Land surface modeling as a tool to explore sustainable irrigation practices in Mediterranean fruit orchards

Olga Dombrowski[1], Cosimo Brogi[1], Harrie-Jan Hendricks Franssen[1], Vassilios Pisinaras[1], Andreas Panagopoulos[1], Sean Swenson[1], and Heye Bogena[1]

[1]Affiliation not available

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O. Dombrowski[1], C. Brogi[1], H.-J. Hendricks Franssen[1], V. Pisinaras[2], A. Panagopoulos[2], S. Swenson[3], H. Bogena[1]

[1]Agrosphere (IBG-3), Forschungszentrum Jülich GmbH, Jülich 52425, Germany

[2]Soil & Water Resources Institute, Hellenic Agricultural Organization, Gorgopotamou, Sindos, Thessaloniki 57400, Greece

[3]Climate and Global Dynamics Laboratory, National Center for Atmospheric Research, Boulder 80305, Colorado, United States of America

Corresponding author: Olga Dombrowski (o.dombrowski@fz-juelich.de)

Key Points :

- The CLM5 irrigation scheme is applied at the point and regional scale and enhanced with the option to use prescribed irrigation data
- Soil moisture dynamics were simulated well using the prescribed data while the default irrigation could not fully reproduce field practices
- Regional simulations using different irrigation scenarios suggest substantial water saving potential for improved irrigation management

Abstract

Irrigation strongly influences land-atmosphere processes from regional to global scale. Therefore, an accurate representation of irrigation is crucial to understand these interactions and address water resources issues. While irrigation schemes are increasingly integrated into land surface models, their evaluation and further development remains challenging due to data limitations, e.g. irrigation amounts and timing, and soil moisture (SM). This study assessed the representation of irrigation and its effect on crop yield in the Community Land Model version 5 (CLM5) through implementation of an irrigation data stream that allows to directly use observed irrigation data. Simulations were conducted at the point scale for two instrumented apple orchards using the CLM5 irrigation routine as well as the implemented data stream. Furthermore, irrigation requirements and the effect of deficit irrigation on crop yield and crop water use efficiency (CWUE) at the regional scale were simulated and discussed. The irrigation data stream performed better in representing observed SM dynamics compared to the standard irrigation routine that could be further improved by implementing more flexible irrigation schedules and irrigation efficiency. At the regional scale, simulated irrigation and yield showed a high sensitivity to climatic changes caused by the topographic gradient. While a 25 % reduction in irrigation had negligible negative effect on simulated yield and CWUE, a reduction of 50 % notably reduced both variables. These effects varied with climatic conditions, soil properties and timing of irrigation. These results showcase how CLM5 could be utilized for irrigation and water resources management.

Plain Language Summary

Irrigation impacts how land and atmosphere interact, both locally and globally. Therefore, it is important to understand the effects of irrigation practices and improve how water resources are managed. Advanced models such as land surface models now include irrigation. However, missing information on irrigation and other data make it difficult to evaluate and improve irrigation in these models. This study looks at how irrigation and crop yield are represented in the Community Land Model (CLM5). The model was tested using observed data and its own prediction of irrigation, and then compared to observed soil moisture and yield in two apple orchards. The model was able to predict changes in soil moisture caused by irrigation. Simulated irrigation was different in timing and amount from the observed one. This could be improved by adding more details to the irrigation routine. Next, irrigation and crop yield were studied in the entire region. Both were sensitive to changes in climate caused by the diverse landscape. A small reduction in irrigation did not negatively affect yield while halving the irrigation caused it to decrease noticeably. These findings show that land surface models like CLM5 can be useful tools for managing irrigation and water resources.

1 Introduction

Irrigation plays a vital role in sustaining global food production by providing a reliable water supply to agricultural systems, especially in semi-arid or arid regions [*McLaughlin and Kinzelbach* , 2015]. With a growing global population and increasing food demands, irrigation contributes significantly to ensuring food security by enabling higher crop yields and reducing the vulnerability of agricultural systems to climate change [*McDermid et al.* , 2023; *Mueller et al.* , 2012]. On the other hand, poor management of irrigation water has led to the depletion of groundwater resources [*Dangar et al.* , 2021;*Scanlon et al.* , 2012; *Wada et al.* , 2010] and water use conflicts in many regions [*Cai et al.* , 2003; *Eshete et al.* , 2020; *Gurung et al.* , 2006]. Apart from quantitative and qualitative effects on water resources [*García-Garizábal et al.* , 2012; *Y Zhang et al.* , 2022], irrigation substantially impacts biogeophysical and biogeochemical processes at the land surface through alteration of the hydrological cycle or energy budget. This has subsequent effects on climate [*DeAngelis et al.* , 2010;*Erb et al.* , 2017; *Ferguson and Maxwell* , 2012; *Gordon et al.* , 2005; *Sacks et al.* , 2009]. The multidimensional role of irrigation calls for increased efforts in effective irrigation management and irrigation impact studies using large-scale approaches. This is crucial not only to meet food demands and mitigate future increases in climate change induced water stress, but also to understand its interactions and feedback mechanisms within the Earth system [*Elliott et al.* , 2014; *McDermid et al.* , 2023].

Modeling can be a powerful tool to simulate complex interactions in agricultural systems, evaluate different irrigation and climate scenarios, and provide decision support for water resources management [*Blyth et al.* , 2021; *Pongratz et al.* , 2018]. This necessitates comprehensive modeling frameworks that combine field-scale representations of crop growth and irrigation with a more holistic assessment of the impacts of irrigated agriculture on water resources and climate at larger scale [*Bin Peng et al.* , 2020]. Process-based crop models include a range of crop parameterizations that provide a unique way to study crop growth processes in response to irrigation practices by using physical and biological principles. However, their main purpose is to simulate yield at the field scale, often over a single growing season, while lacking the interface with the land surface, soil, and climate [*Cheng et al.* , 2020]. Land surface models (LSMs), on the other hand, provide a more holistic representation of the land-atmosphere interactions to capture the feedback mechanisms between irrigation, vegetation, hydrological processes, and climatic conditions beyond the field scale [*Blyth et al.* , 2021]. Conversely, they often lack more detailed physiological and genetic representations of crops and irrigation management [*Lombardozzi et al.* , 2020; *B Peng et al.* , 2018]. This limits the ability of LSMs to reliably simulate yield and irrigation water withdrawals leading to poor model performance and biases in related processes such as carbon, energy, and water fluxes over intensively irrigated regions [*Leng et al.* , 2015;*Lombardozzi et al.* , 2020; *Ozdogan et al.* , 2010; *Z Zhang et al.* , 2020].

In recognition of the important role of human land management, efforts to advance the representation of crops and irrigation in LSMs are ongoing [*Pokhrel et al.* , 2016]. Various land surface models such as ORCHIDEE, the Community Land Model (CLM), and Noah-MP have since added crop modules [*Levis et al.* , 2012; *Liu et al.* , 2016; *Smith et al.* , 2010]. New crop representations have been developed to improve crop growth and management processes [*Boas et al.* , 2021; *B Peng et al.* , 2018] or to add new crop types [*Olga Dombrowski et al.* , 2022; *Fader et al.* , 2015;*Fan et al.* , 2015]. Rather simple irrigation schemes are generally incorporated based on soil moisture thresholds [*de Vrese et al.* , 2016; *Ozdogan et al.* , 2010; *Sacks et al.* , 2009], while more recent developments include the integration of irrigation techniques [*Leng et al.* , 2017; *Yao et al.* , 2022], irrigation water withdrawal from different sources [*Leng et al.* , 2017; *Xia et al.* , 2022], and water availability limitation [*Yin et al.* , 2020]. These studies, however, were performed at river basin, county, or global level with coarse spatial resolutions between 10 and 100 km. Simulated irrigation was validated against rather uncertain statistics like total yearly irrigation water withdrawals, without considering specific irrigation practices. Crop and irrigation data at higher spatial (<5 km) and temporal (e.g. daily or sub-seasonal) resolution is needed to evaluate the representation of local irrigation schedules in LSMs and support irrigation management decisions. However, data to reliably constrain and further develop implemented irrigation schemes is often lacking, e.g. irrigation amount and timing along with continuous soil moisture (SM) observations [*Lawston et al.* , 2017].*Lawston et al.* [2017] first evaluated the sprinkler irrigation scheme of the NASA Land Information System LSM with point and gridded SM observations at 1 km resolution. While the model could not capture the field scale heterogeneity and overestimated irrigation amounts, it captured well the seasonal variability and regional average SM dynamics. The authors did however use a prescribed crop phenology (green vegetation fraction) and did not examine the effect of irrigation on crop yield. A recent study examined the effect of different irrigation setups on maize yield and two water use efficiency definitions using the dynamic crop and irrigation scheme of the Noah-MP LSM [*Huang et al.* , 2022]. They found that modeled crop yield was sensitive to irrigation quantity and timing (in which crop growth stage irrigation was applied) and based on these results recommended an optimal SM threshold to trigger irrigation. While the authors lacked data to accurately assess the irrigation amount and crop yield, their work presents a first use of a LSM to study the effects of deficit irrigation on crop growth, yield and water use efficiency.

The work presented here builds upon previous studies to continue the evaluation and improvement of irrigation representations in LSMs combining local irrigation, SM, and yield observations. In particular, this study applies CLM version 5, with a recent extension to represent deciduous fruit trees, to model irrigation and crop growth in a Mediterranean catchment. Specifically, we aim to: (1) evaluate the existing irrigation scheme of CLM5 and enhance its flexibility to account for local irrigation management practices; (2) assess whether the model can reproduce soil moisture dynamics and crop growth in irrigated apple orchards using the enhanced model capability; (3) examine the potential to improve regional irrigation management by modeling the effect of different irrigation scenarios on crop yield and water use efficiency at the catchment scale.

