



# Combining participatory and modeling approaches to investigate factors and drivers of soil erosion risk in mixed crop-livestock farms

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## Abstract

Soil erosion threatens mixed farms in marginal areas, endangering their cultural and economic role in territories where pastoralist systems are already under pressure for climatic, socioeconomic, and generational factors. The rise in extreme rainfall events worsens soil loss on farmland, underscoring the need to co-develop practices that boost climate resilience in agriculture. This study helps fill the gap in understanding how the integration of farmers' perceptions with spatial modeling can inform land management strategies. We combined farmers' perceptions, model predictions, and farm management to provide an integrated assessment of the soil erosion. We represented the geographical distribution of soil erosion risk through geographical information systems-based RUSLE modeling. Farmers' perceptions on soil erosion were assessed through surveys and fuzzy cognitive mapping conducted across 25 sheep farms. Our model shows that 37% of cropland is at risk, mainly due to land topography and soil cover. Fuzzy cognitive maps reveal that farmers are aware of the main environmental and human-linked soil erosion drivers. Farmers recognize cropping system design, especially using perennial forage instead of annual crops, as key to reducing soil erosion, and also see temporary ditches, reduced tillage, and agroforestry as effective measures. Utilizing a multivariate ordinal logistic regression, we showed that sheep farmers with a higher education level tend to perceive higher soil erosion risk. The number of conservation measures adopted increases when farmers are more aware of soil erosion issues, when they identify a higher number of fuzzy cognitive map connections, and when the predicted soil erosion risk is higher. Farmers' perceptions of erosion risks and soil conservation measures aligned with model predictions on soil erosion, highlighting the importance of systematically involving farmers in research and policy design. Their detailed mental models enhance environmental models and should be considered in the European Common Agricultural Policy for sustainable rural development.

**Keywords** Participatory research · RUSLE · Fuzzy cognitive mapping · Soil management · Ecosystem services

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## 1 Introduction

Soil has a paramount importance in the delivering of agro-ecosystem services in Europe. However, despite its key role in the sustainability of ecosystems and human well-being, effective policies focused on soil conservation are scarce. There is therefore an urgent need to formulate novel and localized strategies for farmers, especially when operating in marginalized agricultural regions (Borrelli et al. 2016). The development of tailored strategies is key for the preservation of rural landscapes as integral components of cultural heritage and economic activities. At both local and landscape levels, farm management is the main driver of land cover change influencing ecosystem functions, processes, and traits (Guerra and Pinto-Correia 2016). This is even more true in case of livestock farming systems, which have been recognized as one of the main causes of land degradation in Mediterranean areas (Panagos et al. 2020). Diversified systems such as mixed farming and agroforestry are emerging as potential solutions for increasing the environmental and economic sustainability of the livestock sector. These systems are renowned for their ability to mitigate soil erosion, enhance carbon sequestration, and promote biodiversity (Palma et al. 2007; Paris et al. 2019). Yet, the transition to diversified systems is complex and requires the active engagement of farmers and their knowledge in the design and implementation of sustainable and locally adapted practices.

Farmers' perceptions, challenges, and preferences play a pivotal role in enabling the transition towards diversified systems and mitigating the use of management practices which favor soil erosion. Previous works document the role of farmers' perceptions on soil erosion control (Bolaños-Valencia et al. 2019), on ecosystem services and their management (Teixeira et al. 2018), and on the risk of biodiversity loss (Velasco et al. 2018). Nonetheless, there is limited knowledge on farmers' perceptions of soil erosion in livestock farming systems, their susceptibility to household characteristics and external factors, and the potential desirability of soil conservation measures. In this study, we integrated farmers' perceptions on soil erosion and modeling approaches to inform the transition to more sustainable livestock systems that value local knowledge and are capable to provide multiple ecosystem services. The study was conducted in southern Tuscany and focuses on the Pecorino Toscano DOP value chain. The region is a relevant study area because livestock systems are predominant in the landscape, providing key cultural, provisioning and regulating ecosystem services. Besides, the region contains a diversity of farming systems and dairy sheep farmers are threatened by a range of social, economic, and environmental challenges, including fluctuating production costs and milk prices, intense price competition, strong competition from cheaper products in international markets, soil erosion, and land degradation (Figure 1). Collectively, these issues have rendered the sheep sector less attractive to younger generations (ISMEA 2022).

**Figure 1** Photos illustrating the key aspects of the case study, including soil tillage and erosion, and sheep farming for the production of Pecorino Toscano PDO (Protected Designation of Origin) cheese (Photocredit: Alberto Mantino and Consorzio Pecorino Toscano PDO).



Focusing on issues of land degradation, between 2010 and 2016, the estimated average rate of soil erosion risk for arable lands in Mediterranean nations shows a noticeable increase: 2.8% in Italy, 1.7% in Spain, and 4.8% in Greece (Panagos et al. 2020). In Italy alone, more than 30% of arable land, primarily concentrated in the Apennines and the adjacent hilly regions, has been affected by severe erosion, with erosion rates exceeding  $33 \text{ Mg ha}^{-1} \text{ year}^{-1}$ , according to the findings of Panagos et al. (2020). These unsustainable rates of soil loss can be attributed to the insufficient adoption of soil conservation measures and alterations in land cover, which stand as contributing factors to the abandonment of land (Panagos et al. 2020).

In this study, we used the Revised Universal Soil Loss Equation (RUSLE) (Renard et al. 1997) to predict soil erosion risk caused by water in the inland hilly areas of southern Tuscany. Vallebona et al. (2016) shows that in 2015, a significant portion of arable land, amounting to 59% in the Province of Grosseto, suffered from severe erosion, characterized by erosion rates  $> 11 \text{ Mg ha}^{-1} \text{ year}^{-1}$ , with some 35% of this area showing rates  $> 33 \text{ Mg ha}^{-1} \text{ year}^{-1}$ . In these areas, the pedo-climatic conditions result in a higher intrinsic vulnerability to water erosion, and the current cropping system is insufficient to preserve soil fertility in terms of preventing erosion (Vallebona et al. 2016). Soil erosion risk refers to the likelihood or potential for soil loss due to various natural or human-induced factors. Concurrently, we employed quantitative surveys and fuzzy cognitive maps (FCM) (Kosko 1986) to comprehensively assess farmers' perceptions of soil erosion with the aim of capturing their awareness of the drivers of soil erosion on their own farm. FCM represents a semi-quantitative research tool designed to address socio-ecological phenomena and capture the knowledge of individuals with a deep understanding of ecosystems or specific environmental issues, such as soil erosion (Özesmi and Özesmi 2004). FCM facilitates the explicit representation of intricate mental frameworks and elucidates causal relationships among concepts (Jetter and Kok 2014). The RUSLE model primarily uses physical data (i.e., rainfall patterns, soil types, topography, and land cover) to estimate erosion risk. Farmers' perceptions, on the other hand, might include social, economic, and personal experiences with land management practices. This comparison can highlight non-physical drivers of erosion risk usually not captured by the model, such as crop rotation practices or labor constraints, and can highlight tailored erosion solutions.

By combining cognitive and quantitative methods, we aimed to explore soil erosion and land degradation processes in a novel manner, capturing the complexity of the phenomenon from a systemic perspective. Specifically, this study seeks to (i) define how farmers perceive the risk of soil erosion and map the primary drivers and consequences of the perceived phenomenon through FCM; (ii) examine

