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1 Control of radiation and evaporation on temperature variability in a WRF regional climate
2 simulation: comparison with colocated long term ground based observations near Paris

3
4 Bastin S.^{(1)*}, Chiriaco M.⁽¹⁾, Drobinski P.⁽²⁾

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6 (1) Université Versailles St-Quentin, Université Paris-Saclay ; Sorbonne
7 Universités, UPMC Univ. Paris 06 ; CNRS/INSU, LATMOS-IPSL, 11 bd d'Alembert,
8 78280 Guyancourt, France.

9 (2) Laboratoire de Météorologie Dynamique, Ecole Polytechnique,
10 Sorbonne Universités, UPMC Univ. Paris 06 ; CNRS/INSU, 91128 Palaiseau, France

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15 * Corresponding author: sophie.bastin@latmos.ipsl.fr; +33180285232

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34

35 Abstract:

36 The objective of this paper is to understand how large-scale processes, cloud cover and
37 surface fluxes affect the temperature variability over the SIRTAsite, near Paris, and in a
38 regional climate simulation performed in the frame of HyMeX/Med-CORDEX programs.
39 This site is located in a climatic transitional area where models usually show strong
40 dispersions despite the significant influence of large scale on interannual variability due to its
41 western location. At seasonal time scale, the temperature is mainly controlled by surface
42 fluxes. In the model, the transition from radiation to soil moisture limited regime occurs
43 earlier than in observations leading to an overestimate of summertime temperature. An
44 overestimate of shortwave radiation (SW), consistent with a lack of low clouds, enhances the
45 soil dryness. A simulation with a wet soil is used to better analyse the relationship between
46 dry soil and clouds but while the wetter soil leads to colder temperature, the cloud cover
47 during daytime is not increased due to the atmospheric stability.

48 At shorter time scales, the control of surface radiation becomes higher. In the simulation,
49 higher temperatures are associated with higher SW. A wet soil mitigates the effect of
50 radiation due to modulation by evaporation. In observations, the variability of clouds and their
51 effect on SW is stronger leading to a nearly constant mean SW when sorted by temperature
52 quantile but a stronger impact of cloud cover on day-to-day temperature variability. Impact of
53 cloud albedo effect on precipitation is also compared.

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57 Key-words: Hymex, CORDEX, temperature variability, SIRTAsite-ReOBS, surface and
58 radiative fluxes, lidar simulator, cloud radiative effects, land surface-atmosphere interactions.

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1. Introduction:

In the context of climate change, the European mean temperature and its summer variability are predicted to increase compared to the present-day conditions (Giorgi et al., 2006; Fisher and Schär, 2009), and this would increase the probability of occurrence of extreme events similar to the heat wave of summer 2003 (Schär et al., 2004; Nogaj et al., 2006), but also their intensity and duration (Gao et al., 2006; Della-Marta et al., 2007). However, despite extreme events are of particular scientific interest due to their brutal societal and environmental impacts (e.g Vautard et al., 2007; Fink et al., 2004), the temperature variability at all time scales (decadal, inter-annual, seasonal, diurnal) also influences human society in numerous sectors of activity including energy production, health, agriculture and more generally economy and ecology. A good characterization and predictability of the temperature variability then helps the population and stakeholders to anticipate and adapt to extreme events and future climate, and helps to estimate air quality (Vautard et al., 2011; Menut, 2003), energy production and eco and agro-systems evolution.

Temperature variability over Europe is influenced by combined effects of i) large scale dynamics which determine the advection of air masses from Atlantique, North-Africa, Artic/Scandinavia or continental Asia (e.g Xoplaki et al., 2004), and ii) regional scale processes including land surface-atmosphere interactions, cloud-radiation feedbacks and boundary layer processes. The leading drivers of temperature variability are specific for each season and depend on the considered time scale (e.g Vautard and Yiou, 2009; Ionita et al., 2012a,b, 2015; Cattiaux et al., 2011). European climate is particularly sensitive to the interactions between cloud-radiation and surface-atmosphere feedbacks which cause large uncertainty in the prediction of future climate (Hawkins and Sutton, 2009; Cheruy et al., 2014). Over southern areas (Mediterranean surrounding areas), evapotranspiration is limited and controlled by soil dryness (Seneviratne et al., 2010): this is the soil-moisture limited regime, where a positive feedback loop can be generated, drier soils leading to warmer and drier air, which may prevent clouds to form thus enhancing shortwave radiation at surface which causes even more drying of the soil. Over northern countries (Scandinavia), where the soil is wetter, the solar radiation is reduced due to high latitudes leading to the limitation of evapotranspiration by energy availability (Teuling et al., 2009): an increase of solar radiation under anticyclonic conditions will be used to evaporate water which damps the temperature increase and may increase cloudiness, thus generating negative feedback loop. Between both,

96 it is a transition area where the regime will evolve from radiative limited (where high
97 temperatures are more likely damped by water release from the soil) to soil-moisture limited
98 (where high temperature are more likely enhanced by the positive feedback loop) in the
99 course of the seasonal cycle. The transition timing will depend on latitude and year (more or
100 less preceding precipitation...). Figure 1 shows the spatial variability of soil moisture and
101 shortwave surface net radiation and their evolution between May and June extracted from a
102 simulation to evidence this transition from southern to northern Europe.

103 These processes are not the only ones that will determine temperature variability: the stability
104 and the thermodynamical properties of the free troposphere can block these feedback loops by
105 modifying the relative humidity of boundary layer top due to the air entrainment (Gentine et
106 al. 2013; Stefanon et al., 2014). The modeling of such climate with accuracy is thus very
107 difficult due to the possible rapid enhancement of initially small departures from observations
108 by these positive and negative feedback loops. This explains why future projections are
109 strongly related with the way models represent present-day variability (Boé and Terray,
110 2014).

111
112 However, model uncertainty is potentially reducible by using specific observations of the
113 current climate because it helps identifying model errors. To evaluate models, previous
114 studies mostly used gridded surface datasets for temperature and precipitation e.g E-OBS
115 (Haylock et al., 2008), or satellite products such as Global Precipitation Climatology Project
116 (Huffman et al., 1997) and sometimes other observations of cloudiness or/and radiative
117 fluxes, e.g Chakroun et al. (under review), Tang et al., (2012) or Betts et al. (2007). This
118 helped in pointing out the difficulties of climate models to reproduce present climate
119 variability and possible sources of errors using correlations. But they did not allow to evaluate
120 the full representation of water and energy cycles and complex interactions between large
121 scale, clouds, land surface, boundary layer, and precipitation because of the different
122 colocalisation, time and spatial resolutions of these climate time scales observations. Now,
123 new long-term observational datasets including standard observations of pressure,
124 temperature, humidity and precipitation colocalized with observations of clouds, surface and
125 radiative fluxes emerge and allow to cross a new border in our understanding of such complex
126 system. Among these datasets, the Canadian Prairie data used by Betts et al. (2014; 2015)
127 really improved the knowledge in the land-surface-cloud-atmosphere coupling over northern
128 part of North America thanks to the use of synergy of observations. However, the sensitivity
129 of climate variability to the different components of this complex coupling depends on the

130 studied area: for instance, according to the study of Van den Hurk et al. (2012), Europe is less
131 sensible than the United States to soil moisture.

132

133 Recently, efforts have been made to create the SIRTA-ReOBS dataset (Cheruy et al., 2013;
134 Chiriaco et al., 2014), which is a reanalysis of observations collected since 2003 at SIRTA
135 (Site Instrumental de Recherche en Télédetection Active; Haeffelin et al., 2005), a site located
136 at about 20 km southwestern of Paris, France (Fig. 1). It includes standard observations,
137 remote-sensing observations of clouds, aerosols, radiative and surface fluxes among others.
138 The aim of this study is to evaluate one simulation performed in the framework of the
139 HYdrological cycle in Mediterranean EXperiment (HyMeX; Drobinski et al., 2014) and the
140 MED-CORDEX (COordinated Regional climate Downscaling EXperiment; Giorgi et al.
141 2009. MED-CORDEX is the Mediterranean focus of CORDEX; Ruti et al., 2015) programs
142 against high quality data of SIRTA-ReOBS. It is a first step to improve the ability of models
143 to reproduce temperature variability over the european transitional climatic area discussed
144 above where the spread of models is generally strong (Boé and Terray, 2014), even if this step
145 is just dedicated to one model at one site. However, this site is of particularly interest since it
146 is located in the suburbs of Paris, an area concentrating several million of inhabitants and lots
147 of human activity, thus very vulnerable to climate variability.

148

149 The next section describes the different datasets used in this study, namely SIRTA-ReOBS
150 and the HyMeX/MED-CORDEX simulations, and the way we compare them. Section 3 deals
151 with the seasonal cycle of temperature which presents a strong bias in summer. The
152 sensitivity of this bias to water availability and clouds is investigated. Section 4 discusses the
153 temperature variability at interannual time scales and focusses on the control of clouds and
154 evaporation during summertime. Section 5 concludes and proposes some perspectives to this
155 work.

156

157 2. Datasets

158

159 2.1 SIRTA reanalysis: SIRTA-ReOBS

160

161 This study is mainly based on observations collected at the SIRTA atmospheric observatory,
162 located 20-km South West of Paris (2.2°E/48.7°N – 160 m of altitude; red star on Fig.1), from
163 2003 to 2013 (Haeffelin et al., 2005). This observatory has collected many observations,
164 which are now synthesized into the so-called “SIRTA Re-OBS dataset” as described in

165 Cheruy et al. (2013) and Chiriaco et al., (2014). After many steps of data quality control and
166 harmonization, the “SIRTA Re-OBS” file contains hourly averages of more than 40 variables
167 at this site. The availability of the variables used in this study is shown in Figure 2. Most of
168 the data used here are well sampled over the period of the study, excepted for the latent heat
169 flux and the lidar profiles so caution is necessary to interpret results using them.

170 The lidar profiles allow defining cloud products based on Scattering Ratio (SR) values, which
171 highlight the contribution of particles to the lidar signal (Annex 1, eq3). $SR(z)$ is equal to 1 in
172 absence of clouds and aerosols. Cloud detection for each profile and at each vertical layer is
173 based on the SR thresholds that have been used in Chepfer et al. (2008, 2010) as
174 following: $0.01 < SR(z) \leq 1$ clear, $1.2 < SR(z) < 5$ unclassified (existence of particles,
175 could be optically thin clouds or aerosols). The threshold of cloud detection without
176 ambiguity is set to 5 ($SR(z) \geq 5$). When the lidar signal is fully attenuated by optically thick
177 clouds, the layers above are obscured and the SR values are very low. Hence a ground-based
178 lidar is better suited to evaluate low clouds occurrence than high clouds.

179
180 By comparing SIRTA's meteorological data with Meteo-France operational ground stations
181 selected for their potential influence on spatial averages within the grid mesh of their model
182 containing the SIRTA site, Cheruy et al. (2013) showed that monthly means of relative
183 humidity and surface temperature at SIRTA were always between the minimum and
184 maximum values observed around. Differences between min and max can reach 10% for
185 relative humidity and 2°C for temperature (even more during the heatwave of 2003) but the
186 covered area is much larger than the size of the grid cell of the simulation used in this study.
187 Champollion et al. (2009) compared observed data at urban and rural sites in May-June 2004
188 over this same area and showed that the nighttime temperature difference can reach several
189 degrees while the daytime temperature is quite similar. For specific humidity, the diurnal
190 cycle is more complex but the difference is less than 1 g kg^{-1} . Thus, we should keep in mind
191 that the amplitude of the model biases could be different using another surface station but the
192 biases can not be attributed to a specific effect of the SIRTA site.

193 194 2.2 HyMeX/MED-CORDEX simulations

195
196 Two 20-year simulations were performed over the Mediterranean basin in the framework of
197 MED-CORDEX (Giorgi et al. 2009; Ruti et al., 2015) and the HyMeX programs (Drobinski
198 et al., 2014). These simulations perform a dynamical downscaling of the ERA-interim data
199 (Simons et al. 2007) at 20 km horizontal resolution over the domain shown on Fig.1.

200 Indiscriminate nudging towards ERA-interim reanalysis is used to constrain the fields above
201 the planetary boundary layer with a coefficient of $5 \times 10^{-5} \text{ s}^{-1}$ for temperature, humidity and
202 velocity components. This reduces the internal variability of the different simulations and
203 allows us to consider that the differences come mostly from the distinct forcings at the surface
204 (Salameh et al., 2010; Omrani et al., 2013, 2015). Both simulations use the same set of
205 parameterizations, except for the surface scheme. This set of parameterizations includes the
206 Single-Moment 5-class microphysical scheme (Hong et al. 2004), the new Kain-Fritsch
207 convection scheme (Kain 2004), the Yonsei University (YSU) planetary boundary layer
208 (PBL) scheme (Noh et al. 2003) and a parameterization based on the similarity theory (Monin
209 and Obukhov 1954) for the turbulent fluxes. The radiative scheme is based on the Rapid
210 Radiative Transfer Model (RRTM) (Mlawer et al. 1997) and the Dudhia (1989)
211 parameterization for the longwaves and shortwaves radiation, respectively. The lower
212 boundary conditions of WRF are provided by two different land-surface schemes. In CTRL,
213 soil moisture can evolve freely by using the sophisticated Rapid Update Cycle land-surface
214 model (RUC: *Smirnova et al.*, 1997 and 2000). In the second simulation, called SURF, the
215 soil moisture availability is prescribed and set to climatological wintertime value preventing
216 any soil moisture deficit condition. This simulation is also at 20 km and was not performed
217 specifically for this study (otherwise we would have applied a seasonal cycle of soil moisture)
218 but helps in interpreting the impact of surface on the results. This sensitivity simulation SURF
219 covers the period January 1989- December 2008, while the CTRL simulation ends in
220 November 2011. Outputs are available every 3 hours. In the following, the CTRL simulation
221 is used by default as it is physically more realistic and covers a longer period. These
222 companion simulations have already been used to understand the impact of soil moisture-
223 atmosphere feedbacks on heat waves over France (Stefanon et al., 2014).

224 Since the horizontal resolution of the simulations is 20 km, we can wonder how much the
225 previous results can be affected by the extraction of model data at the closest grid point of
226 SIRTA coordinates. A comparison between the values at the SIRTA grid point and the grid
227 points around (not shown) suggested that the spatial variability in the model impacts the
228 seasonal cycle of temperature by about 0.5° , with urban grid points being warmer during
229 nighttime in summer, in agreement with observations (Champollion et al., 2009). However,
230 this difference between the grid points is small in comparison with the observed variability at
231 different local stations over this area (Cheruy et al., 2013) and we conclude that using a more
232 complex interpolation procedure than just extracting model data at the closest grid point
233 would not modify the results. Note that the simulation doesn't use a urban module but the soil

234 type of Paris and near suburbs grid points correspond to urban area (less evapotranspiration).
235 However, the difference that can be linked to heat storage in urban areas during winter is not
236 taken into account.

237

238 2.3 Lidar simulator and computation of cloud occurrence

239 To compare consistently the clouds observed by the 532-nm lidar and those simulated by the
240 model, we used a lidar simulator as done in Chiriaco et al. (2006). For this, we have adapted
241 the COSP lidar simulator (Chepfer et al., 2008; 2010) to the WSM5 microphysics
242 parameterization (Hong and Lim, 2006) used in these simulations, and to a ground based lidar
243 (instead of spaceborne lidar). We first vertically interpolated the profiles of cloud properties
244 over a common vertical grid and we computed the vertical profiles of the Scattering Ratio
245 (SR) using the lidar equation (see Annex 1). The properties (size distribution and effective
246 radius) of particles needed to compute SR are not direct diagnostics of the model and are
247 obtained by using the same equations and hypotheses than those used in the WSM5 scheme.
248 SIRTA-ReOBS provides a distribution of SR values observed by the lidar for each hour with
249 available data. Using these SR distributions every 3 hours(to be consistent with simulation),
250 we've computed the seasonal cycle of the vertical profile of cloud occurrence as the number
251 of SR values greater than 5 at each level over the number of SR values greater than 0.01 at the
252 corresponding level (i.e only the profiles that are not fully attenuated). For the simulation we
253 have one instantaneous vertical profile of SR every 3 hours, and we use the same diagnostic
254 for cloud occurrence.

255 To go further in details and provide detailed vertical information on cloud optical and
256 physical properties, SR histograms can be built following Chepfer et al. (2010). For each
257 level, and each SR bin (14 bins between 0.01 and >80), we compute the number of SR values
258 which fall into the bin over the total number of SR values ≥ 0.01 (we still only consider the
259 profiles that are not fully attenuated). The sum of all bins at each level is then equal to 1. It is
260 represented in log for better readability.

261

262 2.4 Monthly mean datasets.

