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Exploiting the land use to predict shallow landslide susceptibility: A probabilistic implementation of LAPSUS-LS

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ABSTRACT

Due to the significant role of land use on the occurrence of rainfall-induced shallow landslides, this factor is commonly employed as a landslide susceptibility predictor. However, the land use classification is oftentimes very broad, neglecting the proven mechanical and hydrogeological role of the land management on slope stability. Given the necessity of including spatially distributed and management-specific inputs, the process-based landscape evolution model LAPSUS-LS was chosen and adapted to achieve a probabilistic approach which takes into account land management as an input by adopting management-specific values of root cohesion. The model was applied to four test sites in the Oltrepò Pavese (Italy), where different vineyard management techniques play a significant role in triggering landslides. The results for the four test areas had, cumulatively, an Area Under the Roc curve greater than 0.73, with false negative cells being < 1 % of the total for all simulations. In the model's application, land use practices characterised by higher root cohesion proved to benefit slope stability, whereas tilled vineyards, shrublands and abandoned vineyards were more prone to the formation of shallow landslides. In addition, we found that the inclusion of management-specific input parameters produced more accurate outputs and that in catchments characterised by average slope angles lower than 15°, varying the vineyard management, did not appear to affect the landslide susceptibility. Due to the model's high dependency on the land use and its ability to include land management, it can take into account the spatial variability of input values such as the root cohesion. Additionally, it can be applied i) to manage current conditions, ii) to explore future land use change, iii) to study less invasive yet beneficial land use management change scenarios and iv) provide farmers of at-risk areas insight on how to improve slope stability.

1. Introduction

Intense and, occasionally, consecutive rainfall events on slopes can lead to the formation of shallow landslides (which are landslides with a depth lower than 2 m; Gabet and Mudd 2006), which regularly damage infrastructures, produce economic loss and endanger human lives (Howard et al, 1988; Montrasio and Valentino, 2008). Multiple factors have previously been discovered to impact shallow landslide susceptibility and they include factors such as land use, lithology, soil texture and geomorphology of the area and topographical factors such as the slope angle, aspect, curvature and Topographic Wetness Index (Baeza and Corominas, 2001; Pereira et al., 2012; Conforti and Ietto, 2021). In particular, the impact of the land use and land use change on the spatial and temporal distribution of shallow landslides has previously been proven (Persichillo et al., 2017; Meneses et al., 2019; Avila et al., 2020; Guo et al., 2023). Different natural and human-controlled land uses are characterised by the presence of vegetation species that can influence slope stability in a unique way (Bischetti et al. 2005; Bischetti et al. 2009; Tosi 2007; Wu, 2012; Cislaghi et al. 2017; Cohen and Schwarz, 2017).

The most widely recognised effect is represented by the mechanical reinforcement provided through the anchorage of the roots in the soil,

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which is directly correlated to the number of roots along the soil profile and to the strength and elastic properties of the roots themselves (Bischetti et al., 2009; Cohen et al., 2011; Schwarz et al., 2013; Stokes et al., 2014; Masi et al., 2021; Mao, 2022). This parameter varies depending on the vegetation and, in the case of cultivated plants, also on the type of agricultural management of those cultivations (Gonzalez-Ollauri and Mickovski, 2017; Bordoni et al., 2019). The impact of the land use on shallow landslides has been proven in the past (Reichenbach et al., 2014; Pisano et al., 2017; Chen et al., 2019; Meneses et al., 2019) as, for instance, bio-engineering techniques exploiting the mechanical reinforcement of some vegetation species can be implemented to increase soil shear strength, reducing the probability of occurrence of these instabilities at catchment or larger scales (de Jesús Arce-Mojica et al., 2019). This implies that some land use types could be effective non-invasive tools in reducing shallow slope instabilities, without modifying landscapes, environment and economic features of an area (Gariano et al., 2018). Due to the significant role of land use on shallow landslide occurrence, this factor is commonly employed as a spatially distributed input parameter in landslide susceptibility estimation at different spatial and temporal resolutions, depending on the data availability (van Westen et al., 2008). It is considered as a predictor variable in data-driven statistical methods for the zonation of a territory in terms of the probability of occurrence of shallow landslides (Hong et al., 2017; Chen et al., 2019; Achu et al., 2020; Chen and Li, 2020; Azarafza et al., 2021; Chen et al., 2021; Chowdhuri et al., 2021; Knevels et al., 2021; Yang et al., 2021). Some authors rely on qualitative land use classifications derived from various sources (Chen et al., 2019; Achu et al., 2020; Chen and Li, 2020; Chen et al., 2021; Knevels et al., 2021; Yang et al., 2021), either referring to the present day land use or, more rarely, spanning decades (Knevels et al., 2021), whereas others assign weights to qualitative land use classes (Hong et al., 2017; Azarafza et al., 2021; Chowdhuri et al., 2021). The resolution of the input land use maps is also relevant, since low-resolution land use maps tend to negatively impact the overall performance of statistical models (Chen et al., 2019; Chen and Li, 2020; Chen et al., 2021). Both statistical and physically based models operate on the assumption that areas will behave similarly if grouped within the same land use, even if, in the case of cultivated plants, different agricultural practices could modify the susceptibility of the hillslope to shallow landslide occurrence (Heshmati et al., 2011); Bordoni et al., 2019). While many slope stability models either consider the root cohesion to be constant or omit it entirely as an input parameter, some models developed in recent years can take into account the role of mechanical root reinforcement in the deterministic estimation of slope stability (Masi et al., 2021; Murgia et al., 2022). For example, HIRESSS (High Resolution Slope Stability Simulator; Rossi et al., 2013), r.slope.stability (Cordoba et al., 2020), modified versions of SLIP (Shallow Landslides Instability Prediction; Montrasio and Valentino, 2008) and TRIGRS (Transient Rainfall Infiltration and Grid-Based Regional Slope Stability Model; Baum et al., 2008; Marin, et al., 2021; Park et al., 2022, Hwang et al., 2023). Moreover, other models such as GIS-FORM (Ji et al., 2022), PRIMULA (Cislaghi et al., 2017; Cislaghi et al., 2018), QDSLaM (Quasi-Dynamic Shallow Landsliding Model; Tarolli et al., 2011; Penna et al., 2014), MD-STAB (Milledge et al., 2014), Ecosfix 1.0 (Mao et al., 2014), SOSlope (Self-Organized Slope; Cohen and Schwarz, 2017), SlideforMAP (van Zadelhoff et al., 2021) SPRIn-SL (Spatial Prediction of Rainfall-Induced Shallow Landslides; Raimondi et al., 2023) and LAPSUS-LS (Claessens et al., 2007) are capable of taking into account the spatial variability of the mechanical root reinforcement(Rossi et al., 2017).

However, the aforementioned models do not consider two aspects which could influence the susceptibility of a territory to the formation of shallow landslides: firstly, in areas where agricultural activities along sloped terrain are practiced, multiple management techniques exist, some of which entail the tillage of the soil up to six times a year whereas others require no mechanical disruption of naturally growing grass (Bordoni et al., 2019), thus, even in areas grouped within the same land use class, different agricultural management techniques can lead to significant differences in slope stability (Straffelini et al., 2022). Additionally, previous models did not specifically consider the influence of the agricultural management on the probability of occurrence of shallow landslides, nor have they been used to create future scenarios of shallow landslide susceptibility according to changes in the land use and agricultural management. Secondly, the existing methods for shallow landslide susceptibility assessment do not usually take into account the effect of vegetation types on soil hydrological properties, namely on the soil hydraulic conductivity. Usually, these methods consider the spatial variation in soil permeability due to differences in physical and geotechnical properties of the soil matrix, neglecting the possible influence of the vegetation features. However, some research carried out in natural woodlands (Archer et al., 2016; Vergani et al., 2016) and in sloped terrain cultivated with vineyards (Biddoccu et al., 2017; Alagna et al., 2018; Bordoni et al., 2019), highlighted a strong correlation between land use and agricultural management and saturated hydraulic conductivity, which may also control the spatial occurrence of shallow landslides, especially in territories with homogeneous geological and geomorphological features (Alessio, 2019). In recent years, probabilistic approaches have been adopted, mostly to fill gaps in input data or to account for uncertainty, with the goal of limiting their negative impact on the performance of predictive models, especially when applied over large spatial extents (Raia et al., 2014; Scalciarini et al., 2017; Marin et al., 2021; Park et al., 2022).