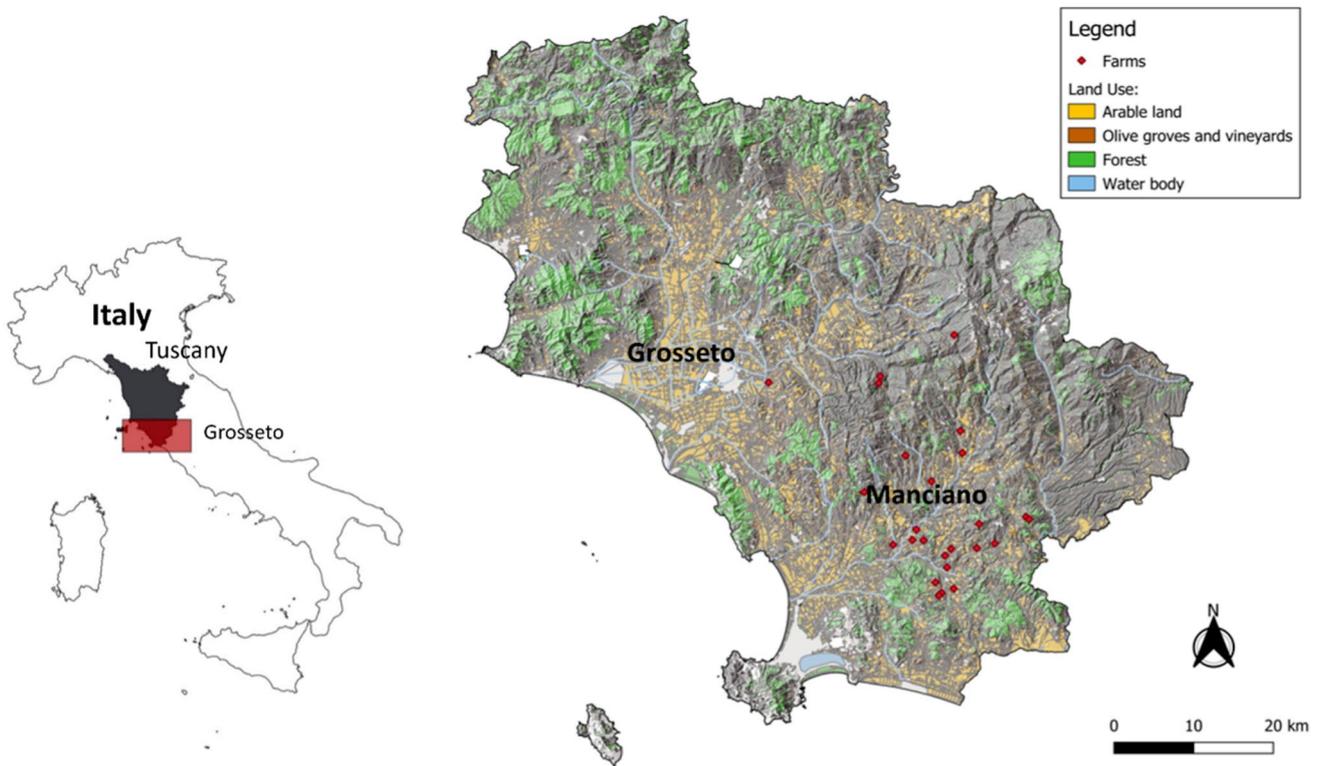
the extent to which farmers' perceptions of soil erosion risk align with predictions from the RUSLE model and factors; and (iii) assess how the variability of farmers' perceptions is explained by farmer characteristics, farming management practices, and modeled soil erosion risks.

## 2 Materials and methods

### 2.1 Site description and research activities

In Italy, the annual economic value attributed to sheep milk production stands at 460 million EUR nationally, while at the regional level (Tuscany), it amounts to 164 million EUR. These figures constitute approximately 1.2% of the total worth of the nation's agricultural production (ISMEA 2022). Country-wise, the sheep sector in Tuscany ranks second in importance after Sardinia, with a gross value of approximately 60 million EUR, which corresponds to 1.7% of the total agricultural production value in the region. The Caseificio Sociale di Manciano is a cooperative which processes sheep milk provided by more than 150 sheep farms characterized by a semi-extensive mixed farming system (ISMEA 2022; Marraccini et al. 2012). The sheep farms belonging to the cooperative are mostly located in the southern area of the Grosseto Province, Tuscany (Figure 2). In terms of heads, Italian dairy sheep farms rear approximately 3.2 million heads nationwide, with around 240 thousand located in Tuscany. In the province of Grosseto, more than 48% of the entire dairy ewe population in the Tuscany region is raised (BDN 2022). The climate in this area is typically Mediterranean, with an average annual precipitation of around 700 mm and an average air temperature of  $15 \text{ }^{\circ}\text{C}$  (Vallebona et al. 2016). The cropping systems of mixed dairy sheep farms primarily focus on cool season annual crops. Durum wheat (*Triticum durum* Desf.), serving as the cash crop, is cultivated in rotation with annual forage crops, usually a mixture of oats and berseem clover. In contrast, the utilization of temporary grasslands, such as lucerne (*Medica sativa*) or biennial legumes like sulla (*Hedysarum coronarium*), for hay and other purposes is not common (Bosco et al. 2021).

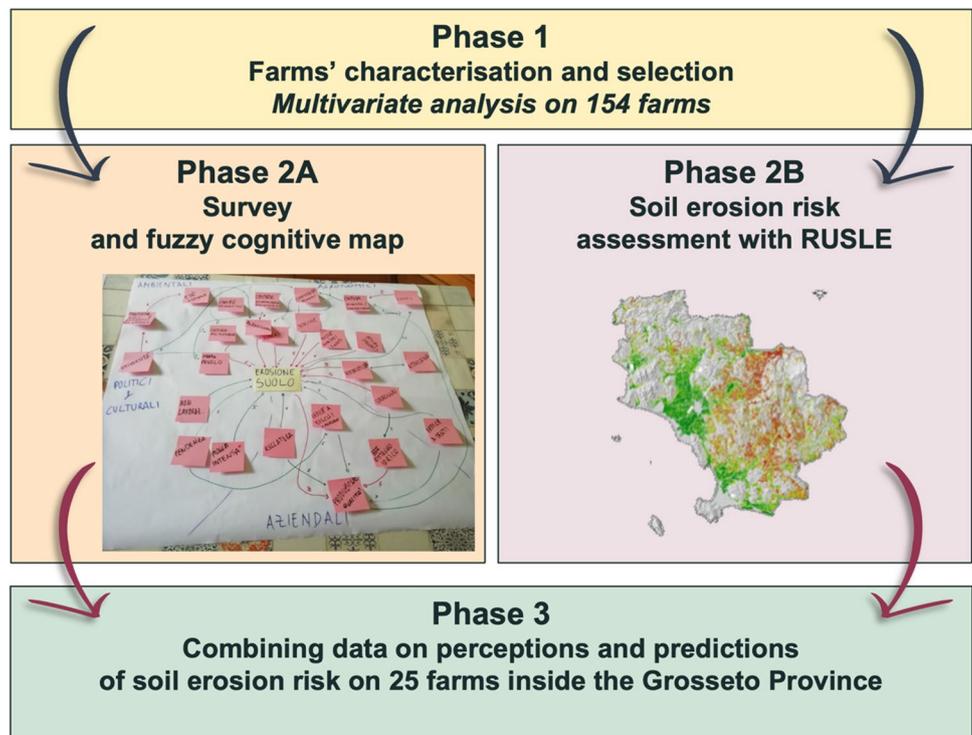
Research activities were organized into four main phases (Figure 3): characterization of the sheep farms and selection of the farmers subsample (phase 1); survey and drawing of FCM to study the perceptions of farmers on soil erosion, focusing on its main drivers and consequences (phase 2A); use of a geographical information systems (GIS)-based RUSLE model to obtain the soil erosion risk at regional and farm levels (phase 2B); combining data on perceptions and predictions of soil erosion risk (phase 3). We summarize each step in the following sections, while we refer the reader to the supplementary material of the manuscript for further details.



**Figure 2** On the left, map of Italy where Tuscany and the study area are highlighted. On the right, map of Grosseto Province where the selected farms (red dots) are located. Different colors show the main

land uses while the darker reliefs highlight the morphological traits of the study area (based on Digital Terrain Model at 10-m interval of Grosseto Province).

**Figure 3** Graphical abstract of the methodology utilized. Characterization of sheep farms and farmer subsample selection (phase 1); survey and FCM mapping of farmers' perceptions on soil erosion drivers and consequences (phase 2A); GIS-based RUSLE modeling of erosion risk at regional and farm scales (phase 2B); integration of perception and model data (phase 3).



## 2.2 Farm selection, surveys, and fuzzy cognitive maps

Phase 1: After having characterized the 154 dairy sheep farms active on the study area, we selected 26 farms as a subsample as described in the supplementary material. The sample size was considered in range based on the average number of individual cognitive maps emerged in previous ecological studies (from a minimum of 13 to a maximum of 56 maps) (Özesmi and Özesmi 2004). Monte Carlo simulations were used to create the average accumulation curve (Figure S6) (Özesmi and Özesmi 2004). This allowed to check whether the selected farmers' subsample was sufficiently representative of the population in the study area.

