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A Regional 100 m Soil Grid-Based Geographic Decision Support System to Support the Planning of New Sustainable Vineyards

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Abstract: A WebGis tool called GoProsit has been developed to support winegrowers in planning a new sustainable vineyard and in the identification of high-quality terroir in Tuscany, Central Italy, by providing various information on soils, climate, hydrological risks, and fertilization. GoProsit, hosted by the web platform GEAPP, is a free, user-friendly, and interactive Geographic Decision Support System (GDSS). Soil data behind the WebGis tool has a 1 ha resolution, achieved by processing the legacy vector-type soil database of the Tuscany Region with the DSMART (Disaggregation and Harmonization of Soil Map Units Through Resampled Classification Trees as supervised classification) algorithm, which disaggregated the map to 297,023 vineyard grid cells. Each grid cell holds climatic and pedologic information, along with physical and chemical features for each horizon of the most probable soil. GoProsit also provides soil maps in image format obtained by georeferencing about 50 historical soil maps (1969–2012). Finally, GoProsit runs and returns the outputs of six models: (a) carbon footprint, (b) potential erosion and maximum vine row length compatible with tolerable erosion, (c) potential water stress, (d) risk of runoff/waterlogging, (e) identification of suitable rootstocks, and (f) nutritional needs before planting. Statistics of the main model results for the investigated area are reported. This promising tool will soon be usable for the whole Italian territory; however, its potential makes it suitable for use in any wine-growing district.

Keywords: new vine plantation; vineyard soil management; digital soil mapping; spatial DSS; agricultural modeling

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1. Introduction

The impact of viticulture on the environment is generally high as morphology, hydrology, and soil characteristics are often modified to enable profitable vine cultivation [1,2]. Besides that, viticultural areas are often located in hilly locations prone to soil erosion [3,4]. Proper soil management, when designing new vineyards and during their whole lifetime, is crucial to guarantee that viticulture is environmentally sustainable, of high quality, and terroir-related [5]. In fact, understanding the distribution and the characteristics of soils could improve terroir acknowledgment.

Viticulture in Tuscany, Central Italy, represents about 8% of the Utilized Agricultural Area but produces about 30% of the regional agricultural income [6]. Many Tuscan wineries expressed the wish to better know the distribution and characteristics of their soils as a base to determine the most appropriate management practices for both the environment and the wine quality (personal communication). The negative impacts of climate change, with more frequent heavy rainfalls and long-lasting drought periods [7], have contributed to increasing the need for winemakers to know soil characteristics. So far, the soil maps and terroir mapping produced by a few Tuscan wine growers are sometimes difficult to overlap with other agricultural and environmental information. Projection studies indicate that 23% of Italian farms are adopting or intend to adopt Agriculture 4.0 technologies by 2024 [8]. Agriculture 4.0 is an extension of the "precision agriculture" concept and refers to the ability to implement well-targeted and efficient tools and strategies aiming at improving the yield and sustainability of agricultural activity and the environmental impact of the entire agrifood chain [9].

In this framework, we developed the GoProsit for Agriculture 4.0 program, an online, freely accessible, and easy-to-use Geographic Decision Support System (GDSS) combining spatial and non-spatial data, based on Geographic Information Systems (GIS) functions. The GDSS has been designed to transfer knowledge and provide operational support to winery companies and decision makers involved in the management of vineyard landscapes at different levels. The scope of this article is the description of the GDSS rationale and functioning, as well as the elaboration of the results provided by the GDSS, as an assessment pattern that can be further applied to any wine district.

To support the sustainable planning of new vineyards, GoProsit brings together data and knowledge from different areas (pedology, hydrology, climate, geomorphology, Life Cycle Assessment, agronomy, modeling, etc.), with a special focus on soil. GoProsit is hosted by the web platform http://www.geapp.net/ [10] and has been applied to 297,023 grid cells. Each grid cell is equivalent to raster pixels with a resolution of 100 × 100 m (1 ha). Over the years, several DSS or DST (Decision Support Tools) have been developed for farmers and many specifically for winegrowers [11,12]. Some of these are specialized in plant health risks, others in irrigation and treatment planning, and, more recently, in assessing and optimizing soil functions [13]. In our view, there was a need to implement a new platform to suggest proper soil management to winegrowers, especially during new plantations, based on multidisciplinary scientific georeferenced information.

2. Materials and Methods

A 100 m grid was obtained for Tuscany (Figure 1) based on the 1 km INSPIRE grid (Version: 1.2, 2021) [14]. Each 100 m nodes were uniquely identified following the official INSPIRE-compliant identification system; about 2,100,000 grid cells were obtained for the whole of Tuscany, and 297,023 grid cells were selected for vineyards with a 150 m buffer, based on the vineyards map made by the Regional Agency for the Agricultural Payments (ARTEA) in 2020 [15].

GeoPackage [16] was chosen as a database container because of several benefits, including that it is an open, standards-based, platform-independent, portable, self-describing, compact format, without limitation on file size for transferring geospatial information.

2.1. Climatic Data

The monthly average, minimum, and maximum precipitation and temperature were assigned to each grid node from the national METEOGRID climatic dataset with a 30 km resolution [17]. According to the World Meteorological Organization (WMO), which defines the "normal standard climates" as the average of climatic variables calculated for a uniform period of 3 consecutive decades, the selected climate reference period was 1981–2010.

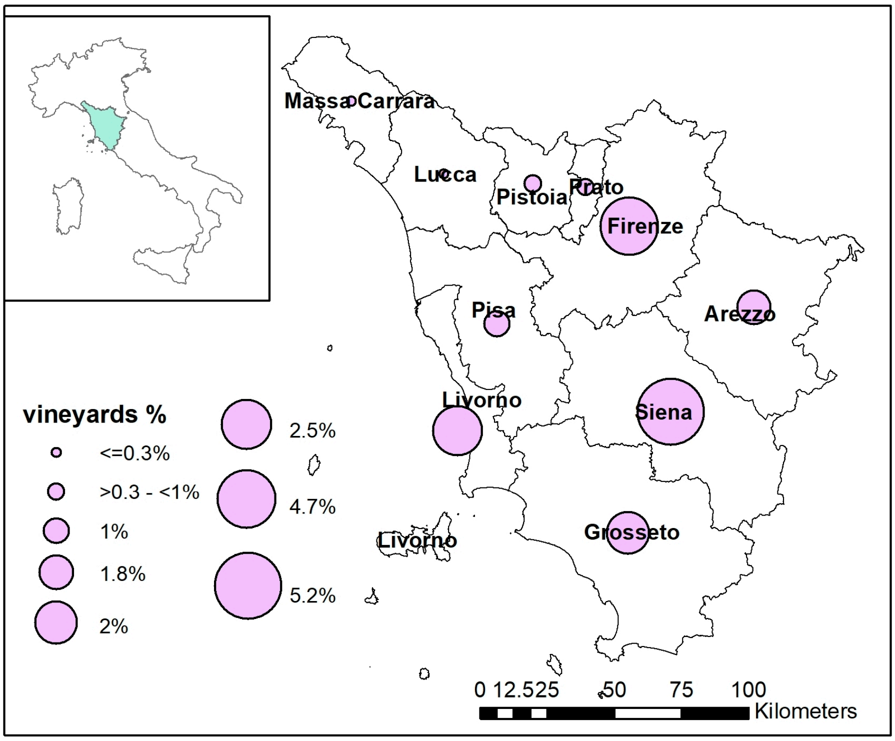

Figure 1. Vineyard saturation in the study area: the Tuscany Region divided into administrative provinces. The graduated symbol varies in size according to the percentage of vineyards within each province. The green part in the upper left the location of the Tuscan region within the Italian territory.

2.2. Downscaling of Tuscany Legacy Soil Database

In Tuscany, soils are described in a regional geographic database that is available online on the Geoscopio portal [18] and the corresponding soil legacy maps which are constantly updated by the Lamma Consortium (Environmental Modelling and Monitoring Laboratory for Sustainable Development). It consists of alphanumeric and geographical archives connected by key fields and contains information about (i) site description: soil qualities, vertical subdivision in master horizons, and related analyses; (ii) area: map units (MU) and pedo-landscapes at various scales; and (iii) data estimated from statistics or expertise: soil typological subunit (STS) and taxonomic classification [19]. The regional database identifies soils within soil map units, each containing one to several soil types called soil type units (STUs), and then splits the STUs up into more pragmatic STSs.

