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The performance of Metop Advanced SCATterometer soil moisture data as a complementary source for the estimation of crop-soil water balance in Central Europe

S. Thaler[1], J. Eitzinger[1,2], M. Trnka[2,3], M. Možný[4], S. Hahn[5], W. Wagner[5] and P. Hlavinka[2,3]

[1]Institute of Meteorology, University of Natural Resources and Life Sciences (BOKU), Gregor-Mendl-Straße 33, 1180 Vienna, Austria; [2]CzechGlobe – Global Change Research Institute CAS, Belidla 986, 4a, 603 00 Brno, Czech Republic; [3]Institute of Agrosystems and Bioclimatology, Mendel University in Brno, Zemědělská 1, Brno 613 00, Czech Republic; [4]Doksany Observatory, Climatology Section, Czech Hydrometeorological Institute, 411 82 Doksany, Czech Republic and [5]Department of Geodesy and Geoinformation, Vienna University of Technology (TU Wien), Gußhausstraße 27-29, 1040 Vienna, Austria

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Author for correspondence: S. Thaler, E-mail: Sabina.Thaler@boku.ac.at

Abstract

Simulation of the water balance in cropping systems is an essential tool, not only to monitor water status and determine drought but also to find ways in which soil water and irrigation water can be used more efficiently. However, besides the requirement that models are physically correct, the spatial representativeness of input data and, in particular, accurate precipitation data remain a challenge. In recent years, satellite-based soil moisture products have become an important data source for soil wetness information at various spatial-temporal scales. Four different study areas in the Czech Republic and Austria were selected representing Central European soil and climatic conditions. The performance of soil water content outputs from two different crop-water balance models and the Metop Advanced SCATterometer (ASCAT) soil moisture product was tested with field measurements from 2007 to 2011. The model output for soil water content shows that the crop model Decision Support System for Agrotechnology Transfer performs well during dry periods (<30% plant available soil moisture (ASM), whereas the soil water-balance model SoilClim presents the best results in humid months (>60% ASM). Moreover, the model performance is best in the early growing season and decreases later in the season due to biases in simulated crop-related above-ground biomass compared with the relatively stable grass canopy of the measurement sites. The Metop ASCAT soil moisture product, which presents a spatial average of soil surface moisture, shows the best performance under medium soil wetness conditions (30–50% ASM), which is related to low variation in precipitation frequency and under conditions of low-surface biomass (early vegetation season).

Introduction

Soil water content is one of the key resources in crop production and is influenced by climate, soil and hydrological conditions as well as vegetation (Saue & Kadaja 2014). Rainfall, irrigation and the capillary rise of groundwater towards the root zone contribute towards crop available water. Soil evaporation, crop transpiration, runoff and percolation losses remove water from the crop stand and increases depletion of available soil water (Allen *et al.* 1998). Under semi-arid conditions, as in many Central European regions, insufficient soil moisture during the vegetation period is a major cause of crop yield reduction or even crop failure. Plants suffer water stress when root zone water supply fails to meet the evapotranspiration demand (Saseendran *et al.* 2015), resulting in a reduction in crop yield quantity and quality. Plant water demand depends on multiple factors, such as genetic characteristics of the specific plant, its stage of growth, accumulated biomass and leaf area, prevailing weather conditions, crop management and soil characteristics (Sastri 1993; Wilhite 1993; Mebane *et al.* 2013).

Knowledge of soil water balance characteristics in cropping systems can help to determine actual crop available water in the root zone and to design effective management strategies to use and conserve soil water (Aydin 2008). With this aim, many modelling concepts have been developed in recent decades to simulate soil and crop water balance processes (Allen *et al.* 1998; White *et al.* 2011). Soil water balance models range from functional, such as the tipping bucket systems models, to mechanistic, which contain models such as those based on Darcy (1856) or Richards' equation (1941; Addiscott & Wagenet 1985). Depending on the degree of simplifications implemented, these models require a number of empirical assumptions to represent the extremely large degree of non-linearity and space-time variability of water

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dynamics in the soil (Porporato *et al.* 2004). The numerous physical processes considered in soil water balance models include water infiltration from rainfall or irrigation, redistribution of infiltrated water in the soil water zone, plant water uptake (mainly in the form of actual evapotranspiration) and percolation out of the soil reservoir. Most of these processes can be described by more or less physically based models of water transport in the soil-plant-root system. Independent of their physical sophistication, they are all based on assumptions (i.e. not considered or unknown specific processes, determining factors of soil water balance) and require field data for estimation and calibration of model parameters (Panigrahi & Panda 2003). Despite this, soil water balance models are useful tools for agro-ecological analyses and practical applications. One of the main uses of soil water balance models is an indication of drought for irrigation scheduling, i.e. procedures determining the timing and amount of crop irrigation requirements (Linker *et al.* 2016). Also under rainfed schemes, these models are powerful tools to predict crop response under different climatic and management scenarios (Campos *et al.* 2016). In addition, models and information about the available supply of soil moisture are of great importance in the context of early warning systems and can optionally be used in dealing with compensation to farmers in cases of extreme event (e.g. drought, moisture surplus) impacts (Možný *et al.* 2012).

However, one must consider uncertainties, which are involved in model applications, as for example caused by incomplete knowledge of the processes and inputs involved for a specific crop and crop environment (Eitzinger *et al.* 2008, 2013*a*). Another main driver for the uncertainty in model outputs are climate, soil and management input data (Bouman 1994; Nonhebel 1994; Pachepsky & Acock 1998; Soltani *et al.* 2004; Masutomi *et al.* 2009). In addition, crop models are sensitive to the variability and spatial scale of the weather data inputs (Semenov & Porter 1995; Mearns *et al.* 1997; Tatsumi *et al.* 2011).

Comparing model results with field observations or intercomparison of different types of model provide information on the performance of the models and reveal their strengths and weaknesses, as several studies in Europe and worldwide have shown (Palosuo *et al.* 2011; Rötter *et al.* 2012; Eitzinger *et al.* 2013*a*; Kollas *et al.* 2015; Battisti *et al.* 2017; Huang *et al.* 2017). This is important in selecting appropriate models for practical applications in water management and helps to validate whether or not a model is better at representing soil water content in comparison with the given soil water measurements.

While in the past plant available water was estimated exclusively by *in situ* measurements or model simulations, in recent years remote sensing has played an increasingly important role in receiving spatial information on soil surface conditions (Martínez-Fernández *et al.* 2016). Several satellite soil moisture products are available from microwave, optical and thermal sensors (Brocca *et al.* 2017). The current study focuses only on active and passive microwave-based products, in particular on the Advanced SCATterometer (ASCAT) soil moisture product. Active radar sensors provide measurements independent of atmospheric conditions and derive important characteristics about the earth's surface, such as surface soil wetness. This is supported by the fact that such satellite products can be acquired day and night, penetrate the vegetation canopy and obtain information about the first few centimetres of the ground below the surface (Wagner *et al.* 2013). By observing the different dielectric responses of wet and dry soil, satellite-based estimates of surface soil moisture (SSM) can be performed using, e.g. measurements from European Remote Sensing satellites 1 and 2 (ERS-1/2) and Metop ASCAT. It should be borne in mind, however, that one limit of remote sensing soil moisture data is that it provides information to a depth of only a few centimetres below the surface.

Reliable estimates of evapotranspiration, water balance and soil water content, with regard to their proper temporal and spatial representativeness, are crucially important when soil-vegetation-atmosphere models are applied. Therefore, any water balance calculations should be tested prior to application at different sites and environments. The main objective of the current study was to assess the quality of two process-based models of different complexity and the Metop ASCAT soil moisture product, as a complementary source for near SSM information, in comparison with field measurements at four sites across a climatic gradient representing rain-fed agriculture of Central Europe. The crop growth model Decision Support System for Agrotechnology Transfer (DSSAT; Jones *et al.* 2001, 2003) and the soil water balance model SoilClim (Hlavinka *et al.* 2011) were used to compare model outputs with field measurements of soil moisture within the 0–40 cm layer, the main root zone of the plant.

Materials and methods

Study sites and the incidence of land cover types on Advanced SCATterometer grid

For the purposes of the study, three locations in the Czech Republic (Doksany 50°27′N, 14°10′E, 158 m a.s.l.; Dyjákovice 48°46′N, 16°18′ E, 185 m a.s.l.; Kroměříž 49°17′N, 17°23′E, 201 m a.s.l.) and one location in Austria (Groß-Enzersdorf 48° 12′N, 16°33′E, 157 m a.s.l.) were chosen (Fig. 1). The area comprising these locations is influenced by a continental-type climate, where winters are usually cold, with frequent strong frosts and limited snow cover, and summers are hot and periodically dry (Table 1). The four locations were situated in the middle of the ASCAT pixel (Fig. 2).

Corine Land Cover data 2006 and 2012 (http://land.copernicus.eu/pan-european/corine-land-cover) were used for assessing land cover within the ASCAT pixel. These data revealed that land use of the four ASCAT grids were characterized by mainly agricultural land use, to similar extents (0.70–0.90), which was also mostly non-irrigated arable land (Doksany = 0.87; Dyjákovice = 0.89; Kroměříž = 0.93; Groß-Enzersdorf = 0.93 of arable land). From further statistical reports of the larger region representing Groß-Enzersdorf, around 0.25 were covered by summer crops (such as maize) and 0.75 by winter crops (such as cereals). The highest acreage of artificial surfaces among all four study site grids was visible in Groß-Enzersdorf with around 0.14, including also some Vienna suburbs. Kroměříž was characterized by a higher acreage of forest and semi-natural areas (0.18). Water bodies occupied only small areas from 0.0 (Dyjákovice) to 0.02 (Doksany and Groß-Enzersdorf) of the grid land cover (Fig. 2).

Soil moisture measurement

All three Czech sites were part of the soil moisture measurement network of climatological stations, which monitor soil moisture content at the 0–0.1 m, 0.1–0.5 m and 0.5–0.9 m layers using sensors placed within the natural soil profile under short grass cover (Možný *et al.* 2012). The stations use three sensors, one horizontal and two vertical. A detailed pedological survey to determine the

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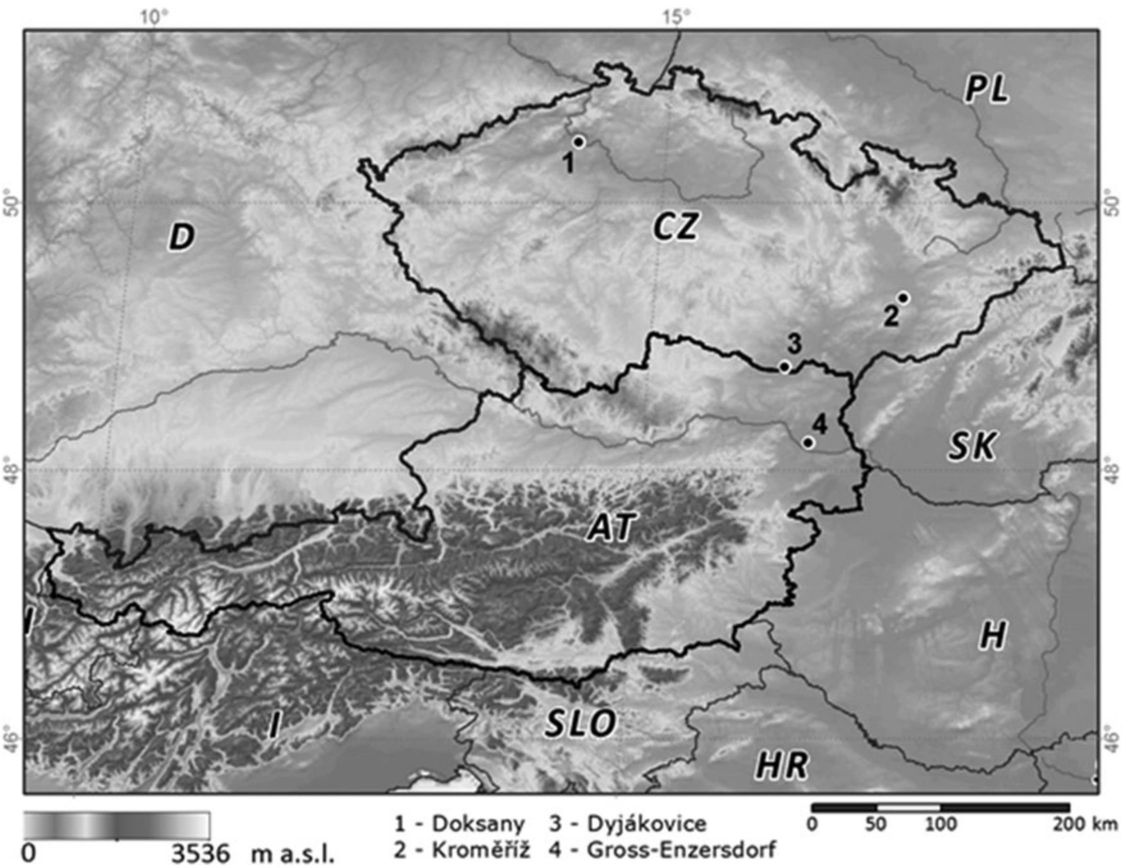

Fig. 1. General map of the four study locations Doksany, Kroměříž, Dyjákovice and Groß-Enzersdorf.

wilting point (lower limit of plant extractable soil water = LL) and field capacity (drained upper limit = DUL) was carried out for all layers (Kirkham 2014). Sensors were first installed at the Doksany station in 1991. Since 1998, the measurement system has also been introduced at other stations. The original measurements using VIRRIB sensors (www.amet.cz) had been gradually replaced by the more accurate TRIFO3G sensors (www.asconsult.cz). Both sensors use the dielectric method to measure soil moisture (Topp *et al.* 1980). TRIFO3G sensors featured a high-quality three-rod probe for permanent use in different soils. The standard length of the 100% stainless steel probe is 0.4 m. TRIFO3G sensors have an accuracy of ±1% for volumetric soil moisture measurements under controlled laboratory conditions and are factory-calibrated for most agricultural soils. Measurements can be carried out in both extreme clay soils and sandy soils.