263 To compare CTRL simulation with SIRTA-ReOBS, we computed the different monthly mean
264 values over exactly the same days and hours, i.e for all 3-hr time steps between 1st January
265 2003 to 30th of November 2011 but when an observed data is lacking for a time step, we
266 remove the corresponding simulated data before averaging. This first dataset is called d1.
267 Note that the number of time steps taken into account depends on the parameters (see Fig.2).

268 However, except for lidar data for which a large part of missing data is due to a weather
269 situation (no observations when precipitation occur), this study shows that missing data do
270 not influence that much the results (at the scales considered here).

271 To compare the different simulations, we also defined two other datasets by reducing the
272 period from 1st of January 2003 to 31st of December, 2008: one (hereafter called d2) in
273 which all 3-hr time steps are considered, that is used to compare CTRL with SURF; the other
274 one in which the time steps without observations are removed (hereafter called d3).

275 A last dataset (d4) is used that covers the longer period 2003-2011 with all 3-hr time steps.

276 Table 1 summarizes the available datasets.

277

278 3. Seasonal cycle: a positive feedback enhancing summertime temperature bias?

279

280 3.1 Seasonal cycle of surface atmospheric parameters.

281

282 We used the SIRTA-ReOBS dataset to evaluate the seasonal cycle of several parameters in
283 CTRL simulation. Figure 3 clearly indicates an overestimate of 2m-temperature (tas) during
284 summertime which reaches 2-3°C while wintertime tas is quite well simulated. This
285 summertime overestimate of surface temperature is consistent with a bad partitioning between
286 sensible and latent heat fluxes and an underestimation of evaporative fraction (EF), as already
287 demonstrated for CMIP5 models over mid-latitudes (Cheruy et al., 2013; 2014). Indeed, we
288 compared the sensible and latent heat fluxes (hfss and hfls respectively) over the available
289 period of these parameters (i.e few for latent heat flux but CTRLd1 and CTRLd2 remain quite
290 similar) (Fig.3e et f). We can see that the simulated sensible heat flux (solid red line) is
291 significantly too strong from spring to fall, while latent heat flux is strongly underestimated.
292 However, compared to the values of heat fluxes averaged over Europe and presented in
293 Stegehuis et al. (2012), the latent heat flux at SIRTA seems stronger than elsewhere, while the
294 sensible heat flux is only slightly weaker than the averaged surrounding fluxes. It is likely due
295 to the fact that the soil type at SIRTA is specific and not represented in the model, thus partly
296 explaining the difference of latent heat flux, but not all. Note also that the maximum value of
297 the latent heat flux appears earlier in the simulation (around May) than in observations (June,
298 in agreement with the averaged fluxes over Europe), decreasing the EF value and reaching a
299 soil-moisture limited regime starting in spring ($EF < \sim 30\%$). Since there are only few data of
300 heat flux, another way to check how much surface fluxes may impact the boundary layer
301 (PBL) characteristics is to plot the seasonal and diurnal cycles of the relationship between tas
302 and humidity at 2 m (huss). We can see on Fig. 4 that the observations show more or less a

303 linear relationship between t_{as} and h_{uss} whatever the season and the time of the day,
304 indicating radiation control of surface fluxes. On the contrary, the simulated relationship
305 indicates a soil-moisture limited regime, since the moisture feeding of PBL is not sufficient in
306 spring and summer during the afternoon, due to weaker latent heat flux, probably due to a
307 lack of moisture availability into the soil. It generates warmer and drier low layers during
308 daytime in spring and summer (Fig.4) and deeper PBL (not shown because this parameter has
309 not yet been reanalysed over this period). The underestimate of precipitation amount in
310 summer (Fig.3b) amplifies the soil dryness and the increase of sensible heat flux but the soil
311 moisture deficit can also be explained by larger incoming solar radiation (Fig. 3c).

312 The overestimate of downwards shortwave flux at surface (SW) (about 60 W m^{-2} , Fig. 3c) is
313 also consistent with the summertime overestimate of temperature. Several studies using WRF
314 over the United States have pointed out this overestimate of SW (e.g Otte et al., 2012;
315 Herwehe et al. 2014) but the consequence was an overestimate of summertime (convective)
316 precipitation due to excess of latent heat flux. Katraglou et al. (2015) also pointed out a
317 positive bias of shortwave radiation in summer over southern Europe using WRF, and suggest
318 that this is induced by Kain-Fristch and Betts-Miller-Janjic convective schemes. Note that
319 downwards longwave flux is slightly underestimated but with a nearly constant bias during
320 the whole year (Fig.3d) so the reasons of the bias are likely not related.

321 To determine if this overestimate of SW is due to inaccurate radiative impacts of clouds or
322 also by a lack of clouds, we use the lidar data and compare observed (OBSd3) and simulated
323 (CTRLd3) cloud occurrences as explained in section 2.3. Fig. 5a and b show that non-
324 precipitating low clouds are missing in the simulation in spring and summer, which is
325 consistent with the overestimate of SW. To go further in details and have an idea about the
326 physical properties of the missing clouds, SR histograms are built (see section 2.3). The
327 comparison of SR histograms (Fig.6) shows that while lidar observations suggest that there
328 are only small differences between winter and summer for non-precipitating clouds (the lidar
329 is switched off when it rains), except they occur at lower levels in winter, the CTRL
330 simulation indicates a strong seasonal cycle of low clouds with a nearly total absence of low
331 clouds of weak SR values during summertime. It means that only the optically thick low
332 clouds ($SR \geq 40$) are simulated by the model, while observations show a high number of
333 optically thin low clouds ($5 < SR < 20$) in summer. These clouds mainly correspond to fair
334 weather cumulus (Chepfer et al., 2013). Note that very thick clouds ($SR \geq 80$) are also
335 missing in the simulation.

336 Hence CTRL simulation suggests the existence of a positive feedback: from spring, the soil
337 dryness induces too weak evaporation fraction, that generates warmer, drier (and likely
338 deeper) PBL during early summer. These conditions are not favorable to low clouds
339 formation, increasing the shortwave surface fluxes arriving at surface and hence enhancing
340 surface fluxes: the available soil moisture is then quickly evaporated (earlier than
341 observations), favoring drier and drier soil in summer and high sensible heat flux, increasing
342 again favorable conditions to warming. This hypothesis is consistent with previous studies
343 (e.g Cheruy et al., 2013; 2014; Fischer et al., 2012).

344

345 3.2 Impact of water availability: importance of diurnal cycle

346

347 To better understand the origin of biases and test the impact of water availability on the CTRL
348 biases, we use the SURF simulation in which soil moisture is always available. We used
349 dataset d2 to compare SURFd2 with CTRLd2 since SURF is not available with dataset d1
350 (see Tab.1). The seasonal cycle of each parameter is represented by dashed blue line in Fig. 3.
351 As shown by this figure, CTRLd1 and CTRLd2 present very similar seasonal cycles, which
352 implies that i) missing data in observations do not influence the results that much in that case;
353 ii) we can directly compare SURFd2 and CTRLd2 with OBSd1.

354 We can see that when soil moisture is available (SURF), the evaporation fraction increases
355 (sensible heat flux (Fig.3e) is reduced to become comparable with observations, and the latent
356 heat flux (Fig.3f) is increased, still not enough comparing to observations, but significantly).
357 The maximum of latent heat flux occurs in July, as in the observations, meaning that the
358 regime becomes radiative limited, and the surface temperature is strongly decreased. The air
359 mass becomes even colder than observations in summer. Figure 4 shows that the boundary
360 layer also becomes wetter than observations, which can explain the weaker latent heat flux
361 since it is related to the humidity gradient between the surface and the lower atmosphere.
362 Such impact of soil moisture on seasonal temperature, also presented in Stefanon et al. (2014)
363 with the same simulations for heat waves, is in agreement with Van den Hurk et al. (2012).
364 However, the monthly means of radiative fluxes are not modified significantly in summer
365 (they are slightly reduced in fall) in SURFd2, as already shown by Stefanon et al. (2014). In
366 terms of clouds, Figures 5b and c show light differences between CTRLd3 and SURFd3 in
367 summer with a bit more very low clouds in summer in SURFd3 and less clouds around 5 km,
368 and more pronounced differences in fall at low levels. Figure 6f confirms the existence of
369 very low clouds of moderate ($20 < SR < 30$) and strong SR ($SR > 60$) in SURFd3 but the

370 difference is not important. The number of attenuated profiles at low levels is also enhanced
371 in SURFd3 (not shown). To better compare the two simulations with the same number of
372 profiles, we thus computed the vertical profiles of cloud occurrence without the lidar
373 simulator (i.e from the condensed water mixing ratio) focusing in summer (JJA) using
374 CTRLd2 and SURFd2 (i.e also including nighttime time steps and precipitating days). The
375 interannual variability is shown in Fig.7a and b and reveals a significant modification of the
376 vertical distribution of clouds below 8 km in summer between the two simulations, more
377 pronounced than when using dataset d3 which is reduced to non-precipitating days and
378 daytime and when using the lidar simulator because of the problem of fully attenuated
379 profiles. We can thus wonder why these differences do not affect the monthly mean of
380 shortwave radiative fluxes.

381 By considering the diurnal cycle of the differences between the two simulations, we can see
382 that most low clouds in SURFd2 appear during nighttime and early morning (fog-like) (Fig.7c
383 and d), generating a decrease of SW in the morning in comparison with CTRLd2 (Fig.7e).
384 This decrease of SW in the morning is almost compensated by an increase in the afternoon
385 due to a difference of cloud occurrence in early afternoon at about 5 km (Fig.7c and d). This
386 can be explained by the atmospheric stability: despite greater relative humidity at surface, the
387 influence of important soil moisture can lead to unfavorable conditions to cloud formation in
388 the afternoon, depending on the large scale conditions that prevail (Boe et al., 2013) and the
389 thermodynamic conditions of free tropospheric air which is entrained into the boundary layer
390 (Gentine et al., 2013). Stefanon et al. (2014) have shown that during heat waves, in the SURF
391 simulation, the probability that the PBL is higher than the level of free convection (LFC) at
392 1500 UTC is zero over France, except over the Alps. We have checked that in general, during
393 daytime, the atmospheric stability is smaller in CTRL than in SURF over this site in summer.
394 Indeed, following the work of Boé et al. (2003) who have shown the strong link between the
395 Total Totals Index (TTI) and precipitation over France, we used this index to test the stability
396 of atmosphere. It is defined by:

$$397 \quad \text{TTI} = \text{Td}_{850} - \text{Ta}_{500} + \text{Ta}_{850} - \text{Ta}_{500}$$

398 where Ta_{850} (Ta_{500}) is the atmospheric temperature at 850 (500) hPa, Td_{850} is the dew
399 point temperature at 850 hPa, and $\text{Ta}_{850} - \text{Ta}_{500}$ is the Vertical Totals Index and $\text{Td}_{850} - \text{Ta}_{500}$
400 is the Cross Totals Index. Higher the TTI, smaller the stability of the atmosphere. We have
401 computed the mean values and standard deviation of TTI over 2003-2008 during JJA. Table 2
402 shows that SURF has lower mean value of TTI, and also higher occurrence of values under 40
403 which corresponds to very low likely convection.

404

405 However, both simulations have difficulties to simulate the non-precipitating clouds. It is
406 possible that the set of parameterizations which is common to the two simulations produces
407 inaccurate eddy diffusivity profiles thus preventing the boundary layer cumuli to form.
408 Microphysics processes can also be involved through the production of raindrops and the
409 surface scheme in the redistribution of energy and moisture. Testing other sets of
410 parameterisation may improve the results as already shown by several authors (e.g Guttler et
411 al., 2013; Garcia-Diez et al., 2012; Jousse et al., 2015). It will be done in a future work.

412

413 So, the surface temperature bias is strongly related to the surface regime (soil-moisture or
414 radiative limited). The RUC soil scheme associated with these boundary layer (YSU) and
415 convective (KF) parameterizations presents an unbalanced hydrological cycle that is returning
416 moisture from land to the atmosphere too quickly, favoring the switch from radiative to soil-
417 moisture regime too early in the seasonal cycle. We saw that wet soil strongly impacts the
418 mean surface temperature. However it does not impact much the monthly mean values of
419 shortwave radiative fluxes but modifies both the vertical distribution of clouds and their
420 diurnal cycle. The year-to-year differences between wet and dry soils are also important as
421 shown by Fig.7a and b. In the next section, despite the strong summer bias, we investigate the
422 relative role of clouds and surface fluxes on the variability of temperature, at interannual and
423 daily time scales, mainly focusing on summer.

424

425 4. Temperature variability: impact of large-scale dynamics, evaporation and clouds

426

427 4.1 Interannual variability of local temperature and extremes

428

429 It is of high importance to evaluate both the ability of the model to represent the temperature
430 variability at present-day and the influences explaining this variability since several studies
431 argue that the climate change signals will depend on the quality of present-day representation
432 (Boé and Terray, 2014; Fischer et al., 2012).

433 Figure 8 shows that the interannual variability of monthly mean temperature is very well
434 captured by CTRL simulation for all months, even during summertime despite the bias. We
435 also plotted the monthly mean temperature of the reanalysis ERA-interim which nudges the
436 CTRL simulation, except within the boundary layer. The fact that CTRL simulation and
437 ERA-interim perform very well confirms that at this scale and this location, the variability of

438 monthly means is mainly controlled by the influence of synoptic circulation, as already
439 suggested by Cattiaux et al. (2011).

440 The interquartile range (IQR) (between the 25% and 75% quantiles of all mean daily
441 temperature of each month) is considered to quantify the variability. It is represented by
442 dashed lines on each subplot of Fig.8. It shows that the distribution of mean daily temperature
443 is predicted with high accuracy by CTRL, even in summer. As analysed in CRU data by
444 Lenderink et al. (2007) over the period 1961-1990, IQR is higher in June and July than in
445 August, and values of IQR are similar despite the different period of analysis. Such good
446 accuracy of IQR by the simulation was not completely expected due to the biases discussed in
447 previous section and the fact that the European climate is strongly dependent on the water and
448 energy budgets (e.g Lenderink et al., 2007; Fisher et al., 2012; Vidale et al., 2007). Different
449 aspects can explain this: i) the western location of this site where the large-scale dynamics
450 strongly influence the interannual variability and modulate the land-surface-cloud-atmosphere
451 feedbacks at interannual time scale (Boe et al., 2013); ii) the fact that neither observations,
452 neither CTRL simulation are in an intermediate state concerning evaporation fraction: the
453 strong soil moisture depletion for all the considered summers in CTRL leads to small year to
454 year variations in evaporative fraction while in the observations, the soil stays wet most of the
455 time due to specific soil conditions. This leads to the same weak variability. It does not mean
456 that surface state does not influence the interannual variability, but its influence is reduced
457 compared to other sites/other models.

458 However, when considering the maximum and minimum values for each year/each month,
459 some discrepancies appear (dash-dotted lines on Fig.8), suggesting that at shorter time scales
460 and for extreme events, the influence of clouds and evaporative fraction becomes more
461 important.

462

463 4.2 Control of surface parameters by radiation and evaporation in summer (MJJAS)

464

465 4.2.1 Relationship between temperature and shortwave net radiation and
466 evaporation.

467

468 To analyse how much the summer temperature is influenced by radiative and surface fluxes,
469 we sorted the daily maximum values of temperature from May to September (Fig.9a) and
470 used it as sorting criterion for evaporation and daily mean of net shortwave radiation (SWnet)
471 (Figs.9b and c respectively). We also did it for each month separately but results are similar in

472 average, except that in August, evaporation is lower thus reducing the variability of
473 temperature. Several datasets are used (see Table 1): dataset d1 for temperature and radiative
474 fluxes; and dataset d4 (model only) for evaporation. Figure 10a compares the annual
475 distribution of the daily observed and simulated SWnet and shows that the spread of values is
476 important in summer, and that simulated values are in the range of observed ones except that
477 very low values of SWnet during summer are missing, in agreement with the lack of clouds
478 discussed in previous section.

479 Figure 9a shows the quantile plots of sorted maximum temperature. Datasets d1 and d3 (see
480 legend on Figure for details) are plotted so that the sensitivity of the results to the length of
481 the datasets can be assessed but the conclusion is that results are not that much affected by the
482 lack of data. This figure shows that: i) CTRL simulation does not tend to overestimate
483 extreme values more than median values since the slopes of evolution of T from the 5th
484 quantile up to the 95th quantile are similar; ii) the slopes in SURF are weaker than for OBS
485 and CTRL, showing similar values than OBS for the lower quantiles and lower values for
486 higher quantiles. This can be explained by the influence of evaporation: indeed, the
487 relationship between temperature and evaporation (Fig.9b) shows nearly constant values of
488 evaporation for CTRL whatever the temperature quantile, while in SURF, evaporation
489 increases with temperature quantiles. As explained by Stefanon et al. (2012), the more intense
490 evaporation damps the warmer temperature and then reduces the temperature variability and
491 the maximum values of temperature. The soil moisture availability in SURF thus strongly
492 contributes to reduce the slope on Fig.10a. In CTRL, the values of evaporation are too weak
493 to exert a control on temperature variability at this daily scale. This suggests a dominant effect
494 of shortwave radiation on the day-to-day temperature variability in CTRL simulation.

