1	Suitability of modelled and remotely sensed essential climate variables for		
2	monitoring Euro-Mediterranean droughts		
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Abstract – Two new remotely sensed Leaf Area Index (LAI) and Surface Soil Moisture 26 27 (SSM) satellite-derived products are compared with two sets of simulations of the **ORganizing Carbon and Hydrology In Dynamic EcosystEms** (ORCHIDEE) and 28 Interactions between Soil, Biosphere and Atmosphere, CO₂-reactive (ISBA-A-gs) land 29 surface models. We analyze the interannual variability over the period 1991-2008. The 30 31 leaf onset and the Length of the vegetation Growing Period (LGP) are derived from **both** the satellite-derived LAI and modelled LAI. The LGP values produced by the 32 33 photosynthesis-driven phenology model of ISBA-A-gs are closer to the satellite-derived LAI LGP than those produced by ORCHIDEE. In the latter, the phenology is based on 34 a growing degree-day model for leaf onset, and on both climatic conditions and leaf life 35 span for senescence. Further, the interannual variability of LAI is better captured by 36 37 ISBA-A-gs than by ORCHIDEE. In order to investigate how recent droughts affected 38 vegetation over the Euro-Mediterranean area, a case study addressing the summer 2003 39 drought is presented. It shows a relatively good agreement of the modelled LAI 40 anomalies with the observations, but the two models underestimate plant regrowth in 41 the autumn. A better representation of the root-zone soil moisture profile could improve the simulations of both models. The satellite-derived SSM is compared with SSM 42 43 simulations of ISBA-A-gs, only, as ORCHIDEE has no explicit representation of SSM. 44 Overall, the ISBA-A-gs simulations of SSM agree well with the satellite-derived SSM 45 and are used to detect regions where the satellite-derived product could be improved. Finally, a correspondence is found between the interannual variability of detrended 46 47 SSM and LAI. The predictability of LAI is less pronounced using remote sensing observations than using simulated variables. However, consistent results are found in 48 49 July for the croplands of Ukraine and southern Russia.

50 **1. Introduction**

The Global Climate Observing System (GCOS) has defined a list of atmospheric, oceanic, 51 and terrestrial Essential Climate Variables (ECVs) which can be monitored at a global scale 52 from satellites. Terrestrial ECV products consisting of long time series are needed to evaluate 53 54 the impact of climate change on environment and human activities. They have high impact on 55 the requirements of the Intergovernmental Panel on Climate Change (IPCC). New ECV products are now available and they can be used to characterize extreme events, such as 56 57 droughts. Soil moisture is a key ECV in hydrological and agricultural processes. It constrains 58 plant transpiration and photosynthesis (Seneviratne et al., 2010) and is one of the limiting 59 factors of vegetation development and growth (Champagne et al., 2012), especially in water-60 limited regions such as the Mediterranean zone, from Spring to Autumn. Microwave remote 61 sensing observations can be related to surface soil moisture (SSM) rather than to root-zone 62 soil moisture, as the sensing depth is limited to the first centimetres of the soil surface 63 (Wagner et al., 1999; Kerr et al., 2007). LSMs are generally able to provide soil moisture 64 simulations over multiple depths, depending upon their structure, i.e. bucket models vs. more 65 complex vertically discretized soil water diffusion schemes (Dirmeyer et al., 1999; Georgakakos and Carpenter, 2006). Their outputs are affected by uncertainties in the 66 atmospheric forcing, model physics and parameters. However, Rüdiger et al. (2009) showed 67 68 the usefulness of using simulated SSM as a benchmark to intercompare independent satellite-69 derived SSM estimates, and Albergel et al. (2013a) used hindcast SSM simulations to provide 70 an independent check on the quality of remotely sensed SSM over time. Conversely, remotely 71 sensed SSM can be used to benchmark hindcast SSM simulations derived from two 72 independent modelling platforms (Albergel et al., 2013b).

73 Leaf Area Index (LAI) is one of the terrestrial ECVs related to the vegetation growth and

74 senescence. Monitoring LAI is essential for assessing the vegetation trends in the climate

75 change context, and for developing applications in agriculture, environment, carbon fluxes and climate monitoring. LAI is expressed in $m^2 m^{-2}$ and is defined as the total one-sided area 76 of photosynthetic tissue per unit horizontal ground area. Monitoring LAI is essential for 77 78 assessing the vegetation trends in the climate change context, and for developing applications 79 in agriculture, environment, carbon fluxes and climate monitoring. The LAI seasonal cycle 80 can be monitored at a global scale using medium resolution optical satellite sensors (Myneni 81 et al., 2002; Baret et al., 2007, 2013; Weiss et al., 2007). Another way to provide LAI over 82 large areas and over long periods of time is to use generic Land Surface Models (LSM), such 83 as Interactions between Soil, Biosphere and Atmosphere, CO₂-reactive (ISBA-A-gs) (Calvet et al., 1998; Gibelin et al., 2006) or ORganizing Carbon and Hydrology In Dynamic 84 85 EcosystEms (ORCHIDEE) (Krinner et al., 2005).

The direct validation of climate data records, based on in situ observations, is not easy at a continental scale, as in situ observations are limited in space and time. Therefore, indirect validation plays a key role. The comparison of ECV products derived from satellite observations with ECV products derived from LSM hindcast simulations is particularly useful. Inconsistencies between two independent products permit detecting shortcomings and improving the next versions of the products.

92 The Mediterranean basin will probably be affected by climate change to a large extent 93 (Gibelin and Déqué, 2003; Planton et al., 2012). Over Europe and Mediterranean areas, the 94 annual mean temperature of the air is likely to increase more than the global mean (IPCC 95 assessment, 2007). In most Mediterranean regions, this trend would be associated with a 96 decrease in annual precipitation (Christensen et al., 2007). In this context, it is important to 97 build monitoring systems of the land surface variables over this region, able to describe 98 extreme climatic events such as droughts and to analyze their severity with respect to past 99 droughts.

