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RESEARCH ARTICLE

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A web-based operational tool for the identification of best practices in European agricultural systems

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Abstract

Under the same perspective of the Sustainable Development Goal (SDG) 15.3 aiming to restore degraded land and soil, one of the current priorities of the new Common Agriculture Policy (CAP) is to overcome the serious environmental problems raised by intensive agriculture. Despite the steps forward guaranteed by new technologies and innovations (e.g., IoT, precision agriculture), the availability of real operational tools, which could help the member states fulfil the high requirements and expectations of the new CAP and SDGs, is still lacking. To fill this gap, in the H2020 Land-Support project, the web-based *best practice tool* was developed to identify, on-the-fly, optimized agronomic solutions to help achieve land-degradation neutrality. The tool's core is the ARMOSA process-based model, which dynamically simulates the continuum soil–plant–atmosphere, combining several cropping systems, crops, nitrogen fertilization rates, tillage solutions, and crop residue management for specific regions of interest. It provides a synthetic "Best Practice index" to identify the optimized local solutions, which combines the production, nitrate leaching, and SOC_-change, according to the end-user dynamic requests. The tool was implemented for three case studies: Marchfeld Region in Austria, Zala County in Hungary, and Campania Region in Italy, which are representative of a variety of different pedoclimatic conditions. In the present work, we report three possible cases of use in supporting best practices aiming toward soil and water conservation: (i) crop production optimization; (ii) impact of management practices (i.e., cover crops) over soil carbon; (iii) lowering the impact of nitrate leaching.

KEYWORDS

agronomic best practice, crop production, decision support system, land degradation, nitrate leaching, soil organic carbon

1 | INTRODUCTION

"Life on land" SDG 15.3 https://https://sdgs.un.org/goals/goal15 aims at "combat desertification, restore degraded land and soil and strive to achieve a land degradation-neutral world."

To achieve this goal, it is not negligible the crucial role of sustainable intensive agriculture. Land degradation is tightly connected to the decline or loss in ecosystem functions and ecosystem services, mainly reflected in a decline in the primary productivity of the land as well as a loss in soil organic carbon stock Schillaci et al. (2023).

Even more, agricultural systems play an important role in the achievement of other Sustainable Development Goals. Specifically, the "zero hunger" SDG 2, among the several actions, requires "the implementation of resilient agricultural practices that increase productivity and production, and that progressively improve land and soil quality."

Undoubtedly, depending on the applied agronomic practices, the effects of agriculture on the environment can be either negative, acting as a factor of land degradation, or positive, contributing to maintaining a good status of health of our land and soils (Streimikis & Baležentis, 2020).

In Europe, the reform for a fairer, greener, and more performance-based Common Agriculture Policy (CAP), for 2023–2027, is driven by the European Green Deal (https://commission.europa.eu/strategy-and-policy/priorities-2019-2024/european-green-deal_en). In particular, the current priority is to face and reduce the important environmental problems caused by not sustainable intensive agriculture, such as water pollution, the loss of soil fertility, climate change, among others.

To achieve such ambitious objectives, the EU CAP for 2023-2027 requires that each Member State should develop a Strategic Plan, including specific actions, funding allocated, and evaluation protocols, which will be later implemented by the competent authorities (National, Regional, on the base of each country). In addition, Article 12 states that "Member States shall define, at the national or regional level, minimum standards, and good practices taking into account specific characteristics of the areas concerned, including soil and climatic conditions, existing farming system, land use, crop rotation, farming practices and farm structures."

From the above, it is self-evident that proper implementation of the CAP and the achievement of the SDGs for facing up to the land degradation processes require adapting measures to local pedoclimatic conditions and existing farming systems (Björklund et al., 2012). However, an important question arises: "How to achieve such local adaptation?" A proper CAP implementation would require (i) to know the pedoclimate of the specific area of interest; (ii) to identify suitable farm management practices according to the pedoclimate (Costantini et al., 2020; Teixeira et al., 2018; Tóth et al., 2020); and (iii) to select the best practices based on the farming system (Serebrennikov et al., 2020).

While the environmental direction to go is clear enough, its practical implementation is still doubtful, considering the need to evaluate the local condition.

In this sense, in the last decade, planners, decision-makers, and farmers could benefit from the usage of many Decision Support Systems (DSS) in many application areas: for example, for irrigation (Ara et al., 2021; Bonfante et al., 2019), for pest and disease control (Kukar et al., 2019), for viticulture (Terribile et al., 2017), for management scenarios of cropping systems (Thierry et al., 2017), among the many others. See recent reviews (Gutiérrez et al., 2019; Zhai et al., 2020) for a thorough analysis. Most of the existing DSS addresses site-specific pedoclimatic conditions but limited management solutions, far from the comprehensive approach, fundamental for representing the variety of agricultural systems and for quantifying the effects of the CAP implementation.

More promising is the category of the web-based DSS that allow the development of *what-if* scenario, based on *on-the-fly* modelling in different field of application as manure and inorganic fertilization (Acutis et al., 2014), soil conservation and management (Naudin et al., 2015; Terribile et al., 2015), forest (Marano et al., 2019), olive growing (Manna et al., 2020).

In this work, we present the *best practice tool*, implemented within the H2020 LandSupport (LS) (www.landsupport.eu) project, for the evaluation of locally optimized agronomic solutions in support of agricultural soil conservation by (i) enhancing crop production, (ii) improving soil fertility, that is, increasing the carbon stock, and (iii) reducing nitrate leaching, at different spatio-temporal scales. The tool is based on the process-based ARMOSA (Analysis of cRopping systems for Management Optimization and Sustainable Agriculture) model (Perego et al., 2013; Valkama et al., 2020), which considers several processes in the soil–plant-atmosphere continuum and was specifically enhanced to be launched, in real-time through the LS platform. The ARMOSA results were combined within the tool to easily get a range of good combination/s of management of cropping systems.

Due to these potentialities, in this work we hypothesize that the *best practice tool* could effectively contribute to support the implementation of CAP and other relevant agro-environmental policies. The possibility to support well-informed decisions on how to increase crop productivity and, at the same time, reduce the agricultural environmental footprint and land degradation, makes the *best practice tool* unique in the DSS panorama.

2 | MATERIALS AND METHODS

The core of the *best practice tool* is the dynamical ARMOSA process-based model. However, a clear distinction between the model and the tool must be made, not only in terms of inputs and outputs but also in terms of usage and applications. The integration of ARMOSA within the LS geoSpatial DSS (S-DSS) allowed the application of the model at different spatial scales, leveraging the geospatial potentiality of the LandSupport infrastructure, as it will be better clarified later in the text. Therefore, in this Section, we reported a brief description of the ARMOSA model and a detailed analysis of the dataset implemented as inputs of the tool. Eventually, Section 3 describes the tool functionalities and outputs.

2.1 | The ARMOSA model description

The process-based cropping system ARMOSA model (Perego et al., 2013; Puig-Sirera et al., 2022; Valkama et al., 2020) allows the quantification of the effect of agronomic practices on a wide set of crop and soil-related variables, at a daily time step. The model consists of four main modules, considering: the evapotranspiration processes, the crop growth and development, the water dynamics, and both the cycling of carbon and nitrogen.

Three formulations for the estimation of the reference evapotranspiration are available: Penman-Monteith, Priestley-Taylor, or Hargreaves (Valkama et al., 2020). Potential evapotranspiration is estimated using the FAO 56 approach (Allen et al., 1998), while the actual evapotranspiration is simulated considering the water stress factor (Ferrara et al., 2010; Sinclair et al., 1987), which influences the crop-related processes such as carbohydrate production and photosynthate partitioning.

The canopy is split into five layers, with different light interception, while the crop development is described using the BBCH scale Hess et al. (1997), allowing a detailed representation of the phenology and the thermal time required to reach each crop stage.

The water dynamics is simulated with the bucket approach with travel time (Savabi & Williams, 1995).

Carbon and Nitrogen cycling are simulated using a modified approach of the SOILN model (Johnsson et al., 1987) and three types of organic carbon pools are possible: C-stable, C-litter, and C-manure.

Besides the weather daily variables, the model requires the soil characteristics (texture, bulk density, SOC) for each pedological layer for the initialization, the latter being discretized considering sub-layers of 5 cm, for the daily estimation of the soil-related variables.

