

# Modeling Morpho-Structural Settings Exploiting Bedding Data Obtained Through the Interpretation of Stereoscopic Aerial Photographs

Ivan MARCHESINI, Michele SANTANGELO, Fausto GUZZETTI, Mauro CARDINALI, Francesco BUCCI

*Istituto di Ricerca per la Protezione Idrogeologica, Consiglio Nazionale delle Ricerche, via della Madonna Alta 126, 06128, Perugia, Italy, Tel. +39 075 5014 411*

**Abstract.** Landslide abundance is controlled by multiple factors, including the presence and attitude of beddings, foliation, faults, joints and cleavage systems. Few attempts were made to exploit bedding attitude (BA) data (or data on similar types of rock discontinuities) in statistical or physically based models for regional slope stability analysis. A reason for the lack of applications lays in the complexity of the bedding data, and in the difficulty in the treatment and modelling of circular information. Typically, BA data are collected as point data through field surveys, and suffer from heterogeneity in their spatial distribution. The latter problem is particularly important due to the limited possibility to collect BA data in areas of difficult access. An additional problem lays in the spatial interpolation of the BA data, which are directional data that cannot be interpolated using standard approaches. We build on previous work where we proposed an approach to obtain BA data from bedding traces (BT) i.e., linear signatures of layered rocks on the topographic surface, obtained through the visual interpretation of aerial photographs, and to interpolate the BA data to construct maps showing the geometrical relationship between BA data and slope geometry i.e., maps showing cataclinal, orthoclinal, and anaclinal slopes. In this work, we consider the uncertainties in the definition of the BAs that are used in the production of morpho-structural domain maps, and we investigate the relationships between the morpho-structural domains and landslide abundance in a study area in Umbria, Italy.

**Keywords.** Bedding, bedding attitude, landslide, aerial photographs, GIS.

## 1. Introduction

Bedding planes and other geological discontinuities are known to affect the stability/instability conditions of slopes (Guzzetti et al., 1996; Günther, 2003; Goudie, 2004; Grelle et al., 2011). The geometrical relationships linking the attitude of bedding planes and local topography can be classified considering the angle between the bedding dip direction and the local terrain aspect, and the angle between the bedding dip angle and the slope inclination. Using these two angles, five morpho-structural (MS) domains can be singled out (Grelle et al., 2011): anaclinal (A), orthoclinal (O), cataclinal over-dip ( $C_O$ ), cataclinal dip ( $C_D$ ), and cataclinal under-dip ( $C_U$ ) domains.

Working in Umbria, central Italy, Santangelo et al. (2014) revealed a correlation between the abundance of deep-seated landslides and the local MS setting. Specifically, these authors found that in their study area deep-seated

landslides were most abundant in cataclinal (C) slopes, and were rare in anaclinal (A) slopes. To prepare maps showing the local MS settings, Santangelo et al. (2014) used information on bedding traces (BTs) i.e., linear features marking the geometrical intersection between bedding planes and the topographic surface. To obtain the bedding attitude (BA) of the plane represented by each BT draped over a digital representation of the terrain (i.e., a digital elevation model, DEM), Santangelo et al. (2014) used the approach proposed by Marchesini et al. (2013). In this approach, the BA data are interpolated to obtain raster maps showing the bedding dip direction and inclination. Exploiting the two maps and the DEM, and adopting the TOBIA approach (Meentemeyer and Moody, 2000), the method allows preparing a map showing the local MS setting (Santangelo et al., 2014). The resulting map depends on multiple factors, including the number and distribution of the BTs, the length of the individual BTs, the value of the

constant used for the interpolation (i.e., the “tension”), and the geological complexity of the area. In a recent work, Marchesini et al. (submitted) have examined the influence of the length of the single BTs, and of the value adopted for the “tension” on the MS map, and have proposed a procedure to define optimal values for the two parameters. However, these authors have not considered the uncertainty in the determination of BA data from the BTs.

