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Combined Agro-Hydrological and Flood Modeling Highlights Seasonal and Crop-Specific Flood Regulating Ecosystem Services

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Key Points:

- FLOOD Regulating AgroEcosystem Service (FLORAES) have a seasonality
- Peak flow reductions (FLORAES) are maximum at the end of crop growing seasons
- Different crops under the same climate condition generate different FLORAES

Supporting Information:

Supporting Information may be found in the online version of this article.

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Abstract Flood-Regulating Ecosystem Services (FRES) are widely used to assess the capacity of ecosystems in retaining water during a storm and mitigating hydrological extremes. Agriculture can play a role in the regulation of flood hazard, but the role of specific crop types in influencing flood regulation in small agricultural catchments remains largely unexplored. Indeed, FRES are typically evaluated by comparing the runoff generated in current conditions and a barren land scenario, treating agricultural land use uniformly in space (without distinguishing between crops) and time (without considering that agriculture has a seasonality). This study presents an approach to assess the seasonality of crop-specific FLOOD Regulating Agro-Ecosystem Services (FLORAES). The proposed approach is based on coupling two fully distributed hydrological models: WATNEEDS, an agro-hydrological model that estimates daily soil moisture based on agricultural water demand, and MOBIDIC, which uses the soil moisture conditions derived from WATNEEDS as the initial state to simulate flood hazards during extreme storm events. As a proof of concept for the methodology, we analyzed the upper part of the Ombrone Grossetano river basin (Italy), where agriculture plays a huge role in the local economy. Our results reveal that, under identical climatic conditions, different crops generate distinct initial soil moisture conditions, which can affect flood peak discharges. FLORAES don't contribute to flood mitigation in winter, whereas their contribution at the end of the growing season of each crop is not negligible, reaching the 20% of the peak discharge depending on the crop and the river basin size.

1. Introduction

Agriculture plays a major role at the interface between human activities and hydrological systems. For instance, agriculture is responsible for 70% of global freshwater withdrawals, making it both an important driver and target of water scarcity worldwide (Ingrao et al., 2023). Moreover, agricultural areas are subject to hydrological risk in that they are prone to droughts and exposed to floods. Droughts are tightly connected to losses in agricultural productivity, as water stress limits the productivity of vegetation (Santini et al., 2022). Floods can destroy croplands through the mechanical action of water (Lucaora et al., 2025), prevent access and arability of soils for variable time after the event (Pacetti et al., 2017), and produce a virtual water loss corresponding to the water that has been used by crops that due to the floods are no longer yielding (Galli, Govoni, & Rulli, 2025). Indeed, flood damages are continuously increasing, not only in Italy, due to the conjunct effect of anthropogenic climate change and human interventions on land use (CRED & UNIDSR, 2015). Climate change is leading to the intensification of extreme rainfall, especially of high precipitation quantiles in short durations (Forestieri et al., 2018; Lompi et al., 2025), that generally increase with temperature due to an increase in convective origin precipitation (Berg et al., 2013; Lenderink & Van Meijgaard, 2008; Marra et al., 2024). Flash floods, generated by short-duration and heavy convective rainfall in small river basins, have shown increasing trends (Llasat et al., 2016), and they could rise further in the future under certain climate scenarios (Dallan et al., 2022; Lompi et al., 2025). In addition to that, land use change produces often overlooked changes to how catchments respond to such rainfall events. Previous literature has shown how urbanization and agricultural expansion reduce the permeability and infiltration capacity of soils, inducing greater runoff with respect to natural areas (Dogan & Karpuzcu, 2022; Hao et al., 2024), and thus ultimately reducing the time of concentration in heavily anthropized river basins (De Moraes et al., 2018; Kaviani et al., 2020). As a consequence, the increase of high-intensity short-duration events and the more rapid runoff propagation due to land use change make small agricultural river basins particularly prone to flash flood hazard. On the other hand, though, the changes in flood hydrology in response to land use change, make agriculture not only an object, but also a potential agent of hydrological risk. Indeed, agricultural

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areas contribute to increased local runoff when associated with deforestation (Dogan & Karpuzcu, 2022). Expansion of agriculture translating into forest cover loss has been associated with higher surface runoff and peak flows, even with high variability (Guzha et al., 2018; Kavian et al., 2020). On the other hand, restoring agriculture can also be a productive way to reduce runoff generation in abandoned/barren lands (Owuor et al., 2016). This capacity of an ecosystem to control and reduce runoff is defined as a Flood Regulating Ecosystem Service (FRES) and it is usually assessed by comparing the difference in the runoff of two scenarios under the same climatic conditions: a baseline, representing the actual conditions, and a scenario in which the land use of the environment is changed to barren ground (e.g., as in Pacetti et al., 2024). However, the alterations of the natural hydrological flows caused by agriculture depend on several underlying mechanisms, requiring assessments that account for how agriculture fits within the local landscape, from field scale to catchment scale (Fiener et al., 2011). An important aspect in this is represented by the seasonal cycles of agriculture, and how they fit within local hydroclimatic dynamics and natural seasonal cycles. The seasonal evolution of agricultural lands can produce dynamic changes in soil hydraulic properties (Lu et al., 2020), rainfall interception (Zheng et al., 2018), and antecedent soil moisture conditions (Scholz et al., 2024). Regarding the latter, agricultural areas can have a seasonality in evapotranspirative water demand that differs not only from that of natural vegetation, but also from crop to crop (D'Acunha et al., 2024). In addition to that, irrigation produces a direct alteration of local soil moisture conditions (Zaussinger et al., 2019) that can also propagate along the hydrographic network (Galli et al., 2023). Previous studies have highlighted how the seasonality of antecedent soil moisture conditions can reflect in a seasonality of flood peaks (e.g., Wasko et al., 2020). The overlooked consequence of this is that, if agricultural lands are on a significant portion of the watershed, this seasonality can depend on the seasonality of specific crop covers and associated agricultural practices. In short, approaches and methodologies that assess the role of agriculture in modulating flash flood hazards in small agricultural river basins are as necessary as underrepresented. Ecosystem-based adaptation approaches can represent an interesting perspective in this direction, as they merge agricultural management and flood risk management in a single framework, promoting a more sustainable interaction between human and natural systems (Chong, 2014). In particular, the role of crops and irrigation management in flood hydrology can be conceptualized as a supply of FRES, especially in small agricultural river basins where the demand of FRES is high. Several studies focused specifically on FRES have developed methodologies to value and map the biophysical features that determine flood regulation (Nedkov & Burkhard, 2012). This includes the assessment of flood regulating services in terms of supply, that is the capacity of the environment to provide the service, and demand or request of that service (Stürck et al., 2015). However, only a few studies have assessed the evolution of FRES in time (Mori et al., 2021), and even fewer have considered agricultural areas in a crop-specific way. Previous studies have assessed the flood-regulation role of agroecosystems, but mainly through broad agricultural land-use classes, with limited attention to crop-specific and seasonal soil-moisture dynamics (Marino et al., 2023; Martínez-García et al., 2022). Therefore, the aim of this study is to evaluate how the evapotranspirative seasonality of specific, case-study relevant crops, translates in seasonality of soil moisture, and how this, in turn, provides a seasonal agriculture-specific FRES to mitigate flash flood hazard. Operationally, we aim to assess how crop type modulates peak discharge by assessing the response of the same flood event, occurring in different seasons, to a set of alternative antecedent soil moisture condition scenarios. To do so, we couple an agro-hydrological model to simulate dynamic, spatialized and crop-specific soil moisture trends, with a fully distributed hydrological model, to evaluate how these trends influence rainfall-runoff transformation during extreme precipitation events in different periods of the year. We introduce the FLOOD Regulating Agro-Ecosystem Services (FLORAES) metric to assess the impact of different crops and agricultural management practices on the flash flood hazard of small agricultural river basins.