The disaggregation of legacy soil maps is a current and great challenge in the field of digital soil mapping (DSM), hence, the need to increase the spatial resolution of the Tuscany soil map (downscaling) allocating unique soil classes and their attributes. DSMART (Disaggregation and Harmonization of Soil Map Units Through Resampled Classification Trees as supervised classification) is an algorithm based on data mining that was used for the spatial distribution of soil classes to disaggregate multi-component soil polygon map units into raster class maps and their associated probabilities [20]. DSMART follows the SCORPAN approach formalized in [21], which represents a spatial association between soil forming factors, soil classes or attributes (S), climate (C), organisms (O), relief (R), parent material (P), age (A), and space (N) as a raster stack of covariates, and the occurrence of soil classes or continue soil properties. Soil profiles inherit the covariate values and are used as soil truth sample points in part for supervised classification and in part for accuracy measurement. A subset of 3790 soil profiles was used as ground truth sample points for supervised classification and 421 soil profiles, which was equal to 10% of the whole dataset, as testing data. DSMART was used to predict the most probable STS per pixel and create an explicit model for each STS. According to INSPIRE Data Specification on Soil [22], STS definitions are closely linked to the “derived soil profiles” object class. They are statistical representations of the properties of the soil profiles belonging to STS [23], obtained by calculating the average, standard deviation, range, sample size, and modal value for categorical soil attributes. The statistics of in-depth soil properties were calculated for the "master genetic horizons" (A, B, C, R) of each STS. All of this retains the original soil profile descriptions, so long as pedologists assign genetic horizon code, horizon depth, and thickness during the survey. Running the DSMART v.1.03 R package [24] requires the following main steps:

(1) Use soil profile (training set) and intersected covariate values to build a decision tree to predict the spatial distribution of soil classes or STSs.
(2) Extraction of the subset from the soil database corresponding to the land cover class "agriculture" (farmland STS).
(3) For the sake of simplicity, the most probable STS is assigned at each grid cell (see Figure 2 for more details).

Due to memory allocation issues in the R environment, the elaboration was split into 6 parts, as many as the number of different soil regions in Tuscany. The soil region represents a pedo-landscape unit, scaled at 1:5,000,000; it is the first informative level for the soil map of Italy and, at the same time, is the tool for soil correlation at the continental level [23]. The nodes of the reference grid inherit all the STS statistics.

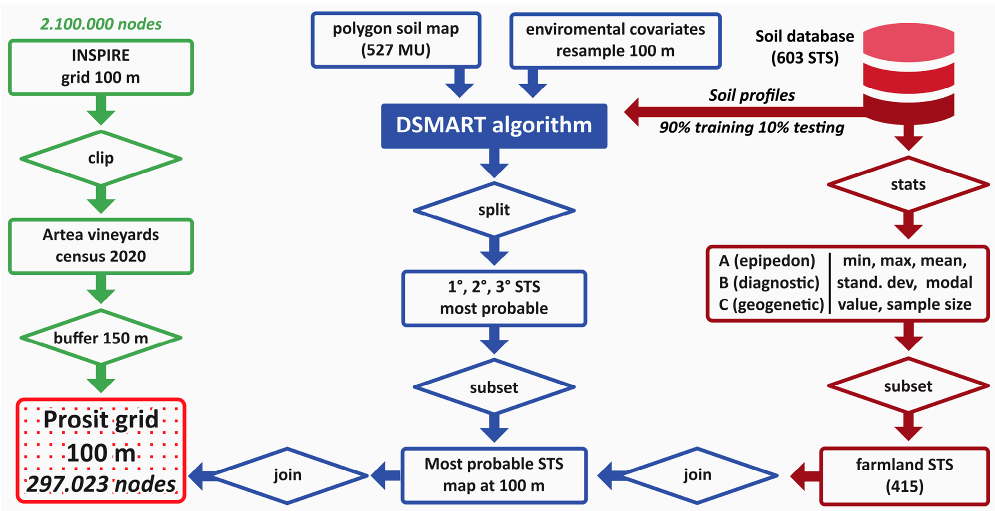

Figure 2. Detailed operational flow of the procedure adopted for downscaling the legacy soil map of the Tuscany Region.

2.3. Digitalization of Existing Paper Maps

The digitalization of 50 already existing paper maps was aimed at harmonizing, preserving, and valuing soil and zoning maps produced in Tuscany over the years. The paper maps were surveyed at various scales, ranging from a maximum detail of 1:3000 to the provincial scale of 1:100,000, and dated from 1969 to 2012. Despite notable differences in quality and intended usage, the digitization of this collection of maps will enable their dissemination and preservation as open data (FAIR—findable, accessible, interoperable, and reusable) [25]. The digitalization was performed by georeferencing the maps using the QGIS software (EPSG: 4326 WGS 84), following the methodologies described in "Mastering QGIS. Packt Publishing Ltd., Birmingham, UK" [26] and the map design techniques from "QGIS Map Design" [27]. Useful information shown in the maps' legend was retrieved in CSV format. Later, maps were incorporated into the WebGis section of the GoProsit digital platform through direct uploading to the Geoserver (Figure 3).

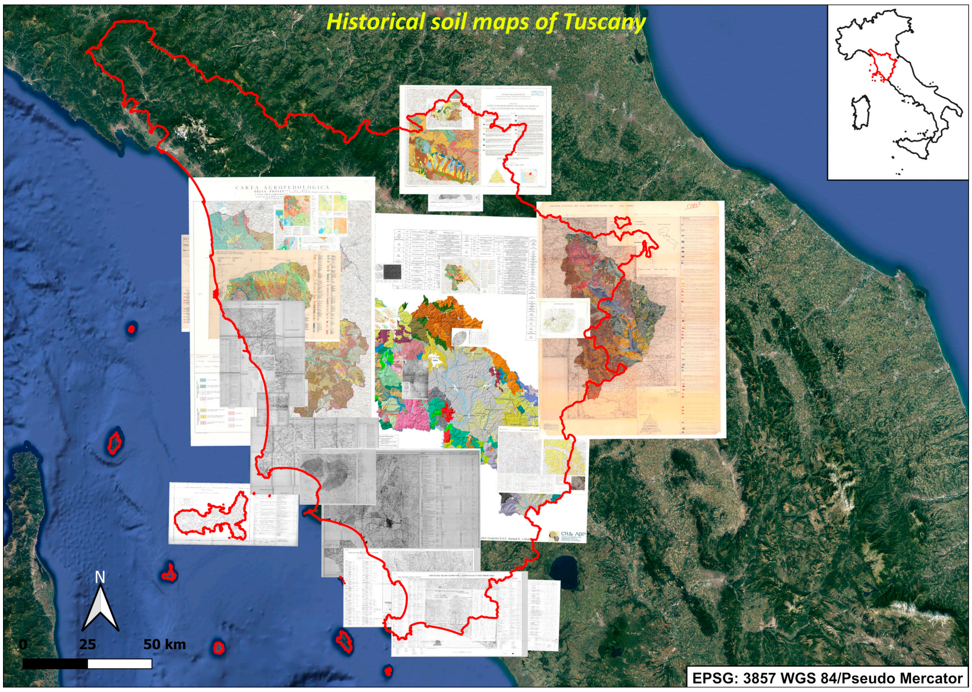

Figure 3. Visualization of the restoration process of historical pedological maps using QGIS software.

2.4. List of Models

The complete list of models used in the GoProsit GDSS is reported in this section; for each of these, the purposes, input variables, and their current availability in the soil database, as well as the intermediate and final outputs, any complementarity with other GDSS models and the bibliography are described. Soil chemical and physical properties are referred to the whole soil profile up to the rooting depth. To calibrate, parameterize and validate the models, three demonstration areas, located in highly representative environments of viticulture in Tuscany, were monitored for three years (summer 2019–summer 2022): (i) the Petra farm located in Suvereto (LI) (lat: 43.033, long: 10.710), 8 ha, 40 m a.s.l., characterized by Luvisols and Cambisols, moderate to gentle slopes, on ancient alluvial deposits, cultivated with Merlot grape variety; (ii) the Montefioralle farm, located in Greve in Chianti (FI) (lat: 43.580, long: 11.301), 6 ha, 380 m. a.s.l., characterized by Cambisols, moderately steep slopes, on Arenite, cultivated with Sangiovese grape variety; and (iii) the Castello di Verrazzano farm (lat: 43.601, long: 11.287), 6 ha, 320 m. a.s.l., characterized by Cambisols and Regosols, steep slopes, on marly limestone flysch, cultivated with Sangiovese grape variety.