The soil water content measurement for Austrian arable soil was taken from an agrometeorological station of a representative site near Groß-Enzersdorf, where the atmospheric model input parameters were measured. The Campbell Scientific CS615 water content reflectometer (Campbell Scientific Inc. 1995) was used to measure the volumetric water content from 0 to 30 cm soil depth under a natural grass canopy. All measured data used are based on 10-min measurement intervals.

The four stations measured volumetric soil water content at different soil depths under short grass cover. The daily mean soil water content at 0–40 cm in the three Czech Sites and 0–30 cm in Groß-Enzersdorf was used to calculate plant available soil moisture (ASM). Plant ASM data were derived from the history of measurements: long-term reasonable minimum was used as the lower limit (i.e. wilting point) and maximum as the upper limit (i.e. field capacity). The result was given as an ASM percentage (%), where the wilting point of soil represented a value of 0% and field capacity corresponded to 100%. In the case of Kroměříž station, observed soil water content was missing for the period from March to 9 June 2010 due to technical problems with measurements and for Groß-Enzersdorf these data were only available from 2007 until 2010. The set of stations included within the study was selected after careful consideration. For this reason, the winter periods were omitted from the analysis, because of problems due to soil water often appearing in the form of ice.

Models for simulating soil-crop water balance applied

Two diverse model approaches were applied, differing in the complexity of simulated processes of crop growth and soil-water balance processes.

(i) Decision Support System for Agrotechnology Transfer is a software application program, which comprises crop simulation models for over 40 crops. They are process-based, management-oriented models, which simulate the daily time-step effects for instance of the cultivar, crop management, weather, soil, water and nitrogen on crop growth, phenology and yield (Jones *et al.* 2001, 2003). The CERES and CSM-CROPGRO models are part of the DSSAT (v4.0.2.0) software (Jones *et al.* 2003). In the current study, CERES-Barley (Otter-Nacke *et al.* 1991) and CERES-Maize (Jones &

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Table 1. Mean annual temperature and precipitation sum (1981–2010) of Groß-Enzersdorf, Doksany, Dyjákovice and Kroměříž as well as the soil water characteristics (up to 1 m soil depth) and area percentage of the different soil classes in Austrian (AUT_soil) and Czech sites (CZ_soil)

	Austria				Czech Republic					
				Groß-Enzersdorf				Doksany	Dyjákovice	Kroměříž
Mean annual temperature (1981–2010)				10.3 °C				9.5 °C	9.9 °C	9.4 °C
Mean precipitation sum (1981–2010)				516 mm				466 mm	500 mm	573 mm
Soil classes	LL	DUL	SAT	Area percentage (%)	LL	DUL	SAT	Area percentage (%)	Area percentage (%)	Area percentage (%)
AUT_soil 1	0.04	0.09	0.14	1.9						
AUT_soil 2	0.11	0.23	0.29	14.7						
AUT_soil 3	0.21	0.4	0.48	61.3						
AUT_soil 4	0.17	0.4	0.47	22.1						
CZ_soil 1					0.12	0.37	0.43	3.9	10.8	32.2
CZ_soil 2					0.13	0.36	0.42	46.8	28.2	52.6
CZ_soil 3					0.14	0.34	0.40	1.8	6.9	8.3
CZ_soil 4					0.16	0.33	0.39	21.1	26.5	1
CZ_soil 5					0.14	0.29	0.42	5.1	0.7	0
CZ_soil 6					0.15	0.27	0.40	20	26.2	1
CZ_soil 7					0.08	0.19	0.40	0.6	0	0.3
CZ_soil 8					0.09	0.18	0.38	0.4	0.7	4.5
CZ_soil 9					0.13	0.20	0.30	0	0.2	0.3
CZ_soil 10					0.06	0.11	0.26	0.2	0	0

LL, lower limit of plant extractable soil water; DUL, drained upper limit; SAT, saturated soil water content.

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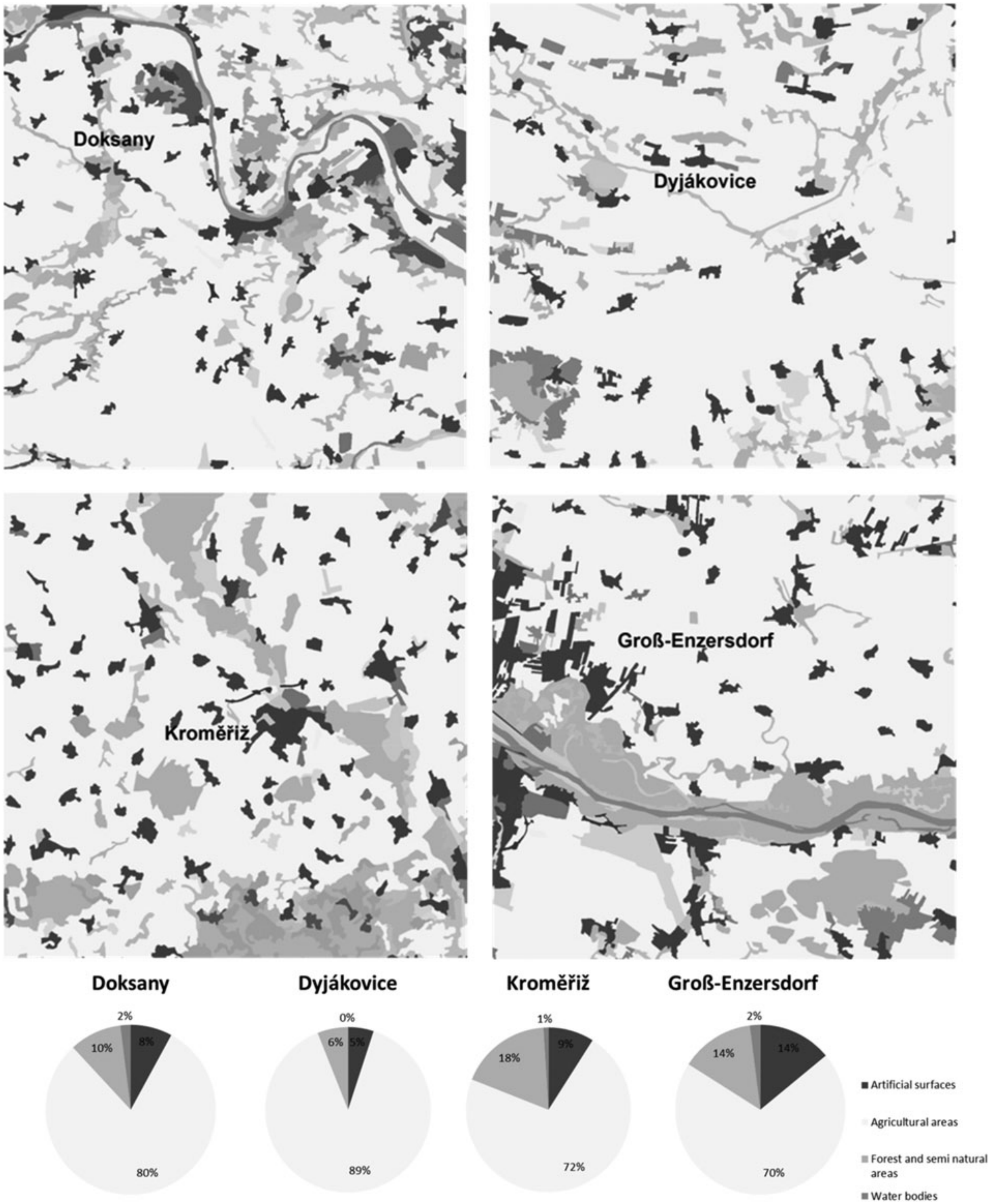

Fig. 2. Corine map 2012 and the land use acreages (in %) according to the Corine Land Cover data 2006 and 2012 of the four investigated grid areas representing years 2007–2011.

Kiniry 1986) were examined. The one-dimensional soil water balance model in DSSAT was developed by Ritchie & Otter (1985; Jones & Ritchie 1991; Jones 1993; Ritchie 1998) and computed the daily change in soil water content by soil layer due to infiltration of rainfall and irrigation, vertical drainage, unsaturated flow, soil evaporation and root water uptake processes. Soil evaporation, plant transpiration and root water uptake processes were separated out in the new DSSAT-CMS into a soil-plant-atmosphere module to create more flexibility for expanding and maintaining the model. Water content varied between LL, DUL and the saturated soil water content (SAT) in each soil layer. Once the water content of a given layer was above DUL, water was drained to the next layer with the 'tipping bucket' approach, a profile-

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wide drainage coefficient. If available, saturated hydraulic conductivity (K_{sat}) for water flow of each specific soil layer could be added to control vertical drainage from one layer to the next. This feature permitted soil to retain water above the DUL for layers that had sufficiently low K_{sat} for water flow. In that case, soil layers may become saturated for sufficient time to cause root death, reduced root water uptake, anoxia-induced stress and decreased nitrogen (N) fixation. Water between SAT and DUL was available for root uptake subject to the anoxia-induced problem, which was triggered when air-filled pore space fell below 2% of total volumetric pore space (Boote *et al.* 2008). Soil water infiltration was the difference between precipitation and surface runoff, which was calculated using the soil conservation service (SCS) method (Soil Conservation Service 1972). In addition, the model included a modification to the SCS-curve number (SCS-CN) method by Williams *et al.* (1984), which compensated for soil layers and also for initial soil water content at the time of precipitation. Irrigation was supposed as an additive component of total precipitation (Jones *et al.* 2003).

The soil-plant-atmosphere module calculated evaporation of water from the soil surface and root water uptake (transpiration) from each layer and communicated this to the soil water balance module. Each day, the soil water content of each layer was updated by adding or subtracting daily water flows to or from the layer as a result of each process (Hoogenboom *et al.* 2003).

(ii) The SoilClim model (Hlavinka *et al.* 2011) was specifically designed and validated to describe soil moisture and soil temperature. The key water balance components of SoilClim are based on a modification of the concept and model formulation in FAO Irrigation and Drainage paper No. 56 (Allen *et al.* 1998), including the Penman-Monteith approach for reference evapotranspiration estimates. SoilClim considered dynamically simulated vegetation cover development, from which crop coefficients (K_c) for estimates of soil evaporation (in case of bare soil) and crop evapotranspiration (after crop emergence) were derived. In addition, changes in root depth, crop height and leaf area index (LAI) and its effect were also assumed. The soil profile was divided into two layers of 0–40 cm and 40–100 cm depth. Also, in this case, the 'tipping bucket' approach was used to estimate soil water content and actual evapotranspiration as a function of water availability. It also considered snow cover effect through the SnowMAUS module (Trnka *et al.* 2010), proportional runoff in case of precipitation above a certain threshold and partial percolation (simplified imitation of macropore flow), but did not account for a capillary rise from deeper layers. Compared with the crop models, it did not account for the lasting effect of drought on the canopy (in principle, the LAI was not reduced as a result of water stress) and it estimated only LAI value, not the total above-ground biomass. Therefore, the crop component and, in particular, negative feedback between drought intensity and biomass development was greatly simplified (Hlavinka *et al.* 2011).