100 This study was performed in the framework of the HYMEX (Hydrological cycle in the 101 Mediterranean EXperiment) initiative (HYMEX White Book, 2008; Drobinski et al., 2009a, 102 2009b, 2010), with the aim of investigating the interannual variability of LAI and SSM ECV 103 products over the Euro-Mediterranean area. While an attempt was made in a previous work 104 (Szczypta et al., 2012) to simulate the hydrological droughts over the Euro-Mediterranean 105 area, this study focuses on the monitoring of agricultural droughts and complements the joint evaluation of the ORCHIDEE and ISBA-A-gs land surface model performed by Lafont et al. 106 107 (2012) over France using satellite-derived LAI. A 18 yr time period (1991-2008) is 108 considered against a 8 yr period (2000-2007) in Lafont et al. (2012). Using the modelling 109 framework implemented by Szczypta et al. (2012), we compare ISBA-A-gs and ORCHIDEE 110 simulations of LAI, and we evaluate new homogenized remotely sensed LAI and SSM 111 datasets. The satellite-derived SSM is compared with ISBA-A-gs simulations of SSM, as 112 ORCHIDEE has no explicit representation of this quantity. The capacity of the two models to represent the interannual variability of the vegetation growth and the impact of extreme 113 events such as the 2003 heat wave is assessed. Finally, the synergy between SSM and LAI is 114 115 investigated using the satellite products and the ISBA-A-gs model.

116 The data, including the leaf onset and the Length of the vegetation Growing Period (LGP) derived from the observed and simulated LAI are first described. Then, anomalies of the 117 118 detrended LAI are compared over the 1991-2008 period with a focus on the 2003 western 119 European drought (Rebetez et al., 2006; Vidal et al., 2010). Lastly, we investigate to what 120 extent SSM observations can be used to predict mean anomalous vegetation state conditions 121 in the current growing season. The interannual SSM variability, resulting from satellite 122 observations and LSM simulations, is used as an indicator able to anticipate LAI anomalies 123 during key periods.

125 **2. Data and methods**

- 126 In this study, several data sets (either model simulations, atmospheric variables, or satellite-
- 127 derived products) were produced or collected, over the Euro-Mediterranean area. In order to

128 force the two LSMs simulations of SSM and LAI (Sect. 2.1), the ERA-Interim surface

- 129 atmospheric variables (Simmons et al., 2010) are used. The ERA-Interim data are available
- 130 on a $0.5^{\circ} \times 0.5^{\circ}$ grid and the LSM simulations use the same grid (Szczypta et al., 2012). The
- 131 1991-2008 18 yr period is considered, as in Szczypta et al. (2012). During this period, SSM
- 132 products from both active (ERS-1/2, ASCAT) and passive (SSM/I, TMI, AMSR-E)
- 133 microwave sensors are available and can be combined (Sect. 2.2), together with LAI products
- 134 (Sect. 2.3). In order to compare the LSM simulations with the satellite products, the latter are
- 135 aggregated on the same $0.5^{\circ} \times 0.5^{\circ}$ grid using linear interpolation and averaging techniques.

136 **2.1 Models**

Although the generic ISBA-A-gs and ORCHIDEE LSMs share the same general structure, based on the description of the main biophysical processes, they were developed independently and differ in the way photosynthesis, transpiration, and phenology are represented. The main differences between the two models are summarized in Table 1. More details about the differences between the two models can be found in Lafont et al. (2012).

142 **2.1.1 ISBA-A-gs**

ISBA-A-gs is a CO₂-responsive LSM (Calvet et al., 1998, 2004; Gibelin et al., 2006; Calvet et al., 2008), simulating the diurnal cycle of carbon and water vapour fluxes, together with LAI and soil moisture evolution. The soil hydrology is represented by three layers: a skin surface layer 1 cm thick, a bulk root-zone reservoir, and a deep soil layer (Boone et al., 1999) contributing to evaporation through capillarity rises. Over the Euro-Mediterranean area, the rooting depth varies from 0.5-1.5 m for grasslands, to 2.0-2.5 m for broadleaf forests. The model includes an original representation of the impact of drought on photosynthesis (Calvet, 150 2000; Calvet et al., 2004). The version of the model used in this study corresponds to the "NIT" simulations performed by Szczypta et al. (2012). This version interactively calculates 151 152 the leaf biomass and LAI, using a plant growth model (Calvet et al., 1998; Calvet and 153 Soussana, 2001) driven by photosynthesis. In contrast to ORCHIDEE, no GDD-based 154 phenology model is used in ISBA-A-gs, as the vegetation growth and senescence are entirely 155 driven by photosynthesis. The leaf biomass is supplied with the carbon assimilated by photosynthesis, and decreased by a turnover and a respiration term. Turnover is increased by 156 157 a deficit in photosynthesis. The leaf onset is triggered by sufficient photosynthesis levels and 158 a minimum LAI value is prescribed (LAImin in Table 1). The maximum annual value of LAI 159 is prognostic, i.e. it is predicted by the model. Gibelin et al. (2006) and Brut et al. (2009) 160 showed that ISBA-A-gs provides reasonable LAI values at regional and global scales under 161 various environmental conditions. Calvet et al. (2012) showed that the model can be used to 162 assess the interannual variability of fodder and cereal crops production over regions of 163 France. The ISBA-A-gs LSM is embedded into the SURFEX modelling platform (Masson et 164 al., 2013), and the simulations performed in this study correspond to SURFEX version 6.2 165 runs.

166 **2.1.2 ORCHIDEE**

167 ORCHIDEE (Krinner et al., 2005) is a process-based terrestrial biosphere model designed to 168 simulate energy, water and carbon fluxes of ecosystems and is based on three sub-modules: 169 (1) SECHIBA (Schématisation des Echanges Hydriques à l'Interface Biosphère-Atmosphère) 170 is a land surface energy and water balance model (Ducoudré et al., 1993), (2) STOMATE 171 (Saclay Toulouse Orsay Model for the Analysis of Terrestrial Ecosystems) is a land carbon cycle model (Friedlingstein et al., 1999; Ruimy et al., 1996; Botta et al., 2000), and (3) LPJ 172 173 (Lund-Postdam-Jena) is a dynamic model of long-term vegetation dynamics including competition and disturbances (Sitch et al., 2003). ORCHIDEE uses a phenology model based 174