Phase 2A: To get specific insights regarding the conditions of the dairy sheep farmers and to investigate whether farmers were perceiving a risk related to the soil erosion, we administered a quantitative survey to the respondents. We collected information on the farm structure, the characteristics of the household, and the main economic activities. Furthermore, farmers were interviewed on specific issues such as climate change and its manifestation, agricultural

policies, and their support. Farmers were asked about the intensity of the soil erosion risk they perceived, if they were perceiving it, its evolution in the last 20 years, and the perceived dynamics in the quality of the soil fertility in the same time frame. A summary of the variables used in this study can be found in Table 1.

We constructed fuzzy cognitive maps (FCM) with 26 sheep farmers to capture their perceptions on soil erosion, including the factors affecting and being affected by soil erosion, with a specific focus on the adoption and effects of soil conservation measures. Besides, emphasis was put on the study of other environmental, managerial, political, and cultural factors that could affect directly or indirectly the adopted agronomic practices and soil erosion. Four farm type categories were identified to reflect the diversity of farming systems in the study area: large, inland, coastal, and innovative farms (we included further details in the supplementary material).

FCM represents a fundamental tool for modeling complex relationships among variables (Özesmi and Özesmi 2004). It is able to make fuzzy ideas and thoughts explicit and to highlight the direct and indirect causal relations

**Table 1** Summary of the selected variables from the survey.

Issue	Variable	Description
Household characteristics	Age	Age of the householder
	Gender	Gender of the householder
	Children	Number of children
	Size	Number of household components
	Education	Level of education of the householder
	Participation in specific training (yes/no)	Whether or not the householder participated in specific courses on sustainable agriculture
Farm characteristics	Production method	If the farm is managed under conventional or organic scheme
	Products sold	Number and types of products sold
	Trade channels	Number and types of channels use to sell the products
	Animals reared	Number and types of animals reared
Research activities	Participation (yes/no)	Whether the householder participated in specific research activities
	Benefits	Number and types of benefits gained from the participation in research project
Common Agricultural Policy	CAP services	Whether or not they think that the CAP considers all the services offered by the farmer
	CAP (I pillar)	Importance of CAP direct payments
	CAP (II pillar)	Importance of CAP rural development plans
	CAP negative	Negative aspects related to CAP
	CAP positive	Positive aspects related to CAP
	Future CAP	Aspects that CAP 2023–2027 should prioritize
Soil characteristics	Soil analysis	Whether farmers conducted soil analyzes, their frequency
	Perception of soil erosion (yes/no)	Whether farmers perceived a soil erosion risk
	Intensity of soil erosion	Intensity of soil removal from field surface
	Soil erosion evolution	Evolution of soil erosion in the last 20 years
	Soil fertility evolution	Evolution of soil fertility in the last 20 years

that might occur among the emerged concepts (Jetter and Kok 2014). We followed and adapted the multi-step FCM approach proposed by Özesmi and Özesmi (2004) to draw and analyze the maps (even though it should be noted that we did not use neural network computation to analyze the map outcomes and simulate different policy options). This approach includes the following steps:

1. Drawing the fuzzy cognitive maps.
2. Controlling the adequateness of the sample size.
3. Coding the cognitive maps into adjacency matrices.
4. Merging individual cognitive maps to form stakeholder social cognitive maps.
5. Analyzing the structure of individual and social cognitive maps with the graph theory.
6. Analyzing the differences in variables among stakeholder groups.
7. Condensing complex cognitive maps into simpler maps for comparison and visualization purposes.

Before the start of the interview, some examples were provided to explain what a FCM is. Once the interviewee understood the process of creating a cognitive map, a poster was shown to the farmer with a central post it is stating: "Soil Erosion." Drawing of the cognitive maps started with the formulation of a guiding question: "Which are the factors that affect soil erosion? And what does soil erosion influence?"

Farmers were asked to first consider agronomic aspects which may affect soil erosion. Subsequently, the facilitator asked, in a consistent way, the influence and effects of managerial, environmental, and political and cultural factors (Messmer et al. 2021) on soil erosion. Afterwards, farmers were invited to explain how the variables mentioned, listed on the poster, affected each other. The relationships among the different factors emerging were displayed by arrows with different directions and colors. Finally, the farmers were asked to give a weight to each arrow/connection, indicating the strength of the relation with values that varied from  $-5$  to  $+5$  (least influential to most influential). The farmers could add more variables to the map at any time during the interview. The process was considered finished when the interviewee had nothing more to add and the final visual output was representing faithfully its ideas (Özesmi and Özesmi 2004). On average, it took 45 min to conclude each map.

The cognitive map data were coded into adjacency matrices (Özesmi and Özesmi 2004). The factors identified by each farmer were listed in both vertical and horizontal axes. The strength of the connections among factors was rescaled from  $-1$  to  $+1$ , with values greater than 0 indicating positive connections that help prevent soil erosion, values less than 0 indicating negative connections that worsen soil erosion, and a value of 0 indicating no connection.

The individual matrices were merged to obtain one social FCM for each farm type and one overall social FCM for the study area was also computed. Social cognitive maps allow the comparison of FCM indices among farm types and offer a more reliable representation of the system, as shared by a larger number of stakeholders. Social FCMs were created assuming that individual maps were equally important, so that a weight of one was given to each individual cognitive map (Özesmi and Özesmi 2004). This was considered realistic, as no interviewed farmer had a leading position in the consortium. Factors were merged and connections were summed among the same variables for all farmers in the group. The weights of the connections were later divided by the total number of farmers belonging to a specific group, to obtain mean centrality values.

Graph theory was later used to analyze the structure of the individual and social matrices (Özesmi and Özesmi 2004). The following FCM indices were computed: the number of variables (F), connections (C), and the number of factors defined as driver (D), receiver (R), or ordinary variables (O). Receiver factors only have ingoing arrows. Drivers only have outgoing arrows. The ordinary variables have both ingoing and outgoing arrows. For each factor, the centrality was determined as the sum of absolute values of ingoing and outgoing arrows. Moreover, all the variables were categorized into seven groups (Messmer et al. 2021):

- 1 *Land management* includes all the activity and operational decisions that can have an effect at field level.
- 2 *Farm management and resources* include the endogenous farm assets together with the strategical choices that may lead the farm in its whole.
- 3 *Ecological services* highlight the provisioning of direct and indirect ecosystem services.
- 4 *Environmental conditions* represent mostly the independent environmental factors.
- 5 *Market conditions* and
- 6 *Policy aspects* are two important categories that include upstream and downstream factors influencing the sustainability of the farm operations.
- 7 *Social aspects* emphasize the traditions and the social context as pure assets characterizing the way farming systems operate.

Furthermore, we calculated additional structural indices of the fuzzy cognitive maps (FCMs) to better understand their properties: (1) FCM density (D): This is calculated as the ratio between the actual number of connections in the map and the maximum possible number of connections given the total number of variables. It measures how densely connected the variables are within the system; (2) Complexity Index (H): This index is obtained by dividing the number of receiver variables (those that only receive influences) by

the number of transmitter variables (those that only send influences). It reflects the balance between input and output variables in the cognitive map, indicating how complex or hierarchical the system structure is; (3) Ratio between Transmitters (C) and Receivers (F): Following Özemi and Özemi (2004), this ratio compares the count of transmitter nodes to receiver nodes, providing insight into the directional flow of influence within the map. FCMapper Vs 1.0 (Bachhofer and Wildenberg 2011) was used to summarize and process the collected data. The FCM visualization was facilitated by considering only the factors that were mentioned at least two times; in addition, only the connections with an absolute weight  $\geq 0.05$  were drawn in the social representations of the maps. Pajek32 Vs 5.13 (Batagelj and Mrvar 1998) was used for the final graphical representation of the social fuzzy cognitive maps. A Kruskal-Wallis test (at  $p \leq 0.10$ ) was performed to analyze the differences in FCM indices and factors relationships among farm groups. Significant Kruskal-Wallis tests were further analyzed using a Dunn post hoc test. The statistical analyses were all based on the 26 individual FCMs and were conducted using R software (R Core Team 2023).