This work aims to adapt and apply a physically based landslide model by incorporating a probabilistic approach, which was chosen with the goal of considering the natural variability of the input parameters, sampling each one at random from a range of measured values, instead of having to select a single representative input, rather than to overcome data gaps. For these purposes, the LAPSUS-LS model (Claessens et al., 2005; Claessens et al., 2007), was selected as a starting point, because unlike many existing physically based susceptibility models, which only allow a single input value for the root cohesion (Murgia et al., 2022), LAPSUS-LS links root cohesion, and soil-specific parameters to a land use map, hence considering the impact of land use and agricultural management for soil hydraulic conductivity and root mechanical reinforcement and their possible variations in every grid cell. In past applications of the model, it proved especially sensitive to changes in parameters related to the vegetation, in particular to changes in root cohesion (Rossi et al., 2017). Furthermore, the aim of this study was to adopt the newly adapted LAPSUS-LS model to both reproduce the current landslide susceptibility and to offer insight into how slope stability might change in the future as a consequence changes in land use or management, by modelling different land use change scenarios, created considering both the land use types that are more affected by past shallow landslides and possible abandonment of previously cultivated areas. The goal is to provide farmers of at-risk areas with insight as to which land uses or management practices can improve slope stability in their properties and therefore with non-invasive tools in reducing shallow slope instabilities, without modifying landscapes, environmental and economic features of an area.

2. Material and methods

A flow chart of the developed methodology is described in Fig. 1.

2.1. The test sites

All the selected test sites (Figs. 2, 3) belong to an area where shallow landslides frequently occur, that of the northeastern portion of the Oltrepò Pavese (Italy): a hilly area located south of the river Po, in the region of Lombardy, representing the northern termination of the Italian Apennines, characterised by elevation ranging between 50 and 600 m.a.s.l and slope angles ranging between 15° and 35° in the north and between 8° and 15° in the southern part (Meisina et al., 2006).

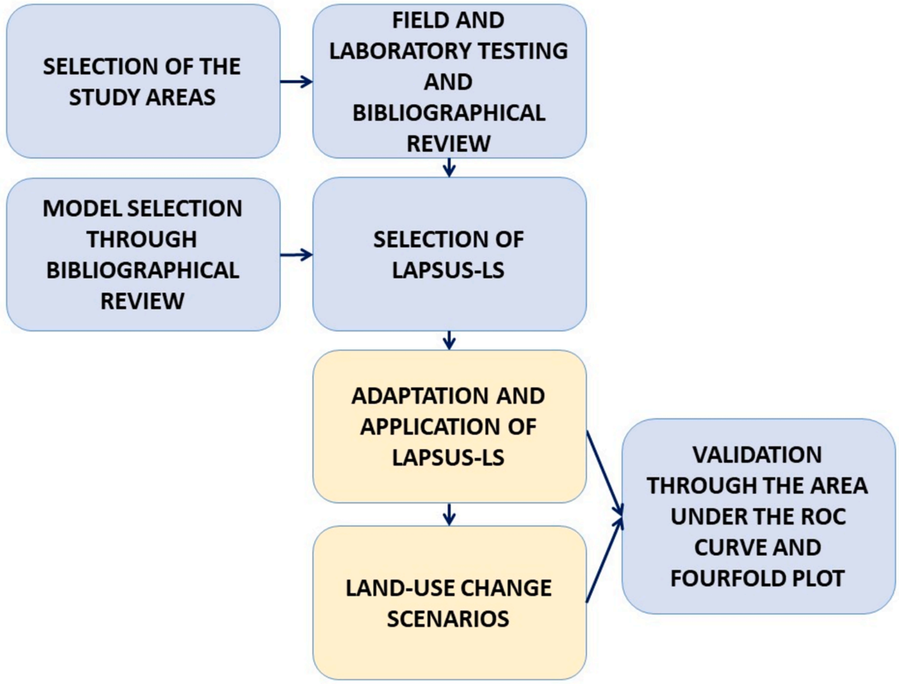

Fig. 1. Flow chart of the adopted methodology.

The land use in this region is characterised by different agro-ecosystems coupled with zones covered by natural vegetation (Bordoni et al., 2019). Viticulture is especially common along sloping terrain, covering 22 % of the entire territory, woodlands such as broadleaves (e.g. black locust trees), Norway maple, European hackberry, buckthorn, European hop-hornbeam, and flowering plants make up 39 % of the territory, while the remaining percentage of the territory is covered by shrublands, urban areas and croplands. For the purposes of this study, shrublands and croplands were grouped within the same land use class, because they were limited in extent and additionally, while they differ from a botanical standpoint (in this area, shrublands are mainly made up of hemicryptophytes and chamerophytes, associated with grass species such as *Festuca* spp. and *Artemisia* spp., whereas croplands are mostly made up of *Medicago sativa*) their Root Cohesion values (RC) in this area are similar, as measured by Bordoni et al. (2020a) in which the authors also highlighted the similarities between the two (RC at 0.3 m from ground level was 1.81 $\pm$ 0.77 kPa in sowed fields and 1.20 $\pm$ 0.53 kPa in shrublands.

Vineyards in this area are managed through three main management techniques (Bordoni et al., 2019): (a) Tillage and Total Tillage (T/TT), which is the tillage of the soil between vine rows, up to 6 times a year; (b) Permanent Grass Cover (PGC), which leaves the inter-rows untouched during the year, allowing for spontaneous grass growth; (c) ALTernating tillage-grass (ALT), the practice of tilling every other row while keeping the rest untouched.

The bedrock lithology is made up, in the northern part of the area, of poorly cemented sandstones and conglomerates overlying marls and evaporitic deposits, while in the southern part it consists of an alternation of calcareous and marly flysches, made up of sandstones and marls and melange complexes (Meisina et al., 2006). The soil thickness ranges between a few centimetres and over 2 m. Slow-moving slope failures can be identified, especially in the central and southern portions of the area, characterised by clayey soils (Meisina et al., 2006).

The present work focuses however on rainfall-induced shallow landslides, which are triggered during intense and, oftentimes, consecutive rainfall events. Despite their typical limited extent, in the order of tens to hundreds of square meters and sliding depths of up to 2 m from ground level, shallow landslides can cause significant damage to infrastructures, human activities and cause the loss of fertile soils (Bordoni et al., 2019). The inventoried landslides which have been used for this study are for the most part classified as translational and roto-translational earth slides which evolve into mud flows (Cruden et Varnes, 1996). A smaller number of landslides are classified as merely translational earth slides that propagate, for the most part, along the line of greatest slope and are not channelised.

In this framework, four test sites were selected to apply the adapted LAPSUS-LS model, in order to include a wide range of features regarding slope angle, vineyard management technique, soil type and number of shallow landslides that occurred in the past (Tables 1 and 2).

The test sites are (see Figs. 1 and 2): Cascina Porcarana (referred to as "CP"), Rio Frate ("RF"), Rio Vergombera ("RV") and Vigna del Fico ("VDF"). As shown in Table 1, soils in the CP, RF and RV test sites are siltier, whereas in the VDF test site they are more clayey. Regarding the adopted management techniques, the CP, RF and VDF are managed through management techniques characterised by higher root cohesions (PGC and ALT; RC of up to 14.07 kPa), whereas both RF and RV include vineyards managed through techniques associated with lower root cohesion rates (T/TT and abandoned vineyards; RC of up to 3.78 kPa; Bordoni et al., 2019). Both areas with multiple landslide events (RF and RV catchments, where landslides occurred between April 27th and 28th 2009 following a cumulated precipitation of 159.4 mm in 62 h) and areas where landslide activity has been nearly absent (CP and VDF) were selected. The vineyards in the area have been planted at the beginning of the 21st century and the slope angles in those are steeper in RF and RV compared to CP and VDF.

