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Satellite-based soil moisture enhances the reliability of agro-hydrological modeling in large transboundary river basins

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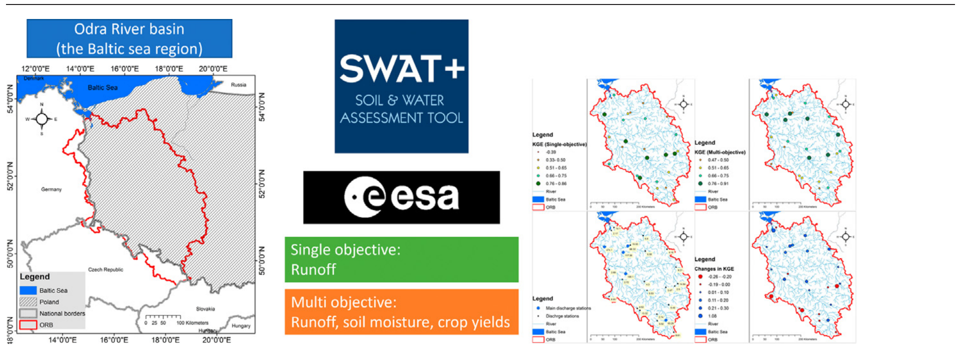
HIGHLIGHTS

- Satellite-based soil moisture (CCI) was used to calibrate the SWAT+ model.
- Single- and multi-objective strategies were employed in runoff of crop yield simulations.
- Model-based soil moisture was calibrated for two layers via employing the SWI index.
- CCI could improve the reliability of the SWAT+ model in transboundary river basins.

GRAPHICAL ABSTRACT



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ABSTRACT

Satellite-based observations of soil moisture, leaf area index, precipitation, and evapotranspiration facilitate agro-hydrological modeling thanks to the spatially distributed information. In this study, the Climate Change Initiative Soil Moisture dataset (CCI SM, a product of the European Space Agency (ESA)) adjusted based on Soil Water Index (SWI) was used as an additional (in relation to discharge) observed dataset in agro-hydrological modeling over a large-scale transboundary river basin (Odra River Basin) in the Baltic Sea region. This basin is located in Central Europe within Poland, Czech Republic, and Germany and drains into the Baltic Sea. The Soil and Water Assessment Tool+ (SWAT+) model was selected for agro-hydrological modeling, and measured data from 26 river discharge stations and soil moisture from CCI SM (for topsoil and entire soil profile) over 1476 sub-basins were used in model calibration for the period 1997–2019. Kling–Gupta efficiency (KGE) and SPAtial EFficiency (SPAEF) indices were chosen as objective functions for runoff and soil moisture calibration, respectively. Two calibration strategies were compared: one involving only river discharge data (single-objective - SO), and the second one involving river discharge and satellite-based soil moisture (multi-objective – MO). In the SO approach, the average KGE for discharge was above 0.60, whereas in the MO approach, it increased to 0.67. The SPAEF values showed that SWAT+ has acceptable accuracy in soil moisture simulations. Moreover, crop yield assessments showed that MO calibration also increases the crop yield simulation accuracy. The results show that in this transboundary river basin, adding satellite-based soil moisture into the calibration process could improve the accuracy and consistency of agro-hydrological modeling.

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1. Introduction

Several complex processes, such as interactions between groundwater and surface water, river flows, crop-related processes, nutrient transport, and anthropogenic effects occur simultaneously in river basins (Fernandez-Palomino et al., 2021; Koohi et al., 2022; Ma et al., 2019). Though understanding these processes on small scales, such as laboratory or controlled farms, seems straightforward, but in the real world, with numerous unpredictable effects on these processes, analyzing and finding precise relations between them is almost unattainable (Fernandez-Palomino et al., 2021; Guse et al., 2016; McDonnell et al., 2007; Sivapalan et al., 2012; Triana et al., 2019). Due to the high variability in the real world, similar farms in the same region by employing the same farm management plan could have different crop yields, or similar water-saving plans in different regions could have totally different outputs (Feng et al., 2006; Fohrer et al., 2001; Gupta et al., 2006; Montanari and Koutsoyiannis, 2012).

In this regard, several types of hydrological models as managerial tools are developed to simulate and project the consequence of different possible scenarios (Devia et al., 2015; Sood and Smakhtin, 2015). In the realm of hydrology, distributed hydrological models are widely used to comprehensively simulate the effects of human-caused activities such as land use changes, and natural-caused effects such as heatwaves and extreme precipitation events on water quantity, quality and crops (Alfieri et al., 2022; Delavar et al., 2022; Eini et al., 2020; Eini et al., 2022a; Ilampooranan et al., 2021; Ma et al., 2019). In several studies, distributed hydrological models have been calibrated only by considering runoff. However, other elements of the hydrological process, such as the share of evapotranspiration in water balance or infiltration rate, can be misrepresented by models; for example, assessing the effect of climate change on the water balance in an intensively irrigated area is not solid when a hydrological model is calibrated only by focusing on runoff (Gupta et al., 2006; Montanari and Koutsoyiannis, 2012; Pokhrel et al., 2012). It is reported that selecting different parameter sets can lead to similarly good results for simulated discharge, which is referred to as equifinality (Abbaspour, 2022; Beven, 2006). One of the possible ways to avoid equifinality is multi-objective calibration, i.e. employing in calibration additional temporal and spatial variables, such as crop yields, soil moisture, base flow, potential and actual evapotranspiration, leaf area index (LAI), infiltration, biomass index, and tile flow can be included in calibration processes (Alfieri et al., 2022; Azimi et al., 2020; Brocca et al., 2017; Brocca et al., 2020; Ciabatta et al., 2016; De Santis et al., 2021; Fernandez-Palomino et al., 2021; Pfannerstill et al., 2017; Pokhrel et al., 2012). For example, Ilampooranan et al. (2021) have used crops as a sensor to increase the reliability of the hydrological model in an agricultural watershed in Iowa. In their research, crop yield calibration reduced the model's parameter uncertainty and predictive ability. Distributed variables such as crop yield, Soil Moisture (SM), and LAI are helpful variables in the calibration step to increase the runoff accuracy and the accuracy of ET or general water balance components (Ilampooranan et al., 2021).

Achieving accurate results by employing hydrological models could be a particular challenge for hydrologists in trans-boundary basins, when adequate measured data is not available freely or the available datasets have different accuracy or resolutions (Aslam et al., 2020; De Lannoy et al., 2022; Hirbo Gelebo et al., 2022; Liersch et al., 2017; Mianabadi et al., 2020; Rougé et al., 2018). The importance of hydrological assessments in transboundary basins is not only related to the comprehensive evaluation of water balance but has an impact on the issues related to international conflict management strategies and sustainable basin-wide management, particularly in the era of climate change (Hajihosseini et al., 2020; Hirbo Gelebo et al., 2022; Khan et al., 2017; Liersch et al., 2017; Mianabadi et al., 2020; Rougé et al., 2018).

