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Mapping slope deposits depth by means of cluster analysis: a comparative assessment

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ABSTRACT

In this work a comparison among slope deposits (SD) maps obtained by integrating field measurements of SD depth and cluster analysis of morphometric data has been performed. Three SD depth maps have been obtained for the same area (SA1) by using different approaches. Two maps have been achieved by implementing both the supervised and unsupervised approaches and exploiting the dataset of SD depths previously collected in a region (SA2) characterized by the same bedrock lithology, although located 35 km far from the SA1. The results have been validated against a reference map based on SD depth measurements acquired during this work within the SA1 and mapped by unsupervised clustering. The outcome of the study shows the feasibility of the methodology proposed to obtain depth maps of SD. Nevertheless the very low map accuracy suggests that relationships among main morphometric variables and slope deposits depth are not constant at regional scale, although considering areas characterized by the same bedrock lithology. Hence, maps of SD depth should be based on depth data specifically acquired within the area under study. In order to improve the exploitation of SD depth datasets outside their provenance area, further research are necessary on clustering algorithms performance as well as additional morphometric and environmental variables to be employed in spatial analysis.

KEY WORDS: Slope Deposits, Morphometric Analysis, Depth of Slope Deposits, Cluster Analysis, Environmental Variables.

INTRODUCTION

Landslides induced by intense rainfall events involving soils (slope deposits - SD) overlying bedrock (Daniels & Hammer, 1992; Arno & Birgit 2013) constitute a source of hazard within hilly and mountainous regions. For this reason, interest of the scientific community has been growing in performing landslide hazards/susceptibility evaluation for wide areas (regional assessment) to support sustainable spatial planning (Van Westen et al., 2006; Wu et al., 2015). The depth of SD is a fundamental parameter (Wu & Sidle, 1995; Terlien et al., 1995; Segoni et al., 2012) when implementing maps of shallow landslide susceptibility by physically based models, such as SHALSTAB (Montgomery & Dietrich, 1994; Dietrich & Montgomery, 1998). Therefore different approaches to estimate the spatial distribution of SD depth have been proposed in the literature (Hsu, 1994; Dietrich et al., 1995; Heimsath et al., 1999; Catani et al., 2010).

The aim of this study is to compare the accuracy of SD depth maps obtained through cluster analysis methods, either by using SD depth measurements specifically acquired within the study area (Trefolini et al., 2015), or by exploiting the same kind of data previously collected within regions located far away from the study area, although characterized by similar geological properties. To this aim, two study areas situated in the Northern Apennines (Fig. 1), both characterized by the same bedrock lithology (sandstone of the *Formazione del Macigno* MAC), have been chosen. For the Study Area 1 (SA1) three different SD depth maps have been obtained: the first (reference map) by using local, specifically acquired, measurements of SD depth, the others (test maps) by exploiting SD depth information collected in the Study Area 2 (SA2).

METHODS

SD depth data have been acquired in the field and have been classified into two groups, as shown in Tab. 1: four depth classes pertain to the group A ("thin SD" with depth ≤ 0.3 m) while three classes to the group B ("thick SD" with depth > 0.3 m). Classes of group A were defined in order to describe the natural non-uniform spatial distribution of thin SD: class A1 is used to describe mainly outcropping bedrock; A2, instead, is used when thin SD prevail; those areas where non-mappable portions of SD deeper than 0.3 m also occur, are classified as either A1B or A2B. The above described SD depth nomenclature shouldn't be regarded to as scale invariant and it refers to a mapping scale of 1:10.000.

Transversal and longitudinal curvatures, flow accumulation and slope have been derived from a DEM with spatial resolution of 10 m and have been used as morphometric variables to describe the morphology of the study areas after being pre-processed. To this aim, for transversal and longitudinal curvatures, the data outside the range of the mean value ± 4.5 standard deviations (outliers) have been removed, while flow accumulation has been normalized by a lognormal

Fig. 1 – Map of the study areas: Study Area 1 (SA1 - red), located around the Carrara town; Study Area 2 (SA2 - orange), located along the left bank of the Serchio river (Map data ©2015 Google). Comparison has been performed among different SD depth maps of the SA1, obtained by SD depth measurements collected either in the same SA1 or in the SA2.

transformation. Then each variable has been rescaled to the same range.

Assuming that, for areas characterized by homogeneous bedrock lithology, spatial distribution of SD depth is correlated with distribution of landforms (hence with morphometric description of ground surface) the above 4-variables morphometric representation has been clustered, and classified by using the SD depth dataset and nomenclature, in order to obtain continuous SD depth maps. With the aim to assess the reliability of the SD depth mapping process, three depth maps have been produced for the SA1 by implementing three different and independent approaches. The reference map SA1-U (Fig. 2) has been obtained by means of unsupervised clustering (ISODATA algorithm), as in Trefolini et al. (2015), by choosing 15 clusters to describe the morphometric space. Thereafter, each morphometric cluster have been assigned to depth classes by analyzing sampling distribution of SD depth measurements, collected in SA1.

