC to April 2nd-00 UTC 2021 of CAMS reanalysis  
 679 PM<sub>10</sub> surface concentration; x refers to the Bambey and + corresponds to Cinzana INDAAF  
 680 stations. For panels b, c and d, PM<sub>10</sub> surface concentration mean differences from March  
 681 28th-00 UTC to April 2nd-00 UTC 2021 between each of the WRF-CHIMERE simulations  
 682 driven by GOCART, MERRA2 and CAMS, respectively, and the CAMS reanalysis.  
 683

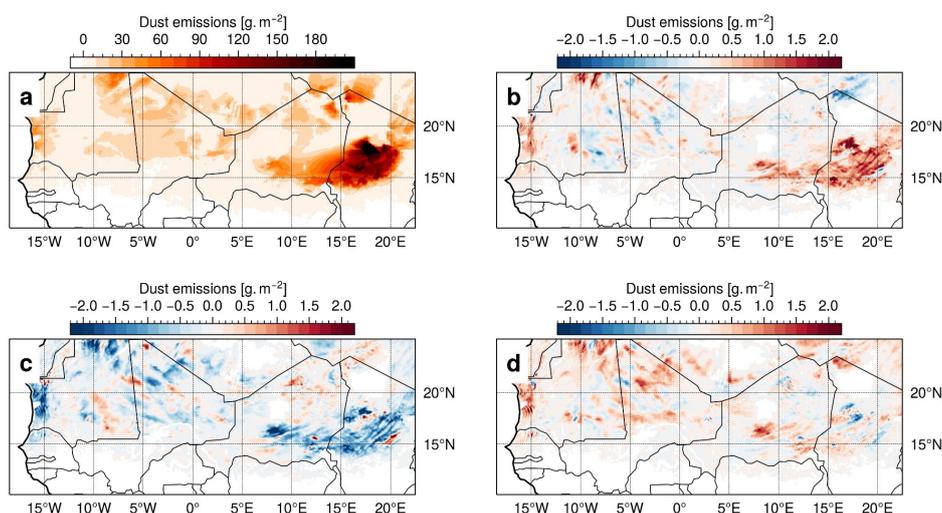
684 Figure 10 illustrates an overestimation of the PM<sub>10</sub> concentrations as compared to the CAMS  
 685 reanalysis. This is particularly evident in dust source areas such as the Bodélé Depression.  
 686 The WRF-CHIMERE simulation driven with the GOCART dataset is the closest to the CAMS  
 687 reanalysis, with a mean estimate 3.6 times higher. However, this ratio reaches 8.6 for the  
 688 simulations driven with the CAMS and MERRA2 reanalysis dataset.



689 The mean standard deviation between the three WRF-CHIMERE simulations is 35% of their  
 690 mean  $PM_{10}$  surface concentration estimate. Consequently the uncertainty in the estimation of  
 691 dust  $PM_{10}$  surface concentration associated with the selection of the dust aerosol initial and  
 692 boundary condition dataset is significant. The discrepancies between the simulation using  
 693 the GOCART climatology and the two other ones using CAMS or MERRA2 reanalysis can  
 694 be partly explained by the differences in the simulated aerosol size distribution, as shown in  
 695 section 3.4.

696  
 697

### 3.6. Dust emissions



698

699 **Figure 11** - a) Total dust emissions flux from March 28th-00 UTC to April 2nd-00 UTC 2021,  
 700 averaged between the three WRF-CHIMERE simulations. For panels b, c and d, total dust  
 701 emissions individual differences between each of the WRF-CHIMERE simulations driven by  
 702 GOCART, MERRA2 and CAMS, respectively, and the mean of the three WRF-CHIMERE  
 703 simulations.