Global gridded datasets have been employed to deal with gaps in the datasets, inadequately measured datasets, or entirely unavailable datasets (Beck et al., 2017; Eini et al., 2019; Eini et al., 2021b; Koohi et al., 2021). Generally, these global (or regional) datasets can be categorized into three groups: purely ground-based, satellite-based, and the combined first two datasets (Brocca et al., 2019; Eini et al., 2019; Eini et al., 2021b; Piniewski et al., 2021). In recent years, remotely sensed datasets have been widely applied in hydrology for calibration and validation steps of models and as ancillary datasets, such as meteorological data, in the set-up step (Alfieri et al., 2022; Eini et al., 2022a). It is highlighted that satellite products can improve the consistency of distributed hydrological models by providing spatially distributed data (Ilampooranan et al., 2021; Ren et al., 2018). Finally, in several studies, the accuracy of results is enhanced by adding new processes or modifying default empirical equations in process-based models (Delavar et al., 2022; Delavar et al., 2020; Eini et al., 2020). All of the mentioned approaches eventually could enhance the model's results for the water balance simulations at the basin scale.

Soil moisture (SM) is one of the most important variables linking energy and water cycle and its knowledge is strategic both for runoff formation and crop development (Azimi et al., 2020; Brocca et al., 2017). This variable, which covers the basin area, influences runoff, land-atmosphere carbon fluxes, vegetation, and evapotranspiration processes (Azimi et al., 2020; Brocca et al., 2020; De Santis et al., 2021; Lal, 2004; Or et al., 2013). In the real world, SM varies not only temporally and in two spatial dimensions but also vertically. Since meteorological parameters, soil texture, land cover and land use, groundwater water table level, and topography are effective on SM, thus, ground-based measuring of this variable requires a large network of spots. Moreover, the model uses parameterization of soil and land cover and climate forcing, which is not always accurate. So having spatially distributed information on soil moisture is paramount to improving their skills and building a robust system (Massari et al., 2014; Ochsner et al., 2013). Gravimetric sampling or Time Domain Reflectometry (TDR) can be considered as the most feasible measurement techniques for determining SM. Simple mechanisms and the capability to determine SM at various depths are the advantages, while being costly and time-consuming are the disadvantages of this method (Azimi et al., 2020; Huisman et al., 2001).

To overcome this issue, SM satellite-based products could be an alternative of in-situ measurements. According to the literature, several SM products from different satellites are available and usable in hydrological simulations. Three satellite missions have been particularly launched for the SM measurements (in 2006, The Advanced Scatterometer (ASCAT), in 2010, the Soil Moisture Ocean Salinity- (SMOS) and, in 2015, the Soil Moisture Active and Passive mission SMAP) (Entekhabi et al., 2010; Kerr et al., 2010; Wagner et al., 2013). One of the largest projects belongs to European Space Agency (ESA), namely, the Soil Moisture CCI project (https://esa-soilmoisture-cci.org/) which uses several active and passive sensors on 13 satellites to provide a globally gridded SM dataset (Brocca et al., 2011; Dorigo et al., 2017). The global SM satellite-based datasets have successfully been applied in flood and runoff modeling in different regions. However, the small infiltration depth (less than 50 mm) and the large spatial resolution (more than 25 km) of the SM products cause critical challenges in hydrological modeling (Azimi et al., 2020; Brocca et al., 2017; Brocca et al., 2011; De Santis et al., 2021; Modanesi et al., 2020). Moreover, Modanesi et al. (2020) stressed the importance of satellite surface soil moisture datasets to provide the highest level of information about the impacts of dry and drought conditions on crop yields in India.

As an agro-hydrological model, the Soil and Water Assessment Tool (SWAT) has been globally employed in simulating agro-hydrological processes, such as surface runoff, evapotranspiration, crop growth, vegetation dynamics, and snow melt (Akoko et al., 2021; Eini et al., 2023; Gassman et al., 2014; Piniewski et al., 2017; Tan et al., 2019; van Griensven et al., 2012; Wang et al., 2019). This model by providing a wide range of tools, such as farm management modules (e.g., irrigation, fertilizer, tillage, grazing, and pesticide), daily and sub-daily runoff modules, land use changes module, water quality module, crop growth module, and options for implementing man-made structures, facilitates users to have comprehensive and reliable assessments of the hydrological cycle within a catchment (Arnold et al., 2012; Gassman et al., 2007). In addition, this model is freely available, and users can modify the core of the model for different purposes (Delavar et al., 2022; Eini et al., 2020). An enhanced version of this model, entitled SWAT+, was recently released (Bieger et al., 2019;

Bieger et al., 2017; Wagner et al., 2022). The new version is extensively changed and provides decision tables in the modeling process to improve the realism of farm management and reservoir operation (Arnold et al., 2018; Wu et al., 2020). In addition, in the SWAT+ model, the new "gwflow" module is included for entirely connected interactions between surface and groundwater simulations (Bailey et al., 2022; Bailey et al., 2020). Several studies have forced SWAT to run or calibrate with remotely sensed datasets. Satellite-based products, such as SM, leaf area index, precipitation, temperature, evapotranspiration, and land use maps, are used in both SWAT configuration and calibration steps (Azimi et al., 2020; Eini et al., 2019; Eini et al., 2022a; Ma et al., 2019; Pfannerstill et al., 2017). The key highlight of these studies is calibration SWAT with satellite-based products enhances model performance. Moreover, multi objective calibration helps to reduce uncertainty range and equifinality of SWAT, especially by employing remotely sensed datasets (Kundu et al., 2017; Rajib and Merwade, 2016; Rajib et al., 2016). Still, according to the literature, application of satellite-based SM in the calibration of the SWAT model in transboundary river basins and different depth of soil is assessed in few studies; in addition, in this study, a new performance indicator (*SPAtial EFficiency* (SPAEF), Demirel et al. (2018)) is used to evaluate the accuracy of SM as a spatial variable. This indicator is developed particularly for spatially distributed variables, and the advantages of employing this indicator is discussed in Demirel et al. (2018).

In this study, a modified version of the SWAT+ model for the first time was calibrated by employing a multi-objective modeling approach that involved not only discharge stations, but also the CCI-SM product (remotely sensed dataset). Two calibration scenarios were tested: the first, conventional one, employing discharge data; and the second one, employing both discharge and satellite-based SM data. The effect of multi objective scenario and single objective scenario on crop yields also was assessed. The Odra (Oder) River Basin (ORB), a large-scale transboundary river basin in Central Europe that drains water from areas in the Czech Republic, Poland, and Germany to the Baltic Sea, is selected as the study area (Eini et al., 2022b; Piniewski et al., 2017).

2. Methodology

2.1. Study area

The Odra River Basin (ORB) is located in Central Europe and is among the largest river basins in European Union (the fifth largest river basin). The mean annual runoff of this transboundary basin is 154 mm (567 m^3/s), and the long-term annual average of precipitation is approximately 650 mm. ORB covers 119,041 km^2, of which 89 % is located in Poland, 4.9 % in Germany, and 6.1 % in the Czech Republic. of the river is approximately 840 km long, with sources in the Sudetes Mountains in the Czech Republic and the estuary to the Szczecin Lagoon connected to the Baltic Sea in its southern part. The great majority of the drainage area spans the Central European Plain, with only southern-most parts being mountainous (Fig. 1). More details are available in Piniewski et al. (2021), Piniewski et al. (2017), and Marcinkowski et al. (2022). The location of ORB and its hydrologic objects are presented in Fig. 1.

The historical crop yield data for major crops (winter wheat, spring barley, rapeseed, and corn) were extracted from Central Statistical Office of Poland (GUS, https://stat.gov.pl/en/topics/agriculture-forestry/) database at province level. The average of crop yields in Wielkopolskie, Zachodniopomorskie, Lubuskie, Dolnośląskie, Śląskie, Łódzkie, and Opolskie provinces were included in this study.