2.4.1. New Vineyard Plant Carbon Footprint (by LCA)

In the framework of GoProsit, the environmental impact of a new vineyard plant has been quantified through a Life Cycle Assessment (LCA) [28]. The methodology for running an LCA analysis in viticulture is detailed, at the European level, in a dedicated Product Environmental Footprint Category Rule (PEFCR) [29]. The LCA method allows the use of different categories of environmental impact, including the Carbon Footprint (CF), which is the estimate of greenhouse gas emissions (GHGs) associated with the production of a good or service, and thus its contribution to global warming. The GHGs that the analysis of agricultural supply chains focuses on are carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (N_2O). Each of these gases has a different Global Warming Potential (GWP), based on which CF results are normalized and expressed in units of CO_2 equivalent (CO_2e). In the CF model presented here, the time horizon is 20 years [30] and the functional unit is the hectare (CO_2e ha^{-1}), meaning that GHG emissions deriving from the establishment of a new vineyard on 1 hectare of land are estimated by considering the GWP of GHGs over

20 years. The processes included in the CF evaluation are as follows: (i) soil excavation, (ii) stripping (removal of surface soil rich in organic matter and its redistribution once the soil has been leveled), (iii) drainage, (iv) leveling, (v) basal fertilization (the pre-planting fertilization), (vi) sowing of green manure before the plantation of the grafted rootstocks, and (vii) soil preparation and planting of the grafted rootstocks. The inputs considered are as follows: (i) diesel used by earthmoving and agricultural machinery, (ii) fertilizers, (iii) green manure seeds, (iv) green manure biomass, (v) grafted rootstocks, and (vi) loss of Soil Organic Carbon (SOC), assuming that a percentage of the carbon contained in the soil is released to the atmosphere during the preparation of the new planting. The flows of these inputs per hectare have been measured in the demonstration area of the Castello di Verrazzano farm. Diesel consumption for earthmoving and leveling works has also been measured in 7 other new vineyard plants in Tuscany located in hilly areas with lower slopes, compared to the Castello di Verrazzano area (slope 26.4%), and in lowland areas (slope < 3.6%). Based on these data, the relationship between diesel fuel consumption and the slope was parameterized, and, subsequently, diesel consumption was estimated in each node of the GoProsit grid based on the average slope (%) described by the GDSS. Diesel consumption of agricultural machinery and green manure seeds were also assessed in the other two demonstration areas (Petra and Montefioralle farms). Finally, the SOC loss observed in the Castello di Verrazzano farm by measuring SOC content before and after the earthmoving and leveling works (4 georeferred soil sampling points and 7 soil profiles) has been compared with studies in the literature [31,32] in hilly regions with lower slopes, and in flat areas ($\leq$3.6%). A linear regression model was applied to estimate the SOC loss when the slope was between 3.6 and 26.4%. The inputs of basal fertilizers were calculated by the model "soil chemical–physical properties as a basis for pre-planting fertilization" (Section 2.4.4), assuming that nutrients supply was carried out by organic fertilizers (compost, digestate, manure, etc.), a common practice in Tuscany vineyards. Flows were converted into CO_2e through specific emission factors (EFs) selected on three LCA databases (Biograce 4d 2023, Agribalyse 3.0.1. and Ecoinvent 3.6). The direct and indirect N_2O soil emissions associated with nitrogen fertilizers and green manure inputs were estimated following the IPCC methodology [30,33]. The CF values obtained with the methodology described above were then corrected by estimating the Soil Organic Carbon (SOC) dynamics, since carbon sequestration or loss from soils affected substantially the CF assessment in agriculture [34,35]. Overall, the CF assessment for the planting of a new vineyard provided a CO_2e ha^{-1} value associated with each node of the GoProsit GDSS. Starting from CF results calculated upon median input parameters, a sensitivity analysis [36] was conducted to evaluate the impact of each input parameter on the CF output and to identify the most impactful ones. The sensitivity analysis was performed by changing the median input parameters by 25% and observing the % change in the output value.

2.4.2. Hydrological and Physical Models

Within the "hydrological and physical models" menu, soil degradation risks related to runoff, water stagnation water stress, and potential erosion are estimated.

Water Stress Risk in the Pre-Planting Phase

The estimation of the risk of water stress in the pre-planting stage aims to prevent conditions of water suffering in the vineyard due to errors made in the design phase. To correctly assess the risk of water stress, it is necessary to consider not only the climate but also other crucial factors, such as soil moisture, vineyard management, and the phenological phase of the vine [37,38]). It is worth bearing in mind that the susceptibility of the vine to water stress varies among the phenological phases; therefore, soil moisture values identifying vine stress tolerance thresholds may be different [39]. For this reason, the model does not just develop a monthly water balance according to Thornthwaite–Mather (T-M) [40], but considers the specific water needs of the vine, evaluating them as a function of the phenological phase in agreement with what was reported by Gaiotti [41]. Starting from the Thornthwaite–Mather balance spreadsheet developed by Armiraglio [42], some improvements were made; in particular, field capacity (FC) and wilting point (WP) have been computed by implementing the Saxton and Rawls equations [43], and the crop coefficient of the vine has been implemented to calculate the actual monthly evapotranspiration. Provided that the model had to simulate the water needs of young plants, the rooting depth was set to 30 cm only. Then, the soil water content referred to this depth interval was converted into soil water potential value (SWP), expressed as MPa, and compared, month by month, to the young plant water stress tolerance thresholds, expressed in MPa, as well. In particular, the tolerance of young plants is always scarce along its annual cycle (SWP $\leq$ 0.2 MPa), except for the shoot lignification phase, where the vine tolerates SWP values up to 0.4 MPa. The result of the comparison provides the effective monthly stress risk expressed in class, as illustrated in Table 1.

Table 1. Intersection between soil water potential values (MPa) and vine water stress tolerance. The monthly vine stress classes are hereafter listed and defined: VH = Very high; H = High; M = Moderate and N = Negligible.

Soil Water Potential (MPa)	Vine Water Stress Tolerance (MPa)	
	August–October 0.2–0.4	**April–July; November <0.2**
>0.6	VH	VH
0.6–0.4	H	VH
0.4–0.2	M	H
<0.2	N	N

Successively, the final output of the model, i.e., the estimate of the annual water stress risk, expressed in classes (Very high, High, Moderate, and Negligible), is determined according to the frequency with which each monthly risk class occurs between April and November.

Erosion Susceptibility by RUSLE Model and Identification of the Maximum Vine Row Length

The estimation of erosion susceptibility in the pre-planting phase is aimed at preventing high soil loss and the triggering of instability phenomena caused by design errors in the new vineyard. Adverse climatic conditions, combined with erodible soils, can cause high soil erosion rates even on gentle slopes, well above the tolerable threshold if vineyard rows are too long [44]. The assessment of the long-term average annual soil erosion in the pre-planting phase was carried out by the well-known RUSLE (Revised Universal Soil Loss Equation) model [45]:

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

where A = soil loss (t ha^{-1} yr^{-1}), R = rain erosivity (MJ mm ha^{-1} h^{-1} yr^{-1}), K = soil erodibility (t ha h ha^{-1} MJ^{-1} mm^{-1}), LS = slope length factor (dimensionless), C = cover-management factor (dimensionless), and P = support practice factor (dimensionless). To estimate the R factor from the national climatic database, the procedure of Diodato and Bellocchi [46] was adopted, as it was able to describe the intra-annual climatic variability, which was more suitable for overlapping the crop calendar of the different cultivated species. K was calculated by the Renard equation [45], which requires the % values of sand, silt, and clay of the surface horizon only. The topographic LS factor was determined in a GIS environment and calculated for each node, starting from the slope (%) value and assuming an average length of the vineyard of 100 m. As regards the calculation of the C factor, it was assumed that the soil was tilled and that there was no vegetation cover. Therefore, a C value of 0.185 was chosen, as suggested by Napoli et al. [47], for cultivated vineyards. Furthermore, since the typical cultivation direction was along the maximum slope, the

P factor should assume the maximum value (1) to indicate the absence of conservation practices. However, a value of 0.8 was chosen, assuming that the new vineyards were equipped with drainage systems. The result of the soil loss model was assessed for each node of the grid and divided into 4 classes: Low, Moderate, High, and Very high for a value lower than 11.2 t ha^{-1} y^{-1}, between 11.2 and 20, 20 and 50, and over 50, respectively. The calculation of maximum row length (L_{max}) was calculated in all the nodes of the GoProsit soil grid, replacing A with the value of 20 t ha^{-1} yr^{-1}, the upper limit of the Moderate class and making L_{max} explicit in the RUSLE formula:

$$L_{max} = \frac{R * K * S * C * P}{A} \tag{2}$$

where L_{max}, on sloping surfaces, has been set between 50 and 100 m to limit downtime during mechanized operations and, at the same time, respect the guidelines of current legislation [48].

Susceptibility to Waterlogging and Surface Runoff: Useful Information to Guide the Hydrological Design of a New Vineyard

The estimation of soil susceptibility to water stagnation and/or surface runoff in the pre-planting phase aims to provide indications of the land set-up systems necessary to prevent possible irreversible damage to future vineyard production. To assess the susceptibility of the soil to trigger surface runoff and stagnation phenomena, the modified T-M water balance has been integrated by implementing the well-known SCS-CN hydrological model [49]. This was necessary to separate the water surplus into two components: surface runoff and deep drainage (seepage). The variables required to run the model include monthly long-term temperature and precipitation values, latitude, exposure and elevation of the site, soil information such as texture (% weight of sand, silt, and clay), soil depth (m) (depth to the rock or to the impervious horizon with respect to water flows), and the contents in coarse fragments (% vol.). In addition, it is assumed that in the pre-planting phase, the soil is bare, and recently tilled; therefore, the curve number value was associated with the use of the soil coded as "vineyards with inter-row tilled". The model computes the runoff coefficient (RC) value, defined as the ratio between the total average annual runoff and the respective annual meteoric precipitation. A logical intersection between the RC values and the site slope (%), both converted into classes, returns the estimation of the level of risk, differentiated in runoff or waterlogging in relation to the vineyard steepness (Table 2).

Table 2. Intersection between runoff coefficient (RC) and site slope classes to provide runoff and waterlogging risk classes, hereafter listed and described as follows: "N" = Negligible for both runoff and waterlogging phenomena, "M(S)" = Moderate waterlogging, "M(R)" = Moderate runoff, "H(S)" = High waterlogging and "H(R)" = High runoff.