2. Methods

2.1. Seasonal Flood Regulating Agro-Ecosystem Services

We investigate the seasonality and crop-specificity of flood regulation provided by agriculture. More specifically, we aim at quantifying variations in peak discharge for an extreme event with a given return period, as a consequence of coupled changes in the day of occurrence of the event and in the crop-specific land cover (Figure 1). To do so, we run a spatially distributed agro-hydrological model to obtain daily, landcover- and crop-specific, long-term average, spatialized time series of soil moisture (Section 2.2), and we define the design storm events through an extreme frequency analysis (Section 2.3). Then, we extract daily snapshots from the soil moisture time series and use them as antecedent soil moisture conditions for a fully distributed rainfall-runoff

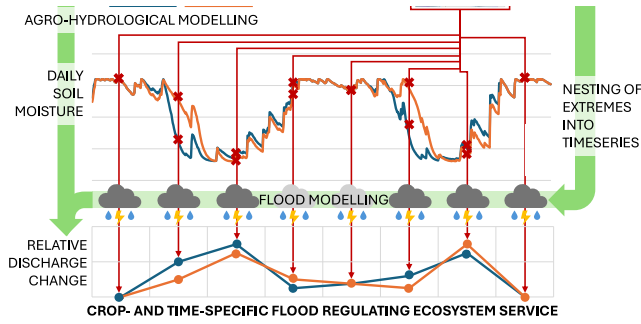


Figure 1. Schematic illustration of the methodology to assess seasonal crop-specific flood regulating ecosystem service.

2.2. Agro-Hydrological Modeling

We use the agro-hydrological model WATNEEDS (Chiarelli et al., 2020) to simulate spatially distributed soil moisture conditions, accounting for the seasonalities of crops grown in the study area. These then provide initial conditions for the flood modeling. The main WATNEEDS inputs are climate data, crop data, and soil data.

Climate data are precipitation and reference evapotranspiration. For precipitation, we bias-correct the CHIRPS 0.05° resolution daily rainfall grids (Climate Hazards Group, 2015) with local rain gauges timeseries from Tuscany region (SIR - Toscana, 2025). We do so to combine the spatial granularity of CHIRPS with the dynamic accuracy of local timeseries. To assess the impact of this choice we conduct a sensitivity analysis by replacing these data with a spatial interpolation of the rain gauges timeseries, and we report the results in Figure S1 (Supporting Information S1). We use the linear scaling method (Teutschbein & Seibert, 2012), adjusting the daily rainfall based on the mean monthly rainfall, as:

$$P_{\text{cor}}(d) = P_{\text{CHIRPS}}(d) \cdot \frac{\mu_m(P_{\text{obs}}(d))}{\mu_m(P_{\text{CHIRPS}}(d))} \quad (1)$$

Where $P_{\text{CHIRPS}}(d)$ is the daily rainfall in the CHIRPS data set and $P_{\text{cor}}(d)$ is the adjusted rainfall with linear scaling, that is, with the scalar factor evaluated as the ratio of the monthly rainfall in the observed and CHIRPS data sets. The rain gauges used for the correction are in Figure 2. For reference evapotranspiration, we use Penman-Monteith-based computations built on ERA5 Land reanalysis data (Singer et al., 2021). Crop and land cover data, as well as soil properties, are taken from case study-specific regional databases, combined, where necessary, with reference data from global data sets (see Section 3).

WATNEEDS computes the soil water balance for the active layer of the soil at daily timestep and user-defined resolution. Specifically, for each land and crop cover i in pixel j , the daily variation in soil moisture is described as follows:

$$\frac{\Delta S_{i,j}}{\Delta t} = P_{\text{eff}} - ET_{a,i,j} - D_{i,j} - R_{i,j} \quad (2)$$

Where: P_{eff} is effective rainfall, based on the assumption that a land-cover-specific proportion of precipitation is immediately directed to surface runoff. This hypothesis derives from Hoogeveen et al. (2015), and the specific values used for different land cover classes are those reported by Chiarelli et al. (2020) and Galli et al. (2023). In particular, Galli et al. (2023), performed a sensitivity analysis of downstream effects in response to changes in this interception fraction, finding negligible results for croplands.

$ET_{a,i,j}$ is the actual evapotranspiration. This is obtained starting from the potential evapotranspiration:

$$ET_{a,i,j} = k_{c,i} \times ET_{0,j} \quad (3)$$

Where $ET_{0,j}$ is the reference evapotranspiration and $k_{c,i}$ is the dynamic crop coefficient.

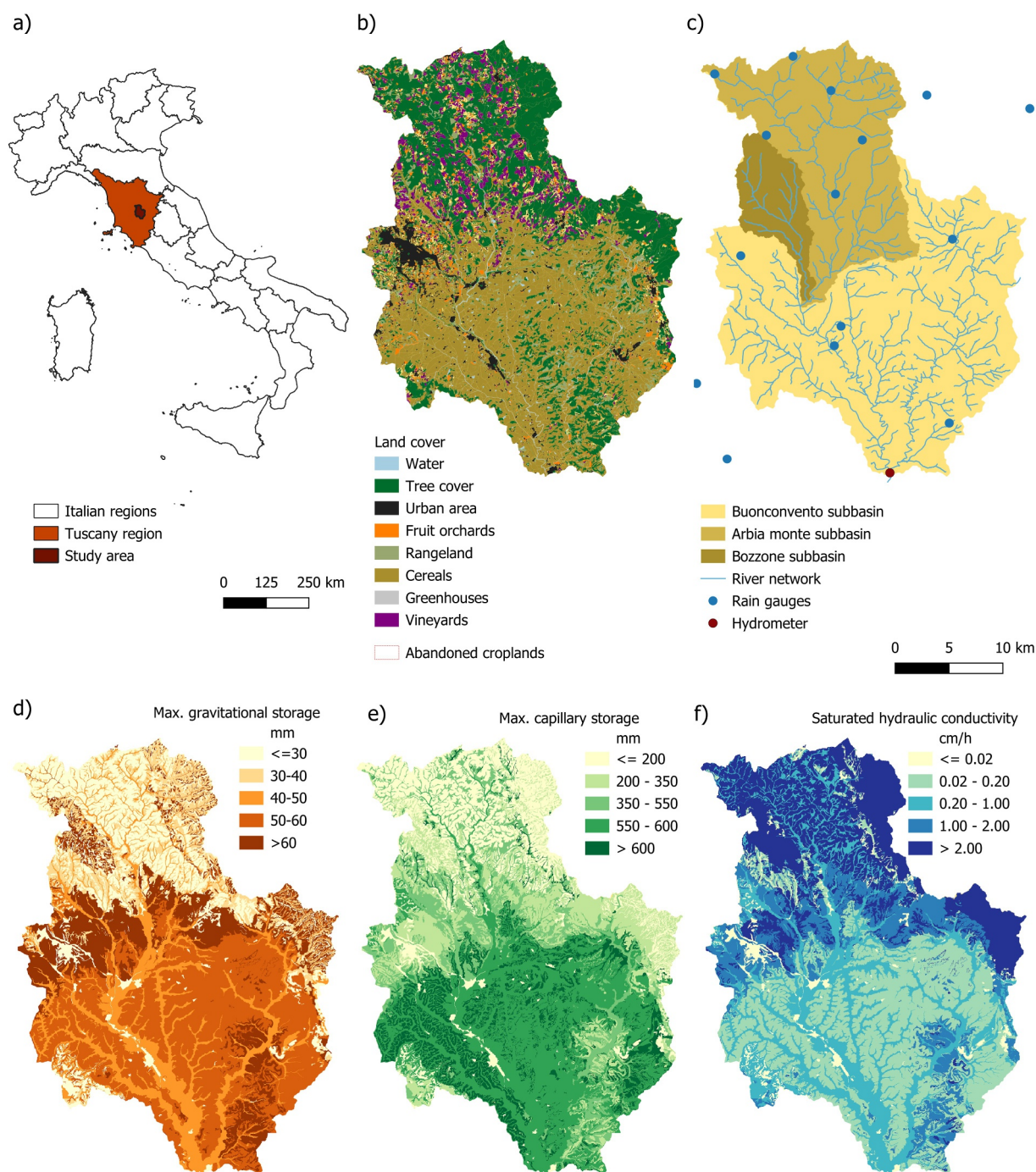


Figure 2. Location and key data for the case study. (a) Location of the test watershed within the Tuscany Region and Italy; (b) land cover map including different croplands; (c) river network, selected subbasins, and location of rain gauges and hydrometer; (d–f) hydraulic properties of the soil.

