Resolving effects of leaf pigmentation changes and plant residue on the energy balance of winter wheat cultivation in the ORCHIDEE-CROP model

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Abstract. Crop management impacts climate not only through changes in carbon stocks and greenhouse gas budgets, but also through changes in the heat budget. However, the latter aspect remains only partially represented in current cropping system models. The coupling of dedicated crop models with land surface models may be an attempt to quantify those effects, but is hampered by the simplistic representation of surface albedo as a mix of soil albedo and a static vegetation albedo controlled by vegetation cover. Here, we developed ORCHIDEE-CROP, a land surface model integrating the cropping system model STICS, by incorporating time-varying albedo from crop pigmentation during foliar yellowing and post-harvest crop residue soil cover. We further parameterized the effect of crop residues on surface roughness and soil evaporation affecting the heat budget and partitioning between latent and sensible heat fluxes. Using 10 site simulations, we quantified the impacts of these processes on soil temperature, soil moisture, water and heat fluxes of winter wheat crops. Incorporating foliar yellowing and post-harvest residue cover increased surface albedo by an average of 0.07±0.03 during the foliar yellowing period and 0.02±0.02 during the residue cover period, accordingly inducing surface cooling by -1.55±0.93 °C and -1.90±0.88 °C. During

each period, sensible heat flux changed by -8.10±4.18 W m^{-2} and -7.44±3.98 W m^{-2}, while latent heat flux decreased by -6.84±1.41 W m^{-2} and -5.15±4.03 W m^{-2}. Spatiotemporal variability in these effects was driven by site-specific meteorology and soil properties. Simulations of drying climate scenarios reveal that crop residues left on the field can progressively increase plant available water over multiple years under dry conditions. This study underscores that crop pigmentation has a minor influence on water-heat process, while residues moderately modulate surface energy partitioning with significant spatial heterogeneity, and demonstrates the potential of its management for climate mitigation. The refined modelling framework enables simultaneous assessment of the biogeochemical and biophysical impacts of field operations on the Earth System.

1 Introduction

Agriculture and climate are interconnected by greenhouse gas, energy and water budgets (IPCC, 2014; Wu et al., 2016; Chen et al., 2024). These interactions create a dual challenge that agricultural systems are both vulnerable to climate change impacts (e.g., droughts, extreme weather) and significant contributors to global emissions. Adaptive management practices are therefore critical for enhancing agricultural resilience and sustainability while simultaneously reducing the anthropogenic disturbances of the environment and climate. To quantify complex spatiotemporal climate impacts of management practices, coupling land surface models with dedicated crop modules represents a promising strategy. These models are effective tools for simulating biophysical and biogeochemical processes at the agriculture-climate interface, such as crop physiological growth, yield dynamics, and the exchange of carbon, water, and energy between agroecosystems and the atmosphere (Brisson et al., 2003; Fisher et al., 2014; McDermid et al., 2017). By capturing these processes, land surface models provide essential insights for projecting future climate-agriculture feedbacks under varying management scenarios (Arora et al., 2023; Timlin et al., 2024). However, a key limitation arises from the inconsistency between the diversity and complexity of real-world agricultural management practices and their overly simplistic representations in current land surface models. This gap significantly hinders the ability of land surface models to reliably predict climate impacts, particularly at regional or farm-specific scales where management decisions are highly required (Fisher et al., 2020). A key example of the limited ability of land surface models in representing biophysical processes of agriculture-climate interactions is their treatment of crop albedo dynamics.

Surface albedo, as the fraction of incoming solar radiation that is reflected by the soil and crops, plays a critical role in both radiative and non-radiative climate processes (Seneviratne et al., 2018). Crops and their residues exhibit distinct albedo due to specific traits (e.g., leaf pigmentation, canopy structure) and management practices (e.g., tillage, residue retention, irrigation). For example, existing research shows an averaged albedo of 0.16-0.19 for winter wheat (Şerban et al., 2011; Sieber et al., 2022; Lei et al., 2024), of 0.18-0.20 for soybean (Costa et al., 2007; Lei et al., 2024), and of 0.15-0.18 for corn (Jacobs et al., 1990, Lei et al., 2024). These albedo differences directly affect global climate by changing the radiative forcing at the top of the atmosphere (Stephens et al., 2015). In addition, changes in surface albedo modify the surface energy balance, potentially redistributing energy into latent and sensible heat fluxes as a non-radiative process. However, land surface models generally use simplistic parameterization of static soil and crop albedo. When temporal dynamics are included, they are typically limited to changes in the fractional coverage of soil and vegetation. (Dalgliesh et al., 2016; Wu et al., 2016; Hoogenboom et al., 2024). Lacking the mechanisms to represent changes in crop pigmentation, they are unsuited to quantify climate effects of managements or crop breeding which affect crop residue or crop pigmentation (e.g., no tillage, pale crops) (Drewry et al., 2014).

Winter wheat, as a major cereal crop, undergoes distinct phenological stages that are accompanied by changes in canopy pigmentation and surface reflectance (Zhang et al., 2022). During its growth cycle, winter wheat transitions from chlorophyll-dominated green leaves to senescent yellow leaves post-maturity, where reduced chlorophyll levels expose light-reflecting carotenoids (Féret et al., 2017). Additionally, crop residues left on the field post-harvest introduce additional albedo variability compared with bare soil in conventional tillage systems, with the extent of this fluctuation depending on the baseline bare soil albedo and residue management practices (Simão et al., 2021). Generally higher albedo of vegetation than bare soil in most croplands in Europe possibly induces an increase in surface albedo when covering residues on the soil (Pique et al., 2023). Such physiological development of winter wheat and residue coverage thus the impact the climate by surface albedo, offsetting a portion of warming from greenhouse emissions. However, it is difficult for current land surface models to quantify and evaluate these effects because they are generally ignored or parameterized using simplified assumptions (Davin et al., 2014; Seiber et al., 2022; Yu et al., 2024).

This study simulates the biophysical impacts of winter wheat phenology and residue management on surface energy balance through albedo-mediated processes in the ORCHIDEE-CROP land surface model. To achieve this, we improved the model by refining the representation of foliar pigmentation and crop residue effects on albedo dynamics, as well as their influence on soil evaporation and surface roughness based on observations from 10 European cropland sites. Sect. 2 details the datasets and methodology used for model parameterization. We briefly review the baseline modelling representation of surface albedo, hydrology, roughness, and energy fluxes before introducing our modifications in ORCHIDEE-CROP. These improvements refine albedo dynamics, soil evaporation, and surface roughness, with two simulations for evaluating the albedo-mediated impact of residue retention conducted under both current and drying climate scenarios. Sect. 3 presents the results of these refinements, while Sect. 4 analyses the contribution of albedo changes, driven by foliar pigmentation and crop residues, on modulating surface temperature, latent heat, and sensible heat fluxes. We also discuss the potential of crop residue management for climate adaptation and mitigation. Finally, Sect. 5 summarizes our findings and conclusions. By incorporating albedo dynamics influenced by crop pigmentation and residue management, this study enhances the realism of coupled cropland surface models and demonstrates its impacts on field-level energy balance under present and future idealised climate.

2 Data and methods

The improvement of the ORCHIDEE-CROP model is illustrated in Fig. 1 and structured into six subsections: (1) Datasets (Sect. 2.1); (2) Introduction of the ORCHIDEE-CROP model (Sect. 2.2); (3) New parameterization of the ORCHIDEE-CROP model (Sect. 2.3); (4) Model calibration (Sect. 2.4); (5) Model simulations (Sect. 2.5); (6) Model evaluation (Sect. 2.6).

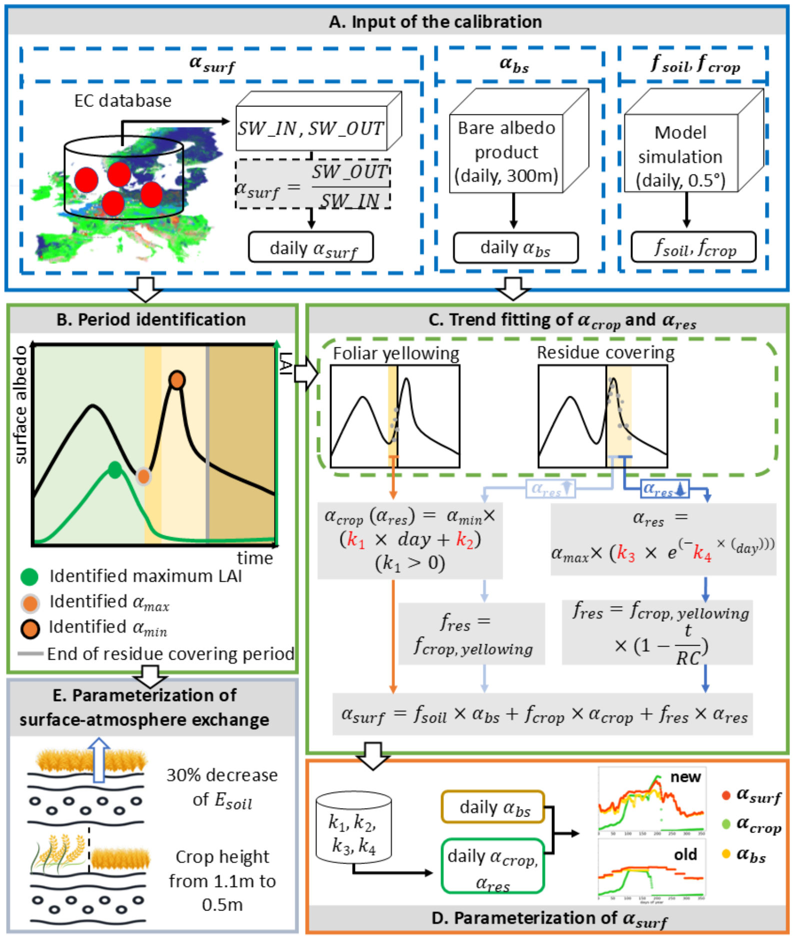

Figure 1 The procedure of parameterization of crop and residue albedo (α_{surf} and α_{res}), soil evaporation (E_{soil}) and surface roughness (Z_0) in the ORCHIDEE-CROP model. Panel (A) illustrates the input datasets for albedo calibration. α_{soil} and α_{surf} are bare soil albedo (α_{soil}) and surface albedo (α_{surf}), respectively. f_{crop} and f_{soil} are the gridded fractions of crop (f_{crop}) and residues (f_{res}), respectively. *SW_IN* and *SW_OUT* are half-hourly incoming (*SW_IN*) and outgoing (*SW_OUT*) solar radiance observed at seven eddy-covariance (EC) sites. Panel (B) shows the identification of foliar yellowing and residue covering periods based on time series of α_{surf} (black curve) and leaf area index (*LAI*, green curve). α_{min} and α_{max} are the identified minimum and maximum α_{surf}. The shallow-green, orange, yellow and brown areas show the conceptual growing, maturity,

residue covering and bare soil periods of winter wheat. Panel (C) describes trend fittings for crop albedo (α_{crop}) and α_{res}. Features in two plots have the same meanings with the ones in Panel (B). $f_{crop,yellowing}$ is the fraction of crop during the foliar yellowing period. *RC* is the duration of residue covering. k_1, k_2, k_3 and k_4 are the fitting parameters during foliar yellowing and residue covering periods. *Day* and *t* are the days of α_{surf} increase during residue covering period. Panel (D) illustrates parameterization of α_{surf} as a weighted combination of α_{crop}, α_{res} and α_{soil} in ORCHIDEE-CROP model. The daily α_{surf} in orange in the upper plot is derived from the new calibrated process based on k_1-k_4, compared to the old model (plot below). Panel (E) presents parameterization of surface-atmosphere exchange. E_{soil} is the soil evaporation and the dotted vertical line represents the harvesting date of winter wheat.