2.2. Configuration of agro-hydrological model

The new version of SWAT, namely, SWAT+, was used in this study. This study uses a modified version of SWAT+. In the modified version, minor and major errors in some subroutines in standard SWAT+, such as misnamed variables related to groundwater module, water quality module, wrong initialized constant values for surface processes, evapotranspiration module, tillage operations, crop simulation module, and lateral flow module, were fixed and some improvements in wetland condition were made. These modifications and codes are available on https://github.com/andrejstmh/SWATplus. The model was set up in the QGIS interface, which is also an open-access software, using the QSWAT+ plugin (SWAT+ installer v.2.1.4, https://swat.tamu.edu/software/plus/).

The ORB was divided into 1476 subbasins and 20,000 hydrologic response units (HRUs). The pre-defined watershed delineation option was chosen in the setup process and the subbasins and channels from the Poland SWAT model setup of Marcinkowski et al. (2022) were used. The ORB model contains 176 lakes (natural lakes and reservoirs), the management schedules of 11 major crops (including winter wheat, spring barley, corn, silage corn, sugar beet, potato, rapeseed, cabbage, apple, and fescue, which are all rainfed), and the tile drainage system. Weather data (precipitation, maximum and minimum temperature, humidity, wind speed) were extracted for each of the subbasins from a 2 km regional dataset (Piniewski et al., 2021), and solar radiation was extracted from Copernicus ERA5 global dataset (https://cds.climate.copernicus.eu/). The Penman-Monteith method was chosen for calculating potential evapotranspiration. Daily runoff (26 discharge stations, source: The Institute of Meteorology and Water Management (IMGW-PIB), Warsaw, Poland) and satellite-based SM were calibrated for the period 1997–2019 (1997–1999 warm-up period, 2000–2010 calibration, and 2011–2019 validation). Details of used digital layers, including the 50 m resolution digital elevation model, land use map, and soil map, are described in Marcinkowski et al. (2022).

The management schedules of mentioned crops is based on potential heat unit (PHU), and essential operations such as fertilizer, planting, tillage, harvest or harvest and kill were included in the model. In the modified version of used SWAT+ model, crops module is based on number of days to maturity and potential heat units.

2.3. Satellite-based SM dataset

This study employed ESA (European Space Agency) CCI (Climate Change Initiative) SM version 07.1. This product spans more than 40 years (1978–2021), and different active and passive sensors are used to generate this dataset. This product has three active, passive, and combined products; data are freely available at https://esa-soilmoisture-cci.org/. The resolution of this product is 0.25° and has daily time step. We have employed the combined dataset, which increases the chance of taking at least one sensed SM for a particular day and pixel, thus decreasing the number of data gaps. Additionally, combined satellite-based datasets generally perform better than individual sensor datasets (Modanesi et al., 2020). This product has been used in several studies with different purposes in different regions with diverse climates and has shown relatively good accuracy (Almendra-Martín et al., 2021; Dorigo et al., 2017; Kovačević et al., 2020; Ma et al., 2017; McNally et al., 2016; Modanesi et al., 2020; Zhang et al., 2019; Zhang et al., 2021). This dataset was extracted over the 20,000 HRUs, and average-weighted time series were calculated for each subbasin (1476 subbasins).

According to the literature, satellite-based SM datasets should be corrected due to the large-scale resolution and irregular time intervals on surface and depth (Albergel et al., 2008; Wagner et al., 1999). In this regard, Soil Water Index (SWI) is proposed. This method corrects the anomalies of satellite-based SM and is based on an exponential filter equation. In this study, SWI is employed to match the depth of simulated SM and satellite-based SM. Moreover, SWI is used in several studies with different proposes, and the effectiveness of this method for adjusting the SM time series is highlighted (Brocca et al., 2010; Dorigo et al., 2015; Dorigo et al., 2011; Liu et al., 2011). A comprehensive explanation and different applications of this index are presented in Massari et al. (2014) and additional features of this index can be found in Wagner et al. (1999), and Ceballos et al. (2005).

2.4. Objective functions

Finding an appropriate objective function for multi-objective calibration and validation is controversial, especially when one or more datasets are satellite-based products and spatially distributed over the study area.

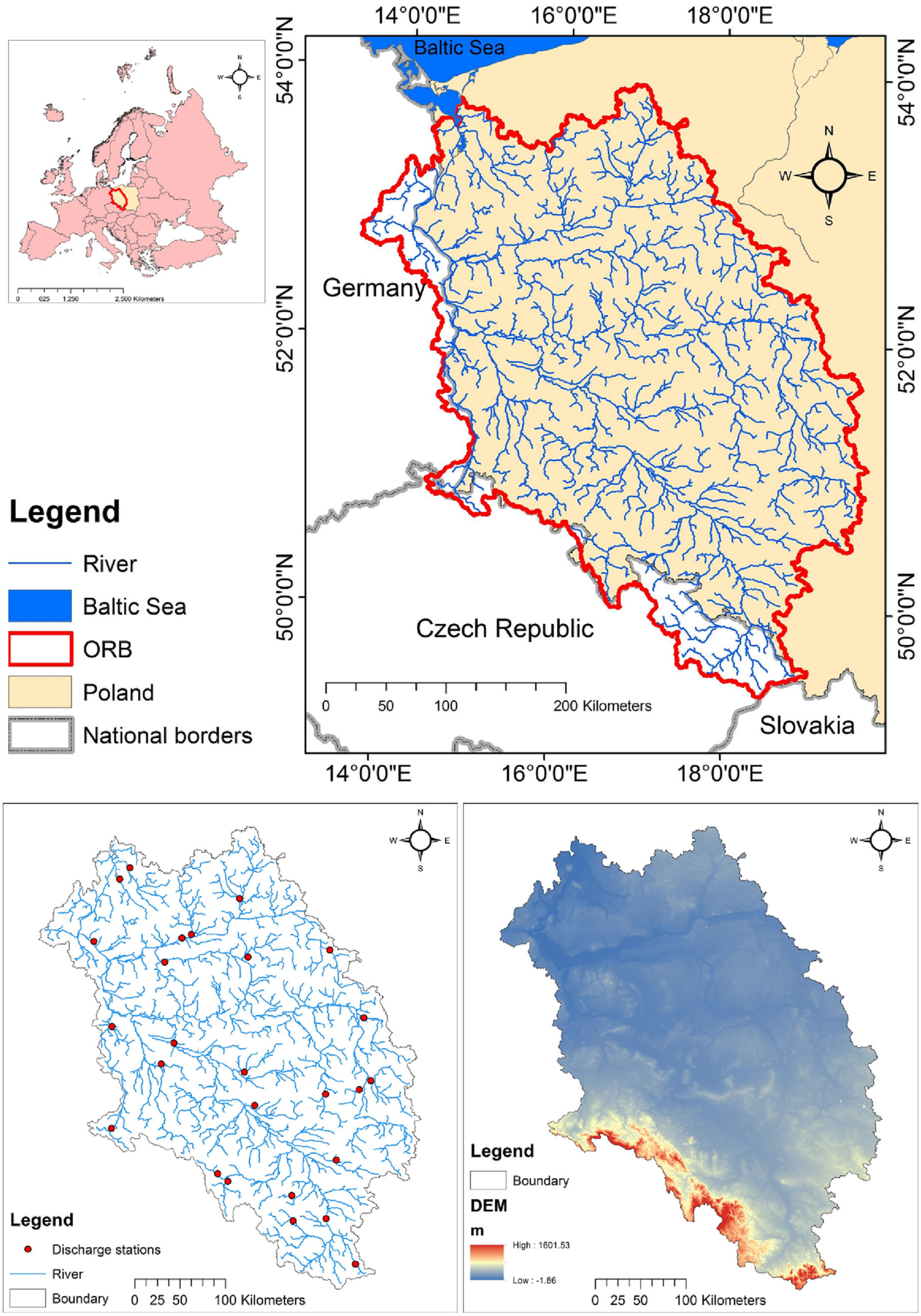

Fig. 1. The location of ORB in Europe, rivers, discharge stations, and topography.