2.2. Model description and adaptation

LAPSUS-LS was originally created as a way to account for the role of landslides in the evolution of landscapes by calculating the location and expected quantity of landslide-displaced materials within the LAPSUS modelling framework (Schoorl et al., 2000; Schoorl et al., 2002; Claessens et al., 2005; Claessens et al., 2007). It is a reduced complexity physically based model, in which the displaced material, after a critical rainfall threshold is surpassed, is transported downward and either split between cells through a double multiple flow approach (Claessens,

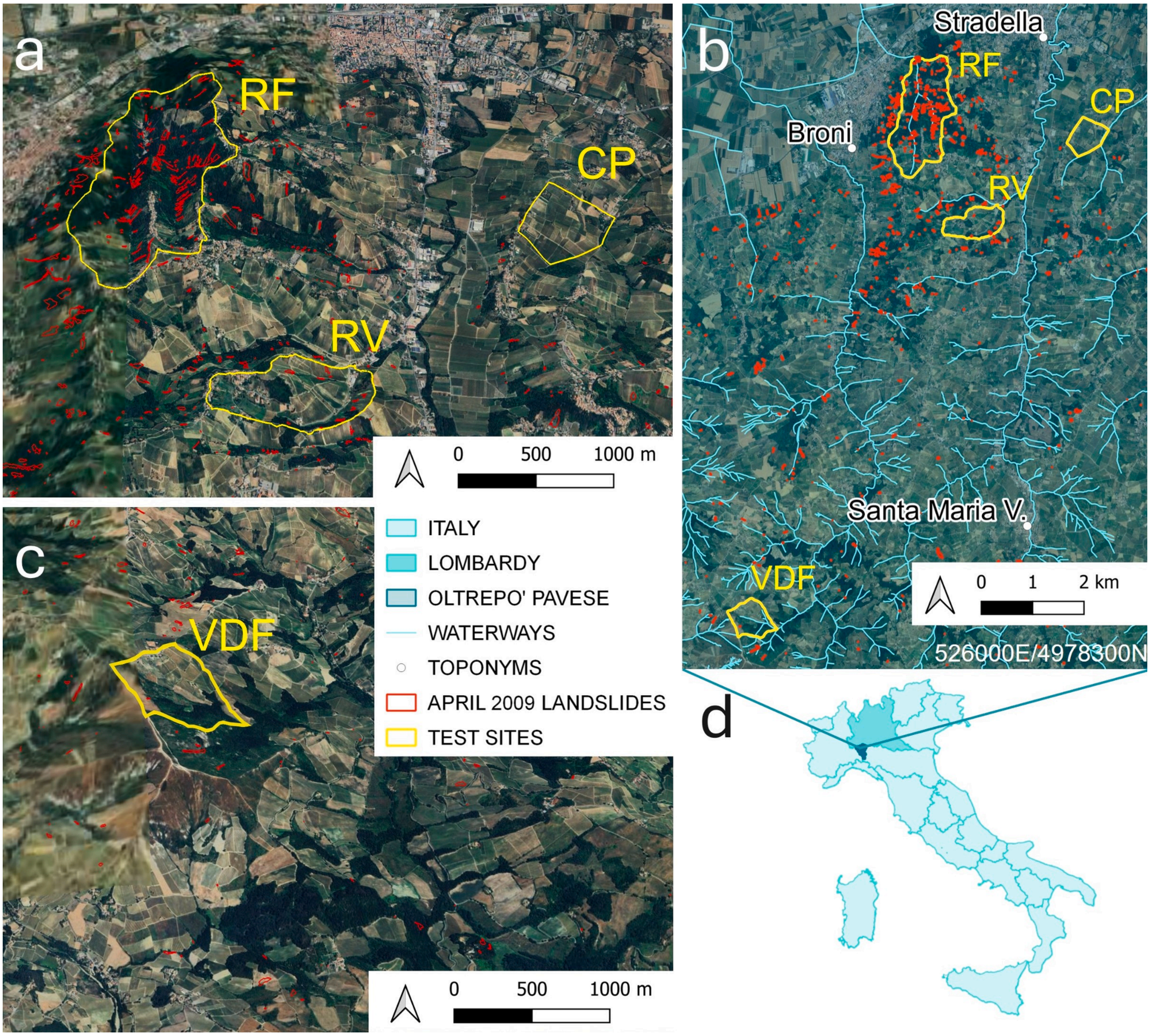

Fig. 2. Study area location in the region of Lombardy (Italy) (d) and the location of the 4 test sites (a, c) in the Oltrepò Pavese including drainage network (b), where "CP" refers to the catchment "Cascina Porcarana", "RF" refers to "Rio Frate", "VDF" refers to the catchment "Vigna del Fico" and "RV" to "Rio Vergombera". Panels a and b zoom into more detail, including landslide locations in red.

2007) or transferred entirely to the steepest neighbour according to a convergence factor, which depends on the slope gradient of the downstream cells (van Gorp et al., 2015).

The original model requires two rasterised inputs: a DEM and a land use map, and associated to each class of the latter, a set of soil and vegetation parameters: General cohesion ("COH" in kPa; which combines soil cohesion and mechanical root reinforcement), internal friction angle ("IFR" in rad), soil unit weight (also referred to as "Bulk density"; "BD" in g/cm^3), soil transmissivity ("T" in m/s; the result of the product between soil permeability and soil thickness). The sliding depth was calculated as a function of the soil bulk density (BD), gravity (angle) and soil cohesion (Cs), assuming always sufficient soil depth available (Claessens et al., 2005; De Sy et al., 2013).

To introduce conditions for limited regolith or shallow soils, a soil depth map and a map of the soil units have been introduced, as along with the soil depth dependent transmissivity, dependent on soil-saturated hydraulic conductivity, with the goal of increasing accuracy. Furthermore, the total cohesion, dependent on root reinforcement and on soil cohesion, can be calculated on a cell-by-cell basis according to the distribution of the effects of different land uses, of the different agricultural management practices and of the different soil units.

Moreover, to take into account the spatial variability of each parameter, the model was adapted so that at each iteration it samples randomly each input parameter from a range of acceptable values and associates the randomised value to all the cells within the same class. The model repeats the process n times: it samples n sets of input parameters, then runs the physically based model, binarizes the outputs (which are the maps of the predicted source areas) in "stable" and "unstable" cells and compiles a probability map based on the number of times each cell was calculated as the former or the latter. While at each iteration only a single input value of bulk density, soil cohesion, friction angle and saturated conductivity is selected for each homogeneous soil class and a single value of root cohesion is selected for each land use and land management, the output is the result of 100 plausible combinations.