Site Slope (%)	**RC Class**		
	High	**Moderate**	**Negligible**
<5	H(S)	M(S)	M(S)
5–10	M(S)	M(S)	N
10–20	M(R)	M(S)	N
20–35	H(R)	M(S)	N
35–45	H(R)	H(R)	M(R)
>45	H(R)	H(R)	H(R)

2.4.3. Identification of Most Suitable Rootstocks

The choice of rootstock is crucial when planning a new vineyard. The primary function of the rootstock is to protect the vines from soilborne pests, and this should be the first aspect to be considered when selecting the rootstock. Almost all the commercially available rootstocks are resistant to Phylloxera (*Daktulosphaira vitifolia*), while the same is not true for pathogens such as nematodes. Furthermore, the rootstock allows us to modulate the vegetative–productive response of the vine on the basis of soil characteristics, compatibility with the cultivar, and oenological objectives [50,51]. Starting from a set of 15 rootstocks, (K5BB, SO4, 420A, 1103P, 110R, 140Ru, 101.14, 196.17, Gravesac, 41B, Fercal, M1, M2, M3, M4) were identified among the most used ones, the application allows us to exclude the rootstocks considered unsuitable because of the pedoclimatic characteristics of the site. The characteristics or properties considered can be found directly in the database or be derived, and concern fertility class, total limestone, salinity, acidity, risk of water stress, and waterlogging. The soil assessments inherent in the chemical and physical soil properties refer to the whole rootable volume. For the fertility class estimation, texture and the associated potential fertility, useful soil depth (<50, 50–100, or $\geq$100 cm), and rock fragments percentage (0–35 or $\geq$35%) were simultaneously considered. This property must be considered to appropriately choose rootstocks based on the vigor they confer on the plant. Regarding the evaluation of water stress and waterlogging risk, the outputs of the relative models were employed. Each characteristic or property is assessed using the evaluation criteria specific to the vine, available in the technical and scientific literature [51–56].

2.4.4. Soil Chemical–Physical Properties as a Basis for Pre-Planting Fertilization

This model refers to "nutritional needs". A proper calibration of fertilization, based on pedo-environmental and agronomic specificities of the cultivation area, is functional to balance vine nutrition and reduce environmental pollution risk [56,57]. Ordinarily, pre-planting fertilization (also known as "basal fertilization") is carried out with the main purpose of restoring optimum levels of organic matter and lacking mineral elements in the soil (often strongly impacted by pre-planting earthworks), so as to improve soil fertility and maximize the efficiency of fertilization in the following stages of vine growth and development (training and production stages) [57,58]. Following a widely shared view among guidelines for fertilization in the various fields of agricultural production, the amount and type of amendments and/or mineral elements to be applied for basal fertilization vary according to soil features, as resulting from a proper interpretation of analytical data provided by soil chemical–physical analyses and concerning the available nutrient status (K, P, Mg, micro-nutrients) soil texture, pH, limestone, organic matter, cation-exchange capacity [57]. As a general rule, mineral nitrogen is excluded from basal fertilization due to its high mobility in the soil and the still reduced vine root development during the early years of growth, which would raise the risk of N loss from the soil. For similar reasons, the supply of other nutrients in mineral form is also limited to those with low mobility and only in cases of proven deficit with respect to pre-defined sufficiency thresholds (P, K, Mg, and several micro-nutrients) [57]. A central role in pre-planting fertilization is usually given to organic matter as an improver of soil physical properties (soil structure, density, water retention capacity), a slow-release reserve of essential nutrients (especially nitrogen and phosphorus) and an enhancer of soil microbial activity and biodiversity. The main objective of this model is to provide information on soil chemical–nutritional status and an estimation of the organic matter and nutrient requirement for pre-planting fertilization of vineyards. The model was intended as an easy-to-use tool to support farmers in choosing the most appropriate management of soil basal fertilization in relation to the vineyard specificities. The methodological approach is based on criteria and algorithms compliant with the National and Regional Guidelines for Integrated Production [57,59,60], validated over years through agronomic field trials carried out across Italian regions for a wide range of crops, and periodically updated. Schematically, the model works through two main processing steps:

(1) Chemical–nutritional characterization of the soil based on STS statistics [54] to provide the final user with a deeper knowledge of soil fertility across the whole soil profile depth and possible limiting chemical conditions to vine growth. Soil properties selected include texture, coarse fragments, bulk density, pH, salinity (electrical conductivity), total

limestone, organic C, total N, C/N ratio, cation exchange capacity (CEC), exchangeable Ca, Mg and K, Mg/K ratio, percentage of exchangeable Na (ESP) and available P.

(2) Estimation of OC and mineral nutrient requirements (K, P, and Mg) for basal fertilization. In this second step, the model estimates OC and mineral nutrient requirements for restoration/maintenance of optimum levels of soil basal fertility. The analytical values of SOC and nutrients (weighted means across soil horizons up to a depth of 30 cm) are compared to reference sufficiency thresholds, defined as a first approximation in relation to three main soil texture aggregated classes (based on USDA classification [61]): coarse ("sand", "loamy sand" and "sandy loam"), medium ("loam", "silty loam", "silt", "clay loam", "sandy clay loam" and "silty clay loam") and fine ("sandy clay", "silty clay" and "clay"). For lacking mineral nutrients, the fertilizing unit requirement is estimated. The estimation uses nutrient-specific correction factors to be applied to the deficit amount, which takes into account nutrient interaction with soil properties that are most involved in controlling nutrient availability and fertilizer use efficiency. In particular, the K correction factor ("fixation factor") is related to soil clay content, whereas the P correction factor ("immobilization factor") is a function of soil total limestone and clay content. If the availability of a given nutrient falls within or above the average range of sufficiency, its requirement for basal fertilization is assumed to be zero [57]. Unlike mineral elements, the supply of organic matter for basal fertilization (in the form of amendments such as compost or manure) is always encouraged by fertilization guidelines, due to the multiple benefits of soil organic matter to soil fertility and ecosystem services. However, the criteria for its quantification are less defined and mostly indicative. In general, SOC analytical value is judged by comparison with reference values referred to as "normal", which increase as soil texture varies from "coarse" to "fine". In addition, maximum limits are set to the amendment amounts, established at 15 t ha^{-1} dry matter (d.m.) for soils poor in OC, 13 t ha^{-1} d.m. for soils with "normal" SOC content, and 9 t ha^{-1} d.m. for soils with a high OC content. Amendments supplies of less than 9 t ha^{-1} d.m. are always admitted, regardless of SOC analytical result. The above-said restrictions respond to the logic of preventing excessive organic matter inputs, exceeding soil capacity to integrate it into a balanced equilibrium, which would introduce a risk of nitrogen loss from soil following SOM mineralization [55]. Taking this approach into account, the quantification of OC requirement for basal fertilization was carried out as follows: in situations of CO deficiency, the model calculates the OC units necessary to restore the normal level, plus a maintenance share based on the average annual rate of SOC mineralization (estimated according to soil texture and the C/N ratio). For soils with a normal SOC content, instead, only the maintenance amount is calculated. In any case, if the OC requirement exceeds the maximum permitted input, the latter is provided as the final result.

3. Results and Discussion

In this section, we report the general results obtained with the DSMART algorithm, the GDSS implementation, its graphical interface, and the results of the models run for the entire wine-growing territory of Tuscany.

3.1. Soil Data Elaboration

The first result to be evaluated is the downscaling of the legacy soil map of Tuscany. Each grid node inherits all the attributes and the relative values of the corresponding "most probable" STS. As a first elaboration and general result, an overall descriptive statistic of the soil properties was performed on the whole set of farmland STS (N = 415) (Table 3). The list of parameters in Table 3 also represents the input required to run the models. The list in Table 4 represents the outputs of the models on the whole dataset. For this work, tables with descriptive statistics and graphs were obtained using the data analysis toolbar of Microsoft® Excel® for Microsoft 365 MSO (Version 2401 Build 16.0.17231.20236) 64-bit.

Table 3. Descriptive statistics of Tuscan soil database parameters used for modeling in vineyard grid cells. In case of ordinal classes, only the class with the highest frequency (modal) is reported; in case of interval scale, typical boxplot descriptors are reported. Minimum value, Q1: 0.25 quantile, Me = Median; Mo = Modal class for category attributes, Q3: 0.75 quantile, and maximum value.