495
496 When considering the influence of shortwave (Fig. 10c), CTRL shows a linear relationship
497 between SW and daily maximum temperature quantile up to the 75th quantile, with a
498 difference of about 100 W m^{-2} between the value at the 75th quantile and the one at the 5th
499 quantile (hereafter called ΔSW). In SURF, SW goes on increasing at the higher temperatures.
500 Stronger SW favors stronger evaporation when soil moisture is available and thus explains the
501 evaporation-temperature relationship in SURF. The observations present a weaker ΔSW ,
502 close to zero, indicating that the short wave radiation contributes stronger to the day-to-day
503 temperature variability in the model. In the model, for quantiles up to the 75th one, the
504 temperature is controlled by the synoptic situation that prevails and which induces strong
505 variations of SW depending on the dominant cloud cover. For the higher temperatures, the

506 averaged value of SW stays the same. The temperature of the day will then likely depend on
507 the variability of SW within a bin (due to the cloud cover) and the heat storage in the
508 boundary layer during the preceeding days (Miralles et al., 2014).

509

510 4.2.2 Role of clouds on temperature variability and bias

511 The shortwave downwards and net radiations depend on the presence, altitude, optical
512 thickness and properties of clouds and on the solar zenith angle and surface albedo. To better
513 consider the role of clouds and to reduce the effect of the change in solar zenith angle
514 between May and end of September, we thus use the effective cloud albedo (α_{cloud}) as defined
515 by Betts (2007):

$$516 \quad \alpha_{\text{cloud}} = -\text{SWCRE}/\text{SW}_{\text{clear}}$$

517 where

$$518 \quad \text{SWCRE} = \text{SW} - \text{SW}_{\text{clear}}$$

519 is the cloud radiative effect (CRE) on shortwave. The effective cloud albedo represents the
520 fraction of the clear sky flux reflected by the cloud field. Figure 10 shows a comparison
521 between the observed short-wave fluxes, cloud radiative effect and cloud albedo and the
522 simulated ones in CTRLd1.

523 The absence of low clouds (Figs.5 and 6) induces an underestimate of cloud radiative effect
524 (cloud albedo), as shown by Figs.10b and c. Indeed, Figure 10c shows the seasonal cycle of
525 α_{cloud} from monthly means at 12 UTC and its interannual variability. It shows that the bias
526 between CTRL (red) and OBS (black) is significant, especially in summer, although the
527 spread of daily values is important (Fig.10b). The black and red dashed lines which represent
528 the monthly means of the surface albedo for observations and simulation respectively,
529 indicate that despite the resolution of the model and the fact we compare at one single site, the
530 surface albedo is very well simulated in average and can not explain differences in net fluxes.
531 The cloud albedo bias is partly due to an underestimate of strong negative values of SWCRE
532 (Fig.10b) but all categories of clouds contribute to this underestimate as indicated by Fig.10d.
533 Indeed, for all values of simulated α_{cloud} except very opaque simulated clouds, most values are
534 negatively biased. Figure 10f indicates that while the number of α_{cloud} values in summer
535 shows a decreasing linear trend from 20% of values for the first bin ($\alpha_{\text{cloud}} < 0.1$) to 0% for the
536 last bin ($\alpha_{\text{cloud}} = 1$) in observations, more than 50% of simulated α_{cloud} values correspond to
537 very low values (< 0.1). It confirms what has been analysed with the lidar (Fig.6). Note that
538 the linear trend for the other bins is quite similar. In winter (Fig.10e), the distribution is

539 different with a peak at 0.7-0.8, which is represented by the model, although a little bit
540 underestimated (also note the higher number of low values as in summer).

541 Following Betts' methodology (e.g. Betts et al., 2006; Betts, 2009), Figure 11a stratifies
542 temperature anomaly in summer (MJJAS) by cloud albedo. Temperature anomaly is chosen
543 here instead of temperature since we are interested in the effect of clouds on the temperature
544 variability. Temperature anomaly is computed as the difference between the temperature of
545 the day and the average temperature of this julian day over the 9 years (2003-2011) and then
546 stratified by α_{cloud} with 50 samples in each bin.

547 Figure 11a confirms that while the amplitude of seasonal cycle of temperature is dominated
548 by surface fluxes (Fig.3), the cloud cover influences the surface temperature variability. It is
549 in agreement with Fig. 9c, but, by using effective cloud albedo instead of SWnet and
550 temperature anomaly instead of temperature quantile, it removes the effect of seasonal cycle
551 of SWnet that likely contributes to the relationship in Fig.9c. It thus allows to detect finer
552 scale of variability. In average, the stronger the cloud albedo is, the stronger the cooling is
553 important in summer, but the dispersion is important, even more for values of α_{cloud} less than
554 0.5. Most cloudy free days ($\alpha_{\text{cloud}} < 0.1$) correspond to a positive anomaly of temperature,
555 while about 70% of anomalies are negative for $\alpha_{\text{cloud}} > 0.5$. The model tends to underestimate
556 the effect of warming of clouds of weak albedo ($\alpha_{\text{cloud}} < 0.3$), as shown by Fig.11b. The effect
557 of clouds on temperature variability is modified over wet soils as shown by Fig. 11b: SURF
558 underestimates warming of optically thin clouds more than CTRL (warmer temperature are
559 damped by evaporation) and overestimates cooling of clouds more than CTRL (more fog in
560 the morning). The interpretation of Figs.9c and 11a, b is that in observations, clouds often
561 exist whatever the synoptic situation, which induces the same average values of SW in each
562 bin of temperature (mainly driven by synoptic situation as shown previously). However,
563 inside a bin, the variability of SW values is high and days without clouds tends to enhance the
564 maximum temperature. On the contrary, in the model, fair weather low clouds are not
565 simulated, and then, high temperature are associated with high SW values with lower
566 variability inside each bin. Positive temperature anomalies associated with absence of clouds
567 is then not enhanced (Fig.11b).

568 The daytime precipitation (between 09 and 18 UTC) stratified by cloud albedo (Fig.11c)
569 shows that the probability of occurrence of rain increases for cloud albedo greater than 0.4 for
570 simulations and observations but the mean rain rate does not significantly increase, except in
571 OBS for the highest values of cloud albedo (Fig. 11d). Higher than 0.4, the probability of rain
572 increases a bit more quickly for SURF and CTRL than for OBS. The occurrence reaches 50%

573 for simulations while only 35% in observations for opaque clouds. However, Fig.11d shows
574 that it rains very lightly in SURF during daytime (even the 80th percentile is around 1
575 mm/3hr). CTRL and OBS have similar values of rain rate for median (around 1 mm/3hr) and
576 even up to 80th percentile (around 2-3 mm/3hr, except for the highest values of cloud albedo
577 which reach 5 mm/3hr in OBS), but extreme values (95th percentile) are significantly stronger
578 in OBS than CTRL (reaching 20 mm/3hr in OBS and less than 10 in CTRL; not shown),
579 which is expected when comparing a local rain rate with a 20x20 km² grid cell (Chen and
580 Knutson, 2008).

581
582

583 5. Conclusion

584

585 The objective of this paper is to understand how cloud cover and surface fluxes control the
586 temperature variability over the SIRTA site and in the model. This is of particular importance
587 since this site is located in a climatic transitional area where models usually show strong
588 dispersions. A schematic diagram showing the temperature range of observations and
589 simulations as a function of surface conditions and surface net radiation summarizes the study
590 (Fig.12). The main results of the study are:

591 • The large scale conditions have a strong impact on the interannual variability of
592 temperature: this can be explained by the north-western location of the site, thus
593 directly under the influence of air masses from the Atlantic. It is likely that this control
594 is reduced over Central Europe.

595 • The soil moisture exerts a strong control on the seasonal cycle of the temperature. The
596 transition from radiation to soil moisture limited regime that occurs earlier in
597 simulations than in observations leads to an overestimate of summertime temperature
598 in CTRL simulation. Bullock (2014) already observed this unbalanced hydrological
599 cycle with NOAH surface scheme. The role of the surface scheme is not demonstrated
600 here. Indeed, the soil dryness is associated with an overestimate of shortwave
601 radiation. Consequently, the soil dryness can be attributed either to the excessive
602 energy arriving at surface or to an unbalanced hydrological cycle or both. The
603 overestimate of SW is consistent with a lack of low clouds in the simulation.
604 However, it couldn't be demonstrated the feedback between the dryness of the soil and
605 the lack of low clouds. Indeed, a wetter soil produces colder and wetter low
606 atmospheric layers but also more stable atmosphere during daytime preventing the
607 formation of low clouds. We would need to test other set of parameterizations to

608 improve our understanding of the model behavior and test what happens when the
609 radiative limited regime dominates until July and when clouds exist. This work is
610 underway. Also, Herwehe et al. (2014) and Alapaty et al. (2012) demonstrated that
611 introducing subgrid-scale cloud-radiation feedbacks in regional climate simulations
612 significantly decreases the summertime overestimate of SW. It is not sure that the
613 absence of subgrid scale cloud-radiation feedbacks plays such important role in our
614 simulation since it seems that convective clouds are not so numerous in the simulation
615 due to the too dry atmosphere but it will be investigated using WRF version 3.7 in the
616 next future.

- 617 • At shorter time scales, the control of surface radiation becomes higher. In CTRL (dry
618 soil and no clouds), higher temperatures are linearly associated with higher SW, the
619 main driver being presence/absence of clouds depending on the synoptic situation. A
620 wet soil (SURF) mitigates the effect of radiation due to modulation by evaporation.
621 Observations show a stronger variability of cloud cover in summertime, and then a
622 stronger impact of cloud cover on temperature variability within each range of
623 temperature but no relationship between mean SW and temperature quantile. The
624 effect of clouds on temperature variability in CTRL also exists, even if more lightly.
- 625 • Both in observations and simulations, clouds with albedo less than 0.4 are non-
626 precipitating clouds and for higher albedo effects, occurrence of precipitation
627 increases but not the average rain rate. However, clouds with very high albedo effects
628 are particularly missing in simulations, generating lighter strong precipitation events.

629

630 In a future study, the quantification of warming by clouds will be addressed in more details.
631 Other models participating to HyMeX/MED-CORDEX programs will also be evaluated
632 against SIRTa-ReOBS to better explain the diagnosed spread. This study should be extended
633 to other french sites which produce similar reanalysis of observations in a context of french
634 and european concertations.

635

636

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period and frequency	2003-2011 observations sampling only	2003-2008 all days, every 3hr	2003-2008 observations sampling only	2003-2011 all days, every 3hr
OBS	OBSd1	-	OBSd3	
CTRL	CTRLd1	CTRLd2	CTRLd3	CTRLd4
SURF	-	SURFd2	SURFd3	

876 Table 1: list of datasets used.

877

	TTI mean value	TTI standard deviation	occurrence of values < 40
CTRL	43.5	2.3	35%
SURF	41.6	2.7	57%

878 Table 2: Total Totals Index (TTI) mean value and standard deviation for CTRL and SURF
879 simulations. The last column indicates the percentage of values under the threshold of 40.

880

881
882 List of Figures:

883
884 Fig.1 Domain of the simulation and location of SIRTA site (red star). Colormap presents
885 a) the soil moisture of May averaged over 2000-2009; (b) same as a) for June; c) the
886 shortwave surface net radiation of May averaged over 2000-2009; d) same as c) for
887 June.

888
889 **Fig.2** Observations availability: Blue histograms indicate the number of days with
890 measurements (the maximum being 3256 over the period of the study) for each
891 parameter. Red bars indicate the average number of hours per day with measurements
892 (only considering 0, 3, 6, 9, 12, 15, 18 and 21 UTC). rlds stands for 'radiative longwave
893 downwards at surface', rlds is the same but upwards, rlds and rlds are the same for
894 shortwave and rlds/rlds are for clear sky fluxes. tas is for temperature at 2-m. hurs
895 and huss are respectively relative and specific humidity at 2-m, pr is for precipitation,
896 hfss and hfsl are for sensible and latent heat fluxes respectively. SRLidar is for Scattering
897 Ratio from lidar signal

898
899 **Fig.3** Mean seasonal cycle of temperature (a), rain rate (4 lower lines, without circles)
900 and occurrence of precipitation (lines with circles) (b), downwards shortwave radiative
901 flux at the surface (c), downwards longwave radiative flux at the surface (d), sensible
902 heat flux (e) and latent heat flux (f) averaged over period d1 (solid lines) and d2 (dashed
903 lines). Black line is for observations, red is for CTRL and blue for SURF simulations (see
904 legend for details). Vertical bars indicate one standard deviation for observations

905
906 **Fig.4** Monthly mean of surface humidity as a function of monthly mean surface
907 temperature at 4 hours (03, 09, 15, 21 UTC). Colors represent the month of the year (see
908 correspondance on panel a). Each cross is for one month/one year from 2003-2008.
909 First row is for observations, second row for CTRL simulation, third row for SURF
910 simulation

911
912 **Fig.5** Seasonal cycle of occurrence of clouds computed from SR values in OBSd3 (a),
913 CTRLd3 (b) and SURFd3 (c). The occurrence is the number of cloudy profiles ($SR \geq 5$)
914 over the number of profiles for which $SR \geq 0.01$;

915
916 **Fig.6** SR histograms for lidar observations (first row) and simulated lidar profiles from
917 CTRL simulation (second row) and SURF simulation (third row) during winter (DJF-left
918 column) and summer (JJA-right column). The common dataset d3 is used. The white
919 vertical solid line indicates the limit between clouds ($SR \geq 5$) and clear or unclassified
920 atmosphere. The horizontal dashed lines indicate the low clouds layer.

921
922 **Fig.7:** a), b): Interannual variability of vertical profiles of cloud occurrence computed
923 from condensed water mixing ratio values in JJA in CTRLd2 (a) and SURFd2 (b); c) and
924 d): Diurnal cycle of vertical profiles of cloud occurrence computed from condensed
925 water values averaged over JJA for CTRLd2 (c) and SURFd2 (d). e: Diurnal cycle of the
926 difference between CTRLd2 and SURFd2 of the shortwave flux arriving at surface
927 averaged over JJA;

928

929 **Fig.8** :Interannual variability of monthly mean surface temperature anomaly at SIRTA
930 (solid line). Red is for CTRLd1, black is for OBSd1 and blue is for ERAI extracted at
931 SIRTA grid point. Dashed lines indicate the inter-quantile range (between the 25% and
932 75% quantiles) of all data (all years) for each month. Dash-dotted lines indicate the
933 maximum and minimum anomalies for each month of each year
934

935 **Fig.9** Maximum temperature as a function of temperature quantile averaged over May
936 to September. b) Same as a) for latent heat flux. c) Same as a) for downwards shortwave
937 radiative flux at surface. The correspondance of the different lines is given by the
938 legend.
939

940 **Fig.10** a) Annual distribution of simulated total (red crosses) and clear sky (light blue
941 circles) shortwave net fluxes and observed (black crosses) total one. b) SW simulated
942 Net Cloud radiative effect (blue circles), downwards CRE (red crosses) and observed
943 downwards CRE (black crosses). c) Seasonal cycle of simulated effective surface cloud
944 albedo at 12 UTC in red solid line. Black solid line is for observed cloud albedo at 12UTC.
945 Shaded areas represents the interannual variability of the monthly mean values. Dashed
946 lines are for the monthly means of surface albedo (red for CTRLd1 and black for OBSd1).
947 d) Simulated downwards α_{cloud} as a function of α_{cloud} bias (defined as simulated α_{cloud}
948 minus observed one). e) Distribution of values with a given effective cloud albedo in
949 winter. Black line is for observations, red line for simulation. f) same as e) in summer
950

951 **Fig.11** a) Relationship between α_{cloud} and temperature anomaly of MJJAS from 2003 to
952 2011. Temperature anomaly is computed as the difference between the temperature of
953 the day and the average temperature of this julian day over the 9 years and then
954 stratified by α_{cloud} with 50 samples in each bin. The solid line corresponds to the 50th
955 quantile and the shaded area covers the values between the 20th and 80th quantile. Red
956 is for CTRLd1, black is for OBSd1. SURFd2 is in blue and the 20th and 80th are shown in
957 dashed blue lines instead of shaded area. b) Relationship between α_{cloud} and the
958 difference of temperature anomaly between simulation and observations. c) Probability
959 of rain occurrence as a function of α_{cloud} . d) Relationship between rain rate (only wet
960 days) and α_{cloud}
961

962 **Fig. 12:** Evolution of temperature as a function of surface conditions and net radiation.
963 Blue circles corresponds to the SURF behavior in January (J), May (M) and July (Ju).
964 Light green are for observations and Orange ones are for CTRL. The bigger the circle,
965 the enhanced variability. Min and max values of temperature and amplitude of these
966 values are mainly driven by large scale circulations.
967