It must be noted that LAPSUS-LS cannot take rainfall into account, however in this application, all landslides occurred during a single event, that of April 27th-28th 2009, so that differences in rainfall

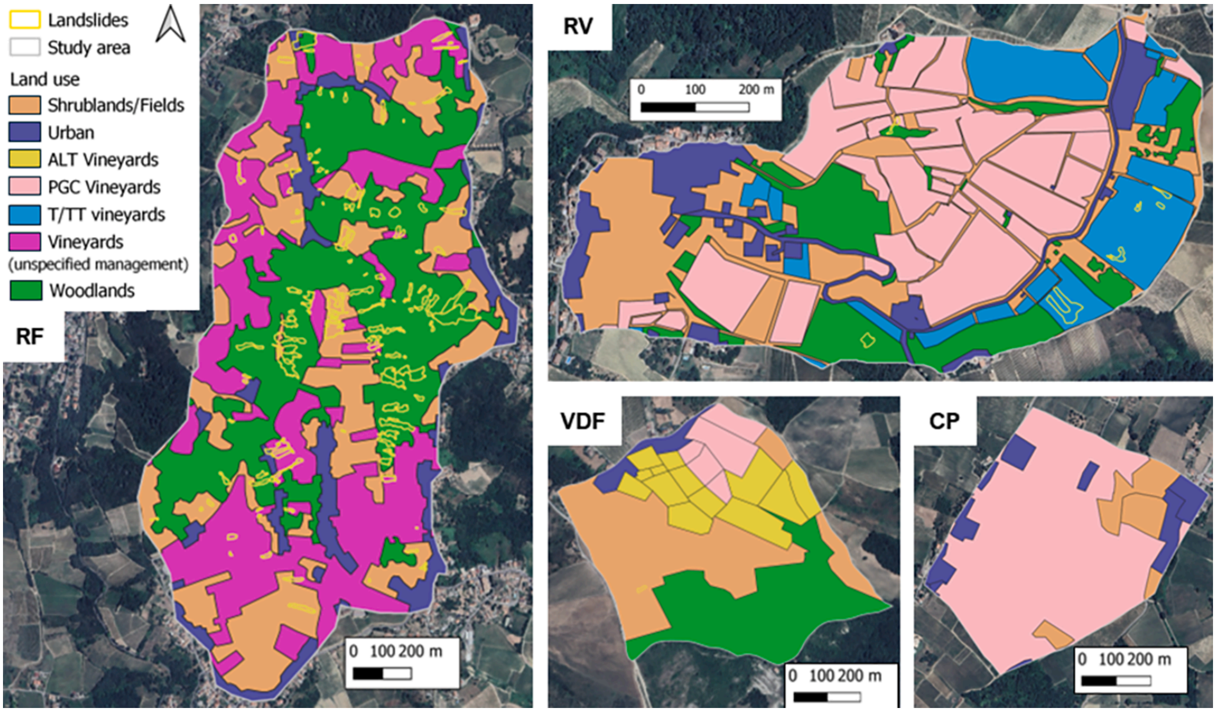

Fig. 3. Land use and the location of past landslides in the 4 test catchments: "CP" refers to the catchment "Cascina Porcarana", "RF" refers to "Rio Frate", "VDF" refers to the catchment "Vigna del Fico" and "RV" to "Rio Vergombera". Abandoned vineyards in the RF catchment are currently classified as "woodlands". Shrublands and sowed fields were grouped within the same class.

Table 1
An overview of the features of the selected test sites, which includes the average slope angle in vineyards, the vineyard management techniques, the soil type and the number of past shallow landslides. The geotechnical characteristics of the RF test site were measured by Zizioli et al. (2013) and are a range instead of an average value and are identified by an asterisk (*).

Site	Area (km^2)	Average Slope Angle in vineyards (°)	Vineyard management	Soil characteristics		Past shallow landslides (nr)
				Average Silt %	Average Clay %	
CP	0.36	8.8	PGC	65.0	33.0	0
RF	1.93	21.0	Unspecified management/abandoned	20.0–59.0*	12.0–27.0*	145
VDF	0.45	11.3	ALT, PGC	68.3	25.6	7
RV	0.54	16.1	ALT, PGC, T/TT	45.2	46.0	1

Table 2
Overview of the differences between the test sites. The thresholds for the slope angle and the clay percentage provided in this table were chosen to best highlight the differences between the catchments and are not based on the impact of those factors on landslide susceptibility.

	Slope angle		Vineyard management		Clay percentage		Past landslides	
Site	<15°	>15°	Lower RC (up to 3.78 kPa)	Higher RC up to 14.07 kPa)	<45 %	>45 %	Yes	No
CP	x			x	x			x
RF		x	x		x		x	
VDF	x			x	x		x	
RV		x	x	x		x	x	

quantity can be neglected within each catchment.

The original output was the elevation change within the DEM or volume of mobilised sediments (in m^3), however due to the lack of measured volumetric data, calibrating the quantity of mobilised sediments would not have been possible, so a binarised output was preferred.

The main output of the implemented model is a probabilistic map of the cells which could lose soils in the occasion of a landslide-triggering event, based on the main predisposing factors of shallow slope instability: it can be approximated as the spatial distribution of potential shallow landslide source areas, representing in this way a susceptibility distribution.

2.3. Input parameters of the model

The adapted model requires the following set of input parameters for each test site: a) DEM, b) lithological map, c) land use map, d) soil depth map, e) the range of distribution of Root Reinforcement and Saturated Hydraulic Conductivity for each land use class, and f) the range of Soil Cohesion, Unit weight and Friction Angle for each class of the lithological map (Tables 3, and 4).

Table 4 shows the range of distribution (minimum and maximum values) for the soil and root input parameters required by the model. Unit weight, soil cohesion and friction angle were measured through undisturbed samples collected in each study area for the shallowest soil layer. As described by Bordoni et al., (2015), the geotechnical characterisation of the deposits was performed according to the guidelines of the ASTM (American Society for Testing and Materials) and it involved an assessment of the physical parameters of the materials (grain size

Table 3
Overview of the input maps.

Map	Resolution	Description	Source
DEM	1X1 m	Acquired with LiDAR technology between 2008 and 2010	Italian Ministry for Environment, Land, and Sea as part of the Extraordinary Environmental Remote Sensing Plan (available on the national Italian geoportal under the tag “Piano Straordinario di Telerilevamento per l’Ambiente”).
Lithological map	1:10000	Lithological map of the area	Meisina et al. 2006
Land use map	1:10000	For RF: DUSAF 2007 land use map	Lombardia & ERSAF, 2010
	–	For CP, VDF and RV: the 2009 land use was reconstructed as part of this work	High resolution orthophotographs, field surveys, and interviews to local landowners
Soil depth map	–	Calculated according to a formula developed originally for the RF and RV test sites and validated in the field	Zizioli et al. 2013

distribution, bulk density, Atterberg limits) and the application of both direct shear testing using Casagrande’s shear box and triaxial tests to calculate the shear strength parameters in terms of the effective stresses (ASTM Committee D-18 on Soil and Rock; 2015).

These ranges have been already adopted for shallow landslide triggering models by different deterministic approaches (Zizioli et al., 2013; Bordoni et al., 2015) or implemented by new measurements of these parameters carried out along the soil profiles, while the saturated hydraulic conductivity ranges were measured for each land use class in the field along the first 0.5 m of soil horizons through a constant head permeameter device (Bordoni et al., 2019). Mechanical root reinforcement ranges of each land use class were derived from measurements carried out by Bordoni et al., (2020a) 0.3 m from ground level, except for the values of woodlands in the RF test site, which were derived from literature. In this site, woodlands are almost entirely comprised of black locust trees (*Robinia pseudoacacia*), whose typical values of root reinforcement were measured at around 4–5 kPa by Zhang et al., (2014).

2.4. Validation methods

Since the goal is to test the ability of the model to identify areas susceptible to the formation of shallow landslides (source areas), the modelled soil depletion areas are compared to the distribution of the source areas of past landslides. The source areas of the landslides were estimated as 25 % of the landslide body through a semi-automatic method implemented by Galve et al., 2015; Galve et al., 2016 which has been adopted previously for this area since it is considered to be a reliable approximation (Bordoni et al., 2020b).

To assess the performance of the proposed model, it was necessary to establish a probability threshold above which a cell is classified as unstable, so for the purpose of the present research, three different cutoffs were tested, namely 50, 60 and 75 %. In literature, landslide susceptibility is considered low to very low for probabilities lower than 40 %, while between 40 to 60 % the susceptibility is considered moderate and probabilities higher than 60 to 70 % range from high to very high (Lin et al., 2017; He et al., 2021).