The input data about the agronomic management regards the cropping system (i.e., crop rotations, sowing and harvesting dates, residue management), irrigation (water amount and timing, automatic irrigation), nitrogen fertilization (mineral or organic, amount, timing, application depth, C/N ratio, ammonia nitrogen over total nitrogen) and tillage. Its effects on soil variables, namely bulk density, and organic carbon pools are simulated, as a function of till depth, timing, degree of soil layers mixing, and % of soil perturbed by tillage.

The mixing of two or more consecutive soil layers determines pool mixing and their recalculation (e.g., C-litter and soil water content). Eventually, the soil water retention curve parameters and the bulk density are daily computed, based on the evolution of soil organic carbon and the effect of tillage.

While integrated into the *best practice tool*, ARMOSA returns the crop yield at harvest for field crops and the above-ground biomass for forage crops in (Mg ha^{-1}), annual nitrate leaching at the bottom profile (kg NO_3-N ha^{-1} year^{-1}), the annual change of the soil organic carbon stock in the first 30 cm top layer (Mg C ha^{-1} year^{-1}). The model was calibrated and validated against data from 16 sites throughout Europe (Puig-Sirera et al., 2022; Valkama et al., 2020). Recently, a global sensitivity analysis of the ARMOSA model has been carried out to highlight the key parameters in the simulated processes associated with crop yield and nitrate leaching (Colombi et al., 2024).

2.2 | Regional implementation sites

Within the LS S-DSS, the *best practice tool* was implemented to work for three regional scales: Marchfeld Region in Austria, Zala County in Hungary, and Campania Region in Italy. As it is clear from the plots in Figure 1, many climates, morphologies, and soil types are present in the three areas. Moreover, their different spatial extensions involve multiple Public bodies, with different authorities and expertise.

The southern Austrian Region of Marchfeld, with an area of around 1000 km^2, has an altitude ranging between 160 and 180 m a.s.l. The climate is characterized by a mean annual precipitation of around 550 mm, a mean air temperature of 9–10°C and the mean annual reference evapotranspiration of 800 mm, and can be described as cold with warm summer (Dfb, Peel et al. (2007). Given these characteristics, Marchfeld represents a strategic region for agricultural production. The dominant soil types are Chernozem and Fluvisol, characterized by humus-rich surface horizons and sandy deep horizons, followed by fluvial gravel from the former river bed of the Danube. Two hundred five soil mapping units were recognized, as shown in the upper left panel of Figure 1.

Zala County, with an area of around 3800 km^2, is located in Hungary and has a mean altitude of around 110 m a.s.l. The climate is characterized by a mean annual temperature of 10°C, by a mean annual precipitation of 660–800 mm, a mean annual reference evapotranspiration of 600 mm and can be described as cold with warm summer (Dfb, Peel et al. (2007). Zala is the largest river in the County and is encompassed by drained swamps along its way to Lake Balaton, which is the biggest lake in Central Europe. The dominant soil types are brown forest soils, texture differentiated meadow and peat bog soils, and less developed (or eroded) soils. Eleven soil mapping units were recognized, as shown in the upper right panel of Figure 1.

Campania Region, with an area of around 14,000 km^2, is located in southern Italy. Its fundamental geomorphological features are (i) the Apennine mountain, whose altitude ranges from 1000 to 2000 m a.s.l.; (ii) the coastal plains; and (iii) the low-altitude hills and alluvial valleys. The mean annual temperature, over the entire region, is 10–12°C, the mean annual rainfall and reference evapotranspiration range, according to the location, between 900 mm (western and eastern parts of the region) and 2000 mm (in the central part of the Apennine mountain) and between 800 and 1000 mm, respectively (De Vita et al., 2012; Pelosi et al., 2020). Therefore, the climate can be described as Mediterranean-temperate with hot summer (Csa, Peel et al. (2007), with an important seasonality, with hot-dry summers and moderately cool-rainy winters. Among the three regional areas is the most variable in terms of climate, soil, and morphology. The dominant soil types are Andosols due to the presence of several volcanoes (i.e., Flegrean fields, Vesuvius) and Inceptisols. Two hundred thirty soil mapping units were recognized, as shown in the lower right panel of Figure 1.

2.3 | *Best practice tool* input dataset

The input datasets for the three case studies are summarized in Table 1. For each theme, the following information is reported:

1. the source database and the spatio-temporal resolution;
2. the format of the database (e.g., raster, point, list);

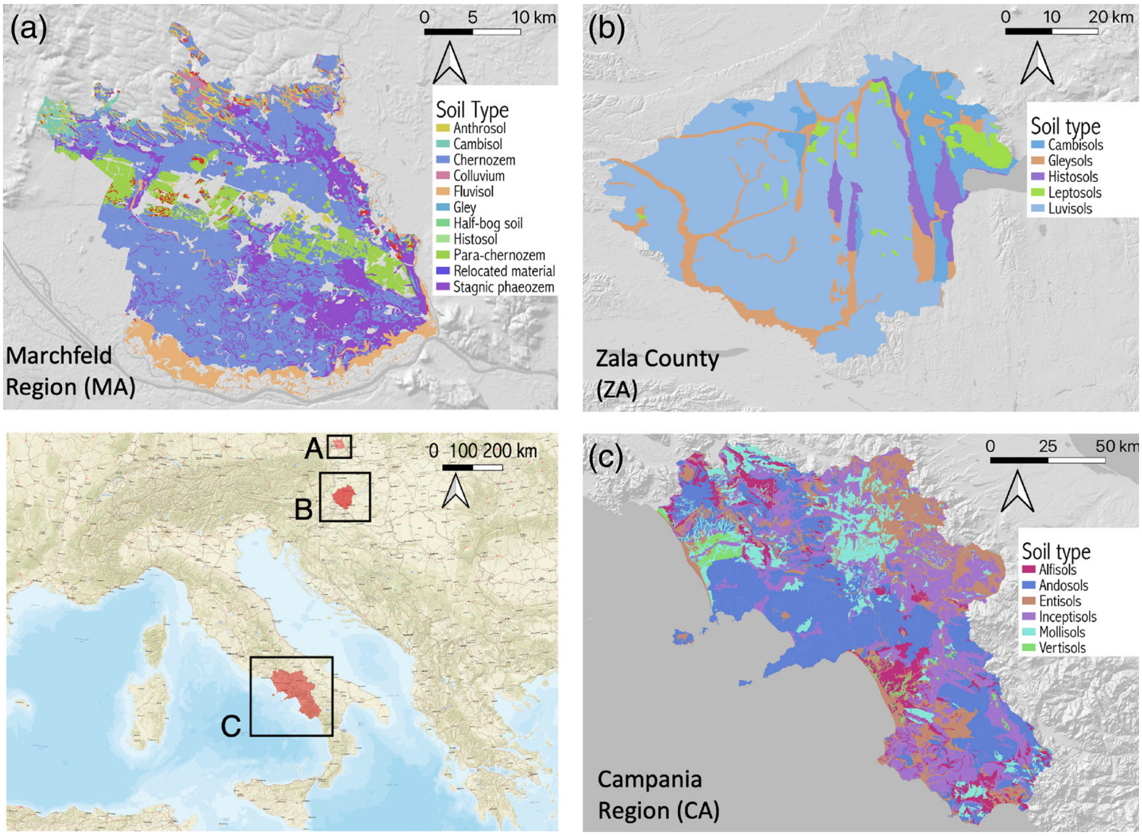


FIGURE 1 Localization of Marchfeld Region, Austria (upper left panel), of Zala County, Hungary (upper right panel) and of the Campania Region, Italy (lower right panel). The colored polygons in the plots represent the soil units for each case study. [Colour figure can be viewed at wileyonlinelibrary.com]

3. the description of the data contained in the files;
4. the parameters obtained by the dataset;
5. the models applied to process the data;
6. the examples of outputs from the chosen models.

More details about each input dataset are reported in the following Sections.

2.3.1 | Crop type and management

From the National Institutes of Statistic (https://www.istat.it, for Italy, https://www.statistik.at, for Austria, and https://www.ksh.hu, for Hungary), we derived, ranking the utilized agricultural areas, the most commonly cultivated crops for each region.

Moreover, to apply the tool to actual and optimized scenarios (i.e., sowing and harvesting dates, fertilization rates, and timing), input data were retrieved from regional surveys that were taken with local farmers and public authorities.

The crops that can be possibly chosen and their % area to the total utilized area for arable crops are listed below:

1. Marchfeld Region: maize (11%), oil seed rape (1.6%), potato (4.1%), soybean (4.7%), sugar beet (3.1%), sunflower (3.5%), winter wheat (32.5%).
2. Zala County: maize (33%), oil seed rape (9.4%), potato (1%), soybean (4.5%), sunflower (4%), winter wheat (20%).
3. Campania region: maize (11%), winter wheat (9.7%), alfalfa (8%), cauliflower (1%), fennel (1%), garlic (0.3%), potato (3%) and tomato (2%).