Potential evapotranspiration is limited by soil water availability through a stress coefficient k_s , which decreases linearly from 1 to 0 as the soil moisture decreases from the maximum allowable depletion, that is the soil moisture level below which crops enter water stress conditions, to the crop wilting point.

$D_{i,j}$ is deep percolation below the root zone. The process is set on when soil moisture is higher than field capacity, and is modulated by soil moisture level and maximum infiltration rate (Chiarelli et al., 2020):

$$D_{i,j} = \text{Inf}_{\max,i} \times \frac{S_{i,j} - FC_{i,j}}{S_{\text{sat},i,j} - FC_{i,j}} \quad (4)$$

Where $\text{Inf}_{\max,i}$ is the maximum infiltration rate, $S_{i,j}$ is current soil moisture, $FC_{i,j}$ is field capacity, and $S_{\text{sat},i,j}$ corresponds to saturation.

$R_{i,j}$ is runoff, which is computed as saturation excess:

$$R_{i,j} = S_{i,j} - S_{\text{sat},i,j} \quad (5)$$

Deep percolation and runoff are computed as consecutive corrections to soil moisture within the daily calculation: if the soil moisture exceeds field capacity after adding precipitation and subtracting evapotranspiration, deep percolation is computed and subtracted from the soil moisture; if, after this step, soil moisture exceeds saturation, it is set to saturation and the excess is considered as runoff.

From this water balance, we extract daily spatialized soil moisture series for each land/crop cover. The series are separated into gravimetric and capillary soil moisture using field capacity values as a threshold. This subdivision is supported and commonly adopted both in agro-hydrological modeling (Allen et al., 1998) and in distributed hydrologic models, including the one used in this study (Castillo et al., 2015). Thus, capillary soil moisture is calculated as the sum of the soil moisture components between the wilting point and field capacity, and below the wilting point. Any remaining moisture above field capacity is accounted as gravimetric moisture.

We run WATNEEDS for the period with sufficient rain-gauge observations over the study area, namely 2005 to 2022. Then, we compute the daily long-term average of the daily gravimetric and capillary soil moisture outputs. Thus, we get a synthetic 1-year soil moisture series that represents the average soil moisture trend according to historic weather data. We also include two synthetic years representing dry (25th percentile) and wet (75th percentile) conditions. For what concerns spatial resolution, we run WATNEEDS to simulate vertical flows of each possible crop-specific land cover at 250 m resolution, thus obtaining one daily time series of 250 m resolution soil moisture maps for each possible crop-specific land cover.

2.3. Extreme Frequency Analysis and Flood Modeling

Design storm events are defined with a frequency analysis of extreme rainfall to produce the input forcing of MOBIDIC. The extreme frequency analysis is done with the Simplified Metastatistical Extreme Value (SMEV) distribution. SMEV (Marra et al., 2019) is a simplified version of the MEV (Marani & Ignaccolo, 2015), which evaluates extreme rainfall with a given return period using more information than in the classical annual maximum approach. Indeed, SMEV uses the cumulative distribution of the ordinary event $F(x; \theta)$, usually with a Weibull distribution, and the average number of events in each year n , as:

$$\text{SMEV}(x) = [F(x; \theta)]^n \quad \text{with} \quad F(x; \theta) = W(x, \lambda, \kappa) = 1 - e^{-\left(\frac{x}{\lambda}\right)^\kappa} \quad (6)$$

where λ and κ are respectively the scale and the shape parameter of the Weibull distribution. The rainfall quantiles are evaluated in the 24 hr duration, that is time of concentration of the river basin, for more return periods (2, 10, and 100 years). The SMEV distribution has been chosen as non-asymptotic methods have been demonstrated to have greater fitting performances than asymptotic competitors (Vidrio-Sahagun & He, 2022). This is true especially for short time series, as methods relying only on annual maxima would utilize too few data points. However, a comparison between SMEV and the regional Intensity Duration Frequency curves of the Tuscany Region is provided in Supporting Information S1 (Figure S2 in Supporting Information S1), even if the set of data is different as they are updated at the 2012. The comparison shows that the more frequent extreme precipitation is underestimated by the official IDFs, and this could be related with the high number of extreme events which have occurred recently in the area after 2012 (e.g., Lompi et al., 2022).

The results of the extreme frequency analysis are the input of the MOBIDIC (“MOdello di Bilancio Idrologico Distribuito e Continuo” in Italian) distributed and continuous hydrological balance model (Castelli et al., 2009; Castillo et al., 2015; Yang et al., 2014). MOBIDIC is a fully-distributed hydrological model in which the

precipitation in each cell is partitioned into infiltration, surface runoff, and soil water storage, depending on soil saturation. The water that infiltrates in the soil is further separated into capillary storage and gravitational storage. Therefore, in the model there are fluxes between the two storages (interflow) and outside the storages (evapotranspiration and percolation to the groundwater). The groundwater storage contributes to baseflow, while surface storage generates direct runoff. Local runoff is propagated downstream according to the flow direction and accumulation obtained from a digital elevation model and through the drainage network, allowing the model to reproduce flood hydrographs at the catchment outlet by accounting for both timing and attenuation of the flood wave. For this reason, MOBIDIC can be used both as a continuous hydrological model and for single-event scenarios. MOBIDIC has been chosen as it is fully distributed as WATNEEDS, and can have a very good description of the initial soil moisture conditions in the soil, which can vary in each cell for each crop scenario, favoring the coupling of the two models (see Section 2.4). Besides the initial soil moisture conditions provided by WATNEEDS and the precipitation obtained by the extreme frequency analysis, MOBIDIC needs the hydraulic conductivity of the soil, K_{sat} , available in the Tuscany Region open data. K_{sat} is estimated in the database from soil-horizon properties using texture-dependent pedotransfer functions: Brakensiek et al. (1984) for fine- and coarse-textured soils and HYPRES/Wösten et al. (1998) for medium-textured soils, with a correction for rock-fragment content following Torri et al. (1994).

MOBIDIC is run with a 15 min time step, as this is the resolution of the precipitation data in the Tuscany region, and it has been calibrated on the most sensitive parameters (Yang et al., 2014) with Monte Carlo simulations. The objective function to evaluate model performances, that is to measure the differences between modeled and observed discharges for a set of events selected with a Peak Over Threshold (POT) on the catchment outlet hydrometer, are the Nash Sutcliffe model efficiency (NSE) and the Magnitude of the Peak (MP), which are described in the next equations:

$$NSE(\theta) = 1 - \frac{\sum_{t=1}^N (q_{obs,t} - q_{mod,t}(\theta))^2}{\sum_{t=1}^N (q_{obs,t} - \bar{q}_{obs})^2} \quad (7)$$

$$MP(\theta) = |\max(q_{obs}) - \max(q_{mod}(\theta))| \quad (8)$$

Where $q_{obs,t}$ and $q_{mod,t}$ are respectively the observed discharge in t -time step, and $\bar{q}_{obs}$ is the mean of the observed discharge. MP is the absolute difference between the peaks of the observed and modeled hydrograph. Although MOBIDIC can account for general land-surface and vegetation-related properties, it does not explicitly represent crop-specific processes such as crop calendars, phenological stages, crop coefficients, rooting depth or irrigation requirements. This is why coupling the two models was necessary (see next section) and why the best set of MOBIDIC parameters is kept unchanged across the different crop scenarios.

2.4. Model Nesting and Flood Regulation Agro-Ecosystem Services

To evaluate the flood regulation agro-ecosystem services (FLORAES), we force MOBIDIC with the same precipitation event on different days of the year separately. This means that we extract maps of capillary and gravimetric soil moisture from the WATNEEDS synthetic 1-year time series in correspondence of the day on which we impose the precipitation event and use them as initial soil moisture conditions in MOBIDIC. This one-way nesting, from WATNEEDS to MOBIDIC, is designed to evaluate the marginal effect of crop cover on flood regulation through soil moisture changes, purposely leaving out other potential feedback. In the calibration phase, the soil moisture conditions of the baseline scenario are extracted from the full WATNEEDS timeseries, instead of from the 1-year synthetic time series, and used as antecedent soil moisture conditions for each event used in the calibration of the model.