The validation of the model’s performance was carried out through the use of the AUC (area under the ROC curve; Han et al., 2011; He et al., 2021) and the four-fold plot of the confusion matrix (Fawcett, 2006; He et al., 2021), which were applied to all four test sites simultaneously as the number of landslides occurred in some test sites, namely CP and VDF, was very low.

Lastly, the fourfold plot was employed as a mean to assess the

Table 4
Comparison between measured input values and the value range chosen for modelling, compiled from various sources(a) Bordoni et al., (2019), (b) Bordoni et al., (2020a), (c) Persichillo et al., (2017); (d) Bordoni et al., (2015); (e) Zhang et al., (2014); (f) Zizioli et al.(2013) and (g) parameters measured within the last year as part of the present work. “RC” stands for “Root Cohesion”, “Ksat” stands for “Saturated Conductivity” and the mentioned vineyard management practices “ALT”, “PGC” and “T/TT” are respectively “Alternated tillage”, “Permanent Grass Cover” and “Tillage/Total Tillage”. RF, CP, VDF and RV identify the selected test sites. The column “Nr of tested samples” refers to the number of samples collected and tested to obtain each measurement. The parameter is marked with a “*” when only a mean value was available. For the RF catchment, the geotechnical parameters presented were measured by Zizioli et al., (2013) for the soil located in correspondence of the Rocca Ticozzi Conglomerates, where most landslides occurred.

Parameter		Measured range	LAPSUS-LS input range	Nr of samples tested	Source
RC (kPa)	Shrublands/Fields	0.67–2.58	0.67–2.58	23–56	b
	Vineyards ALT	0.90–14.00	0.90–14.00	23–56	b, g
	Vineyards PGC	3.00–8.12	3.00–8.12	23–56	b, g
	Vineyards T/TT	0.34–3.78	0.34–3.78	23–56	b
	Vineyards (all managements)	0.34–14.07	0.34–14.07	23–56	b, g
	Woodlands	9.30–12.16	9.30–12.16	23–56	b
	Black locust trees	4.00–5.00	4.00–5.00	2	e
Ksat (m/s)	Shrublands/Fields	$1.70 \bullet 10^{-8} - 1.00 \bullet 10^{-5}$	1.70•10-8 – 1.00•10-5	3	a, g
	Vineyards ALT	$1.00 \bullet 10^{-7} - 9.45 \bullet 10^{-7}$	1.00•10-7 – 9.45•10-7	3	a, g
	Vineyards PGC	$6.40 \bullet 10^{-11} - 1.00 \bullet 10^{-7}$	6.40•10-11 – 1.00•10-7	4	a, g
	Vineyards T/TT	$1.00 \bullet 10^{-6}$ m/s $-5.55 \bullet 10^{-6}$	1.00•10-6 m/s –5.55•10-6	3	a, g
	Vineyards (all managements)	$1.00 \bullet 10^{-6}$ m/s $-5.55 \bullet 10^{-}$	1.00•10-6 m/s –5.55•10-	3	a, g
	Woodlands	$6.40 \bullet 10^{-11} - 1.00 \bullet 10^{-5}$	6.40•10-11 – 1.00•10-5	3	a
Soil cohesion (kPa)	RF	1.80*-2.00	1.80–2.00	~ 3	d, f
	CP	1.80–2.50	1.80–2.50	2	g
	VDF	1.85–1.85	1.85–1.85	~3	d, g
	RV	1.80–1.85	1.80–1.85	~ 3	d, g
Friction angle (rad)	RF	0.42*-0.56	0.42–0.56	~ 3	d, f
	CP	0.49–0.57	0.49–0.57	2	g
	VDF	0.45–0.50	0.45–0.50	~3	d, g
	RV	0.45–0.47	0.45–0.47	~ 3	d, g
Unit weight (g/cm^3)	RF	1.52–1.86	1.52–1.86	~ 7	d, f
	CP	1.69–2.02	1.69–2.02	21	g
	VDF	1.33–1.73	1.33–1.73	61	d, g
	RV	1.50–2.02	1.50–2.02	85–91	d, g

accuracy of the prediction. It is a visual representation of the confusion matrix, which displays the four possible outcomes of the model: true positive (TP), true negative (TN), false positive (FP) and false negative (FN) (Fawcett, 2006; He et al., 2021).

2.5. Land use change scenarios

For each test site, both the present conditions were modelled and a land use change scenario was simulated according to the following criteria:

i. Most landslides in the RF catchment have occurred in currently abandoned vineyards. The tested land use change scenario aims to evaluate how slope stability might change, according to LAPSUS-LS, if the spontaneously grown black locust trees, which make up most of the woodland areas in the catchment, were to be eradicated and those areas were to be brought back to their former land use of ALT vineyards.
ii. The CP test site has been stable in the past few decades. The tested scenario investigates whether the landslide susceptibility would change if the current PGC vineyards were to be managed through T.
iii. Similarly, to the CP test site, VDF vineyards have not been experiencing shallow landslides in the past decades and the proposed land use change scenario evaluates if shallow landslide susceptibility would increase if ALT and PGC vineyards were to be changed into T.
iv. The RV catchment has been experiencing soil mobilisation on the northwest-facing sector, where T is the most commonly adopted vineyard management technique. The tested scenario investigates whether choosing ALT as a preferred management technique would improve slope stability in the most landslide-prone areas. Additionally, to test the benefit of including management-specific parameters into the model, it was run for the RV test site using as inputs values a range of Ksat and of RC which includes all management techniques.

3. Results

3.1. Susceptibility maps

This section provides the susceptibility maps which were obtained through the application of LAPSUS-LS using as inputs both the conditions which were present in 2009 (the box labelled as "a" in the upcoming figures) and the proposed land use change scenarios (boxes "b" and "c").

For the RF catchment, the simulation which was carried out using the original April 2009 land use conditions as inputs (Fig. 4a) predicted 52 % of all cells as unstable and of those 36 % would fall under the classification of "very high" susceptibility. The areas which are predicted as unstable are located in correspondence of the steepest slopes, since 24 % of the area is steeper than 30°.

On the other hand, for the land use change scenario, which entailed the reclamation of the abandoned vineyards (where black locust trees currently grow), only 21 % of the total cells were deemed unstable for at least half of the simulations and of those 12 % fall into the > 75 % probability range (Fig. 4b).

In the CP catchment, two simulations were carried out using LAPSUS-LS, the former considering the real land use distribution (Fig. 5a) and the latter a hypothetical scenario of change in vineyard management along the interrow (Fig. 5b). Both did not significantly modify the susceptibility of the area and no shallow landslides were predicted, nor they were ever recorded in this area in the past few decades, and neither simulation had any cells exceed the susceptibility threshold of 25 %.