Two objective functions were employed for discharge and SM values in this study. The first is a ground- and point-based dataset and the second is a satellite-based dataset distributed over ORB. According to the literature, the Kling–Gupta efficiency (KGE) (Kling and Gupta, 2009) is widely used for discharge calibration (Knoben et al., 2019), and in this study, it also is selected for the discharge accuracy evaluation. For the distributed variable, a relatively new metric, *SPAtial EFficiency* (SPAEF), is used (Demirel et al., 2018; Koch et al., 2018). SPAEF reflects correlation, coefficient of variation, and histogram overlap of the observed datasets (i.e., CCI-SM) and model's output (i.e., SWAT+) (Koch et al., 2018). In this study, we have used SPAEF based on time variation in each subbasin. Monthly SMs are assumed that are map pixels, and then, SPAEF for each subbasin was calculated. These two metrics are proposed to evaluate the accuracy of distributed hydrological models, particularly if one or more variables are spatially distributed over the study area, such as SM or evapotranspiration variables.

2.5. Calibration strategy

In the first step which is a single-objective (SO) calibration of discharge, KGE indicator was selected as an objective function. The second step which is a multi-objective (MO) calibration of discharge and soil moisture, KGE and SPAEF indicators were employed in calibration process. It should be mentioned that before starting to calibrate the model, crop yields were assessed and crop parameters, such as PHU (Potential Heat Unit), biomass/energy ratio, base and optimum temperature, and harvest index were fixed.

For discharge simulations at 26 discharge stations (2000–2010 calibration, and 2011–2019 validation), SWATplus-CUP (https://www.2w2e.com/home/SwatPlusCup) SUFI-2 (SPE) algorithm (Abbaspour et al., 2015) was used with 500 simulations in each iteration. For calibration of SM and calculating SPAEF indicator, a script in R programming language was used. The monthly river discharge was calibrated in discharge stations and SM was calibrated over subbasins at monthly time steps. In the SO step, the weight of objective function (maximizing KGE) for each discharge station was chosen based on long-term average of observed runoff. In the MO step, the objective function was maximizing KGE (for discharge) and SPAEF (for SM) indicators at the same time and both of these parameters had the same weight in the final multi-objective function. It should be mentioned that in the MO step, the same list of parameters, which were used in SO step, was also recalibrated with the similar initial ranges.

In the SWAT+ model, the SM output is the plant available water content in the soil. Its values can vary between the wilting point (0 mm of H_2O) and saturated conditions (value depending on the soil bulk density). SWAT+ provides SM at daily, monthly, and yearly time steps for the entire soil profile and 300 mm of topsoil for each HRU. In this regard, firstly, by employing the SWI index, the CCI-SM dataset was matched according to the depth (topsoil and entire soil profile) of the model's SM output, then the adjusted SM was employed for calibration. In the MO step, the constant value of the wilting point of each soil type was firstly added to the SWAT+ SM outputs at HRU level, and was then used in calibration process.

The calibration step includes sensitive parameters of the SWAT+ model in the study area. The parameter selection was done based on the authors' experience, sensitivity analyses in SWATplus-CUP software (comprehensive description of sensitivity analyses and uncertainty analysis in the SWAT model are available in Abbaspour et al. (2015), Yang et al. (2008) and Abbaspour et al. (2007)), and suggested parameters in the literature (Abbaspour et al., 2018). Moreover, discharge stations were classified into six groups according to the subbasins' land use and soil type for spatial calibration of influential parameters.

3. Results

3.1. Single-objective calibration approach

As mentioned before, in the SO step, discharge stations were calibrated without considering the SM spatial distribution. Sixteen parameters for each discharge station groups were calibrated. In the SWAT+ model, one of the newly introduced parameters is PERCO (percolation coefficient, which varies between 0 and 1). This parameter regulates percolation from the base soil layer and can be employed to control percolation if an impervious layer or high water table exists (Wagner et al., 2022). According to the analyses, this parameter was the most influential parameter on discharge in the current study. In the first step, this parameter was calibrated and fixed to a value of 0.96, which in general results in relatively high percolation; then, other parameters were calibrated (Table 1). The model generally shows good accuracy in runoff simulations (according to Knoben et al. (2019)), and average KGE for all discharge stations is ~0.60 and ~0.63 in the calibration and validation periods, respectively. The results for the main discharge stations are presented in Table 2, and Fig. 2 presents the KGE index in all the discharge stations. However, in the north of the basin, there is a discharge station with the lowest KGE (−0.39, average runoff = 2.17 m^3/s). Fig. 2 shows that the model in the south of the basin (mostly mountainous) has the lowest accuracy in runoff simulations.

3.2. Multi-objective calibration approach

3.2.1. Adjusting the SWI index

Based on the SWI index, the satellite-based SM dataset was adjusted. In Fig. 3, the effect of the SWI method on CCI SM at basin level is presented, and SWAT+ model SM in three different conditions, including, before calibration, the calibrated model only with runoff, and calibrated model with runoff and SM at daily steps, are shown (for the period 2000–2019). As it is visible, the soil water content in the SWAT+ model is underestimated. In this regard, SM was added to the calibration process. As mentioned, these variables were calibrated for two levels, including 300 mm of topsoil and the average available water content in the entire soil profile. Calibration and validation were done on the subbasin level, meaning 1476 SM times-series were extracted from CCI SM, then were adjusted using SWI and employed in calibration and validation periods.

3.2.2. SM and runoff calibration

The objective of MO strategy was to maximize the SPAEF index for SM and KGE for runoff. In MO strategy, the same set of parameters for each of the discharge station groups, which was previously used in the SO strategy (Table 1), was now used also in the MO calibration strategy. The soil available water content (AWC) was the most sensitive parameter in SM calibration, according to sensitivity analyses in SWATplus-CUP (Table 1). The accuracy of runoff simulations for discharge stations significantly increased (average of KGE in all discharge stations is ~0.67 in the calibration and ~0.69 in the validation periods) compared to the SO approach. It should be mentioned that for 16 discharge stations improvements in KGE were achieved, and for 10 discharge stations (mainly close to mountains), the

Table 1
Final values of calibrated parameters for both calibration strategies (average values across calibration groups) and initial parameter ranges.