175 on Growing Degree Days (GDD) for leaf onset. The parameters of the GDD model were 176 calibrated by Botta et al. (2000) using remotely sensed NDVI observations. The LAI cycle simulated by ORCHIDEE is characterized by a dormancy phase, a sharp increase of LAI over 177 178 a few days at the leaf onset, a more gradual growth governed by photosynthesis, until a 179 predefined maximum LAI value has been reached (LAImax in Table 1). Note that the 180 prescribed LAImax is not necessarily reached in a simulation over a grid cell. The senescence 181 phase presents an exponential decline of LAI. The leaf offset depends on leaf life span and 182 climatic parameters. The ORCHIDEE 1.9.5.1 tag was used to perform these simulations. 183 Only the ORCHIDEE LAI variable is used since the simple bucket soil hydrology version of 184 this version of ORCHIDEE has no explicit representation of SSM (Table 1). An attempt was 185 made by Rebel et al. (2012) to compare the soil moisture simulated by ORCHIDEE with the AMSR-E SSM product. They concluded that the shallow soil moisture estimates they derived 186 187 from the ORCHIDEE simulations were not an explicit representation of SSM and could not be compared with the AMSR-E SSM product. Instead, they compared the AMSR-E SSM 188 with the root-zone soil moisture simulated by ORCHIDEE, and they observed that the 189 190 satellite-derived SSM had a much faster reaction time and a much shorter characteristic lag-191 time than the simulations. This can be explained by the shallow penetration depth (<5 cm) of the C-band microwave signal measured by AMSR-E, which is not representative of deep soil 192

193 layers.

194 **2.1.3 Design of the simulations**

In this study, the two models use the same spatial distribution of vegetation types, based on the ECOCLIMAP-II (Faroux et al., 2013) database of ecosystems and model parameters, over the area 11°W - 62°E, 25°N - 75°N (Fig. 1) covering the Mediterranean basin, northern Europe, Scandinavia and part of Russia. Further, ISBA-A-gs and ORCHIDEE are driven by the same atmospheric forcing, the ERA-Interim global ECMWF atmospheric reanalysis

(projected onto a $0.5^{\circ} \times 0.5^{\circ}$ grid). ERA-Interim tends to underestimate precipitation, as 200 201 observed over France by Szczypta et al. (2011) and over the Euro-Mediterranean area by Szczypta et al. (2012). In the latter study, the monthly Global Precipitation Climatology 202 203 Centre (GPCC) precipitation product was used to bias-correct the 3-hourly ERA-Interim precipitation estimates over the whole Euro-Mediterranean area. The resulting 3-hourly 204 precipitation was indirectly validated using river discharges simulations and observations. 205 The two models are driven by the 3-hourly atmospheric variables from the bias-corrected 206 ERA-Interim and perform half-hourly simulations of the surface fluxes, of soil moisture and 207 208 of surface temperature, together with daily LAI simulations. Irrigation is not represented. The 209 daily LAI values are produced for each Plant Functional Type (PFT) present in the grid-cell. 210 Similarly, daily mean SSM values are produced for each PFT. The grid-cell simulated LAI 211 (SSM) is the average of the PFT-dependent LAI (SSM) multiplied by the fractional area of 212 each PFT. The model runs are performed at a spatial resolution of $0.5^{\circ} \times 0.5^{\circ}$, over the ECOCLIMAP-II 213

- 214 Euro-Mediterranean area, corresponding to:
- 103 ecosystem classes used to map the fractional coverage of twelve plant functional
 types (PFT) (see Figs. 7 and 9 in Faroux et al. (2013), respectively);
- 8142 land grid cells.

The fractional coverage of the various PFTs is provided by ECOCLIMAP-II at a spatial resolution of 1 km, aggregated at a spatial resolution of 0.5°, and the two models account for the subgrid variability by simulating separate LAI values for each surface type present in the grid-cell. ISBA-A-gs simulates separate SSM values for each surface type present in the gridcell. Figure 2 shows the spatial distribution of the dominant vegetation types over the studied domain.

224 **2.2 ESA-CCI surface soil moisture**

225 The European Space Agency Climate Change Initiative (ESA-CCI) project dedicated to soil 226 moisture has produced a global 32-yr SSM time series described in Liu et al. (2011, 2012). The ESA-CCI SSM product is today the only multi-decadal SSM dataset derived from 227 228 satellite observations. The daily data are available on a 0.25° grid and can be downloaded 229 from http://www.esa-soilmoisture-cci.org/. Several SSM products based on either active or 230 passive single satellite microwave sensors were combined to build a blended harmonized time 231 series of SSM at the global scale from 1978 to 2010: scatterometer-based products from ERS-1/2 and ASCAT (July 1991-May 2006 and 2007-2010, respectively), and radiometer-based 232 233 products from SMMR, SSM/I, TMI, and AMSR-E (November 1978-August 1987, July 234 1987–2007, 1998–2008, July 2002–2010, respectively). The method used to combine the different data sets is described in details in Liu et al. (2011, 2012) and takes advantage of the 235 236 assets of both passive and active systems. In most of the Euro-Mediterranean area, active 237 microwave products are used. The passive microwave products mainly cover North Africa. In 238 some parts of the area (e.g. in Spain), the average of both active and passive microwave 239 products is used (see Fig. 14 in Liu et al. (2012)). It must be noted that the sensing depth of 240 microwave remote sensing observations is limited to the first centimetres of the soil surface. 241 The ESA-CCI dataset was used by Dorigo et al. (2012) to analyze trends in SSM, while Muñoz et al. (2013) and Barichivich et al. (2014) showed its strong connectivity with 242 243 vegetation development. Loew et al. (2013) have assessed this product and showed that the 244 agreement with other soil moisture datasets from modeling studies as well as with rainfall 245 data is generally good. The ESA-CCI SSM temporal and spatial coverage is much better after 1990 than before but is limited at high latitudes due to snow cover and frozen soil conditions. 246 247 2.3 GEOV1 LAI