### 2.3 The Revised Universal Soil Loss Equation

Phase 2B: the estimation of the spatially distributed soil erosion risk for the whole Province of Grosseto, Tuscany, was carried out with a Revised Universal Soil Loss Equation (RUSLE) approach proposed by Renard et al. (1997) (Figure 3). The RUSLE is the most applied empirical model worldwide due to its simplicity in predicting long term annual average soil losses based on modest data input (Borrelli et al. 2021). It estimates the gross erosion risk caused by the sheet and rill processes, without considering the deposition and sediment yields (Borrelli et al. 2021). In this study, we used a vegetation index obtained from a Sentinel 2A satellite images (<https://dataspace.copernicus.eu>) to describe the inter-annual variability of crops and the spatiotemporal occurrence of tillage operations (Borrelli et al. 2018). The model was suitable and robust as it allowed consistent comparisons among soil erosion risk predictions at farm level. This model was not validated as its main purpose was not to quantify the effective amount of soil that was threatened to be eroded every year, but to discriminate among predicted soil erosion risks among different farms in relative terms.

According to RUSLE, the annual soil loss can be estimated as follows:

$$A = R \times K \times LS \times C \times P \quad (1)$$

where  $A$  is the average soil loss ( $\text{t ha}^{-1} \text{ year}^{-1}$ ),  $R$  is the rainfall erosivity factor ( $\text{MJ mm h}^{-1} \text{ ha}^{-1} \text{ year}^{-1}$ ),  $K$  is the soil erodibility factor ( $\text{t h MJ}^{-1} \text{ ha}^{-1} \text{ year}^{-1}$ ),  $LS$  is the slope length and steepness factor (dimensionless),  $C$  is the cover

management factor (dimensionless), and  $P$  is the support practice factor (dimensionless). Due to the lack of information to accurately define  $P$ -factor at regional level, it has been set at 1 (Vallebona et al. 2016).

All the information necessary to define the different factors were collected at regional level and clipped considering the Grosseto province borders. The derived factors were overlapped using the RUSLE equation in a GIS environment (QGIS version 3.16), resulting into an updated spatially explicit annual soil erosion risk map for the Grosseto province. Later, the maps of farm parcels, made available by the regional public database ARTEA (2019), allowed to identify the cultivated fields (polygons) for each of the farms involved in this study. Because one of the selected farms was located outside the province of Grosseto, the analysis was performed on 25 farm surfaces. Taking the average of the erosion rate of all polygons belonging to the same farm, weighted by the surface of each polygon, we obtained the annual average soil erosion risk at farm level. The methodology used for calculating all the parameters is reported in the supplementary material section (S7).

In order to investigate which parameters were influencing the RUSLE model outcomes to a greater extent, we followed the global sensitivity analysis (GSA) approach used by Estrada-Carmona et al. (2017). This GSA approach, designed by Harper et al. (2011), uses random forest (RF) and regression tree (CART) to rank factors and to analyze the relationships among model parameters respectively.

The randomForest 4.6-2 R package was used to normalize the node impurity values of each parameter of the RUSLE model and thus to obtain their relative importance. We used R package rpart 4.1-9 to perform a CART analysis to visualize the most meaningful interactions among factors. By then, it was clear which factor combinations resulted in lower or greater estimates of soil erosion risks (Estrada-Carmona et al. 2017). The dataset used to perform all these statistical analyzes was the whole polygons ( $n = 996$ ) that represented all the cultivated fields belonging to the farms that were studied in the Grosseto province area ( $n=25$ ).

### 2.4 Matching farmers' perceptions, farm management, and RUSLE estimates of soil erosion risk

The final part of the study aimed at investigating how farmers' perceptions of soil erosion risk were linked to farm management and aligned to the modeled erosion risk. To pursue these aims, we compared the data obtained from the surveys, the FCMs, and RUSLE model by using the farm coordinates.

Firstly, since the RUSLE outputs were expressed in terms of Mg soil loss  $\text{ha}^{-1} \text{ year}^{-1}$ , we aggregated the average soil loss into five categorical erosion risk classes (*very low*, *low*,

*medium, severe, or very severe*) adapting the thresholds obtained from Panagos et al. (2021). Soil erosion thresholds, ranging from very low ( $<2 \text{ t ha}^{-1} \text{ year}^{-1}$ ) to very severe ( $>22 \text{ t ha}^{-1} \text{ year}^{-1}$ ), indicate increasing levels of degradation, with values exceeding  $11 \text{ t ha}^{-1} \text{ year}^{-1}$  (severe) considered critical for intervention, while any soil loss surpassing natural formation rates ( $1\text{--}2 \text{ t ha}^{-1} \text{ year}^{-1}$ ) indicates unsustainable conditions (low and medium). We used Cohen's kappa statistics to measure the agreement of the RUSLE categorical scales and the farmers' perceived soil erosion risk based on survey results (Bamutaze et al. 2021). Cohen's kappa is a statistical test that measures the agreement between two nominal scales, while accounting for the possibility of agreement occurring by chance (Cohen 1960). This test was chosen because it allows us to quantitatively evaluate how well the farmers' perceptions align with the RUSLE model predictions.

Secondly, a multivariate ordinal logit regression (Bilder and Loughin 2014) was conducted to further analyze the correlation among farm structures, farmers' perceptions on soil erosion risk, and RUSLE estimates. A proportional odds logistic model was built considering the soil erosion risk classes as ordinal outcome and several continuous and categorical variables as explanatory ones. The selection of the variables occurred to address the research aim while keeping meaningful the statistics. For these reasons, six explanatory variables were selected, avoiding those that had high correlation coefficients ( $r > 0.7$ ). Here following the variables considered in the multinomial ordinal logit analysis:

- i. Soil erosion risk—assuming five different values: very low (1), low (2), medium (3), severe (4), or very severe (5). This was the dependent variable, and it was derived from the survey.
- ii. RUSLE predicted soil erosion risk (A);
- iii. Cover management RUSLE factor (C);
- iv. Farm area (extension of the farm area, expressed in hectares, including both forest and agricultural lands);
- v. Number of SC measures—it resumed the number of soil conservation practices knew or adopted by the farmers, as emerged from the FCMs.
- vi. Soil erosion centrality—derived from FCMs, it represented the sum of all ingoing and outgoing factors related to soil erosion control. It meant of farmers' awareness on soil erosion issue.
- vii. Farmers' education—it represented the education, expressed in terms of years of studying and resulting from the survey, of each farmer.

The interpretation of the ordinal logit results was based on the odds ratio (OR) (Bilder and Loughin 2014). This analysis was conducted using the polr function of MASS R package (Venables and Ripley 2002).

### 3 Results and discussion

Our results show that (i) predicted soil erosion risks by RUSLE do not significantly differ among farm types; (ii) the farmers' perceptions of the drivers were aligned with the RUSLE factors, identifying slope length and steepness, soil and land cover management, and rainfall as the main drivers of soil erosion; however, the perception of risk by farmers does not match the model predictions; and (iii) farmers identified the influence of many agricultural practices to reduce soil erosion and (iv) factors such as farmers' education level, farm area, and the number of soil conservation measures enumerated by the farmers in the FCM have the most significant influence on the perceived severity of soil erosion. This research aimed to explore how sheep farmers perceive the risk of soil erosion and how their knowledge and experiences, agricultural practices, and predicted soil erosion risk are interconnected.

#### 3.1 Perception of soil erosion risk, factors, and drivers

From the results of the quantitative surveys conducted on 26 selected farms, it emerged that 92% of the interviewed farmers affirmed to perceive a risk connected to soil erosion. Thirteen percent of farmers said that the risk intensity was low, 42% medium, 38% high, and 8% very high. Most farmers (80%) believed that in the last 20 years, the intensity of soil erosion had increased. Nevertheless, only 55% of farmers said that in the same period, soil fertility had decreased. Only 12% of the interviewed farmers said they perform a soil analysis once a year; interestingly, 66% of them stated that soil erosion increased, and soil fertility decreased in the last 20 years. No significant difference emerged in perceived soil erosion intensity among farm groups ( $p > 0.1$ ).

FCM results underlined how large, inland, coastal, and innovative farmers had similar perceptions of the soil erosion risk in the study area (Tables 2 and 3). During the mapping process, 26 interviewees identified 74 different factors and 366 connections. Based on the community representation of all farmers, the five strongest factors that caused soil erosion were as follows: extreme rainfall events (relative weight of  $-0.67$ ), plowing ( $-0.56$ ), steep slope ( $-0.35$ ), clay soil ( $-0.16$ ), and stone removal ( $-0.14$ ). These five factors represented more than 88% of the total negative indegree of soil erosion control (Table 1). The five most important factors that limit soil erosion were as follows: the presence of temporary ditches (0.66), forage crops (0.63), land maintenance (0.38), the presence of trees in arable fields and in their surroundings (0.27), and no till farming (0.27). These factors represented 44.4% of the total positive indegree of soil erosion control (Table 4).