Similarly, for the VDF test site, both the simulation run with real

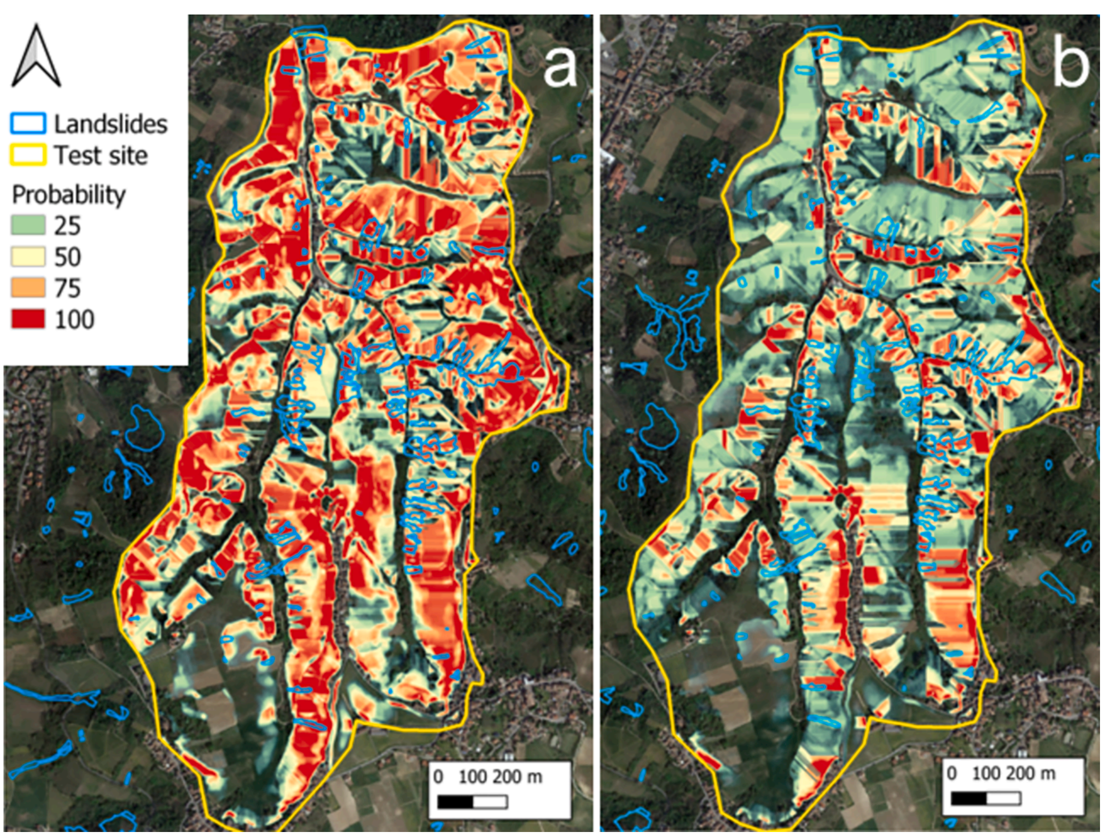

Fig. 4. LAPSUS-LS simulations for RF for real conditions (a) and for a land use change scenario (b).

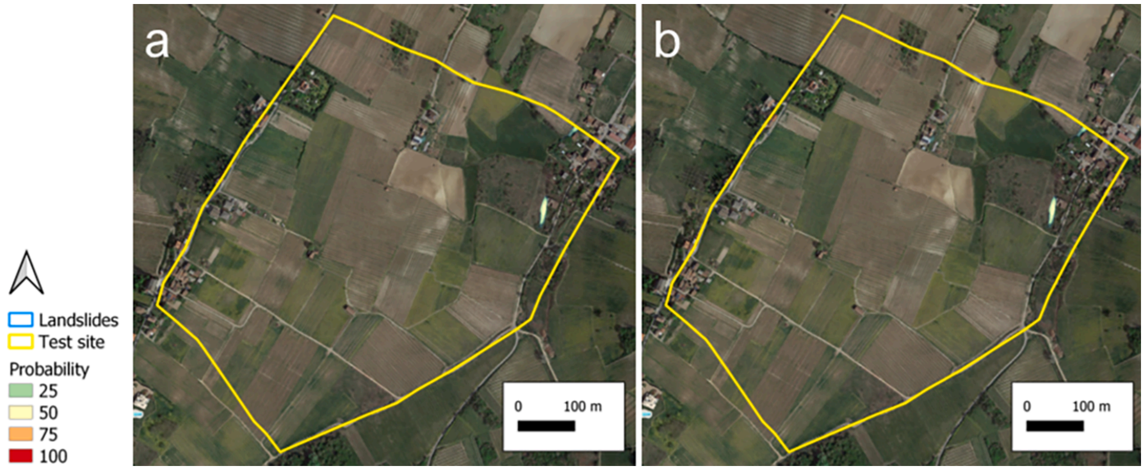

Fig. 5. LAPSUS-LS simulations for CP for real conditions (a) and for a land use change scenario (b).

inputs (Fig. 6a) and the land use change scenario (Fig. 6b), which entailed turning PGC and ALT vineyards into T vineyards, predicted that vineyards in the area would remain stable under this circumstance, meaning that no cells located in vineyards exceeded the 50 % susceptibility threshold. In the area, only the shrublands, where one landslide has occurred in the past, have been predicted as unstable in the southern portion of the catchment.

Fig. 7 shows the probabilistic landslide maps of the RV test site and in the first simulation, obtained using the real 2009 inputs (Fig. 7a), shows most of the unstable cells are located along the SE sector, where the slope angles are steeper (about 25°) and where the vineyards are managed through T and TT, compared to the SW sector where the slope angle is on average 15° and the vineyards are managed through ALT and PGC. For the second simulation, which entailed adopting the ALT management technique for vineyards which are currently managed through T and TT, LAPSUS-predicted a decrease in the number of unstable cells (Table 5; Fig. 7b). The last simulation (Fig. 7c) also adopted the April 2009 input parameters, however the different vineyard management techniques were not taken into account and the result was a significant worsening of the model's performance by failing to identify the majority of unstable cells. (Table 6).

The AUC of the simulation which considers the management technique (Fig. 7a) is 0.86, whereas the AUC of the simulation which does not (Fig. 7c), is of 0.52 and therefore the performance is significantly worse.

The percentage of cells in a stability range regarding each simulation in provided in Table 4, which highlights how the susceptibility changes when running LAPSUS-LS using the current land use, compared to the proposed land use change scenarios. In RF and RV, the general hillslope susceptibility decreased in the proposed scenarios, whereas in CP and VDF it remained unchanged.

3.2. Performance of the models

To assess the performance of the model when simulating the present land use conditions, the area under the ROC curve and the values of the indexes of the confusion matrix (TP, TN, FP, FN) were calculated for each tested instability cutoff (50 %, 60 % and 75 %; Table 5, Fig. 8).

With higher cutoffs, the AUC decreases, as do the TP and FP rates, whereas the TN and FN rates increase. The 50 % cutoff therefore proved best in the identification of unstable cells, with the highest TP and lowest FN rates, identifying 85 % of all unstable cells in the area.

By adopting the 60 % cutoff, the percentage of correctly identified unstable cells decreased to 79 %, while a 75 % cutoff, only identified 67 % of all unstable cells in the areas.

For the RV catchment, removing all management-specific input and using average RC and Ksat values worsened the performance significantly. For the 50 % cutoff, the TP rate went from 0.5 % to 0.02 % while the TN rate went from 68.91 % to 97.48 %. The FN rate increased significantly, from 0.09 % to 0.23 % while the FP rate dropped from 30.5 % to 2.27 %.

4. Discussion

The results of the application of the implemented LAPSUS-LS model seem to be encouraging, since the AUC ranges between 0.77 (50 %

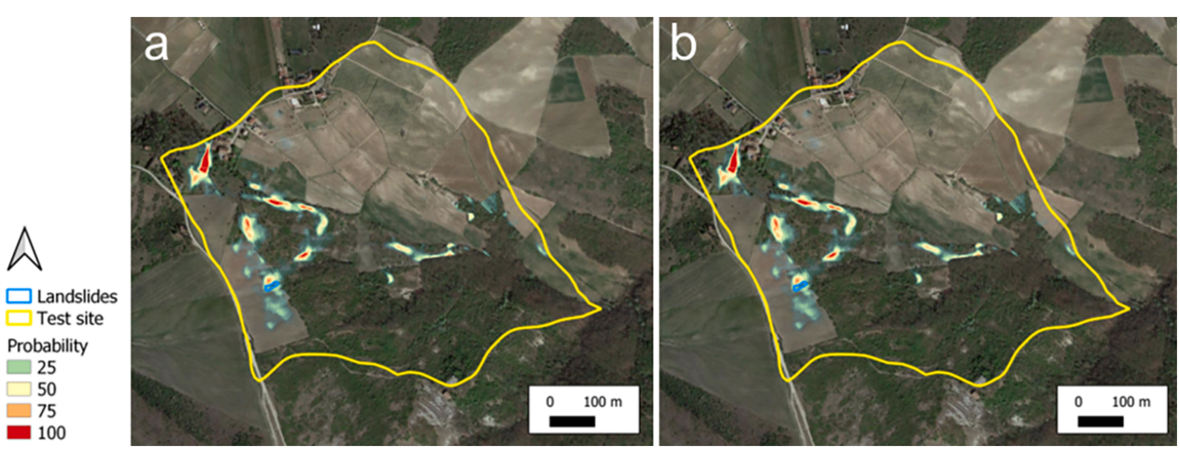

Fig. 6. LAPSUS-LS simulations for VDF for real conditions (a) and for a land use change scenario (rightb).