The European Copernicus Global Land Service provides a global LAI product in near-real-248 time called GEOV1 (Baret et al., 2013). This product was extensively validated and 249 benchmarked with pre-existing satellite-derived LAI products using an ensemble of ground 250 observations at 30 sites in Europe, Africa, and North America (Camacho et al., 2013). It must 251 252 be noted that this direct validation does not completely address the seasonality of LAI as for a given site, LAI observations are available at only one or very few dates. It was found that the 253 GEOV1 LAI correlates very well with in situ observations ($r^2 = 0.81$), with a root mean 254 square error of 0.74 m²m⁻². The GEOV1 scores are better than those obtained by other 255 products such as MODIS c5, CYCLOPES v3.1, and GLOBCARBON v2. A 32-yr LAI time 256 series based on the GEOV1 algorithm was produced by the GEOLAND-2 project. Ten-daily 257 present 258 available 1981 to and data are from can be downloaded on 259 http://land.copernicus.eu/global/. For the period before 1999, the AVHRR Long Term Data 260 Record (LTDR) reflectances (Vermote et al., 2009) are used to generate the LAI product at a spatial resolution of 5 km. From 1999 onward, the SPOT-VGT reflectances are used to 261 262 generate the LAI product at a spatial resolution of 1 km. The harmonized time series is 263 produced by neural networks trained to produce consistent estimates of LAI from the reflectance measured by different sensors (Verger et al., 2008). 264

265 **2.4 Seasonal and interannual variability**

266 **2.4.1** Surface Soil Moisture

In this study, we focus on the seasonal and interannual variability of SSM after removing the trends from both satellite-derived and simulated time series. The detrended time series at a given location and for a given 10-daily period of the year is obtained by subtracting the leastsquares-fit straight line. The same 10-daily periods as for the GEOV1 LAI product are used. Hereafter, this quantity is referred to as SSMd, for both satellite observations and model simulations. In order to characterize the day-to-day variability of SSMd, anomalies are calculated using Eq. (6) in Albergel et al. (2009). For each SSMd estimate at day (*j*), a period *F* is defined, with F = [j-17d, j+17d]. If at least five measurements are available in this period of time, the average SSMd value and the standard deviation are first calculated. Then, the scaled anomaly *Ano*_{SSM} is computed:

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279
$$Ano_{SSM}(j) = \frac{SSMd(j) - SSMd(F)}{stdev(SSMd(F))}$$
(1)

280

This procedure is applied to the ESA-CCI SSM observations and to the ISBA-A-gs SSMsimulations.

283 2.4.2 Leaf Area Index

284 Three metrics are calculated to characterize LAI seasonal and interannual variability: the leaf 285 onset, the leaf offset, and the monthly (or 10-daily) scaled anomaly, for both satellite observations and model simulations. The LGP is defined as the period of time between the 286 287 leaf onset and the leaf offset of a given annual cycle. The leaf onset (respectively, offset) is 288 determined as the 10-daily period when the departure of LAI from its minimum annual value 289 becomes higher (respectively, lower) than 40% of the amplitude of the annual cycle (Gibelin et al., 2006; Brut et al., 2009). This method is sufficiently robust to be applied to both 290 291 deciduous and non-perennial vegetation, and to evergreen vegetation presenting a sufficiently marked annual cycle of LAI. Camacho et al. (2013) have shown that the neural network 292 293 algorithm used to produce GEOV1 (Baret et al., 2013) was successful in reducing the saturation of optical signal for dense vegetation (i.e. at high LAI values). Since the saturation 294 295 effect is the main obstacle to the derivation of LGP from LAI or other vegetation satellite-296 derived products, it can be assumed that the GEOV1-derived LGP values are reliable.

The interannual variability of LAI for various seasons is represented by monthly or 10-dailyscaled anomalies defined as:

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$$300 \quad Ano_{LAI}(i, yr) = \frac{DLAI(i, yr)}{stdev(DLAI(i, :))}$$
(2)

301

302 where DLAI(i, yr) represents the difference between LAI for a particular month (*i* ranging 303 from 1 to 12) or 10-day period (*i* ranging from 1 to 36) of year yr and its average interannual 304 value, and stdev(DLAI(i,:)) is the standard deviation of DLAI for a particular month or 10-305 day period. This procedure is applied to the GEOV1 observations and to the ORCHIDEE and 306 ISBA-A-gs LAI simulations. In the case of GEOV1, in order to cope with shortcomings in 307 the harmonization of satellite-derived products, the calculation of DLAI is made separately for the 1991-1998 AVHRR and for the 1999-2008 SPOT-VGT periods. It was checked that 308 309 the resulting time series have a zero mean and present no trend.

Finally, the Annual Coefficient of Variation (ACV), is computed as the ratio of the standard
deviation of the mean annual LAI to the long term mean annual LAI, over the 1991-2008
period. ACV characterizes the relative interannual variability of LAI.

- 313 **2.4.3 Correlation scores**
- 314 In this study, the Pearson correlation coefficient (r) is used. Squared correlation coefficient
- 315 (r^2) plots are used when all the corresponding r values are greater or equal to zero. When r
- 316 presents negative values, r is plotted instead of r^2 .
- 317 **2.4.4 Leaf Area Index vs. Surface Soil Moisture**
- 318 In order to assess to what extent LAI anomalies are related to the SSMd anomalies observed a
- 319 few 10-day periods ahead, the Pearson correlation coefficient between 18 SSMd values (one
- 320 value per year over the 1991-2008 period) and 18 DLAI values is calculated on a 10-daily
- 321 basis. For each considered 10-day period, SSMd is compared to DLAI values at the same

322 period, and to hindcast DLAI values obtained 10 days, 20 days, 30 days, 40 days and 50 days later, from March to August. Preliminary tests based on the satellite-derived products showed 323 324 that significant correlations were mainly obtained over cropland areas. An explanation is that LAI is more representative of the biomass production for annual crops than for managed 325 326 grasslands or natural vegetation, or that natural vegetation in water-restricted areas is better adapted to changing water variability than crops. Therefore, the correlation coefficients are 327 computed for the grid cells with more than 50% of croplands (according to the 328 329 ECOCLIMAP-II land cover data). The scores are calculated with hindcast SSMd and DLAI for 10-daily time lags derived from either (1) the SSM and LAI simulated by the ISBA-A-gs 330 331 LSM or (2) the ESA-CCI SSM and GEOV1 LAI products.