**Table 2** Means and standard errors of FCM indices per each category of factors for the four farm groups. Within a row, different letters indicate significant differences according to the Dunn-test (Kruskal-Wallis test,  $p$ -value < 0.1).

FCM index	$p$ -value	Large farm (n=4)		Inland farm (n=7)		Coastal farm (n=6)		Innovative farm (n=9)	
Interview time (min)	0.33	30.75	-4.5	49.71	-10.44	44.5	-5.66	40.67	-3.52
Factors (nr.), F	0.61	20.75	-2.1	22.14	-1.75	22	-1.55	23.67	-1.52
Connections (nr.), C	0.27	26.25	-1.65	34.14	-4.45	32.5	-2.14	34.22	-3.37
Transmitters (nr.), T	0.39	9.75	-1.84	9.71	-0.84	8.5	-1.28	10.67	-0.71
Receivers (nr.), R	0.34	1.25	-0.75	1	-0.31	1.83	-0.4	1.78	-0.32
Ordinary variables (nr.), O	0.71	9.75	-0.48	11.43	-1.53	11.5	-1.43	11	-1.19
Land management (nr.)	0.4	8.25	-0.48	8.57	-1.02	8.17	-0.91	10.67	-1.09
Farm management (nr.)	0.31	5	-0.41	3.71	-0.36	4.67	-0.71	4.22	-0.55
Ecological properties (nr.)	0.04	3.75	-0.25	3.57	-0.65	5.33	-0.33	3.22	-0.49
Environmental conditions (nr.)	0.12	1.75	-0.85	1.43	-0.48	1.5	-0.56	2.78	-0.28
Cultural and social aspects (nr.)	0.03	0.75	-0.75	2	-0.31	0.5	-0.22	0.89	-0.26
Market aspects (nr.)	0.37	0.25	-0.25	0.86	-0.34	0.17	-0.17	0.67	-0.33
Policy factors (nr.)	0.27	1	-0.41	2.14	-0.51	1.67	-0.49	1.22	-0.15
Density	0.69	0.07	-0.01	0.07	-0.01	0.07	-0.01	0.06	-0.01
Complexity	0.33	0.11	-0.07	0.11	-0.04	0.22	-0.06	0.16	-0.02
C/F ratio	0.581	1.28	-0.06	1.51	-0.13	1.51	-0.12	1.43	-0.09

**Table 3** Summary of the FCM statistics used to interpret the differences among the four farm types regarding soil erosion control and other main factors. Within a row, different letters indicate significant differences according to the Dunn-test (Kruskal-Wallis test,  $p$ -value < 0.1).

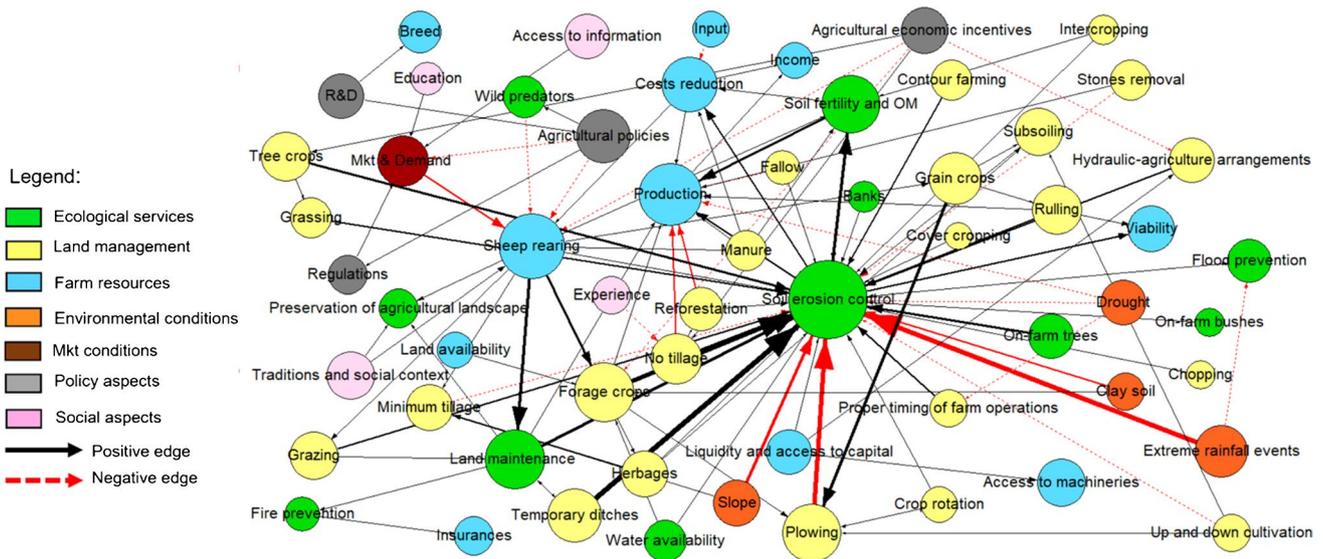
FCM interpretation	$p$ -value	Large farm (n=4)		Inland farm (n=7)		Coastal farm (n=6)		Innovative farm (n=9)	
Soil erosion control (centrality)	0.23	8.78	0.45	8.21	0.97	9.3	0.65	11.17	1.09
Soil erosion control (indegree)	0.05	7.15	0.28	7.19	0.89	7.48	0.32	9.78	0.8
Soil erosion control (outdegree)	0.22	1.63	0.18	1.01	0.21	1.82	0.37	1.39	0.3
Causes of soil erosion control (nr)	0.17	10.5	0.65	10.4	1.04	10.5	0.76	13.33	0.9
Consequences of soil erosion control (nr)	0.24	3	0.41	1.86	0.26	3	0.58	2.22	0.46
SC measures (nr.)	0.38	4.25	0.48	5	0.9	4.67	0.76	6.22	0.76
Minimum tillage-soil erosion control	0.35	-0.38	0.1	0.09	0.19	-0.33	0.19	-0.08	0.16
Subsoiling-soil erosion control	0.41	0	0.08	0.39	0.17	-0.07	0.16	0.16	0.23
Sheep rearing (centrality)	0.59	2.78	1.03	3.83	1.43	2.65	0.66	1.72	0.45
Sheep rearing (indegree)	0.33	1.43	0.65	2.47	0.92	0.57	0.33	0.41	0.21
Sheep rearing (outdegree)	0.36	1.35	0.46	1.36	0.54	2.08	0.45	1.31	0.31
Land maintenance (centrality)	0.43	1.75	0.69	1.66	0.79	2.55	0.66	1.1	0.35
Land maintenance (indegree)	0.59	0.83	0.3	0.54	0.29	1.47	0.65	0.82	0.35
Land maintenance (outdegree)	0.04	0.93	0.41	1.11	0.51	1.08	0.15	0.27	0.13
Forage crops (centrality)	0.93	1.65	0.75	1.46	0.38	2.08	0.6	1.77	0.51
Forage crops (indegree)	0.7	0.75	0.43	0.5	0.24	1.07	0.46	0.71	0.39
Forage crops (outdegree)	0.98	0.9	0.37	0.96	0.26	1.02	0.2	1.1	0.24
Production (indegree)	0.45	1.9	0.29	2.41	0.59	0.17	0.17	0.11	0.11
Agricultural policies (centrality)	0.12	0.4	0.4	1.77	0.42	0.77	0.3	0.8	0.24
Agricultural policies (outdegree)	0.29	0.4	0.4	1.33	0.33	0.77	0.31	0.73	0.22

FCM results underlined how large, inland, coastal, and innovative farmers had similar perceptions of the soil erosion risk in the area.

Based on the community FCM of all farmers (Figure 4), mitigation of soil erosion contributed most to the provisioning of agroecosystem services (AES), in particular

**Table 4** Major factors affecting soil erosion control either positively (+) or negatively (−) according to farmers’ perception.