Each tool run is a combination of practices, which can be set by the user on-the-fly and are automatically simulated for each of the selected crops by the ARMOSA model, as adapted for the LandSupport platform. In the dynamic link with the *best practice tool*, the model simulates two or three alternatives for each of the simulated practices, which are crop-specific. The alternatives to agronomic practices are:

1. Fertilization system: conventional (based on mineral fertilization), organic (based on manure fertilization).
2. Fertilization rate reduction from the optimal rate: 0%, −15%, −30% (this reduction is simulated for either mineral or organic fertilization).
3. Tillage: ploughing (simulated at 30 cm soil depth with a high level of soil disturbance), minimum tillage (simulated at 10 cm soil depth with reduced soil disturbance), sod seeding (no soil disturbance).
4. Retaining crop residue: no, yes (incorporation into the soil is simulated according to the soil depth at which the tillage operation is simulated).

TABLE 1 Description of data type and examples of the use of the main databases employed for the *best practice tool*.

Theme	Source database-(spatial/time) resolution-years of production	Type of file	Data	Parameters (obtained by dataset)	Applied model	Example of model outputs
Soil	MA soil mapping dataset-1:10,000-2018 ZA soil mapping dataset-1:100,000-2018 CA soil mapping dataset-1:250,000-2020	Polygons and tables	Main soil morphological, chemical, physical parameters	Soil hydraulic properties, soil depth	Clipping spatial data from database; zonal statistics	Soil data within the ROI
Climate	ERA5 land reanalysis data-9 km/h-1980/2021 EURO-CORDEX/CMCC-COSMO-CLM data-12 km/daily-2020/2021	GRIB NetCDF	Rainfall, temperature, rel. humidity, radiation, etc.	Daily precipitation, daily evapotranspiration	Fao-Penman Monteith (Allen et al., 1998)	Daily precipitation and potential evapotranspiration for each soil unit
Crop type	Local info-punctual-2021	List	Most-commonly grown crops, Seeding and harvesting dates fertilization rate and timing	Crop parameters	ARMOSA	Production SOC_change Nitrate leaching
Legal restriction to land use	Natura 2000; hydrogeology restriction-punctual-2019	Polygon	Legal boundaries	Limit and type of restriction	Presence/absence of restriction	Surfaces under restriction

Note: MA stands for Marchfeld region, ZA stands for Zala County and CA stands for Campania region.

5. Cover crop cultivation: no, yes. When the "yes" option is selected, the system simulates the cultivation of a cover crop during the period between two crop seasons. A summer cover crop (crotalaria, *Crotalaria juncea* L.) or a winter cover crop (rye, *Secale cereale* L.) are simulated, according to the period of the year in which it is fallow. The cover crop can be added to the rotation if a minimum time interval of 3 months occurs between two subsequent crops.

According to the above lists of crops and related management practices, a total 504 combinations (7 crops $\times$ 2 fertilization system $\times$ 3 fertilization rate opts $\times$ 3 tillage opts $\times$ 2 crop residue opts $\times$ 2 cover crop opts) for Marchfeld and Zala and a total of 576 combinations (8 crops $\times$ 2 fertilization system $\times$ 3 fertilization rate opts $\times$ 3 tillage opts $\times$ 2 crop residue opts $\times$ 2 cover crop opts) for Campania are possible to the end-users.

2.3.2 | Soil

For the three case studies, the soil dataset, available within the LS infrastructure, contains information on the soil profiles representative of the soil polygons.

This dataset is composed of two different parts:

1. a table with the hydro-pedological features of each representative soil, such as horizon depths, water retention and hydraulic conductivity curve parameters, texture, organic carbon, and bulk density;
2. a geo-referenced file with the geo-spatial attributes of each soil polygon, that is, their location and area.

An extract of the above table with hydro-pedological features can be found at the following link https://doi.org/10.5281/zenodo.10409816. When the end-user, through the LS graphical user interface, draws a Region of Interest (ROI), that is, a region where to perform simulations, the intercepted soils are identified and, automatically, their hydro-pedological features are retrieved using a unique identifier (soil ID), which associates the table with the geo-referenced file.

2.3.3 | Climate

Reanalysis data (Hersbach et al., 2020; Pelosi et al., 2020) were chosen as the reference source of past climate and were obtained from the ERA5-Land dataset, which has a global coverage, from 1981 to present. Hourly data were aggregated on a daily scale, as required by the ARMOSA model. The following variables were considered: wind, temperature, surface pressure, solar radiation, and precipitation.

Climatic scenarios, with the Representative Concentration Pathways, RCPs, 4.5 and 8.5 were retrieved from the EURO CORDEX and CMCC-COSMO-CLM models, at daily time-step, from 2006 to 2100. The following variables considered: mean, maximum and minimum temperature, and total precipitation.

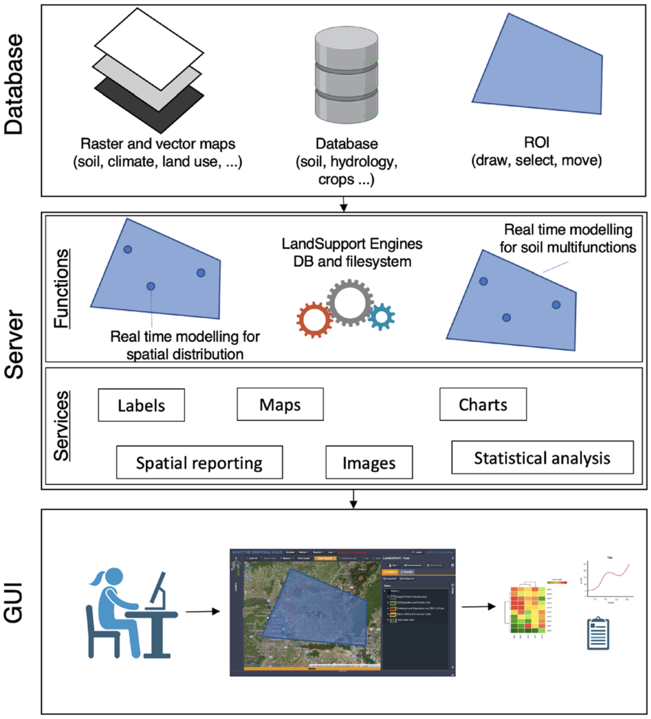


FIGURE 2 Workflow of the functions and technological components of the LandSupport GCI architecture. Figure adapted from Bancheri et al. (2022). [Colour figure can be viewed at wileyonlinelibrary.com]

3 | THE LANDSUPPORT PLATFORM AND THE *BEST PRACTICE TOOL* IMPLEMENTATION

Thanks to the geoSpatial DSS developed within the H2020 LandSupport project, interested users can interact, in real-time, with digital maps and geo-spatial data. The open-source web platform is customized for different types of end-users (from farmers and farmer associations, farmer's advisers, public authorities/policymakers to researchers) and deployed at different spatial scales (European, national, regional, and local).

The acquisition, storage, management, and visualization of both static and dynamical data, such as raster or point data, and the on-the-fly modelling applications are possible thanks to the Geospatial Cyber-Infrastructure (GCI) (Figure 2), which represents the core of the system. Through a Graphical User Interface (GUI), the end-users can access to more than 100 S-DSS tools, according to his/her specific scopes. On the server side, a management layer, called middleware, takes care of these end-user requests. It includes services, processes (e.g., data retrieval both from a database for vector and raster layers and tables), flows, and functionalities to ensure the overall execution of the system. Finally, when elaboration results are completed, the GUI receives a notification from the middleware, for their presentation as tables, graphs, maps, and pdf informative files.

A more comprehensive description of the functionalities and the methodological issues are reported in Terribile et al. (2015), Bancheri et al. (2022).

Through the web page of the project, the user can enter in the platform and, after having selected the desired regional scale, he/she can find the *best practice tool* under the *CAP, Agriculture and Forestry-Cross-compliance and conditionality* menu in the Toolbox panel, Figure 3.