- 332
- 333 **3 Results**
- 334 **3.1 Modelled vs. observed SSM**

335 Figure 3 shows the absolute (original SSMd data) and anomaly (Ano_{SSM}) correlation between 336 the ISBA-A-gs SSM simulations and the ESA-CCI SSM product for the 1991-2008 period. In 337 general, good absolute positive correlations are observed over all the sub-regions of Fig. 1. 338 The best anomaly correlations are observed over the croplands of Ukraine and southern 339 Russia. However, negative correlations are observed in mountainous areas of the 340 Mediterranean basin, in southern Turkey (Taurus mountains) and in western Iran (Zagros 341 mountains). In order to understand the negative absolute correlations in Fig. 3, we plotted 342 (Fig. 4) the same figure as Fig. 3, except for the 2003-2008 period over which the AMSR-E 343 product is available, using either the ESA-CCI blended (active/passive) product or the 344 original AMSR-E product. While the results obtained with the blended product are similar to 345 Fig. 3 over the whole domain and those obtained with AMSR-E are similar to Fig. 3 over the 346 Mediterranean basin, the negative correlations are not observed in the AMSR-E product.

Over Northern Europe and Russia-Scandinavia, the correlations obtained for AMSR-E are 347 348 lower than with the blended product. This shows that the blending technique used by Liu et 349 al. (2012) is appropriate, apart from mountainous areas in southern Turkey and in western 350 Iran where the active product is used, whereas the passive product is more relevant in these 351 regions. Although the extreme 2003 year has more weight in the time series considered in Fig. 4, Fig. 3 and the top sub-figures of Fig. 4 are similar over western Europe. This shows 352 that the consistency between ESA-CCI and ISBA-A-gs SSM is preserved during contrasting 353 354 climatic conditions. Figure 5 compares the absolute and anomaly correlations r^2 of the blended product and of AMSR-E over the 2003-2008 period. Higher values are generally 355 356 observed for the blended product. The AMSR-E product is more consistent with the ISBA-A-357 gs simulations than the blended product over 24 % of the grid cells for the absolute 358 correlations, and over 17 % of the grid cells for the anomaly correlations.

359 **3.2 Simulated and observed phenology**

Figures 6 and 7 present leaf onset and LGP maps derived from the modelled LAI and from 360 361 the GEOV1 LAI. Consistent leaf onset features (Fig. 6) are observed across satellite and 362 model products: while the vegetation growing cycle may start at wintertime in some areas of the Mediterranean basin (e.g. North Africa, southern Spain), the leaf onset occurs later in 363 364 northern Europe (from February to July) and even later in Russia-Scandinavia (from April to 365 August). In contrast to leaf onset, results are quite different from one data set to another for 366 LGP (Fig. 7). In general, the two models tend to overestimate LGP. However, the LGP values produced by the photosynthesis-driven phenology model of ISBA-A-gs are closer to the 367 368 satellite-derived LAI LGP than those produced by ORCHIDEE. On average, ORCHIDEE gives relatively high LGP values (180±28 day), compared to ISBA-A-gs and GEOV1 369 (138±41 day and 124±44 day, respectively). The largest LGP differences between GEOV1 370 371 and ISBA-A-gs are obtained in the Iberian Peninsula and over Russia-Scandinavia, where

372 GEOV1 observes longer and shorter vegetation cycles, respectively. Figure 8 presents the 373 differences of the two LSM simulations in leaf onset dates and LGP values (in days). It 374 illustrates the overestimation of LGP in northern Europe by the two LSMs, and in other 375 regions by ORCHIDEE.

376 Figure 9 shows the simulated and observed average annual cycle of LAI for the three regions 377 indicated in Fig. 1. It appears clearly that GEOV1 tends to produce shorter growing seasons 378 than the other products, apart from the Mediterranean basin where the GEOV1 and ISBA-A-379 gs annual cycles of LAI are similar. In Russia-Scandinavia, the end of the growing period in ISBA-A-gs presents a delay of about one month. This delay is not associated to a marked 380 381 delay in the leaf onset (Fig. 6). This contradiction is related to very low LAI value of ISBA-382 A-gs at wintertime. The prescribed minimum LAI value (LAImin in Table 1) is lower than 383 the GEOV1 observations at wintertime and this bias has an impact on the leaf onset 384 calculation. If LAImin was unbiased, the maximum LAI would probably be reached earlier. On the other hand, the prescribed maximum LAI value in ORCHIDEE is higher than the 385 386 observations, especially in the Mediterranean basin. On average, the prognostic LAImin of 387 ORCHIDEE is higher than for the other products. Figure 9 shows that the ORCHIDEE delay 388 in the leaf onset over northern Europe and Russia-Scandinavia is caused by minimum LAI values reached in March (one to two months after GEOV1) and maximum LAI values 389 390 reached one month after GEOV1 (in July for northern Europe and in August for Russia-391 Scandinavia).

392 3.3 Representation of the interannual variability of LAI

In order to assess the interannual variability across seasons, 10-daily Ano_{LAI} values were put end-to-end to constitute anomaly time series for each of the three LAI products (GEOV1, ISBA-A-gs, ORCHIDEE). Figure 10 presents maps of the Pearson correlation coefficient between the simulated LAI anomalies and the observed ones. Overall, ISBA-A-gs is better

397 correlated with GEOV1 than ORCHIDEE (on average, r = 0.44 over the considered area, 398 against r = 0.35 for ORCHIDEE) and slightly better scores are obtained by the two models 399 over croplands (r = 0.48 and 0.36, respectively). Similar results are obtained considering 400 either median or mean r values. The best correlations (r > 0.6) are obtained over the Iberian 401 Peninsula, North Africa, southern Russia, and eastern Turkey. At high latitudes (northern 402 Russia-Scandinavia), the year to year changes in LAI are not represented well by the two 403 models. In these areas, the vegetation generally consists of evergreen forests presenting little 404 seasonal and interannual variability in LAI. Moreover, up to 50% of the remotely sensed 405 reflectances are missing, mainly due to the snow cover, clouds, high sun and view zenith 406 angles.

Figure 11 presents the relative interannual variability of LAI, i.e. the ACV indicator defined in Sect. 2.4.2. Figure 11 shows that ACV is generally higher for ISBA-A-gs than for GEOV1, except for Scandinavia and northern Russia. Conversely, ACV is generally lower for ORCHIDEE than for GEOV1, except for croplands of Ukraine and southern Russia. In these areas the ORCHIDEE mean annual LAI is extremely variable (ACV values close to 50% are observed), and this variability is more pronounced than in the GEOV1 observations (ACV values are generally below 25%).