2 Materials and Methods

2.1 Study Area

Located in central Greece, the Pinios Hydrologic Observatory (PHO) covers an area of approximately 45 km^2 (Figure 1). The PHO was established in 2015 to study the Pinios catchment hydrological processes and, ultimately, to support local authorities in the sustainable management of water resources [*V Pisinaras et al.* , 2018]. It is characterized by a Mediterranean climate with an annual precipitation of 500 to 1200 mm, and highest precipitation amounts in the winter months, annual potential evapotranspiration of approximately 1100 mm, and annual average air temperature of 15 °C [*Bogena et al.* , 2018]. The area displays a range of altitudes from 1500 m in the northern part down to less than 200 m in the plain. The mountainous part of the catchment features steep slopes and is covered by forests, mixed with shrubs and grassland, while the southern plain is primarily characterized by agriculture and small villages. In the plain, sandy loam soils dominate while sandy clay loam and loamy soils also occur [*V Pisinaras et al.* , 2018]. The PHO is located in one of the most productive agricultural areas in Greece owing, among other factors, to widespread irrigation practices that account for over 85 % of the local freshwater consumption [*Panagopoulos et al.* , 2018]. The main cultivation are apple and cherry orchards (i.e., ˜78 % of agricultural area) that are irrigated between May and October. There are a few other rainfed fruit and nut tree orchards in the area with < 5 % coverage. Annual crops including corn, cereal (mainly winter wheat), and potato are grown on the remaining agricultural land. They are partially irrigated, depending on precipitation occurrence, but cover a negligible part of the total irrigated area. Irrigation in the orchards is typically applied through micro sprinklers and the demand is almost entirely met by abstraction from the alluvial groundwater system through water wells, most of which are privately owned. Overexploitation of groundwater in the area due to poor irrigation management practices, amongst others, has previously been reported by *Panagopoulos et al.* [2018] and *Vassilios Pisinaras et al.* [2023] resulting in the decline of groundwater levels.

Within the PHO, irrigation management in two irrigated apple orchards, hereafter referred to as S09 and S10, was studied (Figure 1). Both orchards have a size of around 1.2 ha, with a mild southern slope of <5 %. The soil texture is sandy loam and sandy clay loam with a high gravel content (13-29 %) (Table 1) and many larger cobbles (>64 mm according to *Wentworth* [1922]), especially below 30-50 cm depth. Trees are planted in rows, oriented North-South with 3.3 m distance between rows and an in-line distance of 1.5 m (approximately 2020 trees ha^{-1}). The trees in S09 and S10 were planted in 2013 and 2015 respectively, with a mixture of 3 to 5 different varieties. Trees are pruned to a height of 3.5 m throughout the winter season and residues are mulched back into the soil. Bud burst typically occurs in the second half of March while fruit development starts with the end of flowering in mid to late April. Harvest dates range from late August to mid-November depending on the harvested variety. Major leaf fall starts in late October and continues until mid-November, sometimes until early December. Trees are irrigated with a micro sprinkler system with a maximum flow rate of 60 L $hour^{-1}$ that is installed below the canopy, halfway between the tree stems of the same row. The irrigation season typically starts in May and continues until October. Orchards are fertilized with 80 kgN ha^{-1} at the end of flowering in April. Pest and fungicide treatment is applied prior to flowering and after flowering until late June. The grass in the alleys is generally mowed once a month starting in March or April and mowing material is left on the ground. During periods of intense heat, the actively growing grass cover provides a cooling effect to protect the apples from heat damage.

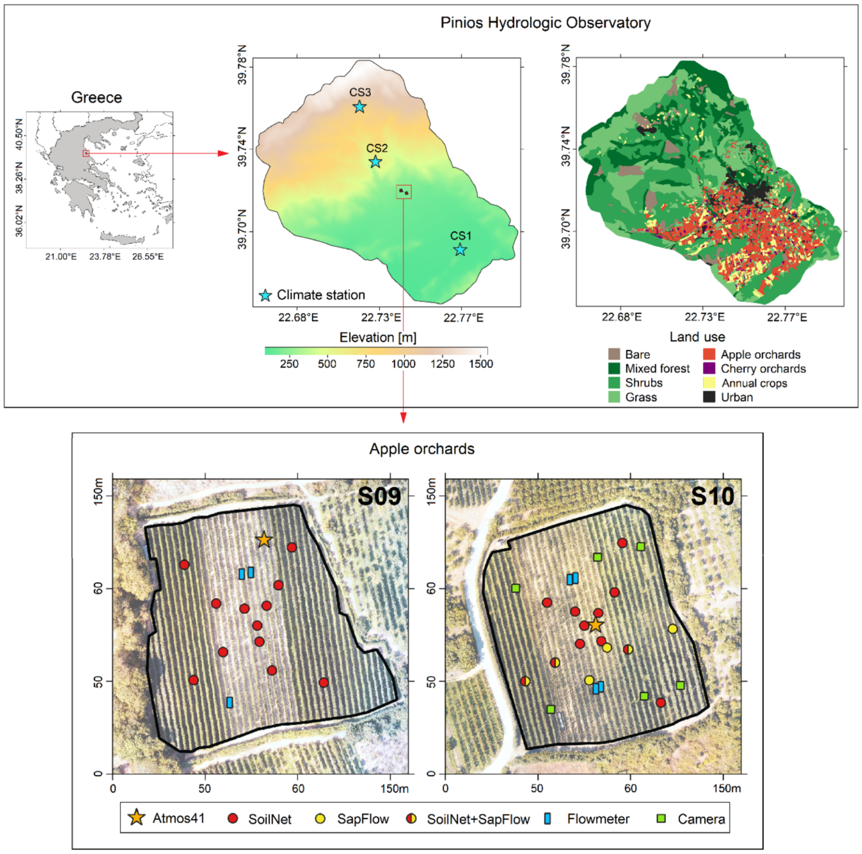

Figure 1: Top left: Map overview of Greece and of the study area location. Top right: Elevation and land use of Pinios Hydrologic Observatory with the locations of climate stations. Bottom: Apple orchards S09 and S10 with instrumentation.

Table 1: Main characteristics of the two apple orchards (S09 and S10).

Orchard ID	Altitude (m.a.s.l.)	Size (ha)	Size (ha)	Apple varieties	Soil depth (cm)	Sand content (%)	Clay content (%)	Soil organic carbon content (%)	Gr co (%
S09	200	1.24	3	3	0-30 30-60 60-90	64.5 63.0 59.9	17.8 21.9 24.6	1.5 1.2 0.7	23. 13.
S10	190	1.13	5	5	0-30 30-60 60-90	64.3 65.8 65.4	12.5 12.7 13.7	1.44 0.86 0.66	28. 28.

2. 2 Data Sources

The meteorological data that are necessary to drive CLM5 including precipitation, air temperature, atmospheric pressure, wind speed, relative humidity, and incoming solar radiation, were acquired from three meteorological stations located at different altitudes within the PHO (Figure 1) as well as two stations located in the orchards S09 and S10. For the agricultural plain, detailed soil texture and organic matter information was collected during an extensive soil sampling campaign. In total, 116 locations were sampled with one sample from the topsoil (0-50 cm) and a second sample from the subsoil (50-100 cm) (Figure 2). In addition to the point measurements, the LUCAS topsoil physical properties for Europe soil map [*Ballabio et al.* , 2016] and the European Soil Database (ESDB) derived data product [*Hiederer* , 2013] provide soil information for the area at a resolution of 500x500 and 1000x1000 m, respectively (Table 2). These data sources were combined to create soil texture (point measurements+LUCAS) and soil organic carbon (point measurements+ESDB) maps for model input (Figure 2). In a first step, for the unsampled regions, data points were extracted from the map products in a sampling density equal to the average density of the soil sampling locations (˜580x580 m). Next, the extracted points were combined with the sampled points to a single set of data points (Figure 2). Then, the points were interpolated to the target resolution of 100x100 m using ordinary kriging and a spherical variogram model with a radius that included 30 measurements around an estimation point. Topographic information was available through the European Digital Elevation Model (EU-DEM) [*Copernicus* , 2016], version 1.1 at a spatial resolution of 25x25 m (Figure 1). Detailed maps of the agricultural fields and orchards were provided by the Hellenic Payment and Control Agency for Guidance and Guarantee Community Aid while the land use of the remaining area was digitized from satellite imagery, using ArcGIS® software by Esri (Figure 1).

Orchard scale SM data were retrieved from S09 and S10, which were equipped for extensive monitoring in September 2020 (Figure 1). SM was monitored via a SoilNet wireless sensor network [*Bogena et al.* , 2010; *Bogena et al.* , 2022] with 12 nodes per orchard. Each node had six SMT100 SM sensors (Truebner GmbH, Neustadt, Germany) divided into two separate profiles which were installed at 5, 20, and 50 cm depth as well as two TEROS21 soil matric potential (SMP) sensors (METER Group Inc., Pullman, USA) installed at 20 cm depth. Irrigation amounts were recorded with TW-N flowmeters (TECNIDRO, Genova, Italy), installed at different irrigation sectors within the orchards. Meteorological data was collected by the cost-effective but reliable all-in-one Atmos41 weather station (METER Group Inc., Pullman, USA) installed above the canopy in each orchard [*O. Dombrowski et al.* , 2021]. A more detailed description of the instrumentation and setup used to monitor SM dynamics, irrigation, and meteorological variables is given in*Brogi et al.* [2023]. Additionally, S10 was equipped with six SFM-1 sapflow sensors (ICT International Pty Ltd, Armidale, Australia) to estimate whole-tree transpiration. The sapflow sensors were installed on the trunk of six trees to represent, as much as possible, the orchards' trees in terms of height, perimeter, and vigor covering all five varieties. The installation and data correction followed the procedure outlined in *Burgess* [2018]. Phenology of the three main apple varieties was monitored using six phenocams (SnapShot Cloud 4G, Dörr GmbH, Germany) installed in S10.

Table 2: Main characteristics of the different soil data products used for the surface file creation of the regional case.