The end-user can interact with the tool pop-up panel and, according to the following steps, can perform his/her real-time simulations:

1. choose a Region of Interest (ROI), a region where to perform simulations, or an Administrative Limit: the ROI could be pre-defined or appositely drawn, while the choice of an Administrative Limit can be done at NUTS level, till level 3;
2. select the crop on which to evaluate the best practices;
3. choose a climatic dataset between the current (2010–2020), near future (2030–2050) and far future (2070–2090), with two different RCP scenarios (4.5 and 8.5);
4. chooses the management practice/s to evaluate, between (i) considering an organic cropping system and/or (ii) inserting a cover crop and/or (iii) optimizing the fertilization and/or (iv) modifying the tillage and/or (v) retaining the crop residue.

Different combinations of the chosen management practices are simulated dynamically and on-the-fly for the selected ROI and crop. By clicking on the "evaluate" button, the GCI will perform the simulations and the end-user will get the results. For each of the soil polygon within the ROI and selected scenario, the tool returns: (i) the mean annual crop yield, (ii) the mean annual nitrate leaching, and (iii) the mean annual change of the soil organic carbon stock in the upper soil layer (0–30 cm). Moreover, a "best practices index" (I_{BP}) is provided, which is computed as:

$$I_{BP_i} = W_{N\_Leach} \times \frac{1}{\frac{N\_Leach_i}{N\_Leach_{min}}} + W_{Prod} \times \frac{Prod_i}{Prod_{max}} + W_{SOC\_Change} \times SOC\_Change_i^* \tag{1}$$

where:

$$SOC\_Change_i^* = \begin{cases} \dfrac{SOC\_Change_i}{SOC\_Change_{max}} & \text{if } SOC\_Change_{min} > 0 \\ \dfrac{SOC\_Change_i + |SOC\_Change_{min}|}{SOC\_Change_{max} + |SOC\_Change_{min}|} & \text{if } SOC\_Change_{min} < 0 \end{cases} \tag{2}$$

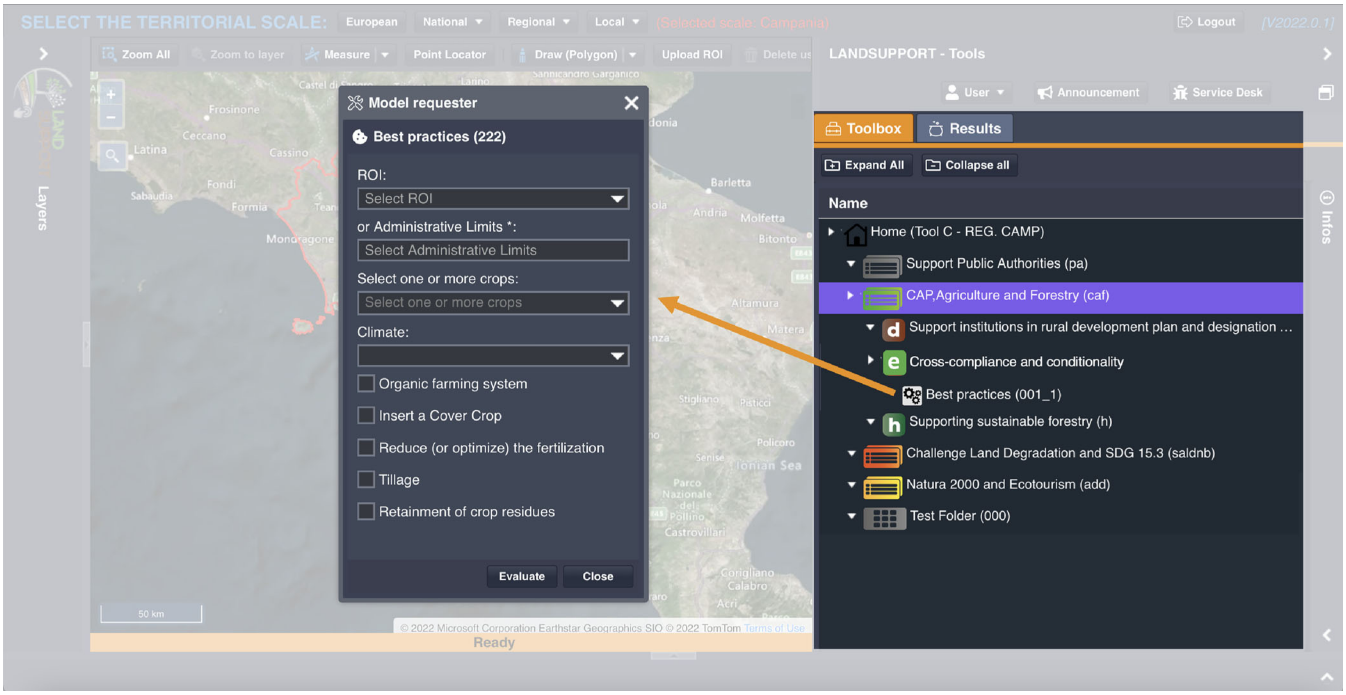


FIGURE 3 The *best practice tool* panel requests involve the choice of the ROI or the Administrative Limits, the crop, the climate, and five management options, on which the best practices are evaluated. [Colour figure can be viewed at wileyonlinelibrary.com]

N_Leach_i (kg NO_3-N $ha^{-1} year^{-1}$) is the leaching associated with the i_{th} combination, N_Leach_{min} (kg NO_3-N $ha^{-1} year^{-1}$) is the minimum leaching of all combinations simulated in the single run. Since the nitrate leaching negatively impacts the environment, the inverse of the ratio between N_Leach_i and N_Leach_{min} is considered in Equation 1, to properly decrease the I_{BP_i} when the leaching is bigger. $Prod_i$ (Mg ha^{-1}), $Prod_{max}$ (Mg ha^{-1}) are, respectively, the production associated with the i_{th} combination and the maximum of all combinations in the single run. Eventually, to account for the positive and negative values of the SOC_Change_i we propose the Equation (2): SOC_Change_i (Mg C $ha^{-1} year^{-1}$), SOC_Change_{min} (Mg C $ha^{-1} year^{-1}$) and SOC_Change_{max} (Mg C $ha^{-1} year^{-1}$) are, respectively, the SOC_Change associated to the i_{th} combination and the minimum and maximum of all combinations in the single run. The weights W_{N_Leach} [%], W_{Prod} [%] and W_{SOC_Change} [%] are real-time assigned by the user, according to the pursued scope. The sum of the three weights must be 100.

The user can then sort the I_{BP} values to identify the best combinations of practices, according to his/her specific goals (e.g., increase in soil organic carbon). Eventually, the value of I_{BP} is plotted in bar plots for each of the evaluated practices.

It is clear that by combining all the available crops and management practices, together with the spatial variability of the soils and the dynamic possibility to change the weights of the output variables, the GCI should take care of an important number of model runs. Considering only one soil type and one crop, all the possible combinations of management are 72 (2 for the organic cropping choice, 2 for the cover crop insertion, 3 for the reduction of fertilization, 3 for the tillage changes, and 2 for retaining crop residue). It is easy to understand how the number of runs explodes considering multiple soils within the ROI. Therefore, the *best practice tool* leverages the COMPSs runtime system (Ramon-Cortes et al., 2018) for parallel execution of applications in a set of distributed resources. As shown in Figure 4, the middleware is in charge of the retrieval of the model input data both from Rasdaman (climate data) and from the PostgreSQL/PostGIS database, for vector layers, and tables (soil units, soil properties, model parameters and more).

Once data are collected from the data sources, COMPSs is responsible for the parallel model runs for all the simulation points. The implementation includes a COMPSs task that simulates with the proper input parameters, loading the soil profiles from the PostGIS database; a *runSimulation* task is executed for each configuration and each soil profile. The result of the computation is a pair of tables with the values of crops and indicators. Figure 5 shows an example of the execution graph of the model runs managed by the COMPSs runtime: each of the 10 blue circles, which represent the simulation runs, coming from the *main* process (e.g., a single model run over 10 soil profiles) are executed in parallel to speed up the computation time. Eventually, as soon as a single simulation run ends, it will notify the *Barrier* of the end of execution and its results.

It is worth further highlighting that the parallel based tool implementation within the LS GCI makes it possible to apply the ARMOSA model in a geospatial domain, at different spatial scales (from the farm to the regional scale), for one or several years and multiple combinations of inputs, obtaining results, represented in different ways, in few minutes, after the end-user real-time request.