704

705 In terms of dust emissions (Fig. 11), the Bodélé Depression is, as expected, identified as  
 706 the primary dust source area, with emissions reaching up to  $244 \text{ g/m}^2$ . The differences of the  
 707 simulations with each of the three dust aerosol initial and boundary conditions dataset,  
 708 relative to their mean, exhibit highest values in the source zones located at the Bodélé  
 709 Depression and the South Atlas. Nevertheless, it is worth noting that there is a factor of 100  
 710 in between the emissions in the Bodélé area (approximately  $200 \text{ g/m}^2$ ) and the observed  
 711 differences between the three simulations. Consequently, the uncertainties in dust emissions  
 712 resulting from the choice of the dust aerosol initial and boundary conditions dataset can be  
 713 considered negligible. As emissions are primarily influenced by surface wind, it can be  
 714 inferred that the uncertainty generated by the dust aerosol driving dataset on the surface  
 715 wind is negligible too, which is confirmed by Fig. S4. Additionally, the size distributions of the  
 716 aerosols emitted during the case study are found to be identical (not shown). Therefore, the  
 717 differences in AOD and dust concentration may be attributed to the dust flows at the  
 718 boundaries of the domain and are not linked to differences in simulated dust emissions  
 719 within the domain. However, there is no observational data available to enable a quantitative



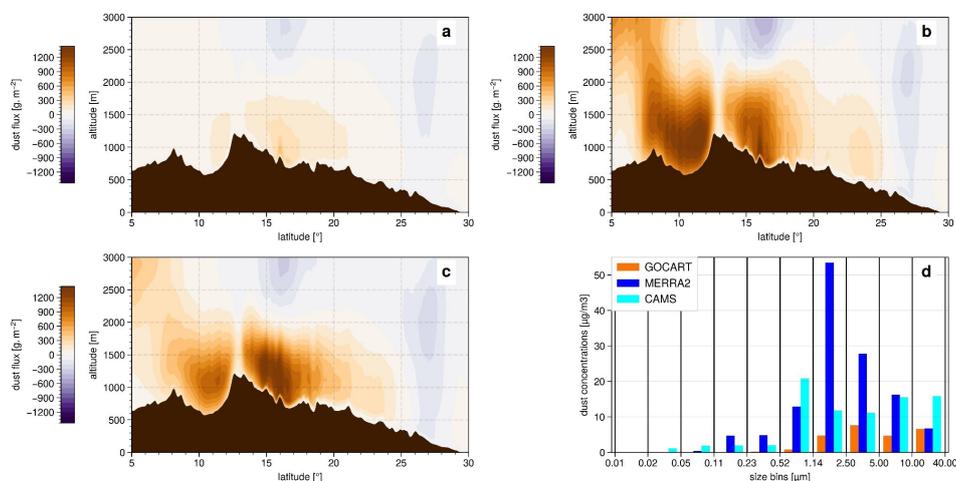
720 evaluation of the accuracy of the emissions computed within the WRF-CHIMERE  
721 simulations.

722

723

### 3.7. Dust boundary flux

724



725

726 **Figure 12** - Cumul of the dust flux at the eastern boundary of the simulation from March  
727 28th-00 UTC to April 2nd-00 UTC 2021 for the WRF-CHIMERE simulation with a) GOCART,  
728 b) MERRA2 and c) CAM5 as dust aerosol initial and boundary conditions dataset; d) Dust  
729 size distribution at the eastern boundary limit average during the case study period, from the  
730 surface to 200hPa and over latitude. In panel abc, the dust flux is derived as the product  
731 between the dust aerosol concentration and the zonal wind, and positive values of the dust  
732 flow indicate a flow entering the simulation domain.

733

734 As shown in Fig. 1b, the dust event is associated with a strong Harmattan flow,  
735 characterised by a northeasterly flow in the lower layer. It is thus interesting to quantify the  
736 dust inflow associated with each of the dust aerosol initial and boundary conditions dataset  
737 for the eastern domain boundary. The lowest dust flux is observed with GOCART (Fig. 12a),  
738 with a maximum of approximately 480 g/m<sup>2</sup>. In contrast, MERRA2 and CAM5 (Fig. 14 b  
739 and c respectively) exhibit higher dust fluxes, with maximum values of around 1650 g/m<sup>2</sup>.  
740 The maximum flow is around 10°N for MERRA2, while for CAM5, it is closer to 16°N. Given  
741 that GOCART is a climatology, it is reasonable to expect a lower dust flux compared to the  
742 CAM5 and MERRA2 reanalyses, which are real case simulations incorporating data  
743 assimilation of AOD. This is particularly true for the presented case study, which involves an  
744 intense dust event associated with a Harmattan flow.