To match the 250 m resolution of WATNEEDS outputs and the 50 m resolution MOBIDIC grid, we take the crop/land-cover specific soil moisture maps by WATNEEDS and remap them to the 50 m resolution crop-specific land cover map, modified according to each scenario.

Ecosystem service supply refers to the capacity of ecosystems to provide goods and services that contribute to human well-being (Burkhard et al., 2012). In this study, the supply of the flood-regulating agro-ecosystem service provided by different crops is represented by the FLORAES indicator, which describes the potential contribution

of the agricultural land cover with a given crop to flood regulation. The FLORAES of a given land/crop cover scenario are defined as the percentage difference between the flood peak in the selected scenario and the flood peak in the barren scenario, starting from the same event. Because the same event is forced multiple times in the year, the FLORAES are not a single value but rather a seasonal time series of values. A statistical comparison to assess if there are significant changes generated by different crops is performed. The paired Wilcoxon signed-rank test (Wilcoxon, 1945) is applied to determine whether the overall percentage differences between two FLORAES series are significant over the whole calendar year. Then, the Kruskal–Wallis (Kruskal & Wallis, 1952) test is used to evaluate whether these FLORAES have a seasonal dependence. Lastly, to test if there is a difference in the FLORAES seasonality, a harmonic regression model, in which the annual cycle is represented by sine and cosine terms of the Julian day (Stolwijk et al., 1999), has been used by evaluating the interaction terms between scenarios and the harmonic components with an F -test.

Since MOBIDIC is a fully distributed hydrological model, FLORAES can be computed for each reach of the river basin. The results have therefore been extracted in three points to understand how FLORAES change with respect to the river basin area. Indeed, floods in large river basins are usually less influenced by land use and antecedent soil moisture conditions (Blöschl et al., 2007).

The results are shown for the three design events with a return period of 2, 10, and 100 years to analyze the sensitivity of the FLORAES with the intensity of the extreme precipitation. The same rainfall event causes different flood peaks during the year based on antecedent soil moisture conditions in the river basin that partially depend on the available crops (scenarios).

3. Data and Case Study

We test the FLORAES methodology on the upper part of the Ombrone Grossetano river basin (Figure 2). This basin is particularly suited as a pilot case for our methodology, as it is exposed to frequent flash flood events, it presents a sensible prevalence of agriculture in its landscape (Figure 2b), it has a well-established monitoring network (Figure 2c), and an overall satisfactory availability of data to inform the modeling chain.

Crop-specific land cover maps are obtained by combining the ARTEA (Agenzia Regionale Toscana per le Erogazioni in Agricoltura - Tuscany Regional Agency for Agricultural Provisions) regional database for Tuscany and the regional land cover map of Tuscany. In particular, we use ARTEA for agricultural areas and the regional land cover elsewhere. The combination of the two vector maps is then rasterized at 10 m resolution.

To evaluate FLORAES, the current scenario is compared with different crops, as well as a barren scenario as a common benchmark. Given that ARTEA provides a single class for all annual herbaceous crops, often subject to rotation, we base the set of scenarios on changes to this class, attributing different annual herbaceous crops to it. We consider as baseline the scenario where winter wheat is attributed to the annual herbaceous crops class, as this is the most common annual crop in the area according to ISTAT data. Then we attribute sunflower to this class, because it is also very common in the region and it has a radically different seasonality from wheat, which other typical annual herbaceous crops in the region (e.g., barley) do not have. Given the relative abundance of abandoned croplands in the study area, we include a scenario of reclamation of these lands, where we introduce a leguminous fodder crop. Indeed, leguminous cover crops are traditionally used within crop rotations in mediterranean contexts for their role as nitrogen fixators (Saia et al., 2016; Scavo et al., 2025), and, for analogous reasons, they are increasingly being suggested as nature-based solutions for the reclamation of degraded lands (Wang et al., 2023). Crop growth parameters are taken from Allen et al. (1998) and Chapagain and Hoekstra (2004), while crop calendars are mainly retrieved from grey literature on local agricultural practices. Regarding soil data, maximum infiltration is derived from the Harmonized World Soil Database (FAO et al., 2012), while the maximum storage capacity is derived from high-resolution soil property maps available in Tuscany's regional database (Regione Toscana, 2025).

Discharge and rainfall data for model calibration are downloaded from the Hydrological Regional Service. All rain gauges with at least 10 years of rainfall data in the area have been used to calibrate the model and to evaluate extreme rainfall for the different return periods, as the uncertainty of the quantile estimation with short time series length is reduced using a meta-statistical approach for the extreme frequency analysis (see Section 2.3). The rain gauges and hydrometer are shown in Figure 2c.

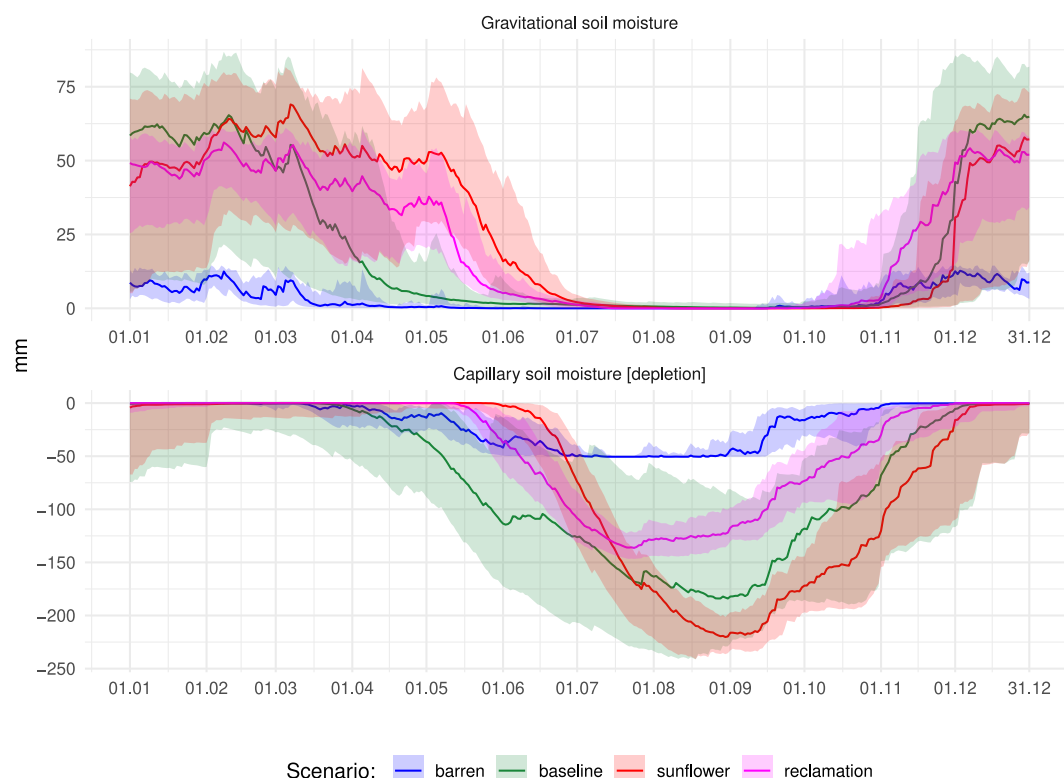


Figure 3. Capillary and gravimetric soil moisture under different scenarios. Moisture levels are expressed in mm to account for varying critical zone depths across scenarios. The central values are daily long-term medians while the range corresponds to the daily long-term interquartile range. Both medians and interquartile ranges are taken from spatialized model outputs and averaged over the portion of the study area interested by modeled crop changes in each scenario. Capillary soil moisture is reported as depletion with respect to field capacity, while gravitational soil moisture is reported as the excess with respect to field capacity. This means that the two graphs can be read together as the overall soil moisture series, with field capacity being the boundary between them.

