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Determining the best ISUM (Improved stock unearthing Method) sampling point number to model long-term soil transport and micro-topographical changes in vineyards

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A R T I C L E I N F O

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A B S T R A C T

Advances in soil erosion measuring tools and micro-topography modelling will contribute to our understanding of land degradation processes and help to design correct erosion mitigation measures in agricultural fields. Vineyards being one of the most degraded agricultural landscapes, it is necessary to accurately predict soil erosion levels within them. One possible method to achieve this goal in vine plantations is ISUM (improved stock unearthing method). To apply ISUM, it is necessary to detect the graft unions which are recognised as passive bioindicators of the original micro-topography at the time of planting. In this paper, we propose a methodology to determine: (i) how many measuring points are necessary to reach the best estimate of soil erosion for developing current soil surface level maps; and (ii) which spatial interpolation method is the best to map the micro-topographical changes. ISUM was applied in the Ruwer-Mosel valley vineyards (Germany) using 18 measuring points at 10 cm intervals between opposite pair graft unions of 1.7 m inter-row distance. Several interpolation methods were used to map the micro-topography changes and anisotropic ordinary kriging (OK) emerged as the best as judged by the performance statistics of the coefficient of determination and the root-mean-square-error. Our findings demonstrated that soil erosion rates were 40.1, 39.4, 25.0, 38.9, 37.9, to 64.8 Mg ha^{-1} yr^{-1} over the 40 years since the establishment of the vineyard studied, when using 18, 15, 10, 7, 5 and 2 measuring points, respectively. We propose that ISUM can be standardised as using measuring points at 10 cm intervals.

1. Introduction

Advances in soil erosion measuring tools are crucial for the proper assessment of soil erosion rates (Seeger, 2017). Such tools will contribute to a better understanding of soil erosion processes and, subsequently, land degradation and desertification dynamics (Nearing et al., 2017; Panagos et al., 2017). Accurate information on erosion processes will improve the design of erosion control strategies required for a planet that suffers from the abuse of natural resources (Keesstra et al., 2018). Although soil formation processes and their factors are relevant for the understanding of soil quality and properties (Calleja-Cervantes et al., 2015), human impacts are more predominant in soil erosion processes (Tarolli, 2016), particularly the topographical changes that occur at the hillslope and pedon scales. Human-induced water erosion is repeated in ploughed and tilled vineyards (Ramos et al., 2015). The erosion problem is more extreme in vineyards compared with other agricultural landscapes that also experience high erosion problems such as in olive groves (Taguas et al., 2015), citrus (Liu et al., 2012) and cereal crops (Zhang and Nearing, 2005).

Novara et al. (2018) recently quantified soil erosion rates higher than 16 Mg ha^{-1} yr^{-1} in a vineyard and demonstrated that negative impacts on soil carbon sequestration and plant vigour can also occur. This

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negative dynamic is commonly found in conventional vineyards where the use of machinery enhances soil compaction, and the application of herbicides keeps soils bare during the rainiest seasons (Biddoccu et al., 2017a; Komac and Zorn, 2005). Cover crops, buffer strips of grass, and straw mulches have been considered as the most effective soil erosion control measures in vineyards (García-Díaz et al., 2017; Novara et al., 2019). However, due to water competition where rainfall is limited, farmers perception is negative and the focus is usually on the increase of productivity of high-quality grapes and wine (Marqués et al., 2015; Vaudour, 2002), and they do not in many cases implement erosion control measures.

The high soil erosion rates occurring within a high number of conventional vineyards necessitates new research to demonstrate the negative consequences of soil erosion in bare soils in order to win the support of farmers to take erosion control measures seriously (Rodrigo-Comino, 2018). In this regard, the stock unearthing method (SUM) can be considered as a useful tool for monitoring the soil erosion processes. Graft unions used as passive bioindicators of topsoil level changes (Brenot et al., 2006) have been applied in several research areas with different land management systems, lithologies and climate conditions such as in France (Paroissien et al., 2010), Spain (Casalí et al., 2009), Italy (Biddoccu et al., 2017a), and Germany (Rodrigo-Comino et al., 2016). This method was improved (ISUM or improved stock unearthing method) by Rodrigo-Comino and Cerdà (2018) in Eastern Spain by including 3 extra measuring points within the inter-row areas. This improvement allows for solving a major limitation of SUM which assumes that the inter-row areas remain planar, thus underestimating the soil erosion rates (Brenot et al., 2008). This improved tool was tested in vineyards within the same region but with different ages and soil management systems (Rodrigo-Comino, 2018). However, some issues of ISUM must be addressed prior to standardising it for larger area applications. Therefore, the main objectives of this paper were to determine: (i) how many measuring points are necessary to achieve the best accuracy of soil mobilisation rates, and for modelling micro-topographical changes; and (ii) which interpolation method is the most suitable for mapping the current soil surface level changes.

2. Materials and methods

2.1. Study area

The study plot (1.7 m inter-row distance and 51.3 m along the paired rows, 87.2 m^2) is located within the viticultural region of the Mosel valley in the little village of Waldrach close to Trier, Rhineland- Palatinate, Germany (Fig. 1; centred at 49.7418N; 6.7524E). The vineyard (40 years old) is located on the Ruwer River, a tributary of the Mosel River which flows from the south at the Hünsrück Mountains, at elevations from 500 m a.s.l. to approximately 200 m a.s.l. in the north (Richter, 1980). The lithology is characterised by Devonian greywackes, slates and quartzites partially overlain by Pleistocene silts deposited near the Ruwer River. The slope inclination oscillates from 15° to 30° with a convex morphology (Rodrigo-Comino et al., 2016).