745 There are also significant differences in both quantity and distribution by aerosol size bin  
746 (Fig. 12d). MERRA2 exhibits a strong dominant mode for the class between 1.14 µm and  
747 2.50 µm, while CAM5 shows significant values from 0.52 µm to 40 µm, with a maximum for  
748 the size class between 0.52 µm and 1.14 µm. Finally, the GOCART model displays a lower  
749 variability between 1.14 µm and 40.00 µm, with the maximum occurring for the size class  
750 between 2.55 µm and 5.00 µm.

751 The eastern dust fluxes at the boundary significantly vary depending on the dataset used as  
752 dust aerosol initial and boundary conditions, both in terms of quantity and size distribution.



753 The reanalysis dataset, CAMS and MERRA2, are expected to provide a more accurate  
754 representation of dust flux in terms of quantity as they are real case simulations assimilating  
755 observational data in their calculations, as compared to GOCART which is a climatology.  
756 However, GOCART provides a more comprehensive description of aerosol size distribution  
757 with seven classes, in comparison to CAMS, which has only three classes but proposes a  
758 higher horizontal resolution. While GOCART considers the effect of aerosol size to be  
759 essential, CAMS assumes the horizontal resolution to be a key parameter. MERRA2 is the  
760 most comprehensive of the three datasets, with the highest horizontal resolution, and an  
761 aerosol size distribution that is close to the GOCART one with five classes. Despite the  
762 absence of observational data that would permit a quantitative evaluation of the eastern dust  
763 fluxes, the aforementioned elements suggest that the MERRA2 dataset might be more  
764 accurate.

765 As a result, and in consideration of the negligible uncertainty in dust emissions within the  
766 simulation domain related to the choice of the dataset for dust aerosol initial and boundary  
767 conditions (see 3.6), these differences in eastern dust fluxes appear to account for the  
768 uncertainties of the simulated aerosol concentrations (see 3.5) and AODs (see 3.3).

769

### 770 3.8. Discussions

771 The evaluation of the GHI at the Zagtouli solar power plant and the Banizoumbou site (Fig.  
772 2) shows a clear improvement in its estimation when WRF is coupled to CHIMERE rather  
773 than not as the local MAE is reduced by around 75%. This confirms the relevance of  
774 incorporating the dust radiative effect with a coupling approach, in comparison with the  
775 operational forecasts currently employed based on meteorological models alone. During the  
776 dry season, dust events similar to the one presented here, with emissions at Bodélé and  
777 then transport of the plume westwards, are common. This work therefore calls for  
778 forecasters in the photovoltaic sector to better account for the desert dust cycle in their  
779 forecast products. This local evaluation also highlights the potential benefits of using a  
780 regional model rather than a global product, as the WRF-CHIMERE simulations outperform  
781 the CAMS gridded solar radiation product with an average MAE reduced by approximately  
782 38% at the Zagtouli solar farm and by 70% at the Banizoumbou site, which is closer to dust  
783 sources. These discrepancies are corroborated by the regional comparison presented in  
784 Figure 3, which reveals that the mean WRF-CHIMERE GHI estimate is 5% lower than the  
785 CAMS solar radiation dataset. Additionally, the latter does not exhibit a geographical pattern  
786 with lower GHI estimation along the dust plume trajectory, in contrast to the WRF-CHIMERE  
787 simulations. Furthermore, the comparison indicates that the incorporation of dust in the  
788 simulation reduces surface solar radiation by 18% for this case study. In light of the  
789 anticipated expansion of PV production in West Africa, this point underscores the potential  
790 consequences of such dust events if they are not accurately predicted.