Metop Advanced SCATterometer soil moisture

ASCAT is a real-aperture radar onboard the series of Metop satellites. Two Metop satellites are currently operational in the same sun-synchronous orbit (Metop-A since 2006 and Metop-B since 2012), separated by 50 min. The launch of a third and final Metop satellite (Metop-C) is planned in 2018. The ASCAT instrument measures the Normalized Radar Cross Section (NRCS), also called backscatter, at C-band (5.255 GHz) in vertical polarization (VV) (Figa-Saldaña *et al.* 2002). The spatial resolution of the ASCAT Level 1b backscatter products is either 25–34 km or 50 km, depending on the filter size used to average the Level 1b full resolution product. The revisit time for central Europe is usually once or twice a day for one Metop satellite. The SSM product was retrieved from the backscatter measurements, using a time series-based change detection approach initially developed for the ERS-1/2 scatterometers by Wagner *et al.* (1999). A new inter-annual vegetation correction has been used in the soil moisture retrieval algorithm, which deviates from the original formulation using climatology in order to account for seasonal vegetation biases. This new feature and other improvements are planned for implementation in the official Metop ASCAT soil moisture products generated and distributed by the Satellite Application Facility on Support to Operational Hydrology and Water Management (H SAF, http://hsaf.meteoam.it) project in the near future. The derived SSM product had a spatial resolution of 25–34 km and corresponded to a depth of 2–3 cm. The soil moisture information was defined by the degree of saturation ranging from 0% (dry, corresponds to a wilting point) to 100% (wet, corresponds to saturated soil water content). In order to obtain soil moisture at deeper soil layers from remotely sensed SSM products, the so-called soil water index (SWI) can be computed. The soils in the study areas were mainly medium soil types according to their soil water storage capacity and did not vary much. The SWI attempted to estimate root-zone soil moisture using an exponential filter approach proposed by Wagner *et al.* (1999) based on a two-layer water balance model. The computation of SWI depended only on a single parameter, the characteristic time *T*, defined in days. This related to infiltration time and characterized the temporal variation of soil moisture in the root-zone profile. However, *T* could not be related to a certain depth, since the infiltration rate depended on various soil properties. An appropriate *T* value needed to be empirically defined depending on the study area and application. In the current study, SWI was computed using $T = 2$ days (ASCAT SWI T2), which gave a good compromise between high-frequency components from precipitation events and root-zone changes. There could be a certain absolute bias related to the applied soil water capacity; however, relative trend changes should still be well represented, which was the focus of the comparison. The impact of spatial variability of precipitation on soil water balance was normally higher relative to the soil impact during summer in the case study region. An attempt to assess the quality of ASCAT SWI using *in situ* data from the International Soil Moisture Network had shown good agreement (Paulik *et al.* 2014), giving confidence in the root-zone representativeness of SWI. This approach is simple, but no study has yet shown that advanced approaches give superior results that would justify the added complexity of the approach (Manfreda *et al.* 2014). In addition, more and more researchers are attempting to relate profile and SSM directly with statistical methods such as neural networks. These methods also work quite well despite being, in practice, as simple as the SWI.

Data processing

The time period considered in the current study for comparison of the different approaches of soil water content determination ranged from 2007 until 2011. For the evaluation, only the months

March to September were used. Maize and spring barley crops were simulated in daily steps with the CERES models, while SoilClim simulated grass, maize and spring barley, also daily. The different plants were simulated on the one hand to cover the whole growing season with crops (spring barley and maize) and on the other hand to achieve a plant diversity representative of the region. The growing season for spring barley was from March until July, and for maize was from May until September/October. The DSSAT simulations included only the period of sowing until maturity, whereas SoilClim simulations covered the whole year; both models started their simulations one day before a predefined sowing date (see below).

The model input requirements included weather and soil conditions, plant characteristics and crop management (Hunt *et al.* 2001). Weather input data were obtained from the weather stations Doksany (CZ), Dyjákovice (CZ) and Kroměříž (CZ), provided by the Czech Hydrometeorological Institute, as well as Groß-Enzersdorf (A), available from the Austrian Met Service (ZAMG) (Fig. 1). The data contained daily maximum and minimum temperature, solar radiation, precipitation, wind speed and air humidity for the period 2007–2011.

Ten soil classes according to available water capacity were applied to the Czech sites Doksany, Dyjákovice and Kroměříž and four at the Austrian site Groß-Enzersdorf in Marchfeld (Table 1) (Thaler *et al.* 2012, 2017). The relative ASM for the first soil layer of 0–40 cm depth was used to calculate an area-weighted average of the region, forming the basis for soil moisture comparisons. ASM was derived from the soil classes and finally, the model results for each soil profile were recalculated/averaged based on spatial representation.

To validate the two CERES models, simulated outcomes were compared with measured results obtained from field trials. The CERES barley model for spring barley was calibrated for the cultivar 'Magda' using agrotechnological, phenological, yield and weather data from an experimental site at Fuchsenbigl, Marchfeld (48°12′N, 16°44′E, 157 m a.s.l.) for the periods 1989–95, 1998 and 2001/02. The discrepancy between simulated and observed dates of anthesis and physiological maturity varied from 0 to 7 days, and the simulated yield was within 20% of the measured values for each year ($R^2 = 0.57$, $RMSE = 623$ kg/ha) (Eitzinger *et al.* 2013*b*). The CERES-maize model was calibrated in the same way and verified for the periods 1998–1999 and 2001–2002 using data for the cultivar 'Parzival'. The difference between simulated and observed dates of maize anthesis for calibration varied from 0 to 4 days. Simulated grain yields mostly agreed with the measured data ($R^2 = 0.93$, $RMSE =$ 153 kg/ha) and the deviation in annual yield predictions was <20%.

SoilClim was not calibrated using any specific cultivars because the real representation of cultivars within individual regions was unknown. Spring barley, maize and grass parameters were based on calibrations described in Hlavinka *et al.* (2011). For grass, the cover was approximated not directly to certain species but for typical regularly cut cover from meteorological stations. This calibration was based on Allen *et al.* (1998) and soil moisture measurements from four stations in Central Europe and 14 stations in the USA (Hlavinka *et al.* 2011).

All simulations were conducted for rain-fed farming conditions for spring barley, maize and grass, respectively. The sowing date was calculated with predefined temperature sums from 1 January: a temperature sum of 80 °C was used as sowing date for spring barley and 520 °C for maize (temperature base 0 °C). This approach was selected since there were no experiments that would appropriately represent the conditions through the all selected regions and included years. Further initial conditions of soil water content according to measured values on grassland sites one day before sowing were added in both models. For spring barley, grass can be used as a good reference, because grass is not actively growing earlier at the case study site after the winter period when barley is sown, and thus the water balance after the dormant winter period should be very similar. Maize is sown about 4–6 weeks later where grass is already growing, having additional water use as compared with bare soil. The difference in evaporation of short grass compared with bare soil is, however, relatively small (K_c factor about 0.2 *v.* 0.4) and the uncertainty from, e.g. spatial precipitation variability in comparison with the other scales applied can be much higher. The relatively small error coming from this assumption is therefore limited. Spring barley was fertilized with 40 kg N/ha, 25 kg phosphorus (P)/ha and 170 kg potassium (K)/ha at tillering (growth stage (GS) 21–23, Zadoks *et al.* 1974) and 40 kg N/ha at stem elongation or jointing (GS 31–33), the amount that farmers currently use in these areas. Maize simulated fertilization of 80 kg N/ha, 39 kg P/ha, 166 K/ha at tillering (GS 21–23) and 55 kg N/ha at stem elongation or jointing (GS 31–33).

Methods used for evaluating and comparing model performance

The DSSAT crop growth models, soil water balance model (SoilClim) and remote sensing based (Metop ASCAT) estimated soil moisture were evaluated with measured soil moisture values. Here, ASM, calculated from the model outputs and measured values, and the degree of saturation (%) from ASCAT SWI T2 were compared. The comparison of soil moisture measured by remote sensing satellites and *in situ* instruments was complicated by the fact that different spatial and temporal variabilities (e.g. land use, soil composition, mean soil water content, etc.) influenced the soil moisture characteristics (Nicolai-Shaw *et al.* 2015). In order to verify the spatial and temporal representativeness, soil moisture from two global land surface models was used as an additional data source. The ERA-Interim/Land data set from the European Centre for Medium-Range Weather Forecasts represented a global atmospheric reanalysis including 6-hourly land surface parameters for the period 1979–2010 (Balsamo *et al.* 2012). The spatial resolution of the data set was approximately 80 km and soil moisture information was provided for four depth layers (0.00–0.07 m, 0.07–0.28 m, 0.28–1.00 m and 1.00–2.55 m). The second data set was based on the Noah model provided by NASA's Global Land Data Assimilation System (GLDAS) and contained atmospheric and land surface parameters on a global 0.25° grid (Rodell *et al.* 2004). From early 2000-ongoing, the GLDAS Noah data set provided 3-hourly soil moisture observations for four layers (0.00–0.10 m, 0.10–0.40 m, 0.40–1.00 m and 1.00–2.00 m). For both land surface models, soil moisture from the second layer was used as a qualitative reference in order to understand soil moisture dynamics at a spatial scale comparable with Metop ASCAT. Global Land Data Assimilation System and ERA-Interim/Land were used only for the visual presentation and not for calculations.

In the current study it was hypothesized that, (i) at site level, ground-based modelling should provide estimates of soil moisture with higher accuracy compared with the Metop ASCAT soil moisture product and (ii) the process-based crop model (DSSAT)

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should provide superior results compared with the simple water balance model (SoilClim), particularly under frequent water stress conditions. In addition, it was expected that (iii) the Metop ASCAT soil moisture product would provide a good estimate of annual changes in water availability and that (iv) it would be able to distinguish extreme (drought/wet) seasons, making it a potential tool for regional drought monitoring.

For assessing and comparing model performance, a set of statistical parameters was calculated: the root mean square error (*RMSE*), the mean absolute error (*MAE*), the percent bias (*PBias*), the index of agreement (*d*) and the least-squares coefficient of determination R^2. The measured values were used as 'ground truth' references for the relative changes, not for absolute soil water content. The relative change (decreasing or increasing of soil water content trend at any time) should be reflected regardless of vegetation cover, in particular for short-term changes chiefly driven by precipitation and soil evaporation. Differences in evaporation from vegetation may, however, introduce slight biases depending on the season and crop-specific water needs.

Beside the classical model performance metrics, Triple Collocation Analysis (TCA) was also applied. This is a statistical tool used for error characterization, first introduced by Stoffelen (1998) and defined as follows:

$$i = \alpha_i + \beta_i \Theta + \varepsilon_i \quad i\,\mathrm{elem}\,[X, Y, Z]$$

where $[X, Y, Z]$ presents three spatially and temporally collocated data sets; Θ is the unknown true soil moisture state; α_i and β_i are systematic additive and multiplicative biases of data set i in terms of the true state, and ε_i is additive zero-mean random noise. The following assumptions are made by the error model: (i) true soil moisture signal and the observations are linear, (ii) signal and error stationarity, (iii) errors and the soil moisture signal are independent (error orthogonality), and (iv) errors of the three spatially and temporally collocated data sets are independent (zero error cross-correlation) (Gruber *et al.* 2016). More detail about the computation and consequences if certain assumptions are not met can be found in Gruber *et al.* (2016). Triple Collocation Analysis simultaneously estimates the error variances of three spatially and temporally collocated data sets, which are related linearly to the hypothetical (unknown) truth with uncorrelated errors, introduced a new representation of the error in terms of Signal-to-Noise ratio (*SNR*):

$$SRN_i[dB] = 10\log(SNR) = 10\log\frac{\beta_i^2\sigma_\Theta^2}{\sigma_{\varepsilon_i}^2}$$

The *SNR*, expressed in dB, indicates the relationship between signal variance and noise variance; σ_i^2 presents the data set variances. For example, 0 dB means that the signal variance is equal to the noise variance, and ±3 dB means that the signal variance is twice/half that of the noise variance. Triple Collocation Analysis does not assume any of the data sets to represent the 'ground truth' (Gruber *et al.* 2016).

Results

Overall assessment of model performances for the four study sites

Five years (2007–2011) of daily *in situ* soil moisture measurements for all four weather station sites together were compared with model data and the Metop ASCAT soil moisture product. The linear regression model was able to explain between 23% (ASCAT SWI T2) and 58% (CERES-Barley) of the variance by the model (R^2); thus, from poor correspondence to rather good. The relative average difference between model estimates and *in situ* measurements (*RMSE*) for ASM was 19–21% in all crop models and 26% in the ASCAT SWI T2. The lowest variation and *RMSE* could be found in CERES-Barley, the highest in ASCAT SWI T2 (results not shown).

The comparison between measured and different simulated or estimated soil moisture for all four study areas separately is presented in Fig. 3. The data sources include point-scale from *in situ* data, plot-scale from model simulation and large-scale from satellite data. In Doksany, SoilClim and ASCAT SWI T2 show good agreement with measured values. In the time-frame 2007 and 2009, ASCAT SWI T2 captured soil moisture in Djakovice very well. In Kroměříž, ASCAT SWI T2 underestimated ASM during the two humid vegetation periods 2010 and 2011, whereas the models fit well with *in situ* values. The models and Metop ASCAT in Groß-Enzersdorf agree very well between 2007 and 2009. Comparing the time series to ERA-Interim/Land and Noah GLDAS indicates that both global land surface models show only large-scale variations and are not able to capture the fine daily changes of a single *in situ* station. Normally, data are matched in order to remove systematic differences related to scale, layer depth and measurement/model characteristics (Brocca *et al.* 2013).

A 30-day moving average, showing the differences between soil moisture measured, simulated and estimated, is presented in Fig. 4. This approach should help to remove seasonal influences and uncover similar short-term anomalies. The daily soil moisture values were compared with the moving average and it was determined whether they exceeded or fell below the mean values. Seasonal biases can be seen in all data sources due to scale differences, different layer depth and seasonal biases based on shortcomings of the measurements and models.

Often, SoilClim-Maize simulated ASM better than CERES-Maize; furthermore, in all the stations apart from Doksany, ASCAT SWI T2 showed good agreement, especially in 2009 and 2010.

The site-specific model and ASCAT SWI T2 performances are included in Table 2 based on measured soil water content. During the 5 years investigated (March–September periods), the analogies between Doksany and Kroměříž were very striking. In fact, in both cases, the crop model DSSAT and ASCAT SWI T2 underestimated soil moisture in the first soil layer, whereas SoilClim generated overestimates. Moreover, for these sites the lowest *MAE* (10–16% ASM), *RMSE* (14–21% ASM) and highest *d* (0.8–0.9) results could be found in CERES-Barley and CERES-Maize. On the other hand, the *PBias* for ASCAT SWI T2 showed the best average tendency of the simulated values (−7%) in Doksany.