Parameter Input Models Data						
Site	**Min**	**Q_1**	**Me./Mo.**	**Q_3**	**Max**	**Unit Measure**
elevation	0	103	229	307	1019	m. a.s.l.
aspect	5	145	191	233	350	°
slope	0	5	9	12	68	%
Climate						
air temperature	10.3	13.3	13.8	14.3	15.7	°C
precipitation	625	781	790	813	1028	mm
Soil quality						
rooting depth	20	89	110	132	250	cm
root impediment			paralithic contact			class
intern. drainage			well drained			7 ordinal level
Soil layer (0–30 cm)						
available P	4	10	12	16	77	mg/kg
bulk density	0.33	1.39	1.46	1.5	1.86	g/cm^3
field capacity	19.6	66.1	75.3	96.1	147	mm
wilting point	11.1	33.5	38.8	50.4	103	mm
coarse fragments	0	1.5	6	18.5	73	g/100 g
org. carbon	0.1	0.9	1.1	1.3	7	g/100 g
tot. nitrogen	0.2	0.7	1	1.3	8.0	g/kg
Soil-derived profile, from surface to bedrock, 1 to 4 master horizons (A, B, C, R)						
horizon type			B			class (A, B, C, R)
upper limit	0	0	34	54	106	cm
lower limit	2	40	72	101	250	cm
coarse fragments	0	0	6	24	90	g/100 g
clay	0	19	27	38	80	g/100 g
silt	1	31	38	45	92	g/100 g
sand	1	18.8	32	48	98	g/100 g
tot. carbonates	0	0	7	15	84	g/100 g
org. carbon	0.06	0.48	0.77	1.13	7.0	g/100 g
tot. nitrogen	0.00	0.46	0.79	1.15	8	g/kg
reaction	4.2	7.1	7.7	8	8.7	pH H_2O
exchang. Ca^{2+}	0.2	10.5	14.9	19.7	97	meq/100 g
exchang. Mg^{+}	0.08	1.32	2.29	3.49	27	meq/100 g
exchang. K^{+}	0	0.23	0.31	0.45	23	meq/100 g
ESP	0	0.9	1.9	3.3	83	meq/100 g
CEC	0.7	14.9	19.8	24.5	60	meq/100 g
electr. conduct.	0.01	0.12	0.16	0.26	7.6	(1:2.5) dS/m

All the predicted soil classes were ranked based on the probabilities raster maps to generate three "most probable" STS (first, second, and third most probable STS) in each node. Finally, the first most probable map, generated using the highest probability value, was used as the final map and for prediction accuracy assessment. The goodness-of-fit measures were applied to the training dataset equivalent to 421 soil profiles, accounting for 10% of the total dataset. In 20% of cases, the predicted first most probable soil class matched the one recorded for the profile by expert pedologists in the soil correlation process. The overall accuracy increased up to 65% if also determined by the second and third most probable STS, which generally do not differ much from each other in their main characteristics. The direct prediction of STS soil classes has a greater advantage than the predictions of each single continuous parameter. The STS is "overall soil variation" and, conceptually, is already a three-dimensional soil body with horizons described in both horizontal and vertical sections. Computing wide portions of landscape (soil region) characterized by many STS can compromise our accuracy results, certainly decreasing the possibility of predicting the right STS. However, as suggested by [62] and confirmed in this study, we should take into account the taxonomic distance when evaluating the accuracy of predicting soil classes. This metric quantifies the separation between soil classes, giving partial credit to some incorrect allocation. For example, Profondi Stagnic Luvisols vs. Cutanic Stagnic Luvisols could be a misclassification, but their taxonomic distance is minimal; therefore, DSMART may suggest harmonizing them. Overall, soil properties varied across a wide range of values (Table 3). However, some extreme values may refer to borderline agricultural areas captured from preliminary 150 m GIS buffer operation on vineyards shapefile. Table 4 reports the overall results of the applied models. The model results will be discussed in the following paragraphs. However, the overview provides a snapshot of the median situation of Tuscan vineyards. It is interesting to highlight that (i) in the analyzed nodes, the median CF estimated for a new vineyard and the soil loss due to erosion are very high (15.1 t CO_2e/ha and 12.3 t/ha, respectively); (ii) the seven most frequently recommended rootstocks among those considered are shown; and (iii) the soils of Tuscan vineyards result deficient in organic matter, but not in potassium phosphorus and magnesium, at least in 75% of the grid nodes analyzed. It is clear how such information, georeferenced in wine-growing districts everywhere in the world, can be extremely interesting for supporting agricultural policies useful to the territory.

Table 4. List of the output parameters for the GEAPP models; typical boxplot descriptors are reported. Minimum value, Q1: 0.25 quantile, Me. = Median; Mo. = Modal class for category attributes, Q3: 0.75 quantile and max value for whole dataset, maximum value.

Models' Outputs						
Eco-Sustainability	**Min**	**Q_1**	**Me./Mo**	**Q_3**	**Max**	**Unit Measure**
carbon footprint	0	5.6	15.1	28.5	91.0	t CO_2e/ha
Water stress						
cuttings water stress			Negligible			4 classes
Hydrological and physical models						
erosion susceptibility			Low susceptibility			4 classes
soil loss	0.1	6.2	12.3	18.8	115	t/ha
max. length of rows	50	100	100	100	100	m
Water limitations						
runoff risk			Medium risk			3 classes
waterlogging risk			Stagnation moderate			3 classes
Rootstock						
suitable rootstock			M1–M3–M4–41B–420A–Gravesac–Fercal			15 rootstocks (42 clusters)
Soil OC and nutrient requirement for basal fertilization						
Potassium (K_2O)	0	0	0	0	300	kg/ha
Phosphorus (P_2O_5)	0	0	0	0	102	kg/ha
Magnesium (MgO)	0	0	0	0	250	kg/ha
Organic C	0	0.92	1.10	7	7	t/ha

3.2. Graphical User Interface, Digitalized Maps, and WebGis

The GoProsit section of the GEAPP web portal (https://www.geapp.net/, accessed on 18 February 2024) is divided into four main sections. The central one is a terrain map, containing the demonstration areas of the PROSIT project and a constellation of georeferenced points (grid nodes) throughout the viticultural areas of Tuscany (Figure 4). The left panel contains the navigation tools, while the side panel with a tree menu can access the models, the description of the STS, and the 50 georeferenced historical soil maps.

In the right display, we can see all the information about the selected grid nodes and model outputs. As for the historical soil maps, these are displayed through a Web Map Service (WMS) provided by CREA's Geoserver Web Server (Figure 5).

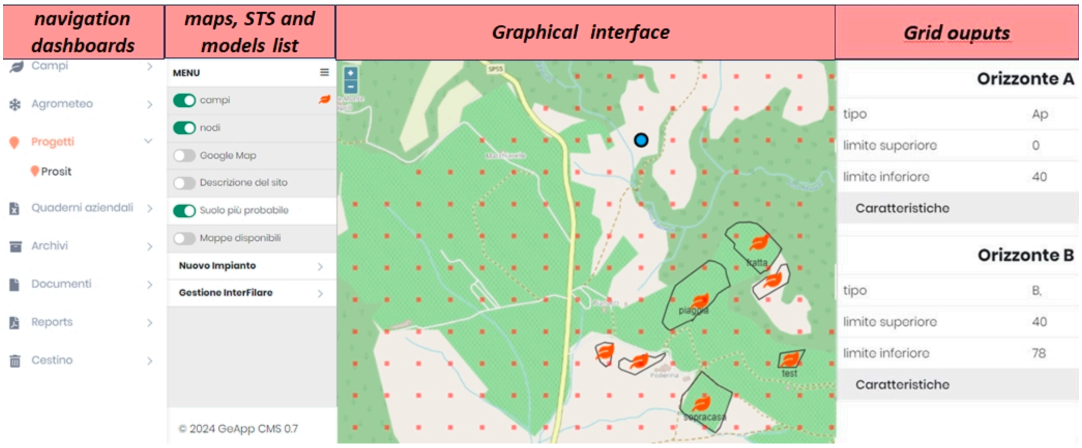

Figure 4. Dashboard, accessing soil information through the GEAPP platform via four different sections.

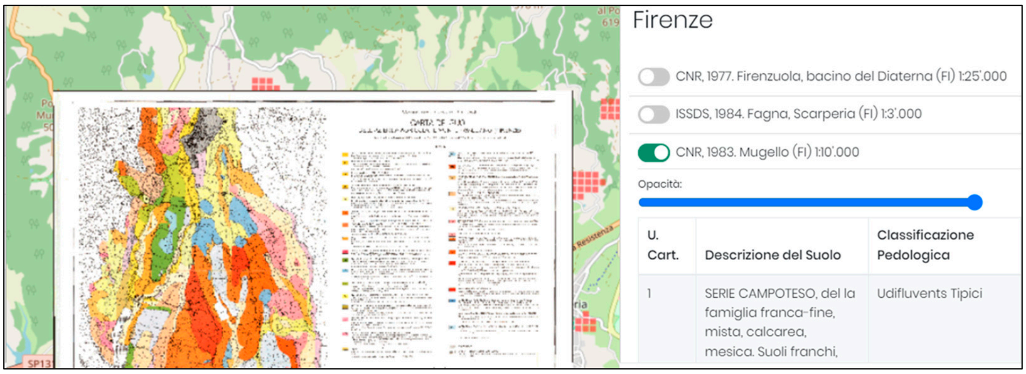

Figure 5. Example of georeferenced historical soil maps integrated into the GoProsit platform; the legend of the map units is shown in the right panel.

On the right of the map, in the "point grid outputs" section, farmers and experts can access a complete overview of the soil type units and soil properties of each selected area with input, output, and intermediate data of the models with over 200 variables deriving from the grid. The information can be visualized intuitively through the GDSS, with colors and symbols representing the different soil typological units and their properties.