2.1 Datasets

2.1.1 Daily surface albedo from site observation

To derive surface albedo (α_{surf}, unitless) from site observation, we combined datasets from two sources: (1) eddy-covariance measurements from the Integrated Carbon Observation System (ICOS) Data Portal (Dumont et al., 2023; Schmidt et al., 2023; Buysse et al., 2023; Brut et al., 2023; Brümmer et al., 2023; Tallec et al., 2023; Bernhofer et al., 2023), and (2) satellite-derived products at farms belonging to the ClieNFarm project. From the ICOS network, we obtained the half-hourly incoming and outgoing solar radiance (*SW_IN* and *SW_OUT* (W m^{-2})) from 2000 to 2020 at eight wheat cultivated sites (BE-Lon, CH-Oe2, DE-Geb, DE-Kli, DE-RuS, FR-Aur, FR-Gri, FR-Lam) (Fig. S1). Data were quality-controlled and gap-filled using uniform methods (Pastorello et al., 2020). Details of quality filtering and preprocessing of α_{surf} are shown in Text S1.1. The daily shortwave mid-day α_{surf} was calculated from average values of *SW_IN* and *SW_OUT* from 11:00 to 13:00 Central European Summer Time at each site (Lin et al., 2022):

$$\alpha_{surf} = \frac{SW\_OUT}{SW\_IN} \quad (1)$$

At six farms across two ClieNFarm sites (UK-Rookery, UK-Winwick, UK-Allerton, BE-AH, BE-BM, BE-LB) where direct radiation measurements were unavailable, we estimated surface albedo at 5-day intervals and 300-m resolution using Sentinel-2 (S2) reflectance data. A 10% cloud cover threshold was applied for quality filtering, and retrievals followed the framework developed by Lin et al. (2023). Across the selected 10 sites, we chose only the years in which winter wheat was cultivated, and obtained a total of 33 winter wheat years.

2.1.2 Meteorological data from site observation

We utilized the half-hourly meteorological observations from flux towers in the winter wheat years at eight ICOS sites to force the ORCHIDEE-CROP model. The observations include *SW_IN*, surface pressure (*Pa*), near-surface specific humidity (kg kg^{-1}), rainfall rate (kg m^{-2} s), snowfall rate (kg m^{-2} s), near-surface air temperature (K), and near-surface eastward and northward wind components (m s^{-1}). The FLUXNET_DATA tool was applied (https://forge.ipsl.jussieu.fr/orchidee/wiki/Scripts/FluxnetValidation/DataProcessing) to fill in the flux-towers data gaps using 6-hourly ERA-interim products (Vuichard and Papale, 2015). We then averaged all gap-filled variables to a 6-hour time step to meet the requirement of the model input. At two ClieNFarm sites with no flux observations, the meteorological variables from the hourly 0.25° ERA-interim product were extracted and interpolated to exact site coordinates to provide meteorological forcing data.

In 10-year simulations for the current climate scenario from 2010 to 2020 (Sect. 2.5), the processed climate forcing data from each year obtained from the ICOS Data Portal was used to drive the model. For the drying climate scenario, the driest year at each site was identified based on the lowest annual precipitation. All meteorological variables from this year were then used to force the simulation. This ensures that the drying climate scenario is driven by a coherent and physically realistic set of meteorological conditions. Yearly-averaged meteorological variables in the driest year for each site are presented in Table S1.

2.1.3 Management practice, bare soil albedo and LAI

Management practices for winter wheat years at all sites (Table S2) were obtained from a crop management database provided by site managers. Key practices, including sowing, harvesting, and tillage dates, were prepared as input for the ORCHIDEE-CROP model.

Bare soil albedo (α_{soil}, unitless) was prescribed using a high-resolution 5-day, 300-m European α_{soil} dataset derived from 10 m S2-α_{surf} observations covering the period 2018-2020 (Yu et al., in review). This dataset demonstrated sufficient skills in resolving daily soil dynamics at the field scale in European fragmented croplands. Since the model is run at site scale, the α_{soil} dataset was extracted at each site position, and linear interpolation was applied to convert the data to a daily time step, aligned with the model temporal resolution.

Due to the absence or sporadic leaf area index (*LAI*, $m^2\ m^{-2}$) measurements found at ICOS sites (Table S3), we used continuous satellite-based *LAI* datasets to identify the timing of peak *LAI* at those sites. *LAI* at each site was extracted from the 4-day, 500-m *LAI* product from the MODIS (MCD15A3H) (Myneni et al., 2015). Daily *LAI* dynamics were derived through linear interpolation combined with a Savitzky-Golay filter (window length=15) to smooth the trend and remove the outliers. MODIS-derived *LAI* was used to constrain the onset of the maturity period, rather than to reproduce absolute *LAI* values. The *LAI* comparison between MODIS product and site measurements is shown in Fig. S2. We used MODIS-derived but not S2-derived *LAI* product, because the temporal coverage of the latter is insufficient to match the available site observations.

2.2 Introduction of the ORCHIDEE-CROP model

The ORCHIDEE-CROP model is a branch version of the process-based land surface model, ORCHIDEE (Krinner et al., 2005), which incorporates a generic crop phenology and harvest module, along with simplified nitrogen fertilization parameterization based on the process-based STICS formalism (Wu et al., 2016). It simulates biophysical and biogeochemical interactions in croplands, as well as plant productivity and harvested yield. A detailed model description is available in Wu et al. (2016). This study employs a previously developed model version calibrated against LAI, flowering and harvesting dates, and crop yield for both winter wheat and maize (https://github.com/yangsssu/ORCHIDEE-CROP.git). In the present study, only winter wheat is considered. The derived climate and management information drive the model as forcing data (Sect. 2.1.2 and 2.1.3). Winter wheat is the only vegetation type considered in this analysis. To assess the impact of physiological development of winter wheat and residue coverage on surface energy balance and water-energy fluxes, we describe below the key processes governing surface energy balance (Sect. 2.2.1), α_{surf} dynamics (Sect. 2.2.2), hydrology (Sect. 2.2.3), the surface roughness (Sect. 2.2.4), as well as crop growth and development (Sect. 2.2.5).

2.2.1 Surface energy balance

The ORCHIDEE-CROP model simulates the surface energy budget by:

$$R_n = LE + H + G \quad (2)$$

Where the net radiation (R_n, W m^{-2}) governs land-atmosphere water and heat exchange, driven by the partitioning of LE, sensible heat fluxes (H, W m^{-2}) and soil heat fluxes (G, W m^{-2}). R_n is determined by the net short-wave radiation budget (S_n, W m^{-2}) and the net long-wave radiation budget (L_n, W m^{-2}) (Ducoudré et al., 1993).

$$R_n = S_n + L_n = (1 - \alpha_{surf}) \times SW\_IN \quad + L \downarrow - L \uparrow \quad (3)$$

Where $L\downarrow$ is the down-welling longwave radiation (a model input variable). $L\uparrow$ is the upwelling longwave radiation emitted by the land surface, which is estimated by surface temperature (T_{surf}, K) (a model input variable) based on Stefan-Boltzmann law.

Since α_{surf} directly influences R_n, we next describe its formulation in the ORCHIDEE-CROP model.

2.2.2 Surface albedo dynamics

The model calculates α_{surf} in step t for both the visible and near-infrared domains by the area-weighted sum of foliar albedo (α_{crop}, unitless) and α_{soil}:

$$\alpha_{surf}\,(t) = (1 - f_{crop}(t)) \times \alpha_{soil}(t) + f_{crop}(t) \times \alpha_{crop,constant} \quad (4)$$

Where f_{crop}(t) and 1-f_{crop}(t) represent the fractions of winter wheat and bare soil covering the surface area of the model pixel; $\alpha_{crop,constant}$ of winter wheat is set as the default value of 0.1 and 0.3 for visible and near-infrared ranges of α_{crop}, respectively. α_{soil}(t) is derived from daily α_{soil} dataset (Sect. 2.1.4). Since α_{surf} affects radiation absorption, it influences soil moisture availability and, consequently, soil evaporation (E_{soil}).

2.2.3 Hydrology

The ORCHIDEE-CROP model computes soil water budget by considering the three reservoirs of canopy interception, snow packing and 11 soil layers (MacBean et al., 2020). The water fluxes at soil surface include water input to the soil by throughfall, snowmelt and irrigation, and water output from soil by surface runoff, bare soil evaporation and drainage. Here, we mainly described the calculation of E_{soil} and the soil water content (SWC, kg m^{-2}) in different soil layers.

The ORCHIDEE-CROP model calculates LE by accounting for snow sublimation, canopy interception and transpiration, E_{soil} and floodplain evaporation. A β-model is used to compute E_{soil} by inducing a series of resistances.

$$E_{soil}\,(t) = (1-\beta_1) \times (1-\beta_5) \times \beta_4 \times r_{au} \times v \times C_d \times (q_{surf} - q_{air}) \times dt \quad (5)$$

Where β_1, β_4 and β_5 are dimensionless scaling factors representing soil moisture and surface resistance effects for snow sublimation (β_1), soil evaporation (β_4) and floodplain evaporation (β_5), respectively; r_{au} (kg m^{-3}), v (m s^{-1}), C_d (-), q_{surf} (kg kg^{-1}), and q_{air}(kg kg^{-1}) are the air density, wind speed, drag coefficient, saturated surface air moisture, and specific humidity, respectively. The bulk formulation yields evaporation in kg m^{-2} s^{-1}, which is integrated over the model time step (dt) to obtain kg m^{-2}. This quantity is then expressed in mm day^{-1} using the equivalence 1 mm = 1 kg m^{-2}.