	European Soil Database Derived data	**LUCA**
Underlying observational data	European Soil Database, Harmonized World Soil Database, Soil-Terrain Database	LUCA
Resolution (m)	1000x1000	500x50
Soil texture	Yes	Yes
Organic matter	Yes	No
Depth ranges (cm)	0-30, 30-100	0-20

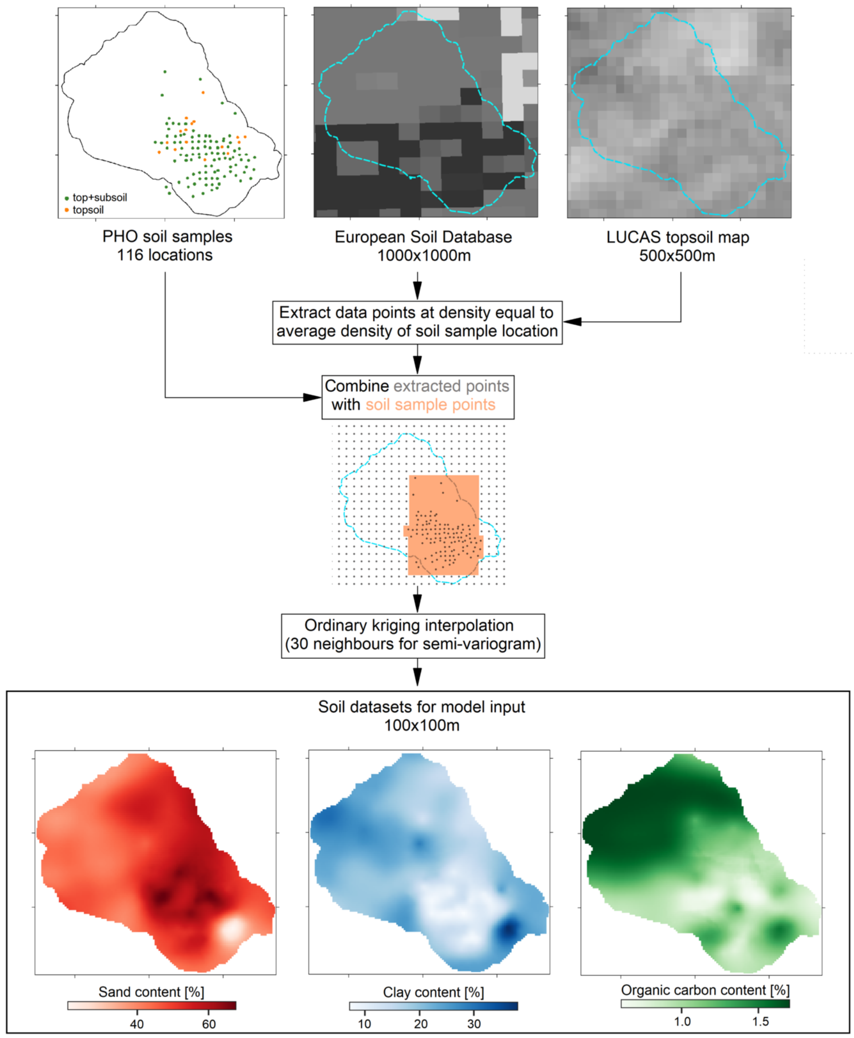

Figure 2: Top, from left to right: Soil sampling locations within the Pinios Hydrologic Observatory, soil data from the European soil database and the LUCAS topsoil map. Bottom: Soil texture input datasets of sand, clay, and organic carbon derived from the three data sources.

2.3 The Land Surface Model

2.3.1 The Community Land Model

The Community Land Model v.5 (CLM5) used in this study is the latest version of the land component in the Community Earth System Model (CESM) as described in detail by *D M Lawrence et al.* [2019]. CLM5 simulates land surface energy fluxes as well as hydrological, biogeophysical, and biogeochemical processes that are driven by atmospheric input variables in combination with soil and vegetation states and characteristics [*D Lawrence et al.* , 2018]. These processes are simulated on different subgrid units within a grid cell. Subgrid units include (1) the land unit defining the land use category (e.g., vegetated, urban, crop), (2) the column that is represented by 20 soil and 5 bedrock layers and resolves state variables and fluxes of water and energy in the soil, and (3) the patch level capturing biogeophysical and biogeochemical differences between plant functional types (PFTs) (e.g., broadleaf deciduous forest, evergreen shrub, maize, soy). The one-dimensional multilayer vertical water flow in the soil is simulated using a modified Richards equation [*Dingman* , 2015]. Soil hydraulic parameters for these calculations are derived from pedotransfer functions of sand and clay [*Clapp and Hornberger* , 1978; *Cosby et al.* , 1984] and organic properties of the soil [*D Lawrence and Slater* , 2008]. With version 5 of CLM, a plant hydraulic stress routine was introduced that uses a simple hydraulic framework to model water transport along a water potential gradient from soil via plant to atmosphere [*Kennedy et al.* , 2019]. The new configuration replaces soil potential with leaf potential as the basis for plant water stress while root water potential is used to drive root water uptake. A new biogeochemistry and crop module, BGC-Crop, enhanced the representation of major crop functional types and land management practices such as irrigation and fertilization. Unlike natural vegetation that competes for water and nutrients, crops operate on separate soil columns that may be irrigated or non-irrigated, thus allowing for differences in land management [*D M Lawrence et al.* , 2019].

The recent development of CLM5-FruitTree enables the simulation of deciduous fruit trees and associated management practices in CLM5. The main features of the new sub-model include (1) a perennial phenology routine that allows the woody plant parts to remain on the orchard for several years, (2) carbon storage dynamics that enable the regrowth of annual plant parts, (3) an adapted carbon and nitrogen allocation, and (4) the description of typical management practices such as transplanting, pruning, and orchard rotation. Additionally, a new apple plant functional type was parameterized while fertilization and irrigation use the default CLM5 schemes. The complete model development of CLM5-FruitTree is described in *Olga Dombrowski et al.*[2022].

2.2.3 Irrigation module in CLM5

Irrigation is performed individually over each irrigated soil column and responds dynamically to SM based on a daily check at 6 am. If crop leaf area is non-zero and if the available soil water over a specified irrigation depth z_{irrig} (=0.6 m by default) is below a defined threshold, irrigation is triggered. The irrigation amount is based on the SM deficit (?$_{?????}$) that is calculated overz_{irrig}:

$$D_{\mathrm{irrig}} = w_{\mathrm{thresh}} - w_{\mathrm{avail}} \quad \text{Eq. 1}$$

where ?$_{?????}$ is the available SM (mm) and ?$_{????}$ is the irrigation SM threshold (mm) calculated as:

$$w_{\mathrm{thresh}} = f_{\mathrm{thresh}} \left(w_{\mathrm{target}} - w_{\mathrm{wilt}} \right) + w_{\mathrm{wilt}} \quad \text{Eq. 2}$$

where w_{target} is the irrigation target SM (mm),w_{wilt} is the SM at wilting point (mm), and ?$_{????}$ is a tuning parameter. If f_{thresh}= 1 (default), irrigation will be triggered once the available SM is below w_{target}. If $f_{\mathrm{thresh}} = 0$, irrigation is only triggered once the available SM falls below w_{wilt}. Target SM is determined as the sum of SM at the target SM of each soil layer:

$$w_{\mathrm{target}} = \sum_{i=1}^{n_{\mathrm{irr}}} \theta_{target,i} * z_i \quad \text{Eq. 3}$$

where n_{irr} is the index of the soil layer corresponding toz_{irrig}, z_i (mm) is the depth of the soil layer$i$ and $\theta_{target,i}$ is the target volumetric SM value in a given soil layer. Similarly, w_{wilt} is calculated as the sum of SM at wilting point of each soil layer:

$$w_{\mathrm{wilt}} = \sum_{i=1}^{n_{\mathrm{irr}}} \theta_{wilt,i} * z_i \quad \text{Eq. 4}$$

where $\theta_{wilt,i}$ is the volumetric SM value at wilting point in a given soil layer. θ_{target} andθ_{wilt}

are calculated by inverting the equation for soil matric potential (SMP) (Eq. 7.53 in *D Lawrence et al.* [2018]) at the respective depth. By default, the SMP parameters ψ_{target} andψ_{wilt} are set to -34 and -1500 kPa, considered field capacity and permanent wilting point, respectively.

In addition to w_{target}, w_{wilt},f_{thresh}, and z_{irrig}, the user can define the irrigation duration ($?_{?????}$). Irrigation is applied directly to the ground surface at an intensity equal to$\frac{D_{\text{irrig}}}{T_{\text{irrig}}}$. Irrigation parameters are not spatially distributed but are defined globally for a given model domain independent of geographic location or crop type.

2.2.4 Irrigation data stream implementation

To study and evaluate the modeling outcomes under specific observed irrigation practices, an irrigation data stream was implemented in CLM5 to enable continuous prescription of irrigation parameters, i.e., irrigation rate, duration, and start time. These parameters are defined separately for one or multiple crop types and for each grid cell. This allows to account for differences in irrigation management depending on crop type and location to accurately reproduce local management practices. In addition, using the data stream, the applied irrigation amount can be easily adjusted, thus creating different irrigation scenarios while maintaining the same irrigation schedule. As irrigation is prescribed, the irrigation SM threshold that is calculated in the standard irrigation routine is not needed for this implementation.

2.3 Model Implementation

2.3.1 Orchard scale simulations

For the simulations of S09 and S10, CLM5-FruitTree was run in single point mode and forced with hourly meteorological data from the two orchards. Fertilizer amount and soil texture were adjusted according to information provided by the farmer and soil samples. The default parameter file was adapted to account for the local climate and orchards characteristics. Crop parameters such as the different phenological stages were adjusted according to observations from the phenocam pictures, harvest information, and communication with the farmer. In the absence of observed bud break dates, parameters for the bud break prediction model were calibrated such that bud break would occur around the estimated date of 15$^{\text{th}}$ of March using the available local climate data. The modified crop parameters are listed in Table 3. Additionally, the observed irrigation time series was used as input to the irrigation data stream.

In order to balance ecosystem carbon and nitrogen pools and total water storage in CLM5 [*D Lawrence et al.* , 2018], a 200 years model spin-up was performed. For this, the CRUNCEPv7 atmospheric forcing data set from 1986 to 2016 [*Viovy* , 2018] and the parameterized apple plant functional type were used. Using the model state at the end of the spin-up, simulations were then re-initiated from planting in 2013 (S09) and 2015 (S10) using meteorological data from climate station CS1 (2016-2020) and data from the Atmos41 sensors installed in the orchards for the years 2021 and 2022.

Table 3: Local crop parameters for the apple plant functional type.