969 Annex1: lidar equations

970 ATB_{tot} and ATB_{mol} are respectively the attenuated backscattered signals for particles and
971 molecules (ATB_{tot}) and for molecules only (ATB_{mol}) and are given by (1) and (2):

972
$$ATB_{mol}(z) = \beta_{sca,mol}(z) \cdot e^{-2\eta \int_{z_{TOA}}^z \alpha_{sca,mol}(z) \cdot dz} \quad (1)$$

973
$$ATB_{tot}(z) = (\beta_{sca,part}(z) + \beta_{sca,mol}(z)) \cdot e^{-2\eta \int_{z_{TOA}}^z (\alpha_{sca,part}(z) + \alpha_{sca,mol}(z)) \cdot dz} \quad (2)$$

974 Where $\beta_{sca,part}$, $\beta_{sca,mol}$ are lidar backscatter coefficients ($m^{-1} sr^{-1}$) and $\alpha_{sca,part}$ and $\alpha_{sca,mol}$
975 attenuation coefficients (m^{-1}) for particles (clouds, aerosols) and molecules. η is a multiple
976 scattering coefficient that depends both on lidar characteristics and size, shape and density of
977 particles. It is about 0.7 for CALIPSO (Winker, 2003; Chepfer et al., 2008). The ATB_{mol} and
978 ATB_{tot} products are averaged vertically to obtain SR over 40 layers (Chepfer et al. 2008 and
979 2010). SR is given by (3):

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$$SR = \frac{ATB_{tot}}{ATB_{mol}} \quad (3)$$

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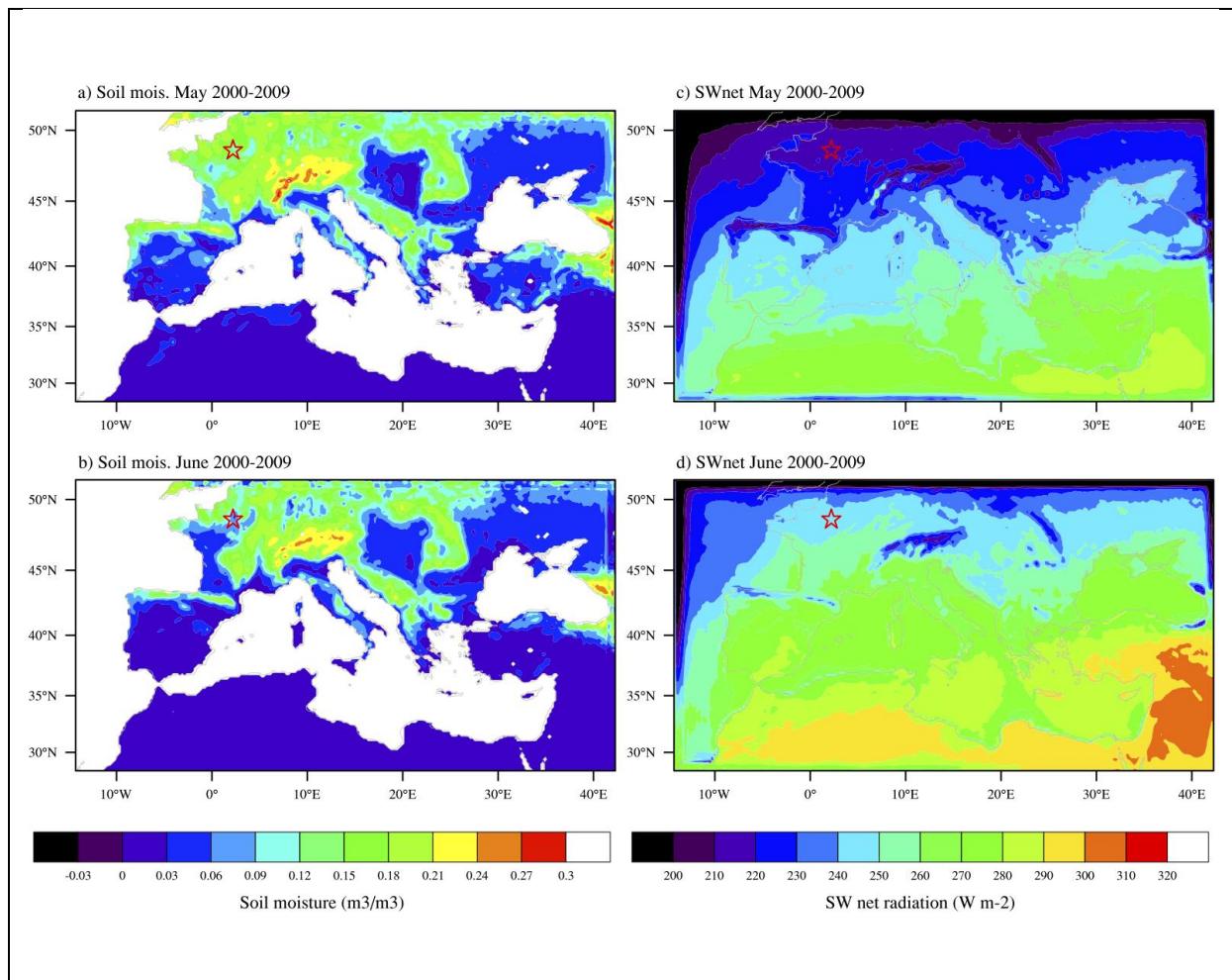


Figure 1: Domain of the simulation and location of SIRTA site (red star). Colormap presents a) the soil moisture of May averaged over 2000-2009; (b) same as a) for June; c) the shortwave surface net radiation of May averaged over 2000-2009; d) same as c) for June.

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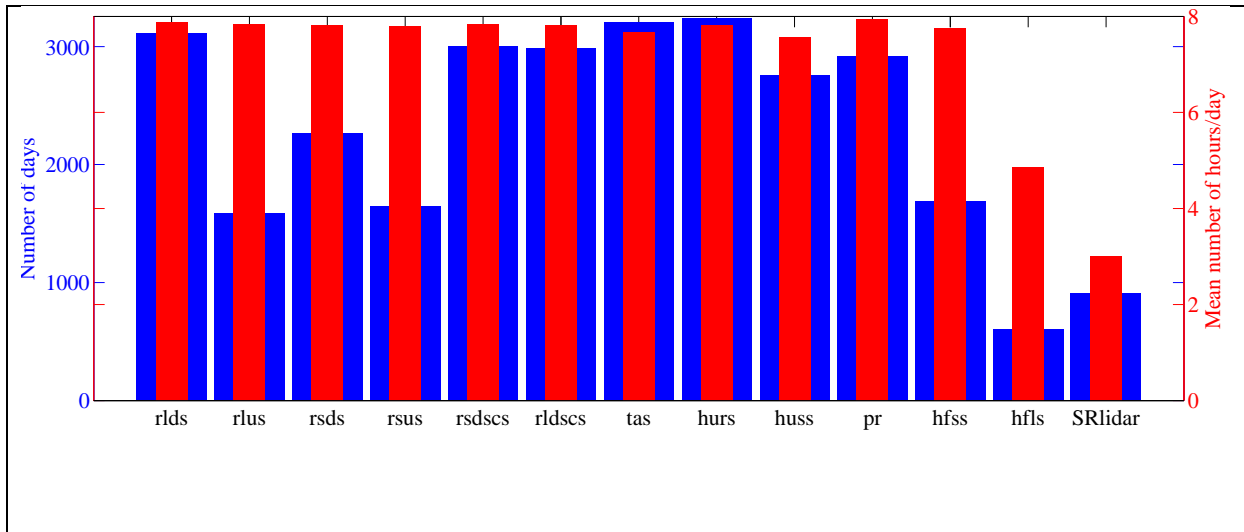


Figure 2: Blue histograms indicate the number of days with measurements (the maximum being 3256 over the period of the study) for each parameter. Red bars indicate the average number of hours per day with measurements (only considering 0, 3, 6, 9, 12, 15, 18 and 21 UTC). rlds stands for 'radiative longwave downwards at surface', rlus is the same but upwards, rsds and rsus are the same for shortwave and rsdscs/rldscs are for clear sky fluxes. tas is for temperature at 2-m. hurs and huss are respectively relative and specific humidity at 2-m, pr is for precipitation, hfss and hfls are for sensible and latent heat fluxes respectively. SRLidar is for Scattering Ratio from lidar signal

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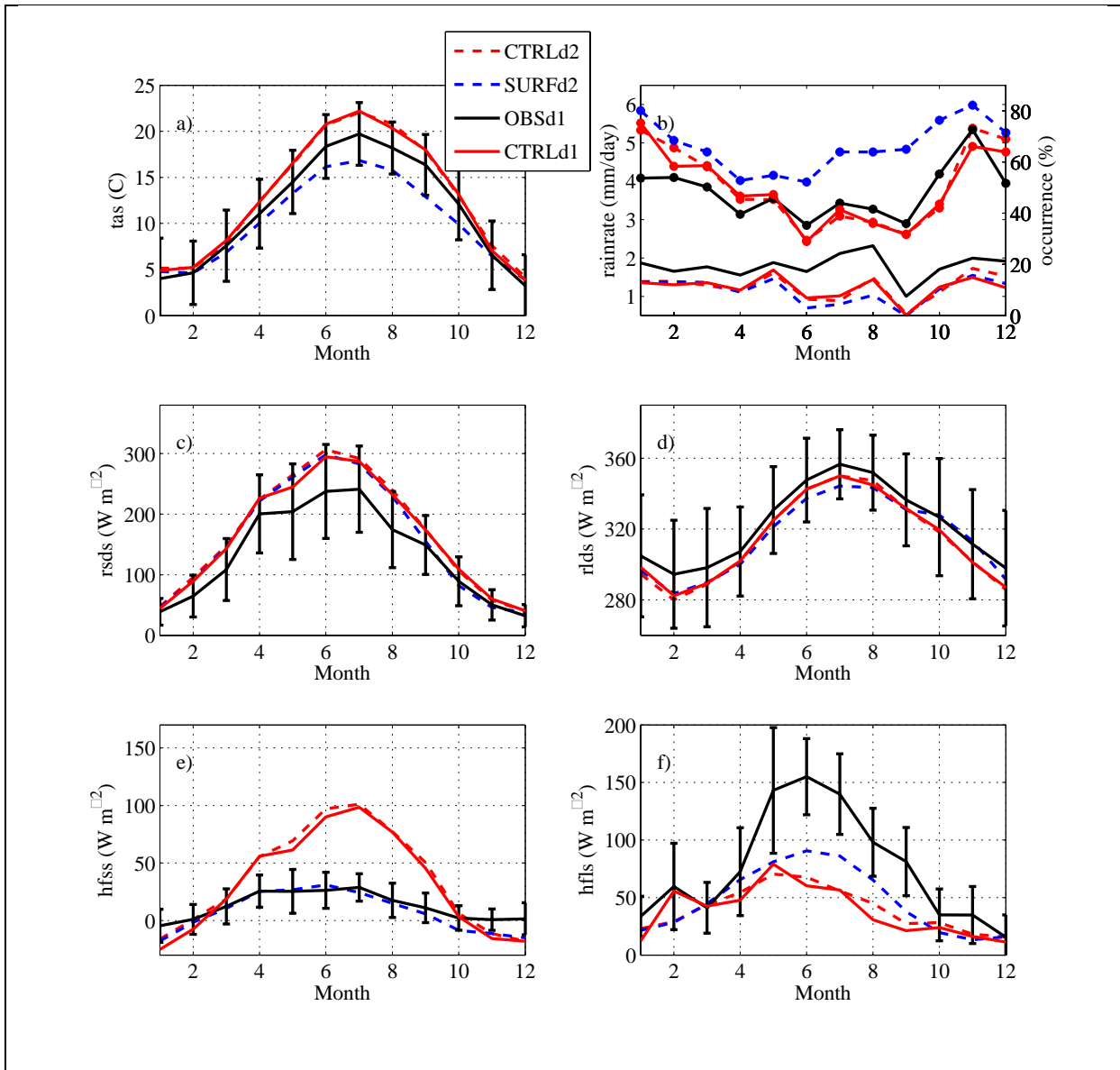


Figure 3: mean seasonal cycle of temperature (a), rainrate (4 lower lines, without circles) and occurrence of precipitation (lines with circles) (b), downwards shortwave radiative flux at the surface (c), downwards longwave radiative flux at the surface (d), sensible heat flux (e) and latent heat flux (f) averaged over period d1 (solid lines) and d2 (dashed lines). Black line is for observations, red is for CTRL and blue for SURF simulations (see legend for details). Vertical bars indicate one standard deviation for observations.

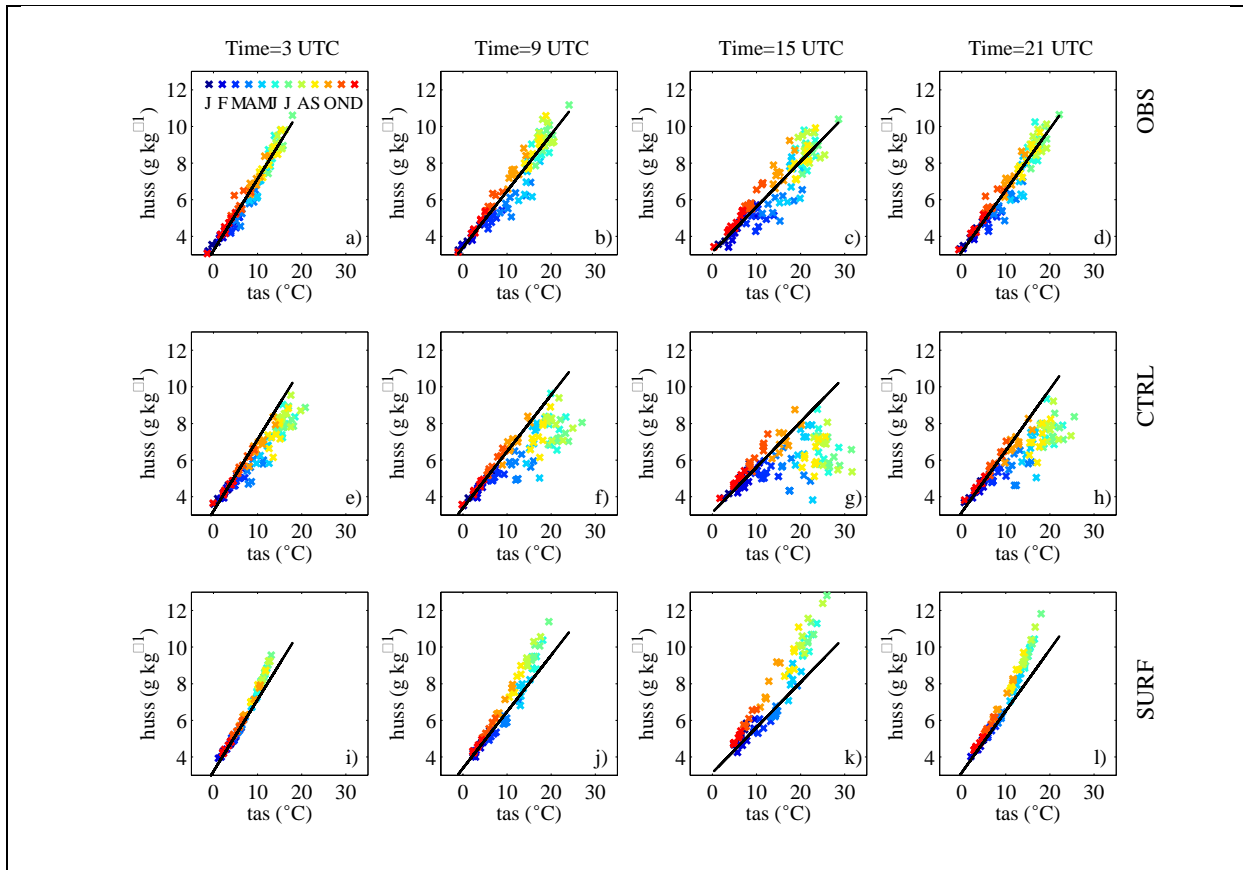


Figure 4: monthly mean of surface humidity as a function of monthly mean surface temperature at 4 hours (03, 09, 15, 21 UTC). Colors represent the month of the year (see correspondance on panel a). Each cross is for one month/one year from 2003-2008. First row is for observations, second row for CTRL simulation, third row for SURF simulation.