791

792 The evaluation of local surface temperature (Fig. 4) reveals contrasting results regarding the  
793 effectiveness of the coupled approach. It demonstrates an average local MAE reduction of  
794 approximately 10% compared to the WRF-only simulation. However, the main differences  
795 occur mainly at night, when no photovoltaic is produced. The regional evaluation in Fig. 5  
796 confirms these contrasting results and indicates a reduction of regional MAE by about 14%  
797 with the coupling rather than WRF alone. The overestimation of surface temperature in dusty  
798 areas with the coupling, not present in the WRF only simulation, reveals the dominant  
799 aerosol warming effect during night time as compared to the cooling effect during daytime.  
800 These statements strongly depend on the accuracy of the ERA5 reanalysis which serves as



801 reference. ERA5 integrates data assimilation but does not consider aerosol information in its  
802 calculation. Due to the limited ground measurements in the Saharan region to constrain the  
803 reanalysis, it is possible that ERA5 underestimates the aerosol effect in dusty areas.

804

805 Nevertheless, despite the improvements demonstrated in solar radiation and surface  
806 temperature estimation, the WRF-CHIMERE simulations exhibit a notable positive bias in  
807 terms of AOD, as evidenced by the local and regional evaluations presented in Figs. 6 and  
808 7. This overestimation cannot be attributed solely to differences in aerosol concentrations, as  
809 the simulations yield markedly disparate surface concentrations of PM<sub>10</sub>, depending on the  
810 dust aerosol initial and boundary condition dataset chosen (Fig. 10) , while this  
811 discrepancies do not appear in the AOD estimates. This excess of aerosol load may be  
812 attributed to an overestimation of emissions within the domain, but this cannot be verified as  
813 there is not any such measurement. The incoming flux of dust in the domain plays a minor  
814 role as shown in Fig. 12 where the flux significantly also varies depending on the dust  
815 aerosol initial and boundary condition dataset employed, while these differences are not any  
816 more present in the simulated AOD estimates. Additionally, the underestimation of aerosol  
817 deposition, by sedimentation (not studied in this research) could be at the origin of the  
818 overestimation of the simulated dust loads. Finally, another potential explanation for these  
819 AOD biases may be the inaccuracies in the dust radiative properties incorporated in the  
820 CHIMERE model calculation (see Table S1 and S2). These depend on the mineralogical  
821 composition of the desert dust particles emitted, which are considered uniform in this work.

822

823

824 The uncertainty associated with the choice of the large scale dust aerosol initial and  
825 boundary condition dataset is very low when considering the variables of interest for solar  
826 production, namely GHI and surface temperature (Fig. 3 and 5). This uncertainty is also low  
827 compared to the performance of simulations for AOD estimation (Fig. 7). This result is similar  
828 when examining dust emissions within the domain, which are nearly identical for the three  
829 coupled simulations (Fig. 11). This can be explained by the fact that dust emissions depend  
830 on the square of surface wind speed which present no significant signature of the selection  
831 of the dust aerosol initial and boundary conditions (Fig. S4). The aerosols emitted within the  
832 chosen domain are much greater than those entering, as the domain accounts for the main  
833 source zones. This is why the simulations are not that sensitive to dust aerosol large-scale  
834 dataset employed. The results regarding the uncertainty associated with the choice of the  
835 dust aerosol initial and boundary condition dataset differs when examining various elements  
836 of the dust life cycle. Indeed, aerosol size distributions vary significantly between the  
837 simulation driven with GOCART on one hand, and simulations driven with CAMS and  
838 MERRA2 on the other hand. GOCART climatology over-represents aerosols larger than 10  
839  $\mu\text{m}$  compared to the CAMS and MERRA2 reanalyses. These differences partially account  
840 for the significant deviation in surface PM<sub>10</sub> concentration estimates (Fig. 10), indicating that  
841 reanalysis-type datasets result in much higher values, up to 3 times higher, compared to  
842 climatological-type data which is closer to ground observations. The dust flux entering the  
843 domain may also partly explain these differences. In fact, this flux is very low with GOCART,  
844 with values up to 3.5 times lower than CAMS and MERRA2 (Fig. 12). The size distribution of  
845 this incoming aerosol flux is also a determining factor.