Soil moisture dynamics are governed by a diffusive multi-layer soil hydrology scheme with 27 soil layers (up to 2 m), based on moisture diffusion principles (Richards, 1931; de Rosnay et al., 2002; Wu et al., 2016). It uses the 1D Richards equation with soil volumetric water content as the state variable in its saturated form, instead of the pressure head (Campoy et al., 2013).

2.2.4 Surface roughness

Surface roughness (Z_0, m) plays a critical role in regulating near-surface turbulence and the water-heat exchange process between the surface and atmosphere (Meier et al., 2022; Chen et al., 2024). E_{soil} depends on Z_0, which modulates atmospheric turbulence and moisture transfer. The ORCHIDEE-CROP model uses the averaged drag coefficients for momentum and heat for winter wheat to compute the grid-averaged roughness height.

$$Z_0(t) = f_{crop}(t) \times \left(\frac{C_k}{\log\left(\frac{Z_{tmp}}{\max\,(H_C \times Z_{0,h},\ Z_{0,bare})}\right)}\right)^2 \quad (6)$$

Where Z_0 (t) is the daily roughness height over each grid cell. C_k (-) is the von Karman constant, which equals to 0.41. Z_{tmp} (m) represents the maximum height of the first atmospheric layer and is determined by air pressure, air temperature, and air density. It is the reference height used for flux calculations and is set to a minimum of 10 m above the ground. This ensures that it remains higher than the canopy height, maintaining the stability of the logarithmic function used in flux calculations. H_c (m) is the winter wheat height which is a time-invariant constant and set to 1.1 m in ORCHIDEE-CROP model. For comparison, maximum H_c of winter wheat during growing seasons measured at five sites has an average of 0.97 m (Table S3). $Z_{0,h}$ equals to 1/16, which is utilized to estimate the roughness height above the canopy. $Z_{0,bare}$ (m) is set as 0.01 m for roughness length of bare soil. Z_0 for the bare soil can be derived by:

$$Z_0(t) = (1 - f_{crop}(t)) \times \left(\frac{C_k}{\log\left(\frac{Z_{tmp}}{Z_{0,bare}}\right)}\right)^2 \quad (7)$$

The ORCHIDEE-CROP model computes a grid effective roughness height (H_{rough}, m) for deriving water-heat fluxes. It combines the zero-plane displacement height (Z_{dis}, m) which is an equivalent height for the absorption of momentum, and the vegetation height weighted by the maximum f_{crop} ($f_{crop,max}$) of winter wheat within each grid (H_{ave}, m):

$$H_{rough} = H_{ave} - Z_{dis} \quad (8)$$

$$Z_{dis} = H_{ave} \times H_{dis} \quad (9)$$

$$H_{ave} = f_{crop,max} \times H_c \quad (10)$$

H_{dis} (m) is used to determine the Z_{dis} based on H_{ave}, which equals to 0.75.

2.2.5 Crop growth and development

Crop development in the ORCHIDEE-CROP model is based on the crop model STICS (Wu et al., 2016). For winter wheat, the crop module simulates nine developmental stages of crop growth and grain filling (Fig. 2.1 in Brisson et al., 2008). The timing and duration of each stage are calculated based on growing degree days, adjusted by limiting functions for photoperiod, vernalization and limited factors (e.g., water and nitrogen). Transitions between stages occur when the threshold values of growing degree days are reached.

In our simulations, sowing dates were prescribed using observed, site-specific management information to ensure consistency with field observations. Subsequent phenological development, including flowering, maturity, and harvest, is driven by growing degree days following the ORCHIDEE-CROP phenology scheme which was calibrated using extensive wheat phenology records from 1941 DWD climate stations across Germany (Su et al., 2025). This approach ensures that modelled flowering and harvesting dates are on average, consistent with observed phenology across a wide range of environmental conditions. We further adjusted the delay between crop maturation and harvest at each site using actual harvest dates at each site which vary depending on practical reasons and weather (Table S2).

2.3 New parameterization of the ORCHIDEE-CROP model

Foliar yellowing of winter wheat after maturation and crop residues remaining on the field after harvest affect α_{surf} and turbulent fluxes but are currently not accounted for. As such, the absence of these key processes presents a gap in understanding and modeling the impact of winter wheat on regional energy and water cycles. We enhanced the ORCHIDEE-CROP model by introducing empirical functions describing α_{surf}, β_4 and Z_0 dynamics as a function of time, f_{crop} and f_{res} for foliar yellowing and crop residues. In addition, to ensure consistency between simulated and observed crop development periods (from sowing to harvest) at each site, the duration between maturity and harvesting in ORCHIDEE-CROP was calibrated using recorded harvesting dates at each site. In each winter wheat year at each site, simulations were performed iteratively with potential maturity-harvest intervals ranging from 5 to 40 days at 2-day increments. The optimal duration for each case was identified when the simulated harvest date matched the recorded management date. The calibrated durations are summarized in Table S2. It means that the site-specific durations of foliar yellowing before harvesting vary across all sites in the new model, compared to the default 14 days in the old model.

The objective of this model development targets a realistic mean effect size expected among European croplands, rather than capturing in detail the site-specific effects. We focus on improving the representation of albedo properties of winter wheat during the yellowing and residue covering period, while associated impacts on surface energy fluxes are evaluated qualitatively rather than through a full recalibration of the hydrological scheme.

2.3.1 Improving albedo dynamics during the foliar yellowing periods

The foliar yellowing period in this model is defined as starting from the maturity date (nmat) and ending on the harvesting date based on analysis of observed α_{surf} dynamics at 10 sites (Sect. 2.4.1).

We replaced Eq. (4) with an equation which uses time varying α_{crop}(t) instead of a $\alpha_{crop,constant}$:

$$\alpha_{surf}\,(t) = (1 - f_{crop}(t)) \times \alpha_{soil}(t) + f_{crop}(t) \times \alpha_{crop}(t) \qquad (11)$$

To simulate the increase in α_{crop} after maturation and before harvesting we chose the following function:

$$\alpha_{crop}(t) = \alpha_{yellowing,start} \times (k_1 \times t + k_2) \qquad (12)$$

Where $\alpha_{yellowing,start}$ is the simulated α_{crop} on the first day during the foliar yellowing period. $k_1$and k_2 represent the fitting parameters that are calibrated at the multi-site scale (see below).

Here, we assumed that f_{crop} remains constant during the foliar yellowing periods ($f_{crop,yellowing}$).

2.3.2 Improving albedo dynamics during the residue covering periods

The residue covering period starts from the harvesting date and ends 90 days after harvesting, or earlier if tillage occurs (Sect. 2.4.1). As α_{surf} continuously increases after harvesting due to the light-colored and evenly distributed straws, we used the segmentation function to describe α_{surf} dynamics from increase to decrease during this period.

The α_{surf} at each time step can be represented by the area-weighted sum of α_{soil} and α_{res}:

$$\alpha_{surf}\,(t) = (1 - f_{res}(t)) \times \alpha_{soil}(t) + f_{res}(t) \times \alpha_{res}(t) \qquad (13)$$

$$\begin{cases} \alpha_{res}\,(t) = \alpha_{yellowing,start} \times (k_1 \times t + k_2) & t\ in\ albedo\ increase\ phase; \\ \alpha_{res}\,(t) = \alpha_{max} \times (k_3 \times e^{-k_4 \times t}) & t\ in\ albedo\ decrease\ phase; \\ \alpha_{res}\,(t) = 0 & otherwise; \end{cases} \qquad (14)$$

Where α_{max} is the simulated α_{crop} on the last day of the albedo increase phase. (1 - f_{res}(t)) represent the daily variation of bare soil fraction. $k_3$and k_4 represent the fitting parameters that need to be calibrated at the site scale (see below).

Here, f_{res} during the albedo increase phase equals to $f_{crop,yellowing}$ and linearly decreases during the albedo decrease stage from $f_{crop,yellowing}$:

$$\begin{cases} f_{res}(t) = f_{crop,yellowing} & t\ in\ albedo\ increase\ phase; \\ f_{res}(t) = f_{crop,yellowing} \times \left(1 - \frac{t}{RC}\right) & t\ in\ albedo\ decrease\ phase; \\ f_{res}(t) = 0 & otherwise; \end{cases} \quad (15)$$

RC is the maximum residue covering period, either equals to 90 days or the tillage date.

2.3.3 Considering the impact of crop residue on soil evaporation during the residue covering periods

Crop residues covering part of soil surface decrease E_{soil} by increasing the soil-to-atmosphere resistance (Horton et al., 1996). The current ORCHIDEE-CROP model does not consider the impact of crop residue on E_{soil}. Previous site-scale observations generally show a 20-50 % reduction in E_{soil} due to the presence of wheat residue compared with bare soil (Unger et al., 1986; Lascano, 1996; Ramos et al., 2024). Based on Eq. (5), we assumed a maximum initial soil conductance (β_4, unitless) reduction of 50 % at the highest f_{res} (Zhao et al., 2020; Raes et al., 2022), with a progressive increase of conductance as daily f_{res} declines during the residue cover period:

$$E_{soil}(t) = (1 - \beta_1(t)) \times (1 - \beta_5(t)) \times (1 - 0.5 \times f_{res}(t)) \times \beta_4(t) \times r_{au}(t) \times v(t) \times C_d(t) \times (q_{surf}(t) - q_{air}(t)) \quad (16)$$

The meanings of all variables are the same as the ones in Eq. (5).

Note that β_4 represents an empirical resistance factor and cannot be directly inferred from observations. Therefore, its value was constrained through sensitivity testing against published experimental reductions in E_{soil} rather than calibrated directly using site-level flux measurements (Fig. S3, Table S4).