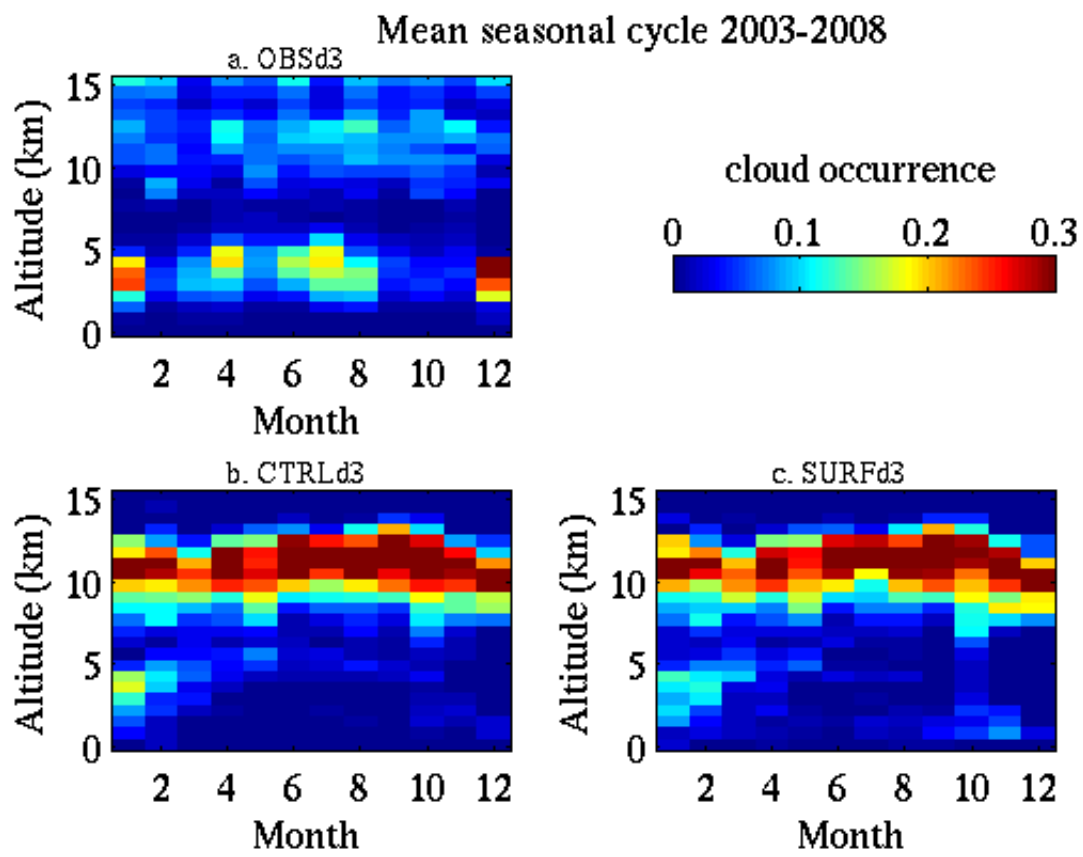


Figure 5: Seasonal cycle of occurrence of clouds computed from SR values in OBSd3 (a), CTRLd3 (b) and SURFd3 (c). The occurrence is the number of cloudy profiles ($SR \geq 5$) over the number of profiles for which $SR \geq 0.01$;

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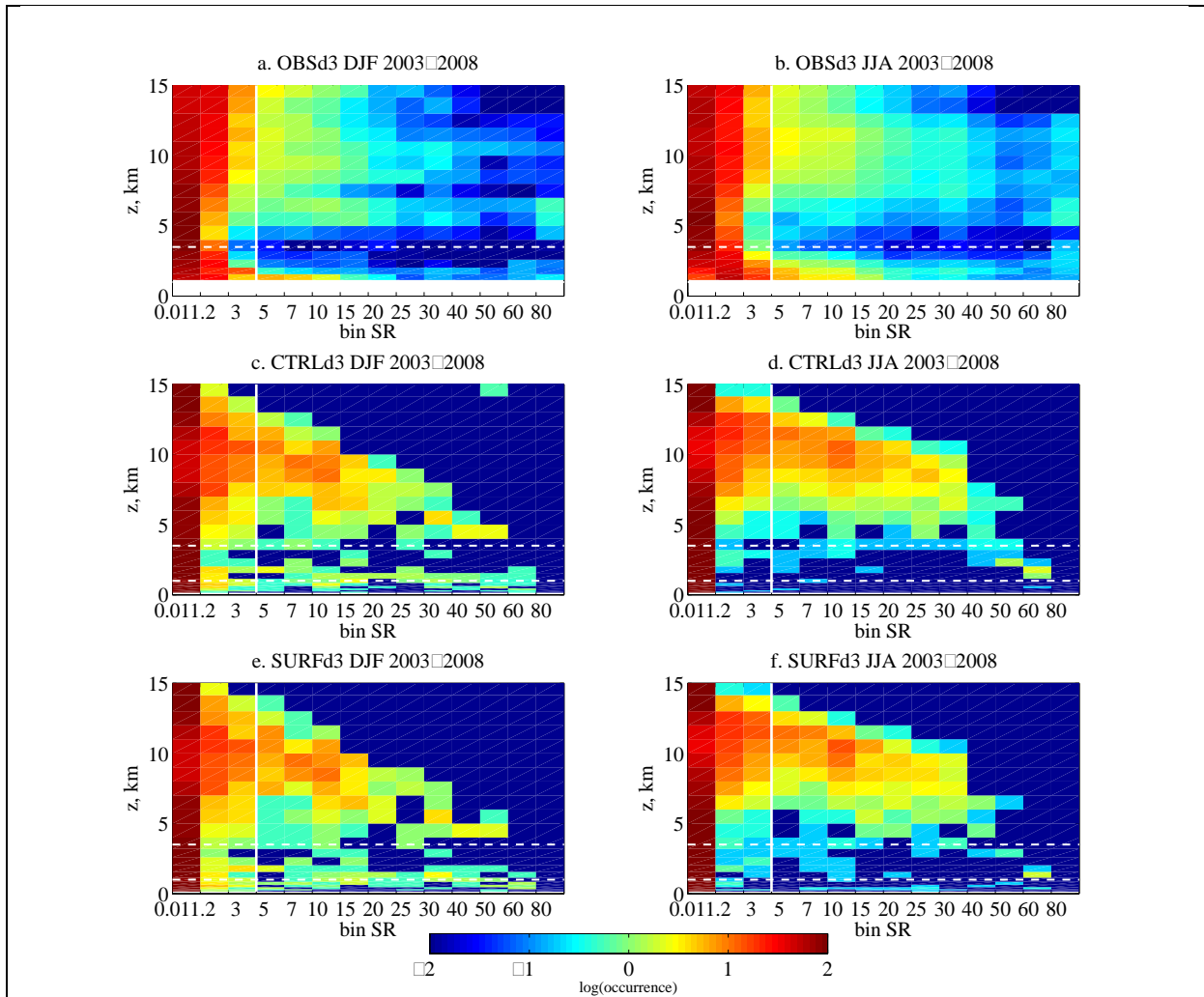


Figure 6: SR histograms for lidar observations (first row) and simulated lidar profiles from CTRL simulation (second row) and SURF simulation (third row) during winter (DJF-left column) and summer (JJA-right column). The common dataset d3 is used. The white vertical solid line indicates the limit between clouds ($SR \geq 5$) and clear or unclassified atmosphere. The horizontal dashed lines indicate the low clouds layer.

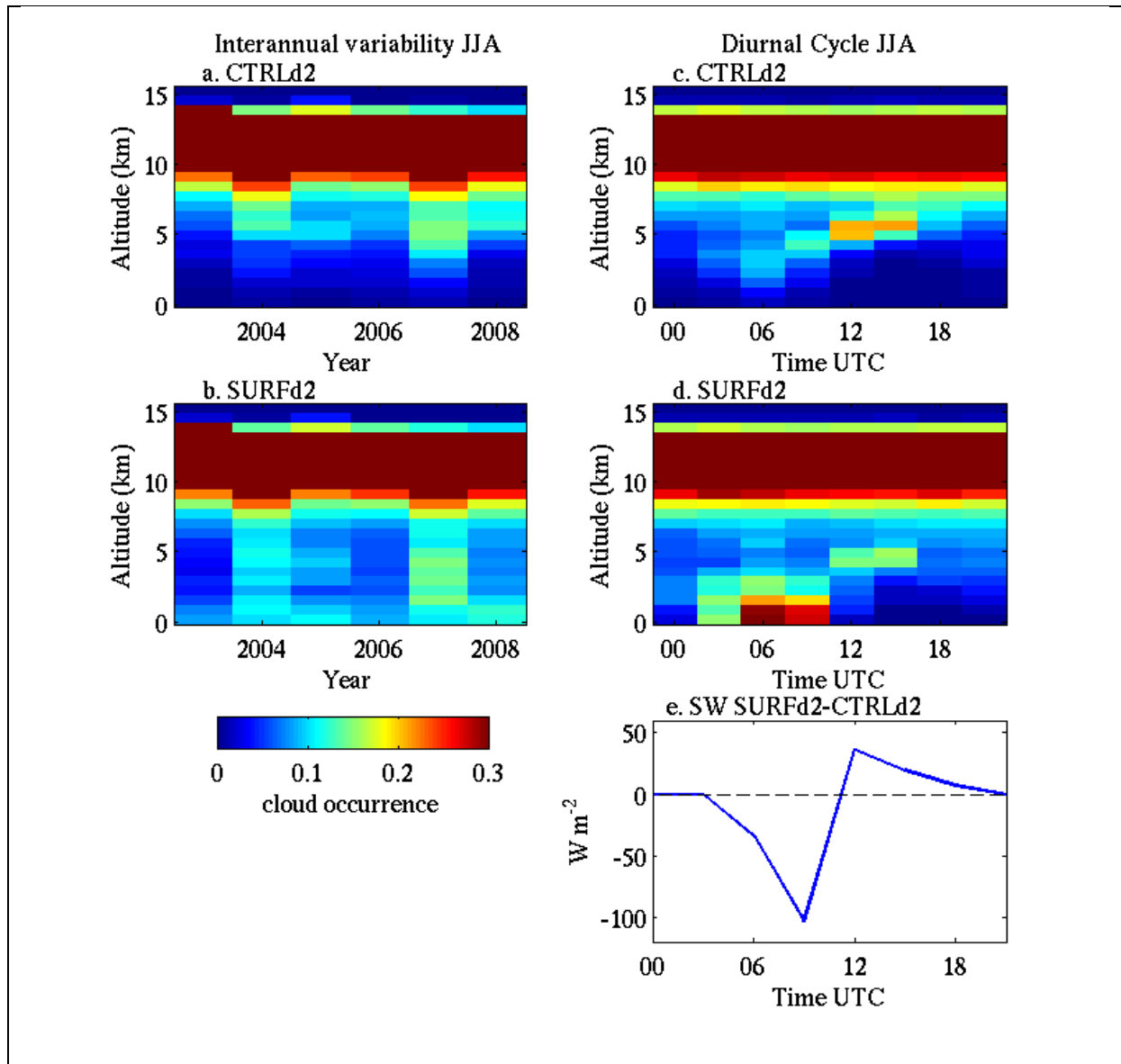


Figure 7: a), b): Interannual variability of vertical profiles of cloud occurrence computed from condensed water mixing ratio values in JJA in CTRLd2 (a) and SURFd2 (b); c) and d): Diurnal cycle of vertical profiles of cloud occurrence computed from condensed water values averaged over JJA for CTRLd2 (c) and SURFd2 (d). e: Diurnal cycle of the difference between CTRLd2 and SURFd2 of the shortwave flux arriving at surface averaged over JJA;

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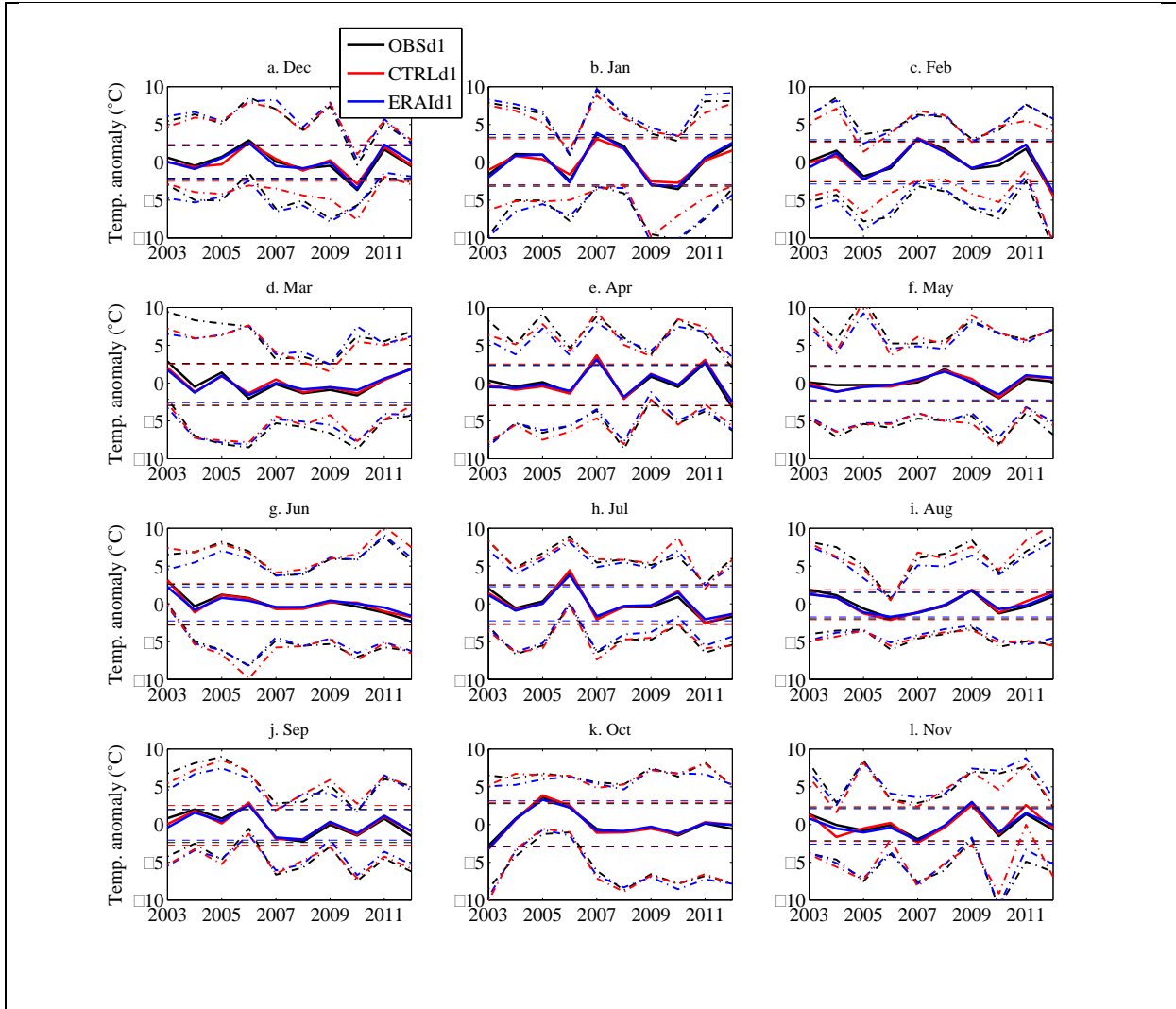


Figure 8: Interannual variability of monthly mean surface temperature anomaly at SIRTa (solid line). Red is for CTRLd1, black is for OBSd1 and blue is for ERAI extracted at SIRTa grid point. Dashed lines indicate the inter-quantile range (between the 25% and 75% quantiles) of all data (all years) for each month. Dash-dotted lines indicate the maximum and minimum anomalies for each month of each year.