Change method	Parameter	Initial range of parameters		Final value	
		Lower band	Upper band	Single-objective	Multi-objective
Absolute value	alpha.gw	0.01	0.1	0.06	0.04
	bf_max.gw	0.01	1	0.29	0.61
	chn.rte	0.05	0.2	0.18	0.08
	deep_seep.gw	0.001	0.2	0.05	0.14
	epco.hru	0	0.3	0.07	0.05
	esco.hru	0.5	1	0.94	0.95
	flo_min.gw	1	5	3.31	3.27
	lat_time.hru	0.5	2	1.04	0.93
	perco.hru	0.85	0.99	0.96	0.96
	revap_co.gw	0.02	0.1	0.023	0.04
	revap_min.gw	4	10	7.05	5.76
	sp_yld.gw	0	0.2	0.09	0.04
Relative value	awc.sol	−0.2	0.2	−0.155	0.14
	bd.sol	−0.3	0.3	0.29	0.02
	cn2.hru	−0.2	0.2	−0.02	0.11
	cn3_swf.hru	−0.5	0.5	−0.29	−0.35
	k.sol	−0.2	0.2	−0.195	−0.02

Table 2
The accuracy of the model in runoff simulations in the main discharge stations.

River and discharge station name	Observed Q (m^3/s)	KGE			
		Single objective		Multi objective	
		Calibration	Validation	Calibration	Validation
Odra at Gozdowice	474.1	0.77	0.78	0.81	0.83
Odra at Cigacice	188.1	0.86	0.81	0.75	0.79
Warta at Skwierzyna	117.36	0.73	0.78	0.84	0.85
Noteć at Nowe Drezdenko	66.32	0.56	0.63	0.81	0.88
Odra at Racibórz-Miedonia	63.28	0.45	0.53	0.67	0.65

KGE values were decreased. The accuracy of the runoff simulations is presented in Fig. 4 and Table 2.

Fig. 5 shows the SPAEF distribution for SM accuracy over sub-basins. As it is visible, SPAEF (average = 0.37 topsoil and 0.31 entire soil profile) shows that the model has relatively better accuracy in SM simulations. According to Fig. 5, there is no visible pattern in the spatial distribution of the model's accuracy in SM simulations. Moreover, SPAEF determines that the model has better accuracy in topsoil SM simulations. This could be expected to the nature of the CCI SM dataset, which is reliable for the 5 cm of topsoil.

3.3. Effect of different approaches on crop yields

In order to have a robust comparison between the SO and MO strategies, crop yields were also assessed. In this regard, the yields of major crops in the ORB, including winter wheat, spring barley, rapeseed, and corn, were extracted from the SWAT+ model for both strategies and were compared with observed data, which is the annual average of mentioned provinces in Section 2.1. It should be mentioned that the SWAT+ model provides the dry weight of crop yields, and for assessments, the observed values were converted from fresh weight to dry weight yields, assuming that humidity equals 15 % and 20 % for winter wheat/spring barley and corn/rapeseed, respectively.

As it is visible in Fig. 6, crops have wider ranges of yields in MO approach, which is closer to observed data (excluding winter wheat). The positive effect of MO approach is most visible in rapeseed yields. Both approaches have a wider estimates of winter wheat and mainly over estimated winter wheat yields.

According to Fig. 7, for barley and wheat the SO approach produced mostly overestimated crop yields compared to the MO approach. The

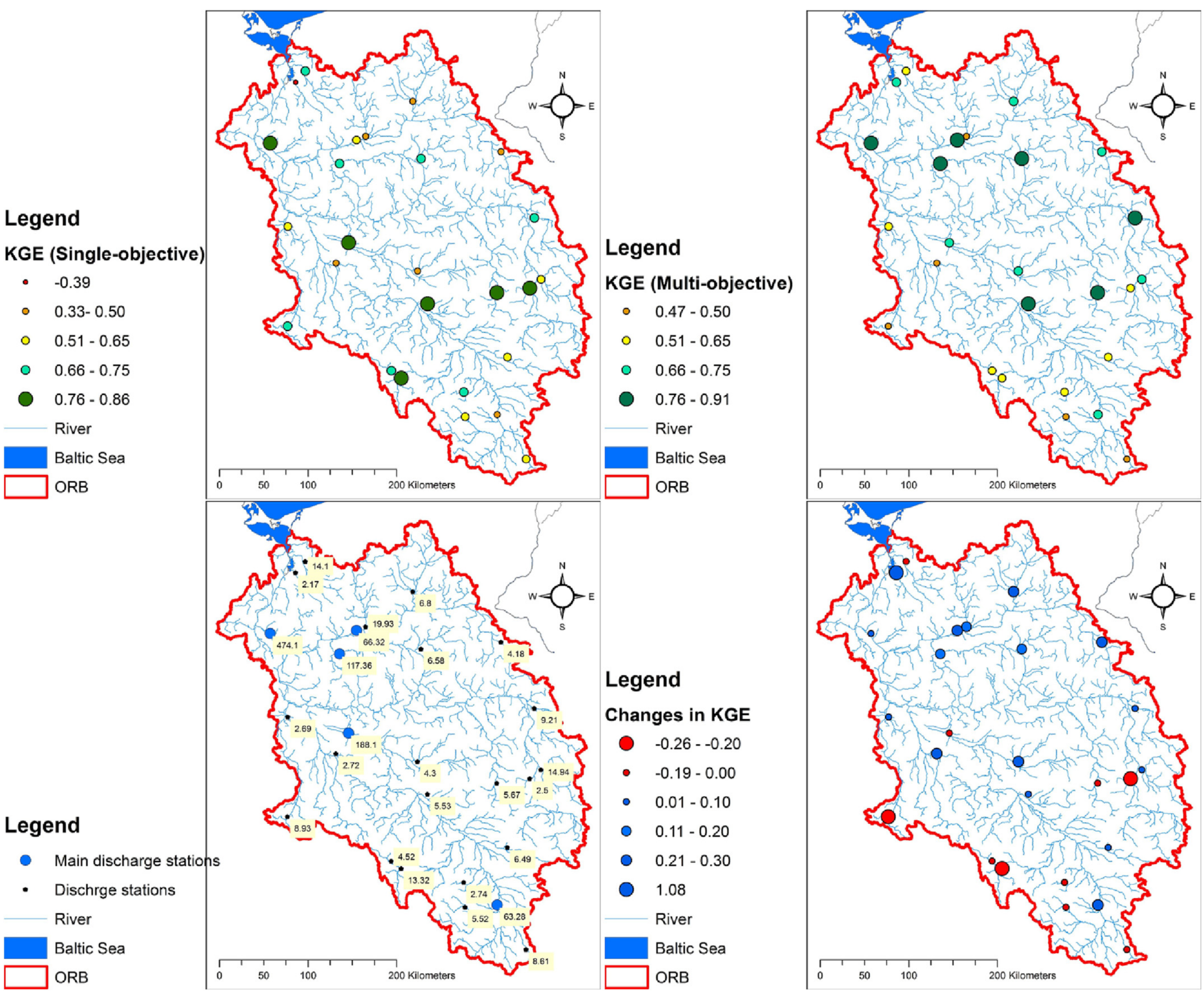

Fig. 2. The spatial distribution of the KGE indicator for both strategies, average of river discharge (down left, m^3/s), and changes in KGE (improvements or reductions for a multi-objective strategy relative to a single-objective strategy).