2.3.4 Considering the impact of crop residue on surface roughness during the residue covering periods

The initial version of the ORCHIDEE-CROP model assumed that $\boldsymbol{Z_0}$ after harvest equals that of bare soil coverage, omitting that (parts of the) stalks remain. To represent the impact of crop residues on $\boldsymbol{Z_0}$ during the residue covering periods, we assumed that the $\boldsymbol{H_c}$ of plant changes from 1.1 m for winter wheat to 0.5 m for crop residues which was found to be optimal for the cutting height for harvest efficiency and soil and water conservation (MacMaster et al., 2000). $\boldsymbol{f_{crop}}$ is replaced with $\boldsymbol{f_{res}}$. The new $\boldsymbol{Z_0}$ and $\boldsymbol{H_{rough}}$ are therefore computed by:

$$Z_0(t) = f_{res}(t) \times \left(\frac{C_k}{\log\left(\frac{z_{tmp}}{max\left(0.5 \times Z_{0,h}, Z_{0,bare}\right)}\right)} \right)^2 \quad (17)$$

$$H_{rough} = f_{crop,max} \times 0.5 - f_{crop,max} \times 0.5 \times H_{dis} \quad (18)$$

These two formulations remain identical to Eqs. (7) and (8), but with adjusted parameter values for canopy height and fractional cover to represent crop residues.

2.4 Model calibration

The parameters of α_{surf} dynamics were calibrated using data from 10 sites with 33 winter wheat site-years. α_{surf} and LAI observations were applied to identify foliar yellowing and residue covering periods at the available sites (Table S2).

2.4.1 Identifying the periods of foliar yellowing and residue covering from site observation

At the site scale, we assumed that foliar yellowing (i.e., α_{surf} increase) begins when maturity is reached due to the absence of observational data supporting a temporal gap between these two phases.

In the model, α_{surf} starts to increase with a delay after maximum LAI is reached and ends with a delay after harvest. Post-harvest α_{surf} dynamics were divided into two stages: (1) an initial α_{surf} increase driven by light-colored, evenly distributed straw, followed by (2) a α_{surf} decline due to the dominating effects of decomposition of residues.

α_{surf} dynamics were parameterized by identifying critical temporal thresholds. The minimum α_{surf} between the LAI peak and harvest marked the onset of foliar yellowing, which is approximately 22.3 days (95% bootstrap CI: [20.6-23.6] days, n=33) pre-harvest computed by site observation. This delay is longer than the default 14-day assumption between maturity date and harvest in the old ORCHIDEE-CROP model. The maximum α_{surf}, constrained to occur in 30 days post-harvest, divided residue-driven α_{surf} into an increase phase (harvest to maximum α_{surf}) and a decline phase from post-maximum α_{surf} to tillage. Without tillage, the residue covering period persists for 90 days post-harvest (Kriauciuniene et al., 2012). On average, the maximum α_{surf} occurs 13.4 days (95% bootstrap CI: [10.5-15.9] days, n=33) after harvest based on site identification, while the configuration in the old ORCHIDEE-CROP model does not consider the timing of maximum α_{surf}. Due to the lacking information of maximum α_{surf} during residue covering period in the old model, we utilized 15 days after harvesting as the boundary of these two phases in the ORCHIDEE-CROP model at all sites for simplification.

2.4.2 Parameter optimization of albedo dynamics

Daily α_{surf} and α_{soil} observations, as well as and information on area of bare soil exposure were utilized to calibrate the empirical parameters k_1, k_2, k_3 and k_4 for α_{crop} and α_{res} (Eqs. 12 and 14). The $\alpha_{yellowing,start}$ (Eq. 12) was replaced by the α_{surf} observation at the beginning of the foliar yellowing period. The simulated f_{crop} from the old model and calculated f_{res} (Eq. 13) were used due to the lack of observation of fraction changes.

Data collected from 10 sites with 28 winter wheat years (n = 485 daily α_{surf} observation) were used to train k_1, k_2, k_3 and k_4 in Eqs. 12 and 14. Data from the remaining five winter wheat years (n = 179 daily α_{surf} observation) were utilized for testing. Finally, calibrated k_1, k_2, k_3 and k_4 were incorporated into the ORCHIDEE-CROP model to simulate the albedo dynamics affected by foliar yellowing and residue covering for all 10 sites.

2.5 Model simulations

Simulations were performed for 10 sites with 14 farms (Table S2) with the new ORCHIDEE-CROP model version and with the original version of this model (Table 1) for the years for which observations were available. The experiments aimed to evaluate the impact of the parameterizations of α_{surf}, β_4 and Z_0 on water-energy cycles during the foliar yellowing and residue covering periods. In the following, we refer to ORC-D as the default ORCHIDEE-CROP model configuration prior to any modifications, where "D" denotes the default setup. To test the respective impacts of the five model modifications we used five different configurations of the improved model. Configuration ORC-AE includes modifications to α_{surf}, β_4 and Z_0 during foliar yellowing and residue covering periods, where "A" refers to surface albedo and "E" to energy-related parameters. Configuration ORC-A includes only the modified α_{surf}, while ORC-E incorporates adjustments to both β_4 and Z_0. To further disentangle the individual impacts of β_4 and Z_0, ORC-Z_0 modifies only the Z_0, and ORC-β_4 refers to only the modification of the β_4. Prepared climate forcing data (Sect. 2.1.2), soil texture (sand, silt and clay contents) and crop management information (i.e., sowing date, tillage date, residue covering periods) (Sect. 2.1.3) at each available site were applied to drive the model. Note that all other management practices prescribed in this model (e.g., nitrogen fertilization) were set as default due to the lack of historical implementation records. There is no irrigation consideration in this analysis.

Table 1 Overview of simulation experiments and model configurations.

Names of experiments	Periods	Surface albedo	Parameter of soil conductance	Surface roughness	Crop & residue fraction	Test purpose
ORC-D		-	-	-	-	Control simulation
ORC-AE	Foliar yellowing	√	-	-	√	Combined impacts of surface albedo, soil resistance and surface roughness
	Residue covering	√	√	√	√	
ORC-A	Foliar yellowing	√	-	-	√	Isolated impact of surface albedo
	Residue covering	√	-	-	√	
ORC-E	Foliar yellowing	-	-	-	√	Combined impact of soil resistance

	Residue covering	-	√	√	√	and surface roughness
ORC-β_4	Foliar yellowing	-	-	-	√	Isolated impact of soil resistance
	Residue covering	-	√	-	√	
ORC-Z_0	Foliar yellowing	-	-	-	√	Isolated impact of surface roughness
	Residue covering	-	-	√	√	

* '-' means there is no change, whereas '√' denotes that the corresponding parameter is modified relative to ORC-D;
*The temporal evolution of foliar and residue albedo, soil resistance parameter, surface roughness, as well as changes in crop and residue fractions, follows the parameterizations described in Sect. 2.3, unless stated otherwise.

In addition, we conducted a 10-year simulation (2010-2020) under current and idealised drying climate scenarios to quantify the cumulative effects of residue soil cover on water and heat fluxes for the new and old models at six sites if 10-year climate forcing data is available (Table S2). The meteorological forcing data for both scenarios followed the methodology described in Sect. 2.1.2, where the current climate scenario used observed annual climate data from ICOS, and the drying climate scenario was driven by climate forcing from the driest year (defined as the year with the lowest annual rainfall). The meteorological forcing of the driest year was repeated over the simulation period to construct a persistent dry condition. At each site, the sowing and harvesting dates were the averages of the years where observations were available. The residue covering periods were assumed to persist for 60 days following winter wheat harvest in each year.

2.6 Sensitivity analysis

We performed sensitivity tests of the major parameters (i.e. k_1, k_4, β_4, Height, duration of α_{surf} increase during residue covering period (D_{up})) linking to the α_{surf} variation and the responses of the energy and water budgets, particularly for the ones without enough constraints from field observations. The sensitivity test was conducted by changing the parameters by ±10%, ±20% and ±30% from the initial calibrated values. Their impacts on T_{surf}, H, E_{soil} and LE were evaluated.

2.7 Model evaluation

We evaluated the performance of ORCHIDEE-CROP with and without modification against observations of α_{surf} at site scale. The sites used for evaluation were independent from the ones used for calibration of α_{surf}.

We computed the coefficient of determination (R^2) and RMSE as quality indicators for simulation-observation comparison of α_{surf} during the site calibration and model simulation processes (Wright 1921, Carbone and Armstrong 1982):

$$R^2 = 1 - \frac{\sum_i^n (y_i - f_i)^2}{\sum_i^n (y_i - \underline{y})^2} \quad (19)$$

$$RMSE = \sqrt{\sum_i^n \frac{(f_i - y_i)^2}{n}} \quad (20)$$

Where n and i are the number of data and the data i in n in dataset; y_i and f_i are the value of observed data i and the value of fitted data i; $\underline{y}$ is the mean of the observed data.

With the calibration of the simulation of harvesting date for all sites, we further compared the simulated surface temperature (T_{surf}), *LE, H* from the old and new models against observation during the foliar yellowing and residue covering periods. For each variable, a paired t-test was also used to test the null hypothesis that the mean paired difference between the simulations from the old and new models is equal to zero.

3 Results

3.1 Evaluation of surface albedo dynamics in the refined ORCHIDEE-CROP model

During the albedo calibration phase, the estimated parameter values of k_1, k_2, k_3 and k_4 (Eqs.12 and 14) are 0.013 (95% CI: 0.012-0.013), 1.005 (95% CI: 0.998-1.017), 0.895 (95% CI: 0.889-0.902) and 0.0022 (95% CI: 0.0017-0.0026), respectively. Using these calibrated parameters, the relationship between observed surface albedo (α_{surf}) and the parameterized α_{surf} representation used to constrain the model shows a moderate correlation with an R^2 of 0.54 during the foliar yellowing period and of 0.62 during the residue covering period for five testing sites. The corresponding RMSE has values of 0.04 and 0.03, respectively (Fig. 2). The least-squares regression in these two fitting models captures the mean tendency of the data unlike models that consider them constant, but falls short of reproducing full variation, as it minimizes average errors rather than explaining outliers.

The refined ORCHIDEE-CROP configuration (ORC-AE), represents the new model version with effects of the modified α_{surf} and the refined soil conductance (β_4) and surface roughness (Z_0), was used to simulate α_{surf} dynamics at all 33 site years, which were evaluated independently against observations (Fig. S4a,b). This independent evaluation shows a substantially stronger agreement, with significantly higher Pearson correlation coefficients compared to the default model configuration (ORC-D).