414 **3.4 The 2003 drought in western Europe**

The 2003 year was marked, in Europe, by two climatic events which had a significant impact on the vegetation growth. The first one was a wintertime and springtime cold wave, which affected the growth of cereal crops in Ukraine and in southern Russia (USDA, 2003; Vetter et al., 2008). The second one was a summertime heat wave following a long Spring drought, which triggered an agricultural drought over western and central Europe (Ciais et al., 2005; Reichstein et al., 2006; Vetter et al., 2008; Vidal et al., 2010). Figure 12 shows the observed and simulated monthly *Ano*_{LAI} values from May to October 2003. Negative values correspond 422 to a LAI deficit. In May and June, the impact of the cold wave in eastern Europe is clearly 423 visible in the GEOV1 satellite observations. In the same period, the impact of the heat wave 424 appears in western and central regions of France. At summertime, the impact of drought on 425 LAI spreads towards southeastern France and central Europe and tends to gradually disappear 426 in October. The LSM LAI anomalies show patterns that match the two climatic anomalies 427 (drought in western and east-southern Europe; cold winter and spring in northern European 428 Russia) but tend to maintain the agricultural drought too long in comparison to GEOV1. The 429 Ano_{LAI} values derived from the simulations of the two models remain markedly negative in 430 October 2003, while the observations show that a recovery of the vegetation LAI has 431 occurred, especially in the Mediterranean basin area.

432 **3.5 Predictability of LAI anomalies**

- 433 Figure 13 presents the time lag for which the best correlation between SSMd and DLAI is
- 434 obtained (see Sect. 2.4.4), for the second 10-day period of May, June, and July. For a large
- 435 proportion of the cropland area (75%, 92%, 94% in May, June, July, respectively) significant
- 436 correlations (p-value < 0.01) are obtained with the model. A much lower proportion is
- 438 average time lag of the model ranges between 16 and 20 days, and the average time lag of

obtained with the satellite data (1%, 5%, 14%, respectively). For the three months, the

- 439 satellite-derived products ranges between 18 and 34 days. In April (not shown) nearly no
- 440 correlation is found with the satellite data, while 45% of the cropland area presents significant
- 441 correlation for the model, with an average time lag of 34 days.
- 442

- 443 **4 Discussion**
- 444 **4.1 Representation of soil moisture**
- 445 In the two LSMs considered in this study, soil moisture impacts the LAI seasonality and
- 446 interannual variability. The interannual variability of the simulated LAI is often driven by

447 changes in the soil moisture availability, which for the soil models of the versions of ORCHIDEE and ISBA-A-gs used in this study results from rather simple parameterizations. 448 In particular, the ability of distinct root layers to take up water and to interact with a detailed 449 soil moisture profile is not represented. Therefore, while the difficulty in representing the 450 451 modelled LAI interannual variability, as illustrated in Sects. 3.3 and 3.4, can be partly 452 explained by shortcomings in the phenology and leaf biomass parameterizations, another 453 factor is the inadequate simulation of root-zone soil moisture. For example, the difficulty in 454 simulating the vegetation recovery in the Mediterranean basin in October 2003 (Fig. 12) can 455 be explained by shortcomings in the representation of the soil moisture profile and by the fact 456 that Mediterranean vegetation is rather well adapted to drought with mechanisms of 457 'emergency' stomatal closure (Reichstein et al., 2003) that prevent leaf damage and 458 cavitation. In addition, many European tree and shrub species have deep roots and can access 459 ground water to alleviate drought stress. The soil hydrology component of the ISBA-A-gs 460 simulations performed in this study is based on the force-restore model. The root zone is 461 described as a single thick soil layer with a uniform root profile. After the drought, this 462 moisture reservoir is empty, and the first precipitation events have little impact on the bulk 463 soil moisture stress function influencing photosynthesis and plant growth. In the real world, the high root density at the top soil layer permits a more rapid response of the vegetation 464 465 growth to rainfall events. The implementation of a soil multi-layer diffusion scheme in ISBA-466 A-gs (Boone et al., 2000; Decharme et al., 2011) is expected to improve the simulation of 467 vegetation regrowth. Similar developments are performed in the ORCHIDEE model 468 following de Rosnay and Polcher (1998) and d'Orgeval et al. (2008).

Moreover, LSM simulations are affected by large uncertainties in the Maximum Available
Water Capacity (MaxAWC). The MaxAWC value depends on both soil (e.g. soil density, soil
depth) and vegetation (e.g. rooting depth, shape of the root profile, capacity to extract water

472 from the soil in dry conditions) characteristics. Calvet et al. (2012) showed over France that 473 MaxAWC drives to a large extent the interannual variability of the cereal and forage biomass 474 production simulated by ISBA-A-gs and that agricultural yield statistics can be used to 475 retrieve these MaxAWC values. It is likely that the correlation maps of Fig. 10 could be 476 improved adjusting MaxAWC. In ISBA-A-gs, LAImax is a prognostic quantity related to the 477 annual biomass production, especially for crops. Therefore, LAImax values derived from the GEOV1 LAI data could be used to retrieve MaxAWC or at least better constrain this 478 479 parameter together with additional soil characteristic information and a better soil model.

480 **4.2 Representation of LAI**

481 Apart from indirectly adjusting MaxAWC (see above), the GEOV1 LAI could help
482 improving the phenology of the two models.

483 In ISBA-A-gs, the LAImin parameter could be easily adapted to better match the 484 observations before the leaf onset. In particular LAImin is mostly underestimated over 485 grasslands (not shown). Improving the whole plant growth cycle is not easy as the ISBA-A-gs 486 phenology is driven by photosynthesis and, therefore, depends on all the factors impacting 487 photosynthesis, including the absorption of solar radiation by the vegetation canopy. For 488 example, preliminary tests using a new shortwave radiative transfer within the vegetation 489 canopy (Carrer et al., 2013) indicate that this new parameterization tends to slightly reduce 490 the LGP value (results not shown).