Factor	Impact on soil erosion control	Description	Relative weight
Extreme rainfall events	−	High volume of rainfall concentrated in a short time	−0.67
Plowing	−	Turning soil upside down through tillage	−0.56
Steep slope	−	Portion of land with 15% slope or more	−0.35
Clay soil	−	Soil characterized mostly by clay	−0.16
Stone removal	−	Taking off stones from the soil for field preparation	−0.14
Minimum tillage	−	Agricultural preparatory field works that aim at minimizing the disturbance of soil structure and life; in this case, we referred to the operation of tine or disk harrowing, at different depth levels (from 15 to 20 cm).	−0.14
Temporary ditches	+	Seasonal ditches done in and at the borders of fields	0.66
Forage crops	+	Multi-year forage crops as lucerne.	0.63
Land maintenance	+	All activities that aim at carrying on agricultural practices (e.g., livestock rearing, goods production)	0.38
On-farm trees	+	On-farm presence of trees without a productive purpose	0.27
No tillage	+	Zero tillage and direct seeding	0.27
Tree crops	+	Growing tree crops like vine, olive, and fruit tree crops	0.1



**Figure 4** FCM based on the whole farmers community ( $n=26$ ). For graphical representation, only factors that were mentioned at least twice by the farmers are shown in the figure. Only connections with an absolute weight  $> 0.05$  are displayed in the figure. Different circle sizes represent the relative centrality scores of the factors; solid

black lines indicate the positive relations among nodes while red lines correspond to negative interactions among factors; the darker and the thicker the line, the greater is the strength of the relationship. Fuzzy causal weights have been omitted for convenience to ease graphical interpretation.

to the maintenance of soil organic matter and soil fertility (0.38), flood prevention (0.09), and land maintenance (0.07). Together, these three AES represented 38.5% of all outdegree of soil erosion control. Moreover, according to the farmers’ perceptions, avoiding soil erosion enhanced the sustainability of the farming process. In fact, soil erosion control was positively linked with a reduction of costs (0.23), while ensuring production (0.20) and increasing land viability (0.17). These positive externalities of soil erosion

control represented 47.6% of the total soil erosion control outdegree.

In the farming community, forage crops held significant importance, ranking as the fourth most central factor (centrality score: 1.70). These crops, primarily featuring temporary meadow species like alfalfa, are influenced by sheep rearing activities, land availability, and hindered by factors like drought. Perennial crops also play a vital role in limiting soil erosion (0.63). Additionally, land maintenance,

crucial for preventing land abandonment, was highly valued (centrality score: 1.68) and was strongly associated with sheep rearing. Farmers linked it to various AES, especially soil erosion control (48% of land maintenance outdegree). Steep slopes and inadequate agricultural policies are cited as reasons for land abandonment. Coastal and inland farmers prioritize land maintenance more than innovative farmers. These findings are consistent with the research of Salhi et al. (2021), which highlighted that in Mediterranean conditions, farmers attributed soil erosion to a complex interplay of natural and anthropogenic factors.

Overall, FCM results showed that all farmer types are highly aware of the interconnected drivers and consequences of soil erosion by water. Similar perceptions on soil erosion were observed across farm types, suggesting that soil erosion is a common problem threatening all semi-extensive farmers present in the southern Tuscany. In the community-based FCM analysis, it became evident that farmers regarded environmental factors such as rainfall, slope, and soil texture, along with land management practices like plowing and the removal of stones, as the primary contributors to soil erosion. For instance, Pimentel (2006) identified soil characteristics such as medium to fine texture, low organic matter content, and weak structure, as well as land topography featuring long, steep slopes, and the absence of vegetation cover on the topsoil, as the primary culprits for soil loss. Additionally, Pimentel (2006) and Toy et al. (2002) both emphasized the impact of land use changes, such as the conversion of forested areas into cropland or any human activities that result in the removal of vegetation from the soil, as significant factors contributing to soil erosion.

Moreover, the fuzzy cognitive map (FCM) analysis indicated that farmers considered minimum tillage, often referred to as reduced tillage (RT), to be an effective practice for mitigating soil erosion in comparison to deep plowing that in the study area is considered as conventional tillage (CT). These farmers' perceptions align with existing literature that substantiates the positive impact of RT in significantly reducing soil erosion when compared to CT (Quinton and Catt 2004). Furthermore, the community-based FCM revealed that farmers recognized the importance of crop management and cropping system design in enhancing soil erosion control, as shown in Figure 4.

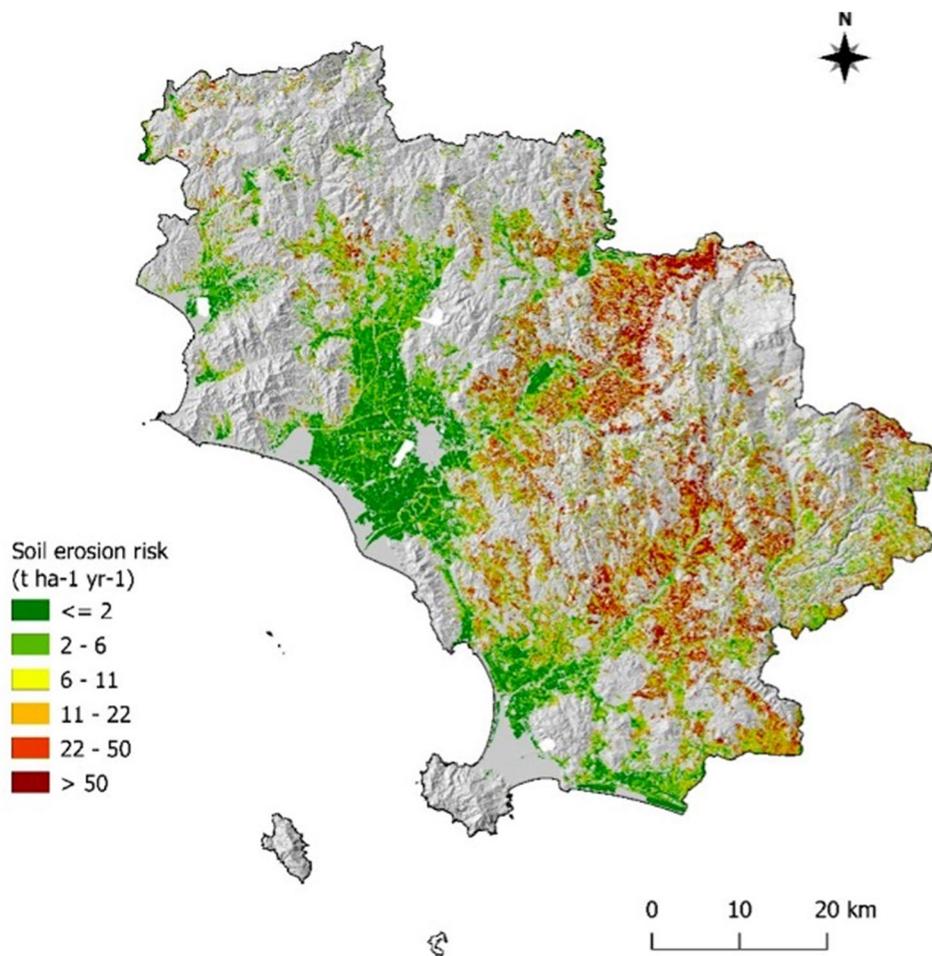
In summary, the alignment between the findings of the FCM analysis and those of previous studies on soil erosion underscores farmers' awareness of the key factors contributing to soil erosion. Specifically, farmers emphasized that the creation of temporary ditches played a crucial role in minimizing soil erosion, particularly in hilly areas. These results closely adhere to European legislation and are in line with the research findings of Bazzoffi et al. (2011). Use of perennial forage crops was identified by farmers as another crucial practice in preserving soil fertility and avoiding soil

erosion. The presence of a constant vegetation cover on topsoil effectively contributes to soil erosion control (Vallebona et al. 2016). In fact, according to Wu et al. (2011), a lucerne crop has higher infiltration rate, higher flow resistance coefficient, and greater roughness coefficient compared to bare soil, determining a reduction of soil erosion. The abandonment of farmland, according to farmers' perceptions, was primarily linked to the presence of steep slopes and the absence of effective policies. These perceptions are consistent with the findings of Fayet et al. (2022), who identified a range of key factors contributing to land abandonment. These factors encompass biophysical constraints, such as steep terrain, poor soil quality, susceptibility to drought, and proximity to forests, as well as institutional and political elements. Additionally, economic and management-related issues, including reduced demand for grazing, geographical remoteness, and scarcity of labor force, were recognized as significant drivers of the decline in land management. FCM outcomes revealed how farmers acknowledged that no-till farming (NT) simultaneously reduces soil erosion risk and crop yield. Farmers share the general idea that NT is one of the most effective SC measures (Ricci et al. 2019). In fact, when NT is combined with the maintenance of crop residues, protects soil against rainfall splash and surface crust formation, reducing significantly soil compaction and runoff (Sun et al. 2015). In a meta-analysis study, Sun et al. (2015) presented findings that, in specific circumstances, question the effectiveness of no-tillage (NT) practices in mitigating soil erosion. Their study indicated that when the soil has a high clay content ( $> 33\%$ ), or when the slope is either  $< 5\%$  or  $> 10\%$ , there was no significant difference between NT and reduced tillage (RT) practices in their ability to control runoff and soil erosion. These results cast some uncertainty on the efficacy of NT in reducing soil erosion, particularly in certain environmental conditions frequently encountered in the Maremma region, characterized by steep slopes exceeding 10%, and heavy soil texture (high presence of clay).