In Groß-Enzersdorf, as in the previous two stations, CERES-Barley performed best (for all the main parameters) followed by SoilClim-Grass. Special mention must be made of the very low *PBias* of just 2.9% in CERES-Maize.

Dyjákovice, on the other hand, behaved differently: the SoilClim simulations (barley and maize) presented the lowest *MAE* (14% ASM), *RMSE* (19% ASM) and *PBias* (−10 to −12%) values and all simulations tended to underestimate the first soil moisture layer. The index of agreement with a value of 0.7–0.8 indicated good simulation quality and the R^2 ranged from 0.4 to 0.6.

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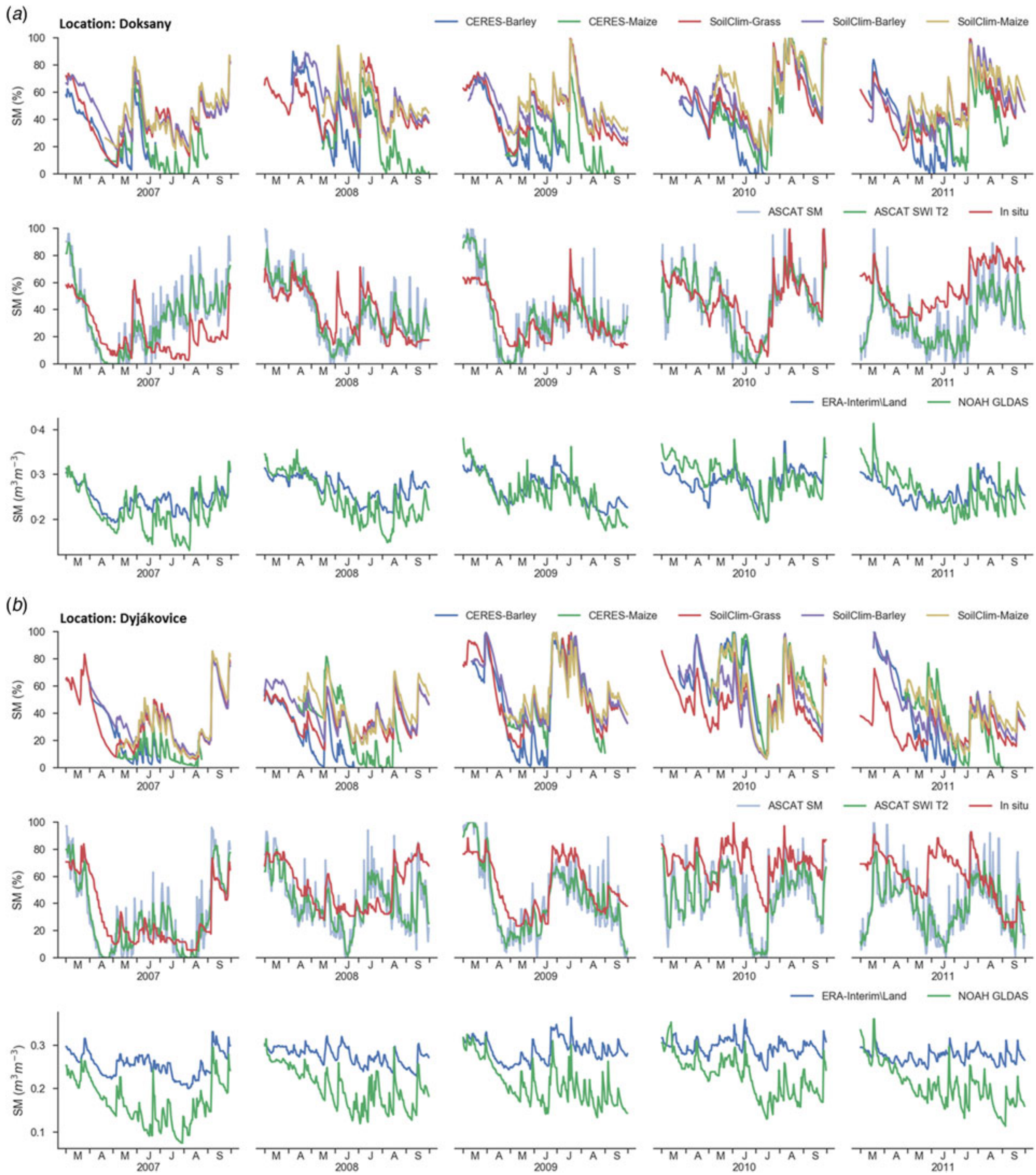

Fig. 3a. The course of *in situ* measured, models simulated (DSSAT and SoilClim), remote sensing (ASCAT SM, ASCAT SWI T2) and modelled (ERA and Noah GLDAS) estimations of soil water content during 2007–2011 in Doksany, Dyjákovice, Kroměříž and Groß-Enzersdorf. Model estimates and *in situ* measurements represent a soil depth of 0–40 cm.

In a second step, TCA was applied for the four study areas. Figure 5 presents the *SNR* and R^2 for measured (*in situ*), ASCAT as well as the different models (third reference). Of particular note was the low R^2 value of ASCAT in the CERES-Maize simulations (with the only exception of Groß-Enzersdorf). This was reflected also by the negative *SNR* for ASCAT, whereas the measured values showed a high signal. In other words, measured and simulated values presented similar signals, whereas ASCAT did not fit in.

It must be noted that the sample size could have an effect on *SNR* since its uncertainty increased with decreasing number of samples (Zwieback *et al.* 2012). This effect could be seen for measured and ASCAT *SNR*, which should indicate a similar behaviour to the third reference. However, the *SNR* values were spread. In addition, the requirements of the error model (see above) might not all be perfectly fulfilled, which was another source of uncertainty in the *SNR* results.

The highest variation could be found in Kroměříž, whereas in Dyjákovice all the three approaches present similar results with an R^2 between 0.4 and 0.6 and *SNR* around 3 dB, meaning that the signal variance was twice as high as the noise variance (except

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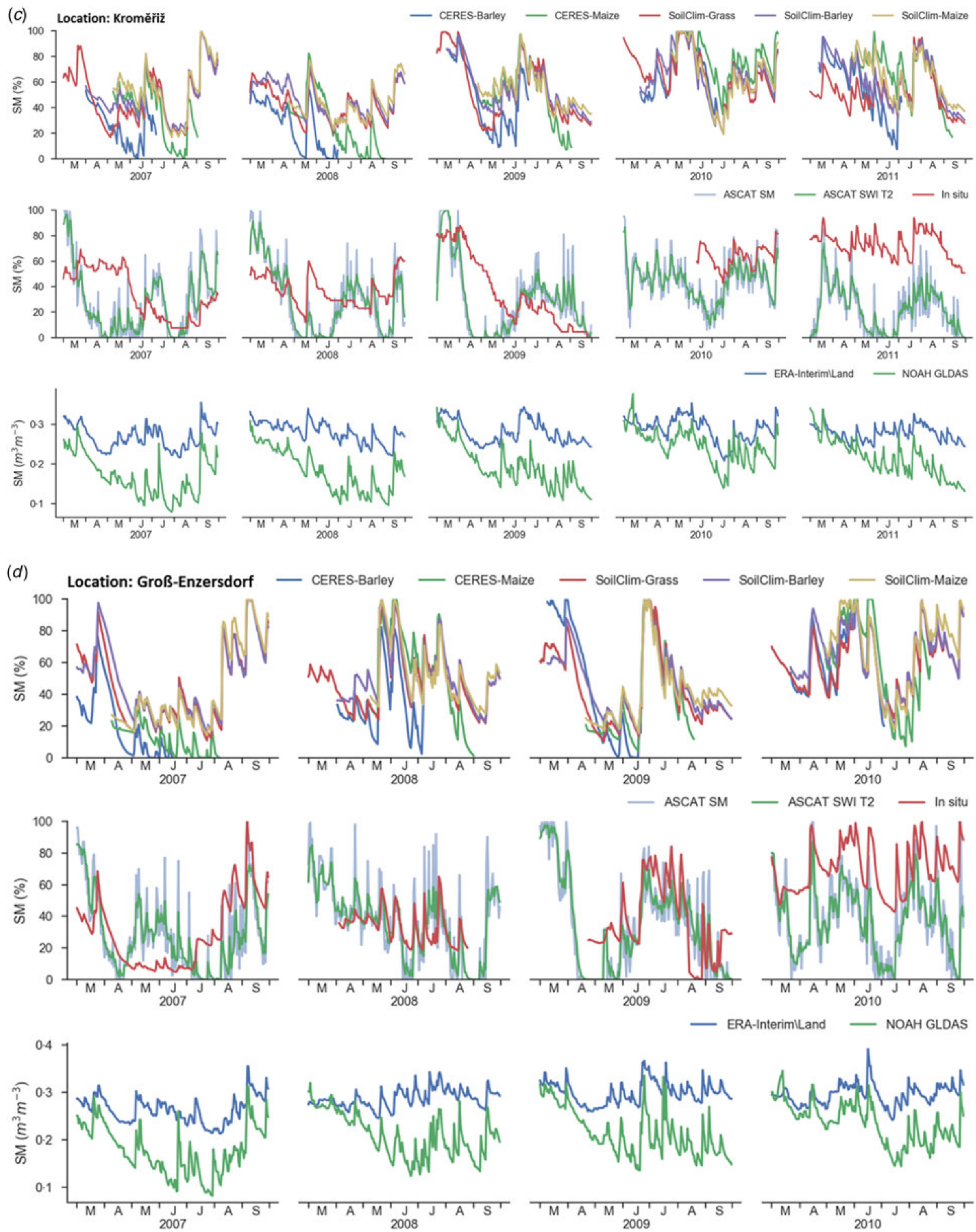

Fig. 3b. Continued.

for CERES-Barley). Dyjákovice was also the study site, which demonstrated a different behaviour for the classic statistical parameters to the other three locations (see above and Fig. 6).

The performance of the model's soil water balance outputs may change during the growing season due to deviations of simulated *v.* real vegetation dynamics, which can influence models' site-specific, as well as ASCAT SWI T2, uncertainties. In the latter, this is an issue of deviations of spatial crop type acreages as it represented grid averaged values. In the following, the differences of simulated and measured soil moisture, *RMSE*, *PBias*

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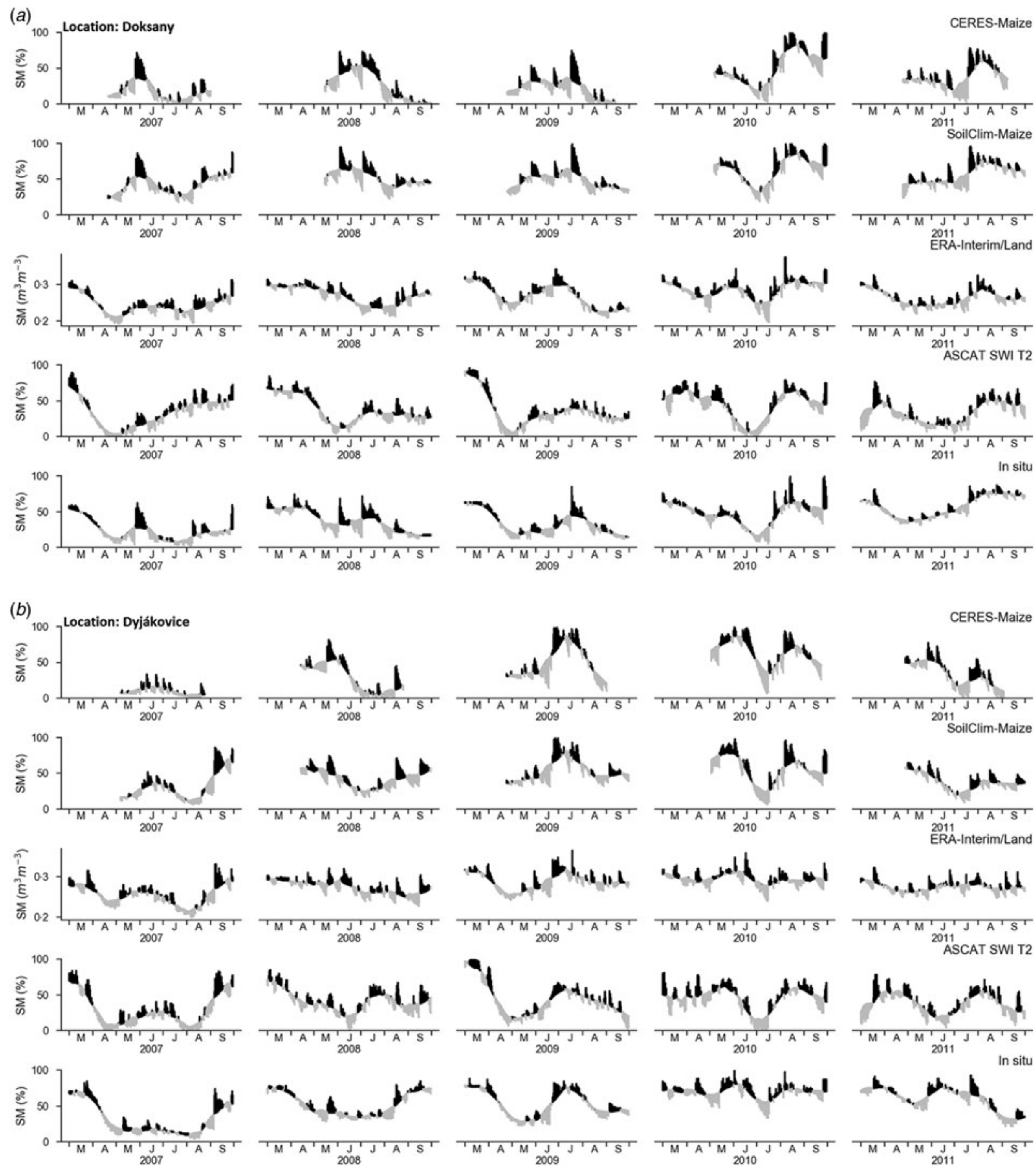

Fig. 4a. 30-day moving average of soil moisture and their daily deviations for CERES-Maize, SoilClim-Maize, ERA-Interim/Land, ASCAT SWI T2 and *in situ* for Doksany, Dyjákovice, Kroměříž and Groß-Enzersdorf (grey = below and black = exceeded the moving average). Model estimates and *in situ* measurements represent a soil depth of 0–40 cm.

and *d* for each study area for monthly as well as growing season time scales are discussed (Tables 3–6).