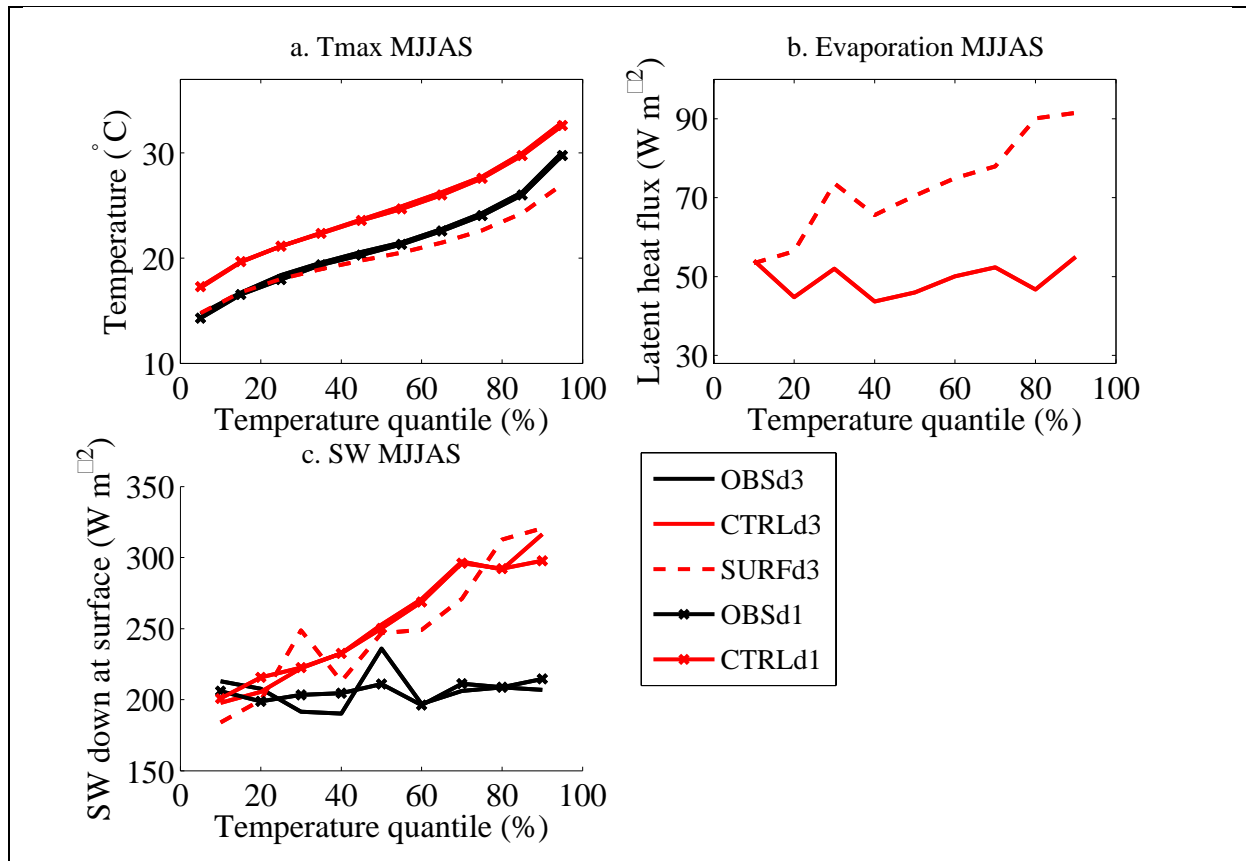


Figure 9: Maximum temperature as a function of temperature quantile averaged over May to September. b) Same as a) for latent heat flux. c) Same as a) for downwards shortwave radiative flux at surface. The correspondance of the different lines is given by the legend.

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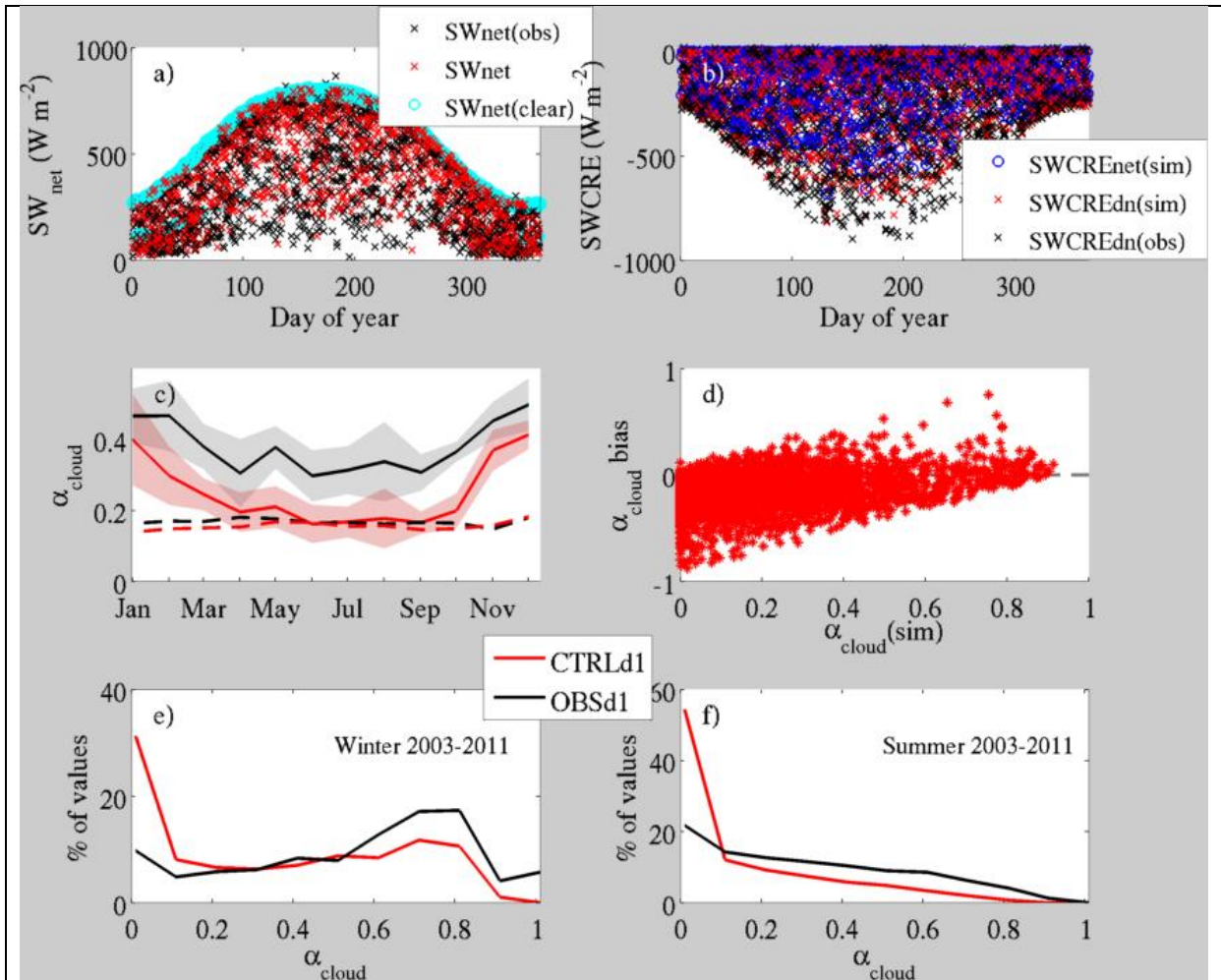


Figure 10: a) Annual distribution of simulated total (red crosses) and clear sky (light blue circles) shortwave net fluxes and observed (black crosses) total one. b) SW simulated Net Cloud radiative effect (blue circles), downwards CRE (red crosses) and observed downwards CRE (black crosses). c) Seasonal cycle of simulated effective surface cloud albedo at 12 UTC in red solid line. Black solid line is for observed cloud albedo at 12UTC. Shaded areas represent the interannual variability of the monthly mean values. Dashed lines are for the monthly means of surface albedo (red for CTRLd1 and black for OBSd1). d) Simulated downwards α_{cloud} as a function of α_{cloud} bias (defined as simulated α_{cloud} minus observed one). e) Distribution of values with a given effective cloud albedo in winter. Black line is for observations, red line for simulation. f) same as e) in summer.

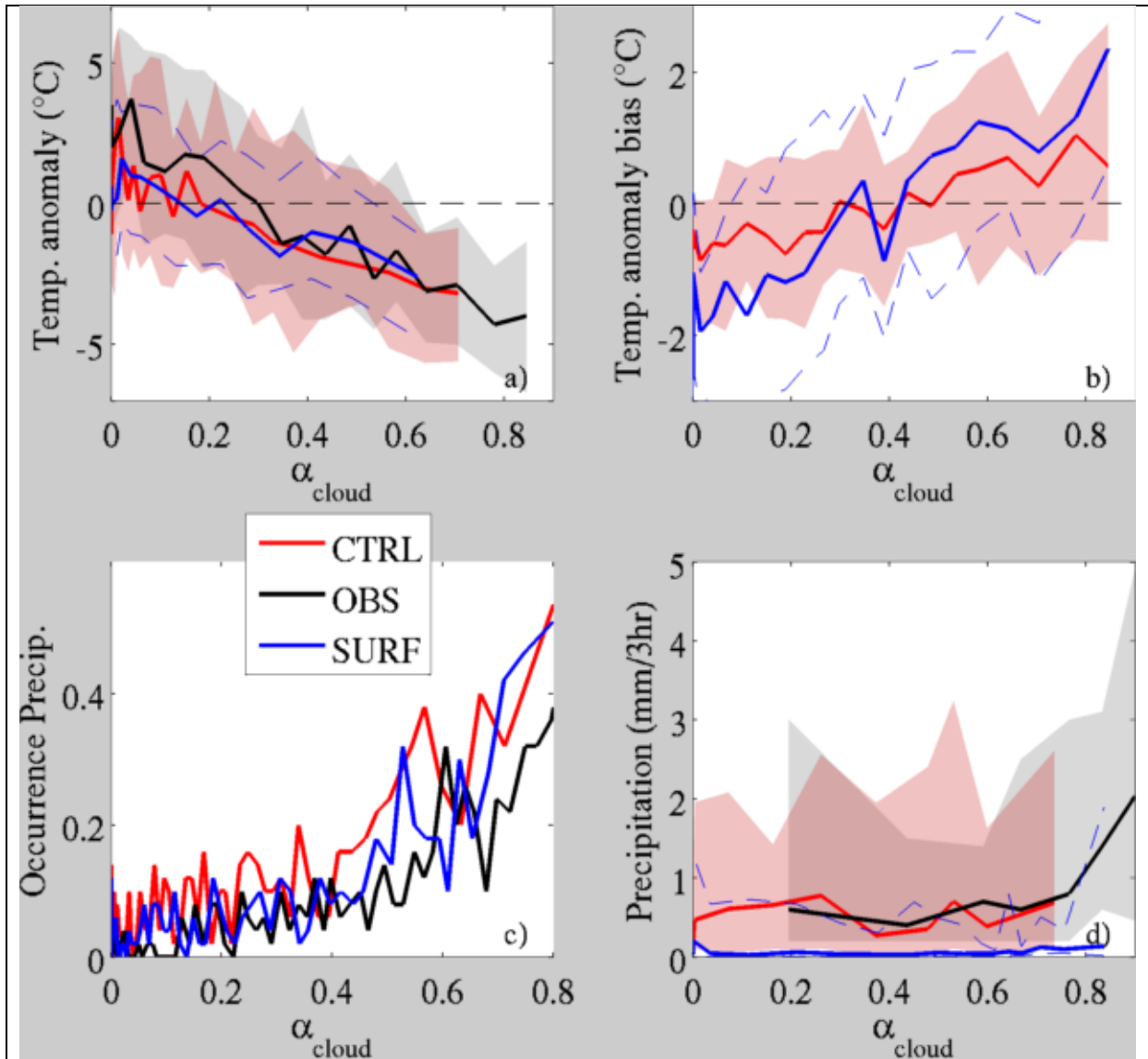


Figure 11: a) Relationship between α_{cloud} and temperature anomaly of MJJAS from 2003 to 2011. Temperature anomaly is computed as the difference between the temperature of the day and the average temperature of this julian day over the 9 years and then stratified by α_{cloud} with 50 samples in each bin. The solid line corresponds to the 50th quantile and the shaded area covers the values between the 20th and 80th quantile. Red is for CTRLd1, black is for OBSd1. SURFd2 is in blue and the 20th and 80th are shown in dashed blue lines instead of shaded area. b) Relationship between α_{cloud} and the difference of temperature anomaly between simulation and observations. c) Probability of rain occurrence as a function of α_{cloud} . d) Relationship between rain rate (only wet days) and α_{cloud} .