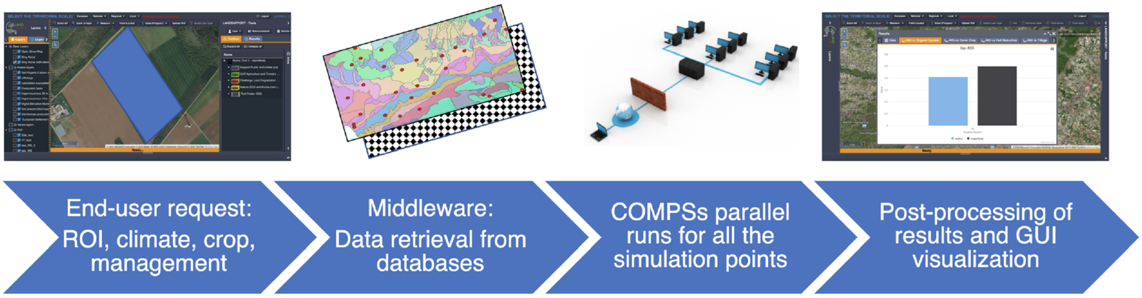


FIGURE 4 Implementation of the *best practice tool* within the LandSupport GCI. Figure adapted from Bancheri et al. (2022). [Colour figure can be viewed at wileyonlinelibrary.com]

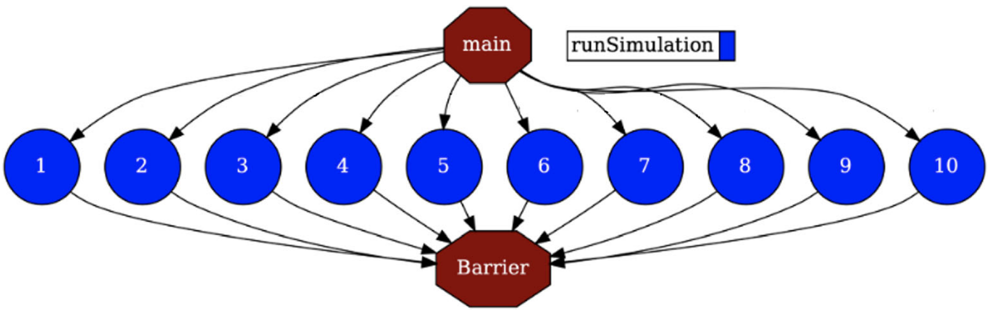


FIGURE 5 Execution graph of the model application using COMPSs: the *main* represents the starting point of a computation task, and each of the 10 blue circles represents the simulation runs, executed in parallel. The *Barrier* receives all the results. [Colour figure can be viewed at wileyonlinelibrary.com]

4 | *BEST PRACTICE TOOL* IN ACTION: EXAMPLES OF ITS APPLICATIONS

Three applications, among the many possible examples, are reported in this section, showing how to run the tool to (i) maximize the crop production, under different pedoclimatic conditions; (ii) evaluate, for planning purposes, the use of different crops and related practices; (iii) evaluate the best practices in the nitrate vulnerable zones. These examples are presented in the light of how to practically address the impact of the management practices on both the productivity and the land degradation sides, to combat the decline in the primary productivity of the land as well as a loss in soil organic carbon stock and water pollution.

It is worth mentioning that multiple interactions, which lasted many months, took place between developers, partners involved in the project (Italian, Austrian, and Hungarian), and local end-users/stakeholders, to finalize the current version of the tool. These interactions mainly concerned the definition of the model inputs for all the involved areas (common crops and managements, seeding and harvesting dates, type, and dose of fertilizers, irrigation amount and type, and more), to obtain a feasible combination of good management practices, locally defined with the possible end-users of the tool. Moreover, the stakeholders were involved in the testing phase, to improve the tool results, introducing the I_{BP} for easy and immediate comparisons of the numerous model runs.

4.1 | Maximization of crop production

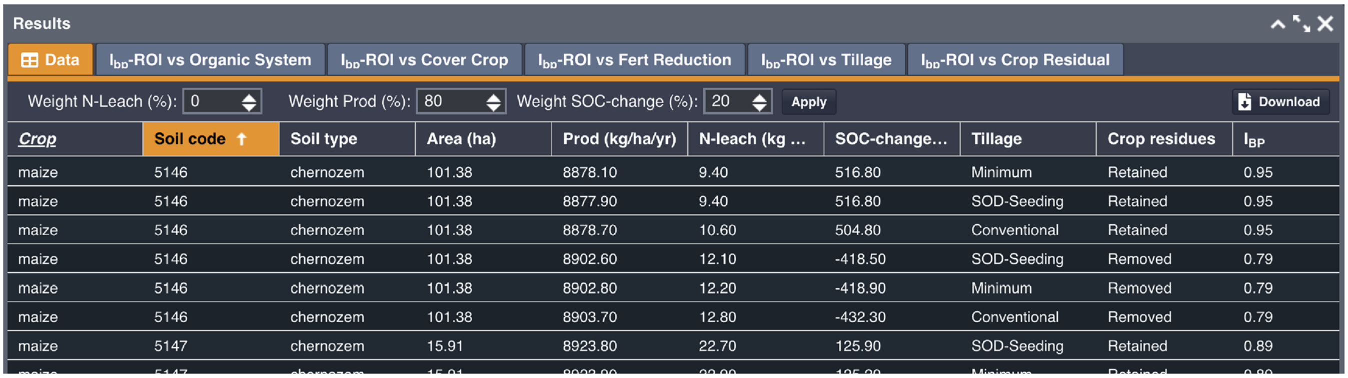
In this application, we used the *best practice tool* for the comparison of different practices within a ROI drawn in the Marchfeld Region. This application could be particularly useful for a farmer, who is interested in maximizing the production of the cultivated crop, by evaluating how different management practices impact his/her income.

In particular, we simulated:

1. a ROI of 166 hectares, with seven soil polygons;
2. the maize, one of the most commonly cultivated crops in the Marchfeld Region;
3. the "Current" climatic dataset (2010–2018);
4. 3 tillage options: conventional, minimum, sod seeding;
5. 2 crop residue management: yes/no.

The combination of all the above cropping system options, led to 42 good management practices (7 different soil units × 6 management combinations) that, thanks to the platform, could be easily ordered by descending I_{BP} to get the best local combination according to the user goal. For this case study, due to the climate homogeneity of the Marchfeld Region, all the polygons were simulated with the same climate data set.

Figure 6 shows an extract of the Results table that could be explored from the GUI. The tab labelled "Data" (in orange) reports information about:



Results

Data | I_{bp}-ROI vs Organic System | I_{bp}-ROI vs Cover Crop | I_{bp}-ROI vs Fert Reduction | I_{bp}-ROI vs Tillage | I_{bp}-ROI vs Crop Residual

Weight N-Leach (%): 0 Weight Prod (%): 80 Weight SOC-change (%): 20 Apply Download

Crop	Soil code	Soil type	Area (ha)	Prod (kg/ha/yr)	N-leach (kg ...	SOC-change...	Tillage	Crop residues	I_{BP}
maize	5146	chernozem	101.38	8878.10	9.40	516.80	Minimum	Retained	0.95
maize	5146	chernozem	101.38	8877.90	9.40	516.80	SOD-Seeding	Retained	0.95
maize	5146	chernozem	101.38	8878.70	10.60	504.80	Conventional	Retained	0.95
maize	5146	chernozem	101.38	8902.60	12.10	-418.50	SOD-Seeding	Removed	0.79
maize	5146	chernozem	101.38	8902.80	12.20	-418.90	Minimum	Removed	0.79
maize	5146	chernozem	101.38	8903.70	12.80	-432.30	Conventional	Removed	0.79
maize	5147	chernozem	15.91	8923.80	22.70	125.90	SOD-Seeding	Retained	0.89

FIGURE 6 Extract of the results table from the LandSupport GUI: each row is related to a different combination of practices. [Colour figure can be viewed at wileyonlinelibrary.com]

1. the chosen crop;
2. the soil code, which is the identifier of the soil polygon in the soil database;
3. the soil type;
4. the area (ha) of each soil polygon within the ROI;
5. the outputs: crop yield, nitrate leaching, SOC_change;
6. a column for each selected practice;
7. the best practice index.

Each column of the table can be sorted and filtered, according to the end-user's needs. Each row is related to a specific simulated combination.

Besides, the end-users can insert the desired weights and, by clicking the "Apply" button, obtain the related best practice index. The other available tab reports the bar plots of the best practice index evaluated for the five possible choices of the management practices of the tool (Organic System, Cover crop insertion, Fertilization reductions, Tillage, and Crop residual) and weighted for the entire ROI.