3.3. Models Results

As reported above, the results and discussion of individual models are also given in general terms over the entire viticultural territory of the Tuscany Region and divided by administrative provinces.

3.3.1. Sustainability Assessment by Carbon Footprint

The median Carbon Footprint of a new vineyard plant in Tuscany is 15.1 t CO_2e ha^{-1}, mainly ranging from 5.6 to 28.5 t CO_2e ha^{-1} (Q1 and Q3, respectively, Table 4). To the best of our knowledge, no studies up until now have evaluated the overall impact of a new vineyard on GHG emissions. However, other works, i.e., [31,32], focused on the impact of new vineyard plants on soil physical, chemical, and biological characteristics, estimating the change in SOC. SOC losses measured in the Verrazzano field (−40% after earthmoving works) were higher if compared with [31,32] (ranging from −6.4% in a flat valley until −33% within the area with slope) and this can be explained by the intense and long-lasting earthmoving works, that exposed a deep layer of soil to oxidation for a long time, and the steep slope of the field that favored erosion when the soil was bare (from March 2021 until April 2022, except for a short period of cover crops grown on ¼ of the land). Based on the previously published literature [63], it was assumed that a negative CF could not be the result and that the minimum limit was zero (Figure 6). As a maximum value, the value derived from "heroic viticulture", defined as viticulture ran on land with a slope above 30% or an altitude above 500 m [64], was chosen, since the CF impact in those cases is driven by exceptional circumstances. Therefore, for grid nodes with these characteristics, the CF value was not calculated by the model. For these reasons, and mostly for the limited information available in the grid about soil nitrogen content, which is needed to calculate basal fertilization, it was possible to calculate the output of the CF model only for 203,644 nodes out of 297,023 (69% of total grid cells).

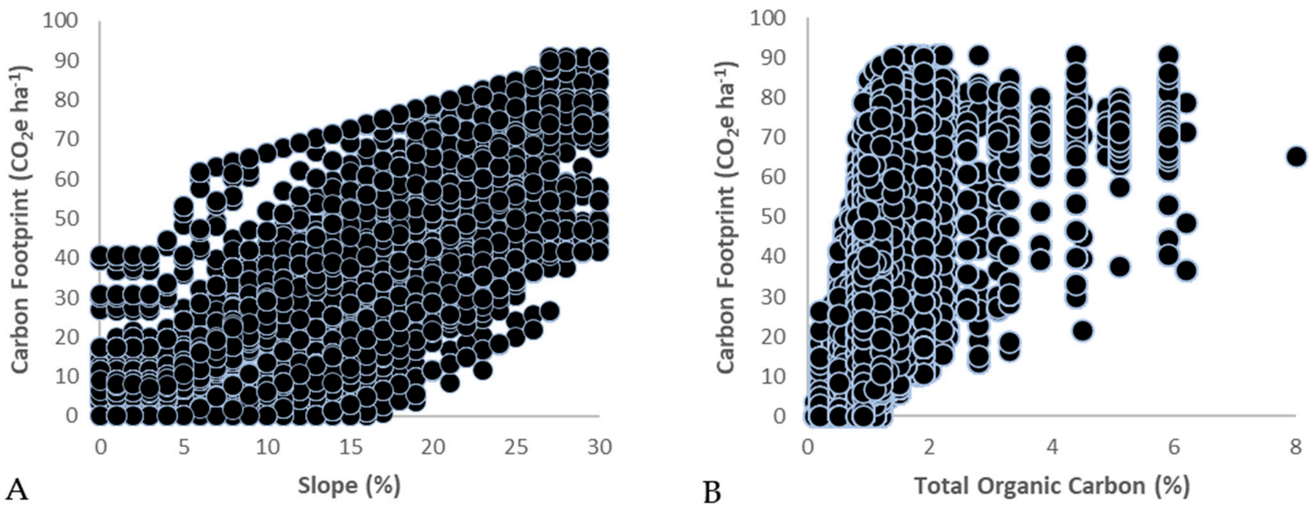

Figure 6. CF model outputs calculated for all grid nodes (203,644) where the information to run the model was available and by excluding "heroic viticulture conditions". CF output is shown in relation to the node estimated slope (**A**) and to the 0–30 cm Total Organic Carbon (**B**). Despite the considerable overlap of the points, it is possible to observe the dispersion cloud of the CF results of the GoProsit GDSS, and the minimum and maximum CF set for the model, as described in the text.

Based on the sensitivity analysis, the main parameter that affects the CF results is the slope and, more specifically, the coefficient that relates the slope and the diesel consumption. The second parameter that highly affects CF results is the soil carbon stock, and in particular the initial SOC and bulk density, despite the median soil carbon stock in Tuscany, was quite low, at 40 t C/ha, ranging from 32 to 46 t/ha (Q1 and Q3, respectively). The CO_2e emissions associated with the production of manure used for basal fertilization and the sequestration of organic carbon associated with green manure were negligible if compared to the CO_2e emissions due to diesel consumption and SOC losses. Therefore, the reduction of diesel consumption due to soil excavation, leveling, and drainage installation, as well as the use of soil stripping or other useful techniques to reduce SOC losses are the key actions that should be put in place to reduce CF of a new vineyard plant. Preserving the carbon stock of agricultural soils by management practices is crucial to curbing global warming [65]. Regarding the location, the lowest CF impact will be observed if new vineyard plants are built in areas with minimal slopes (plains) and with low organic matter content.

3.3.2. Hydrological and Physical Model

The application in the GIS environment of the hydrological models (water stress, erosion, runoff, or waterlogging susceptibility) allows the return of the risk level of each model in all the nodes of the grid within the Tuscany Region.

Water Stress Risk

Regarding water stress, although the vine is defined as an arid-resistant species, high quantities of water are necessary during the driest months to allow the plant to complete its growth cycle [39]. As previously indicated the water stress risk may be determined by both pedological properties and climatic characteristics; in fact, Figure 7A shows that the water stress of a young vine is inversely correlated to soil available water capacity (AWC in mm), while Figure 7B highlights how the stress increases as the average annual temperature is higher and the average annual rainfall lower. It is, however, interesting to note how the modal class is associated with the lowest risk, which affects as much as 85.1% of Tuscany vineyard areas.

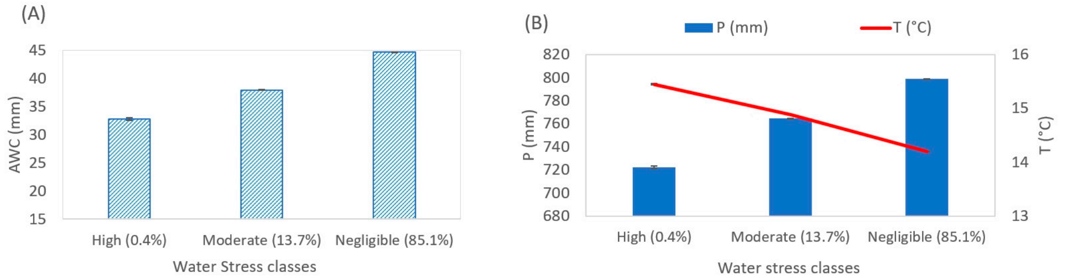

Figure 7. (**A**) Average AWC values (mm) in the different water stress classes. (**B**) Average annual precipitation (P) and mean air temperature (T) in the different water stress classes.

Table 5 lists the distribution of the surfaces (%) occupied by each water stress class per province. It emerges from the data how the class "High" is entirely sited in the Grosseto province (GR), a direct consequence of its specific geographical position: southernmost location and proximity to the sea, where the climate is particularly hot and dry. The "Moderate" class is 50% located in the province of Grosseto, with the remainder divided according to the size of the provinces (Siena > Firenze > Arezzo) Table 5.

Table 5. Percentage distribution of the surface under each water stress class in the different provinces of Tuscany.

Water Stress Class	Tuscan Provinces										Total
	AR	FI	GR	LI	LU	MS	PI	PO	PT	SI	
High	0.00	0.01	**0.38**	0.02	0.00	0.00	0.00	0.00	0.00	0.01	0.43
Moderate	1.15	1.49	**7.11**	0.64	0.06	0.01	0.48	0.03	0.08	**2.76**	13.82
Negligible	12.69	23.49	9.48	4.13	2.05	1.09	6.46	0.75	1.69	23.93	85.75
Total	**13.84**	**25.00**	**16.96**	**4.79**	**2.11**	**1.10**	**6.94**	**0.78**	**1.77**	**26.70**	**100.00**

In these areas, where the water stress risk is higher, it is important to have the possibility of irrigating throughout the vineyard training phase, since the young plants have roots that are still poorly developed and more vulnerable and subject to water stress.