Parameter	**Variable name**
Base temperature for bud burst prediction and GDD summation	baset (°C)
Chilling requirements for bud burst	crequ (chill days
Critical temperature to initiate leaf offset	crit_temp (K)
Final root allocation coefficient until harvest	arootf2 (unitless
GDD needed from bud break to canopy maturity	lfmat (°days)
GDD needed from bud break to harvest	hybgdd (°days)
GDD needed from bud break to the fruit ripening phase	grnrp (°days)
GDD needed from bud break to the start of fruit development	grnfill (°days)
Initial leaf allocation coefficient	fleafi (unitless)

Parameter	Variable name
Maximum canopy height	ztopmx (m)
Maximum harvest date in the northern hemisphere	max_NH_harvest
Maximum LAI	laimx (m^2 m^{-2})
Maximum rooting depth	root_dmx (m)
Planting density	nstem (# m^{-2})
Ratio of height: radius at breast height	taper (unitless)
The slope of the relationship between leaf N per unit area (gN/m2) and Vcmax25top (umol CO2/m2/s)	s_vcad (µmol CO

2.3.2 Regional case simulations

A regional model domain, encompassing the entire PHO, was set up at a spatial resolution of 1 ha. This resolution was a compromise between accounting for the diverse, patchy landscape with small field and orchard sizes (from a few 100 m^2 to some hectares) and a reasonable computational effort. For the land use information, the database of agricultural fields and orchards was combined with the remaining land uses digitized from satellite imagery. Since CLM5 allows to define fractional land use in a single grid cell, the overall area of individual land use classes was still accurately represented.

The slope of the terrain was derived from the EU-DEM. Furthermore, the surface parameter defining the depth to bedrock was adjusted based on the minimum (0.27 m) and maximum (1.3 m) depths available to roots from the ESDB, which were linearly scaled by the slope. In the plain area, the value was set between 10 and 20 m to represent the thick alluvial deposits and prevailing free drainage conditions. Lastly, the maximum fractional saturated area (f_{max}) that controls runoff generation was set to zero for all grid cells containing crops due to the deep groundwater table, gentle sloping in the plain, and assuming that there are no large saturated areas in the fields and orchards. f_{max} was set to 0.16 in the remaining areas of the catchment as extracted from the global dataset. The adjusted parameters for apple were used as described in section 2.3.1 while a separate parameter set was used for cherries to account for the earlier start of the growing season and harvest, and lower productivity as compared to apples. For the sake of consistency, parameters for winter wheat and potato were also modified based on *Boas et al.* [2021] with minor adjustments to growing seasons to account for the local climate [*Dercas et al.* , 2022; *FAO* , 2023].

For the model spin-up, the available global GSWP3 v1 atmospheric forcing data set providing data from 1901 to 2010 at a 3-hourly temporal and 0.5° spatial resolution was used [*Lange and Büchner* , 2020]. The model was spun-up for 720 years until equilibrium for soil carbon and nitrogen pools, soil water storage, and other ecosystem variables was reached for all land uses in the catchment. For the remaining simulations, the model was forced with a 7-year time series obtained from the observational data of meteorological stations CS1, CS2 (2016-2022), and CS3 (2018-2022) in the study area as well as from the two Atmos41 stations in orchard S09 and S10 (2021-2022) (Figure 1). The data was spatially interpolated to the same resolution as the surface data using inverse distance weighting. The interpolation of precipitation and temperature included a weighting factor for elevation variation using a linear correlation between station elevation and mean annual station precipitation and temperature, respectively, as described in *Panagoulia* [1995]. Another short spin-up period of 3 years was performed as the orchards had just reached their maximum lifespan before orchard rotation is initiated and new seedlings need a couple of years to reach the full productivity level [*Olga Dombrowski et al.* , 2022].

2.4 Simulation scenarios

To assess how well CLM5-FruitTree can represent soil moisture dynamics and crop growth in the study area, 1D simulations were first performed in orchards S09 and S10 for the growing seasons 2021 and 2022. Two model set-ups were tested: the first used the default CLM5 irrigation routine with adapted parameterization to approximate the observed irrigation schedule, while the second was prescribed with the observed irrigation through the irrigation data stream. By directly applying irrigation water to the ground surface, CLM5 assumes an irrigation efficiency of 100 % which is hardly achieved in sprinkler irrigation [*Gilley and Watts* , 1977]. For the irrigation data stream, we thus assumed that only 75 % of the water volume measured by the hydrometers is reaching the ground surface while the rest is lost through evaporation from leaf surfaces, transpiration of the grass cover in the orchard alleys, and leakages in the piping system. Modeling results were compared to observed SM and tree transpiration at a daily time step as well as crop yield and development. Pearson's r (r), the root mean square error (RMSE) and the percent bias (%bias) were calculated for statistical model evaluation.

For the regional case, we conducted three simulation experiments to test different irrigation scenarios. Regional data on irrigation outside the instrumented orchards S09 and S10 was not available. Thus, the model was run using the default CLM5 irrigation routine with the same parameterization that was used for the point scale simulations, in the following considered the full irrigation scenario (FI). Based on this scenario, two deficit irrigation scenarios were created for both apple and cherry orchards with 75 and 50 % of full irrigation (DI75 and DI50, respectively) using the irrigation data stream. All scenarios were run over the same 7-year period (2016-2022). To investigate the differences between irrigation scenarios, multi-year averages and seasonal dynamics of irrigation, SM, crop growth or yield, and crop water use efficiency (CWUE) were calculated and compared. In this study, CWUE was defined as the amount of yield produced per unit volume of water consumed [*Ibragimov et al.* , 2007]:

$$CWUE = \frac{Y}{\mathrm{ET}} \quad \text{Eq. 5}$$

where Y is crop yield in t ha^{-1} and $ET$is crop evapotranspiration in mm.

3 Results

3.1 Orchard scale simulations

3.1.1 Soil moisture and matric potential dynamics

3.1.1.1 Outside the irrigation season

Figure 3 and Figure 4 show the SM time series at 5, 20, and 50 cm depth and SMP at 20 cm depth for S09 and S10, respectively. The interquartile range (Q_{25}-Q_{75}), calculated from 24 measurements (12 nodes with two profiles each) for every depth, shows considerable variability in SM, especially in S10 and at 50 cm depth. This reflects the high heterogeneity of soil texture and gravel content that was observed during soil sampling. When comparing the observed SM dynamics in the two orchards, S09 showed 4-12 vol% higher SM on average compared to S10 throughout the measurement period. The soil textural analysis of both orchards clearly showed a higher clay and organic matter content, and lower gravel content in S09 compared to S10 (Table 1). Frequent rainfall during the winter months (631 and 606 mm in 2021 and 2022 respectively) kept the soil close to saturation with average SMP around -8.5 kPa in both orchards. Starting in April the soil gradually became drier causing a steep decline in SMP to around -500 kPa (S09) and -300 to -400 kPa (S10) by mid-May. The decline resulted from low rainfall amounts and increased evaporation demand along with water consumption from the grasses in the alleys and the fruit trees. In addition to the observations, the simulation results using both the standard CLM5 irrigation routine and the irrigation data stream are shown for the corresponding CLM5 soil layers in Figure 3 and Figure 4. Table 4 lists the model quality parameters used to evaluate the simulation results. The model simulations outside the irrigation season, using either irrigation approach, corresponded well to the observed SM in S09. However, in S10, CLM5 overestimated SM in the soil profile by on average 4.5-7.3 vol%. The observed differences in SM between both orchards were not captured by the model where SM values in S10 were only 1-2 vol% higher. In April and May, just before the start of the irrigation season, the simulations showed the strongest deviation from observed values for both orchards as the soil drying was much less pronounced in the simulations.

3.1.1.2 Irrigation season

In 2021 and 2022, the farmer irrigated every 5-7 days starting mid-May through October. Irrigation amounts per event varied strongly and averaged 14 and 25 mm in S09 and S10 respectively (upper panel of Figure 3 and Figure 4). Irrigation increased SM by up to 10 vol% in the top 5 cm and about 5 vol% at 50 cm depth. To represent the observed irrigation schedule, the CLM5 irrigation routine can be adjusted in two ways, by (1) adapting ψ_{target} or (2) tuning thef_{thresh} parameter. Figure 5 shows the effect that different values of these two parameters have on several aspects of the simulated irrigation (e.g., start of irrigation period, number of irrigation events, irrigation frequency) as well as on SM and crop yield. In both cases, a lower parameter value results in a later onset of irrigation, fewer irrigation events and lower total irrigation amounts. However, the parameters have different effects on irrigation frequency, whereby smaller values of f_{thresh} result in less frequent irrigation events while the irrigation volume per event increases (Figure 5). Changing ψ_{target}, on the other hand, has little effect on the irrigation frequency and volume. SM in the upper 50 cm of soil increases with increasing values of both parameters. The increase is exponential forψ_{target} with values ranging between 0.195 and 0.275 cm^3 cm^{-3} and almost linear forf_{thresh} with a somewhat smaller range. Consequently, varying ψ_{target} has a more pronounced effect on yield compared to f_{thresh} for the investigated range of parameter values.

For the model run using the standard irrigation routine, we setf_{thresh} to 0.7 while leaving ψ_{target} at its default value of -34 kPa, which resulted in approximately weekly irrigation events of on average 26 mm per event, starting mid-May. This, however, could only partially reproduce the observed irrigation schedule and SM dynamics compared to using the irrigation data stream. Nevertheless, both irrigation approaches showed fluctuations of similar magnitude compared to the observed values in the upper soil. Less dynamics than observed were simulated at 50 cm depth for both irrigation approaches and both orchards. The wet bias in S10 was still persistent throughout the profile for the simulation using the irrigation data stream while simulated SM based on the default irrigation routine dropped to the range of observed values (Figure 4).

Simulated and observed total yearly irrigation were similar in S09 with the observed effective irrigation being 433 and 458 mm (75% of actual measured irrigation) and simulated amounts being 425 and 439 mm for 2021 and 2022, respectively. In S10, observed effective irrigation amounts were considerably higher than in S09, which could be expected considering the lower observed SM in S10. Compared to the observed 706 and 586 mm, for 2021 and 2022, respectively, the model applied only 393 and 388 mm, which is a result of the simulated wet bias.