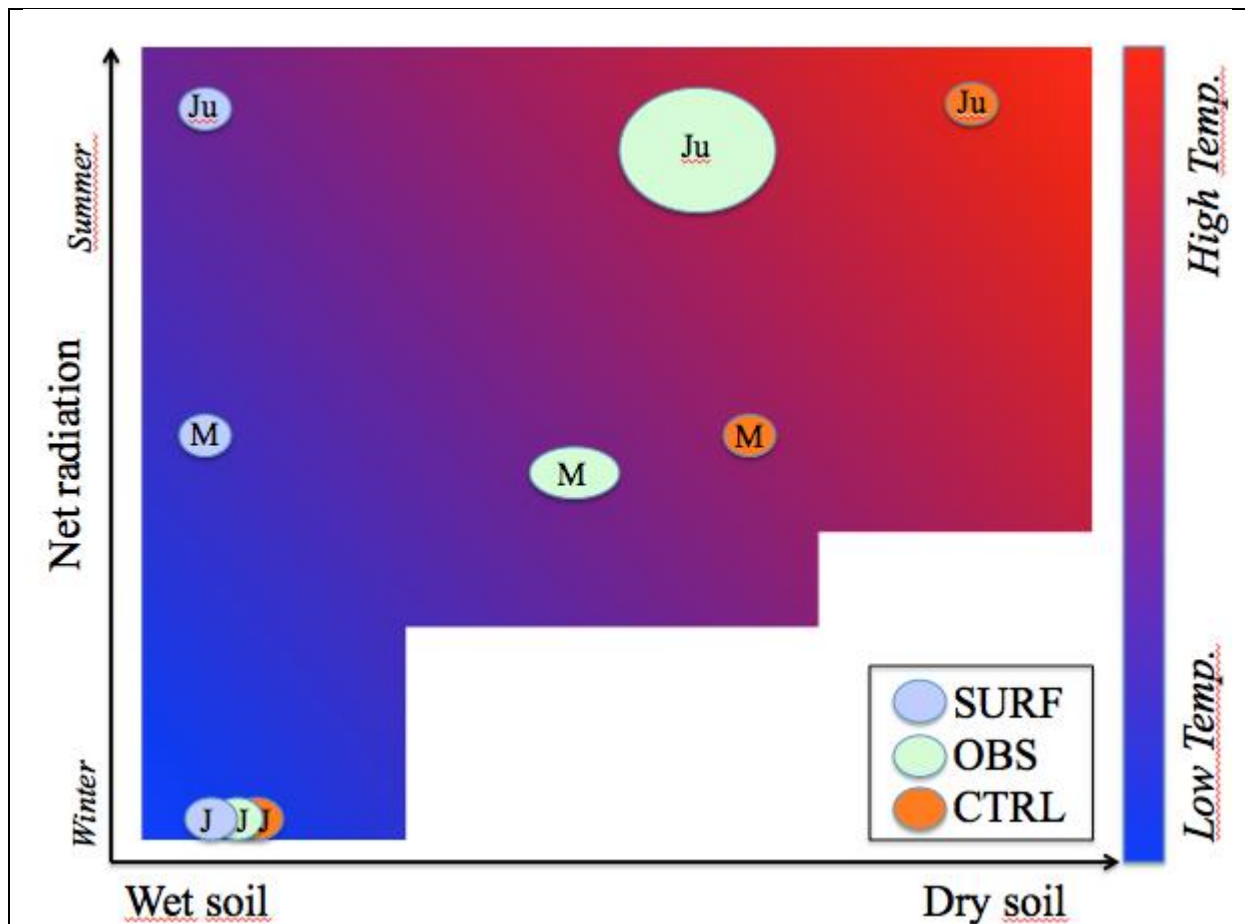


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1013
1014

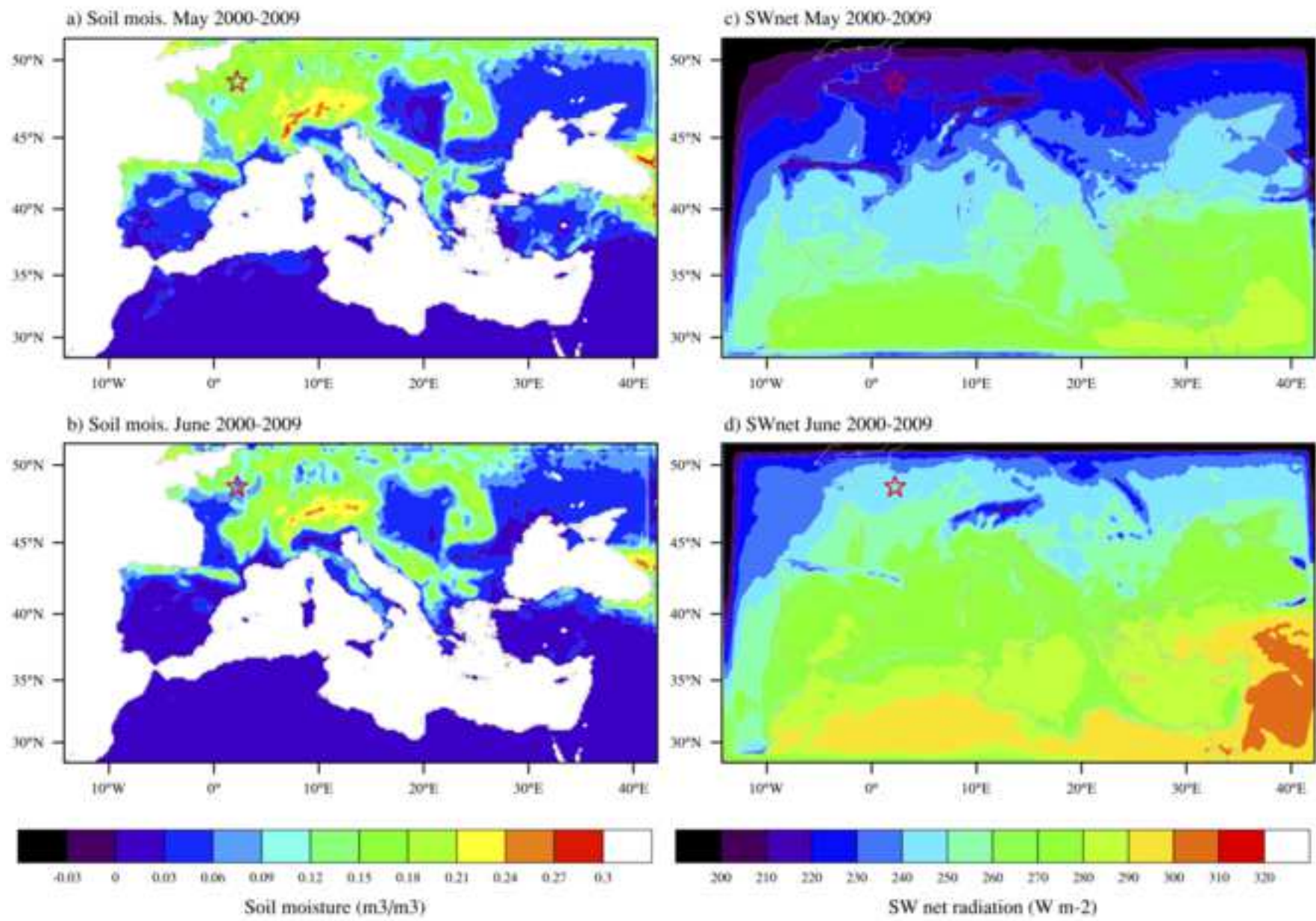


Figure 2

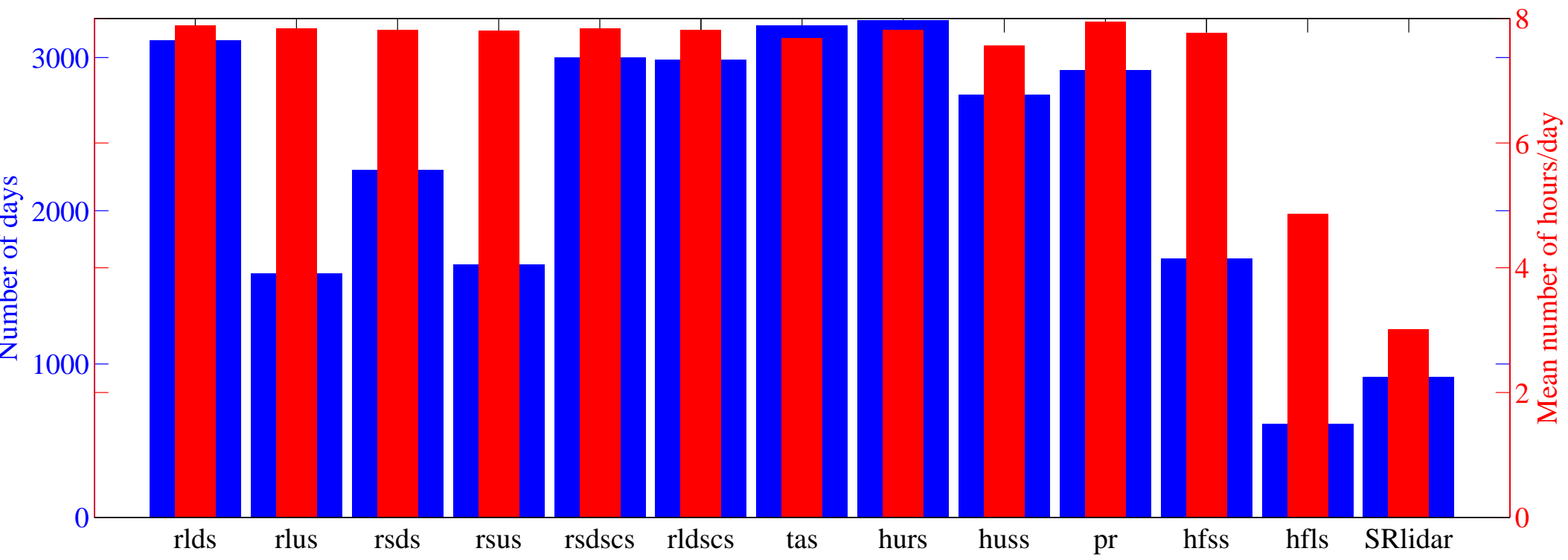


Figure 3

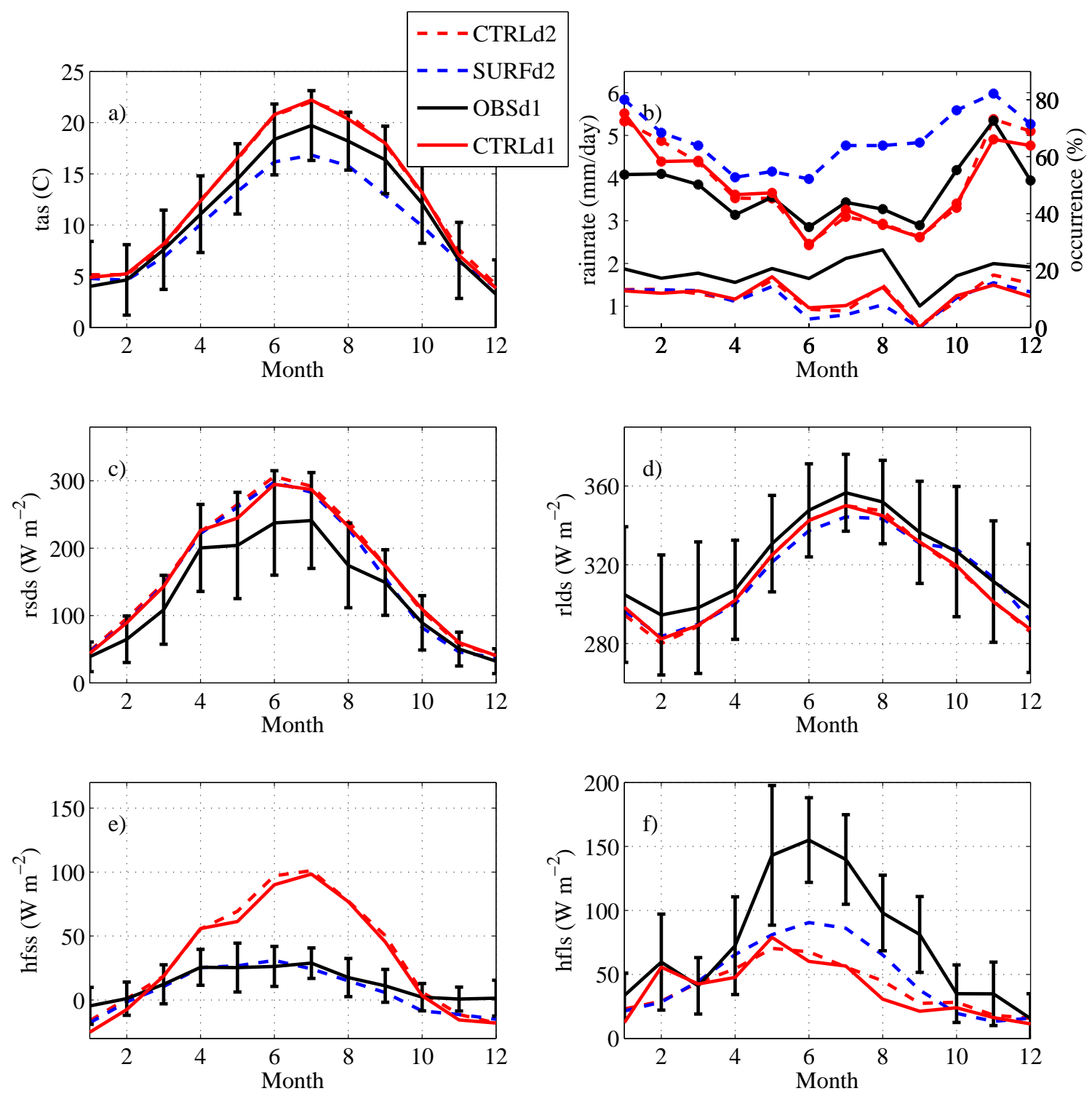
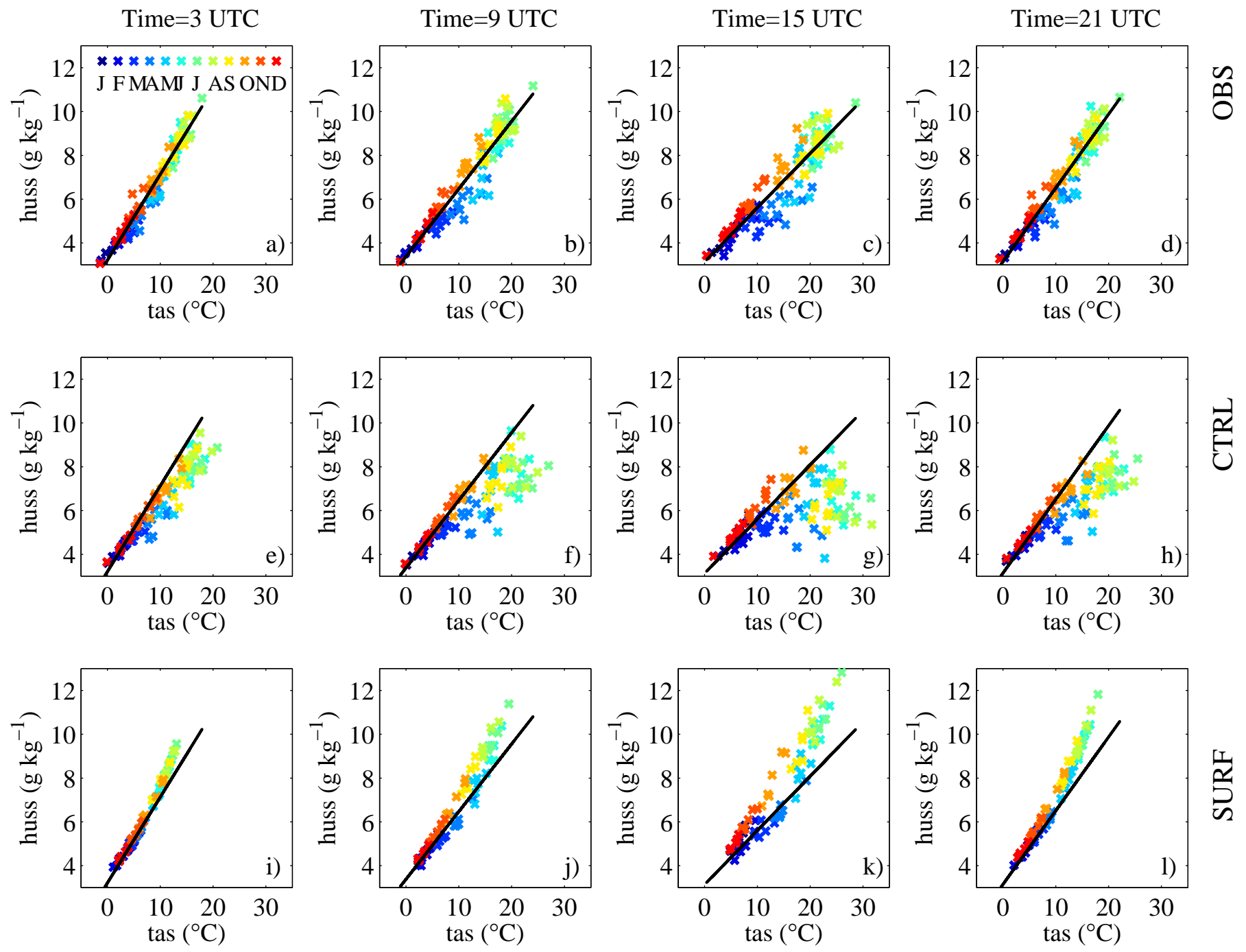


