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Development of a statistical tool for the estimation of riverbank erosion probability

E. A. Varouchakis, G. V. Giannakis, M. A. Lilli, E. Ioannidou, N. P. Nikolaidis, and G. P. Karatzas

School of Environmental Engineering, Technical University of Crete, Chania, Greece

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Correspondence to: E. A. Varouchakis (varuhaki@mred.tuc.gr)

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Abstract

Riverbank erosion affects river morphology and local habitat and results in riparian land loss, property and infrastructure damage, and ultimately flood defence weakening. An important issue concerning riverbank erosion is the identification of the vulnerable areas in order to predict river changes and assist stream management/restoration. An approach to predict vulnerable to erosion areas is to quantify the erosion probability by identifying the underlying relations between riverbank erosion and geomorphological or hydrological variables that prevent or stimulate erosion. In the present work, a combined deterministic and statistical methodology is proposed to predict the probability of presence or absence of erosion in a river section. A physically based model determines the vulnerable to erosion locations by quantifying the potential eroded area. The derived results are used to determine validation locations for the statistical tool performance evaluation. The statistical tool is based on a series of independent local variables and employs the Logistic Regression methodology. It is developed in two forms, Logistic Regression and Locally Weighted Logistic Regression, which both deliver useful and accurate results. The second form though provides the most accurate results as it validates the presence or absence of erosion at all validation locations. The proposed methodology is easy to use, accurate and can be applied to any region and river.

1 Introduction

Erosion has been characterized as one of the most significant environmental problems worldwide (Bakker et al., 2007), particularly in areas such as the Mediterranean region. The landscape in many Mediterranean areas indicates that the combination of climate, topography, soil characteristics and human activity has resulted in short- and mid-term unsustainability (Ruiz et al., 2013). The Mediterranean region is subject to long dry

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periods followed by heavy erosive rainfalls, falling on steep land slopes with fragile soils, resulting in considerable erosion (Grimm et al., 2002).

Riverbank erosion is a complex phenomenon resulting from various factors affecting the balance of ecosystems and it is also geomorphologically important in affecting changes in the river channel course and in the development of the floodplain (Hooke, 1979; Bridge, 2009). Mass-failure processes constitute a significant source of sediment in disturbed streams which occur due to a combination of hydraulic and geotechnical processes that undercut bank toes and cause bank collapse (Simon et al., 2009). Riverbank erosion is a natural geomorphologic process that affects the fluvial environment in many aspects; physical, ecological and socio-economic. It is the result of a complex interaction between the channel hydraulic conditions and the physical characteristics of the banks, both of which are highly variable in nature. Bank retreat affects the riverbed structure and morphology as well as the floodplain morphology and the physical habitat. In addition, riparian land losses and damage to human property and infrastructures lead to direct financial consequences. Moreover, turbidity increase, sediment and debris transport and flood defense weakening reveal a complex combination of arising issues due to riverbank erosion. According to Atkinson et al. (2003), significant parameters affecting erosion are vegetation index (stability), the presence or absence of meanders, bank material (classification) and stream power. Also other factors such as bank height, riverbank slope, river cross section width, riverbed slope and water velocity have been reported to affect the erosion rate (Hooke, 1979; Abam, 1993; Winterbottom and Gilvear, 2000; Rinaldi et al., 2008; Luppi et al., 2009). Therefore, the identification of riverbanks vulnerable to erosion is important for restoration works.

Riverbank erosion is a common phenomenon. However, the prediction of the location and of the extent of riverbank erosion is difficult. Therefore, a range of approaches and methods has been developed and tested. The most important issue concerning riverbank erosion is the identification of the vulnerable to bank erosion areas, in order to predict changes in the river channel form and assist stream management/restoration options. Different methods have been used to predict erodibility, such as analyses of

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historical maps and the use of sequential aerial photographs based on GIS technology. However, riverbank erosion is usually approached by using a combination of bank stability methods and hydrodynamic models to predict the vulnerable areas and estimate the erosion rate (Nardi et al., 2013). Of these two methods, the former has a relatively high degree of inaccuracy, while the latter is too complex to be applied as it requires significant number of data variables.

We are proposing a two prong methodology for the determination of the probability of bank erosion. The development of the methodology which is the objective of this work, involves the application of the Bank-Stability and Toe-Erosion Model (BSTEM 5.2) followed by a statistical model that quantifies the probability of erosion to occur in a specific location. The BSTEM model is a physically-based model, developed by the National Sedimentation Laboratory in Oxford, Mississippi, USA (Simon et al., 2000) and it has been used to simulate the hydraulic and geotechnical processes responsible for mass failure. It represents two distinct processes namely, the failure by shearing of a soil block of variable geometry and the erosion by flow of bank and bank toe material.