4. Results

4.1. Crop-Specific Soil Moisture Trends

Figure 3 shows soil moisture trends for the different crop cover scenarios. Significant differences in soil moisture occur across the scenarios and across seasons. Differences across scenarios are mainly influenced by the different rooting depths of the different crop covers, which makes them able to remove more or less water through evapotranspiration. In particular, barren areas are able to reach much lower depletion levels than all vegetated soils, and, among different crops, sunflower reaches a lower minimum soil moisture than wheat (baseline scenario) and leguminous fodder crop (reclamation scenario). The seasonality of the soil moisture depletion curve is also different across scenarios, due to differences in the onset of the development stage in the spring, which increases the evapotranspiration rate. Wheat, in particular, develops earliest, followed by legume and sunflower, while for barren lands, which do not have a specific seasonality, the depletion is entirely driven by meteo-climatic factors. All scenarios have a negligible average depletion, meaning the capillary soil moisture equals field capacity, roughly between december and march-april, which corresponds to the period where gravitational soil moisture is most present, and thus differentiated across scenarios. Also for gravitational soil moisture, differences can be attributed to differences in rooting depths and crop development stage onsets. Barren lands present again lower levels of gravitational soil moisture than vegetated areas, and sunflower presents the highest moisture and latest depletion.

4.2. Flood Modeling

The results of the calibration for the six events selected with the POT are shown in Figure 4, where the blue hydrographs are the observed discharges in the outlet of the river basin, while the red ones show the modeled

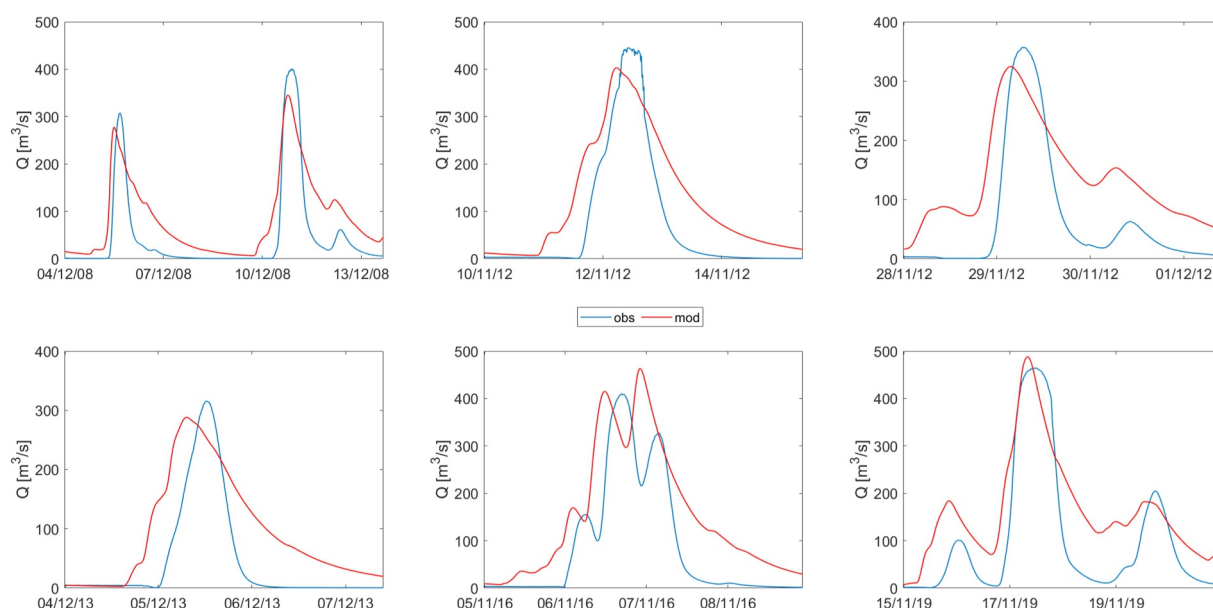


Figure 4. Results of the MOBIDIC calibration showing the observed (blue) and the modeled discharge (red).

discharge obtained with MOBIDIC. The initial soil moisture conditions used for calibration are those simulated by WATNEEDS for the baseline scenario in the 10 days preceding each event.

Since the study's objective is flood hazard assessment, the estimation of the peak is more important than a good estimate of the flood volume. Therefore, the best set of parameters has been chosen to minimize the mean MP, the average error in detecting the hydrographs' peak, which is 9.3%. This choice is associated with lower values in the global performance of the model, that is estimation of the hydrograph shape or flood volume, which are assessed with the NSE. Indeed, there is a trade-off among calibration objectives and no single parameter set generally optimizes hydrograph shape, peak flows and the recession limb simultaneously. The average NSE is anyway 0.582, which corresponds to a “satisfactory” calibration according to Moriasi et al. (2015) for daily time series and it is just slightly below the performance commonly reported for sub-daily hydrological simulations which range from 0.6 to 0.8 (Faghih et al., 2022; Liu et al., 2022).

4.3. Flood Regulation Agro-Ecosystem Services

Figure 5 shows the results of the modeling chain in three outlets of the selected case study: the first column refers to the upper part of the Ombrone river (RB1–766 km²), the second one to the Ambria creek (RB2–295 km²) and the third one to the Bozzone creek (RB3–59 km²). The first row shows the peak of the hydrographs obtained modeling the 2-year rainfall event in the different seasons (similar results for the 100-year event are in Figure S3 in Supporting Information S1). During the summer season, the peak of hydrograph tends to be smaller due to drier conditions, while in autumn and winter the peaks are generally higher. The second row shows the absolute difference in the flood peaks between the two considered scenarios (baseline in green and sunflower in red) and the barren (blue lines). The third row shows the FLORAES, that is the relative difference of the flood peaks. The lines represent the results obtained under average soil-moisture conditions, defined by the median value (50th percentile), whereas the shaded bands describe interannual variability, ranging from drier conditions represented by the 25th percentile to wetter conditions represented by the 75th percentile. The FLORAES tends to be smaller in autumn and winter, as the flood regulating services are higher during the growing season of each crop. Particularly, wheat (baseline scenario) has a flood regulating potential higher than sunflower in spring, while sunflower has higher FLORAES in summer and autumn. This tendency is clear in all the three points of the river basin where the results have been extracted. Although the annual paired comparison between the FLORAES in the two scenarios conducted with the Wilcoxon signed-rank test doesn't show a significant overall difference across the year, the Kruskal–Wallis test reveals a significant seasonal dependence with 5% significance level (Table 1). Moreover, the results of the harmonic regression with scenario–seasonality interaction show that the