The soils are classified as leptic-humic Regosols (IUSS Working Group WRB, 2014). It is remarkable to note that the soils are characterised by 37.9% rock cover fragments and of a silty loam texture (64.7% of silt). The soils' water retention capacity is high, reaching a field capacity (water retention at −33 kPa) close to 30% and a wilting point of about 12.3%. The total organic matter varies during the year due to the use of herbicides by the farmers but has a mean value of 7.9%. A pH value of 7.2 in water solution and 6.4 in KCl are registered for the soils. Therefore, no soil acidification trends are observed. Information on the soil analysis procedures can be found in Rodrigo-Comino et al. (2016).

Other features of the study area are the average annual rainfall of 765 mm yr^{-1}, mean annual temperature of 9.3 °C, and rainfall erosivity of 54.31 MJ mm ha^{-1} h^{-1} yr^{-1} (Rodrigo-Comino et al., 2016). The

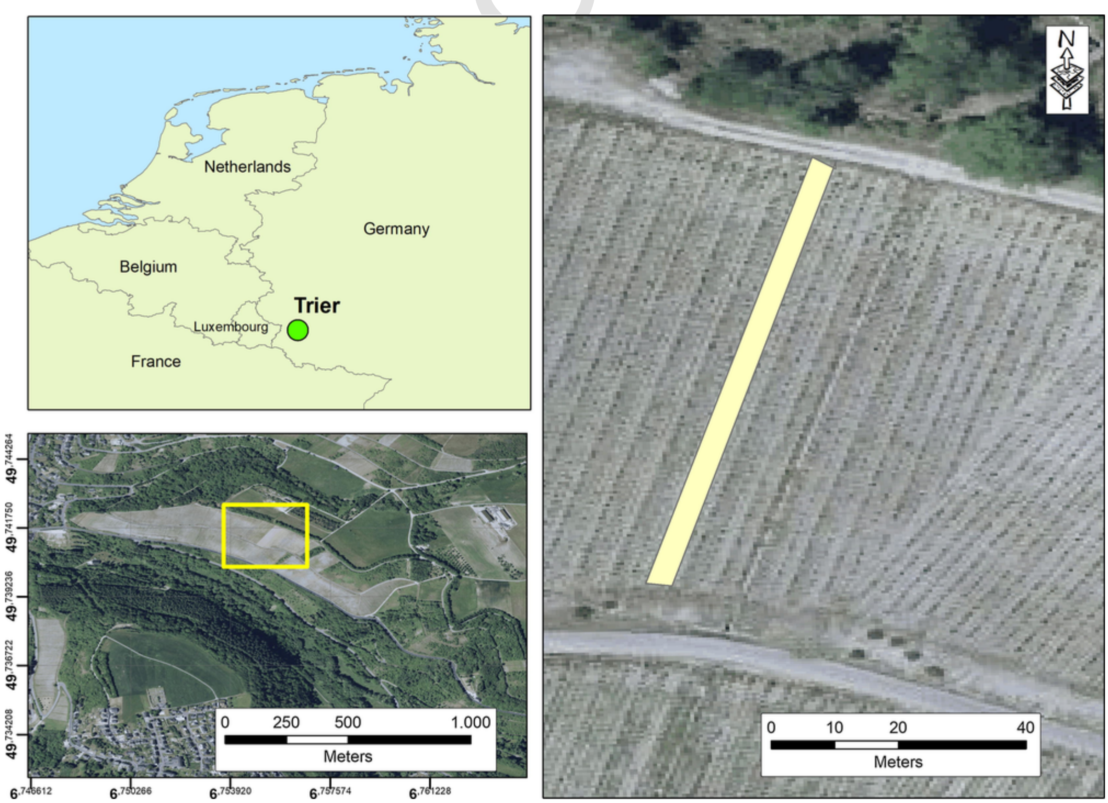

Fig. 1. Location of the study area; yellow polygon shows the studied plot of the paired-vine rows. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

grapevine variety cultivated in this vineyard is *Riesling* under mechanical soil tillage (≈ 20 cm depth) before and after grape harvesting from March to May, and from October to November. Seasonal grass cover appears in the inter-row and row areas. A vine training system based on a plantation framework of 0.9 m (inter-plant separation) × 1.7 m (inter-row separation) is available to enhance the photosynthesis and sugar production, and also to facilitate the mechanical soil tillage. Farmers use herbicides and pesticides during spring and summer to eliminate weeds and fungi growth. Along the embankments and in the inter-row areas, rills and ephemeral gullies caused by wheel tracks and foot trampling can be observed.

2.2. The improved stock unearthing method (ISUM)

The improved stock unearthing method (ISUM) aims to measure the distance between the frontal marks on the graft unions of vines and the current soil surface level in addition to 3 extra measurements in the inter-row areas (Rodrigo-Comino and Cerdà, 2018). After the *Phylloxera* attack during the 19th and 20th, the vines were grafted from the American vine stock, which now shows an unearthing or buried signal. The graft unions give an indication of the real distance above the soil surface level at the time of planting because the original vine stock does not grow vertically (Brenot et al., 2006; Casalí et al., 2009).

Prior to planting in this study area, the soil surface was flattened and the vine roots were inserted into the soil. Nowadays, vines are planted using GPS and small tractors which make this activity fully automated. This vineyard was manually planted, and the graft unions were consistently placed at 2 cm height above the original ground level. This information was confirmed by the farmers in the field through non-formal interviews and it was also observed in new plantations near the study area (Remke et al., 2018). This optimal distance above ground reduces some complications caused by soil moisture, freezing, and fungi plagues on the plants. After planting, only the new part corresponding to the new grape variety grows vertically. Therefore, changes from the theoretical initial conditions due to soil movements can be easily quantified. However, some small imprecisions can be found because this assumption can be violated if the vine is moved because of tractor or animal impacts or if the root strength changes the original position to another angle. This error, that can reach close to 0.5–1 cm, was detected by Rodrigo-Comino et al. (2016) in new plantations in the same area and confirmed by Remke et al. (2018) in other surrounding plantations) by fieldwork observation and non-formal interviews with owners and farmers.