The test map SA1-S (Fig. 3) has been extracted by implementing a maximum likelihood algorithm (Richards & Xiuping, 2006). To this aim, the training dataset has been built by using the measurements collected in the SA2 (about 170 test sites). In order to get values by the four morphometric variables, a neighbourhood of 21 meters around each observation point has been used. Lastly the test map SA1-UM (Fig. 4) has been obtained by performing an unsupervised clustering, as for the reference depth map SA1-U, but in this case clustering has been applied to the morphometric space obtained by mosaicing both study areas. The 15 morphometric clusters have been classified into depth classes by exploiting the SA2 dataset of SD depth.

Depth group	Depth class	Description
A "thin SD"	A1	Continuous or prevailing outcropping bedrock; dSD generally ≤ 0.3 m.
	A1B	As A1, with local not-mappable areas of SD pertaining to group B (SD depth > 0.3 m).
	A2	Continuous or prevailing SD with SD depth generally ≤ 0.3 m.
	A2B	As A2, with local not-mappable areas of SD pertaining to group B (SD depth > 0.3 m).
B "thick SD"	B1	Bedrock generally not outcropping; dSD 0.3-1 m.
	B2	Bedrock not outcropping; SD depth: 1-2 m.
	B3	Bedrock not outcropping; SD depth > 2 m.

Tab. 1 – Nomenclature used for classification of depth of SD (modified from Trefolini et al. 2015).

The test maps (SA1-S and SA1-UM) have been compared with the reference map (SA1-U) and the results are shown by error matrix, as well as producer, user and total accuracies (for definitions and formulas, see Congalton & Green, 2009).

RESULTS

The results of maps comparison SA1-S *vs.* SA1-U are shown in Tab. 2. The total accuracy is very low (20.8%) and the best producer accuracy has been obtained for depth class B1 and the worst for B2. Whereas the best user accuracy has been obtained for depth class A2 and the worst for B2.

The error matrix for comparison SA1-UM *vs.* SA1-U is shown in Tab. 3. For this map the total accuracy is even lower (15.3%). As for SA1-S, map the best producer accuracy has

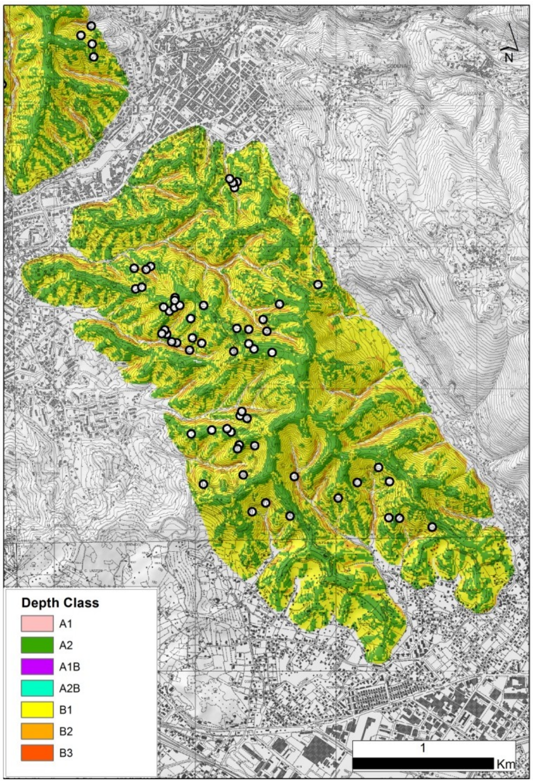

Fig. 2 – Reference map SA1-U: unsupervised classification within SA based on 140 SD depth measurements (white dots) collected in the sam area. Depth classes as in Tab. 1.

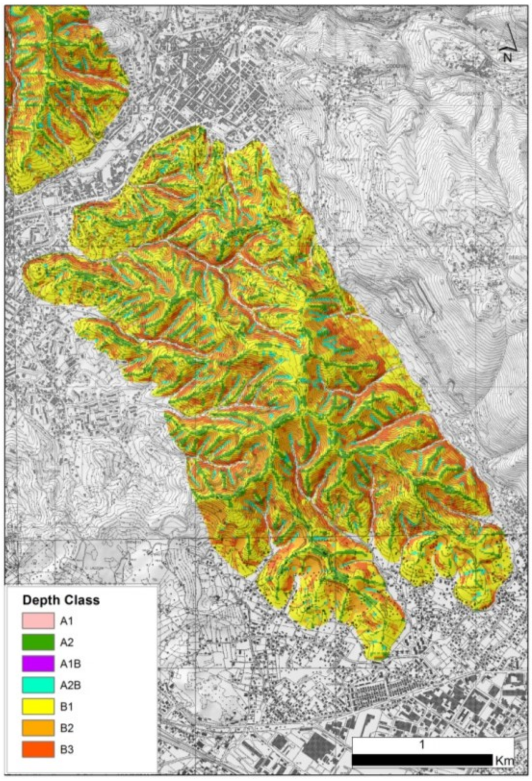

Fig. 3 – Test map SA1-S: supervised classification within SA1 based on 170 SD depth measurements collected in the SA2. Depth classes as in Tab. 1.

been obtained for depth class B1 and the best user accuracy for depth class A2. Furthermore B2 depth class shows the worst producer and user accuracy.