In this paper (i) we first investigate the propagation of the uncertainty typical of the BA data in the production of a MS map, and (ii) we next evaluate the effects of the uncertainty in the BA data on the analysis of landslide abundance in the different morpho-structural domains.

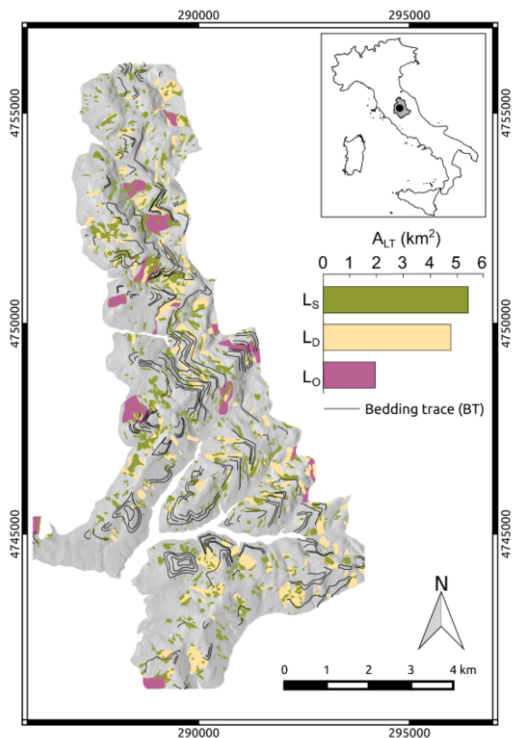
## 2. Study Area and Data

Our study area extends for 50.5 km<sup>2</sup> near the village of Collazzone, central Umbria, Italy. This is the same area studied by Santangelo et al. (2014) (Figure 1). For the area, a 10 m × 10 m resolution DEM, and a multi-temporal landslide inventory map at 1:10,000 scale were available to us (Figure 1). In the inventory landslides are grouped in three classes, including old deep-seated landslides (L<sub>O</sub>), deep-seated landslides (L<sub>D</sub>), and shallow landslides (L<sub>S</sub>). The classification is based on information on the estimated age, depth, and type of the landslides stored in a geographical database (Guzzetti et al., 2006, 2009; Fiorucci et al., 2011). In Figure 1 black lines show the 207 single bedding traces (BTs) identified in the study area. Adopting the procedure proposed by Marchesini et al. (submitted), all BTs longer than 2000 m were split in shorter segments.

## 3. Methods

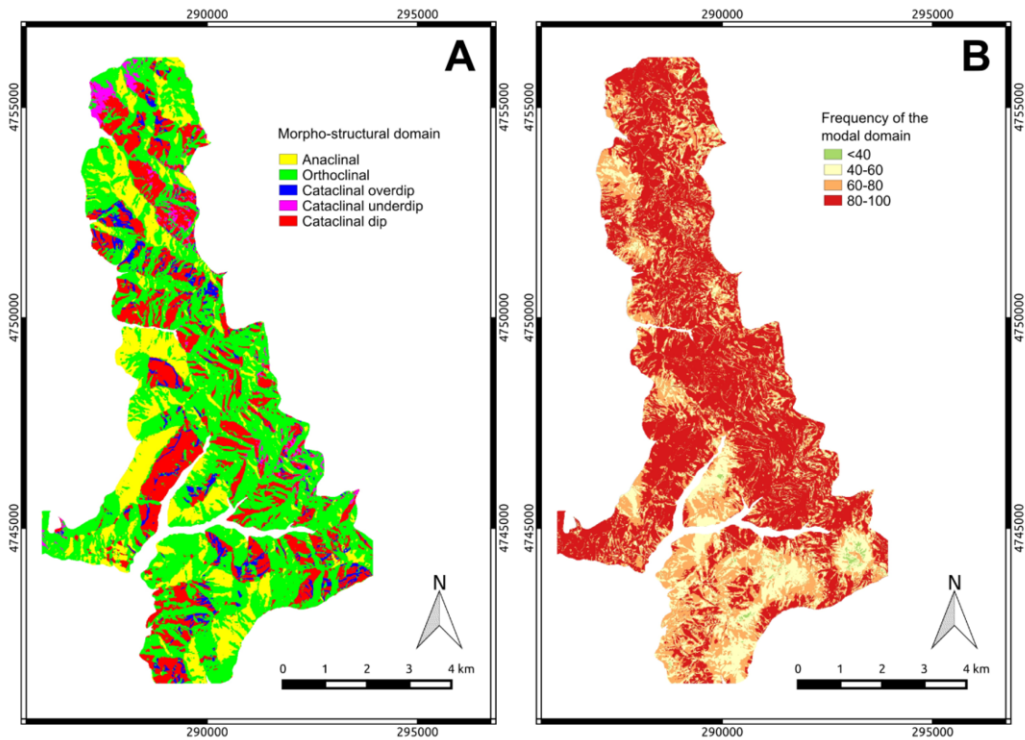
In the procedure proposed by Santangelo et al. (2014), bedding attitude (BA) is obtained triangulating (interpolating) regularly spaced points along each BT draped over a DEM having an adequate resolution. The triangulation results in a three-dimensional GIS raster surface (named “bedding surface”, BS). The median slope and azimuth of each BS are taken to represent the