For each opposite paired-vine along the inter-row, we first identified each vine graft union and then stretched a measuring tape between these paired-points. After that, we used a meter stick to measure the vertical distance between the horizontally stretched measuring tape and the current soil surface at different locations at 10 cm intervals (Fig. 2, $ISUM_{18}$). To avoid difficulties in our measurements in cases where a graft union was buried, the measuring tape was placed at 30 cm above the graft union. Since the original ground level is 2 cm below the graft union, and thus 32 cm below the measuring tape level, the difference between 32 cm and the current measurement at each graft union gives an indication of unburied vine stock when negative and buried when positive (Rodrigo-Comino and Cerdà, 2018).

The same person took the distance measurements of 118 (59 paired-vines) graft unions, from the end part of the graft union to the actual surface level. Including the additional 16 inter-row measuring points, a total of 1,062 points were measured within the 91.8 m^2 study area (1.7 m × 0.9 m). Where the soil roughness under the vine generated small dips or rises or the grass cover impaired the visibility of the graft union, the grasses were carefully cut, or soil levelled, not affecting the reading though.

2.3. ISUM maps and interpolation methods

ArcMap 10.5 (ESRI, USA) software was used to process the actual soil surface levels measured during August 2017 in a grid of points ("fishnet") with a pixel resolution of 10 cm. Various geostatistical methods most commonly used in soil sciences (e.g., Kravchenko and Bullock, 1999) were used to develop the ISUM maps and the micro-topographical changes using the Geospatial analyst extension and the semi-variogram generated by ArcMap 10.5 before projecting to Universal Transverse Mercator, UTM (WGS 1984).

2.3.1. Inverse distance weighting (IDW)

Inverse Distance Weighting (IDW) is a quick deterministic interpolator which has basically two decisions to make regarding the power of distance used in the weighting and the number of nearest neighbours. It can be considered as the best method to get an overall understanding of the interpolated area (Li and Heap, 2011) where data is limited. However, it does not offer an assessment of prediction errors. The number of closest neighbouring samples ranging between 10 and 15 was tested to select a number that gave the highest estimation accuracy.

2.3.2. Ordinary kriging

Kriging is a stochastic interpolator that is characterised by its flexibility allowing investigating graphs of spatial auto- and cross-correlation (Baskan et al., 2009). However, it requires at least a sample variogram, which can be isotropic or anisotropic, in addition to the parameter requirements of IDW. Depending on the measurement error model, it may give exact or smoothed results (Fritsch et al., 2011). A variety of output surfaces including predictions, prediction standard errors, probability and quantile can be obtained with this interpolator tool (Govaerts and Vervoort, 2010). Kriging assumes the data provided come from a stationary stochastic process, and are normally-distributed (Lesch and Corwin, 2008; Tabari et al., 2011). The sample variogram is fitted with a variogram model and its adequacy is checked by cross-validation. Spherical, Gaussian and exponential variogram models were tested in this study. The number of closest neighbours was varied between 2 and 5 and the one with the highest estimation accuracy was selected.

2.3.3. Empirical Bayesian Kriging (EBK)

EBK is a Kriging-based interpolation method that accounts for uncertainty in the semi-variogram estimation by simulating several semi-variograms obtained from the given dataset (Gribov and Krivoruchko, 2012). It automates the most difficult aspects of building a valid kriging model and is able to automatically calculate the needed parameters by sub-setting and simulations (Dzakpasu et al., 2014; Sağir and Kurtuluş, 2017). A distinguishing feature of this method is that it takes into account the error introduced by estimating an underlying semi-variogram (Kamble and Aggrawal, 2011; Samsonova et al., 2017). In this study, the cross-validation was performed using varying model parameter values and the number of the closest neighbours between 10 and 15 until the highest estimation accuracy was reached. The subset size and the number of simulations were each taken as 100.

2.3.4. Radial basis functions (RBFs)

RBFs are moderately quicker deterministic interpolators that are considered to be exact. They usually need a higher number of parameters to make decisions compared with IDW or kriging for example; however, no assessment of prediction errors can be done (Fang and Horstemeyer, 2006; Ilati and Dehghan, 2015). With this method, it is not possible to investigate data autocorrelation, thus, it is considered to have less flexibility (Fornberg et al., 2011). Also, this method relaxes the data normality assumption of kriging. The mechanism works with a