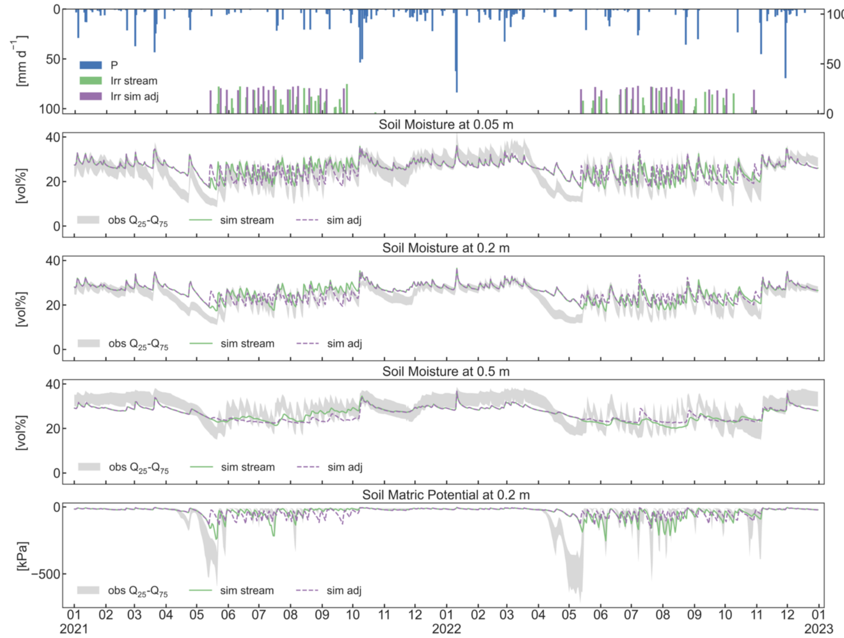

Figure 3: The upper panel shows precipitation, and observed and simulated irrigation for orchard S09 in mm d^{-1}. The central panels show observed soil moisture (SM) as interquartile range between the 25th and the 75th percentile from 24 measurements, simulated SM using the standard CLM5 irrigation routine and the irrigation data stream at 5, 20, and 50 cm depths. The bottom panel shows observed interquartile range and simulations using the two irrigation approaches of soil matric potential (SMP) at 20 cm depth for orchard S09 for 2021 and 2022.

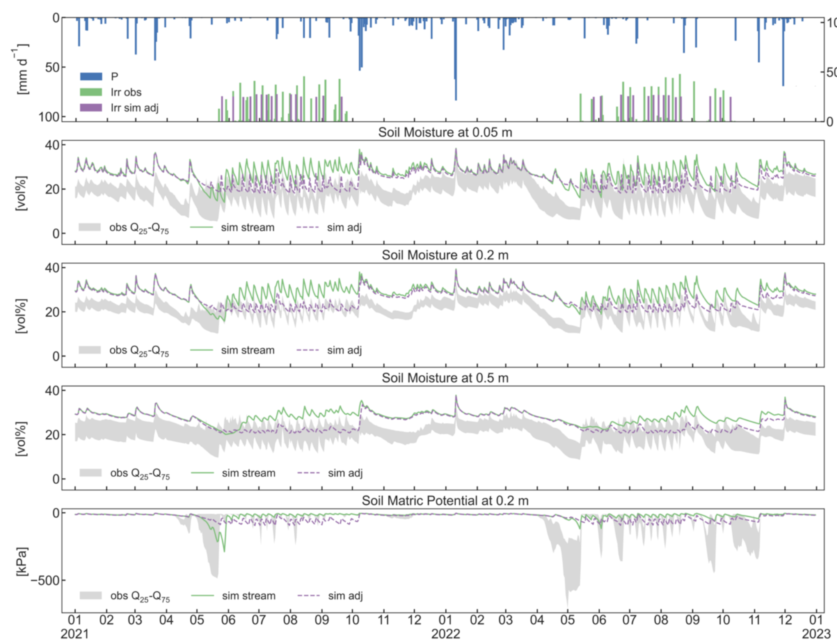

Figure 4: The upper panel shows precipitation, and observed and simulated irrigation for orchard S10 in mm d^{-1}. The central panels show observed soil moisture (SM) as interquartile range between the 25th and the 75th percentile from 24 measurements, simulated SM using the standard CLM5 irrigation routine and the irrigation data stream at 5, 20, and 50 cm depths. The bottom panel shows observed interquartile range and simulations using the two irrigation approaches of soil matric potential (SMP) at 20 cm depth for orchard S10 for 2021 and 2022.

Table 4: Pearson's r (r), root mean square error (RMSE) and percent bias (%bias) for soil moisture (SM) at 5, 20 and 50 cm depth and soil matric potential (SMP) at 20 cm depth in orchards S09 and S10 simulated using the irrigation data stream. The first number refers to 2021 and the second number to 2022. Statistics were calculated for the whole year and for the irrigation season only (21th May to 25th Sep for 2021; 15th May to 10th Oct and 14th May to 2nd Oct for S09 and S10, respectively, in 2022).

		S09	**S09**	**S09**	**S10**	**S10**	**S10**
	Soil depth (m)	**r**	**RMSE (vol%)**	**%bias**	**r**	**RMSE (vol%)**	**%bias**
Whole year 2021/2022	0.05	0.88/0.81	3.97/3.89	13.13/8.18	0.77/0.83	9.55/8.08	50.21/39.89
	0.2	0.88/0.86	3.10/3.23	10.14/9.26	0.75/0.84	8.18/7.68	37.30/35.55
	0.5	0.78/0.80	3.08/3.49	-6.60/-6.63	0.56/0.72	8.06/7.65	37.48/36.13
	SMP (kPa)	0.82/0.63	56.25/89.67	-27.54/-37.14	0.62/0.75	41.65/122.41	-35.44/-76.14
Irrigation season 2021/2022	0.05	0.86/0.74	3.85/3.02	15.47/4.30	0.70/0.83	5.13/8.43	21.13/45.60
	0.2	0.84/0.77	3.00/2.84	10.86/8.10	0.67/0.77	2.3/7.70	4.51/37.32
	0.5	0.48/0.27	3.12/3.74	-6.27/-6.14	0.25/0.45	1.73/7.10	-0.74/33.74
	SMP (kPa)	0.73/0.64	46.61/61.36	-11.08/-7.54	0.65/0.66	52.04/98.86	-81.11/-72.95

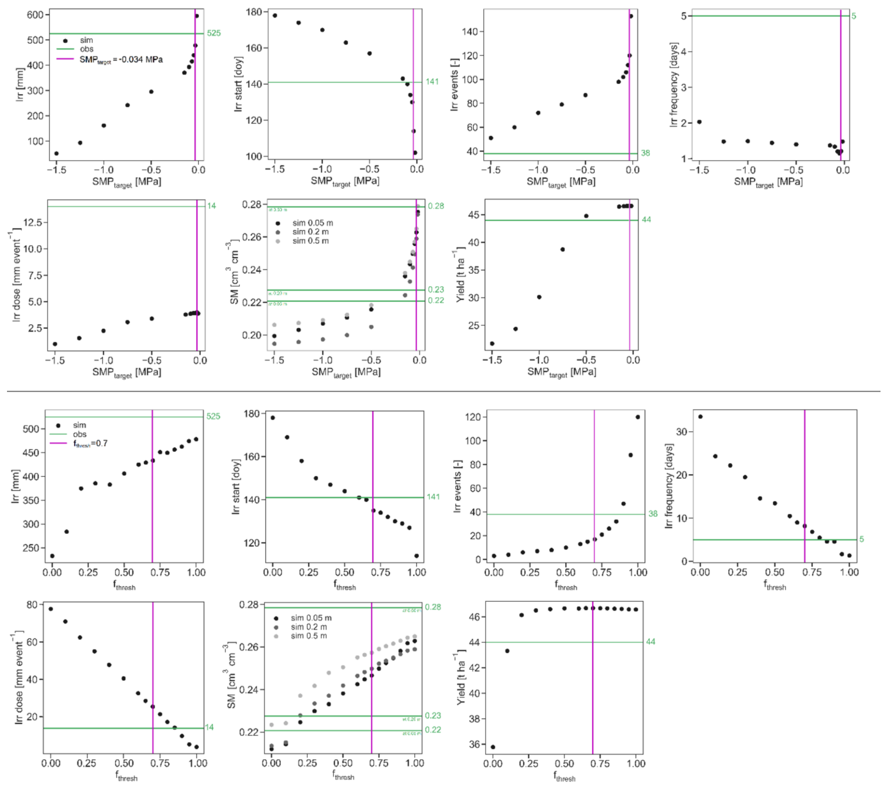

Figure 5: Effect of irrigation target soil matric potential (ψ_{target}) and irrigation threshold fraction (f_{thresh}) on total irrigation amount (Irr), irrigation starting date (Irr start), number of irrigation events (Irr events), irrigation frequency (Irr frequency), irrigation dose per event (Irr dose), soil moisture (SM) at 5, 20, and 50 cm depth, and yield. Shown are yearly average values for S09 and the year 2016.

3.1.2 Tree transpiration and fruit harvest

The comparison of measured sapflow with simulated transpiration expressed as water consumption per tree is presented in Figure 6. Observed sapflow varied significantly between different trees resulting in large inter-quartile ranges. The two model runs showed no difference in simulated tree transpiration despite the difference in irrigation amount and timing. In 2021, CLM5 showed higher values and a slight shift in the seasonal dynamic as a result of a too early onset of leaf development compared to the observed values (LAI_{sim} in Figure 6). Simulated leaf duration and total transpiration agreed well with the measurements in 2022. Tree transpiration peaked in July with a measured monthly average of 12.5 (2021) and 20.2 L tree^{-1} day^{-1} (2022) and simulated values of 25.1 (2021) and 24.5 L tree^{-1}day^{-1} (2022). The better agreement between simulated and observed values in 2022 followed a reinstallation that was performed after partial sensor failure and unreliable measurements that resulted in data gaps for the 2021 growing season. The 2021 data should therefore be handled with care when interpreting absolute values. Simulated maximum leaf area index (LAI) was reached in early July. Full canopy cover in the orchards occurred in the second half of June, so slightly earlier, based on visual inspection of the phenocam pictures (data not shown). Simulated leaf area and hence transpiration fell to zero by December, which broadly agreed with observed sapflow and leaf senescence deduced from the phenocam images.

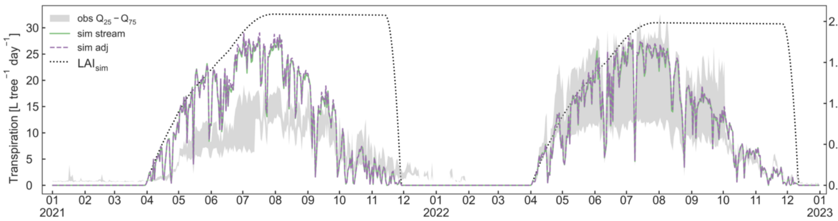

Figure 6: Whole tree transpiration estimated from the sapflow sensors in orchard S10 together with simulated transpiration expressed in liters per tree and day, and simulated leaf area index (LAI_{sim}) for 2021 and 2022.