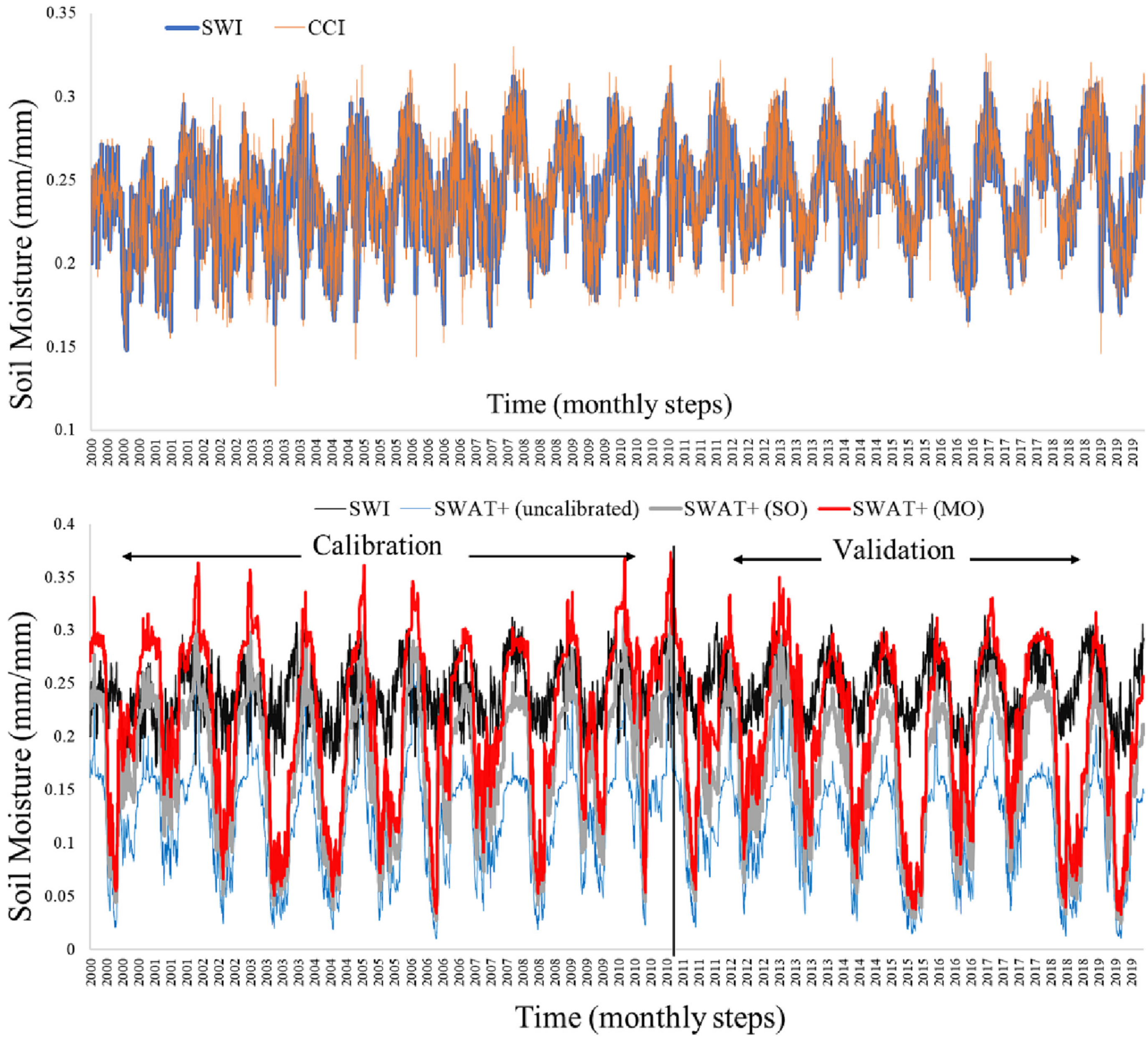

Fig. 3. Basin-averaged changes in SM in the entire soil profile (mm/mm): CCI SM, adjusted SM based on SWI, SWAT+, and the effect of calibration on SM for the period 2000–2019.

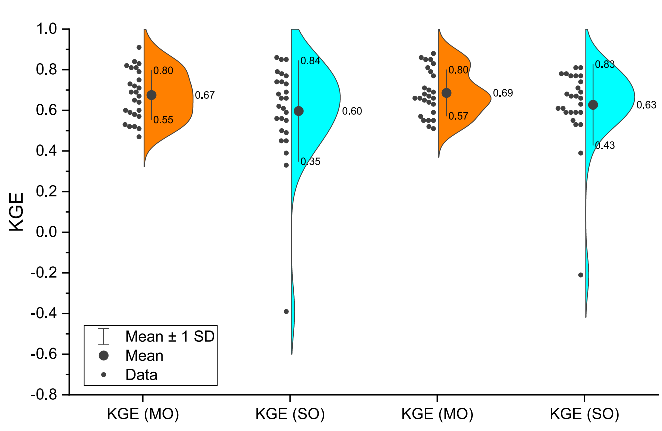

Fig. 4. Distribution of KGE for river discharge in SO and MO approaches.

opposite effect (underestimated yields in SO approach) is visible for rapeseed. For corn, the difference between yield dynamics in SO and MO approaches is very low. The correlation between simulated and observed yields is generally low, mainly due to the fact that numerous anthropogenic factors, not accounted for in SWAT+, can affect crop yields. Moreover, in 2015 Central Europe had experienced a severe drought (Ionita et al., 2017). In this particular year, according to the observed datasets barley, wheat, and rapeseed yields did not change substantially, but corn yields were more sensitive to drought. This is understandable, because drought developed in August–September, mostly after harvest of cereals and rapeseed, whereas corn which is harvested in late summer was more strongly affected. This drop in corn yields is reflected in both SO and MO approaches, however in the MO approach the response is more in line with observations.

The model performance in crop yield simulation is presented in Table 3. To evaluate the performance of SWAT+ in both approaches, mean error (tons/ha), coefficient of determination (R^2) and percentage bias (PBIAS %) were employed. According to the mean error and PBIAS, MO approach performed better than SO approach being close to zero which is the optimum