Performance of available soil moisture estimates at different periods of the growing season

Combining data from all four stations into one data set revealed low deviation of monthly means between measured and simulated ASMs at the beginning of the growing season for CERES-Barley (March), CERES-Maize (April) and SoilClim-Maize (April). In particular, the models at Doksany and Kroměřiže performed better than the other sites and their *RMSE* values were low. SoilClim-Barley and SoilClim-Grass did not show this behaviour to that extent. It should be borne in mind that the measurement sites were under short grass with relatively small changes in root water uptake due to very low seasonal change in active above-ground biomass, in comparison with the simulated crops with a higher seasonal variation of biomass-driven water demand.

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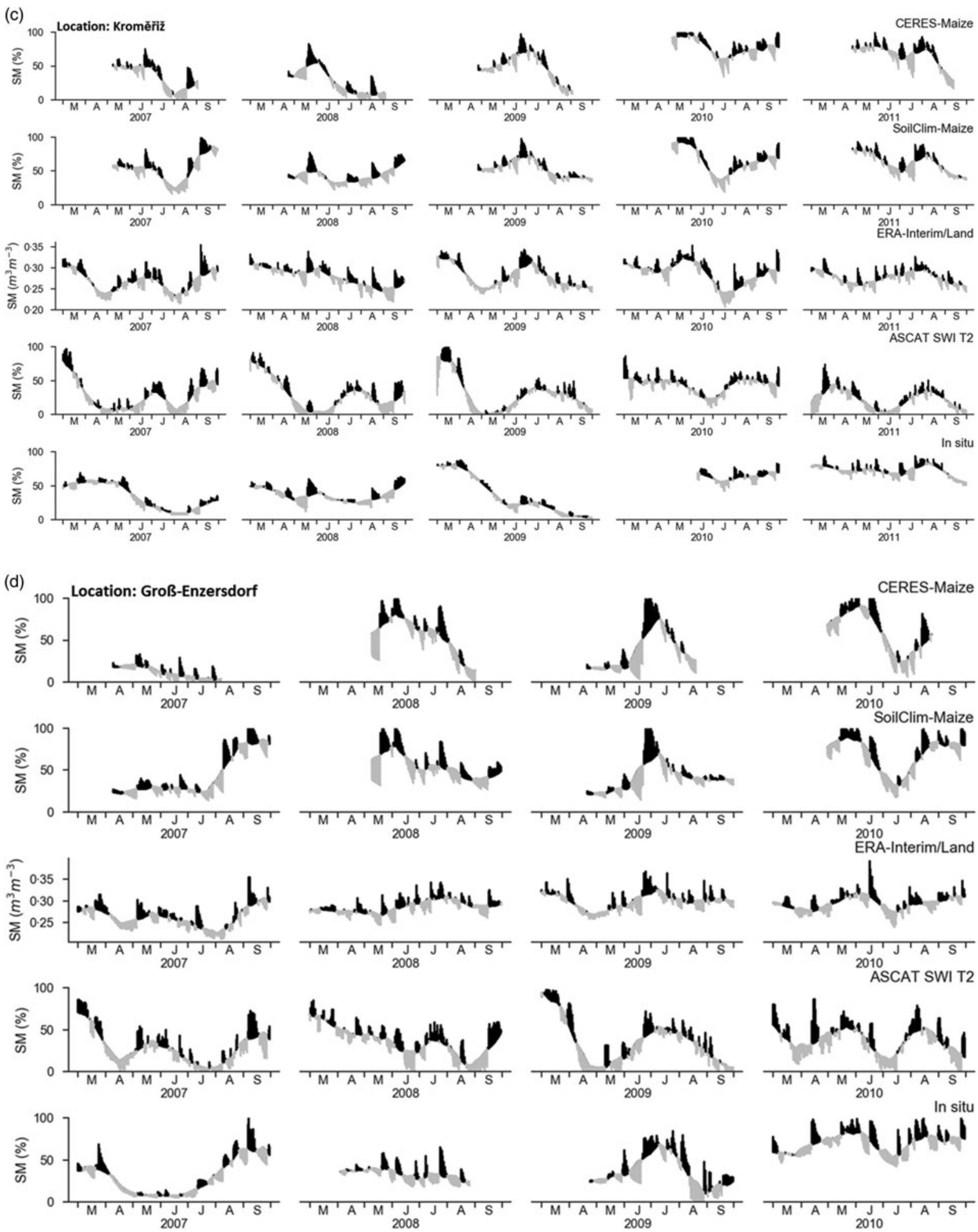

Fig. 4b. Continued.

Thus, the better agreement in the early season with low crop biomass can be explained.

The monthly difference between measured ASM and ASCAT SWI T2-based SM was relatively high compared with ASM based on the crop model outputs. From March until May these differences were mainly negative, and the *PBias* also presented an underestimation (except at Groß-Enzersdorf), but from July the ASCAT SWI T2 estimations were principally overestimated.

At all locations, the CERES models, apart from CERES-Maize in Kroměřiže, showed primarily a negative *PBias* during periods of the fully established canopy (barley: May–July and maize: June–September) caused by seasonal above-ground biomass

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Table 2. Comparative statistics (MAE, RMSE, PBias, d and R^2) of model performance against measured soil water contents for the four study areas from March until September

	MAE (%ASM)	RMSE (%ASM)	PBias (%)	d	R^2	MAE (%ASM)	RMSE (%ASM)	PBias (%)	d	R^2
	Doksany (2007–2011)					Dyjákovice (2007–2011)				
CERES-Barley	10.1	14.0	−11.8	0.9	0.7	18.0	23.9	−24.0	0.8	0.5
SoilClim-Barley	16.6	18.7	34.8	0.8	0.6	14.0	19.2	−12.1	0.8	0.4
CERES-Maize	12.1	16.0	−11.3	0.9	0.6	15.6	21.2	−20.9	0.8	0.6
SoilClim-Maize	19.0	21.4	47.7	0.8	0.6	13.5	18.5	−9.6	0.8	0.4
SoilClim-Grass	12.7	15.7	20.2	0.8	0.6	17.4	22.2	−24.4	0.8	0.4
ASCAT SWI T2	15.1	19.1	−6.8	0.8	0.4	18.3	23.3	−25.5	0.7	0.4
	Kroměřiž (2007–2011)					Groß-Enzersdorf (2007–2010)				
CERES-Barley	16.2	21.1	−22.9	0.8	0.5	12.6	15.2	−14.7	0.9	0.7
SoilClim-Barley	17.0	22.2	16.0	0.7	0.3	15.2	19.2	21.1	0.8	0.6
CERES-Maize	15.9	20.9	13.8	0.8	0.5	17.6	22.8	2.9	0.8	0.5
SoilClim-Maize	18.8	24.5	27.1	0.7	0.3	15.9	19.9	22.5	0.9	0.6
SoilClim-Grass	19.0	23.6	6.4	0.7	0.2	15.6	18.5	11.7	0.8	0.5
ASCAT SWI T2	28.7	34.4	−38.8	0.5	0.1	21.3	25.9	−27.4	0.7	0.3

change. In contrast, the SoilClim soil water content outputs here more often showed a positive *PBias*, with the only exception of Dyjákovice, being the most humid place.

The results from this comparison showed that simulated soil moisture values vary widely at all sites and in all years due to the dynamics in above-ground biomass, besides the weather conditions. However, an almost tripartite behaviour could be found when the incidence of wet periods on soil moisture simulation performances were observed. In fact, DSSAT performed best for dry periods and although ASCAT simulated well for moderate soil moisture, soil water contents and related ASM during wet periods were well simulated by SoilClim (with only a few exceptions) (Tables 3–6).

Performance of available soil moisture estimates under dry, moderate and wet soil conditions

Considering all four sites, soil water contents and related ASM of dry periods were best simulated by DSSAT models while CERES-Maize performed very well under moderate dry and CERES-Barley under extremely dry conditions. Overall, DSSAT models simulated realistically up to 30% ASM. There are only a few outliers observed in Groß-Enzersdorf (April 2009) and Kroměřiže (June–July 2009) for unknown reasons. The *RMSE* values were also quite low in this range, especially in Doksany, being the driest place in the current study (Fig. 6).

Mainly positive differences between simulated and measured soil moisture could be seen during dry periods in all the four locations for the SoilClim simulations (up to 50% ASM). High *RMSE* values were also seen here, especially in Kroměřiže (Fig. 6). The *PBias* showed high positive values during very dry periods, especially in Doksany, Groß-Enzersdorf and Kroměřiže, whereas in humid periods the model generally underestimated (Tables 3–6).

Another very interesting pattern could be seen at Doksany, Dyjákovice and Kroměřiž, where the average monthly *RMSE* (respectively, 20 and 26% ASM) of the ASCAT SWI T2 estimations were considerably higher but at the same time the *RMSE* standard deviation of ASCAT SWI T2 (6 and 10% ASM) was much lower than in the different crop models. An exceptional case was given in Groß-Enzersdorf, where almost all the crop models (with the only exception of CERES-Maize) obtained a very low *RMSE* standard deviation (results not shown).

Advanced SCATterometer SWI T2 grid-based estimates performed at its best for moderate soil moisture conditions at all sites between 30 and 50% of the site-based measured ASM. In this range, the product showed also the lowest *RMSE* values in all cases (Fig. 6). Below about 30% ASM, ASCAT SWI T2 showed a positive difference between observed and simulated ASM, but a negative difference above this limit. The same pattern was shown by *PBias*, with a threshold of 33% ASM. By looking at the whole growing season, ASCAT SWI T2 estimations corresponded best to reality when the measured soil moisture ranged between approximately 30% and 50% ASM (Doksany 38–47; Dyjákovice 31–52; Kroměřiže 34–36 and Groß-Enzersdorf 29–37%) (Tables 3–6).

An extreme drawback of using ASCAT was noticed during very humid periods, where the *RMSE* scored very high (Fig. 6). Advanced SCATterometer was not able to catch high daily precipitation sums. In general, all crop models also showed a negative difference during very humid seasons, but less than ASCAT-based ASM estimates (results not shown).

SoilClim-Maize and Barley showed the best performance in Doksany, Kroměřiže and Groß-Enzersdorf during wet soil conditions. However, for Dyjákovice only SoilClim-Grass was a good predictor for humid periods, whereas during dry periods SoliClim-Maize and Barley showed the lowest differences (until 60% ASM) and shared a similar behaviour with DSSAT (Tables 3–6).

In Doksany and Groß-Enzersdorf, *RMSE v.* mean monthly measured values showed a large spread, whereas Dyjákovice and Kroměřiže showed clearer trends (Fig. 6). In Dyjákovice, the *RMSE* increased with humidity in all approaches. In Kroměřiže, during dry periods, high SoilClim *RMSE* values for coupled to very high ASCAT *RMSE* during wet months could be found.