491 Regarding ORCHIDEE, this study revealed a number of shortcomings in the phenology 492 parameterization. The LGP values were generally overestimated (Fig. 7) and the senescence 493 model for grasses was deficient at northern latitudes, with a much too long growing season 494 ending at the beginning of the following year (Fig. 9). A new version is being developed, in 495 which the phenological parameters are optimized using both in situ and satellite observations. 496 The in situ data are derived from the FLUXNET data base (Baldocchi et al., 2008). For boreal

497 and temperate PFTs, the leaf life span parameter is systematically reduced, leading to a 498 shorter LGP (see e.g. Kuppel et al., 2012). A new phenological model for crop senescence 499 involving a GDD threshold, described in Bondeau et al. (2007) and evaluated in Maignan et 409 al. (2011), results in much shorter LGP values for crops. Finally, a temperature threshold is 409 activated in order to improve the simulation of the senescence of grasslands.

502 **4.3 Can LAI anomalies be anticipated using SSM ?**

The biomass accumulated at a given date is the result of past carbon uptake through 503 504 photosynthesis, and in water-limited regions it depends on past soil moisture conditions. For 505 example, using the ISBA-A-gs model over the Puy-de-Dôme area in the centre of France, Calvet et al. (2012) found a very good squared correlation coefficient values ($r^2=0.64$) 506 507 between the simulated root-zone soil moisture in May (July) and the simulated annual cereal 508 (managed grassland) biomass production. To some extent, SSM can be used as a proxy for 509 soil moisture available for plant transpiration and LAI can be used as a proxy for biomass. In 510 water-limited areas, the annual biomass production of rainfed crops and natural vegetation 511 depends on soil moisture (among other factors) at critical periods on the year.

512 Figure 13The differences in predictability of LAI shown in Fig. 13 may be due to 513 shortcomings in both observations and simulations. Significant correlations with the satellite 514 data are only observed in homogeneous cropland plains, such as in southern Russia, 515 especially in July. The accuracy of satellite-derived LAI and SSM products is affected by 516 heterogeneities and by topography. This may explain why the synergy between the two 517 variables only appears in rather uniform landscapes, while the modelled variables are more 518 easily comparable in various conditions. The ISBA-A-gs simulations present weaknesses 519 related to the representation of the soil moisture profile (Sect. 4.1). In particular, the force-520 restore representation of SSM tends to enhance the coupling between SSM and the root-zone 521 soil moisture (end hence to LAI through the plant water stress). Parrens et al. (2014) showed that the decoupling between the surface soil layers and the deepest layers in dry conditions can be simulated using a multilayer soil model. Apart from these uncertainties, the main reason of the differences in predictability of LAI is probably that the satellite-derived LAI and SSM are completely independent while deterministic interactions between the two variables are simulated by the model.

527 **4.4 From benchmarking to data assimilation**

528 The direct validation of long time series of satellite-derived ECV products is not easy, as in 529 situ observations are limited in space and time (Dorigo et al., 2014). Therefore, indirect 530 validation based on the comparison with independent products (e.g. products derived from 531 model simulations) has a key role to play (Albergel et al., 2013a). In this study, the new ESA-532 CCI SSM product and the new GEOV1 LAI product were compared with LSM simulations. 533 Hindcast simulations can be used to validate satellite-derived ECV products (Sect. 3.1) and 534 conversely, the latter can be used to detect problems in the models (Sect. 4.2). The results presented in Sect. 3.1 suggest that SSM simulations could be used to improve the blending of 535 536 the active and passive microwave products. The most advanced indirect validation technique 537 consists in integrating the products into a LSM using a data assimilation scheme. The 538 obtained reanalysis accounts for the synergies of the various upstream products and provides statistics which can be used to monitor the quality of the assimilated observations. Barbu et 539 540 al. (2011, 2014) have developed a Land Data Assimilation System over France (LDAS-541 France) using the multi-patch ISBA-A-gs LSM and a simplified extended Kalman filter. The 542 LDAS-France assimilates GEOV1 data together with ASCAT SSM estimates and accounts 543 for the synergies of the two upstream products. While the main objective of LDAS-France is 544 to reduce the model uncertainties, the obtained reanalysis provides statistics which can be 545 used to monitor the quality of the assimilated observations. The long-term LDAS statistics 546 can be analyzed in order to detect possible drifts in the quality of the products: innovations (observations vs. model forecast), residuals (observations vs. analysis), and increments
(analysis vs. model forecast). This use of data assimilation techniques is facilitated by the
flexibility of the vegetation-growth model of ISBA-A-gs, which is entirely photosynthesisdriven.

551 In contrast to ISBA-A-gs, ORCHIDEE uses phenological models for leaf onset and leaf offset 552 and the LAI cannot be easily updated with observations. Instead, Carbon Cycle Data Assimilation System (CCDAS) can be used to retrieve model parameters (Kaminski et al., 553 554 2012 ; Kato et al., 2013). Using this technique, Kuppel et al. (2012) have assimilated eddycorrelation flux measurements in ORCHIDEE at 12 temperate deciduous broadleaf sites. 555 556 Before the assimilation, the model systematically overestimates LGP (by up to one month). 557 The model inversion produces new values of three key parameters of the phenology model 558 and shorter LGP values are obtained.

559

560 **5 Conclusions**

561 For the first time, the variability in time and space of LAI and SSM derived from new 562 harmonized satellite-derived products (GEOV1 and ESA-CCI soil moisture, respectively) 563 was analyzed over the Euro-Mediterranean area for a 18-yr period (1991-2008), using detrended time series. The explicit simulation of SSM by the ISBA-A-gs LSM permitted 564 565 evaluating the seasonal and the day-to-day variability of the ESA-CCI SSM. The comparison 566 generally showed a good agreement between the observed and the simulated SSM, and 567 highlighted the regions where the ESA-CCI product could be improved by revising the procedure for blending the active and passive microwave products. ORCHIDEE and ISBA-568 569 A-gs were used to assess the seasonal and interannual vegetation phenology derived from 570 GEOV1. It appeared that the GEOV1 LAI product is not affected much by saturation and was able to generate a realistic phenology. It was shown that GEOV1 can be used to detect 571