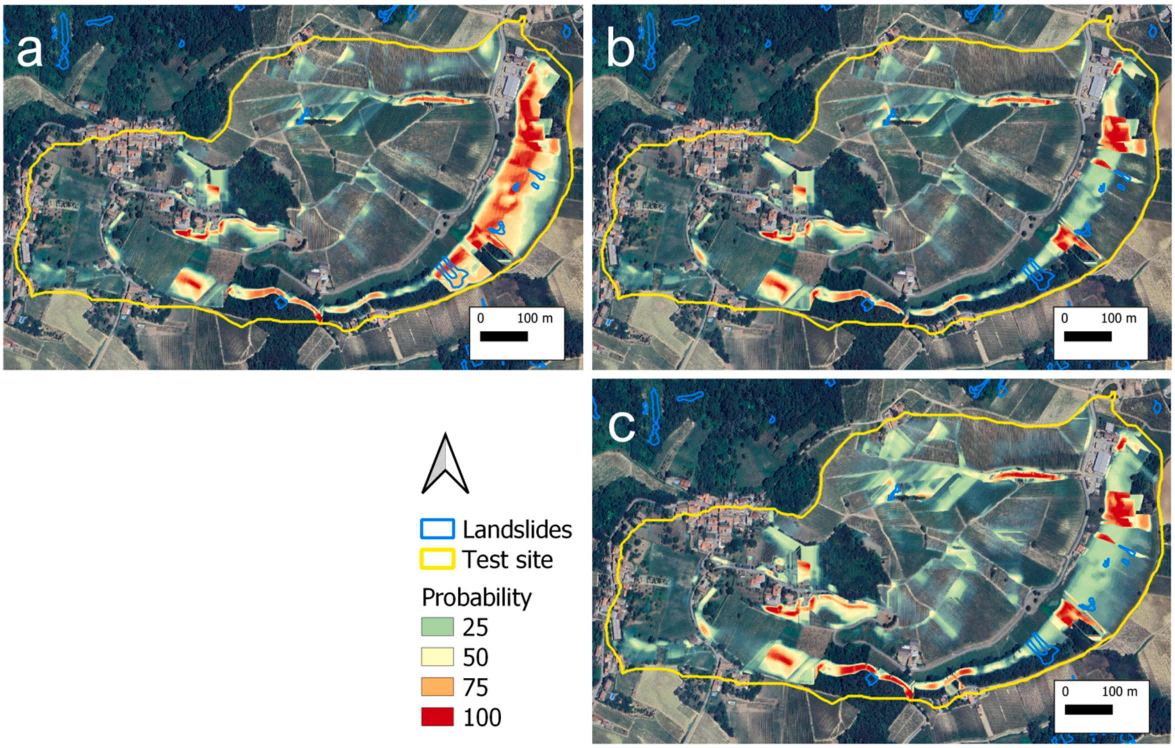

Fig. 7. LAPSUS-LS simulations for RV for real conditions (a), for the land use change scenario (b) and without management-specific inputs (c).

Table 5
Percentage of cells in each stability range.

Simulation	0–25 %	26–50 %	51–75 %	76–100 %
RF – current land use	34 %	14 %	16 %	36 %
RF – scenario	59 %	20 %	9 %	12 %
CP – current land use	100 %	0 %	0 %	0 %
CP – scenario	100 %	0 %	0 %	0 %
VDF – current land use	98 %	1 %	1 %	0 %
VDF – scenario	98 %	1 %	1 %	0 %
RV – current land use	86 %	6 %	4 %	4 %
RV – scenario	91 %	5 %	2 %	2 %
RV – unspecified vineyard management	85 %	10 %	2 %	3 %

Table 6
AUC, TP, TN, FP and FN percentages for the three tested stability cutoffs.

Cutoff	AUC	TP	TN	FP	FN
50 %	0.77	0.5 %	68.5 %	30.9 %	0.1 %
60 %	0.76	0.5 %	72.0 %	27.4 %	0.1 %
75 %	0.73	0.4 %	77.8 %	21.6 %	0.2 %

cutoff) and 0.73 (75 % cutoff), with FN cells being less than 1 % of the total for all simulations. As both the AUC value indicates and the confusion matrix shows, the50%cutoff, meaning that a cell was deemed as unstable if it was calculated as such in at least 50 % of the simulations, guarantees the lowest amount of false negative cells and an overall higher AUC value of 0.77. As expected, the lowest cutoff also results in the highest amount of False Positive cells (about 30.9 % of the total), whereas by selecting as unstable cells those calculated as such at least 75 % of the times, the number of false positives is the lowest overall (21.6 %), but the AUC decreases to 0.73. A cutoff susceptibility of 50 % would fall into what is considered in literature a "moderate susceptibility" (He et al., 2021), whereas cutoffs of 60 and 75 % would align with what is normally classified as a "high" to "very high susceptibility" (Lin et al., 2017; He et al., 2021). A cutoff of 50 % would therefore guarantee the lowest number of unstable cells to be missed (false negatives) and an overall best performance of the model, as testified by the highest AUC value, whereas a higher cutoff (such as 75 %) would be excluding cells which are already considered as high risk. For the sake of protecting those who are potentially at-risk, correctly predicting unstable cells (and therefore obtaining a lower FN rate) is therefore arguably preferable.

The simulations which were carried out, both referring to the present-day conditions and to the land use change scenarios, highlighted the impact of land use and of the land management on slope stability, according to LAPSUS-LS. The results showed that that in some of the catchments higher root cohesions were associated with lower landslide susceptibility rates. This can be observed in both the RF and RV catchments, where the adoption of ALT vineyards in currently abandoned slopes and in T/TT vineyards increased the predicted slope stability. Both model results are supported by literature: Persichillo et al. (2017) observed that in the RF catchment, abandoned cultivated lands, specifically vineyards where natural woodlands grow, are more prone to instability. Similarly, Bordoni et al. 2019; Bordoni et al. 2020a) observed that in the Oltrepò Pavese the probability of failure is lower in PGC and ALT vineyards compared to T and TT vineyards, while Straffelini et al., (2022) noted how vineyards which are tilled frequently are more prone to soil mobilisation, namely land degradation. In the Oltrepò Pavese area, T and TT vineyards are characterised by lower root densities compared to ALT and PGC vineyards (Bordoni et al., 2020), which according to Cohen and Schwarz (2017) is directly correlated with slope stability, with sparce roots systems being linked to higher instability. These findings are also in line with Rossi et al. (2017), according to whom a strong decrease in root cohesion in the original LAPSUS-LS model was associated with increased slope instability.