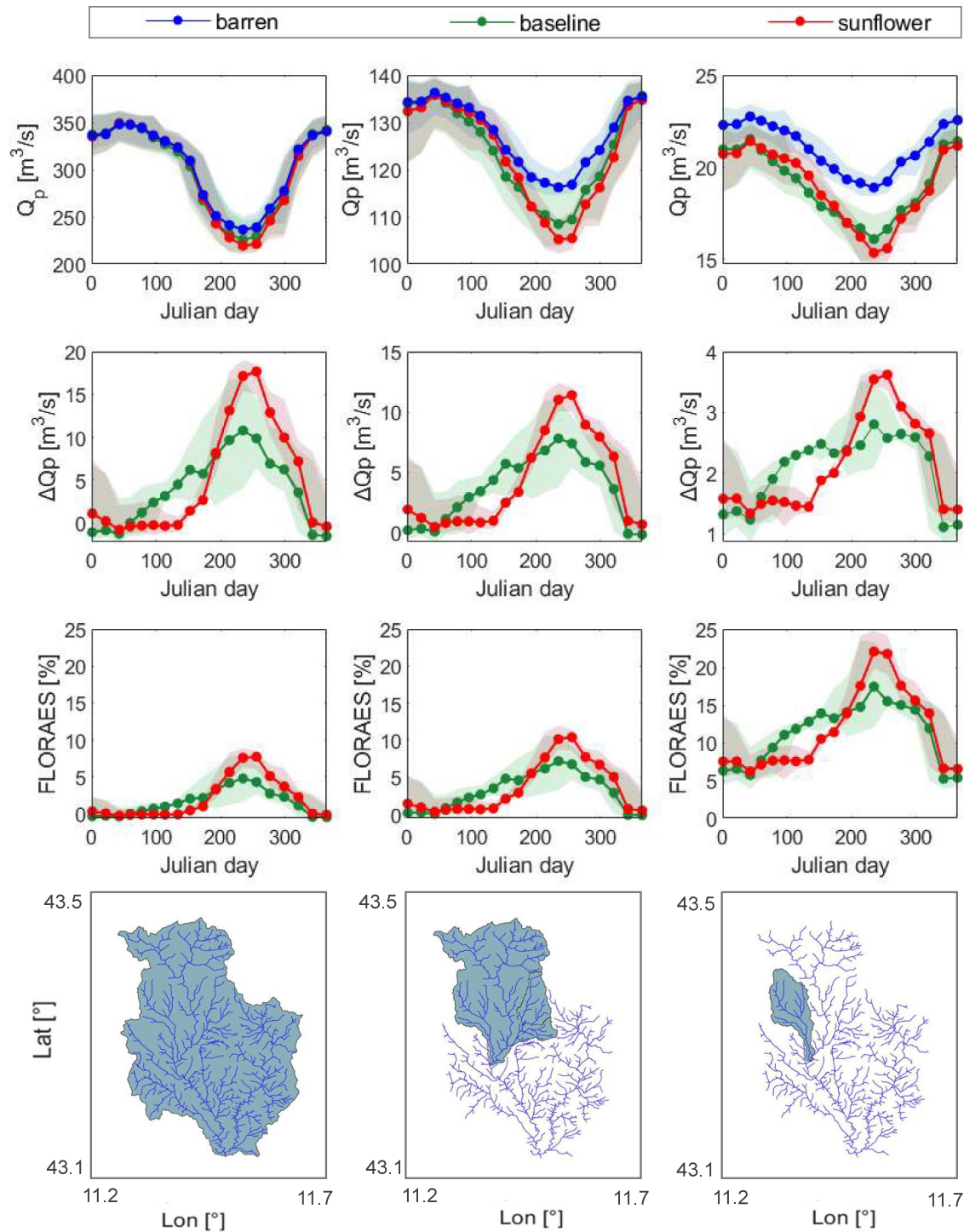


Figure 5. Results obtained in three outlets (RB1 in the first column, RB2 in the second one and RB3 in the third one). The first row shows the seasonal 2 years-flood peak discharge for the three scenarios (barren in blue, baseline in green and sunflower in red); the second row shows the absolute difference between the two considered scenarios (baseline and sunflower) and barren; the last row shows the flood regulating ecosystem services, that is the variation of the peak in relative terms. The confidence bands show the interannual variability using the interquartile range.

seasonality of the FLORAES time series is different. This indicates that the FLORAES are not uniformly distributed throughout the year, but vary significantly among seasons. Therefore, the limited annual significance can be partly explained by the compensation of changes occurring in different seasons.

Table 1

Results of the Three Statistical Tests (p -Value) to Assess if Differences in the Flood Regulating Ecosystem Services Time Series in the Two Scenarios (Baseline and Sunflower) Are Statistically Significant

Test	RB1	RB2	RB3
Wilcoxon	0.314	0.445	0.717
Kruskal–Wallis	0.024	0.014	0.017
Harmonic regression and F -test	0.004	0.001	0.044

The magnitude of the FLORAES changes across different river basin sizes. Indeed, as can be seen in the third row of Figure 5, the seasonality of the FLORAES does not change while the peak of the flood regulation service changes from 8% in RB1 (first column) to 22% in RB3 (third column), that is the small upstream catchment. This result shows how the FLORAES are higher in small catchments and how they can be more effective in regulating flash floods in small river basins.

The same analysis has been conducted also for more extreme events (10- and 100- years events) showing that FLORAES decrease with the return period (Figure 6). Indeed, the flood peak is reduced by a similar amount across the different return periods, but the relative difference with respect to the flood peak decreases.

The higher FLORAES in late summer could be associated with a higher demand of this service because of the seasonality of the extreme short durations storms that cause flash floods, which usually occur in the summer season.

The seasonality of the FLORAES is not aligned with the seasonality of the demand of flood regulating services. The demand of flood regulating services can be defined as the seasonal magnitude of flood peaks requiring regulation, which can be evaluated from a frequency analysis of maximum discharges. Since there is no measure in the Torrente Bozzone, the demand is evaluated in the outlet of the river basin using the Buonconvento hydrometer data. The monthly maximum discharge has been extracted from the time series and a Gumbel Distribution has been fitted for each month to the empirical frequency distribution of these maxima. The results are therefore the monthly 2-year floods, that is the maximum discharge that on average is expected every 2 years in each month. The observed seasonal 2-years flood (demand of the regulating service) is compared with the demand of the baseline and the sunflower scenarios in Figure 7. The blue line (left y-axis of the figure) shows the FLORAES, already shown in Figure 5; the red line (right y-axis of the figure) illustrates the observed 2 years-flood.

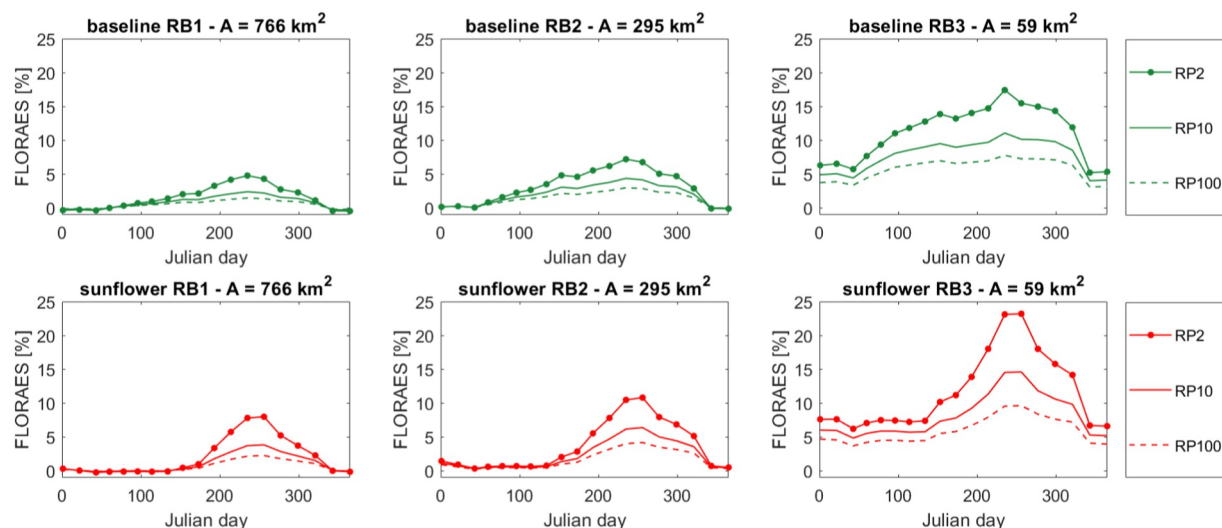


Figure 6. Flood regulating ecosystem services results in the baseline and sunflower scenarios for different return periods (2, 10 and 100 years). The three columns refer to the three river basins.

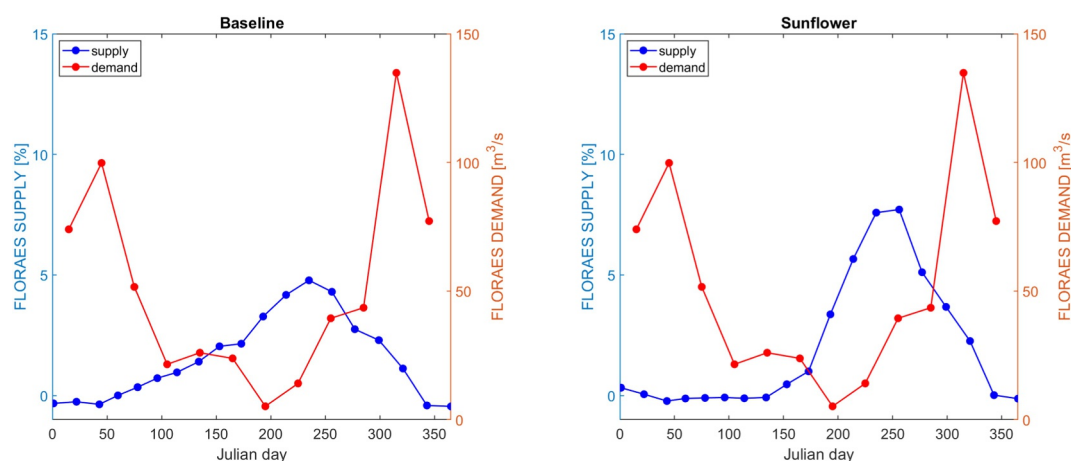


Figure 7. Supply and demand of the flood regulating ecosystem services for the baseline (left) and the sunflower (right) scenarios.