Erosion Risk

The results obtained from the model for estimating erosion risk showed, as expected, that the class representing the maximum erosion susceptibility is characterized by both the highest rainfall and slope values; conversely, the "Negligible" class is associated with the lowest rainfall and slope values. Figure 8 illustrates the average values of both the annual rainfall (mm) and terrain slope (%) calculated on all the pixels belonging to the same erosion class. The surface (%) occupied by each class is also indicated on the x-axis of the graph. The frequency of distribution of the class areas follows the inverse level of danger, as follows: Low > Moderate > High > Very high. Regarding the distribution of the erosion risk within the Tuscany Region, it is to be highlighted the ubiquitous nature of this phenomenon; hence, the distribution of the erosion risk classes is entirely determined by the size of the single provinces compared to the total surface of the region (Siena > Firenze > Grosseto > Arezzo).

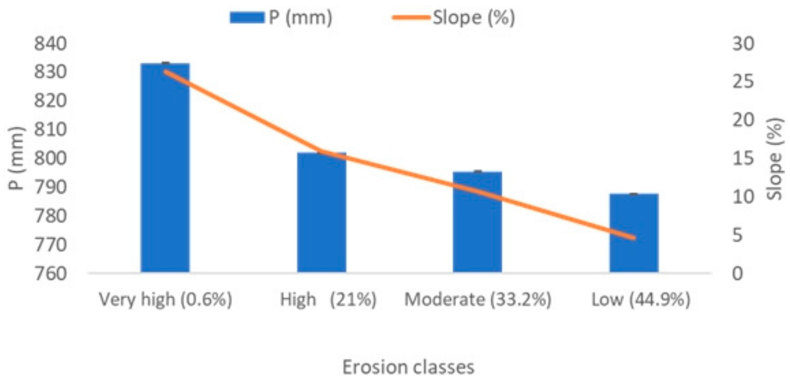

Figure 8. Percentage of the regional surface associated with the different erosion classes as a function of annual rainfall (P) and mean slope (%).

Runoff and Waterlogging Susceptibility

During the realization of a new vineyard, deep tillage is carried out and heavy machinery is used; this often results in severe soil compaction that contributes to increased runoff and erosion. The period immediately following, when the soil is still affected by the disturbance caused by the mechanical operations of deep tillage and leveling and is devoid of vegetation cover, is the most critical both in terms of slope dynamics, if combined with erosion processes, and vine physiology. Planning errors can have consequences, sometimes serious and permanent, on vine production due to the strong decrease in soil fertility or even to the death of the cuttings themselves. If correctly implemented, the hydraulic regulation system is crucial in controlling these risks. When conditions favorable to runoff triggering occur on a slope, the same critical factors can induce water stagnation in the lower part of the slope. Thus, if runoff can generate erosion on the slopes, waterlogging in lowland areas can cause other types of damage, sometimes irreversible for the vine. This species, in fact, does not tolerate prolonged stagnation (some days), a possible cause of rotting of the collar and roots and the consequent withering of the plant itself. It is therefore crucial to have an effective drainage network, superficial and deep, able to intercept and drive away water excess. As the risk level increases, the priority of creating land set-up systems and drainage networks increases. The application in the GIS environment of the modified T-M water balance–SCS-CN, also holds the description of the prevailing risk (R for runoff or S for water stagnation/waterlogging) for each node of the grid, so providing useful information about the vineyard hydraulic set-up. The runoff and waterlogging risk are described in Figure 9A,B. The former shows that the overall phenomenon of runoff and waterlogging, considered together, depends, as expected, on soil texture; as the percentage of sand increases, the susceptibility to runoff and waterlogging decreases; the opposite occurs when considering the clay content. It is also noted that the modal class is represented by the "Moderate" one, which characterizes 78% of the considered area. Figure 9B illustrates separately the runoff from the waterlogging phenomenon considering the slope (%) effect: as the slope increases, the risk of runoff increases; on the contrary, where the terrain is flat, the phenomenon of water stagnation obviously prevails. The distribution of runoff and stagnation risk classes among the different Tuscan provinces is once again strongly influenced by the extension of the single province compared to the entire region.

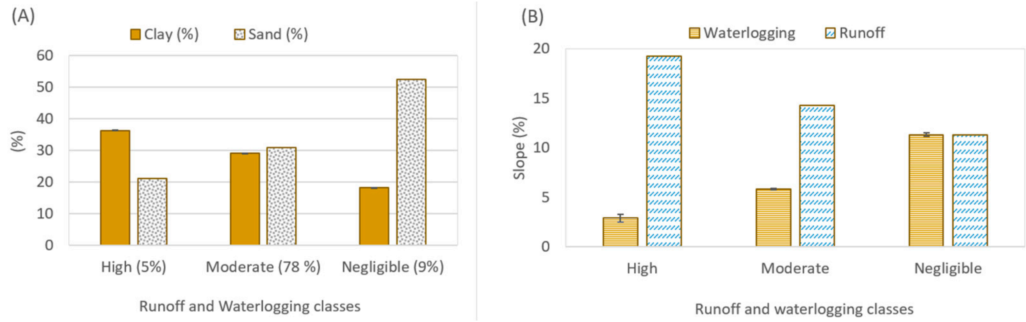

Figure 9. (**A**) Average sand and clay content (%) in the different runoff and waterlogging classes. (**B**) Average slope (%) in the different runoff and waterlogging classes.

3.3.3. Rootstocks Selection

Table 6 shows the results provided by the original tool developed for the selection of the most suitable rootstocks starting from the Tuscany Region soil dataset. Nine groups of rootstocks have been identified, which, overall, are suitable in 98.8% of the considered regional area: in each group, up to a maximum of two limiting factors have been identified. The results are much more affected by fertility and chemical characteristics (total $CaCO_3$, pH, and salinity) with respect to water stress and waterlogging, in which the results not critical (Negligible or Moderate) in the nine groups. The most common limiting factor in Tuscan vineyard areas appears to be the high fertility, either as a single factor or combined with medium salinity or acidic pH, detected in 59.9, 13.6, and 5.9% of the total area, respectively. Only 4.9% of the investigated areas did not exhibit any pedological limitations for vine cultivation (group E), which is why none of the 15 rootstocks considered were excluded.

Table 6. For each group of rootstocks (A–I) associated with specific soil conditions, the number (n.) of suitable rootstocks and the % area with respect to the total in which those specific soil conditions were detected are reported. The limiting factors are highlighted in bold.

Group *	n.	Area %	Fertility Class	Total $CaCO_3$ Class	Salinity Class	pH Class
A	8	59.9	**High**	<Very calcareous	Low	Neutral/ Alkaline
B	7	13.6	**High**	<Very calcareous	**Medium**	Alkaline
C	12	6.5	Medium	**Strongly calcareous**	Low	Alkaline
D	4	5.9	**High**	Non-calcareous	Low	**Acidic**
E	15	4.9	Medium	<Very calcareous	Low	Neutral/ Alkaline
F	14	3.3	Medium	Moderate–Very calcareous	**Medium**	Alkaline
G	11	2.2	**Low**	<Moderately calcareous	Low	Neutral
H	10	1.3	Medium	Non-calcareous	Low	**Acidic**
I	7	1.2	Medium	Very calcareous	**High**	Alkaline

* A: M1–M3–M4–41B–420A–Gravesac–Fercal–101.14; B: M1–M3–M4–420A–Gravesac–Fercal–101.14; C: M1–M2–M3–M4–41B–1103P–K5BB–110R–SO4–420A–Fercal–140Ru; D: M1–M3–Gravesac–Fercal; E: M1–M2–M3–M4–41B–1103P–K5BB–110R–SO4–420A–196.17–Gravesac–Fercal–101.14–140Ru; F: M1–M2–M3–M4–1103P–K5BB–110R–SO4–420A–196.17–Gravesac–Fercal–101.14–140Ru; G: M2–M4–41B–1103P–K5BB–110R–SO4–196.17–Gravesac–Fercal–140Ru; H: M1–M2–M3–1103P–K5BB–110R–196.17–Gravesac–Fercal–140Ru; I: M2–M3–M4–1103P–196.17–101.14–140Ru.

3.3.4. Nutritional Model

Soil OC, exchangeable K, exchangeable Mg, and available P distribution among different content classes as resulting from the Tuscany soil dataset and their estimated requirement for basal fertilization are shown in Figures 10–13.

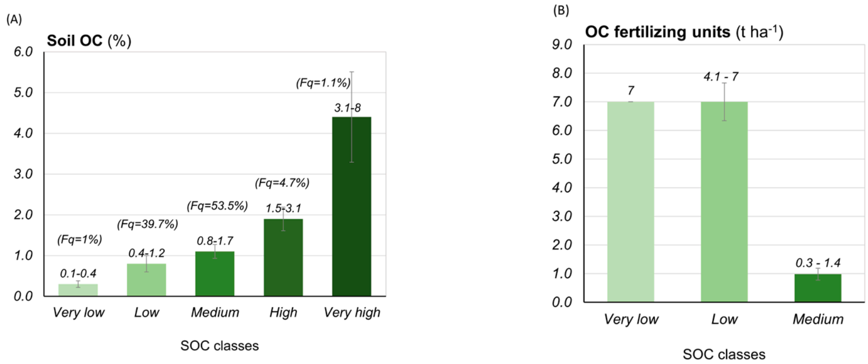

Figure 10. (**A**) Soil Organic Carbon (SOC) distribution among different content classes (relative frequencies in brackets): median value, min–max range, and standard deviation (error bars) within each class ("Very low", n = 2003; "Low", n = 82,893; "Medium", n = 112,025; "High", n = 9760; "Very high", n = 2274); (**B**) OC requirement for basal fertilization as estimated for soils with "Very low" to "Medium" OC content: median values, min–max range and standard deviation (error bars).