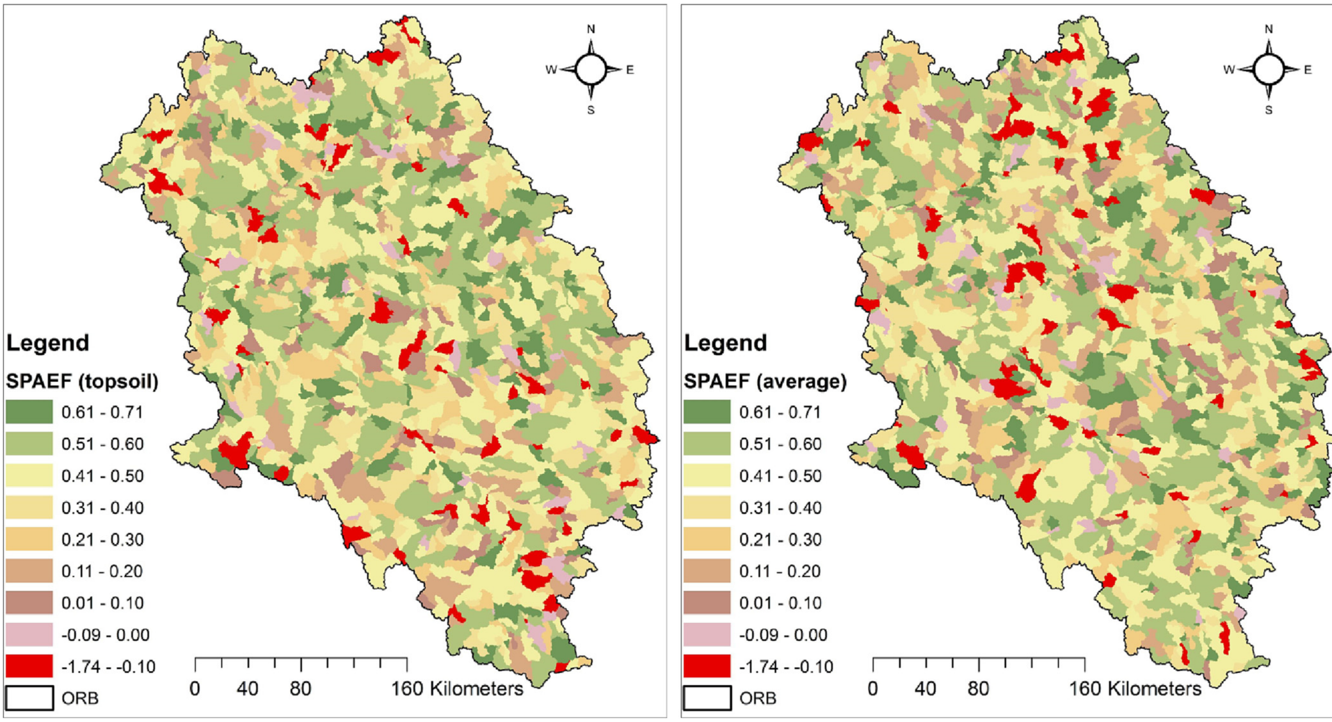

Fig. 5. Accuracy distribution of SM (topsoil and average SM) according to SPAEF.

value for these statistics. As it was already mentioned, correlation between simulated crop yields and observed data is not acceptable.

4. Discussion

In this study the multi-objective calibration enhanced the SWAT+ model's accuracy in river discharge and crop yields simulations. Improving the river discharge simulations and water balance components via multi-objective calibration in the SWAT model was reported before in several studies. For example, Eini et al. (2020), Eini et al. (2021a), and Delavar et al. (2022) have employed runoff, aquifer water table, infiltration rate, crop yields, and ET to increase the model consistency. By providing different distributed outputs, SWAT facilitates multi-objective calibration and robust results for scenario simulations (Delavar et al., 2022). Moreover, Ma et al. (2019) show that MODIS-based LAI significantly enhanced the model flexibility and spatial distribution of vegetation cover in subtropic regions.

Rajib and Merwade (2016) employed a time-dependent Soil Moisture Accounting method in the SWAT model calibration and evaluated SM in different layers in two watersheds in Indiana. They concluded that adding SM into the calibration process leads to higher fitness of simulations and observed datasets and improved efficiency metrics; the same result is observed in our study. In addition, it is mentioned that SM calibration based on in-situ root zone SM provides considerable improvement in SWAT performance (Rajib et al., 2016). The SM, based on Advanced Microwave Scanning Radiometer-Earth Observing System (AMSR-EOS) for 1 cm of topsoil, was used in their study for HRU and sub-basin level, and it improved the model's outputs in terms of root zone SM and runoff with corresponding measured datasets (Rajib et al., 2016). Azimi et al. (2020) showed that satellite-based SM assimilated from SMAP and Sentinel-1 could improve the accuracy of river discharge simulations in the SWAT model.

In the SWAT model, the ET processes start from the HRU level at daily steps, and each HRU has different land use, soil type, and slope (Arnold et al., 2012; Gassman et al., 2007; Gassman et al., 2014). In this regard, calibrating the SWAT model at the HRU level, particularly for distributed variables, could lead to more consistent results (Ma et al., 2019). In the current study, calibration was done at the subbasin level due to a large number of HRUs, large variability of hydroclimatic parameters, which affect the SM values, and the resolution of CCI SM product. Thus, a similar approach could be done in the smaller watershed and evaluate the SM accuracy of the SWAT+ model at the HRU level. Pfannerstill et al. (2017) proposed that expert knowledge could help accomplish hydrologically reliable model results regarding the simulation of runoff and water balance components. Multi-objective calibrated models can be used for water balance and water accounting assessments; in addition, in transboundary basins, these models are helpful for (inter-) national studies (De Lannoy et al., 2022). Moreover, we would like to mention that capturing the dynamic of crop yields in this large basin with a wide range of recorded crop yields was one of our limits. In future works, this limit can be addressed by employing satellite-based datasets such as LAI or canopy height estimations.

The calibration process using SM can change the water balance of the basin and increase the uncertainty of the output; thus it should be mentioned that the water balance of the basin should be checked via available parameters such as ET, crop yields, groundwater recharge, and river discharge (De Lannoy et al., 2022; Delavar et al., 2022; Eini et al., 2020; Koohi et al., 2022). Moreover, it could be recommended to evaluate the effect of root zone soil moisture datasets (such as the dataset which is provided by Grillakis et al. (2021) or Copernicus Global Land service) in improving the accuracy of the SWAT+ model. Furthermore, it could be stated that satellite-based soil moisture data can be validated by in-situ observations and then added into the calibration step this approach can decrease the uncertainty of hydrological modeling; however, in large river basins it could be expected that only short time series of in-situ soil moisture are available. Effect of multi-objective calibration on crop yield, ET, and infiltration rate can be assessed, and this could decrease the uncertainty of comprehensive hydrological modeling.

5. Conclusion

In this study, a transboundary basin in the Baltic Sea region (Odra river basin) was selected to investigate the accuracy of the SWAT+ agro-hydrological model in river discharge, crop yields and soil moisture simulations. A satellite-based soil moisture dataset (CCI SM) was chosen as the observed soil moisture dataset. In the single-objective calibration (only