Generally, fruit harvest in the orchards was performed between 17th of August and 30th of October in a first and second harvest for most varieties. Due to very low apple quantity, harvest in 2022 occurred in a single harvest between 1st Sep and 15th Nov depending on variety. Simulated harvest in 2021 occurred on 12thand 18th Sep for S09 and S10 respectively, and a few days earlier in 2022. The two simulation runs using either the adapted CLM5 irrigation routine or the irrigation data stream showed no difference in harvest amounts. In 2021, simulated yield was close to the observed values while the exceptionally low yield in 2022 was not captured by the simulations (Table 5). Visual inspection of the phenocam images showed significantly less flowers on the trees in 2022 compared to 2021 (data not shown). No extreme weather conditions were observed during the winter 2021/2022 that could explain the reduced flowering. Other possible reasons for the low number of flowers and hence low yield in this year may be related to alternate bearing of the varieties or other factors (e.g., plant physiology or traits, pest and disease or certain management practices) that are not included in the model.

Table 5: Observed and simulated apple yield in t ha^{-1} for orchards S09 and S10 for 2021 and 2022.

	Yield in S09 (t ha^{-1})	**Yield in S09 (t ha^{-1})**	**Yield in S09 (t ha^{-1})**	**Yield in S10 (t ha^{-1})**	**Yield in S**
Year	**obs**	**sim**	**obs**	**obs**	**sim**
2021	44	47	47	47	51
2022	16	49	11	11	50

3.2 Regional simulations

3.2.1 Irrigation signature in the PHO

Figure 7 shows simulated seasonal mean SM and sum of evapotranspiration (ET) within the PHO averaged over the 7-year period. Depicted values represent grid cell averages, meaning they are the weighted average of all land uses in a given cell. During the winter months and into spring, SM is high throughout the catchment, but with a declining gradient along the North-South axis from the mountainous part down to the plain. ET in the catchment is low during winter but starts to increase in spring, revealing a discernible pattern attributed to differences in land use (Figure 1). During the summer months, ET reaches its peak, displaying a distinct irrigation signature with significantly higher ET values of 293 mm on average over irrigated land, as opposed to 214 mm on average in the rest of the catchment. The pattern persists throughout autumn and is also evident in summer and autumn SM, albeit less pronounced due to the lower productivity of rainfed vegetation, resulting in reduced water uptake from the soil. The subsequent analysis will focus exclusively on the irrigated land, more specifically on apple orchards, as they account for 91 % of the total irrigated area.

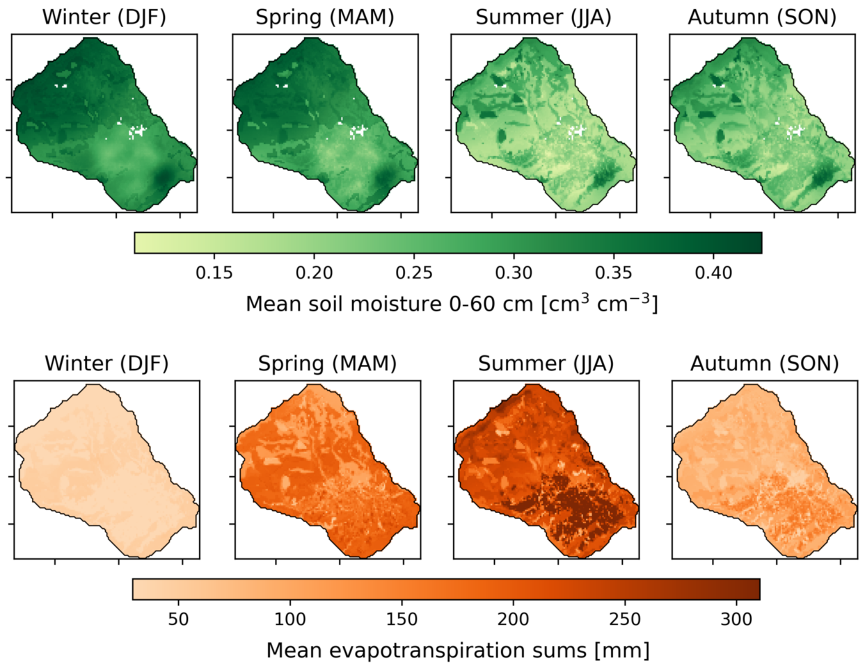

Figure 7: Seasonal mean soil moisture, and evapotranspiration sums in the PHO catchment, averaged over the period 2016-2022.

3.2.2 Simulated spatial patterns

Figure 8 shows average and standard deviation of the 7-year simulation period for irrigation, SM, yield, and CWUE for all apple orchards in the PHO, between 2016 and 2022. Modeling results show a clear spatial pattern that is driven by climatic conditions following the topographic gradient (Figure 1) on the one hand and soil characteristics on the other hand (Figure 2). Average yearly irrigation requirements range between 400 and 450 mm in the plain. The highest values are found in the southeast while considerably lower values occur at higher altitudes in the northern part of the catchment (<200 mm). Harvest values show a similar pattern because cooler temperatures and lower incoming radiation in the northern part of the catchment result in lower crop productivity and thus smaller yields (16-38 t ha^{-1}) compared to the plain where yields are around 50 t ha^{-1} without much spatial variability. In addition to lower crop productivity and thus lower crop water demands, spatial variability in irrigation requirements results from the higher precipitation in the upper parts of the catchment that further reduces the need for irrigation as well as soil textural differences. The latter is most evident in the southern part of the catchment where the higher clay content and the consequently higher water holding capacity of the soil result in increased evaporation (not shown). This in turn generates a greater irrigation demand resulting in slightly lower CWUE of orchards planted on these soils. Soil textural differences are also reflected in the SM plot where areas with a higher percentage of clay or organic matter show higher SM values than areas with sandier soils or soils that are lower in organic matter. CWUE ranges from 57-65 kg ha^{-1} mm^{-1} in the plain to 35-45 kg ha^{-1} mm^{-1} in the northern part of the catchment and largely reflects the spatial patterns of irrigation and harvest whereby high irrigation requirements and low harvest lead to low CWUE. Inter-annual variability (standard deviation plots) within the catchment shows similar patterns for irrigation, harvest, and CWUE and is higher in the northwestern part of the catchment. The higher variability was driven by local temperature differences in some years that delayed the onset of the growing season up to 14 days compared to the remaining orchards. Inter-annual variability of SM is generally low without a distinct spatial pattern.

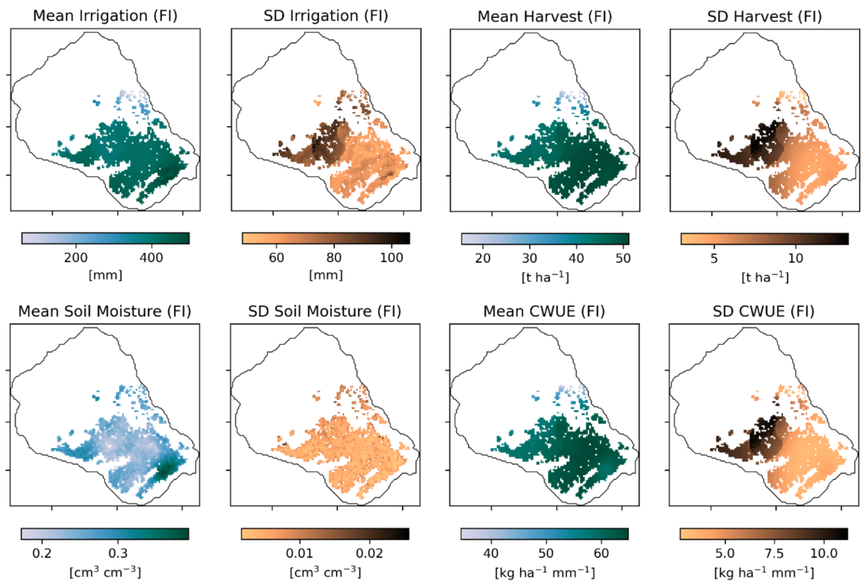

Figure 8: Mean and standard deviation (SD) of average yearly irrigation, soil moisture in the root zone (0-60 cm), harvest, and crop water use efficiency (CWUE) for apple orchards within the PHO between 2016-2022 under full irrigation (FI).

3.2.3 Effect of irrigation deficit scenarios

The effect of deficit irrigation on total irrigation amounts, harvest, and CWUE of apple orchards in the PHO for the moderate irrigation deficit scenario, DI75, and the more severe deficit scenario, DI50, are shown in Figure 9. Yield differences between the FI and the DI75 scenario are almost negligible, ranging from a decline of maximum 3 t ha^{-1} (5 %) to even slight increases in yield. However, the DI50 scenario resulted in a clear decline of simulated yield with up to 12 t ha^{-1} corresponding to a 30 % reduction in yield compared to the FI scenario. Nonetheless, orchards located at high altitudes and in the southeast on clay-rich soils are still barely affected by the higher water deficit (<5 % decline in yield). Overall, annual water savings are highest in the plain, averaging 100-125 mm for DI75 and 210-250 mm for DI50. CWUE shows a differing pattern between both scenarios. While in DI75, CWUE declines slightly in the central part of the plain by around 1 kg ha^{-1} mm^{-1} (2 %), there are large areas that show an increase in CWUE of similar magnitude. The decline in CWUE is concentrated on the orchards growing on soils with a high percentage of sand. For DI50, on the other hand, CWUE is almost exclusively showing a decrease of up to 8.8 kg ha^{-1}mm^{-1} (17 %), though again CWUE for orchards in the higher altitudes and the ones located on soils with higher clay content are less affected.