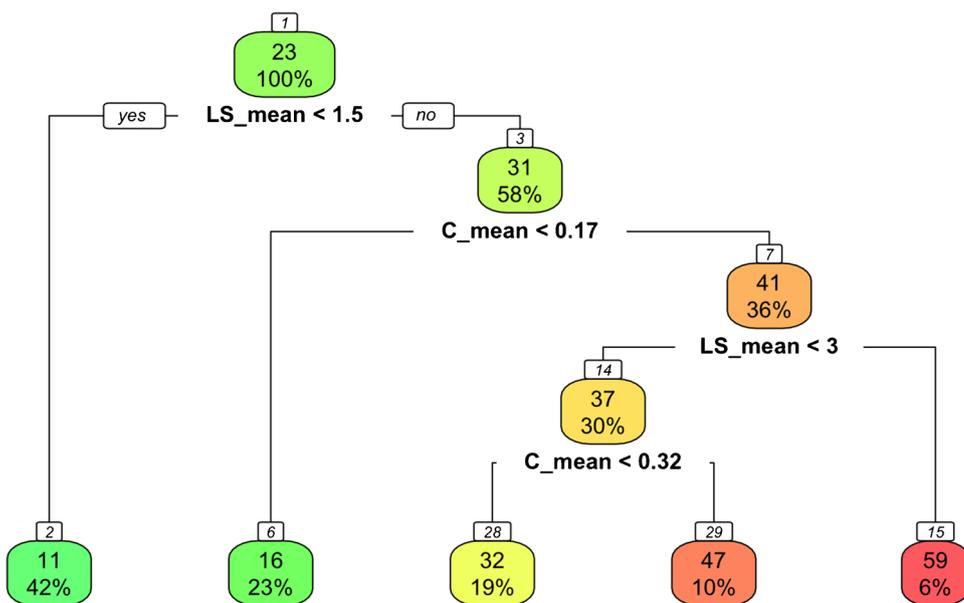
### 3.2 Spatial patterns and intensity of soil erosion risk

According to the RUSLE outcomes, the potential average annual soil loss in cropland (Corine Land Cover 21 and 22) of the Grosseto Province was  $16 \text{ Mg ha}^{-1} \text{ year}^{-1}$ , varying from 0 to  $661 \text{ Mg ha}^{-1} \text{ year}^{-1}$  (Figure 5). These results were obtained when analyzing each pixel ( $10 \times 10 \text{ m}$ ) of the RUSLE raster layer. In contrast, when the pixels were aggregated at field level, the weighted average soil erosion risk calculated for the 996 cropland fields was  $28 \text{ Mg ha}^{-1} \text{ year}^{-1}$ , ranging from 0 to  $127 \text{ Mg ha}^{-1} \text{ year}^{-1}$ . Lastly, when these data were combined at farm scale, the averaged soil erosion risk across the 25 farms was  $27 \text{ Mg ha}^{-1} \text{ year}^{-1}$ . The maximum average soil loss risk at farm level was  $54 \text{ Mg}$

**Figure 5** Spatial changes of RUSLE predicted soil erosion risk for cropland (CORINE land use 21 and 22) in the Grosseto Province (Tuscany, Italy).



**Figure 6** RUSLE decision tree highlighting the relevance of the *LS* (slope length and steepness) and *C* factors (cover management) and their interaction in determining soil erosion rate predictions. The percentages in the boxes refer to the proportion of the overall polygons (*n* = 996) belonging to the specific soil erosion cluster, as explained in the text. The value in the boxes represents the mean soil erosion rates expressed in t ha<sup>-1</sup> year<sup>-1</sup>.



ha<sup>-1</sup> year<sup>-1</sup> and the minimum was 2 Mg ha<sup>-1</sup> year<sup>-1</sup> (Figure S8). No significant differences emerged among the four farm types regarding RUSLE predicted soil erosion risks (Figure S9).

The correlation matrix, based on the 996 polygons representing the 25 farmers' arable lands, highlighted how the *R*, *LS*, *K*, and *C* parameters were not correlated with each other ( $r < 0.5$ ) (Figure S10). Instead, *A* (soil erosion risk) was significantly correlated with the *LS*-factor ( $r = 0.65, p < 0.01$ ) and with the *C*-factor ( $r = 0.57, p < 0.01$ ). In contrast, the *K*- and *R*-factors were not significantly correlated with the soil erosion rate ( $r < 0.5$ ).

The decision tree showed how the soil erosion rates were mostly depending on *LS*-factor, *C*-factor, and on their interactions (Figure 6). Indeed, the analysis showed that *LS*-factor was the most important driver influencing the soil erosion rates. When the *LS*-factor was  $< 1.5$ , 42% of the analyzed polygons had a mean soil erosion rate lower of 11 t ha<sup>-1</sup> year<sup>-1</sup>. As the *LS*-factor had values  $> 1.5$ , the decision tree revealed how the *C*-factor discriminated the highest variability of *A* (58% of the polygons). Finally, the highest soil erosion rates (mean soil loss risk 59 t ha<sup>-1</sup> year<sup>-1</sup>) were registered only for 6% of the polygons when *LS*-factor was greater than 3 and *C*-factor greater than 0.17.

Generally, hilly inland areas, characterized by steep slopes, are more prone to soil erosion compared to coastal ones (Figure 4). This is aligned with the findings of Vallebona et al. (2015, 2016) and it is confirmed by the sensitivity analysis of RUSLE parameters. The analysis identified the *LS*-factor (slope length and steepness) and the *C*-factor (cover management) as main driving factors of *A* (annual soil erosion risk), suggesting how soil erosion results from the interaction of natural and anthropogenic factors (Figure 5).

These findings are in accordance with the FCM results and are supported by the study of Rava (2020), who

conducted a variance-based sensitivity analysis to define the most important RUSLE parameters and their interactions and effects on soil erosion risk. Also, from their study, it emerged how in Italy slope length and steep factor (*LS*-factor) was the most influential parameter, followed by cover management (*C*-factor) and rainfall erosivity (*R*-factor).

The outcomes of RUSLE and the results of sensitivity analysis lead to similar conclusions to those of Borrelli et al. (2016). According to Panagos et al. (2020), the primary driver of soil erosion risk is the *LS*-factor (slope length and steepness), whereas Borrelli et al. (2016) emphasized the paramount influence of the *C*-factor (cover management) in altering soil erosion rates. Consequently, Panagos et al. (2020) deduced that alterations in land cover, such as the transformation of cropland into grassland, carry greater significance and effectiveness in limiting soil erosion compared to variations in implemented SC measures.

These insights hold particular relevance in the context of southern Tuscany, where the conversion of annual herbaceous crops into temporary grassland emerges as a potentially viable and sustainable method to reduce soil erosion. This approach proves effective in reducing soil erosion especially when combined with other SC practices, as detailed in Vallebona et al. (2016).