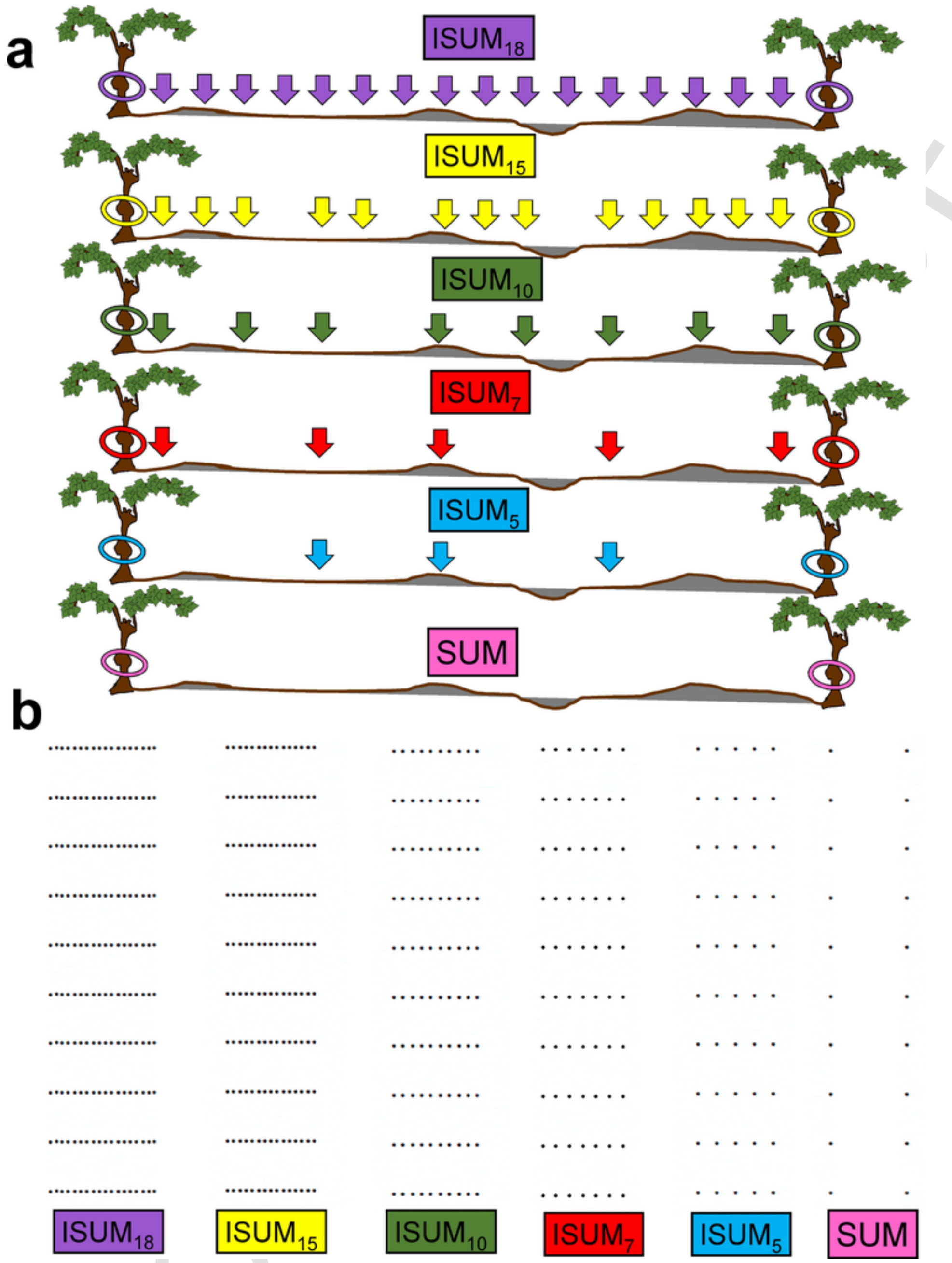

Fig. 2. Cross section of the ISUM measuring points in the field showing the circled graft unions and the grid of points obtained for mapping the current soil surface level. *The original horizontal level partitions the depressions and accumulations of the current soil surface level.

surface that passes through each measured sample point and creates a new surface (Kim and Kasabov, 1999). RBFs are considered by many authors as the best for smooth changes in the data over long distances because, when the values change at short distances, errors can be introduced into the predicted surface (Keshavarzi et al., 2018; Shiri et al., 2017).

In this study, we applied five different models: (i) completely regularised spline; (ii) spline with tension; (iii) multi-quadric; (iv) inverse multi-quadric; and (v) thin plate spline. All data were cross-validated by varying the model parameter values and using different kernel functions. To determine the kernel function, we used the Geostatistical Wizard and Radial Basis Functions, and adjusted the kernel function and kernel parameter, checking the error based on the best results of R^2 and RMSE.

2.3.5. Model calibration

We used the RMSE (root-mean-square-error) and R^2 (coefficient of determination) to assess the models' performance in a cross-validation mode. The smaller the RMSE and the higher the R^2 the better. Finally, to decide how many measuring points are necessary to get the highest accuracy of the different methods, reductions in the performance statistics of $R^2\Delta$ and RMSEΔ were calculated (Shiri et al., 2017) as:

$$'R^2 = R^2_{ref} - R^2_z \quad (1)$$

and

$$´RMSE = RMSE_z - RMSE_{ref} \tag{2}$$

where R^2_{ref} and $RMESE_{ref}$ are the reference performance statistics using all of the 18 measuring points of the inter-row pair-vines values ($ISUM_{18}$), and R^2_z and $RMSE_Z$ are the corresponding values for the reduction in the number of measuring points to 15 ($ISUM_{15}$), 10 ($ISUM_{10}$), 7 ($ISUM_7$) and 5 ($ISUM_5$) as depicted in Fig. 2.

2.4. Soil transport estimations

The total soil transport was estimated in $Mg\,ha^{-1}\,yr^{-1}$ using 18 ($ISUM_{18}$), 15 ($ISUM_{15}$), 10 ($ISUM_{10}$), 7 ($ISUM_7$), 5 ($ISUM_5$) and 2 (SUM) point measurements from the volume difference between the current soil surface topography and the initial soil surface topography (Fig. 2). The horizontal sides of the polygons were defined as the distances between the measuring points used, varying from 10 cm ($ISUM_{18}$) to 170 cm (SUM). The inter-row distance is 170 cm, and this means that the first and last of the 16 measuring points are 10 cm from the graft unions. The height of the polygon is taken as the distance between the botanic marks on the graft union and the inter-row surface levels, taking into account the visible actual rootstock (Rodrigo-Comino et al., 2016). The total soil mobilisation was estimated from the erosion–deposition (ER) equation proposed by Paroissien et al. (2010):

$$ER\,\frac{VxBD}{SxA} \tag{3}$$

Table 1
Descriptive statistics of the soil surface level data (cm).