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Table 3. Doksany: differences of simulated and observed soil moisture, *RMSE* (% ASM), *PBias* (%) and Index of Agreement for month and growing season (gs) 2007–2011

Doksany																																								
Year	2007								2008								2009								2010								2011							
Month	3	4	5	6	7	8	9	gs	3	4	5	6	7	8	9	gs	3	4	5	6	7	8	9	gs	3	4	5	6	7	8	9	gs	3	4	5	6	7	8	9	gs
% ASM (mean)																																								
Measured	51	20	19	22	8	20	23	23	54	58	32	35	45	23	16	38	61	35	20	24	45	30	17	33	63	49	45	29	28	63	55	47	64	41	39	48	59	78	73	57
Simulated-observed values (%ASM)																																								
CERES-Barley	−2	3	0	0				6		19	4	−10	−2			7	6	2	−4	−9	−26			−2	−11	−5	1	−17	−22			−16	3	5	−24	−35	−52			−26
SoilClim-Barley	16	21	17	22	25	21	27	21		20	31	22	14	21	25	19	5	18	21	24	21	13	14	16	−8	6	17	8	15	20	7	10	−9	3	1	−6	−2	−1	−20	−5
CERES-Maize		−11	7	4	−4	−5	−11	−6			−9	16	4	−13	−14	−10		−21	7	6	−10	−22	−16	−11			−3	2	2	19	10	3		−9	−4	−19	−26	−21	−48	−20
SoilClim-Maize		4	23	25	22	22	33	19			18	31	13	17	29	14		−4	28	30	19	10	20	14			25	20	15	21	17	16		−13	9	0	−5	−3	−11	−1
SoilClim-Grass	8	0	12	21	27	16	27	16	4	1	5	18	21	18	21	13	6	4	12	26	21	6	9	12	8	2	3	10	17	17	1	9	−5	−8	−9	−5	0	−12	−24	−9
ASCAT SWI T2	9	−11	−10	−2	31	27	26	10	10	6	−8	−19	−8	9	11	0	23	−14	−3	5	−5	5	8	3	−3	5	6	−21	1	1	−7	−2	−24	−6	−18	−30	−36	−24	−29	−24
RMSE (% ASM)																																								
CERES-Barley	3	5	6	6				5		19	9	11	8			13	6	5	7	10	17			8		7	8	18	10			12	7	9	27	36				25
SoilClim-Barley	16	21	18	22	25	22	27	22		23	31	24	18	22	25	24	9	18	22	24	22	14	15	19		7	18	8	16	22	9	14	14	4	8	9	11	10	20	12
CERES-Maize		3	10	8	6	7		8			7	17	10	14	15	13		4	10	9	14	23	20	15			8	6	11	22	15	14			7	21	31	25	49	25
SoilClim-Maize		14	24	25	22	24	34	25			27	33	18	19	29	25		14	29	30	21	12	20	23			22	20	16	24	18	20			9	4	11	6	11	9
SoilClim-Grass	10	2	15	22	28	18	28	19	6	7	9	20	24	18	22	18	8	4	15	26	23	7	9	15	9	5	5	12	19	19	6	12	8	10	10	7	10	17	24	13
ASCAT SWI T2	16	11	14	12	32	28	27	22	11	8	9	24	13	10	13	14	24	16	11	8	12	8	10	14	15	10	17	22	9	11	13	14	32	9	20	31	37	25	31	28
PBias (%)																																								
CERES-Barley	−4	17	2	−7				1		31	12	−29	−14			4	9	7	−21	−37	−48			−7		−11	2	−60	−55			−18	6	13	−61	−73				−31
SoilClim-Barley	31	101	88	99	314	106	120	89		32	97	64	31	92	154	64	8	51	110	101	47	45	84	53		6	37	27	55	32	13	25	−14	7	2	−12	−3	−1	−27	−8
CERES-Maize		−13	39	16	−50	−27		1			−4	45	9	−57	−89	−6		−12	36	27	−22	−75	−95	−21			−12	6	8	30	19	13			−11	−39	−44	−28	−66	−33
SoilClim-Maize		122	121	112	270	113	147	136			109	91	29	75	177	79		89	141	124	42	33	119	78			46	68	56	33	30	42			16	0	−8	−5	−15	−4
SoilClim-Grass	16	1	62	96	338	83	121	67	8	1	17	53	46	78	132	40	10	10	59	108	48	21	53	36	13	5	7	36	63	27	2	18	−8	−21	−23	−9	−1	−16	−32	−16
ASCAT SWI T2	18	−54	−54	−11	385	140	115	43	19	10	−25	−54	−19	38	68	0	37	−39	−15	22	−12	15	48	8	−4	10	13	−72	5	2	−13	−5	−38	−16	−45	−63	−61	−31	−40	−42
Index of agreement																																								
CERES-Barley	0.9	1.0	1.0	1.0				1.0		0.3	0.9	0.9	0.9			0.9	0.4	1.0	0.9	0.8	0.1			1.0		0.8	0.7	0.6	0.4			0.9	0.8	0.8	0.2	0.2				0.5
SoilClim-Barley	0.4	0.6	0.8	0.7	0.2	0.6	0.5	0.7		0.1	0.5	0.6	0.7	0.4	0.1	0.7	0.2	0.7	0.5	0.5	0.7	0.6	0.4	0.8		0.7	0.5	0.9	0.9	0.5	0.9	0.9	0.4	0.9	0.5	0.8	0.9	0.2	0.3	0.9
CERES-Maize		0.5	0.9	0.9	0.5	0.9		0.9			0.6	0.7	0.9	0.5	0.2	0.9		0.4	0.8	0.8	0.8	0.4	0.2	0.7			0.5	0.9	0.9	0.6	0.9	0.9			0.5	0.3	0.6	0.2	0.1	0.6
SoilClim-Maize		0.3	0.7	0.7	0.2	0.5	0.4	0.6			0.3	0.5	0.7	0.4	0.1	0.6		0.2	0.4	0.4	0.7	0.6	0.3	0.6			0.3	0.7	0.9	0.5	0.8	0.8			0.6	0.9	0.9	0.5	0.4	0.9
SoilClim-Grass	0.7	1.0	0.9	0.7	0.2	0.6	0.5	0.8	0.8	0.7	0.8	0.6	0.6	0.4	0.1	0.7	0.3	1.0	0.6	0.5	0.7	0.8	0.5	0.8	0.5	0.9	0.9	0.7	0.9	0.6	1.0	0.9	0.7	0.7	0.5	0.8	0.9	0.3	0.2	0.8
ASCAT SWI T2	0.6	0.8	0.7	0.7	0.1	0.5	0.5	0.7	0.6	0.7	0.9	0.3	0.7	0.7	0.2	0.9	0.2	0.8	0.7	0.7	0.7	0.7	0.3	0.9	0.4	0.7	0.3	0.5	1.0	0.7	0.8	0.9	0.2	0.7	0.2	0.3	0.4	0.2	0.2	0.6

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Table 4. Dyjákovice: differences of simulated and observed soil moisture, *RMSE* (% ASM), *PBias* (%) and Index of Agreement for month and growing season (gs) 2007–2011

Dyjákovice																																								
Year	2007								2008								2009								2010								2011							
Month	3	4	5	6	7	8	9	gs	3	4	5	6	7	8	9	gs	3	4	5	6	7	8	9	gs	3	4	5	6	7	8	9	gs	3	4	5	6	7	8	9	gs
% ASM (mean)																																								
Measured	69	35	16	18	13	13	50	31	74	55	42	35	37	51	73	54	77	53	28	46	74	45	44	52	72	71	70	76	55	74	71	70	75	66	54	77	69	50	31	60
Simulated-observed values (%ASM)																																								
CERES-Barley		9	−2	−7	1			−8	−25	−28	−26	−28				−21	−2	6	−16	−13	13			−11	−9	1	4	−1	−26			0	12	1	−26	−65	−65			−19
SoilClim-Barley		12	13	17	13	2	6	4	−13	−9	−3	−5	−7	−12	−33	−10	3	17	8	8	7	2	−1	5	−5	5	−9	−31	−29	−8	−29	−16	14	−6	−16	−50	−43	−10	−3	−20
CERES-Maize			−8	−2	−4	−8		−21		−9	10	−1	−31	−38		−25		−21	6	4	8	−9	−33	−3			3	7	−20	−3	−21	−7		−12	−4	−33	−49	−30	−31	−27
SoilClim-Maize			1	18	10	2	12	0		1	11	−1	−10	−9	−25	−12		−16	13	12	1	0	5	0			5	−17	−30	−7	−20	−14		−10	1	−41	−45	−11	4	−23
SoilClim-Grass	−6	−7	−1	16	14	0	7	3	−24	−24	−10	−4	−6	−17	−34	−15	9	1	−2	9	9	−7	−3	2	−9	−21	−29	−24	−27	−16	−36	−23	−30	−40	−32	−47	−42	−17	−7	−31
ASCAT SWI T2	−5	−26	−2	6.6	6.7	−3	10	−2	−7	−15	−7	−16	12	−11	−35	−13	11	−19	−7	−7	−18	−3	−17	−9	−27	−20	−7	−43	−33	−16	−22	−24	−37	−12	−19	−58	−27	1.9	−5	−22
RMSE (% ASM)																																								
CERES-Barley		14	12	10				12	25	28	28	28				25	8	10	18	21				16	9	7	7	11	22			10	7	6	29	65				40
SoilClim-Barley		15	14	18	15	3	9	13	13	10	5	8	10	15	35	15	6	17	8	10	10	5	3	10	4	6	15	33	30	15	29	23	8	10	19	50	44	12	4	28
CERES-Maize			12	8	7	8		9		6	13	18	32	37		25		4	10	11	11	13		11			7	11	22	13	21	16			7	35	50	31	28	34
SoilClim-Maize			13	22	14	2	13	14		9	12	7	11	12	28	15		3	14	12	9	4	5	9			5	22	30	15	21	20			8	42	46	16	12	29
SoilClim-Grass	8	7	5	18	17	2	10	11	24	24	11	8	7	19	36	20	11	8	7	10	11	7	4	9	15	22	30	27	28	21	36	26	31	40	32	48	42	18	8	34
ASCAT SWI T2	14	27	11	10	14	6	13	15	11	17	12	18	16	23	37	21	15	22	9	12	19	10	20	16	30	23	13	45	35	18	25	29	40	16	24	59	28	10	10	31
PBias (%)																																								
CERES-Barley		25	−16	−41				−2	−34	−51	−63	−81				−41	−1	11	−60	−29				−14	−11	1	5	−1	−43			−2	7	2	−49	−85				−39
SoilClim-Barley		34	78	95	100	19	13	44	−17	−16	−8	−13	−19	−23	−44	−20	5	32	28	17	9	4	−3	12	−5	8	−12	−41	−54	−11	−41	−23	9	−9	−30	−65	−63	−20	−10	−33
CERES-Maize			−56	−14	−29	−57		−35		−8	23	−4	−85	−74		−30		−5	23	9	11	−21		5			3	9	−37	−4	−27	−9			−7	−43	−71	−59	−99	−46
SoilClim-Maize			64	120	84	12	24	51		14	27	−3	−27	−17	−34	−11		9	47	25	2	1	11	13			6	−22	−55	−9	−28	−20			1	−54	−65	−23	12	−33
SoilClim-Grass	−9	−19	−5	89	104	3	15	11	−32	−43	−23	−12	−16	−33	−46	−29	12	1	−7	19	13	−15	−7	4	−13	−30	−41	−32	−50	−22	−50	−33	−39	−60	−59	−62	−60	−34	−24	−51
ASCAT SWI T2	−7	−74	−15	37	51	−24	20	−6	−10	−27	−16	−45	34	−22	−48	−21	15	−37	−26	−16	−24	−6	−38	−16	−38	−29	−11	−57	−61	−21	−31	−35	−49	−18	−35	−76	−39	4	−15	−37
Index of agreement																																								
CERES-Barley		0.7	0.3	0.5				0.8	0.2	0.4	0.5	0.2				0.7	0.7	0.9	0.3	0.9				0.9	0.5	0.9	1.0	0.8	0.3			0.9	0.7	0.9	0.4	0.1				0.4
SoilClim-Barley		0.7	0.5	0.4	0.2	1.0	0.9	0.9	0.4	0.6	1.0	0.5	0.5	0.8	0.2	0.8	0.7	0.8	0.6	1.0	0.6	1.0	0.9	0.9	0.8	0.9	0.7	0.4	0.6	0.6	0.4	0.6	0.6	0.8	0.5	0.2	0.3	0.7	0.9	0.6
CERES-Maize			0.4	0.6	0.4	0.6		0.6		0.6	0.8	0.3	0.2	0.5		0.5		0.3	0.4	1.0	0.5	0.8		0.9			0.9	0.8	0.6	0.6	0.4	0.8			0.9	0.2	0.3	0.5	0.2	0.5
SoilClim-Maize			0.5	0.4	0.3	1.0	0.9	0.9		0.5	0.8	0.6	0.4	0.9	0.2	0.7		0.7	0.4	0.9	0.7	0.9	0.8	0.9			1	0.6	0.5	0.6	0.6	0.7			0.7	0.2	0.3	0.5	0.9	0.4
SoilClim-Grass	0.7	1.0	0.8	0.4	0.2	1.0	0.9	0.9	0.2	0.4	0.8	0.6	0.6	0.7	0.2	0.7	0.5	1.0	0.7	1.0	0.6	0.9	0.9	1	0.4	0.5	0.6	0.5	0.6	0.5	0.3	0.6	0.3	0.3	0.4	0.2	0.3	0.6	0.8	0.5
ASCAT SWI T2	0.4	0.6	0.5	0.4	0.3	0.9	0.9	0.9	0.5	0.5	0.6	0.3	0.3	0.4	0.2	0.7	0.4	0.8	0.5	0.9	0.3	0.7	0.4	0.9	0.4	0.4	0.7	0.3	0.5	0.4	0.4	0.5	0.3	0.4	0.4	0.1	0.4	0.7	0.7	0.5

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Table 5. Kroměříž: differences of simulated and observed soil moisture, *RMSE* (% ASM), *PBias* (%) and Index of Agreement for month and growing season (gs) 2007–2011