All the results can be downloaded in .xlsx format by the interested user, by clicking the "Download" button on the top right of the table.

In the case shown in Figure 6, we sorted the results by descending best practice index, filtered by soil type chernozem, which is the dominant soil within the Marchfeld Region. The chernozem is characterized by an A horizon, rich in organic carbon and with high percentages of phosphoric acids, phosphorus, and ammonia. The simulated maize production is around 8900 kg ha^{-1} year^{-1}, the nitrate leaching at the bottom of the soil varies between 9 and 13 kg NO_3-N ha^{-1} year^{-1}, while the SOC_change in the first 30 cm of soil varies between −432 and 517 kg C ha^{-1} year^{-1}. The latter mainly depends on the considered management practice: negative values, which indicate a loss of SOC, are obtained when the crop residue is removed, while positive values, which indicate an increase of SOC, are obtained when the residue is retained. The results obtained are in line with other studies for the same region, for the production (Chen et al., 2018; Novelli et al., 2019), nitrate leaching (Klammler & Fank, 2014) and SOC change (Tiefenbacher et al., 2021).

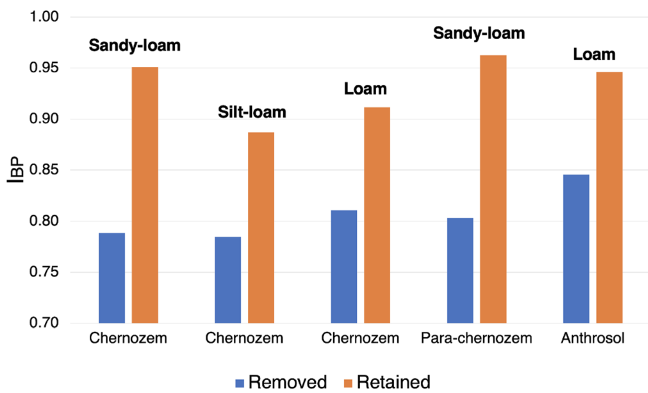


FIGURE 7 Comparison of the best practice index evaluated for three different practices and five soil types within the selected ROI. Each bar is representative of the best practice index value, computed only considering the specific practice, that is, residue removed (blue), residue retained (orange). [Colour figure can be viewed at wileyonlinelibrary.com]

Considering the assigned weights (80% production and 20% SOC change), the highest value of the best practice index (0.96) is obtained for the combination of minimum tillage or sod seeding and residue retained. Among the management practices, it is clear that an important difference is made by the crop residue, which, if are retained in the field, have a great impact of the SOC change. The latter achievement stresses the importance of such management practice to be applied in contrast to the organic carbon decline that is estimated to impact around 45% of in the EU soils Montanarella et al. (2015).

For the same simulation, it is also interesting comparing the results, in terms of I_{BP}, for the five most dominant soils within our ROI considering the impact of the residue management. The latter practices help to reduce erosion, increasing SOC and recycling of nutrients, thus preventing from soil degradation (Villalba-Martínez et al., 2022). A possible improvement of the ARMOSA model and the tool should include the simulation of the negative effect of reduced tillage on weed pressure, which can lead to lower I_{BP} scores. However, in the present study, it is shown that the best scores associated with reduced tillage are obtained when it is in combination with residue retention, which is regarded as a practice that limits weeds growth in conservation agriculture (Nichols et al., 2015).

The bar chart, in Figure 7, clearly shows that there is an important difference between the soils. Even though 3 out of 5 are classified as chernozem, the different soil characteristics, such as the hydraulic properties, horizon depths and OC content play a crucial role in the crop production, nitrate leaching and SOC change. One of the main key features of the LS S-DSS lies in the possibility to fully explore and consider the local pedoclimatic conditions, as requested by CAP and other regulations. Only considering the general soil classification, few considerations and scenario analysis could be carried out Terribile et al. (2011). Exploring the soil dataset (available at this link https://doi.org/10.5281/zenodo.10409816), differences in the textures of the five soils are detected, since they are classified as sandy loam, silt loam, loam, sandy loam and loam. The different soil characteristics determine that the same practice does not have the same benefit, in terms of production and SOC change, for all the types of soil. For example, the silt loam chernozem shows a mean I_{BP} of 0.89, which is the lowest within the investigated ROI, while the sandy loam para-chernozem shows a mean I_{BP} of 0.96, which is the highest within the investigated ROI. This is mainly due to the differences in the SOC change, 125 and 590 kg C ha^{-1} $year^{-1}$, and in the nitrate leaching, 25 and 5 kg NO_3-N ha^{-1} $year^{-1}$, between the silt loam chernozem and the sandy loam para-chernozem, respectively, due to the different initial organic carbon content.

Besides, the soils do not benefit from all practices in the same way: for some cases, such as for the sandy-loam Para-chernozem there is a bigger increase of the I_{BP}, which passed from 0.80 to 0.96, since the big variation in the SOC change due to higher organic matter input from crop residue retention and cover crop cultivation. In a meta-analysis of soil carbon changes due to cover cropping, coarse soils were found with the highest rates of SOC increase after cover cropping (Jian et al., 2020). As a further beneficial effect, in sandy soils organic inputs increase soil organic matter content, which can lead to increasing attainable yields, as shown in a meta-analysis about the additional yield effects of organic inputs matter for arable crops in Europe (Hijbeek et al., 2017).

This example is particularly interesting since it shows how the farmer can maximize crop production, considering the local soil and climatic characteristics, within the investigated field.

4.2 | Reducing the environmental impact using organic farming and cover crops

This application shows the usage of the tool for the assessment of the impact of the adoption of well-recognized management practices by considering different crops. In this case, the end-user could be a farmer or a policy maker, interested in evaluating how the insertion of a cover crop or the usage of an organic system could overall impact, both from the production and the environmental point of view, on a farm, in a what-if scenario analysis, made for planning purposes.

Figure 8 shows the results of the simulation made in Zala County, considering:

1. a ROI of 234 hectares with 1 soil polygon, classified as a silt loam;
2. three crops; maize, sunflower and wheat;
3. the "Current" climatic dataset;
4. two different practices, cover crop -yes/no- and organic system -yes/no-.

For this case, equal weights ($W_{N\_Leach} = 33\%$, $W_{Prod} = 33\%$ and $W_{SOC\_Change} = 34\%$) were assigned to the three model outputs. The bar plots clearly show the variation of the I_{BP} between the 12 cases, leading to the following considerations:

1. the maize benefits from the insertion of the cover crop, increasing the I_{BP} from 0.66 to 0.77, and even more benefits from the organic system, increasing the I_{BP} from 0.66 to 0.87;
2. the sunflower doesn't show benefits from the insertion of the cover crop, I_{BP} remains 0.81 for both alternatives, but benefits from the organic system, increasing the I_{BP} from 0.81 to 0.87;
3. the wheat benefits from the insertion of the cover crop, increasing the I_{BP} from 0.66 to 0.78, and even more benefits of the organic system, increasing I_{BP} from 0.66 to 0.77.

The above results are mainly due to the variation of the nitrate leaching and the SOC change for the cover crop insertion and the use of organic fertilization. For example, in the case of maize, the introduction of the cover crops determines a decrease of the nitrate leaching from 35 kg NO_3-N ha^{-1} $year^{-1}$ to 3 kg NO_3-N ha^{-1} $year^{-1}$, since the winter cover crop acts as a catch crop reducing N losses in autumn and winter (Tadiello et al., 2022). The organic system determines an increase of the SOC change from 278 to 560 kg C ha^{-1} $year^{-1}$ since the use of organic fertilizer such as manure determines the increase of the organic carbon input, especially in combination with crop residue retention, which are the most effective practices increasing the SOC stock (Minasny et al., 2017).

This comparison is particularly useful for the end-user to understand which crop and which practice are the most effective to pursue the specific environmental goals of decreasing nitrate leaching and increasing the SOC while maintaining a good production, in order, for example, to get or set the related incentives.