Sampling method	Mean	Maximum depletion	Maximum accumulation	St. Dev.	Coeff. Var.
$ISUM_{18}$	−12.7	−28.1	10.2	4.6	36.4
$ISUM_{15}$	−12.3	−28.1	10.2	4.7	21.6
$ISUM_{10}$	−12.2	−28	10.2	4.8	23.1
$ISUM_7$	−12.0	−28	10.2	4.8	23.3
$ISUM_5$	−11.7	−28	10.2	4.9	24.1
SUM	−10.5	−22	10.2	5.7	32.8

*ISUM: Improved Stock Unearthing Method; SUM: Stock Unearthing Method; St. Dev.: Standard deviation; Coeff. Var.: Coefficient of variation.

where V (m^3) is the volume, S (ha) is the total area for the considered field unit, A (years) is the age of the vines (40 years-old) and BD is the soil bulk density ($1.4\,g\,cm^{-3}$). The reference value of the soil bulk density was taken as the mean soil bulk density of 36 soil samples collected along the row and inter-row areas.

3. Results and discussion

3.1. Measured points from ISUM survey

Table 1 presents the summary of the descriptive statistics of the 1062measuring point ($ISUM_{18}$) levels and those of the other ISUMs. The distribution of the measured point levels for the different ISUMs is represented in the form of histograms in Fig. 3. All mean values are in the depletion side and increase numerically with the number of measuring points. There was virtually no change in the maximum depletion and the maximum accumulation across the ISUMs with the exception of SUM which recorded a significant decrease of 22% in the maximum depletion compared with the others. Taking only two measurements (SUM), the ability to capture the highest depletion point was lost. However, SUM was sufficient for finding the highest accumulation point because the measuring points are situated under the vines that impede water and soil movement, thus encouraging deposition.

As reported in the literature (Biddoccu et al., 2017a), the highest depletion areas were found in the inter-row areas where the bare soils are easily eroded. Moreover, the more compacted surface due to tractor passes (Arnáez et al., 2012) and trampling effects (Quinn et al., 1980) also account for the reduction in the soil surface level in the inter-row areas. These two mechanical factors were recognised to be vital to the understanding of soil erosion and hydrological processes in Continental European vineyards using modelling techniques (Hacisalihoglu, 2007). Also, our findings confirm that the maximum accumulation points are close to the vines due to the redistribution of the material after each tractor pass and the effect of splash from the wheel track areas.

3.2. ISUM maps using different interpolation methods

After observing that the descriptive statistics are able to introduce some key factors to understanding soil erosion processes in vineyards, maps of the micro-topographical changes were prepared using eight different interpolation techniques for the ISUMs. Table 2 presents the

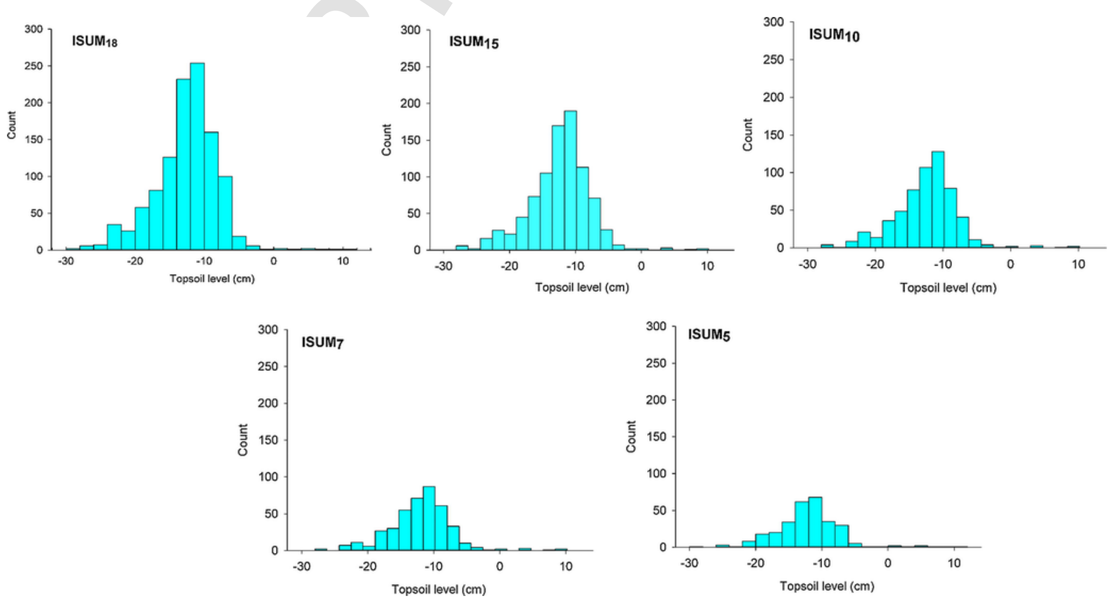

Fig. 3. Histograms of the ISUMs measured levels.

Table 2
Results obtained from the interpolation methods.