DISCUSSION AND CONCLUSION

The maps of SD depth here presented (Fig. 3 and Fig. 4) show a reasonable distribution of SD depth classes. The thin depth classes (group A, Tab. 1) occur mostly in the ridge and nose areas, while thick depth classes (group B) develop along hillslopes with general thickening toward their bottom and in gently sloping areas. This result is in agreement with a general model of soil production, erosion, transport and sedimentation accepted in the literature (Daniels & Hammer, 1992; Arno & Birgit, 2013) and also observed during the field survey. Moreover the maps are not affected by noticeable “salt and pepper” effect. These results support the feasibility of segmentation methods of multidimensional morphometric space for the extraction of SD depth maps.

Whereas, as regards the quantitative comparison between the reference map SA1-U and test maps (SA1-S and SA1-UM), the error matrix show a more complex framework. The A2B and B3 SD depth classes are predicted by the procedure based on SD depth data from the area SA2, but these classes are missing in the fieldwork dataset of the area SA1 and then in the map A1-U. This may account for low general accuracy because class B3 is widespread in the area SA2. Moreover Tab. 2 and

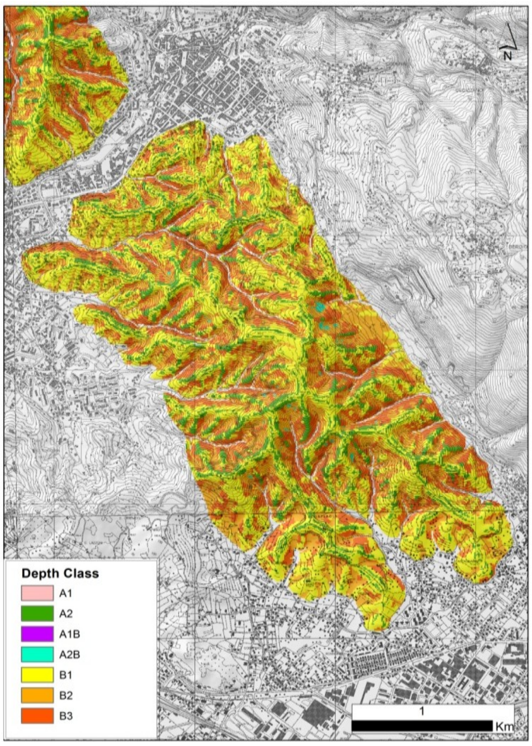

Fig. 4 – Test map SA1-UM: unsupervised classification obtained for the mosaic of SA1 and SA2 based on 170 SD depth measurements collected in the SA2. Depth classes as in Tab. 1

Depth class SA1-U	Depth class SA1-S					Producer Accuracy	User Accuracy	Total Accuracy
	A2	A2B	B1	B2	B3			
A2	24.5	1.7	*49.5*	18.8	5.5	24.5	74.1	
A2B								
B1	6.9	9.4	28.8	*42.1*	12.8	28.8	36.7	20.8
B2	1.7	0.0	0.1	9.2	*89.0*	9.2	13.1	
B3								

Tab. 2 - Error matrix, maps SA1-S *vs*. SA1-U.

Tab. 3 highlight the general tendency of tests maps to develop deeper DS classes: A2 class in the reference map corresponds to B1 for 49.5% and 64.4% in SA1-S and SA1-UM respectively. In the same way, class B1 corresponds mainly to B2 (42.1% and 44.3%). The tendency of the maps obtained by SD depth data related to area SA2 to overestimate depth class is further evident for class B2 of SAI-U, generally corresponding to B3 (89.0% for SA1-S and 96.0% for SA1-UM).

Depth class SA1-U	Depth class SA1-UM					Producer Accuracy	User Accuracy	Total Accuracy
	A2	A2B	B1	B2	B3			
A2	19.8	0.0	*64.4*	3.4	12.4	19.8	72.0	
A2B								
B1	7.7	0.9	22.7	*44.3*	24.3	22.7	25.9	15.3
B2	0.0	0.0	0.4	3.6	*96.0*	3.6	7.0	
B3								

Tab. 3 – Error matrix, maps SA1-UM *vs.* SA1-U.

In synthesis this work shows that predictive modeling of SD depth from one area to another nonadjacent area, although characterized by the same bedrock lithology, without any support by local field data, may be unreliable. Therefore new research are necessary with the aim of improving the exploitation of existing SD depth datasets outside the collection areas. For istance, new variables could be included in the analysis, such as: morphometric (elevation, flow length, aspect, etc.), engineering geology (rock mass quality of bedrock, weathering), land cover and meteo-climatic data.

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