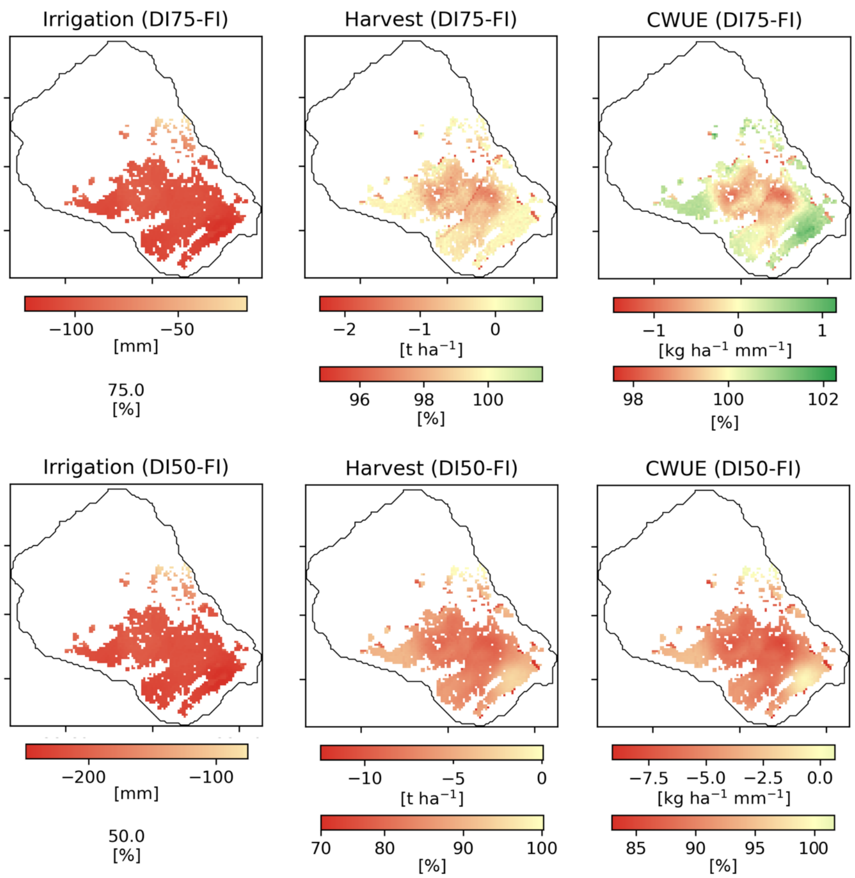

Figure 9: Absolute and relative differences in irrigation amount, harvest, and crop water use efficiency (CWUE) between the full and the 75 % irrigation scenario (DI75-FI), and the full and 50 % irrigation scenario (DI50-FI) for apple orchards within the PHO during the period 2016-2022.

3.2.4 Irrigation and yield at the inter-annual and monthly scale

Yearly irrigation amounts, precipitation during the main irrigation season, and harvest averaged for all apple orchards in the PHO are shown in Figure 10. For the investigated 7-year period, irrigation ranges between 297 and 487 mm while precipitation is around 167-322 mm from May to October. Differences in precipitation drive the inter-annual variability in irrigation requirements whereby drier summer months, such as 2019-2022, result in higher irrigation demand compared to wetter years. Yield ranges between 32 and 55 t ha^{-1}, with 2019 and 2020 being the years with the highest yields due to favorable meteorological conditions (high solar radiation and temperature). Notably, the effect of deficit irrigation on yield is strongest in these two years reducing yield by >12 t $ha^{-1}$for the DI50 scenario. In contrast, both the DI75 and DI50 scenario have negligible effect on yield in the first three simulation years.

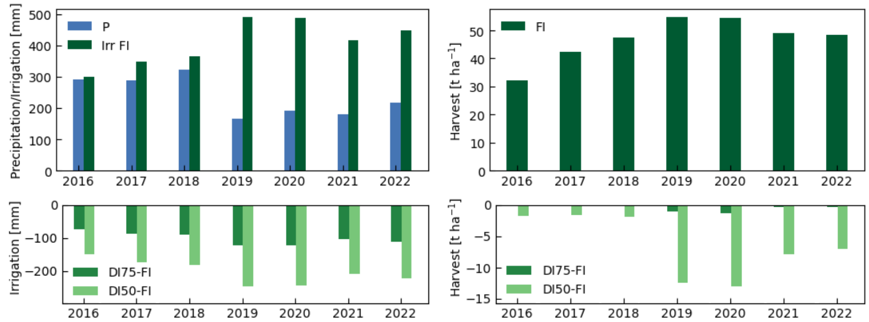

Figure 10: Yearly sum of precipitation during the main irrigation season (May-Oct), irrigation, and harvest averaged over all apple orchards within the PHO from 2016 to 2022, under full irrigation (FI) and the difference for the 75 % and the 50 % deficit irrigation scenarios (DI75 and DI50).

Figure 11 shows the seasonal course of irrigation, precipitation, and fruit growth in the apple orchards averaged over the PHO and the 7-year period. The simulated irrigation season starts in April or May and lasts until October with negligible amounts still applied in November for some years. Monthly irrigation requirements increase sharply between April and June until reaching their peak in August with on average 107 mm per month. Accordingly, August is also the month in which the greatest water savings occur for the deficit scenarios. After that, irrigation declines rapidly. Fruit biomass increases steadily from April to harvest in September with faster growth occurring in the earlier months. While fruit growth is barely affected by a 25 % reduction in irrigation (DI75), for the DI50 scenario it decreases sharply in August and to a smaller extent in July and September. The reduced fruit growth results in a yield loss of on average 0.5 t ha-1 for DI75 and 6.5 t ha-1 for DI50.

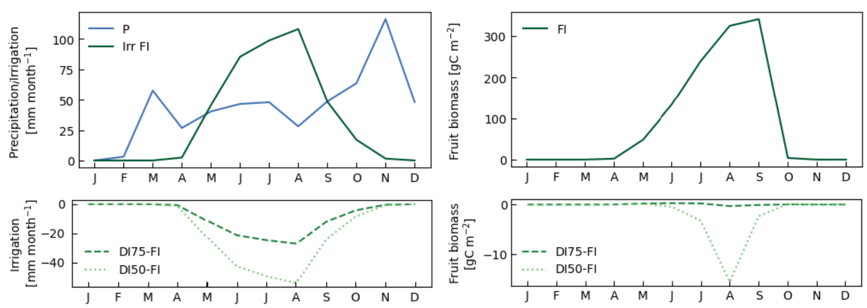

Figure 11: Seasonal pattern of monthly precipitation, irrigation, and fruit biomass averaged over all apple orchards within the PHO and the period 2016-2022, under full irrigation (FI) and the difference for the 75 % and the 50 % deficit irrigation scenarios (DI75 and DI50).

4 Discussion

4.1 Evaluation of the CLM5 irrigation routine

The direct comparison of simulated SM dynamics to observed SM from a dense sensor network in two irrigated orchards gave valuable insights into model performance. Our findings demonstrate that the standard CLM5 irrigation routine lacks the necessary flexibility to represent specific irrigation practices observed in the orchards. Simulated crop growth and transpiration at the orchard scale were not sensitive to the difference in irrigation amount and timing between the two model runs using the standard irrigation routine and the implemented irrigation data stream respectively. However, as differences between the simulated and actual irrigation practices increase, the effects may become more important especially considering runoff generation or sensible and latent heat fluxes that were not analyzed in this study. Similarly, if the irrigation is limited so that the crop experiences some degree of water stress, the timing of irrigation may become more important. This could be further tested by applying different irrigation schedules under various amounts of irrigation using the irrigation data stream.

Prior studies using the irrigation module in CLM were limited to calibrating the target SM or adjusting the irrigation threshold fraction to match gross irrigation requirements reported at the country or regional level, or performed no calibration at all [*Felfelani et al.* , 2018; *Leng et al.* , 2015; *Leng et al.* , 2013;*Zhu et al.* , 2020]. The model, however, does not currently consider restrictions on irrigation schedule, over irrigation, or irrigation efficiency that significantly affect gross irrigation requirements as our results revealed. The newly implemented irrigation data stream can be used to overcome some of these limitations by prescribing crop and farmer specific irrigation schedules and amounts. This allows investigating the irrigation-induced effects on e.g., crop yield, SM, or carbon and energy fluxes under observed irrigation practices and can help to identify existing model biases by removing one possible source of uncertainty. While the use of the irrigation data stream at larger scale is currently hampered by the limited availability of precise information on irrigation practices in most areas [*Felfelani et al.* , 2018], it can serve as a valuable tool to investigate the modeled effect of different irrigation schedules and water availability scenarios. This can offer a basis and direction for further developments of the irrigation routine that are necessary for a more realistic representation of irrigation management practices [*Yao et al.* , 2022].

4.2 Model uncertainties and limitations of this study

4.2.1 Parametric uncertainty

SM dynamics outside the growing season were well reproduced by CLM5, indicating that the model was able to capture infiltration and soil water redistribution in the studied orchards. However, the significant SM bias in S10 suggests structural and parametric uncertainty in the estimation of soil hydraulic properties, probably due to inappropriate pedotransfer functions implemented in CLM5 [*X. Han et al.* , 2015]. *Gao et al.* [2021] found that poor performance of CLM5 in reproducing observed root zone soil moisture was mainly due to uncertainty in porosity estimates. In addition, a high content of rock fragments, which is typical of many Mediterranean soils [*Nijland et al.* , 2010; *Poesen and Lavee* , 1994; *Zalidis et al.* , 2002], can strongly influence the SM regime through non-linearity in soil hydraulic conductivity and by reducing the soils' effective porosity [*Angulo-Jaramillo et al.* , 1997]. For this reason, most pedotransfer functions fail to correctly reproduce the hydraulic properties of stony soils [*Nasri et al.* , 2015], which likely led to biases in simulated SM in S10. Further investigation of the results would be needed to confirm this hypothesis, e.g. data assimilation of observed soil variables could be used to optimize soil hydraulic parameters [*Strebel et al.* , 2022]. In both orchards, the simulations showed a lower simulated SM dynamic in 50 cm depth, which could be the result of uncertainties in the rooting distribution and thus root water uptake within the soil profile. The current parameterization of the vertical discretization of root fraction results in a rather shallow profile while deeper roots may still contribute to root water uptake in the studied orchards. *Shrestha et al.* [2018] encountered a similar issue when analyzing root zone SM on a grassland site using CLM3.5 and were able to improve simulated SM dynamics by increasing the root fraction in deeper layers. This may help to improve the simulated SM dynamics at 50 cm on our study sites.