4.3 | Reducing the nitrate leaching in nitrate vulnerable zone

One of the main objectives of the European Nitrates Directive (ND; Directive 91/676/EEC) is the reduction of nitrate leaching from agricultural sources, by limiting the inorganic and organic fertilizer to crop requirement and the identification of areas, the Nitrate Vulnerable Zones (NVZs), where the concentrations of nitrate in water exceed, or are likely to exceed, the levels set in the Directive. In support of the contrast of water resource degradation, this application shows

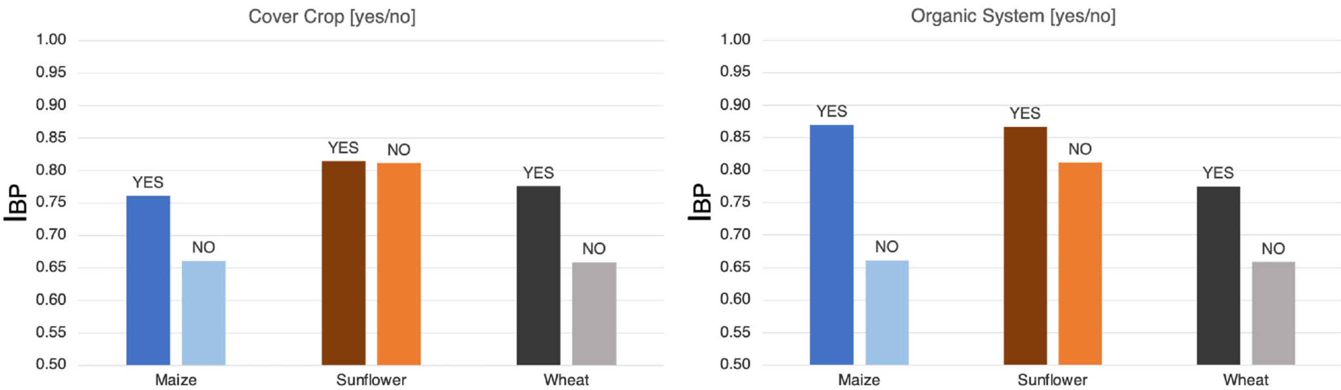


FIGURE 8 The bar plots show the best practice indices computed considering (i) the cover crop [yes/no] and (ii) organic system [yes/no], for three commonly cultivated crops, that is, maize, sunflower, and wheat. [Colour figure can be viewed at wileyonlinelibrary.com]

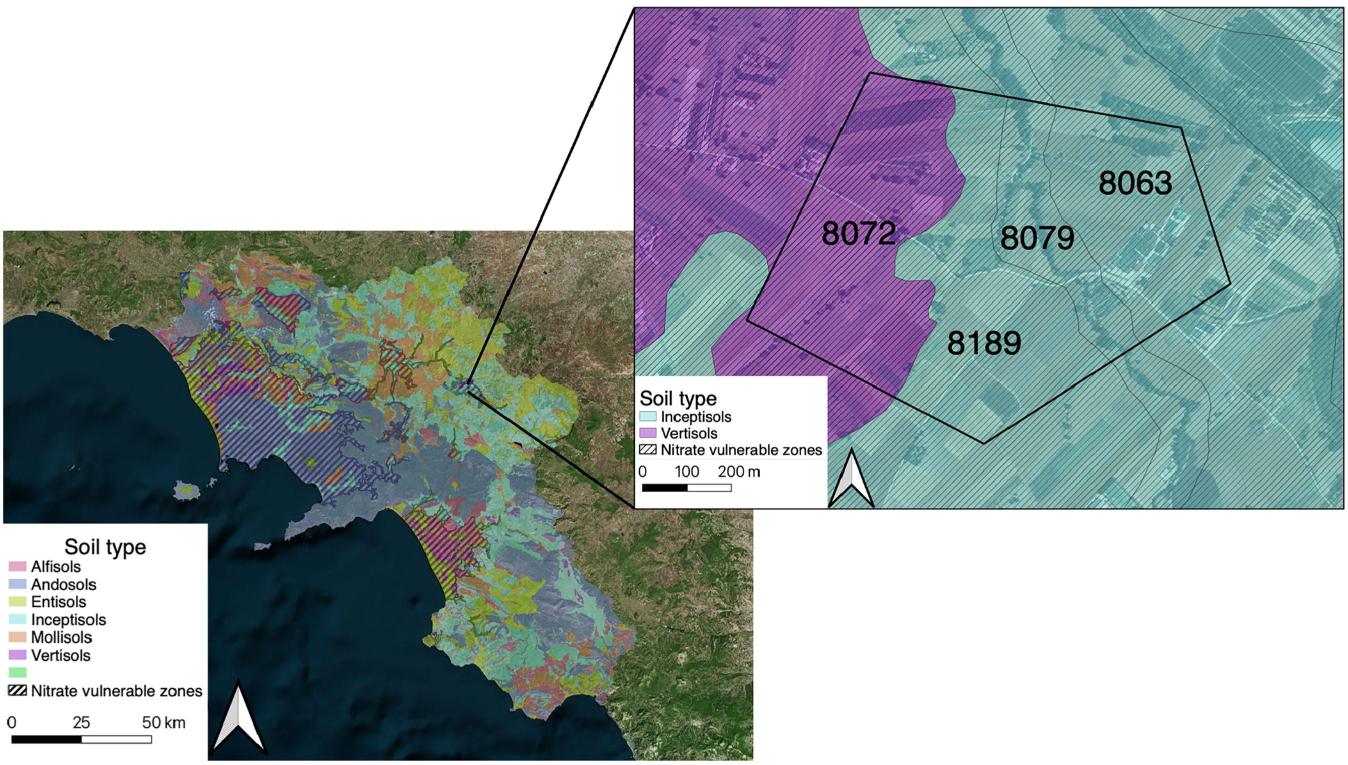


FIGURE 9 Location of the ROI, in the province of Benevento, overlapped to the soil maps and on nitrate vulnerable zone. [Colour figure can be viewed at wileyonlinelibrary.com]

the usage of the tool for the comparison between different practices, in terms of leaching, within the NVZs.

The selected ROI was drawn in an area in the Campania region, in the province of Benevento, classified as a nitrate vulnerable zone by the General Direction of Agricultural policies, Figure 9. Therefore, the public authorities could use the tool to evaluate, for planning purposes, the impact of different practices on a selected crop, for example, the durum wheat, a crop largely cultivated in the Apennines of south Italy.

In particular, we simulated:

1. a ROI of 58 hectares with 4 soil polygons;
2. durum wheat, one of the most commonly cultivated crops in the area;
3. "Current" climatic dataset (2010–2018);
4. organic cropping system;
5. cover crop: yes/no;
6. 3 fertilizer reductions: 0%, 15%, 30%;
7. 3 tillage options: conventional, minimum, sod seeding;
8. 2 crop residue management: yes/no;
9. $W_{N\_Leach} = 50\%$, $W_{Prod} = 50\%$ and $W_{SOC\_Change} = 0\%$.

TABLE 2 Values of the crop production, nitrate leaching and SOC change considering the BaU and the BP combinations for the Campania Region case study.

Combination [–]	Soil type [–]	Production [kg ha^{-1} year^{-1}]	Nitrate leaching [kg NO_3-N ha^{-1} year^{-1}]	SOC change [kg C ha^{-1} year^{-1}]
BaU	Sandy-loam	1590.9	12.5	−1.6
BP	Sandy-loam	1071.2	1.4	86
BaU	Silt-loam	1980.6	22.6	−110.5
BP	Silt-loam	1420.4	2.7	4.4
BaU	Clay-loam	1946.6	26.7	−283.1
BP	Clay-loam	1477.6	3.0	−155.8

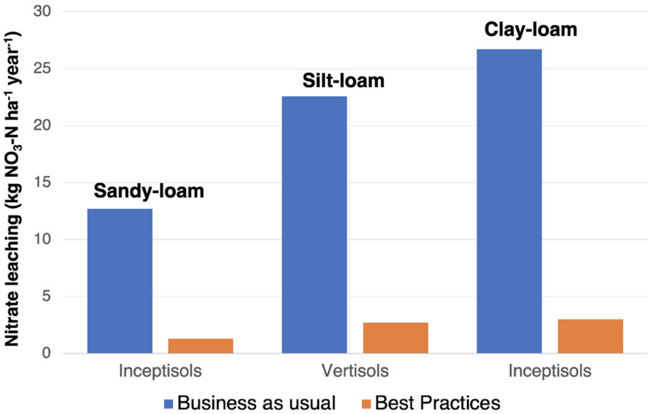


FIGURE 10 Values of the nitrate leaching due to the business as usual combination (blue bars) and the best practice combinations orange bars, obtained for three soils and the wheat, in the ROI, in the province of Benevento, in the Campania Region. [Colour figure can be viewed at wileyonlinelibrary.com]

The Business as Usual (BaU) was considered the combination of inorganic fertilization, no cover crop insertion, no fertilizer reduction, conventional tillage, and no crop residue retained, as reported in detail in (Puig-Sirera et al., 2022) and at http://www.agricoltura.regione.campania.it/disciplinari/2022/frumento.pdf. It is worth mentioning that, according to the I_{BP}, the BaU is not the worst combination of management practices, which is actually when are considered an organic system, no cover crop, a reduction of fertilization of 30%, the sod seeding and no crop residue. As regards the best practices, obtained sorting all the combinations by the I_{BP}, for the silt-loam and clay-loam soils are represented by the combination of organic system, cover crop insertion, 30% of fertilizer reduction, sod seeding and residue removed. For the sandy-loam soil, the BP is represented by the combination of organic system, cover crop insertion, 15% of fertilizer reduction, conventional tillage and residue removed.