The BSTEM has been successfully applied in diverse alluvial environments (e.g., Simon et al., 2000; Simon et al., 2002; Simon and Thomas, 2002; Pollen and Simon, 2005; Pollen-Bankhead and Simon, 2009; Simon et al., 2011). BSTEM was used to simulate the effects of enhanced matric suction from evapotranspiration and decreased soil erodibility driven by the presence of plant roots, quantifying the effects on streambank factor of safety and comparing with the effects of mechanical root-reinforcement (Pollen-Bankhead and Simon, 2010). BSTEM was also used to quantify bank retreat which ranged from 7.8 to 20.9 m among 100 m of riverbank at the Barren Fork Creek site (Midgley et al., 2012). It was also used to quantify the reductions of mass failure frequency and sediment loading from streambanks in the Lake Tahoe in United States (Simon et al., 2009).

The proposed statistical model involves principals of Logistic Regression and Locally Weighted Regression to estimate the probability of erosion occurrence at riverbank locations based on the local effect of independent explanatory variables. The model identifies the underlying relations between riverbank erosion and the geomorphological or hydrological variables that prevent or stimulate erosion. It utilises the available data to detect vulnerable to erosion areas. In addition the erosion occurrence probability can be calculated in conjunction with the model deviance for each independent variable or model form tested. A similar method was introduced and applied successfully to a river in North Wales (Atkinson et al., 2003), for the estimation of the variables that mostly affect riverbank erosion. It has to be mentioned that in this previous stated implementation the simple Logistic Regression was applied. The developed methodology is applied to the Koiliaris River Basin at the island of Crete, Greece.

2 Case study

The Koiliaris River Basin is situated 25 km east of Chania (35°30′49′′ N, 24°01′05′′ E.) and occupies an area of about 130 km^2. Watershed elevation ranges from 0 to 2041 m.a.s.l. with slopes ranging from 1–2 % at low elevations up to 43 % (high elevations) and the total length of the hydrographic network is 36 km (Moraetis et al., 2010). The area has been studied extensively in the last ten years and especially since 2009 as part of the European network of Critical Zone Observatories (Koiliaris CZO). The Koiliaris River Basin as a typical Mediterranean watershed is characterized by varying spatial and temporal hydrologic and geochemical processes. Lithology and geomorphology as well as the climatic conditions in the area have major influence on the hydrologic characteristics of the Koiliaris CZO (Moraetis et al., 2014). The river is mainly fed by the Stylos karstic springs with water originating from the White Mountains and traveling through an extensive karstic system which drains the rain and snow melt at high elevations. It is also fed temporarily, during the rain period (October to April), by the Keramianos tributary stream. Keramianos is the main temporary tributary which drains a watershed sub-catchment characterized by steep slopes, schist geologic formation and degraded erodible soils. As a result, when high rainfall intensities fall upon this area, especially after the dry summer period, surface runoff is induced, transfer-

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ring large quantities of sediments to the Koiliaris River (flush floods) (Moraetis et al., 2010). During these events river flow conditions change dramatically, with the increase in water level and high flow velocities affecting riverbank erodibility up to causing bank failure. Such events occur two to three times a year during the rainy period affecting the riparian area and enhancing soil losses through riverbank erosion. The current study focuses on the downstream section of the Koiliaris River. During September of hydrological year 2013 scaled sticks were installed at twelve locations (Fig. 1) along the river section under study to assess the potential erosion effect on the riverbanks. In addition, measurements of the riverbank slope and of the river cross section width were performed at the same locations. During hydrological year 2013–2014, three flood events were observed (Fig. 2 – red peaks). The hydrochemical station (Gauge Station), strategically located at the intersection of the Koiliaris River with the Keramianos tributary, recorded the water level used to generate the hydrograph. After three flood events during the 2013–2014 hydrological year, the erosion sticks were inspected on February 2014 during a field trip to identify potential erosion at the riverbanks.

3 Methodology

The riverbank erosion at selected sections and locations along the Koiliaris' riverbanks was assessed by applying the BSTEM model. Bank geometry, channel and flow parameters, bank material and bank vegetation and protection parameters were used as input into the BSTEM model to calculate the bank eroded area (L^2). BSTEM was applied to address riverbank erosion at the twelve selected measurement locations along the downstream river section. In addition, based on model's efficiency and the estimations quality, the reliability of BSTEM estimations of a previous similar work which studied eight distance sections at the same downstream area is evaluated.

The bank erosion vulnerability of the Koiliaris' riverbanks was first studied during hydrological period 2010–2011. The downstream section of the river was divided in eight subsections of variable length, starting from the Gauge Station up to pin number 8 on the study area map (Fig. 1). The geomorphological characteristics of the riverbanks and of the riverbed at the start and at the end of each subsection were measured during the first field campaign. The measured variables, along with information regarding bank material, bank vegetation and the most intense flood event, were inserted to the BSTEM model to determine the vulnerability of bank erosion at the different river subsections. The model results for such long distances (min = 20 m and max = 200 m), are interpreted as potential erosion vulnerability of riverbank considering the extent of the estimated eroded area. The model outcome provided 7 subsections with potential to erosion vulnerability and 1 not vulnerable to erosion based on the estimated affected area in comparison to the total area of the banks at the respective river subsection.