The sensitivity experiments performed using two parameters of the CLM5 irrigation routine (Figure 5) and the results from the irrigation scenarios revealed relatively low sensitivity of crop yield to reduced irrigation (Figure 9). The new plant hydraulics introduced by*Kennedy et al.* [2019] advanced the physical basis for hydraulic stress in the model, but there is large uncertainty in its parameterization and in capturing the relationship of plant water stress and SM deficit for different crops. To better quantify the model performance and find the most suitable parameters for apple orchards, comparison of simulations to observations from stressed and non-stressed crops would be necessary. Additionally, sensitivity analysis of plant hydraulic parameters, which was out of the scope for this paper, could help to better constrain these model parameters.

4.2.2 Crop representation

The PHO catchment is characterized by a diversity of small-scale farm holders resulting in considerable heterogeneity in management practices, which cannot be fully captured by the model. While simulated yield was close to observations during a "good" year for the point-scale simulations, according to *Mattas et al.* [2019] average Greek apple production in 2016 was only ~23 t ha^{-1}. This suggests a great variability in orchard productivity, apple cultivars, or type of end product (e.g. apples for direct consumption or for juice) which would necessitate the inclusion of additional crop types and management practices in CLM5. In striving for global applicability, CLM5 and other LSMs face constraints in computational resources and often insufficient observational data to parameterize additional crop types, which results in biases in certain regions, while others are more accurately represented [*Lombardozzi et al.* , 2020]. In our case, the model demonstrated a strong correlation of yield and irrigation with the climatic gradient induced by the topography in the PHO, indicating a high sensitivity to model forcing data. The large simulated differences in yield between orchards in the plain (~50 ton ha^{-1}) vs. the higher altitudes (as low as 16 ton ha^{-1}) may however be exacerbated, as CLM5 employs a single set of parameters for a given crop across diverse geographies and climates. In reality, various cultivars of the same crop type, along with plant physiological adaptations to their environments, can lead to comparable productivity levels despite variations in climatic conditions. This phenomenon is evident in the cultivation of numerous crops, including apples, across climates on a global scale [*Sherman and Beckman* , 2002]. The issue has been addressed by*Lombardozzi et al.* [2020] who recommended further developments in CLM5 to improve phenological triggers and agricultural management, and to include different cultivars. In the future, the incorporation of additional satellite-derived crop data, advanced parameterizations, or the use of crop calendars to constrain these models may help reduce some of the biases [*Pongratz et al.* , 2018; *Yao et al.* , 2022; *Z Zhang et al.* , 2020].

At the orchard scale, we found discrepancies between observed and simulated SM during the growing season that suggest limitations specific to the current representation of orchards. As CLM5 does not allow intercropping, the actively growing grass cover in the orchard alleys is not included in the CLM5-FruitTree sub-model [*Olga Dombrowski et al.* , 2022]. Consequently, our simulations do not account for the additional root water uptake and transpiration as well as interception of the irrigation water from the grasses. The former may explain the smaller simulated decline in SM early in the season compared to the observations, while we considered the latter to some extent by assuming a reduced irrigation efficiency. In doing so, we did however neglect the additional ET flux. *Yao et al.* [2022] developed and tested different irrigation techniques in CLM5 and found an increase in canopy evaporation through increased interception for their implementation of sprinkler irrigation. However, the overall impact on ET and total applied irrigation remained small compared to the control run using the standard CLM5 irrigation. More importantly, accounting for conveyance and application losses would increase the simulated irrigation amount and could lead to more realistic irrigation values [*Yao et al.* , 2022].

Despite these limitations, and though we could not validate the simulation of crop yield and irrigation requirements in the PHO catchment due to the lack of observational data, the reasonable modeling results at the orchard scale give some confidence in the robustness of the regional simulations.

4.3 Implications for irrigation management

We studied the relationship between crop yield and water use efficiency, and irrigation at the regional scale, as it is determinant for a reasonable allocation of irrigation water according to crop needs. For most part of the PHO, CWUE and yield were little affected when irrigation was reduced to 75 %, suggesting that this scenario lies closer to the optimal irrigation that maximizes yield while minimizing water consumption as opposed to the FI scenario. These results are similar to a study by *Li et al.* [2018] who used CLM to schedule irrigation in a citrus orchard in Spain which resulted in 24 % less irrigation compared to the farmers' practices. This could indicate that farmers irrigate too much when water is available and water prices are low [*Latinopoulos* , 2005]. Simulated apple yield was sensitive to a reduction of 50 % of the applied irrigation water causing up to 30 % decline in yields. The effect, however, varied with different meteorological conditions and soil types within the PHO. At higher altitudes, cooler temperatures and lower incoming radiation rather than water scarcity limited crop growth. Irrigation in these orchards could thus be greatly reduced without negatively affecting yield. Moreover, under the same climatic conditions, orchards growing on soils with a higher percentage of clay (southeastern part of the catchment) could maintain similar yield and CWUE under 50 % reduction in irrigation water because of the greater water holding capacity of the soil. This will make orchards growing on these soils less prone to experience to water stress. The effect of deficit irrigation on fruit growth and yield varied between years and throughout the growing season. Years with high productivity and greater dependence on irrigation (due to low rainfall) showed greater yield loss under deficit irrigation (Figure 10). At the seasonal scale, fruit growth showed the highest reduction in August followed by July and September (Figure 11). This was mainly an effect of higher temperature, little rainfall, and larger leaf area that resulted in high irrigation requirements in this month. Apples, similarly to other crops, show different susceptibility to drought stress depending on their growth stages whereby flowering and fruit set as well as fruit development and maturation are highly susceptible to drought. The latter stage falls within the period July-September where the model showed the largest reduction in fruit growth. While the simulated plant water stress is currently linked to environmental conditions rather than capturing plant physiological differences in this stage of growth, it suggests that under limited water conditions, irrigation should be prioritized during these months to maintain reasonable yields.

4.4 Perspectives for further application and model development

The analysis performed in this study displays the current ability and potential way forward of applying CLM5 for irrigation and water resources management at various scales. Prospectively, future applications and research studies should focus on the improvement of input datasets, crop and irrigation parameterizations, and process representation. Input related improvements include the creation of high-resolution climate and land use information, especially crop types and the extent and type of irrigation. Our results clearly showed how climate and environmental heterogeneity (e.g. topography, landuse, soil properties) can greatly affect total crop water requirements, emphasizing the need for spatially explicit modeling for large-scale applications. Model investigation at the orchard scale revealed the importance of soil and crop-specific parameterization to correctly represent soil moisture and phenology dynamics, and harvest time. Extending simulations to larger scales will thus require further improving soil hydraulic parameterization through improved pedotransfer functions [*Vereecken et al.* , 2022] or parametrization of soil hydraulic properties through data assimilation approaches [*Xujun Han et al.* , 2014]. Furthermore, information on crop management and improved differentiation between different crop varieties and cultivars (e.g. different growing seasons and harvest of cherry compared to apple trees) is necessary, as these can result in distinct irrigation seasons and amounts. Concerning irrigation, this could include either crop-specific or spatially explicit values for irrigation parameters that are currently the same for all irrigated crops, hence not reflecting different management strategies or susceptibilities to water stress. Lastly, some processes could be refined or added to represent irrigation requirements more realistically. These include a parameterization of irrigation efficiency, water availability considerations and more flexible irrigation schedules that can be tailored to represent typical field practices. Conducting parallel testing and assessment of future developments covering greater spatial and temporal scales (e.g., in the form of long-term observatories) will be crucial, especially as more accurate irrigation data becomes available.

5 Conclusions

This study assessed the ability of the CLM5-FruitTree sub-model to represent irrigation practices in fruit orchards in a small Mediterranean catchment and explored the effects of different irrigation scenarios on simulated yield and CWUE. The standard CLM5 irrigation routine could not accurately reproduce observed irrigation practices, which motivated the implementation of an irrigation data stream that directly prescribes measured irrigation data. Using this irrigation data stream, observed SM dynamics in the two studied apple orchards were well captured by the model. We did however find some discrepancies between observed and simulated SM, transpiration, and yield that were related to uncertainties in soil hydraulic parameters and limitations in the crop representation, which does, for instance, not account for the active grass cover growing in the alleys.

To examine the potential to improve regional irrigation management using CLM5, we simulated different irrigation scenarios and analyzed their effect on crop yield and CWUE. The model showed distinct effects of deficit irrigation on yield and CWUE for scenarios with 25 % and 50 % reduction in irrigation (DI75 and DI50, respectively) that were tested using the irrigation data stream. While DI75 had negligible negative effect on yield and CWUE, DI50 notably reduced both yield and CWUE. Based on the modeling results, this would suggest substantial water savings of up to 125 mm year^{-1} with little to no effect on apple yields and up to 250 mm year^{-1} when accepting up to 30 % reduction in yield (although potential effects of fruit quality need to be considered as well). These effects varied depending on climatic conditions, soil type, and timing of irrigation. Hence, under limited water availability, irrigation should primarily focus on the summer months July to September and on sandy soils with lower water holding capacity.

The outcomes of this study demonstrate the potential use of CLM5 in irrigation and water resources management research and applications. Future research efforts should focus on improving soil and crop parameterizations, and as well as process representation. Finally, we anticipate that implementing more realistic irrigation schedules in land surface models such as CLM5 will allow for better water resource management at the local and regional level.

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Open Research

The CLM5-FruitTree sub-model used in this work is freely available via Zenodo at https://doi.org/10.5281/zenodo.8154390 [*O. Dombrowski* , 2022] and on Github at https://github.com/odombro/CTSM.git under the branch release-clm5.0_FruitTree. The irrigation data stream implementation is available on Zenodo at https://doi.org/10.5281/zenodo.8290143 [*Swenson* , 2023] and on Github at https://github.com/swensosc/ctsm.git under the branch irrigation_streams.

Climate data from climate stations CS1, CS2, and CS3 from the TERENO sites Agia (TERENO ID: AGIA_K_001, AGIA_K_002, AGIA_CK_003) are freely available via the TERENO data portal [*TERENO* , 2023]. Data collected from the two apple orchards S09 and S10 is available via the TEODOOR database at https://doi.tereno.net/landingpage/doi/10.34731/e1ss-pc69 [*O. Dombrowski and Bogena* , 2023]. Data analysis was performed in Python version 3.10.4 [*PythonSoftwareFoundation* , 2023] available at https://www.python.org/downloads/ and figures were made with Matplotlib version 3.5.2 [*Caswell et al.* , 2022], available under the Matplotlib license at https://matplotlib.org/. The map overview was created with QGIS version 3.12.3 [*Dawson et al.* , 2022] available at https://qgis.org/.

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