846

847 **4. Conclusion and perspectives**



848 This study aims to evaluate the ability of the WRF-CHIMERE coupling to simulate GHI  
849 during a typical dust event in the dry season in West Africa. This event is characterised by a  
850 Harmattan flux associated with significant desert dust emissions over the Bodélé  
851 Depression, with the dust plume subsequently transported westward. This work  
852 demonstrates the utility of coupling a meteorological model with a desert aerosol life cycle  
853 model to represent such events, particularly for improving solar forecasts. Indeed, GHI  
854 estimations are markedly enhanced with this approach compared to using a meteorological  
855 model alone with a 75% reduction of local MAE. Nevertheless, the performance of the WRF-  
856 CHIMERE simulations in representing the aerosol load of this event is more controversial.  
857 There is an overall overestimation of AOD and PM<sub>10</sub> surface concentration by the coupled  
858 model in the North Sahelian-Saharan zone.

859 This work also aims at investigating whether the performance of the simulations can be  
860 improved by changing the dust aerosol initial and boundary condition dataset, and to  
861 estimate the uncertainty associated with this choice. The results show that this selection has  
862 almost no influence on the estimation of the solar radiation, surface temperature and AOD.  
863 On the contrary, the choice of the dust aerosol initial and boundary condition dataset has a  
864 significant impact on the surface PM<sub>10</sub> concentration and the aerosol size distribution.

865  
866 This work outlines new research perspectives. Firstly, we observe the difficulty of evaluating  
867 simulations in West Africa due to the scarcity of available observations. Establishing a  
868 denser measurement network or conducting observation campaigns, particularly for GHI,  
869 would help research on solar estimation and forecasting in this region. Additionally, the  
870 WRF-CHIMERE simulations demonstrate significant biases in terms of AOD and PM<sub>10</sub>  
871 surface concentration which are not fully explained here. One potential explanation for this is  
872 an overestimation of dust emission, for which no evaluation is possible. Furthermore,  
873 studying aerosol deposition (not conducted in this work) would complement the study of the  
874 desert aerosol life cycle. On the one hand, an underestimation of deposition might be a  
875 contributing factor to the overestimation of the simulated aerosol load. On the other hand,  
876 dust deposition on solar panels affects solar production by masking the available solar  
877 radiation (soiling effect), and this should be taken into account in forecasting systems to  
878 conduct optimised cleaning operations. Finally, the study focuses on a typical dust event  
879 during the dry season, presenting essentially aerosol-radiation interaction. It could be  
880 beneficial to test such simulation configuration for more complex cases involving cloud  
881 presence. Indeed, the interaction between aerosols and clouds have a significant impact on  
882 solar forecasting by increasing albedo, extending cloud lifespan, and promoting cloud  
883 formation through increased condensation nucleus concentration (indirect aerosol effects).

884  
885 **Code and data availability**

886 WRF namelist configuration files, CHIMERE parameter files, Python codes exploited in this  
887 study and GOCART climatology data can be found on the following Zenodo repository:

888 <https://zenodo.org/records/10808476>

889 ERA5 data can be found on the Copernicus Climate Data Store service :

890 <https://cds.climate.copernicus.eu/cdsapp#!/home>

891 CAMS data were downloaded on the Copernicus Atmosphere Data Store service :

892 <https://ads.atmosphere.copernicus.eu/cdsapp#!/home>

893 MERRA2 data can be found on the dedicated platform from NASA :

894 <https://goldsmr5.gesdisc.eosdis.nasa.gov/data/MERRA2/>



895 Data from AMMA ground measurements stations can be accessed from the dedicated  
896 website : <https://amma-catch.osug.fr/-jeux-de-donnees->  
897 INDAAF web page allows access to the data : <https://indaaf.obs-mip.fr/catalogue/>  
898 AERONET data measurements and inversion products are available through the following  
899 link: <https://aeronet.gsfc.nasa.gov/>  
900 The MODIS satellite observations are available on the “Level-1 and Atmosphere Archive &  
901 Distribution System Distributed Active Archive Center” platform from NASA :  
902 <https://ladsweb.modaps.eosdis.nasa.gov/>  
903

#### 904 **Author contributions**

905 LC, SA, CL conceptualised the study. LC performed the simulations, the analysis and the  
906 editions of the figures. LC, SA, CL, GB, BM, GS, CB, RL and JT discussed the results. LC  
907 wrote the paper

#### 909 **Competing interest**

910 The contact author has declared that none of the authors has any competing interests.

911

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926

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