Kroměříž																																								
Year	2007								2008								2009								2010								2011							
Month	3	4	5	6	7	8	9	gs	3	4	5	6	7	8	9	gs	3	4	5	6	7	8	9	gs	3	4	5	6	7	8	9	gs	3	4	5	6	7	8	9	gs
% ASM (mean)																																								
Measured	54	56	54	27	15	10	25	34	50	38	34	33	27	30	45	37	80	70	40	22	25	11	4	36				68	55	63	70	64	80	71	75	67	74	82	59	72
Simulated-observed values (%ASM)																																								
CERES-Barley		−15	−36	−10	11			−9	−4	−5	−14	−29				−11	3	−5	−19	17	27			12				7	−18			4	0	−1	−19	−41	−31			−17
SoilClim-Barley		−9	−12	21	26	29	52	15	11	20	13	0	11	10	4	9	4	1	1	41	42	31	31	20				−3	−18	−2	−3	1	4	3	−12	−21	−12	−11	−23	−11
CERES-Maize			−4	23	13	7	−7	0		−1	15	5	−15	−22	−45	−11		−23	7	45	41	11	6	13				20	4	8	11	14		4	4	5	−7	−15	−35	−6
SoilClim-Maize			4	28	25	27	55	19		5	15	3	8	10	10	6		−15	13	47	40	28	36	17				2	−18	−5	1	1		9	5	−11	−13	−14	−17	−11
SoilClim-Grass	17	−16	−25	18	30	25	53	14	10	7	6	−1	12	5	2	7	13	−12	−11	41	45	26	27	19				4	−16	−7	−7	2	−23	−23	−26	−20	−10	−17	−27	−21
ASCAT SWI T2	11	−44	−46	−11	13	5	21	−7	24	5	−28	−29	8	−6	−24	−7	−1	−50	−38	−4	14	21	11	−7				−42	−21	−11	−23	−19	−50	−33	−59	−64	−48	−47	−49	−50
RMSE (% ASM)																																								
CERES-Barley		17	37	19	7			25	5	6	16	29				16	5	9	22	22				18				10	20			14	4	5	22	41				26
SoilClim-Barley		10	13	25	28	32	53	30	12	20	15	3	13	11	5	12	5	6	13	42	43	32	31	30				16	20	3	7	13	7	5	14	21	15	15	23	16
CERES-Maize			8	25	21	15		19		4	16	12	16	24		18		10	17	46	42	12	0	32				19	9	10	13	13			8	9	12	20	41	17
SoilClim-Maize			7	30	27	32	56	35		7	15	5	10	11	11	11		3	19	47	40	29	37	35				12	20	7	5	12			6	13	15	16	17	14
SoilClim-Grass	18	21	26	24	33	29	54	31	11	8	7	4	14	6	4	10	14	16	21	42	46	26	28	30				13	19	8	9	13	24	23	26	20	13	21	27	22
ASCAT SWI T2	29	44	47	17	20	16	24	31	26	11	31	30	13	15	25	23	18	52	40	9	16	23	15	29				45	24	12	25	27	54	34	60	64	49	48	49	52
PBias (%)																																								
CERES-Barley		−27	−67	−36	26			−42	−8	−13	−41	−87				−32	2	−7	−48	77				−2				1	−34			−10	−1	−1	−25	−61				−24
SoilClim-Barley		−15	−21	79	178	287	204	57	22	53	39	−1	40	34	8	26	4	1	3	186	172	291	715	69				−19	−32	−3	−5	−14	4	5	−16	−32	−17	−14	−39	−15
CERES-Maize			−8	86	90	66		43		0	44	16	−55	−73		−15		−18	17	206	167	98	3	96				26	7	14	15	15			5	7	−10	−19	−64	−9
SoilClim-Maize			7	107	166	269	220	118		15	43	9	31	33	22	27		−4	32	213	162	263	835	149				−9	−33	−8	2	−11			7	−16	−18	−18	−29	−13
SoilClim-Grass	31	−29	−46	68	200	254	210	42	20	20	18	−3	46	16	5	19	16	−17	−27	185	183	242	629	52				−6	−28	−12	−11	−14	−29	−33	−35	−29	−13	−21	−46	−29
ASCAT SWI T2	20	−77	−85	−42	86	55	81	−21	49	12	−83	−86	31	−19	−52	−19	−1	−72	−96	−19	57	191	252	−19				−65	−37	−17	−33	−36	−62	−47	−79	−96	−64	−58	−83	−69
Index of Agreement																																								
CERES-Barley		0.2	0.1	0.4	0.4			0.5	0.6	0.7	0.8	0.2				0.7	0.7	0.9	0.5	0.5				0.9				0.6	0.2			0.7	0.9	0.8	0.4	0.2				0.4
SoilClim-Barley		0.3	0.3	0.3	0.3	0.2	0.2	0.4	0.3	0.3	0.8	0.9	0.3	0.7	1.0	0.8	0.6	0.9	0.2	0.3	0.2	0.3	0.1	0.7				0.4	0.5	1.0	0.8	0.7	0.8	0.8	0.6	0.4	0.8	0.5	0.3	0.7
CERES-Maize			0.4	0.3	0.4	0.5		0.8		0.8	0.8	0.6	0.3	0.4		0.7		0.1	0.2	0.3	0.2	0.6	0.9	0.4				0.4	0.8	0.6	0.6	0.7			0.7	0.7	0.8	0.4	0.2	0.6
SoilClim-Maize			0.4	0.3	0.3	0.2	0.2	0.4		0.6	0.8	0.8	0.3	0.8	0.9	0.8		0.4	0.4	0.3	0.2	0.3	0.1	0.4				0.5	0.5	0.7	0.9	0.8			0.8	0.6	0.8	0.5	0.4	0.8
SoilClim-Grass	0.5	0.1	0.2	0.3	0.2	0.3	0.2	0.4	0.4	0.6	1.0	0.9	0.3	0.9	1.0	0.9	0.3	0.8	0.2	0.3	0.1	0.3	0.1	0.7				0.5	0.5	0.8	0.7	0.7	0.2	0.3	0.3	0.4	0.8	0.4	0.3	0.6
ASCAT SWI T2	0.0	0.1	0.1	0.4	0.4	0.4	0.3	0.5	0.2	0.6	0.5	0.2	0.2	0.4	0.7	0.6	0.2	0.3	0.3	0.8	0.2	0.3	0.3	0.7				0.2	0.3	0.5	0.3	0.4	0.1	0.2	0.2	0.1	0.3	0.1	0.2	0.3

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Table 6. Groß-Enzersdorf: differences of simulated and observed soil moisture, RMSE (% ASM), PBias (%) and Index of Agreement for month and growing season (gs) 2007–2010

Groß-Enzersdorf																																
Year	2007								2008								2009								2010							
Month	3	4	5	6	7	8	9	gs	3	4	5	6	7	8	9	gs	3	4	5	6	7	8	9	gs	3	4	5	6	7	8	9	gs
% ASM (mean)																																
Measured	42	21	8	8	18	47	62	29		37	39	31	33	24		33		25	28	46	65	26	20	37	58	71	80	75	54	78	77	70
Simulated-observed values (%ASM)																																
CERES-Barley	0	2	−2	−3				−9		−9	−1	10	−19			1		41	−16	−24				10	−13	−12	−15	−5	−31			−9
SoilClim-Barley	24	33	21	22	8	9	16	19		3	21	31	26	22		18		35	−2	0	0	12	11	10	−5	−2	−5	−6	−20	−6	−5	−6
CERES-Maize		−3	10	2	−14	−45		−18			22	46	29	−2		21		−8	−11	−7	1	0	−20	0		−8	−2	11	−28	−29		−10
SoilClim-Maize		2	21	22	5	16	21	13			26	35	23	19		21		−2	−5	1	−5	15	19	4		−2	6	−3	−23	−4	6	−1
SoilClim-Grass	24	18	19	24	5	7	18	16		−3	11	30	27	16		14		20	−10	−1	3	6	10	7	−1	−16	−19	−5	−19	−10	−6	−11
ASCAT SWI T2	21	−8	26	18	−13	−32	−19	−1		8	0	−6	6	−11		3		−5	−20	−10	−16	12	−11	−1	−17	−34	−28	−41	−34	−27	−50	−33
RMSE (% ASM)																																
CERES-Barley	11	8	6	7				8		10	20	20	13			17		14	18	26				21	11	14	17	8				14
SoilClim-Barley	26	34	22	23	14	12	18	22		6	27	33	26	25		25		15	6	14	11	23	17	15	3	8	6	8	21	14	7	12
CERES-Maize		5	12	7	18	24		13			31	47	30	12		33		8	12	20	14	19		16			7	12	32	37		25
SoilClim-Maize		8	22	22	11	18	22	19			34	38	23	20		30		3	5	14	14	26	22	17			7	7	24	17	6	14
SoilClim-Grass	25	19	20	25	14	11	19	20		7	25	32	27	18		24		3	10	15	15	21	15	15	7	17	20	8	20	17	7	15
ASCAT SWI T2	29	12	27	20	19	34	21	24		11	7	11	15	11		11		25	22	14	17	24	18	20	25	36	29	43	37	29	52	37
PBias(%)																																
CERES-Barley	−1	10	−29	−48				−4		−25	−4	30	−39			−2		53	−55	−48				−43	−18	−18	−19	−6				−16
SoilClim-Barley	58	160	258	289	43	18	26	64		10	54	99	77	99		64		61	−6	−1	−1	48	54	13	−5	−3	−6	−7	−37	−8	−7	−10
CERES-Maize		16	129	27	−77	−93		−11			54	146	86	9		80		−33	−38	−15	2	−28		−15			−2	14	−51	−40		−16
SoilClim-Maize		49	254	284	25	33	34	57			65	112	68	82		82		−11	−17	2	−8	58	92	12			7	−4	−43	−5	7	−5
SoilClim-Grass	58	87	234	312	26	15	28	55		−12	29	94	81	72		50		−9	−36	−3	5	24	48	3	−2	−23	−24	−7	−35	−12	−7	−15
ASCAT SWI T2	51	−41	319	236	−68	−68	−30	−3		21	1	−20	17	−32		0		−99	−70	−22	−24	48	−53	−26	−30	−48	−35	−55	−64	−34	−65	−47
Index of agreement																																
CERES-Barley	0.8	0.9	0.5	0.3				1.0		0.3	0.6	0.7	0.6			0.6		0.1	0.3	0.8				0.7	0.2	0.8	0.7	0.9				0.8
SoilClim-Barley	0.5	0.5	0.1	0.1	0.4	0.9	0.8	0.8		0.6	0.5	0.5	0.6	0.4		0.5		0.0	0.6	0.9	0.8	0.7	0.4	0.9	0.5	0.9	0.9	0.9	0.5	0.7	0.9	0.9
CERES-Maize		0.6	0.2	0.3	0.4	0.1		0.3			0.4	0.3	0.5	0.5		0.5		0.1	0.5	0.9	0.7	0.8		0.9			0.9	0.8	0.3	0.4		0.7
SoilClim-Maize		0.6	0.1	0.1	0.4	0.8	0.7	0.9			0.4	0.4	0.6	0.4		0.5		0.2	0.8	0.9	0.7	0.6	0.4	0.8			0.9	1.0	0.5	0.6	0.9	0.9
SoilClim-Grass	0.5	0.7	0.1	0.1	0.3	0.9	0.7	0.8		0.2	0.5	0.5	0.6	0.4		0.5		0.3	0.6	0.9	0.7	0.6	0.4	0.9	0.7	0.7	0.6	0.9	0.5	0.7	0.9	0.8
ASCAT SWI T2	0.2	0.6	0.1	0.2	0.2	0.5	0.7	0.6		0.4	0.8	0.8	0.7	0.7		0.8		0.0	0.3	0.9	0.5	0.7	0.5	0.8	0.4	0.5	0.5	0.4	0.4	0.5	0.3	0.5