Kernel function/anisotropy*	ISUM	Kernel parameter	Prediction errors in cross-validation				
			Mean	RMSE	R^2	Δ RMSE	Δ R^2
OK Isotropy*	$ISUM_{18}$	–	−0.057	2.865	0.594	0.00	0.00
	$ISUM_{15}$		−0.015	3.159	0.535	−0.29	0.06
	$ISUM_{10}$		−0.076	3.493	0.449	−0.63	0.14
	$ISUM_7$		−0.130	4.038	0.301	−1.17	0.29
	$ISUM_5$		−0.171	4.620	0.151	−1.76	0.44
OK Anisotropy*	$ISUM_{18}$	–	−0.022	2.842	0.617	0.00	0.00
	$ISUM_{15}$		0.004	3.073	0.558	−0.23	0.06
	$ISUM_{10}$		−0.096	3.476	0.454	−0.63	0.16
	$ISUM_7$		−0.053	3.877	0.350	−1.03	0.27
	$ISUM_5$		−0.153	4.320	0.255	−1.48	0.36
IDW	$ISUM_{18}$	–	−0.115	2.859	0.610	0.00	0.00
	$ISUM_{15}$		−0.068	3.207	0.527	−0.35	0.08
	$ISUM_{10}$		−0.222	3.657	0.399	−0.80	0.21
	$ISUM_7$		−0.258	4.199	0.247	−1.34	0.36
	$ISUM_5$		−0.079	4.665	0.121	−1.81	0.49
EBK	$ISUM_{18}$	–	−0.022	2.900	0.604	0.00	0.00
	$ISUM_{15}$		0.000	3.007	0.577	−0.11	0.03
	$ISUM_{10}$		−0.130	3.516	0.442	−0.62	0.16
	$ISUM_7$		−0.159	4.104	0.271	−1.20	0.33
	$ISUM_5$		−0.040	4.629	0.136	−1.73	0.47
CRS	$ISUM_{18}$	22.81	−0.009	3.253	0.548	0.00	0.00
	$ISUM_{15}$	0.27	−0.028	3.254	0.528	0.00	0.02
	$ISUM_{10}$	0.19	−0.085	3.572	0.443	−0.32	0.10
	$ISUM_7$	0.37	−0.118	4.081	0.287	−0.83	0.26
	$ISUM_5$	0.27	−0.097	4.579	0.165	−1.33	0.38
ST	$ISUM_{18}$	11.03	0.000	3.038	0.587	0.00	0.00
	$ISUM_{15}$	0.17	−0.024	3.219	0.534	−0.18	0.05
	$ISUM_{10}$	0.12	−0.082	3.571	0.443	−0.53	0.14
	$ISUM_7$	0.29	−0.119	4.080	0.286	−1.04	0.30
	$ISUM_5$	0.31	−0.072	4.576	0.161	−1.54	0.43
M-Q	$ISUM_{18}$	0	0.010	2.920	0.608	0.00	0.00
	$ISUM_{15}$	0	0.012	3.202	0.541	−0.28	0.07
	$ISUM_{10}$	0	−0.027	3.523	0.458	−0.60	0.15
	$ISUM_7$	0	−0.028	4.038	0.329	−1.12	0.28
	$ISUM_5$	0	−0.248	4.624	0.193	−1.70	0.41
IM-Q	$ISUM_{18}$	0.16	−0.008	3.341	0.534	0.00	0.00
	$ISUM_{15}$	16.50	−0.032	3.431	0.501	−0.09	0.03
	$ISUM_{10}$	20.75	−0.082	3.632	0.438	−0.29	0.10
	$ISUM_7$	12.09	−0.170	4.147	0.265	−0.81	0.27
	$ISUM_5$	13.73	−0.026	4.567	0.159	−1.23	0.37
TPS	$ISUM_{18}$	1e+020	0.037	3.104	0.582	0.00	0.00
	$ISUM_{15}$	1e+020	0.053	3.379	0.521	−0.28	0.06
	$ISUM_{10}$	1e+020	0.093	3.524	0.486	−0.42	0.10
	$ISUM_7$	0.041176	0.108	4.177	0.343	−1.07	0.24
	$ISUM_5$	1e+020	−0.311	4.768	0.220	−1.66	0.36

ISUM: Improved Stock Unearthing Method; OK: Ordinary Kriging; IDW: Inverse Distance Weighting; EBK: Empirical Bayesian Kriging; CRS: Completely Regularised Spline; RBF: Radial basis functions; ST: Spline with Tension; M-Q: Multi-quadric; Inverse Multi-quadric. IM-Q; TPS: Thin Plate Spline. RMSE: Root mean square error.

cross-validation results of the interpolation methods, selecting the best model parameter sets as dictated by the performance statistics for each ISUM. The results show that the best maps can be modelled using up to 10 points which has an acceptable ΔR^2 value between 0.1 and 0.2. In order of decreasing performance, the methods identified were OK (with anisotropy), IDW, RBF (Multi-quadric) and EBK (Table 2). Our results can be considered valuable for this kind of study. This is notwithstanding that others, such as Biddoccu et al. (2017b) and Brenot et al. (2008), have indicated that OK and IDW are the best methods since they are the most applied methods in the literature (Fang and Horstemeyer, 2006; Fritsch et al., 2011; Kravchenko and Bullock, 1999; Samsonova et al., 2017). We suggest that authors should test all possible methods prior to developing ISUM maps and elucidate how many points should be used. At the catchment scale only, and specifically in vineyards, Chevigny et al. (2014) highlighted the idea of testing different interpolation methods when using the stock unearthing method to assess topsoil level changes. This paper also confirmed that this procedure is necessary to determine the best method, and it is also necessary to compare measurements in different regions of the world. This confirmation also gives insights into the design of field campaigns to apply ISUM for larger areas.