inclination and dip direction of the local bedding. For each BT, the two values are assigned to a point located in the centre of a box bounding the BT.



**Figure 1.** Map showing (i) the extent and morphology of the area (shaded relief), (ii) the distribution of old deep-seated landslides (L<sub>O</sub>), deep-seated landslides (L<sub>D</sub>), and shallow landslides (L<sub>S</sub>), (iii) the 207 bedding traces (BT) identified in the area through the visual analysis of stereoscopic aerial photographs; and (iv) the total landslide area for each landslide type (A<sub>LT</sub>). Modified from Marchesini et al. (submitted).

In this work, we performed a spatially random sampling of 100 pairs of values of the slope (inclination) and the corresponding azimuth (dip direction) of each triangulated BS, and we assigned the single pairs to the points representing the locations of the BAs (i.e., the centres of the bounding boxed encompassing the individual BTs). Using this approach, we prepared 100 BA maps using the same set of locations for the points representing the BA data, and different values for the dip direction and inclination of the BS. Next, we interpolated the BA maps and applied the TOBIA approach (Santangelo et al. 2014) to obtain 100 different maps showing MS domains. For the interpolation,



**Figure 2.** (A) Map showing for each  $10\text{ m} \times 10\text{ m}$  grid cell the most frequent (modal) MS domain in a set of 100 MS maps. (B) Map showing the frequency of the modal MS domain in a set of 100 MS maps.