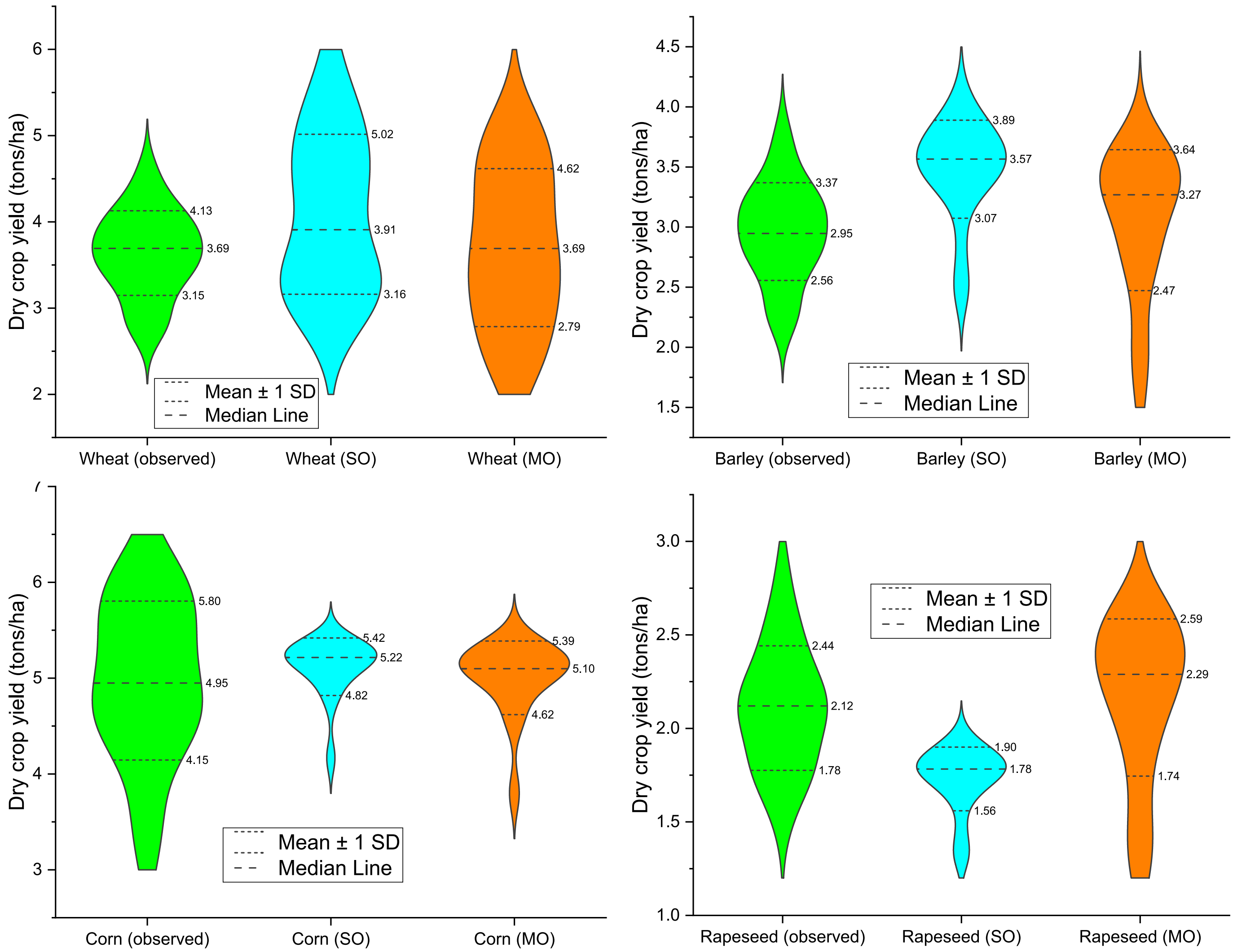

Fig. 6. Distribution of major crop yields in SO and MO strategies with the observed data (for period 1999–2019 for winter wheat, barley, and rapeseed; for period 2004–2019 for corn).

discharge) approach, the SWAT+ model showed good accuracy in runoff simulations, and the average KGE was above 0.60 and 0.63 in the calibration and validation periods, respectively. Satellite-based soil moisture was adjusted with SWI index and was added to the calibration step as the second variable in the multi-objective approach. In the multi-objective approach (discharge and soil moisture), the accuracy of simulations in river discharge stations substantially increased (KGE = 0.67 in the calibration and 0.69 in the validation periods) compared to the single-objective approach. The SPAEF index indicated that adding soil moisture in the calibration process (as we did using MO approach in this study) could improve the model's reliability. Moreover, assessing crop yields shows that multi-objective calibration also could improve the accuracy of model in estimating crop yields. The current results and presented approach can be used in transboundary river basins and regions that lack observed data, and it is important for climate change studies since this method delivers a robust model. It will also be a useful approach for model-based water accounting studies. Moreover, we recommend comparing different soil moisture products (especially high-resolution products) in future studies and trying to capturing dynamic of crop yields.

CRediT authorship contribution statement

Mohammad Reza Eini: Conceptualization, Methodology, Software, Writing – review & editing. **Christian Massari:** Conceptualization, Methodology, Writing – review & editing. **Mikołaj Piniewski:** Conceptualization, Methodology, Writing – review & editing.

Data availability

Data will be made available on request.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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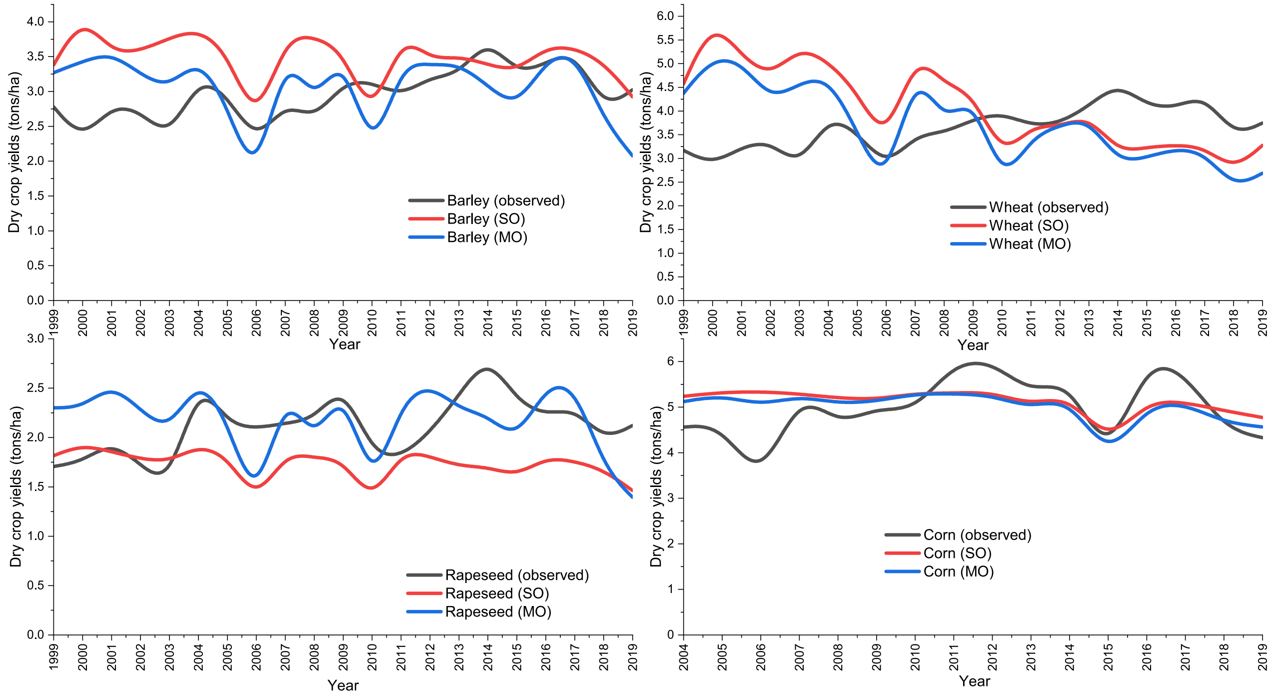

Fig. 7. Temporal variation of basin-averaged simulated (SO and MO) and observed crop yields in the ORB.

Table 3
Performance of SWAT+ in crop yields simulations for both approaches.

	Winter wheat		Barley		Rapeseed		Corn	
	SO	MO	SO	MO	SO	MO	SO	MO
Mean error (tons/ha)	0.45	0.06	0.52	0.09	−0.38	0.06	0.14	0.03
R^2	0.32	0.14	0	0.08	0	0.05	0.18	0.31
PBIAS %	12	1.7	17	3.2	−18	2	2.9	0.6

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