On the other hand, in CP and VDF, which are the catchments characterised by the lowest average slope angles (<15°), the adoption of different vineyard managements did not impact the overall slope stability. This finding is in line with Bordoni et al. (2020a), who calculated that the failure probability exceeded 50 % for slope angles greater than 17-18° for T and TT vineyards, which rose to 25-33° for PGC and ALT

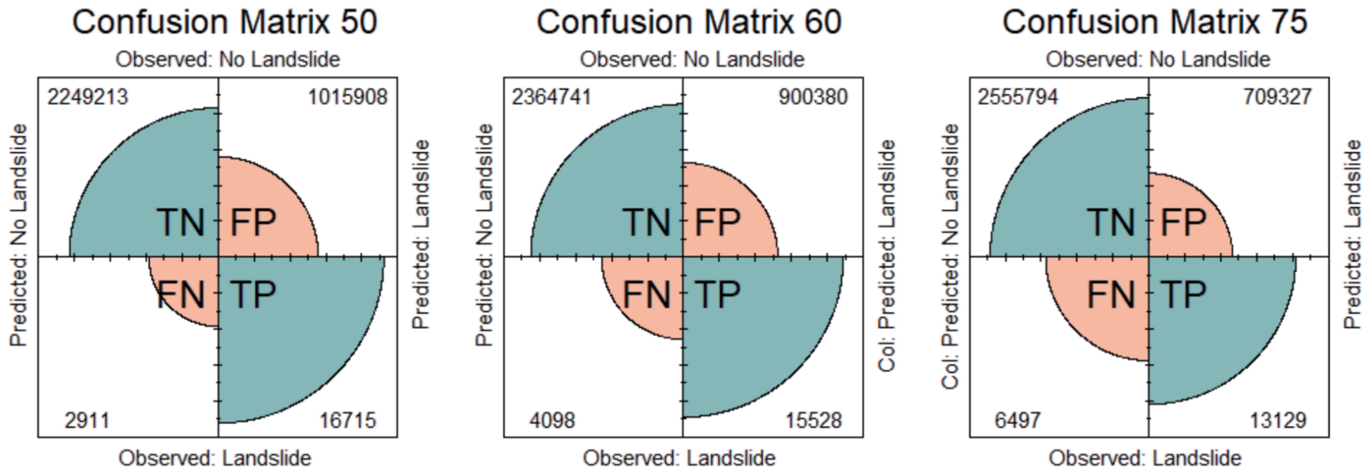

Fig. 8. Fourfold plots for the tested probability cutoffs (from left to right: 50%, 60% and 75%).

vineyards. In this framework, it would be expected that in catchments characterised by lower slope angles, the vineyard management would not appear to affect the landslide susceptibility, according to LAPSUS-LS, while remaining a critical parameter for steeper slopes. However, for steeper slopes, such as those in the RF catchment, where 24 % of the area is characterised by slopes steeper than 30°, the model predicts, in the land use change scenario, that the stabilising action of the roots might be enough to reduce landslide susceptibility considerably.

For the original LAPSUS-LS model, lower values of bulk density were associated with increased sediment displacement caused by increased infiltration. However in all four test sites the distribution in bulk densities is rather similar, making it difficult to evaluate the impact of the geotechnical characteristics of the soil on slope stability. The distribution of the measured bulk densities is lower in the VDF catchment compared to the others, however the slope angles in this test site do not exceed the threshold of 17° identified by Bordoni et al. (2020a) which would make landslide triggering more likely.

Additionally, the simulations proved that the adapted model benefitted from the inclusion of management-specific input parameters, which in the RV catchment resulted in a more accurate mapping of past landslides. Mao et al. (2014) similarly proved, through the application of the model Ecosfix 1.0, that the root distribution is especially impactful of slope stability and that taking into account more complex inputs related to the land use can prove beneficial. Zizioli et al., (2013) applied different physically based models (SINMAP: Tarboton, 1997; Pack et al, 1999; SHALSTAB: Montgomery and Dietrich, 1994; TRIGRS: Baum et al., 2008; SLIP: Montrasio, 2000) to calculate the landslide susceptibility in a study area located in the Oltrepò pavese which includes both the RF and RV catchments. They observed that the success rate for all models was similar: for all landslide types, SINMAP had an AUC of 0.7965, SHALSTAB had an AUC of 0.7846, TRIGRS an AUC of 0.7943 and SLIP and AUC of 0.7852, which is in line with the findings of this work (AUC of 0.77 for the 50 % cutoff). The models' performances however improved when removing the shallow landslides occurring in correspondence of road slopes (about 80 % accuracy with a 20 to 30 % false positive rate), which are however not present in the test sites chosen for this work. Zizioli et al., (2013) identified that the maximum False positive rates were predicted for a) the steepest slopes, b) the south-facing slopes and c) the areas in which high root cohesion rates contribute to slope stability in reality, but are not accurately taken into account in the models. While the first observation is true for the implemented LAPSUS-LS model, the other two are not. On the contrary, LAPSUS-LS predicted different slope susceptibility rates for similar slope angles based on the different root cohesions, which can be observed in both the RF and RV catchments, where it was possible to reduce the probability of occurrence of landslides by changing the land management in the different land management change scenarios.The model still has some limitations, which were true for the original model structure: it cannot directly take into account the hourly precipitation rates which have triggered the landslide event (Guo et al., 2023), which does not allow for the effect of different management techniques on the hydrogeological behaviour of the slope to be studied in detail. Compared to the original model structure, the adapted model presented here also no longer offers a quantitative estimation of the displaced material; it now produces a probability map instead and the new structure requires as input a soil depth map, which might be difficult to produce or unreliable if calculated.

However, both the importance of the land use as a spatially distributed input and the possibility of taking into account the natural range of each input parameter through a probabilistic framework could make the adapted LAPSUS-LS model an effective, non-invasive tools in reducing shallow slope instabilities. It can be used to assess the feasibility of the adoption of non-invasive stabilisation techniques, such the adoption of management techniques which have been linked to lower landslide frequency, to reduce slope instability and consequently the loss of revenue, without modifying landscapes, environment and economic features of an area (Gariano et al., 2018). The model can also be adapted for different test sites by changing all of the acceptable input value ranges and the instability cutoff percentages based on needs, making it highly exportable.

5. Conclusions

In this study we adapted the existing physically based landslide model LAPSUS-LS to adopt a probabilistic approach, which strongly relies on the land use as a variable to predict the landslide susceptibility. The implementation of a probabilistic framework also allows the model to = take into account the spatial variability of all input parameters, namely the soil depth, the root cohesion, the geotechnical parameters and the DEM-derived features. The modelling of both present-day conditions and land use change scenarios have predicted that the land uses and vineyard managements with lower root cohesion (T and TT vineyards, shrublands and abandoned vineyards) are more prone to the formation of shallow landslides. The impact of the land use and land management seemed however to be limited for catchments characterised by average slope angles lower than 15°. In addition, these results highlighted the importance of taking into account the vineyard management techniques when modelling the susceptibility to the formation of shallow landslides.

The new implementation of LAPSUS-LS can predict present-day conditions with an AUC which ranged between 0.73 and 0.77, with False Negative cells always being < 1 % of the total in all simulations.

Although it must be noted that the model cannot take into account the precipitation rate directly, it can be used to investigate different land use and land management techniques, allowing the user to both simulate present conditions and to make land use and management change scenarios.

Proving the beneficial effects of vineyard management change on the slope stability of a risk area would mean providing the population with a non-invasive stabilisation technique to reduce soil mobilisation and reduce revenue loss. Additionally, the model can be adapted and exported to any existing land use, because each land use class is associated with a value range assigned by the user.

In the future, a user interface will be built within the framework of the LAPSUS 7.0 model to make the implemented model freely available to users worldwide (see https://www.lapsusmodel.nl).

CRediT authorship contribution statement

A. Giarola: Writing – original draft, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **J.M. Schoorl:** Writing – review & editing, Software, Methodology, Data curation. **J.E.M Baartman:** Writing – review & editing, Software, Methodology, Data curation. **M. Bordoni:** Writing – review & editing, Validation, Supervision, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **P. Tarolli:** Writing – review & editing, Supervision. **F. Zucca:** Writing – review & editing, Supervision. **T. Heckmann:** Writing – review & editing, Software. **C. Meisina:** Writing – review & editing, Supervision, Project administration, Methodology, Funding acquisition, Conceptualization.

Declaration of competing interest

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

Data will be made available on request.

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Data availability.

The original LAPSUS-LS model's source code is available at www.lapsusmodel.nl and the software will soon be available in version 7.0 of LAPSUS.

For further information regarding the version of the model developed as part of this project, please contact the authors.

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