572 shortcomings in the LSMs. In general, the ISBA-A-gs LAI agreed better with GEOV1 than 573 the ORCHIDEE LAI, for a number of metrics considered in this study: LGP, 10-daily Ano_{LAI}, 574 ACV. In contrast to ORCHIDEE, the ISBA-A-gs plant phenology is entirely driven by 575 photosynthesis and no degree-day phenology model is used. The advantage is that all the 576 atmospheric variables influence LAI through photosynthesis. Also, the regional differences 577 between ISBA-A-gs and the GEOV1 LAI can be handled through sequential data assimilation 578 techniques able to integrate satellite-derived products into LSM simulations (Barbu et al., 579 2014). As shown in the latter study, though the main purpose of data assimilation is to 580 improve the model simulations, the difference between the simulated and the observed LAI 581 and SSM can be used as a metric to monitor the quality of the observed time series. On the 582 other hand, ISBA-A-gs is very sensitive to errors in the atmospheric variables, and bias-583 corrected atmospheric variables must be used (Szczypta et al., 2011).

Finally, the use of SSM to predict LAI 10 to 30 days ahead was evaluated over cropland areas. Under certain conditions, the harmonized LAI and SSM observations used in this study present consistent results over croplands, and SSM anomalies can be used to some extent to predict LAI anomalies over uniform cropland regions. The combined use of satellite-derived products and models could help improve the characterisation of agricultural droughts.

589

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2007.

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- 954 Table 1 Summary of the characteristics of the ORCHIDEE 1.9.5.1 tag and ISBA-A-gs
- 955 SURFEXv6.2 configurations used in this study.

Biogeophysical process	ORCHIDEE	ISBA-A-gs
Photosynthesis	 Farquhar et al. (1980) for C3 plants, Collatz et al. (1992) for C4 plants 	Goudriaan et al. (1985), modified by Jacobs et al. (1996) ; same model for both C3 and C4 plants but specific parameter values
Main parameter of photosynthesis	Maximum carboxylation rate (<i>V</i> c,max)	Mesophyll conductance (<i>g</i> _m)
Impact of drought on photosynthesis parameters (response to root-zone soil moisture)	Linear response of <i>V</i> c,max (McMurtrie et al., 1990)	- Log response of g_m - Linear response of the maximun saturation deficit for herbaceous vegetation (Calvet, 2000) - Linear response of the scaled maximum intercellular CO ₂ concentration for woody vegetation (Calvet et al., 2004) - Drought-avoiding response for C3 crops, needleleaf forests - Drought-tolerant response for C4 crops, grasslands, broadleaf forests
Soil moisture profile	No explicit representation of SSM ; two-layer soil model ; the depth of the layers evolves through time in response to "top-to-bottom" filling due to precipitation and drying due to evapotranspiration (Ducoudré et al., 1993)	Explicit representation of SSM (0-1 cm top soil layer) ; three- layer force-restore model (Boone et al., 1999 ; Deardoff, 1977, 1978)
Phenology	 LAImax is prescribed LAImin is prognostic Growing degree days (Leaf onset model was trained using satellite NDVI data (Botta et al., 2000)) 	 LAImax is prognostic LAImin is prescribed Photosynthesis-driven plant growth and mortality





Figure 1: The Euro-Mediterranean area (11°W - 62°E, 25°N - 75°N) considered in this study







964Figure 2: Dominant vegetation type (either grasslands, crops, or forests) over the 8142 land965grid-cells $(0.5^{\circ} \times 0.5^{\circ})$ considered in this study, derived from the 1 km ECOCLIMAP-II data966base.



971 Figure 3: Comparison between the detrended ESA-CCI SSM and the detrended SSM
972 simulated by ISBA-A-gs over the 1991-2008 period: Pearson correlation coefficient for (left)
973 absolute values, (right) scaled anomalies (Eq. (1)). White areas over land correspond to *r*974 values lower (higher) than 0.1 (-0.1).



977 Figure 4: Same as Fig. 3, except for the 2003-2008 period and (top) ESA-CCI vs. ISBA-A-

978 gs, (bottom) AMSR-E vs. ISBA-A-gs.





Figure 5: Detrended SSM ESA-CCI vs. AMSR-E, (left panel) absolute and (right panel) anomaly squared correlation coefficients (r^2) with the detrended ISBA-A-gs SSM, over the 2003-2008 period. Note that r^2 values are plotted for grid cells corresponding to positive rvalues, only.

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Figure 6: Mean simulated leaf onset values derived from the (top) GEOV1 LAI satellitederived product and (middle) ISBA-A-gs LAI, and (bottom) ORCHIDEE LAI. The period
used to produced the mean vegetation annual cycle is 1991-2008 for the three data sets.















Figure 9: Mean monthly values of the ISBA-A-gs and ORCHIDEE LAI simulations, and
GEOV1 LAI observations over the 1991-2008 period, for the three sub-regions of Fig. 1
(from left to right: Mediterranean basin, northern Europe, and Russia-Scandinavia).







Figure 10: Pearson correlation coefficient (*r*) between the scaled LAI 10-daily anomalies
derived from detrended simulations (left, ISBA-A-gs ; right, ORCHIDEE) and detrended
GEOV1 satellite observations, over the 1991-2008 period, at grid cells presenting significant
positive correlations (p-value < 0.01).



1017 Figure 11: Annual Coefficient of Variation (ACV) of LAI over the 1991-2008 period (left,

- 1018 GEOV1 ; middle, ISBA-A-gs ; right, ORCHIDEE).



1024 **Figure 12:** Scaled LAI monthly anomalies from May to October 2003. From top to bottom:

1025 GEOV1 satellite observations, detrended ISBA-A-gs and ORCHIDEE simulations. Units are

1026 dimensionless and correspond to standard deviations.



1029Figure 13:Predictability of LAI 10-daily differences from SSM over croplands from May to1030July, based on detrended (top) ISBA-A-gs simulations and (bottom) satellite-derived products1031(GEOV1 LAI and ESA-CCI SSM). The colour dots correspond to four time lags providing1032the highest squared coefficient correlation (r^2) for the predicted LAI anomaly over the 1991-10332008 period. The results are given for the second 10-day period of each month at grid cells1034presenting significant LAI anomaly estimates (p-value < 0.01).</td>