### 3.3 Perceived vs modeled soil erosion risk at farm level

Overall, farmers and RUSLE model tended towards a classification of soil erosion risk in the study area as moderate or high. However, there was low level of agreement among RUSLE categories of risk and farmers' perceptions of the intensity of risk. In fact, when the RUSLE modeled soil erosion risk was categorized as very severe (68%), only 6% of farmers perceived the risk as very severe, 72% of

**Table 5** Distribution of modeled and perceived soil loss by water erosion on farm sites ( $n=25$ ). The table presents the distribution (%) of soil erosion severity levels as assessed by the RUSLE model and by farmers' perceptions. Columns represent erosion severity classes:

very low ( $< 2 \text{ Mg ha}^{-1} \text{ year}^{-1}$ ), low ( $2\text{--}6 \text{ Mg ha}^{-1} \text{ year}^{-1}$ ), moderate ( $6\text{--}11 \text{ Mg ha}^{-1} \text{ year}^{-1}$ ), severe ( $11\text{--}22 \text{ Mg ha}^{-1} \text{ year}^{-1}$ ), and very severe ( $> 22 \text{ Mg ha}^{-1} \text{ year}^{-1}$ ). Dashes (–) indicate no responses were recorded in those categories.

	Very low (%)	Low (%)	Moderate (%)	Severe (%)	Very severe (%)
RUSLE Overall Categorization of Soil Erosion Rates	4	4	0	24	68
Farmers' Overall Perceptions	8	12	36	36	8
Farmers' perceptions among those the RUSLE predicted very severe soil erosion	6	12	41	35	6
Farmers' perceptions among those the RUSLE predicted severe soil erosion	17	17	33	17	17
Farmers' perceptions among those the RUSLE predicted low soil erosion	–	–	–	100	–
Farmers' perceptions among those the RUSLE predicted very low soil erosion	–	–	–	100	–

them perceiving it as severe or moderate. The percentage of matching between the model and the farmers' perceptions increased to 17% under the severe soil erosion risk category (24%). When the soil erosion risk was predicted as low (4%) or very low (4%), all the farmers perceived the risk as severe (Table 5). A Cohen's kappa test revealed that there was no level of agreement between the two rates of soil erosion risk on the same farm ( $k = 0.02$  and  $p < 0.05$ ). There are few considerations we can elaborate starting from these findings: first, 92% of the farmers live in an area which has a modeled risk considered severe or very severe. The RUSLE model computes these risks based on categories which are adjusted to the European context, while farmers perceived the risk based on their context. The perceived soil erosion is normalized for what farmers experience on their farm and in relation to what other farmers in the same region are experiencing. This "normalized" evaluation leads only 44% of the farmers to declare a severe or very severe level of perceived risk.

Finally, we present the main findings of the multivariate ordinal logit regression (Table 6). The odds of having a higher rather than a lower perceived soil erosion intensity was estimated to be 1.07 [ $\exp(0.07)$ ] times higher for those with higher RUSLE modeled soil erosion risk, keeping all other variables constant. When farm areas were smaller, the odds of having a higher soil perceived erosion were expected to be 2.0% [ $1 - \exp(-0.03)$ ] higher than farmers with bigger farm areas, keeping all the other variables constant. As the number of SC measures was lower, the odds of having a higher soil perceived erosion were 1.43 times [ $\exp(0.36)$ ] that of those that mentioned a higher number of SC practices, keeping the other variables constant. The odds of having a higher rather than a lower soil perceived erosion intensity was estimated to be 1.09 ( $\exp(0.09)$ ) times higher for those with a higher number of FCM connections, keeping all the other variables constant.

**Table 6** Regression coefficients for farmers' perceived soil erosion intensity. Odds ratios (OR) resulted from the  $\exp$  (coefficient). Significance level:  $p$ -value  $< 0.01$  (\*\*\*);  $< 0.05$  (\*\*);  $< 0.10$  (\*). SE means standard error.

Variable	Coefficient	SE	$p$ -value	OR
RUSLE predicted soil erosion risk (A)	0.07*	0.04	0.09	1.07
RUSLE cover management factor (C)	-2.72	6.46	0.67	0.07
Farm area	-0.03***	0.01	0.01	0.98
Soil conservation measures	-0.36*	0.21	0.09	0.7
Number of FCM connections	0.09	0.06	0.11	1.1
Farmers' education	1.45*	0.82	0.08	4.27
AIC	78.6			

The probability of having a higher perceived soil erosion intensity was 4.27 times higher for those farmers with higher education level, keeping all the other variables constant.

As per farmers' perceptions, agricultural policies and economic incentives had a greater influence than cropping system design (Figure 4). This perspective aligns with the findings of Freluh-Larsen et al. (2016), who recognized that policies such as CAP cross-compliance and environmental measures proposed under the two CAP pillars serve as crucial tools in advancing and achieving sustainable soil management across Europe.

According to farmer's perceptions, soil erosion control measures and policies should consider a set of integrated management practices (Table 4), such as the construction of temporary ditches, use of forage crops, inclusion of trees in arable fields and in their surroundings, and no till farming. These practices can be integrated in diversified agroforestry systems (e.g., alley cropping) that combine arable and perennial crops with grazing animals (Tranchina et al. 2024). The adoption of these practices becomes even more relevant in face of climate change due to increased rainfall intensity, especially in hilly areas (Table 4 and Figure 5). Diversified agroforestry systems and similar approaches have the potential to efficiently integrate beneficial practices to reduce soil erosion, bolster carbon storage, increase system resilience, and maintain satisfactory agricultural yields (Palma et al. 2007), and therefore, need to be promoted with adequate policies and subsidies.

## 4 Conclusion

This study aimed to fill in the knowledge gap on the concurrent assessment of soil erosion by quantitative and cognitive approaches. Specifically, we investigated the following: (i) how farmers perceive the risk of soil erosion and map the primary drivers and consequences of the perceived phenomenon through FCM; (ii) the extent to which farmers' perceptions of soil erosion risk align with predictions from the RUSLE model and factors; and (iii) we assessed how the variability of farmers' perceptions is explained by farmer characteristics, farming management practices, and modeled soil erosion risks. The combination of cognitive and quantitative methods allowed us to study soil erosion and land degradation process in an unexplored way, capturing the complexity of the phenomenon from a systemic perspective. This combination enables us to explore the richness in farmers' perceptions which a mathematical model such as RUSLE is not able to capture. Furthermore, the use of maps has highlighted how farmers are able to recognize a series of suitable practices to mitigate the causes of soil erosion. The farmers' perceptions of soil erosion drivers were aligned with the RUSLE factors; however, the perception of risk by

farmers does not align the model predictions. On the one hand, this signals a shortcoming of farmers' interpretation of the phenomenon (biased by their own definition of the magnitude of the risk and their interpretation), but on the other hand, this also signals a multidimensionality of their perception that the RUSLE model is not equipped to capture.

In this perspective, we advocate that farmers should be more systematically included into scientific research and policy design processes to address specific environmental issues. Farmers' mental models also add value to environmental models because they capture variables in greater detail, including their interconnectivity. As such, European CAP and its application in member states should include all the relevant stakeholders, beginning with farmers and scientists, to co-design the roadmap of sustainable, context-specific rural development.

**Supplementary Information** The online version contains supplementary material available at <https://doi.org/10.1007/s13593-025-01036-z>.

**Authors' contributions** Conceptualization: S.D.L., M.O., M.R., H.T.M., and A.M.; methodology: S.D.L., M.O., M.R., H.T.M., and A.M.; investigation: S.D.L., M.O., and M.R.; data curation: S.D.L., M.O., M.R., H.T.M., M.M., and A.M.; writing—original draft preparation: M.R., M.O., S.B., and A.M.; writing—review and editing: M.R., S.D.L., M.O., H.T.M., and S.B., P.B., M. M., and A.M.; supervision: H.T.M., P.B., M.M., and A.M.; funding: A.M., S.B., and P.B. All authors have read and agreed to the published version of the manuscript.

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**Data availability** The data that supports the findings of this study are made available at the following link: <https://doi.org/https://doi.org/10.5281/zenodo.15624697>.

**Code availability** The code used to analyze the data and to produce figures is available from the corresponding author on reasonable request.

## Declarations

**Ethics approval** This study was performed in line with the principles of the Declaration of Helsinki. The questionnaire and methodology for this study were approved by the Ethics Committee of the Scuola Superiore Sant'Anna of Pisa (Ethics approval number: 26/2021, date: 29 June 2021). Informed consent was obtained from all individual participants included in the study.

**Competing interests** The authors declare no competing interests.

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