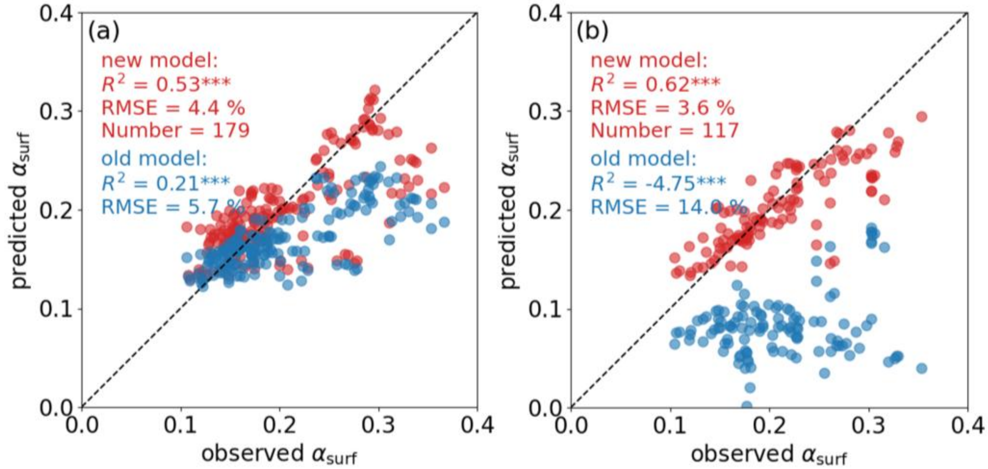

Figure 2 The comparison of daily surface albedo (α_{surf}) predictions derived from calibration models with and without explicit albedo parameterizations against independent observation from five sites in Europe during (a) the foliar yellowing and (b) residue covering periods. Coefficient of determination (R^2) and root mean square error (RMSE) are shown in the upper-left corners of each panel. '***' shows the comparison passes the significance level of 0.01. The dotted black line is the 1:1 line.

ORC-AE captured observed α_{surf} evolution during the foliar yellowing and residue covering periods at all five sites. Using FR-Gri as an example (Fig. 3), ORC-D without considering their effects on α_{surf} dynamics shows substantial biases in α_{surf} during the same period. The results of α_{surf} at all five sites can be found in Fig. S5. α_{surf} increases with the development of crops *LAI* in spring due to the enhanced reflected solar radiation of leaves compared to darker soil followed by a stable period before crops reach maturity. After the crop has reached maturity, the yellowing of aboveground crop biomass increases α_{surf}. This increase is reversed after harvest as dead and dying plant material (i.e., residues) start decomposing. Although the refined model can describe α_{surf} trends in both foliar yellowing and residue covering periods, substantial biases in α_{surf} remain for other periods which were not addressed in this study. This results from inaccuracies of estimating bare soil albedo (Yu et al., in review), from the growth of weeds which are not resolved in ORCHIDEE-CROP, and from the simplistic representation of vegetation albedo dynamics before maturity is reached.

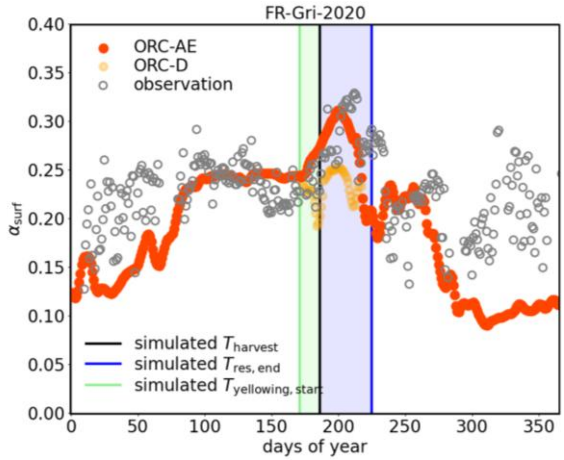

Figure 3 The comparison of surface albedo (α_{surf}) predicted from the old (orange dots, ORC-AE) and new (red dots, ORC-D) ORCHIDEE-CROP models and observations at Grignon site in France (gray dots) in 2020. ORC-AE represents the new model version with effects of the modified α_{surf} and the refined soil conductance (β_4) and surface roughness (Z_0), while ORC-D suggests the initial version of the model. The observed α_{surf} is computed from site radiation measurements through the Integrated Carbon Observation System (ICOS) Data Portal. The green, black and blue solid lines are the simulated start of the foliar yellowing period (shallow green area) ($T_{yellowing,\ start}$), harvesting date ($T_{harvest}$) and the end of residue covering period (shallow blue area) ($T_{res,\ end}$), respectively.

3.2 The impact of improved surface albedo, surface roughness and soil conductance on soil evaporation, surface temperature and soil water content

Compared with the standard version of ORCHIDEE-CROP (ORC-D), statistically significant changes in averaged surface temperature (T_{surf}) are detected across sites in ORC-AE and ORC-E ($p<0.05$ in t-test), resulting from modifications in surface albedo (α_{surf}), surface roughness (Z_0), and soil conductance (β_4) (Table S5). In contrast, improving albedo alone (ORC-A) does not lead to statistically significant changes in soil evaporation (E_{soil}) during the foliar yellowing period ($p>0.05$). Soil water content (*SWC*) generally does not exhibit statistically significant changes ($p>0.05$) in any of the three model configurations. This indicates that, except for *SWC*, site-averaged differences in the targeted variables are detectable and exhibit consistent signs and magnitudes across sites.

ORC-AE leads to a statistically significant reduction in E_{soil} relative to ORC-D during foliar yellowing period, with an averaged decrease of -0.18±0.08 mm d^{-1} (Fig. 4a). A slightly smaller but consistent reduction of E_{soil} (-0.17±0.14 mm d^{-1}) occurs during the residue covering period. Changes in β_4 and Z_0 (ORC-E) exert significant impacts on E_{soil} that are comparable in magnitude to those in ORC-AE during both periods, whereas changes in α_{surf} alone (ORC-A) cause relatively minor and statistically insignificant reductions in E_{soil} for the same periods. The influence of crop residues on E_{soil} disappears within approximately 40 days after residue coverage (Fig. S6a, Fig. S7a).

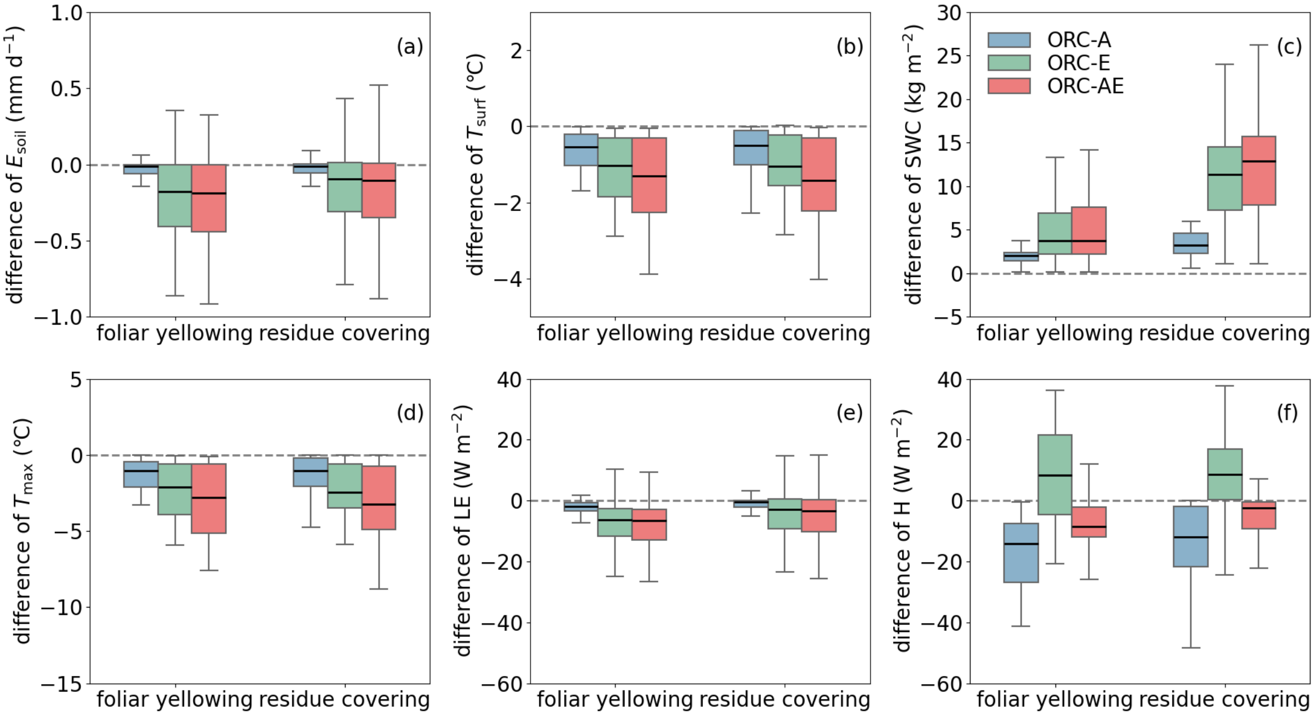

Figure 4 The average effect of model improvements for yellowing and residues cover on daily soil evaporation (E_{soil}), surface temperature (T_{surf}), the total soil water content up to 2 m (*SWC*), the maximum daily surface temperature (T_{max}), the latent heat flux (*LE*) and the sensible heat fluxes (*H*) across 12 sites. Shown are the simulated differences between three configurations of the refined model and old model: ORC-A represents the effect of the modified surface albedo (α_{surf}), ORC-E shows the effect of refined soil conductance (β_4) and surface roughness (Z_0), and ORC-AE indicates the effect of both modifications. The solid and dotted black lines within each box indicate the mean and median daily values across sites and timepoints, respectively. The box spans the interquartile range, covering the 25th percentile (lower bound) to the 75th percentile (upper bound). Black crossbars at the top and bottom represent the dataset's minimum and maximum values. The grey dotted vertical line in each plot represents zero on the y-axis.

The reduced E_{soil} in ORC-AE leads to a modest but not significant increase in *SWC* over 2 m soil depth during the residue covering period among all sites (13.30±8.02 kg m^{-2}) (Fig. 4c, Table S5). The combined effect is comparable to the sum of the individual contributions from α_{surf} (ORC-A) and from β_4 and Z_0 (ORC-E), suggesting an approximately additive effect. Although statistically insignificant, this weak water conservation signal persists toward the end of year, with gradual infiltration into deeper soil layers (Fig. S8).

Incorporating changes in α_{surf}, β_4 and Z_0 in ORC-AE results in a statistically significant reduction in T_{surf} during foliar yellowing and residue covering periods with averaged cooling of -1.55±0.93 °C and -1.90±0.88 °C over all sites, respectively, relative to ORC-D simulation (Fig. 4b). The factorial simulation experiments show that this cooling effect is mainly driven by changes in E_{soil} and Z_0 (ORC-E), whereas increased α_{surf} alone produces a weaker and statistically insignificant T_{surf} reductions. Interaction among α_{surf}, β_4 and Z_0 (ORC-AE) lead to a dampened overall effect compared to individual effects of these factors on T_{surf}. The reduction in T_{surf} tends to weaken over approximately 60 days of decreasing residue coverage (Fig. S6d, Fig. S7d).