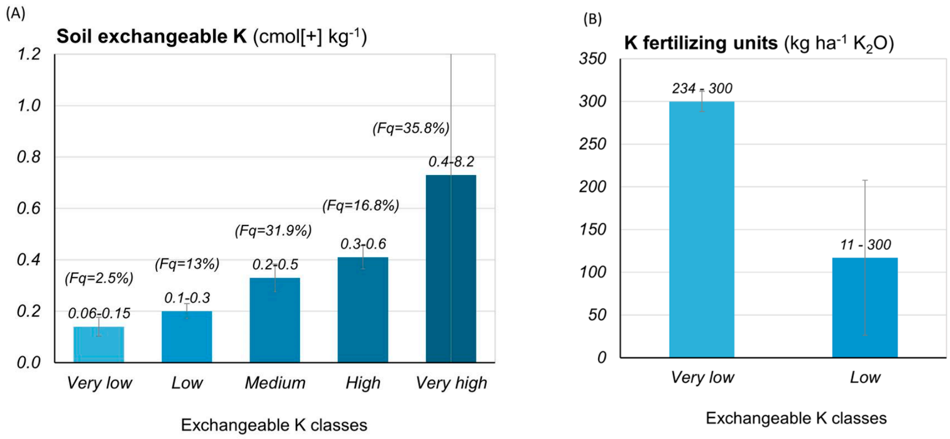

Figure 11. (**A**) Soil exchangeable K distribution among different content classes (relative frequencies in brackets): median value, min–max range, and standard deviation (error bars) within each class ("Very low", n = 6811; "Low", n = 34,810; "Medium", n = 85,878; "High", n = 45,229; "Very high", n = 96,428); (**B**) K requirement for basal fertilization as estimated for soils with "Very low" to "Low" exchangeable K content: median values, min–max range and standard deviation (error bars).

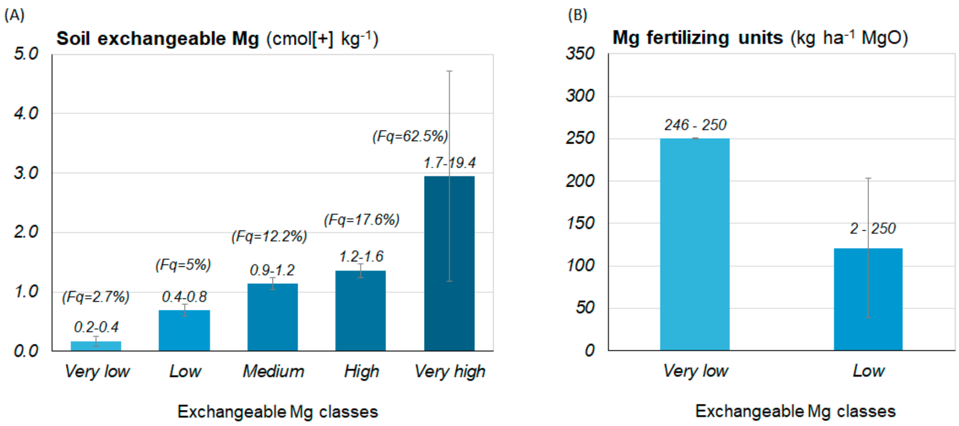

Figure 12. (**A**) Soil exchangeable Mg distribution among different content classes (relative frequencies in brackets): median value, min–max range, and standard deviation (error bars) within each class ("Very low", n = 7101; "Low", n = 13,235; "Medium", n = 32,458; "High", n = 47,036; "Very high", n = 166,735); (**B**) Mg requirement for basal fertilization as estimated for soils with "Very low" to "Low" exchangeable Mg content: median values, min–max range and standard deviation (error bars).

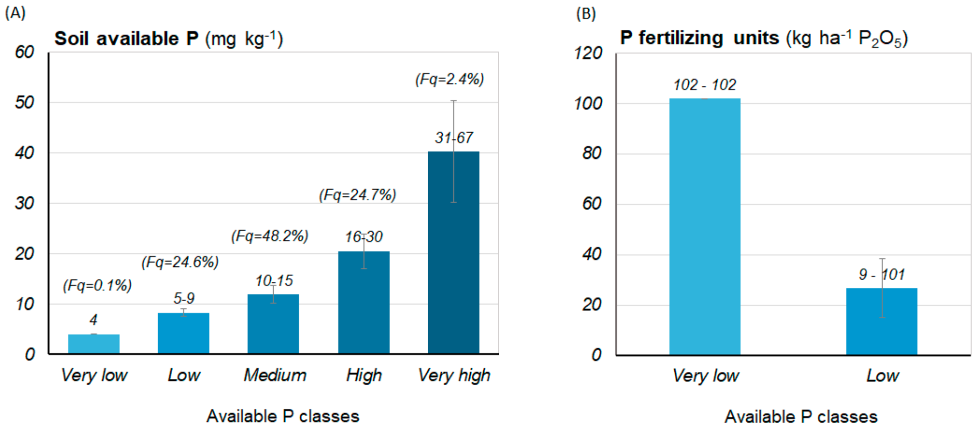

Figure 13. (**A**) Soil available P distribution among different content classes (relative frequencies in brackets): median value, min–max range, and standard deviation (error bars) within each class ("Very low", n = 225; "Low", n = 66,668; "Medium", n = 130,574; "High", n = 66,758; "Very high", n = 6520); (**B**) P requirement for basal fertilization as estimated for soils with "Very low" to "Low" available P content: median values, min–max range and standard deviation (error bars).

SOC and nutrient contents varied across a wide range. Correlation analysis confirmed a number of expected relationships among soil properties. Soil total N was significantly related to SOC (n. observations = 238; total N = 0.301 + 0.725*SOC, R^2 = 0.656, $p < 0.0001$), soil CEC was positively related to both clay and SOC content (n. observations = 392; CEC = 5.753 + 0.387*Clay + SOC*2.609, $R^2{}_m$ = 0.383, $p < 0.0001$). No significant correlation was found for exchangeable K, whereas exchangeable Mg was weakly related to soil CEC (n. observations = 353; Mg = 0.642 + 0.095*CEC, R^2 = 0.130, $p < 0.0001$).

SOC content mostly averaged from "medium" to "low" (93% of the dataset), falling below 1.2% in 40% of records, which consistently reflects the range of SOC levels commonly found under long-term vine growing in Tuscany.

Soil organic matter is generally the focus of pre-planting fertilization, due to its multifunctional role in soil fertility and the strong impact it may undergo under pre-planting earthworks. The latter often involves land leveling and/or mixing of the soil profile by deep plowing, resulting in the outcropping of underlying layers that are very poor in organic matter [31].

The estimated range of OC requirement for basal fertilization, corresponding approximately to 36 to 60 t ha^{-1} of cattle manure and 13 to 22 t ha^{-1} of compost, is consistent with the OC inputs usually provided by vine growers.

As for soil exchangeable K, exchangeable Mg, and available P contents, only in a minority of cases (15.5%, 7.6%, and 24.7% of the whole dataset, respectively), were below the average sufficiency levels. In these cases, organic fertilization alone is often enough to cover the theoretical deficit, with the advantage of a slow nutrient release preventing them from chemical immobilization or leaching.

4. Conclusions

The soil information underlying GoProsit does not claim to replace a proximal or site-specific pedological survey, but it has the advantage of offering a wealth of decision support information. The designated area can range from the size of a hectare to tens of hectares, or even the entire region. The soil foundational data and climate information within each grid node are sufficient for running all the models. The comprehensive assessment of Carbon Footprint (CF) for a new vineyard, including the consideration of organic matter loss along with the availability of essential macronutrients, are topics that, to the best of our knowledge, have not been addressed in the literature before. Our results indicate that establishing a new vineyard can have a significantly higher impact than managing a mature vineyard or cultivating on arable land. It is important to note that this impact should be considered amortized over the productive lifespan of the vineyard. For the first time, the DSMART technique was used for the Italian territory and was found to be necessary to assign unique STS to each grid cell from the "aggregated" vector soil map of the Tuscany Region and from its subsequent use in models at a local scale. Although the pedological and climatic information provided does not always have a degree of detail suitable for supporting managing decisions at the scale of a single vineyard, GEAPP is nevertheless an undoubtedly useful tool for technical and political planning at the district and regional levels. One possible solution to overcome the limitations inherent in the regional database and make model results more reliable at the farm scale is to integrate the system with an interactive user interface (GUI) that allows users to update the data with site-specific information. However, the decisional pattern presented in this manuscript generates a GDSS suitable for use in any wine-growing district, providing useful information for farmers, researchers, agricultural consultants, and policy makers, and opening new perspectives in soil management during new vineyard planning.

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