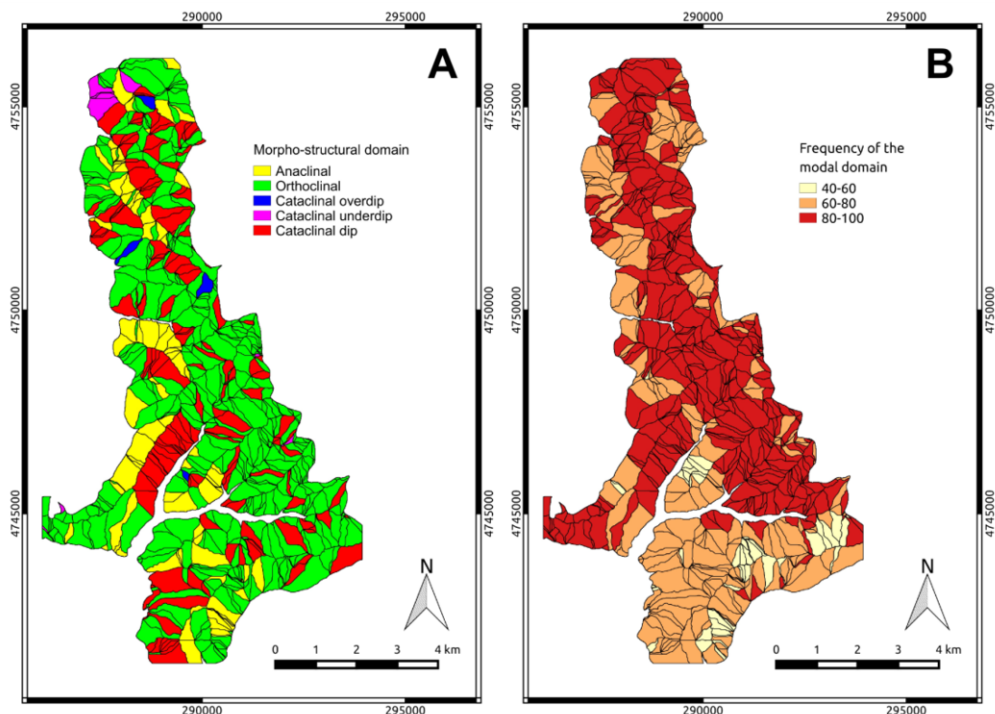
we adopted the Regularized Splines with Tension (RST) algorithm (Hofierka et al., 2002), setting the tension value to the optimal value of 30 proposed for the study area by Marchesini et al. (submitted).

#### 4. Results and Discussion

Exploiting the set of 100 different MS domain maps, we produced (i) a map showing, for each  $10\text{ m} \times 10\text{ m}$  grid cell, the most common MS domain (i.e., the “modal” domain map, Figure 2A), and (ii) a map showing how many times the most frequent domain occurs in each cell (i.e., the map of frequency of the modal domain, Figure 2B). The first map (Figure 2A) represents a central tendency of the MS classification, and is similar to the map presented by Santangelo et al. (2014) and by Marchesini et al. (submitted). This was expected, as both authors have used the median value (a measure of the central tendency of the distribution) of the azimuth and the dip direction of the bedding surfaces (BSs) as the

value for the bedding dip angle and dip direction. The second map (Figure 2B) shows a measure of the robustness of the classification. A value of 90 indicates that the considered grid cell was attributed to the same MS domain by 90% of the maps, and a value of 20 indicates that the grid cell was attributed to the same MS domain only by 20% of the maps. We argue that higher values are indicative of a more robust (consistent) MS classification. Visual inspection of Figure 2B reveals that the majority of the grid cells (56.2%) have values  $> 80$ . We consider this an indication of the robustness of the MS domain classification. Further inspection of Figure 2B reveals that a number of grid cells (18.6%) have values  $< 60$ . These areas, where the MS domain classification is less robust, concentrate in the southern part of the study area. We maintain that the poorer classification is the result of a reduced number of the BTs (Figure 1), and to the nearly horizontal inclination of the beddings (Figure 3) in the southern part of the study area.

We have aggregated the grid-cell-based information on the MS domains shown in Figure



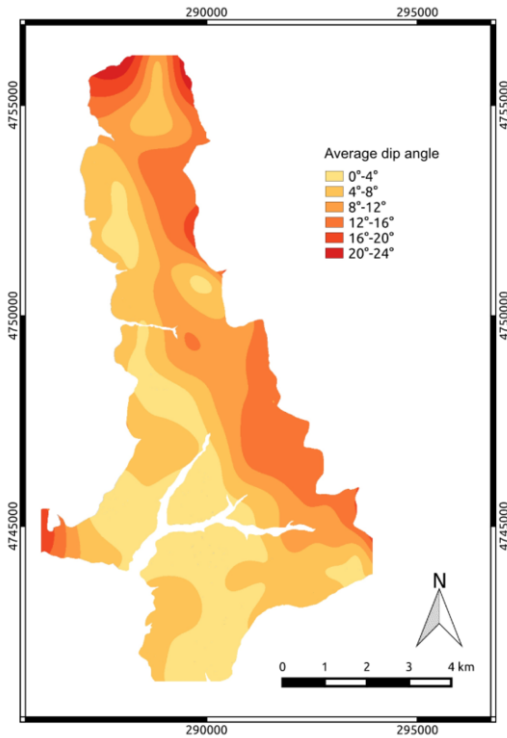
**Figure 3.** (A) Map showing slope units (Carrara et al., 1991) classified based on the most frequent (modal) value of the MS domain in each slope unit. (B) Map showing slope units classified based on the average of the frequencies of the modal MS domains, shown in Figure 2B.