3.3 The impact of improved surface albedo, surface roughness and soil conductance on latent and sensible heat flux

Relative to ORC-D simulation, statistically significant changes in latent heat fluxes (*LE*) induced by modifications in surface albedo (α_{surf}), surface roughness (Z_0), and soil conductance (β_4) are detected across sites for ORC-AE, ORC-A, and ORC-E configurations ($p<0.05$ in t-test) (Table S5). Changes in sensible heat fluxes (*H*) are also statistically significant for ORC-AE and ORC-A, whereas modifications in Z_0 and β_4 alone (ORC-E) do not produce statistically significant changes in *H* ($p>0.05$). This suggests that the modified model configurations capture systematic variations in surface water and energy exchanges when averaging across sites.

Modified α_{surf}, β_4 and Z_0 in ORC-AE leads to statistically significant reductions in *LE* during foliar yellowing and residue covering periods, with the changes of -6.84±1.41 W m^{-2} and -5.15±4.03 W m^{-2}, respectively (Fig. 4e). This process is primarily controlled by changes in β_4 and Z_0, represented by comparable reductions in *LE* by ORC-E. While α_{surf} alone (ORC-A) plays a more limited role, the effect remains statistically significant. The corresponding changes in the *H* are also statistically significant and of similar magnitude to those in *LE* induced under the combined effect of α_{surf}, β_4 and Z_0 during the foliar yellowing and residue covering periods, with averaged decreases of -8.10±4.18 W m^{-2} and of -7.44±3.98 W m^{-2}, compared to the ORC-D simulation (Fig. 4f). In both periods, direct radiative effects associated with increased α_{surf} (ORC-A) contribute most strongly to the reduction in *H*, whereas changes in the surface-atmosphere energy exchange (ORC-E) leads to only a slight, statistically not significant increase on *H*. Consistent with T_{surf} response, the influence of crop residues on *H* weakens over approximately 60 days of residue cover (Fig. S6c, Fig. S7c).

3.4 Effect of soil residues on soil water availability on multi-year timescale

The 10-year simulation under current climate shows a minor short-lived increase in *SWC* at the soil depth of 0.25 m (relative root depth of winter wheat in ORCHIDEE-CROP model) due to the presence of crop residues. Averaged over the simulation length and across six sites, total *SWC* is 0.24±0.60 kg m^{-2} (2.81±6.15%) higher than in the simulation without crop residues (Fig. 5a). No clear carry-over effect of *SWC* savings from one growing season to the next is observed at any site. This is because increased drainage losses compensated for reduced bare soil evaporation (Fig. S9). Soil temperature (T_{soil}) at 0.25 m soil depth penetrable by winter wheat roots decreased by an average of -0.37±0.77 °C (7.56±5.96%) over the 60 days of residue covering periods across sites, with no consistent temporal evolution during the 60-day residue covering periods over 10 years

(Fig. 5b). The largest reduction in T_{soil} occurs shortly after harvest, coinciding with the largest increase in α_{surf} due to residue presence compared to simulation without residue effects.

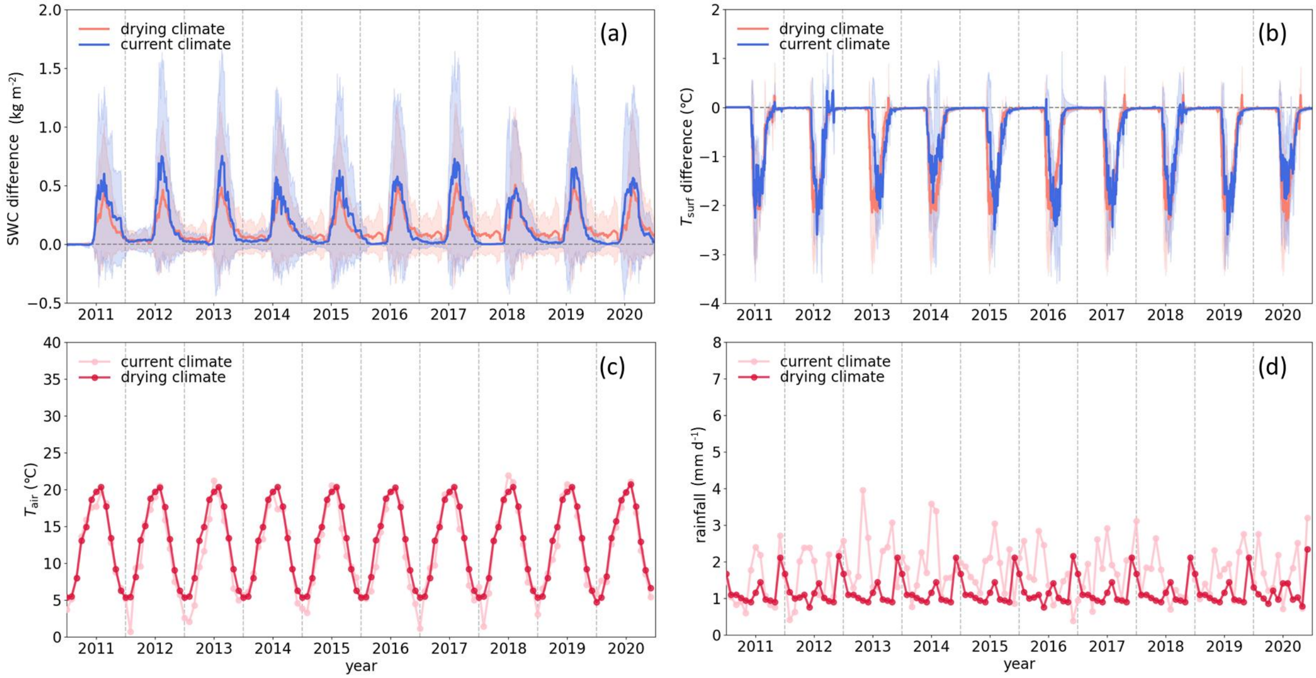

Figure 5 The 10-year cumulated effect of new parameterization of surface albedo (α_{surf}), surface roughness (Z_0) and soil conductance (β_4) on (a) soil water content (*SWC*) and (b) simulated daily soil temperature (T_{soil}) at the soil depth of 0.25 m under current and drying climate scenarios at six sites from 2011 to 2020. Monthly temperature and rainfall are obtained from the meteorological variables of 6-hourly 0.5° CRU-JRA product (v2.4), shown in (c) and (d). Shown are differences between results from ORC-AE and ORC-D. ORC-AE represents the new model version with effects of the modified α_{surf} and the refined β_4 and Z_0, while ORC-D suggests the initial version of the model.

In the drying climate scenario, the meteorological forcing corresponds to a single dry year that is repeatedly applied over the 10-year simulation. Therefore, this experiment represents persistent dry conditions, and temporal changes reflect the sustained system response rather than interannual variability.

Under these conditions, the presence of crop residue shows a similar increase in *SWC* at 0.25 m soil depth under current climate, with an average increase of 0.23±0.53 kg m^{-2} (3.01±5.97%) compared to simulations without residues (Fig. 5a). Results from the final simulation year are consistent with the multi-year average, indicating a stable response over time.

Although no systematic temporal evolution is observed in near-surface SWC (at the soil depth of 0.25 m), deeper soil layers (50% soil depth) exhibit a gradual accumulation of soil moisture over the simulation period (not shown). This phenomenon likely reflects the sustained effect of reduced E_{soil} and enhanced soil water retention at depth. In contrast, superficial SWC responds more rapidly to short-term fluctuations in soil water balance, limiting the emergence of longer-term accumulation signals.

E_{soil} suppression by crop residues enhances soil water retention, underscoring their critical role in mitigating drought stress under persistent dry conditions. As diminished water input (e.g., rainfall) (Fig. 5d) restricts both runoff and infiltration, water loss is governed primarily by E_{soil}. Consequently, the decrease in E_{soil} by crop residues allows more water to remain in the soil, leaving more residual moisture available for the next growing season, potentially enhancing crop development by alleviating water stress.

Average T_{soil} at 0.25 m soil depth decreases with a statistically significant trend by an average of -0.42±0.80 °C (-8.42±3.58%) over years (Fig. 5b), consistent with the sustained effects of residue-induced surface cooling.

3.5 Sensitivity of energy and water processes to parameters

Sensitivity analyses reveal pronounced nonlinear responses of land surface water and energy processes to parameter dynamics (Fig. S10). For T_{surf}, k_1 exhibits the highest sensitivity, as it governs the rate and ceiling of 15-day surface albedo increase and consequently modulates available surface radiation during the residue covering period (Fig. S10a). A ±30% perturbation in k_1 induces 8.69% and 30.78% enhancements in surface cooling, respectively. This reflects a nonlinear response, as k_1 controls not only the rate of albedo increases but also the initial value of the subsequent decay phase (Sect. 2.3.2). Combined with the gradual decrease in residue fraction over time, changes in k_1 modify the cumulative contribution of residue albedo to surface radiation, leading to enhanced cooling in both cases. In contrast, T_{surf} is only weakly affected by the hydrological parameter β_4 (-4.46% / +2.98% change in surface cooling for ±30% variations), consistent with the scenario simulations (Fig. 4b). The parameter D_{up} also shows limited influence on T_{surf} (-8.35% / +2.53% change in cooling for ±30% variations).

For E_{soil}, β_4 is the dominant control (Fig. S10b). A decrease or increase in β_4 from the baseline by 30% results in a 62.48% reduction or 100.85% increase in the decline of E_{soil}, respectively. The parameters k_1, k_4, and D_{up} also influence E_{soil}, with a ±30% variation leading to -32.40% / -35.53%, -17.72% / +22.35%, and -29.49% / -18.57% changes, respectively.

For H, D_{up} exerts the strongest control, followed by k_1 and β_4 (Fig. S10c). Adjusting these parameters by ±30% alters H by -10.53% / +56.34%, -42.55% / +36.77%, and -27.60% / +27.33%, respectively. β_4 is also the most sensitive parameter for LE, reflecting its dependence on E_{soil}. ±30% variations in β_4 yield +89.78% / -62.16% changes in LE (Fig. S10d). In contrast, the strong sensitivity of E_{soil} to k_1 does not propagate to LE, with only -2.66% / +8.21% changes observed under equivalent k_1 perturbations (Fig. S10c and d).