The image shows the peak of the monthly 2 years flood and the reduction of that peak that can be provided by the crops. It is clear that the demand and the supply of the flood regulating ecosystem service have different seasonality, with the peak of the demand in the wet season (autumn and winter) and the peak of the supply in spring (wheat) or late summer (sunflower). Nevertheless, sunflower has a greater FLORAES in all the wet seasons providing an important flood regulating service for the more extreme events.

Figure 8 shows the FLORAES of the abandoned fields that have been replaced with legumes (reclamation scenario). The comparison is done with the baseline scenario as the legumes have been added in the abandoned fields of this scenario. For this reason, the FLORAES of the reclamation scenario is generally higher than the baseline scenario. Particularly, the FLORAES of the reclamation scenario shows the same seasonality of the baseline scenario, as the selected legumes have a similar calendar to wheat. Indeed, for this scenario the Kruskal & Wallis test shows a statistically significant seasonality, and the harmonic regression with the F -test explains that it is the same for the FLORAES of the baseline and reclamation scenarios. The difference between the two scenarios can be seen just from May to October in the outlet of the river basin, while there is a constant difference across all the year in the small upstream catchment. A small difference between the two scenarios is found also in the Ombrone monte, but cannot be seen since it is very small with respect to the peak of the discharge in the downstream part of the river basin.

5. Discussion

Differences in FLORAES can be used to derive suggestions for flood risk management strategies. The results have highlighted a series of elements that can have interesting implications for the integrated management of agriculture and flood risk. There is indeed a small but non-negligible flood regulation service provided by agriculture. Previous studies also highlight that agriculture's contribution to flood regulation is marginal (Stürck et al., 2015), even though our in-depth modeling approach identifies crop-season combinations where this effect becomes more relevant. The effect is also more evident in smaller subcatchments as their peak flow depends more strongly on their land cover pattern (Blöschl et al., 2007), but in general it can be registered also in the Ombrone Monte watershed, the most extended one. Even more evident is the seasonality of the FLORAES, which depends on the seasonality of the crop considered. Seasonality is often regarded as a critical gap in current flood risk research, including the seasonality of precipitation extremes themselves but also the seasonality of antecedent moisture conditions (Scorzini et al., 2026; Wasko et al., 2020). Therefore, seasonal FLORAES could become an element in the refinement, for instance, of alert systems. A dynamic and crop-specific accounting of antecedent soil moisture conditions in flood alert systems could contribute to increasing their reliability.

The peak in FLORAES corresponds rather to the end of the crop growing season than to its peak (e.g., end of spring/beginning of summer for wheat, end of summer for sunflower). From the modeling point of view, this means that there is a lag occurring between the peak in evapotranspirative demand, the peak in soil moisture depletion (Figure 3) and the peak in FLORAES (Figures 5 and 7), most likely caused by the dynamic nature of the

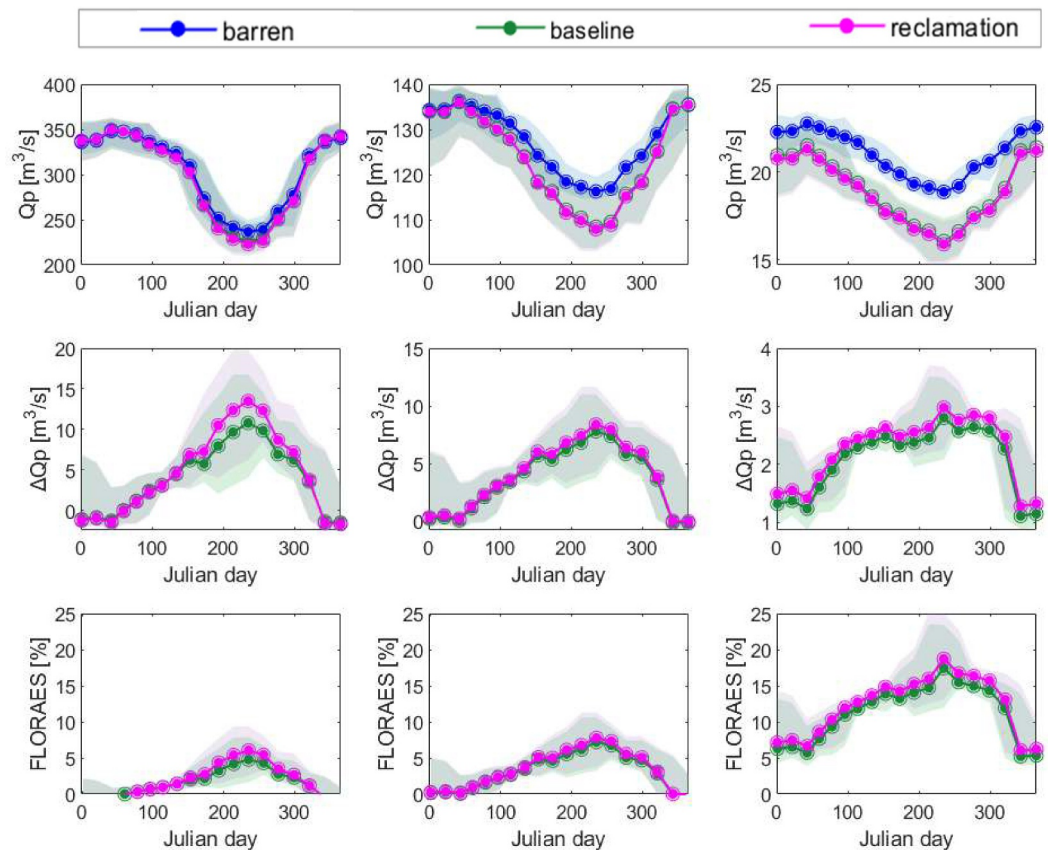


Figure 8. Flood regulating agroecosystem services of the baseline (green) and reclamation (magenta) scenario in the study area for the 2-year return period.

feedbacks between these processes. From the perspective of the transfer of the FLORAES concept into policy and practice, this means that there will likely be a perception misalignment deriving from the fact that agriculture does not provide the most FLORAES when it is most functional, but later.

The baseline and sunflower scenarios are evaluated with respect to a hypothetical barren benchmark scenario to be able to quantify the marginal FLORAES of specific crop fields. In the reclamation scenario, the areas that are changed have been retired from agricultural use. In Figure 8, FLORAES associated with the hypothetical reclamation of these areas are tangible despite the limited presence of these areas in the basin. Thus, from the policy perspective, the FLORAES resulting from the reclamation of these areas points even more than the other scenarios to the opportunity of considering agriculture as a nature based solution for the management and regulation of hydrological flows, which gain importance in terms of flood risk mitigation in the case of small agricultural basins. Moreover, while in many cases extensively restoring natural vegetation is unlikely to be technically and economically feasible, it could be of interest to investigate how more realistic changes within agricultural areas, such as the reclamation of abandoned lands, can affect flood risk.

The comparison between FLORAES supply and demand (Figure 7) shows that the peak FLORAES supply is mainly in (late) summer, while the peak in demand is in autumn and winter. On one hand, this points to the need of caution in considering FLORAES as an entirely effective service. On the other, it provides room for interesting considerations in the light of climate change, which is increasing the frequency and magnitude of convective precipitation events, more typical in the season where the FLORAES supply reaches its peak. Indeed, several studies have shown that extreme precipitation at short durations will increase, especially in the summer season in a warmer climate (e.g., Bador & Alexander, 2022; Pichielli et al., 2021). Moreover, according to Faccini et al. (2021), almost half of the flash floods of the last 20 years along the coasts of Liguria and Tuscany occurred in September and October.