2 using “slope units”, where a slope unit is a terrain subdivision based on hydrological regions bounded by drainage and divide lines (Carrara et al., 1991).

For the purpose, we classified each slope unit using the modal value of the grid cells shown in Figure 2A in each slope unit. Inspection of Figure 4A reveals the abundance of orthoclinal (O), anacinal (A), and cataclinal dip ( $C_D$ ) slopes, and the lack of cataclinal underdip ( $C_U$ ), and cataclinal over dip ( $C_O$ ) domains. Figure 4B portrays the average value of the frequency shown in Figure 2B. Figures 2 and 4 provide different (and complementary) representations of the same general result. Despite the redundancy, we consider important to aggregate the BA data on slope units. Partitioning an area into slope units has the advantage of discretizing the territory into terrain units that maximize terrain homogeneity within a single unit and heterogeneity between distinct units (Guzzetti, 2006; Alvioli et al., 2014). In addition, slope units are simple to recognize on a map and in the field, can be used to describe

different landforms, and are well suited to evaluate landslide hazard (Guzzetti et al., 2006).

Even though large parts of the study area were attributed a low level of uncertainty ( $> 80$  in Figures 2B and 4B), there are parts of the study area where the uncertainty associated to the modal MS domain is significant ( $< 60$  in Figures 2B and 4B). A question is how this uncertainty in the classification affects the analysis of the landslide abundance in the different MS domains. To answer the question, we computed the proportion of the different MS domains affected by the three different landslide classes,  $P(\text{MS}_i | L_O)$ ,  $P(\text{MS}_i | L_D)$ ,  $P(\text{MS}_i | L_S)$ , where  $i$  is one of five MS domains, and we compared them to the proportion of the MS domains in the entire study area  $P(\text{MS}_i) = N\{\text{MS}_i\} / N\{T\}$ , where  $N\{\text{MS}_i\}$  is the number of grid cells of the  $i$  MS domain in the study area, and  $N\{T\}$  is the total number of grid cells in the entire study area. For the comparison, we considered all the 100 computed MS domain maps.