4. Discussion

4.1 Surface energy and land-atmosphere interaction jointly regulate surface temperature during foliar yellowing and residue covering periods

Foliar yellowing and residue coverage cool the surface across all sites by regulating the surface energy balance and redistributing net radiation to latent and sensible energy fluxes (Fig. 4a). Compared with the initial expectation of the dominant impact of α_{surf}, the larger surface temperature (T_{surf}) decrease in ORC-E than that in ORC-A reveals that the cooling from the surface-atmosphere water-heat exchange due to modified soil conductance (β_4) and surface roughness (Z_0) drives the change in T_{surf}. Previous work indicated that no-tillage systems with residue coverage on European scale cooled the surface by about 2 °C during hot summer days due to increased α_{surf} (Davin et al., 2014). Our simulations at site scale further highlight that the local changes in turbulent processes can exert a comparable control on T_{surf}, relying on different spatial scales, climate conditions, phenological stages and surface properties (McDermid et al., 2018).

While foliar yellowing and residue coverage induce an albedo-driven redistribution of surface energy budget across all 10 European sites, the interplay between surface energy available and the surface-atmosphere water-heat exchange causes substantial variation in the strength and periods of cooling. The increased Z_0 due to winter wheat and residue coverages in these two periods enhances surface-atmosphere turbulent heat exchange, potentially promoting more efficient heat dissipation and surface cooling (Winckler et al., 2019; Meier et al., 2022). For example, isolating the impact of increased Z_0 due to foliar yellowing and residue coverage (ORC-Z_0), both contribute more to the cooling impact than ORC-β_4 across all sites (Fig. S11a). However, the extent to which this surface cooling persists also depends on the hydrological fluxes between surface and atmosphere. Crop residues potentially warm the surface by decreasing soil evaporation (E_{soil}) (Hu et al., 2018). It can be realized by lowering β_4 via shielding the soil from direct solar radiation and wind (Fig. S11a), and by reducing near-surface wind speed and enhancing aerodynamic drag via increasing Z_0 (Fig. 4a, Fig. S11b). Similar to residue coverage, foliar yellowing has a comparable influence on E_{soil} due to the continuous coverage provided by winter wheat (Fig. 4a). The associated decline in transpiration, driven by reduced stomatal conductance under lower net radiation, contributes to potential warming (not shown). Residue-induced suppression of E_{soil} during residue coverage and radiation-induced decline in transpiration during foliar yellowing, both redirect energy partitioning from latent heat flux (*LE*) towards sensible heat flux (*H*), likely offsetting surface cooling (Fig. 4f) (Ramos et al., 2024).

4.2 Distinct controls on LE and H during foliar yellowing and residue covering periods

To isolate the drivers of turbulent flux changes during crop yellowing and residue cover periods, we analyzed results from two key model configurations: the surface-atmosphere interaction experiments (ORC-E) and the radiative forcing experiments (ORC-A). Our simulations revealed that the surface-atmosphere interactions (ORC-E) dominate a decreased *LE* in both periods (Fig. 4e and Fig. S6b), with this effect jointly mediated by changes in β_4 and Z_0 (Fig. S11d), while α_{surf}-driven radiative impact is less important. In contrast, less surface energy available with a higher albedo during crop yellowing and the residues cover period, together with the subsequently altered turbulent fluxes, contributed to a weak reduction in *H* during these periods due to their opposing effects (Fig. 4f, Fig. S6c). During this process, the enhanced *H* is primarily mediated by Z_0 (Fig. S11c).

The different underlying drivers behind changes in LE and H can be explained by the following: LE represents the energy needed for water vaporization and is therefore constrained by available energy and moisture transport efficiency (Chen et al., 2020). In contrast, H is driven by direct surface-atmosphere heat transfer via conduction and convection, governed by the land-air temperature gradient and turbulent heat exchange (Myhre et al., 2018). For example, we found that during the residue covering period, the changes in β_4 and Z_0 (ORC-E) tend to increase H, while the albedo-induced reduction in net radiation (ORC-A) acts in the opposite direction by limiting the available energy for sensible heating (Fig. 4f). These results highlight that changes in LE and H are not controlled by a single mechanism but emerge from the combined and counteracting effects of radiative forcing and surface-atmosphere coupling. This is consistent with earlier findings pointing to a critical role of surface-atmosphere interactions in shaping energy partitioning and near-surface thermal dynamics (Koster et al., 2004; Seneviratne et al., 2010; Dare-Idowu et al., 2021; Denissen et al., 2022; Hsu et al., 2023).

The individual impacts of α_{surf} (ORC-A) and of surface-atmosphere exchange (ORC-E) on the changes in LE and H differ from the combined effect of both (ORC-AE), especially during the residue covering period (Fig. 4). This indicates a strong nonlinear interaction between energy and water dynamics driven by crop residues (Hsu et al., 2021). For example, the decreased LE reduces H during the residue covering period by weakening near-surface turbulence, leading to a residual negative impact on H not explained by ORC-A and ORC-E alone (Fig. 4f, Table S5). The complex feedback mechanisms between radiation partitioning and surface-atmosphere coupling (Hsu et al., 2021; Hsu et al., 2022) demands for modelling solutions which take into account both interactions.

It should be noted that in both periods, the averaged difference in surface energy fluxes (i.e. LE and H) over all sites between the new and old models are generally modest (Fig. 4e and f) and at similar magnitudes as model uncertainty (Table S5), which masks a substantial spatiotemporal variability in effects of yellowed leaves and covered residues. Temporally, residue-induced albedo enhancement peaks within the first 15 days after harvest and weakens as residues decompose, causing short-lived but locally significant perturbations in water and heat fluxes (Fig. 3, Fig. S5-S6). The residue impact on the water-heat processes persists for an additional 1 month beyond residue removal through tillage or natural decomposition (Fig. S7). Spatial variations in climate, soil properties, and management practices amplify local differences in residue impacts. For example, we found that during the residue covering period, BE-Lon exhibits the largest mean relative decrease in LE in the new model compared to the old model (-27.42±26.20%), whereas the change at DE-Geb is minimal (5.73±64.90%). This contrast arises because the higher soil moisture and sandy texture at BE-Lon support greater evaporative fluxes, whereas the limited soil water and clay-rich soil at DE-Geb favor energy dissipation as sensible rather than latent heat (Dumont et al., 2023; Buysse et al., 2023). In addition, long-term simulations show the accumulated residue impact on heat budgets. The 10-year simulation under the drying climate scenario shows a low but statistically significant cooling trend, with a yearly average of -0.3 °C (Fig. 5). This demonstrates that even modest instantaneous flux changes can generate meaningful long-term surface cooling effects.

4.3 Implication for climate change mitigation and adaptation

With approximately 60 % of global croplands having higher T_{surf} than surrounding natural biome types, elevated temperatures, particularly during extreme heat and drought events, pose a major issue for crop yields and food security (Lobell et al., 2012; Lesk et al., 2022; Chen et al., 2024). Our simulations across all sites suggest that residue coverage alleviates heat stress by significantly decreasing maximum surface temperature (T_{max}) during approximately 30-day residue covering period and for up to 50 days afterward (Figs. S6e and S7e). This result aligns with previous findings on the cooling effect of crop residues (Davin et al., 2014; Webber et al., 2018; Su et al., 2022). Reduced surface T_{max} after crop harvest mitigates heat stress on soil biota, providing a more favorable growing environment for subsequent crop cycles (Hatfield et al., 2015). Sustained temperatures above 30 °C can stress mesophilic soil microbes, inhibiting decomposition and nutrient cycling (Pietikäinen et al., 2005). Our simulations show that residue cover reduces T_{max} beyond 30 °C on 26 % of days during the residue period and 3.8 % of days afterward, underscoring its role in regulating soil thermal condition. This buffering effect modifies microbial activity and soil organic matter decomposition rates depending on specific climate and environment, thereby influencing greenhouse gas emissions from soil respiration (Knight et al., 2024).

The increase in *H* during residue covering period reveals an increased surface-air temperature gradient due to the decreased T_{surf}, possibly leading to a warmer lower atmosphere which cannot be quantified by the land surface model only (Fig. 4, Fig. S6c, Fig. S7c). This shift in energy partitioning from *LE* to *H*, driven by reduced E_{soil} due to residue coverage, might mitigate surface warming but could intensify regional heat stress. Consequently, it introduces uncertainty regarding the role of crop residues as a climate mitigation strategy. Notably, the use of fixed air temperature forcing data partially explains the increase in *H* because the constant air temperature ignores atmospheric feedback (Luyssaert et al., 2014). As a result, the climate mitigation potential of residue management remains uncertain, and its regional impact on energy partitioning cannot be fully determined. It is essential to consider not only surface cooling but also changes in air temperature, as the latter is more directly linked to climate dynamics. A coupled simulation, feasible with ORCHIDEE-CROP, would be needed for future studies.

Soil water content (*SWC*) dynamics play a key role in regulating the land-atmosphere interactions, as the increase in surface soil *SWC*, as due to residue effects on roughness and soil resistance, can decrease *H* partitioning via promoting E_{soil} (Myhre et al., 2018). The 10-year simulations further highlight that residue coverage has the potential to increase *SWC* and thereby buffer drought stress, particularly under drier conditions with fewer rainfall events (Fig. 5, Fig. S9). In such condition, *SWC* remains high in the upper 1 m soil for extended periods of up to three months. An earlier review suggested that dry soil condition might result in soil compaction and reduced hydraulic conductivity (Singh et al., 2018). It limits infiltration and slow downward water percolation, which might hinder the underlying mechanism of the *SWC* retention in the upper soil detected by ORCHIDEE-CROP model. Notably, soil texture modulates this effect. For example, rapid water infiltration into deeper layers in sandy soils with high drainage reduces surface *SWC* availability for cooling and plant uptake (Fatichi et al., 2020; Wankmüller et al., 2024), highlighting how soil hydraulics constrain residue efficacy. The sustained *SWC* also fosters soil biota activity (e.g., fungi, earthworms), which enhance soil structure through aggregate formation and organic matter decomposition (Li et al., 2009). Improved soil structure increases water-holding capacity, creating a positive feedback loop where residue-induced *SWC* retention supports biological activity, which in turn amplifies long-term moisture retention. This synergy reveals that residue effects on *SWC* persist beyond immediate rainfall events, particularly in water-limited systems. External factors such as tillage timing and precipitation frequency also affect the biophysical impacts of crop residues (Konapala et al., 2020). Early tillage, as observed at the FR-Gri site in 2018 (three weeks after harvest), retains more *SWC* in the topsoil and removes the residue cover, thereby temporarily enhancing E_{soil} and *LE* after the end of residue covering (Fig. S12). The strong soil water retention capacity of the silt loam soil at this site further contributed to this effect (Houot et al., 2000). This process underscores the importance of management practices in regulating the diverse hydrological and thermal effects of residue covering. Targeted strategies are also essential to optimize water utilization, particularly facing warmer and drier climates (Swain et al., 2025).