Fig. 4 presents $ISUM_{18}$ maps using various interpolation methods to show how it is possible to model soil surface variations from −20 cm to +8 cm. For example, the EBK map shows the high depletion mainly

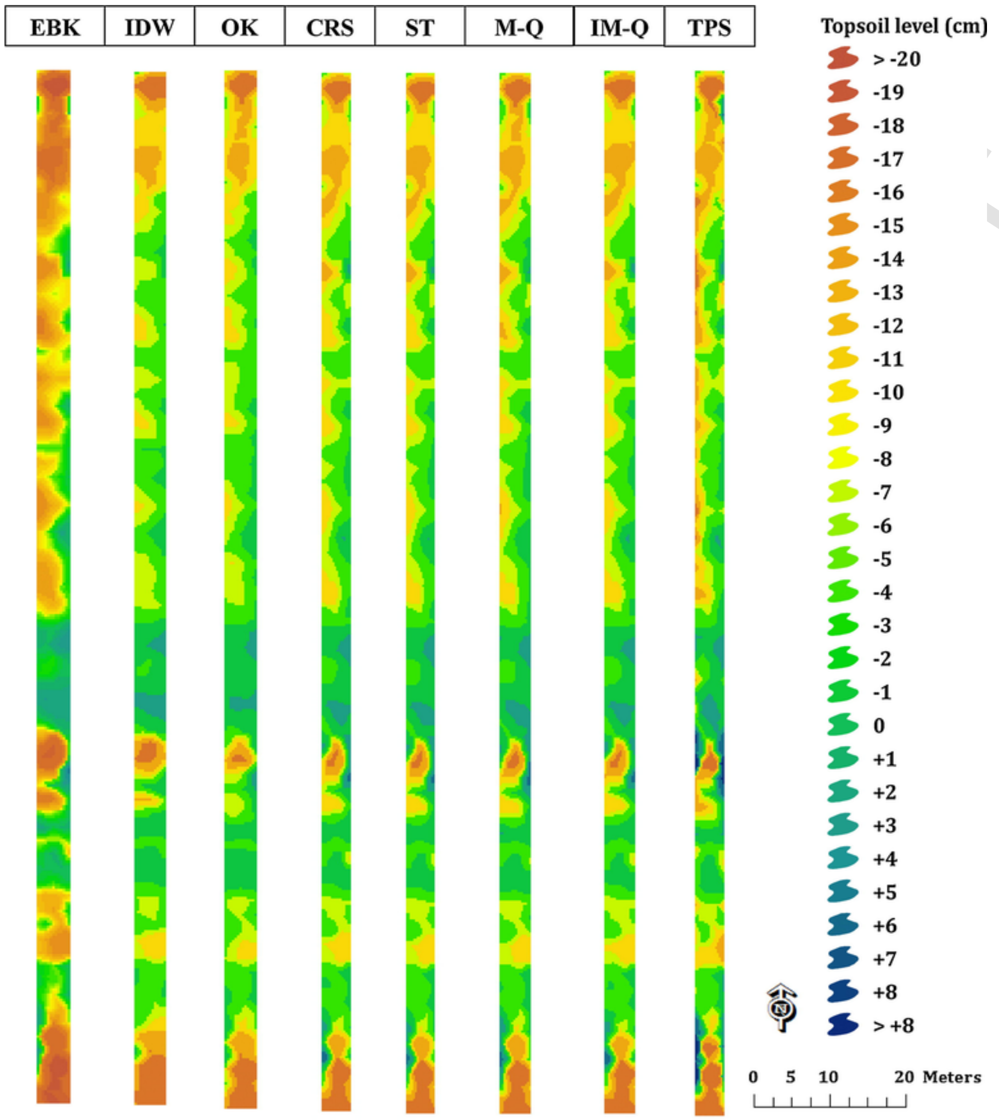

Fig. 4. $ISUM_{18}$ maps obtained from the different interpolation methods; OK: Ordinary Kriging; IDW: inverse distance weighting; EBK: empirical Bayesian kriging; CRS: Completely Regularized Spline; ST: Spline with Tension; M-Q: Multi-quadric; Inverse Multi-quadric (IM-Q); TPS: Thin-Plate Spline.

near the summit and the footslope, thus overestimating soil depletion. Among others, TPS and IM-Q maps show the highest accumulation areas, confirming sink areas of sediment accumulation. The rest of the maps for the other methods apparently show high similarities among them, although the predicted errors have demonstrated that RBF obtained the worst performance statistics.

3.3. Soil depletion and accumulation results

Table 3 shows the estimated total soil transport during the 40 years since the start of the plantation using the erosion-deposition equation (Paroissien et al., 2010). The calculated soil transport values corroborate the findings of Rodrigo-Comino et al. (2016) that soil depletion mainly occurs in the sloping vineyards of the Ruwer-Mosel valley instead of sedimentation. Using SUM an erosion rate of 3.3 Mg ha^{-1} yr^{-1} was obtained in an adjacent vine row by these authors. Our calculated erosion rates range from 64.8 obtained by SUM to 40.1 Mg ha^{-1} yr^{-1} with $ISUM_{18}$, and $ISUM_{15}$ obtained similar values to $ISUM_{18}$ reaching 39.4 Mg ha^{-1} yr^{-1}. We observe a break when we use 10 measuring points with only 25.0 Mg ha^{-1} yr^{-1} being obtained. On the other hand, $ISUM_5$ and $ISUM_7$ registered 38.9 and 37.9 Mg ha^{-1} yr^{-1}, respectively, which are definitively close to $ISUM_{18}$ and $ISUM_{15}$. This confirms that the $ISUM_5$ applied in the Valencian vineyards for the first time could be accurate (Rodrigo-Comino and Cerdà, 2018). These soil transport estimates confirm that 5 measurements (2 under the vines plus 3 in the inter-row) achieve the same result as 7 or very similar to 15 and 18 measurements. By selecting a smaller number of measuring points, time spent in the field would be reduced considerably, but the results

Table 3
Estimates of total soil transport.