Table 2 reports the values of the crop production, nitrate leaching and SOC change considering the BaU and the BP combinations. All soils show an important % of nitrate N leaching reduction of around the 90% passing from BaU to the BPs.

Figure 10 shows the variation of nitrate leaching for the three dominant soils in the ROI, classified as Vertisols and Inceptisols. The blue bars represent the starting value of the nitrate leaching obtained for the BaU combination, while the orange bars represent the value of the nitrate leaching obtained for the Best Practices (BPs) combination.

As in the previous case, the generic classification of the soil, retrieved from the soil maps, is not fully informative, concerning the effective soil response in terms of nitrate leaching, further underling the importance and power of the *best practice* tool. Exploring the soil dataset (available at this link https://doi.org/10.5281/zenodo.10409816), differences in the textures of the soils are detected, since they are classified as sandy loam, silt loam and clay loam. For all soils the nitrate leaching is very low [the maximum simulated value is 14 mg l^{-1}, simulating the BaU combination with the *Nitrate fate tool* presented in Bancheri et al. (2023)], and it further improved after the consideration for the best practice option. More specifically, it is interesting to see the high leaching potential of the sandy loam is dumped by its low organic carbon content, which further benefit by the adoption of an organic system, a cover crop insertion, the 15% of fertilizer reduction, a conventional tillage and the residue removed.

An analogous application of the tool, considering the wheat and climate change scenarios, was presented in Puig-Sirera et al. (2022) for a local scale application in the same area, considering the different tillage and residue management. The interested reader could refer to that work for further details.

Eventually, the end-user can explore several intermediate combinations (e.g., by not considering the cover crop insertion for local customs or economic reasons) or changing the weights assigned to the three outputs of the ARMOSA model, fully exploiting the potentiality of the tool.

5 | DISCUSSIONS AND CONCLUSIONS

Urgent research and policy attention are required to combat and reverse the land degradation and deterioration of soils and natural resources, due to farmers' agricultural practices, upon which future productivity depends (Hossain et al., 2020).

Currently—at least for the European member states—it is imperative to fulfil the high requirements and expectations of the new CAP, synthesized by the clause of “No back-sliding”: Member States will be required to “aim higher” concerning the environment and climate, on the way they use CAP funds, respect to the previous (current) policy periods.

TABLE 3 Example of alternative DSS tools for the optimization of the local crop management practices.

Name	Case studies	Type	Applied methods	Availability
LS—*best practice tool*	Campania (IT), marchfeld (AT) and zala (HU)	Dynamical, real-time	Crop-growth, water transport and nitrogen balance	Web-based, free and open-source
OCCASION	Southern France	Static scenarios	Weather generator + tailor-made evolutionary optimization algorithm for optimal irrigation + crop-growth and water transport	-
LandCaRe—MONICA	Uckermark district, North-East Germany and west of Dresden, South-East Germany	Dynamical, real-time	Crop-growth, water transport and nitrogen balance	Web-based
GIS-based DSS	Andhra Pradesh in India	Static scenarios	Crop-growth, water transport and nitrogen balance	Web-based

This work aimed to present the *best practice tool*, as a very flexible operative instrument to be used for the evaluation of best agronomic solutions for enhancing crop production by taking into account the imperative goal of reducing the nitrate leaching and improving the soil carbon stock, and hence the soil fertility.

The *best practice tool*—potentially—can contribute to the several CAP requirements such as the *Conditionality Obligations* (Art. 12), where Member States shall define "minimum standards and good practices taking into account the specific characteristics of the investigated areas, including soil and climatic conditions, existing farming system, land use, crop rotation, farming practices and farm structures"; *Farm Advisory Services* (Art. 13) for advising farmers and other beneficiaries of CAP support; *Schemes for the Climate and the Environment* (Art.28) where Member States shall "provide support for voluntary schemes for the climate and the environment (ECO-SCHEMES) and establish the list of agricultural practices beneficial for the climate and the environment"; and finally, the *Environmental, Climate and other Management Commitments* (Art. 65).

Among the many decision-support tools for agriculture that are potentially available to different users, the majority are not used, making their impact almost nil.

Other examples of similar decision-support tools are reported in Table 3: OCCASION (Schütze & Schmitz, 2010), which aims at quantifying the impacts of climate change on irrigation activities and couples the LARS-WG stochastic weather generators and the SVAT model (Mo et al., 2005) to simulate crop productions, crop yields, water and nitrogen conditions; LandCaRe DSS, an interactive decision support system (Wenkel et al., 2013), where the dynamical process model MONICA can be used to simulate the interconnections between site characteristics, specific weather conditions, crop rotation, water, nitrogen and carbon dynamics in soil and plant, the plant development, biomass growth and yield formation in a daily time step; a GIS-based DSS (Kadiyala et al., 2015) integrating a Decision Support System for Agrotechnology Transfer (DSSAT) crop simulation model and a Geographical Information System (GIS) component. The novelties of the *best practice tool* are given by its dynamical and real-time features, its process-based modelling approach, its web-based and free availability. The *best practice tool* overcomes the major limitations of OCCASION DSS, which is based on pre-loaded scenarios, of LandCaRe DSS and of GIS-based DSS, since the *best practice tool* it gives immediate support to the interested end-user through a dynamical, specific user-defined index, who can change the weights according to his (her specific objectives, for the identification of the best local practices options, among many different good practices.

Although there is no guarantee of its success and widespread use, there are two important distinctive points of the *best practice tool* that make it unique in the panorama: (i) the combination of runs, on-the-fly, of the cropping system model and (ii) the what-if analysis procedure. No scenario analyses are already pre-loaded on the LandSupport platform. Each user, through several alternative features, can build his/her scenario analysis varying—for a specific soil and climate—five management alternatives and three weighted outputs.

Given the robustness of the ARMOSA model, some limitations of the presented tool may come from the input dataset. For example, the soils' properties are obtained from the soil map for each of the regions (or subregions) and the model's results depend on their spatial resolution and the quality of pedological and hydraulic parameters. Moreover, different climatic datasets can be used, with a finer spatial resolution to obtain more detailed results at small-size farm levels. Eventually, the crop database only considers the arable crops, and not, for example, olive and grapevine, which are very diffuse in the Campania Region.

However, future integration of new datasets and further implementations for new regions and applications will be possible whenever they are available, leveraging the great flexibility of the LS-GCI. In addition, the process based modeling approach make it suitable—in the early future—to run the model on soil and climate data inserted by the farmer, thus evaluating very site specific condition/s. Upon request, other possible alternatives can be added by the developers to the system, which remains up-to-date. Furthermore, it will be possible to interact, in the back-end, with the *best Practice tool* through the services made available by the LandSupport web-API, which allows the end-users to use the tool as a standalone, disconnecting the LandSupport toolbox from the current GUI platform.

AUTHOR CONTRIBUTIONS

Marialaura Bancheri: Conceptualization, methodology, writing—original draft, writing—review & editing. **Angelo Basile:** Conceptualization, methodology, writing—review & editing, visualization, funding acquisition. **Fabio Terribile:** Conceptualization, methodology, writing—review & editing, supervision. **Giuliano Langella:** Software, data curation. **Marco Botta:** Software, data curation. **Daniele Lezzi:** Software. **Federica Cavaliere:** Software, data curation. **Marco Colandrea:** Software. **Luigi Marotta:** Software. **Roberto De Mascellis:** Data curation. **Piero Manna:** Data curation. **Antonietta Agrillo:** Data curation. **Florindo Antonio Mileti:** Data curation. **Marco Acutis:** Conceptualization, software, writing—review & editing. **Alessia Perego:** Conceptualization, methodology, software, writing—original draft, writing—review & editing.

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CONFLICT OF INTEREST STATEMENT

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

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are openly available in Zenodo at https://doi.org/10.5281/zenodo.10409816.

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