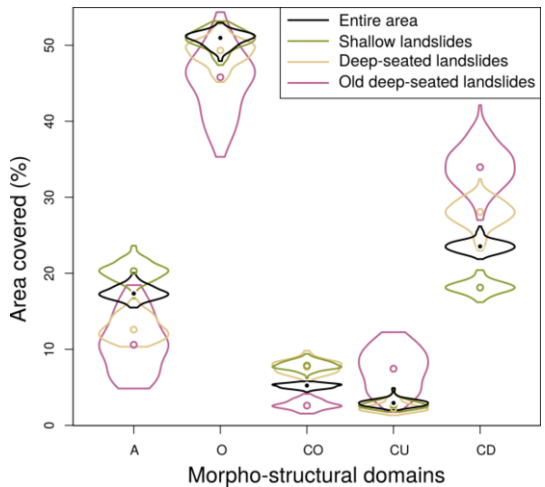


**Figure 4.** Average value of the bedding dip angle.

Results are summarized in Figure 5, in which the black “violins” show the distribution of the values of  $P(MS_i)$  for all the 100 MS maps. The green lines represent the distribution of the proportion of the MS domains in areas affected by shallow landslides,  $P(MS_i | L_S)$ . The light brown and the purple lines represent the distribution of the proportion of the MS domains in areas affected by deep-seated landslides,  $P(MS_i | L_D)$ , and by old deep-seated landslides,  $P(MS_i | L_O)$ , respectively. In Figure 5, the points (shown using the same colour of the corresponding “violin”) show the mean values of the distributions. Visual inspection of Figure 5 reveals that the statistical distributions of the proportions of the MS domains in the different landslide classes ( $L_O$ ,  $L_D$ ,  $L_S$ ) are different from the distributions obtained for the entire area. For the old deep-seated landslides ( $L_O$ ), the anacinal domain (A) is less abundant than in the entire area, whereas for the shallow landslides ( $L_S$ ) the opposite occurs. The poor overlap between the statistical distribution of the anacinal (A) setting in landslide areas and in the entire study area suggests that the two distributions are different.

This is confirmed by a very small value of the Kolmogorov-Smirnov (KS) p-value  $< 2.2 \times 10^{-16}$ .

This is not the case, at least for  $L_S$  (KS p-value = 0.1545) in the orthoclinal (O) domain where significant overlap exists with the distribution of the MS domains for the entire area. In cataclinal over dip ( $C_O$ ) slopes,  $L_S$  and  $L_D$  exhibit larger proportions than in the entire area, and larger than the  $L_O$ . Further inspection of Figure 5 reveals that in the cataclinal under dip ( $C_U$ ) domain only the statistical distribution of the proportions in  $L_O$  has a significant (KS p-value  $< 2.2 \times 10^{-16}$ ) difference, as opposed to that in the entire area. Finally, it is worth mentioning that the cataclinal dip ( $C_D$ ) domain is significantly more represented in  $L_O$  and  $L_D$ , when compared to the entire area. This is not the case for  $L_S$ , where the domain is poorly represented.



**Figure 5.** “Violin plot” (a combination of a box plot and a kernel density plot) showing for the different MS domains the statistical distribution of old deep-seated landslides ( $L_O$ , purple), deep seated landslides ( $L_D$ , light brown), shallow landslides ( $L_S$ , green), and the entire area (black). A, anacinal; O, orthoclinal;  $C_O$ , cataclinal over dip;  $C_U$ , cataclinal under dip;  $C_D$ , cataclinal dip.

## 5. Conclusions

We have investigated the effects of uncertainty in the definition of bedding attitude (BA) data obtained from information captured from bedding traces (BT) mapped visually through the interpretation of stereoscopic aerial photographs.

We have further evaluated the extent to which the uncertainty in the definition of the BA data affects the delineation of morpho-structural (MS) domains.

Analysis of the data revealed statistically significant evidence that cataclinal dip ( $C_D$ ) slopes host more old deep-seated landslides ( $L_O$ ) and deep-seated landslides ( $L_D$ ) than shallow landslides ( $L_S$ ). We conclude that  $C_D$  slopes are more susceptible to these two landslide types. The same landslide types are less abundant in the anaclinal domain (A), which is therefore less susceptible to old deep-seated ( $L_O$ ) and deep-seated ( $L_D$ ) landslides. Shallow landslides ( $L_S$ ) exhibit an opposite behaviour, and we argue that their abundance in the anaclinal (A) and cataclinal over dip ( $C_O$ ) is a result of the abundance of steep slopes in the two MS domains (Marchesini et al., submitted). Our work confirms that, even considering the uncertainties associated to the initial definition of the BAs, the influence of the beddings on the abundance of the deep-seated landslides is significant, in our study area.

More generally, our study suggests that the MS settings can play an important role in the assessment of landslide susceptibility in areas where deep-seated landslides are present. We argue that statistical and physically based models should exploit information on the local MS setting where the susceptibility of deep-seated landslides is ascertained.

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