4.5 Uncertainty and Limitations

Despite improvements to the ORCHIDEE-CROP model in simulating crop albedo changes associated with foliar yellowing and crop residues, as well as their biophysical climate impacts, uncertainties and limitations remain.

α_{surf} shows the most consistent improvement across sites, reflecting its direct control by the new parameterizations for foliar yellowing and residue covering (Fig. 2, Fig. S4a,b). However, degraded performance is observed at two sites (DE-Geb in 2014 and FR-Aur in 2019; Fig. S5a,c). At these sites, the refined configuration simulates higher α_{surf} during foliar yellowing and residue covering than estimated by site radiometer measurements. Surface conditions shown by the site photos suggest that the discrepancy may be related to limitations in the spatial representativeness of point-scale observations, which is further investigated in Text S1.2. T_{surf} also significantly improves, especially during the foliar yellowing period (Fig. S4c,d). In contrast, *LE* and *H* exhibit moderate improvement during the residue covering period and little to no improvement during the crop growth and foliar yellowing periods (Fig. S4e-g). This performance is expected, as *LE* and *H* during the growing season are primarily governed by transpiration processes not recalibrated in this study. During the residue covering period, remaining biases in *LE* and *H* likely arise from unrepresented processes associated with residue cover, such as water interception and retention by residues and soil hydraulic heterogeneity. Limitation in the representation of land-atmosphere coupling in ORCHIDEE also contributes to persistent uncertainties in simulated turbulent fluxes (Sect. 4.3).

The ORCHIDEE-CROP model has biases in simulating water and energy fluxes, and the performance of the new model in capturing water-energy fluxes does not improve to the previous version when evaluated against site-level measurements at six sites (Fig. S4). Both the new and old models overestimate *LE* and *H* during foliar yellowing periods, while underestimating *LE* and overestimating *H* during residue covering periods. This overestimation during foliar yellowing periods might come from a systematically excessive vegetation-atmosphere coupling strength for crops in ORCHIDEE itself compared with observation (Zhang et al., 2022). Observations indicate that *LE* is higher during periods of residue coverage compared to periods of bare soil (Fig. S13). However, it is not clear to what extent the observed difference in *LE* between periods is driven by differences in weather conditions or the presence/absence of residues. One possible source of bias during the residue covering period may be the simplification of model parameters. In the present version of ORCHIDEE-CROP, the effects of crop residues on surface-atmosphere coupling are quantified by modulating β_4 and Z_0. Both variables are described with uniform assumptions to balance model complexity with the scarcity of data to constrain parameterization. Specifically, the impact of residues on β_4 was represented by an initial reduction factor of 0.5 at the start of the residue covering (Sect. 2.3.3). While residue influence on $Z_0$was prescribed using a fixed residue height (0.5 m), derived from the average of measurements across five winter-wheat sites (Sect. 2.3.4, Table S3). These parameter choices are uniform across all sites and therefore cannot explicitly represent local variation in residue characteristics, soil properties, atmospheric conditions and management practices. As a result, the model is incapable of fully resolving site-specific residue impacts, which potentially contributes to the bias of simulated LE and H at certain sites.

The sensitivity analysis also highlights the uncertainties introduced by parameter selection (Fig. S10). The β_4 and k_1 exert strong control over the spatiotemporal partitioning of available energy between LE and H. The use of fixed parameter values and limited calibration at a few sites inevitably contributes to model uncertainty and constrains the representation of local variability.

We manually adjusted the total conductance of soil evaporation, transpiration and interception in ORCHIDEE-CROP by scaling it with 1+f_{soil} during residue cover periods (Chapin et al., 2011). The simulations showed improved agreement with observed T_{surf}, LE and H (Fig. S14), indicating that the net biophysical impact of residue cover is enhancing surface-atmosphere water and heat exchanges despite inhibiting soil evaporation, which is not well described in the current model. A test of quantifying the residue impact on E_{soil} at 15 field experiments distributed globally shows that residue cover exceeding 80% leads to an approximately 20-30% reduction in E_{soil} during the residue covering period (not shown). Therefore, the assumed 50% initial decline in β_4 in the improved model (Eq.16) might overestimate residue impacts, potentially explaining the lower E_{soil} and LE simulated across sites in the new model compared with both the initial model version and observations (Fig. S4).

Accordingly, the limited and statistically insignificant differences in simulated SWC between ORC-D and ORC-AE should be interpreted with caution. In the current model configuration, crop residues primarily affect the land surface through surface albedo, roughness effects, and a simplified treatment of soil evaporation resistance. Processes that are closely linked to residue management, such as the effects of tillage on soil hydraulic properties and the longer-term influence of soil organic matter on soil physical characteristics, are not yet explicitly represented. Therefore, the present simulations are particularly well suited for assessing the biophysical energy-balance impacts of residue cover, while the representation of soil water responses remains an area for further model development.

For example, specific hydrological processes impacted by crop residues were not accounted for here, such as water interception on the surface of residues, and uptake/release of water from residues (Kozak et al., 2007, Swella et al., 2015). Rainfall interception by residues alters the timing and magnitude of soil water input and enhances evaporation from residue surfaces, thereby modifying surface moisture and heat exchanges (Mitchell et al., 2012; Thapa et al., 2021). However, contrasting evaporation drivers in soil and residue layers introduce complexity to surface evaporation processes. The omission of these processes likely increases model uncertainty in biophysical simulations under variable rainfall conditions.

The input data used to drive the model introduces several structural uncertainties. First, while site-based meteorological forcing (e.g., air temperature, wind speed, humidity) ensures high representativeness, meteorological observations and direct radiation measurements were unavailable at two ClieNFarm sites comprising six farms (UK-Rookery, UK-Winwick, UK-Allerton, BE-AH, BE-BM, and BE-LB; Table S2). For these sites, simulations were instead driven by the hourly 0.25° ERA-interim product and surface albedo was derived from Sentinel-2 products. This substitution inevitably limits the ability of our model to reproduce site-specific water and energy dynamics. A comparison between satellite-derived albedo at 300 m spatial resolution and albedo calculated from shortwave radiation measurements representative for a few m^2 at eight sites reveals systematic differences (Fig. S15). These differences are likely attributable to spatial scale mismatch, cloud screening effects, and surface heterogeneity, which together dampen albedo variability in the satellite product. While satellite-based albedo enables inclusion of the six field sites, these substitute values introduce additional uncertainty in the simulated surface energy fluxes. Second, the bare soil albedo dataset used to estimate surface albedo carries uncertainties related to quality-restricted training samples (Yu et al., in review). For example, the vegetation index thresholding used to identify bare soil may also include mixed surfaces such as crop residues, introducing bias in soil albedo retrievals. Also, the spatial aggregation from 300 m to 0.5° smoothes the field variability of bare soil albedo, reducing the reliability of the model simulation. Third, the incomplete representation of management practices in our model, including fertilizer and pesticide application as well as physical operations like tillage, limits the model's capacity to reproduce observed variations in crop phenology, soil water content, and surface fluxes across years.

Based on these concerns, evaluating residue effects requires a context-specific approach that accounts for the interactions among climate, soil, and crop characteristics. Process-based land surface models provide an effective framework for such assessments at varying scales, as they explicitly represent the coupled biophysical and ecological mechanisms controlling surface energy and water exchanges. This approach provides an opportunity to guide residue management strategies under variable environmental settings. Future model developments should include explicit residue modules and site-specific parameterization to better capture spatial heterogeneity in residue impacts on energy and water fluxes. For example, integrating the canopy interception modules developed by crop models to ORCHIDEE-CROP is a good strategy to better represent the residue impact on the hydrological dynamics, such as CropSyst and RZWQM (Kozak et al., 2007). Moreover, an open-sourced global database from dedicated field trials monitoring energy exchange is required for parametrizing and evaluating this model development.

5. Conclusion

Here we improved the simulation of winter wheat cultivar in the ORCHIDEE-CROP model by taking into account the impact of foliar yellowing and crop residues on water and energy balance of winter wheat cultivations based on observations from 10 cropland sites. The simulated surface energy budget and partitioning of latent and sensible heat fluxes show a cooling impact of residues and crop yellowing. A complex interplay between radiative and turbulent processes controls the strength of these effects. The improved ORCHIDEE-CROP model, with its representation of land surface albedo, surface roughness, and soil conductance for residue covering, provides a valuable tool for quantifying biophysical impacts and guiding localized residue management strategies at regional to global scale. However, conclusions regarding soil water benefits or optimal management practices remain dependent on future model developments that further improve the representation of soil hydrological responses to residue management, including interactions with soil organic matter dynamics and tillage practices. By identifying optimal residue management practices, this approach can contribute to sustainable agriculture and inform policy development in the context of climate warming.

Code and data availability

The model code used in this study is archived at https://doi.org/10.5281/zenodo.15230286 (Yu et al., 2025). All the data and the codes for data analysis and figure creation are available at https://doi.org/10.5281/zenodo.15234443 (Yu 2025a). All data used in this study are publicly available. The original ecosystem flux data at available sites can be derived from the Integrated Carbon Observation System (ICOS) Data Portal at https://data.icos-cp.eu/. The MODIS LAI data (MCD15A3H) can be downloaded from Land Processes Distributed Active Archive Center (https://lpdaac.usgs.gov/products/mcd15a3hv006/ DOI: https://doi.org/10.5067/MODIS/MCD15A3H.006). The MODIS aerosol product (MO(Y)D04_L2) can be downloaded from Level-1 and Atmosphere Archive & Distribution System Distributed Active Archive Center (https://ladsweb.modaps.eosdis.nasa.gov/ DOI: https://doi.org/10.5067/MODIS/MOD04_L2.061). The Sentinel-2 bare soil albedo datasets can be downloaded from https://doi.org/10.5281/zenodo.15271053 (Yu 2025b).

Author contributions

DG, RL, and PC conceptualized and designed the study. KY modified and implemented the model, conducted formal analysis of the results, and led the writing of the original draft with contributions from all co-authors. AP and MC contributed data curation by providing management information from ClieNFarm sites. All authors participated in reviewing, editing, and finalizing the manuscript.

Competing interests

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

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