Sampling Method	Total Soil Transport		
	m^3 ha^{-1}	Mg ha^{-1}	Mg ha^{-1} yr^{-1}
$ISUM_{18}$	−9.54	−13.6	40.1
$ISUM_{15}$	−9.36	−13.4	39.4
$ISUM_{10}$	−5.95	−8.5	25.0
$ISUM_7$	−9.01	−12.8	38.9
$ISUM_5$	−9.01	−12.9	37.9
SUM	−15.40	−22.1	64.8

*ISUM: Improved Stock Unearthing Method; SUM: Stock Unearthing Method.

would not be so accurate, at least, in this area. Thus, these results are useful in helping future standardisation of ISUM for larger plot sizes. However, it is important to remark on the importance of the specifications of the study area in question. Sometimes the wheel track areas are very well pronounced, and omitting measurements in the upper and lower parts could lead to significant errors in the developed models as was observed in Slovakia (Lieskovský and Kenderessy, 2014), Northern Spain (Casalí et al., 2009; Flaño et al., 2008), Portugal (Serpa et al., 2017) and Slovenia (Komac and Zorn, 2005).

3.4. Challenges and future research questions

Results obtained in this study using ISUM_{18} (16 measurements in the inter-row areas and 2 in the vine stocks) are much lower than the results obtained with SUM as reported in the literature, e.g., in Burgundy in France with 23 $\mathrm{Mg\,ha^{-1}\,yr^{-1}}$ (Brenot et al., 2008), in Navarre in Spain reaching 30 $\mathrm{Mg\,ha^{-1}\,yr^{-1}}$ (Casalí et al., 2009) and in the Aosta Valley in Italy with 15.7 $\mathrm{Mg\,ha^{-1}\,yr^{-1}}$ (Biddoccu et al., 2017b). All of the study areas investigated by these authors are situated in the Mediterranean region with some influence of the continent and/or the Atlantic Ocean. However, applying ISUM_5 in another Mediterranean vineyard in Valencia (Eastern Spain), Rodrigo-Comino and Cerdà (2018) registered only −2.5 $\mathrm{Mg\,ha^{-1}\,yr^{-1}}$ which is too far from our estimations. Therefore, SUM and ISUM_5 applied in different regions cannot be compared as the differences could be due to an artefact in the method applied or due to the regional differences in soil mobilisation that could vary significantly across rows and inter-row areas. Therefore, standardisation of the method (interpolation and number of measurements) should be considered mandatory. We confirm that less than 10 cm separation of inter-row measurements (> 15 measuring points in this study area) and 2 at the base of the pair graft unions could be enough to achieve a reasonable estimation of soil mobilisation rate and to model micro-topographical changes. It is proposed that future measurements should check ISUM accuracy in other countries or other techniques such as rainfall simulators (Iserloh et al., 2012) on erosion plots (Mekonnen et al., 2016). Also, it is suggested that ISUM is compared with other measurements and estimations at different scales (Raclot et al., 2009) and soil parameters such as organic carbon (Garcia et al., 2018). Larger scales would make possible the modelling of rills and ephemeral gullies, and areas of accumulation (Ben-Salem et al., 2018; López-Vicente et al., 2015). A key research topic will be to determine the effect of soil erosion on soil quality and plant vigour as ISUM can show the spatial distribution of soil mobilisation and their effect on plant production. ISUM can also help to understand the impact of soil erosion on the soil physical properties such as infiltration and saturated hydraulic conductivity, and on grape production and wine quality.

It is recognised that the original micro-topography of the inter-row area 40 years ago is not possible to be known precisely. The original stock unearthing method (SUM) is applied only to measure the distance between the graft unions and the soil surface, and the estimation of elevation differences is done for these points only. The soil compaction of the row area cannot be the same as the inter-row area where tillage is carried out. The original inter-row area surface may have been subjected to wheel tracks and foot trampling effects before the occurrence of soil mobilisation processes. Therefore, further research for reconstruction of the original soil surface through modelling techniques is required, or the measurements should start soon after the plantation of the vineyards (Remke et al., 2018).

The initial measurement of the distance between the soil surface and measuring tape was taken only once during August. We selected this month due to fact that it reflects natural soil settling/compaction after the mechanical tillage applied in spring and prior to disturbing the soil surface after the harvest. However, for future research, we will improve the methodology by taking the same measurements at least three times per year so that we can include the average value and discuss the seasonal variability of soil surface topography.

Our analysed area is thin and long, which could indicate that the obtained results may be determined by these particular points distribution. However, this aspect has to be investigated thoroughly. As we measured only one row, a logical next step would be the application of ISUM to more rows in order to increase the area and, subsequently, the width. Possibly, we could observe if differences in the current soil surface map exist because of the new points distribution pattern.

Moreover, new research on strategies to reduce soil mobilisation from areas that are likely to register high erosion rates but where the studies of soil erosion are scarce should also be carried out such as in South Africa, China, Iran or Turkey among others (Rodrigo-Comino, 2018). Another research topic using ISUM would be a focus on measuring areas where there is an establishment of vegetation cover on the soil surface, which is well-known as a good practice that farmers should be encouraged to follow (Marqués et al., 2015). Finally, since the paleo-surface is well-recognised because of the graft union, the use of new technologies such as drones or cameras should be considered mandatory to help increase the number of points and to assess larger areas (Remke et al., 2018; Tarolli et al., 2019).

4. Conclusions

The improved stock unearthing method (ISUM) can be considered as a useful tool for the estimation of soil mobilisation rates and modelling of micro-topographical changes. This research has given insight into the minimum number of measuring points in the inter-row areas required to obtain reasonable accuracy in the estimation of erosion rates, and surface levels for generating precise maps using interpolation methods. Starting with a maximum of 10 cm separation of measuring points, we established that this should be sufficient for estimation of soil mobilisation rates. Moreover, Ordinary Kriging emerged as the best interpolation method for the best ISUM (8 points in the inter-row areas) map for assessing micro-topographical changes in this area. These results highlight the steps that should be taken to standardise ISUM and to perform field measurements across other vineyards. Further, it is not known whether results under different land management systems, parent materials, ages and climate conditions will alter the findings.

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Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.compag.2019.03.007.

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