Figure 4



Mean seasonal cycle 2003-2008

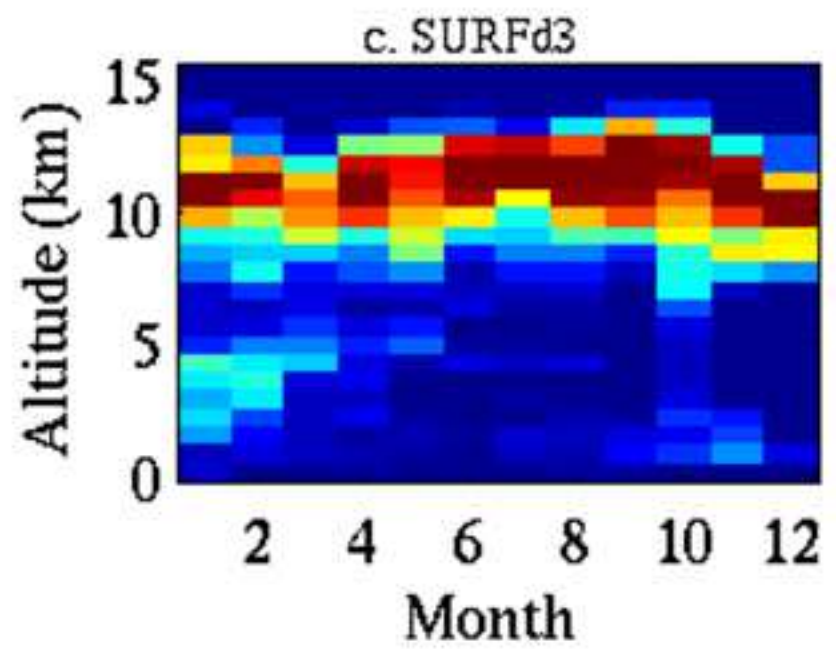
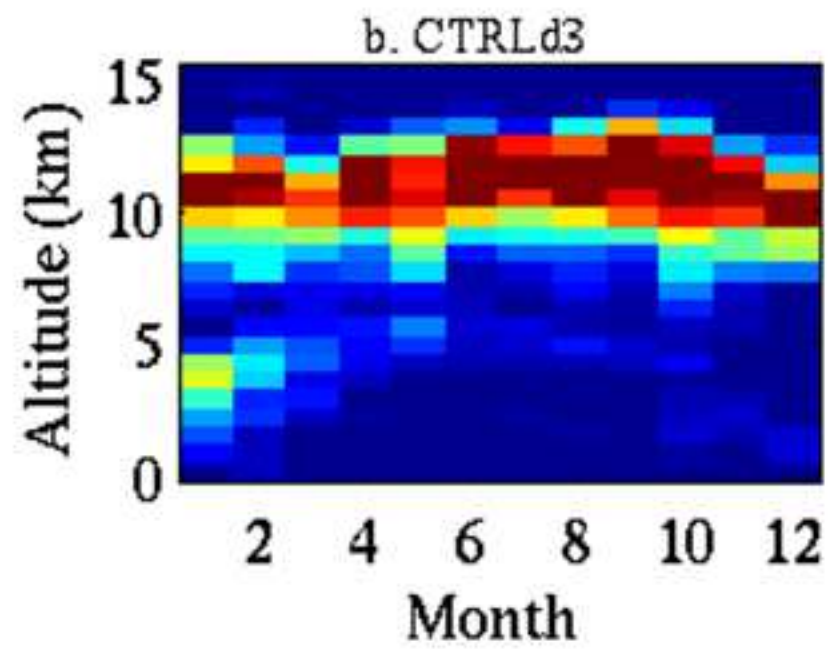
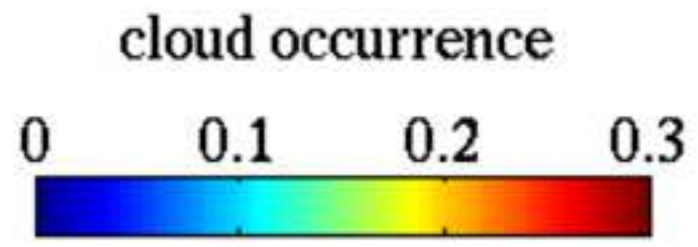
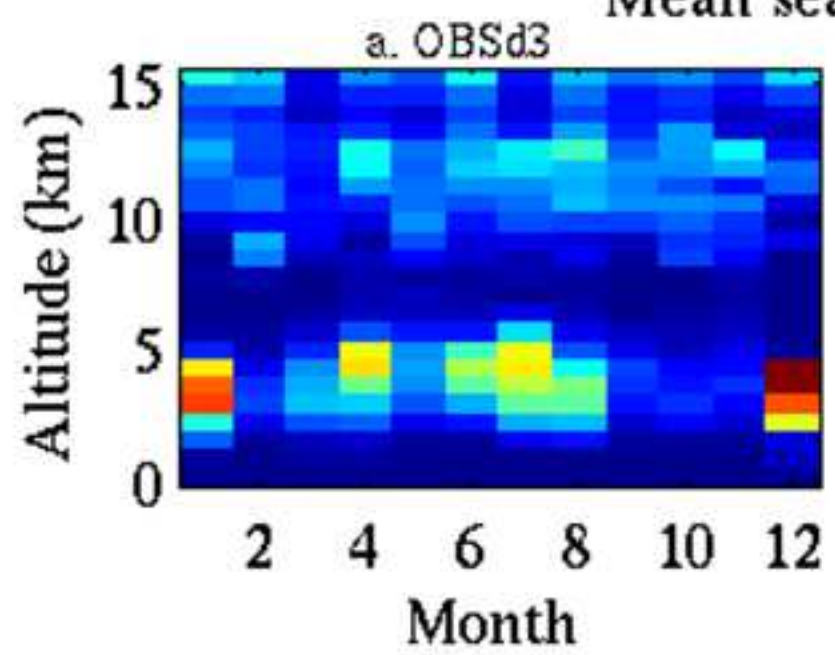
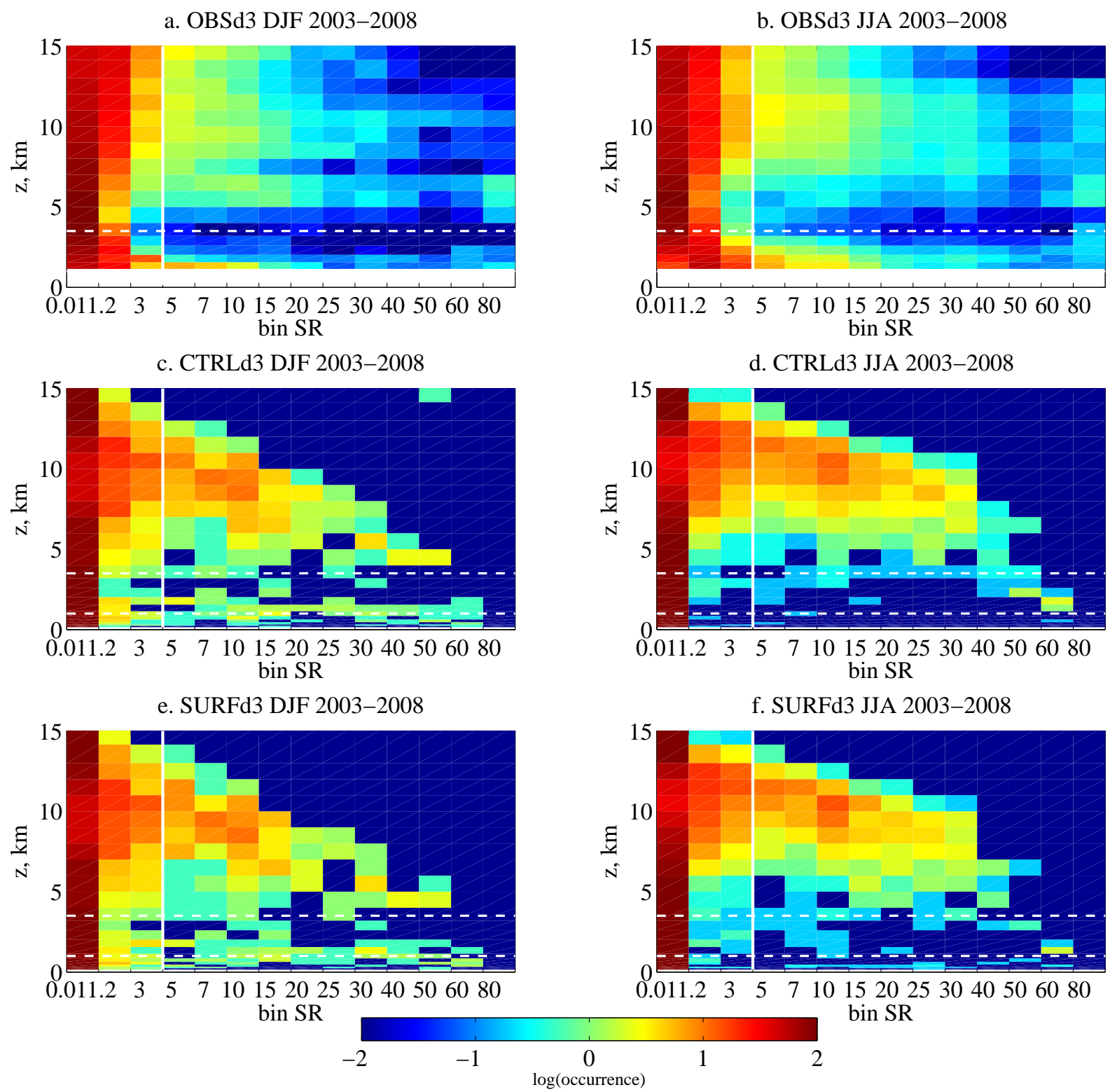


Figure 6



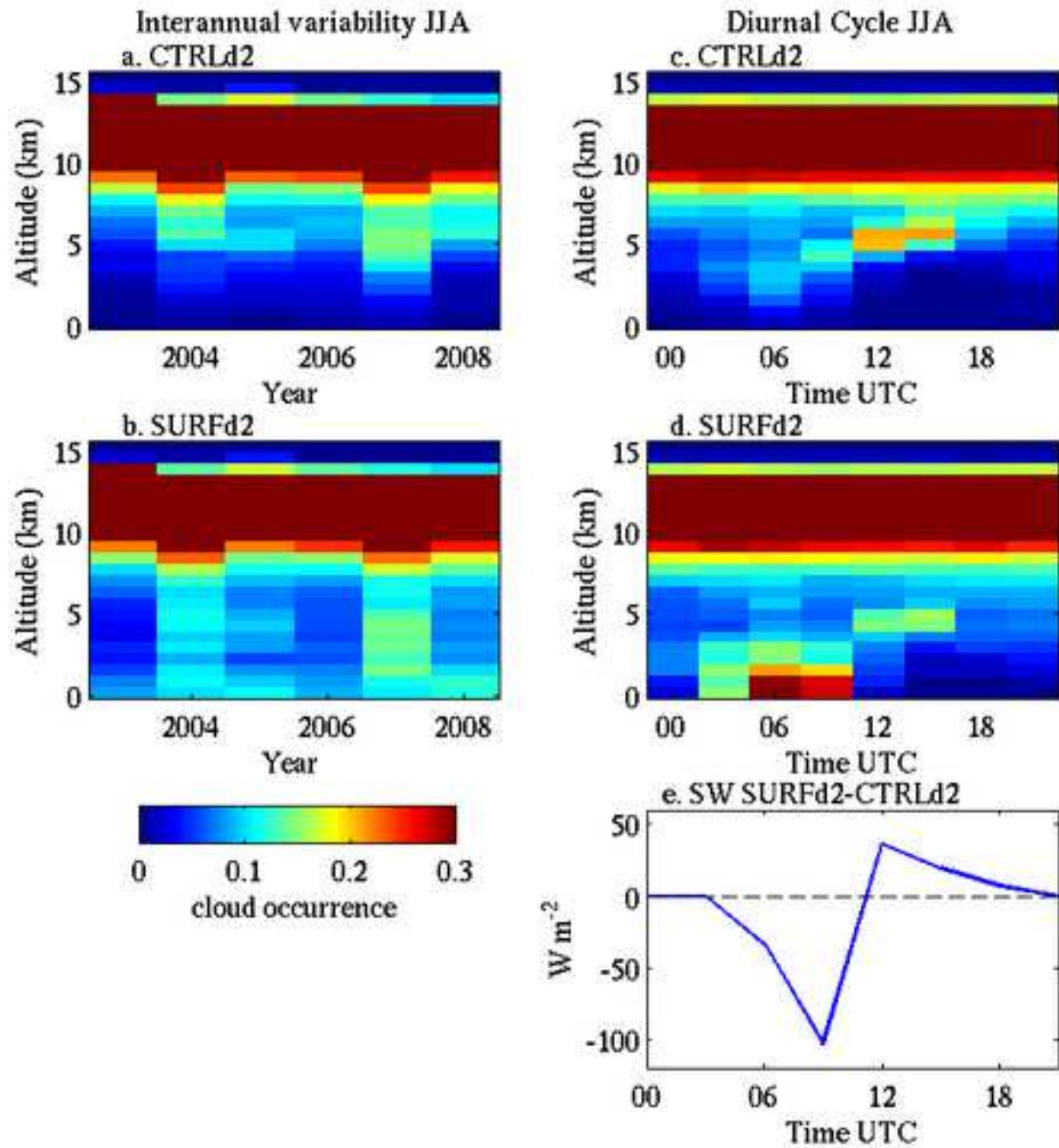


Figure 8

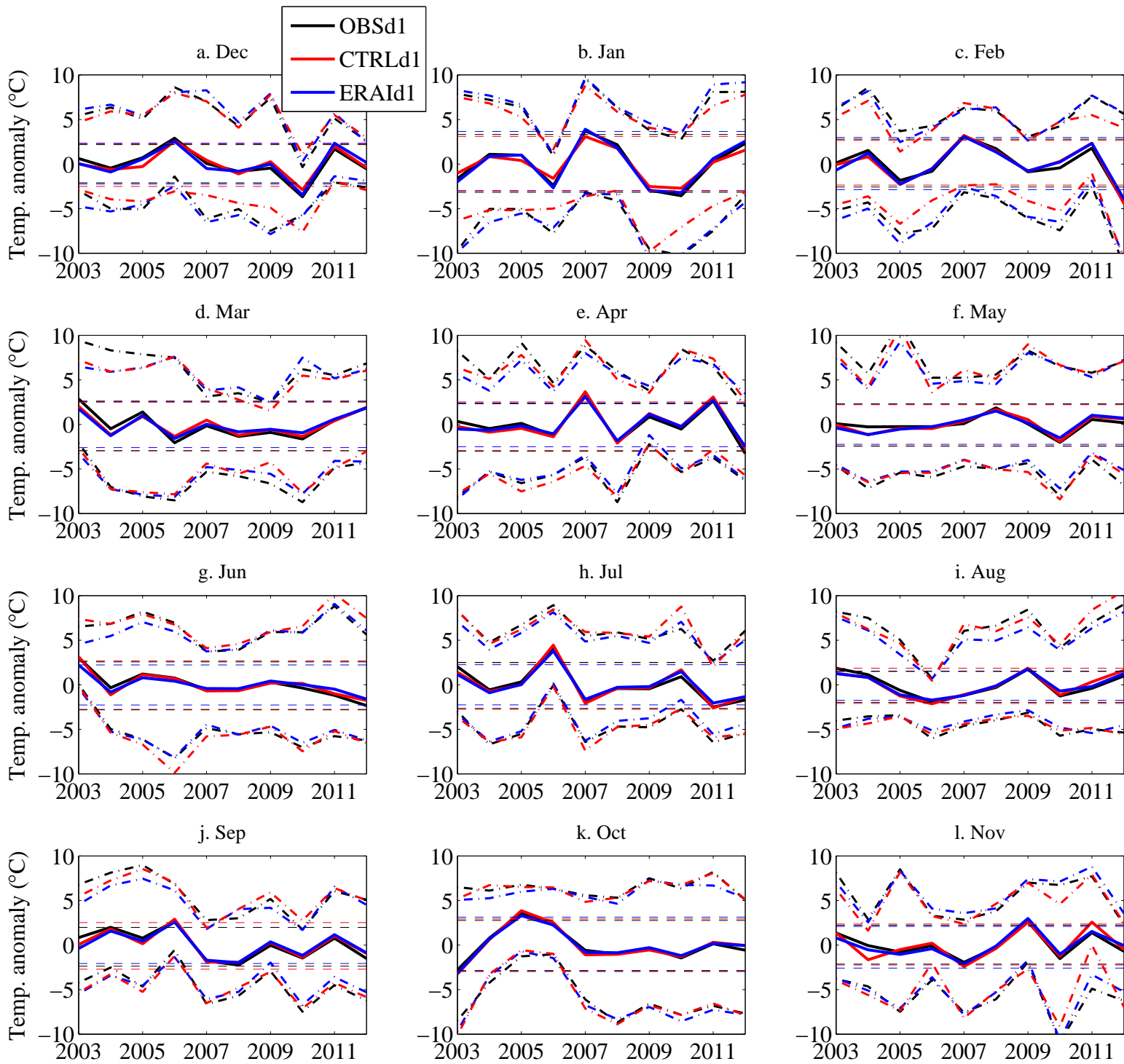
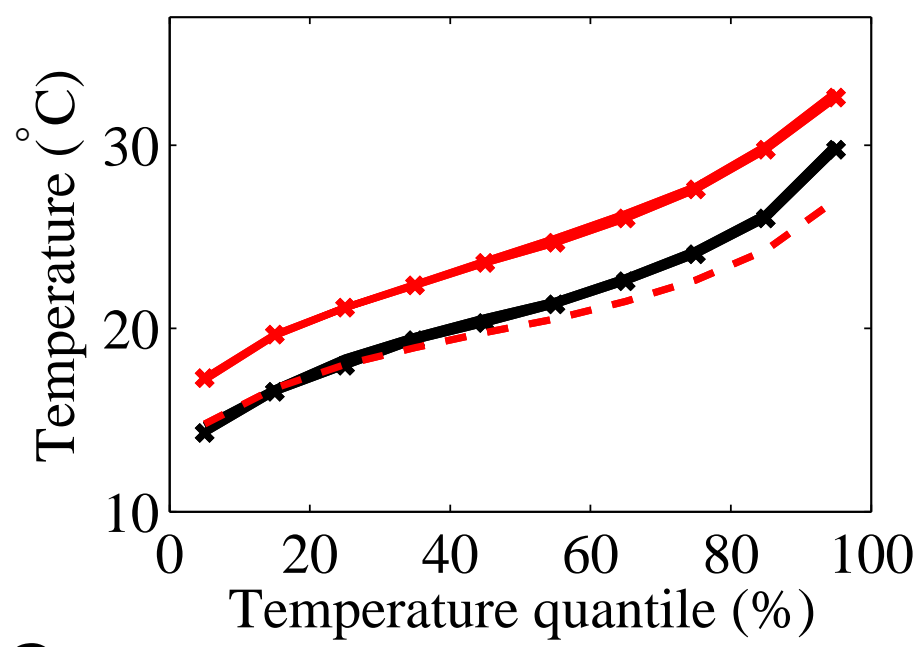
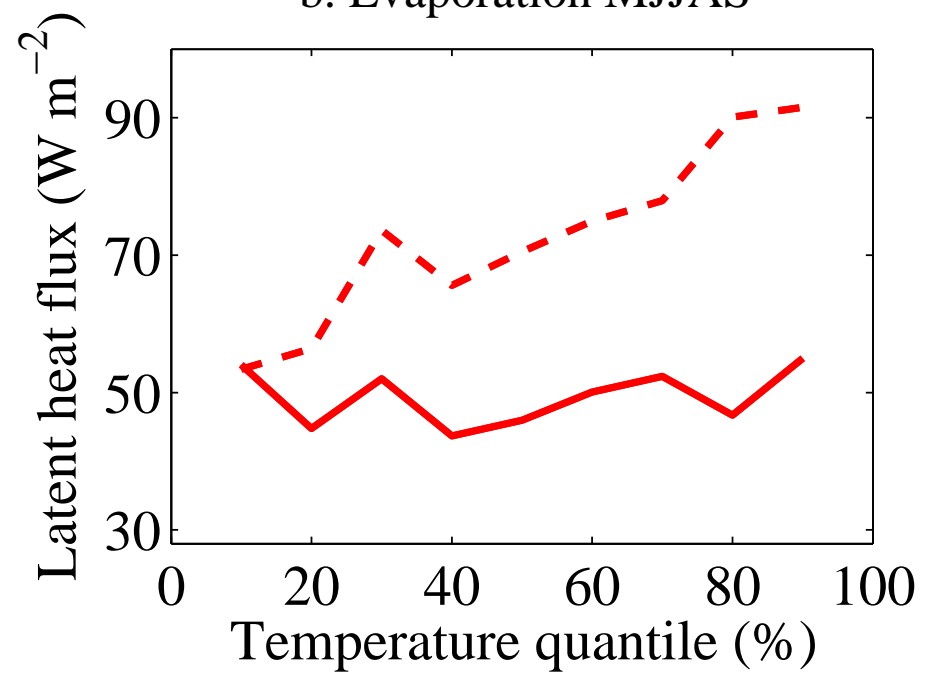


Figure 9

a. Tmax MJJAS



b. Evaporation MJJAS



c. SW MJJAS