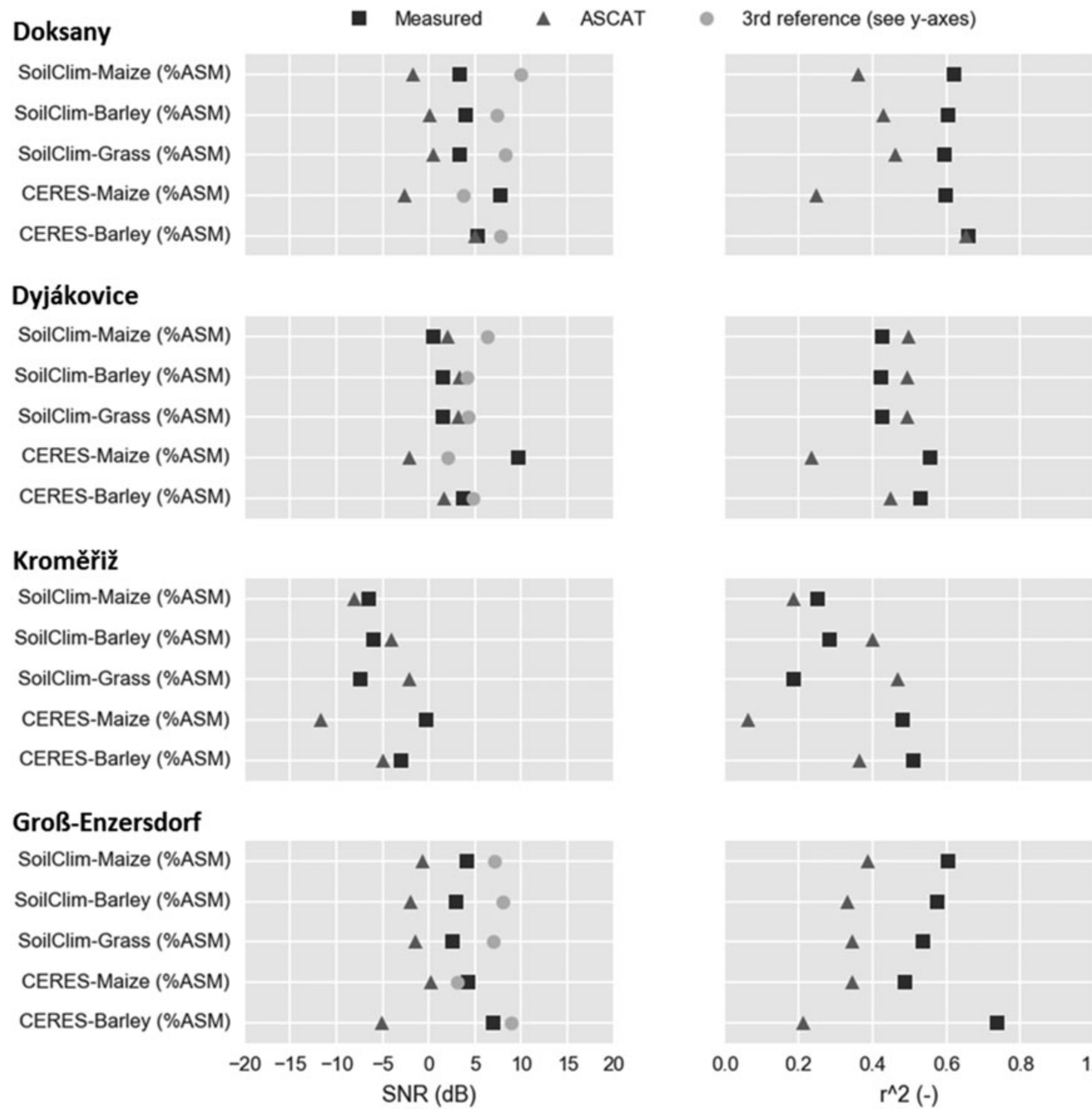

Fig. 5. Triple Collocation analysis and r^2 for Doksany, Dyjákovice, Kroměříž and Groß-Enzersdorf. Measured = point scale, third reference = local scale (different models) and large scale = ASCAT.

Model ranking

In the next step, potential seasonal changes of model performance in the estimation of ASM was investigated. For each month during the period 2007–2011 the first three best models, which fit to the measured soil moisture, were identified. The result was based on the difference of measured and simulated values and filtered out (Table 7).

As already indicated previously, the CERES simulations in arable regions performed better in the first 5 months, under conditions of canopy establishment (March–April: CERES-Barley and May–June: CERES-Maize). SoilClim performed at its best in August and September. It seemed that this model performs better under grass and bare soil conditions, which could be caused by the better representation of the real canopy cover and related seasonal root water uptake of measurement sites. ASCAT SWI T2 came in second and third place, respectively, in the three summer months.

Discussion

Due to climate change, water scarcity, drought frequency and severity are increasing globally, especially affecting agriculture and food production. Even locally, changes in the modelled and observed soil water content have been reported, especially in May and June (Trnka *et al.* 2015*a*) and explained by a significant increase of temperatures and global radiation and decrease in precipitation (Trnka *et al.* 2015*b*), together with significant shifts in weather circulation patterns (Trnka *et al.* 2009). These changes have been recently attributed to increased carbon dioxide (CO_2) concentrations (Brázdil *et al.* 2015); moreover, the frequency of drought in recent decades is among the highest ever recorded in the past 500 years (Brázdil *et al.* 2013). Therefore, decision-makers in the agriculture and hydrology sectors need to improve water use efficiency, especially in crop production, which was shown to be particularly affected (Hlavinka *et al.* 2009; Thaler *et al.* 2012; Eitzinger *et al.* 2013*b*). At the same time, soil moisture

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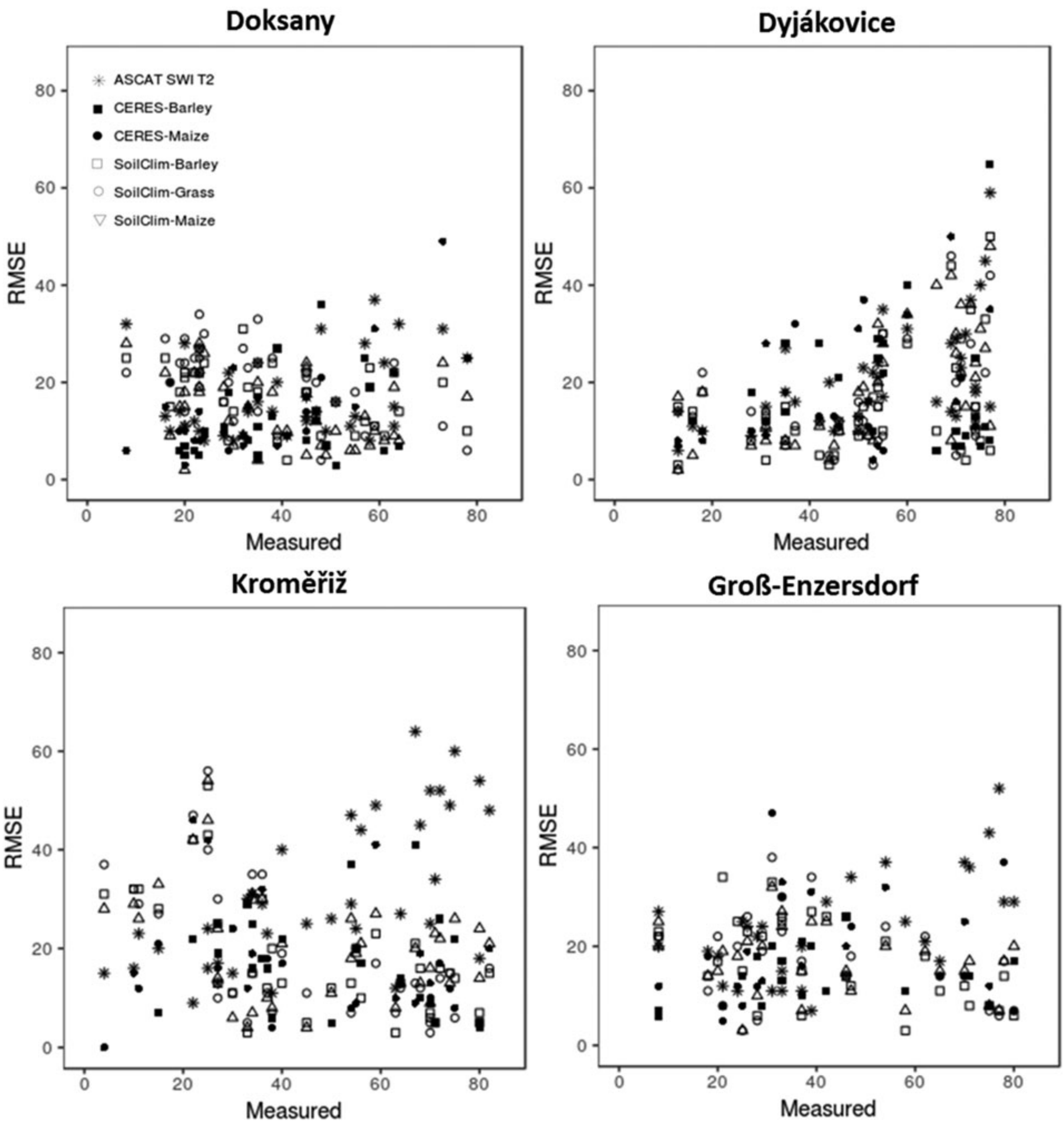

Fig. 6. Mean monthly measured values and RMSE for the four study sites Doksany, Kroměříž, Dyjákovice and Groß-Enzersdorf.

availability has been shown to be important for grassland production (Trnka *et al.* 2006) and also for various tree species including fir (Büntgen *et al.* 2011), oak (Rybníček *et al.* 2015) and beech (Kolář *et al.* 2016). The status and development of soil wetness are therefore crucial, becoming a key aspect for well-informed decision making, and relevant tools and methods should deliver representative and reliable spatial information to farmers at the field scale. Remote sensing products such as ASCAT can provide valuable data on spatial soil wetness conditions. Nevertheless, their intrinsic weaknesses lie in representing only surface layers, as well as not always having the fine spatial resolution needed. By combining tools such as site-based crop water balance models with remote sensing methods, a potential for better-performing spatial estimates can be obtained. In the current study, two different crop model (incl. soil-crop water balance) approaches and ASCAT SWI T2 estimates were compared with measured soil water content at four sites under short grass, representing Central European soil and climatic conditions. The comparison included different time scales from daily to yearly for three different main crops and several soil types, and offers insight into seasonal influences of model performance related to crop and weather conditions. The study period was 2007–2011 and included the main growing season months March until September. Here the uppermost soil layer (0–40 cm) was analysed.

The initial hypothesis stated that models driven by local precipitation measurements and site-representative soil characteristics would provide estimates of soil moisture with higher accuracy on the site level in comparison with ASCAT SWI T2. In addition, it was expected that the process-based crop models of DSSAT would provide better results compared with the simple

Table 7. The first three best ranking models according to their performance on estimated monthly mean ASM against ASM based on measured soil moisture (2007–2011). Maize simulations only start with month May, whereas CERES-Barley simulations ending in June, and were therefore not considered in the remaining months

	March	April	May	June	July	August	September
1	CERES-Barley	CERES-Barley	CERES-Maize	CERES-Maize	CERES-Maize	SoilClim-Maize	SoilClim-Barley (for bare soil)
2	SoilClim-Grass	SoilClim-Barley	CERES-Barley	CERES-Barley	ASCAT SWI T2	SoilClim-Grass + ASCAT SWI T2	SoilClim-Grass
3	SoilClim-Barley	SoilClim-Grass	SoilClim-Barley + SoilClim-Grass	ASCAT SWI T2	SoilClim-Grass	SoilClim-Barley	SoilClim-Maize

water balance model SoilClim, due to better-simulated dynamics of soil layer specific root water uptake. In case of daily simulations for all the four stations together, the model CERES-Barley presented the lowest variation and overall tended to underestimate soil moisture (average $BPias = -14.2\%$). A negative bias was also reported by Eitzinger *et al.* (2004) in their study based on lysimeter data on similar soil, due to deviations in root water uptake in the deeper soil layers. Advanced SCATterometer SWI T2 daily estimations are, as expected due to spatial averaging, the weakest and their variation is high. The standard deviation of the model prediction error is around 20% ASM for SoilClim-Barley and SoilClim-Grass and not essentially higher as in DSSAT (19% ASM). On the other hand, SoilClim generally overestimates soil moisture.

Although comparisons of *in situ* soil water measurements can be affected by the high spatial variability of soil water balance determining factors on the small scale, seasonal changes can be represented well. Moreover, the measurement sites are characterized by homogenous permanent grass canopies (and root distribution) reducing spatial inhomogeneity of soil water content.

Regarding the specific model performances during dry periods, it can be observed at all four study sites that DSSAT better simulates the first soil moisture layer (up to 50% ASM measured soil moisture), whereas SoilClim simulations fit quite well during humid months. Therefore, as it was assumed that the process-based crop model DSSAT provides more realistic results in comparison with the simple water balance model SoilClim under frequent water stress conditions, which can be explained by specific processes simulated in more detail and dynamics such as the root and crop growth. On the other hand, DSSAT reacts sensitively to humidity and shows the highest deviations during moist periods. A possible explanation could be that the interception losses are not captured well in the model.

Advanced SCATterometer SWI T2 shows poor results on daily statistical parameters. However, if a longer period, such as a month or a growing season, is taken into account, ASCAT SWI T2 results are more reliable and can deliver a good soil moisture estimate. The model predicts values reasonably well, particularly during conditions of low surface biomass (early vegetation season) of the areas under evaluation. This can be related to the fact that the scatterometer returned better estimates of the water content in the soil layer when the lack of vegetation allowed the signal more ground penetration.

Hence, ASCAT provides good estimates of annual changes in water availability and was able to distinguish extreme (drought/wet) seasons. The performances of Metop ASCAT soil moisture was positively validated and could represent a complementary source for the estimation of crop-soil water balance in Central Europe, e.g. in regional drought monitoring. Furthermore, the *in-situ* values should be critically judged, because their data quality can be influenced by different measurement errors, for example sensor changes, replacement or calibration, power failure. Due to such limitations of *in situ* measurements, ASCAT SWI T2 shows more reliability in long-term observations since it is more stable and better at tracking changes from year to year. For *in situ* measurements, the potential spatial variability at a small scale has to be considered for comparisons at differing scales.

During early and late crop stages, the crop models and ASCAT SWI T2 estimations present a low deviation compared to the measured grass-soil water content. It is an effect of reduced water take up by crops/plants from deeper soil layers during these periods and less expressed vertical soil water differences.

Knowing the time-dependent changing performances of the different methods, depending on changing soil wetness and crop conditions, ranges of varying uncertainty regarding model application and recommended model choices could be given. Advanced SCATterometer SWI T2 performance at its best under medium soil wetness conditions and related to the low variation of precipitation frequency and the amount is obvious. Soil crop water balance models require, in case of more extremes towards drought and wetness, reliable predictions. A significant improvement of spatial estimates of ASM could, therefore, be reached by considering annual actual acreage of crop types, even without high spatial (field-based) crop simulation efforts, especially in regions with similar agroecological (soil, climate, land use) conditions.

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