Higher FLORAES derive essentially from higher soil moisture depletion, reducing the antecedent soil moisture conditions in correspondence to the hypothetical rainfall extreme. This means that there is a potential trade-off between water stress and FLORAES, with more water-intensive crops creating higher FLORAES because of their higher evapotranspiration rates. This could be limited on one hand by water stress itself, reducing evapotranspiration rates, and on the other, in drought situations, by the loss in infiltration capacity of dried soils, which is not accounted for here. Evaluating this trade-off more comprehensively can open interesting perspectives for a better understanding in drought-flood feedbacks in agriculture, as well as for a more integrated management of agriculture and flood risk.

Another point of interest that remains unexplored is the effect of irrigation. Irrigation is not accounted for here because it is not performed in the study area. However, increasing risk of droughts might lead to wider implementation of emergency irrigation strategies relying for example on small reservoirs. More generally, further studies may focus on areas where irrigation is traditionally performed, to evaluate how such a direct and, to some extent, abrupt anthropogenic alteration of soil moisture patterns can influence FLORAES.

Our study is aimed specifically at quantifying flood peak modulations generated by different crop types and seasonalities through antecedent soil moisture conditions. This clearly introduces a series of scoping limitations. For instance, while the one-way coupling between models allows to “place” the same extreme event in different times of the year, we do not look at how this event remodulates soil moisture in the following days, which could be of high interest to explore crop- and season-specific variability in terms of recovery from, and resilience to, flood events. Moreover, we simulate the change in crop mainly as a dynamic change in evapotranspiration, associated with a change in thickness of the critical zone due to different rooting depths. This means that, for instance, variations in hydraulic properties induced by the mechanical action of roots on the soil are not accounted for. Previous literature has shown that this factor can have variable impacts on different soil hydraulic properties (Lu et al., 2020). More in general, field studies show that the influence of agriculture on soil properties depends rather on how crops are coupled with specific practices (e.g., irrigation, tillage) and the overall rotation (Saha et al., 2024), while here we necessarily limit the scope to steady state crop cover scenarios. Another parameter that might be influenced by cropland seasonality is rainfall interception. As reported in the Methods section, slight changes in the overall interception rate attributed to croplands has negligible watershed-scale effects. However, different crops with different seasonalities can lead to different rates of evaporation from interception during the years, even if this should be, at least partially, implicitly accounted for in the crop coefficient formulation used here (Allen et al., 1998).

Future studies might expand the scope, for instance by including post-flood cropland recovery dynamics, by moving toward a more direct modeling of soil properties, and by implementing more explicit dynamic vegetation interception formulations (Deng et al., 2022).

Other limitations to this study derive for instance from the harmonization of the characteristics of the soil necessary for the coupling of the two models. The control volume of WATNEEDS is the active layer of the soil, thus determined by rooting depth for vegetated surfaces, while MOBIDIC has two separate control volumes for gravimetric and capillary soil moisture. Separating WATNEEDS moisture into gravimetric and capillary based on field capacity has a strong physically rooted justification (Allen et al., 1998; Castillo et al., 2015), yet it introduces simplifications on the dynamics of percolation and the soil depth that may increase the uncertainty of the results. Moreover, the input data on soil characteristics also had to be adapted to this framework, and, even though hardly quantifiable, uncertainty associated with the estimation of soil characteristics propagating into the modeling chain must be acknowledged. Also, while almost all soil parameters are taken from a regional database, the maximum infiltration rate was taken from another database due to limited availability (see Methods). While this parameter is used only in WATNEEDS to separate excess moisture between runoff and deep percolation, and thus has limited impact on the MOBIDIC nesting at the core of this study, the risk of internal inconsistencies is present. Future applications of this methodology should evaluate the opportunity cost of merging different databases versus indirectly retrieving missing data from a single source.

Further limitations of the study derive from the choices of meteorological inputs. The rainfall scenario generating the flood in MOBIDIC is not seasonal, since the same event is forced, with no changes, onto different days of the year. Instead, extreme precipitation has a variability within the year with different probability of occurrence for each month. Future development will consider circular statistics (Pewsey et al., 2013) to assess the timing and the distribution of extreme precipitation occurrence throughout the year (Treppiedi et al., 2025, 2026). However, a

constant extreme rainfall all over the year could overestimate the flood peaks in summer, with an underestimation of the FLORAES, which increase for more moderate floods. Moreover, many studies are pointing to an intensification of extremes in the summer season (Gründemann et al., 2023; Pichelli et al., 2021), and this may contribute to a more spread-out seasonality of extreme precipitation, reducing the traditional autumn concentration.

A bias correction has been performed for gridded rainfall data based on rain gauges measurements. While this allows to retain spatial gradients of gridded data while improving their local accuracy, it can also generate uncertainty about the impact on the results of such a choice with respect to for example spatial interpolations of measurements. The sensitivity analysis we conduct by rerunning the baseline scenario of WATNEEDS over the basin shows that the sensitivity of soil moisture to these two alternative rainfall inputs is limited, supporting the stability of the results. The same was not possible for reference evapotranspiration, a key input to WATNEEDS, given the lack of local observational data of reference evapotranspiration. However, the capacity of WATNEEDS to accurately reproduce evapotranspirative dynamics has been tested at different resolutions, especially for Italy (Galli, Nanesha, et al., 2025). Yet, while here we use ET₀ data based on the FAO-Penman Monteith formulation, further studies may rely on simpler formulations to allow the incorporation of local data for example in regions with sufficient availability of temperature data from local weather stations.

6. Conclusion

The assessment of flood regulating ecosystem services is crucial for understanding and quantifying the natural capacity of landscapes to mitigate hydrological extremes. Understanding the spatio-temporal distribution of ecosystem services can provide insights for integrating ecological processes into land-use planning, climate adaptation strategies, and disaster risk reduction frameworks. Typically, flood-regulating ecosystem services are evaluated by considering only agricultural land use, without a specific in-depth analysis of the role of different crops in regulating runoff in small river basins. To the best of our knowledge, this represents the first attempt to evaluate the seasonality of crop-specific flood regulation ecosystem service. In this approach, we couple two hydrological models to evaluate soil moisture conditions at the beginning of extreme events and the resulting hydrological response, as reflected in flood hydrographs. The results show that different crops under the same climatic conditions generate varying soil moisture conditions based on their growing seasons, with a cascading effect also on the flood-regulating ecosystem service. Based on the climatic conditions of the analyzed study area, the seasonality of the ecosystem service shows that agriculture does not play any role in mitigating flood hazard in winter, while different crops can have a different role in providing this service at the end of the growing season in summer. The supply of the FLORAES is not aligned with the peak of the demand in the autumn season, while it can be an important factor to be considered for extreme and short-duration storms that usually happen in late summer in the study area. This suggests that small river basins in which agriculture is predominant could experience a different flood hazard based on the specific crops cultivated in the area.

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Availability Statement

The WATNEEDS code for long-term agro-hydrological modelling is derived from Chiarelli et al., 2020, while the MOBIDIC code for flood event hydrological modelling is available at the following link: <https://github.com/mobidichydro/MOBIDICpy> (Castelli et al., 2009; Yang et al., 2014). Gridded rainfall data for long-term agro-hydrological modelling are retrieved from CHIRPS (Climate Hazards Group, 2015) and bias-corrected with data from Tuscany region (SIR - Toscana, 2025). Discharge and rainfall data for flood event hydrological modelling are also taken from the Hydrological Regional Service of Tuscany (SIR - Toscana, 2025). Evapotranspiration is retrieved from Singer et al., 2021. Crop and land cover data are taken from ARTEA and the Tuscany regional land cover map. Crop parameters are taken from Allen et al. (1998) and Chapagain and Hoekstra (2004). Maximum infiltration rate is derived from the Harmonized World Soil Database (FAO et al., 2012). Maximum storage capacity and saturated hydraulic conductivity are derived from soil property maps available in Tuscany's regional database (Regione Toscana, 2025).

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