At the beginning of hydrological year 2013–2014, a second field campaign was designed to identify at this time the vulnerable to erosion locations. Therefore, twelve riverbank locations were selected along the aforementioned eight subsections and scaled sticks were installed at these locations. Six months later, at the end of the wet period and after three flood events (Fig. 2), the presence or absence of erosion was visually identified. Two of those locations were selected at restored parts of the river section to denote stable riverbank locations, not vulnerable to erosion.

The concept of the second campaign was to develop and apply a statistical model that, taking into account a series of explanatory variables, would determine the probability of riverbank erosion at local scale. Therefore, measurement points were necessary to develop the appropriate model. Furthermore, a series of validation points were necessary to validate the model efficiency. Thus, the endpoints of each subsection from the first campaign were used because an overall estimate of the riverbank vulnerability was available from the BSTEM results.

However, in order to be certain of the BSTEM prediction efficiency, it was decided to test the model by using the twelve locations of the second campaign. Therefore the measured geomorphological (explanatory) variables at those locations and the three flood events of the wet period of hydrological year 2013–2014 were considered to assess the cumulative effect on bank erosion. It has to be mentioned here that during the

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inspection, end of the wet period of hydrological year 2013–2014, it was possible only to identify the potential erosion of the bank at the specified location and just around it. Therefore, the eroded area was roughly determined. The BSTEM model though has the capacity to quantitatively calculate the eroded area (L^2). The interpretation of the significance of the estimated eroded area was determined through a statistical process that involves the 25th and 75th percentiles of the estimated values. Therefore, the eroded area can be classified to significance levels. Under the 25th percentile the erosion is categorized as not significant and over 75th as significant. The in between values are signified as erosion.

The probability of erosion at the riverbanks of the Koiliaris River was estimated considering a series of easy to determine independent geomorphological variables. To approach this issue, the method of Logistic Regression was applied. The reason for this choice is the ability of the methodology to link related dependent and independent variables by converting their relationship to a probability of presence or absence of the dependent variable. In addition, it can be modified to account for locally spatial correlated independent variables. Therefore, the proposed statistical model is extended to predict the erosion probability locally and to consider spatially correlated independent variables that their values vary with location.

3.1 Logistic regression

Riverbank erosion can be simulated by a regression model using independent variables that are considered to affect the erosion process. The impact of such variables may vary with geographical location and, therefore, a spatially non-stationary regression model is preferred instead of a stationary equivalent. Locally Weighted Regression (LWR) is proposed as a suitable choice. This method can be extended to predict the binary presence or absence of erosion based on a series of independent local variables by using the Logistic Regression (LR) model. It is referred to as Locally Weighted Logistic Regression (LWLR). The two independent variables considered herein were river cross section width and bank slope.

In statistics, LR is a type of regression analysis used for predicting the outcome of a categorical dependent variable (e.g. binary response) based on one or more predictor variables (continuous or categorical). The method can be used along with LWR to assign weights to local independent variables. LWR allows model parameters to vary over space in order to reflect spatial heterogeneity (Atkinson et al., 2003; Lall et al., 2006). The probabilities of the possible outcomes are modelled as a function of independent variables using a logistic function. LR measures the relationship between a categorical dependent variable and, usually, one or several continuous independent variables by converting the dependent variable to probability scores. Then, a LR is formed, which predicts success or failure of a given binary variable (e.g. 1 = "presence of erosion" and 0 = "no erosion") for any value of the independent variables.

The LR model is based on the logistic function, a common sigmoid function. The mathematical form is represented by the following equation:

$$p(\boldsymbol{x}) = \frac{1}{1+\exp(-\boldsymbol{x})}, \quad (1)$$

$$\boldsymbol{x} = \beta_0 + \sum_{k=1}^{K} \beta_k x_k, \; k = 1, \ldots K, \quad (2)$$

where $p(\boldsymbol{x})$ is the probability of the dependent variable, $0 \leq p(\boldsymbol{x}) \leq 1$, associated with a given location, K is the number of the respective independent variables, β_0, β_k, $k = 1, \ldots K$ are the logistic regression coefficients estimated from n sample observations and x_k are the independent variables (Menard, 2001; Atkinson et al., 2003; Ozdemir, 2011). The regression coefficients are estimated by using maximum likelihood estimation.

The goal of LR is to derive estimates for the $K+1$ unknown parameters $\beta_0, \beta_1, \ldots, \beta_K$ by maximizing the likelihood function given in Eq. (3):

$$L\left(\boldsymbol{\beta}/y_1,\cdots,y_n\right) = \prod_{i=1}^{n} (p(\boldsymbol{x}_i))^{y_i} (1-p(\boldsymbol{x}_i))^{1-y_i}, \quad (3)$$

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where n is the sample size, $\boldsymbol{x}_i$ represents the values of the independent variables for the ith sample (Eq. 2), $p(\boldsymbol{x}_i)$ is determined by Eq. (1) and y_i is the value of the dependent variable for the ith sample. As the equations are non-linear, the solution was numerically estimated using Newton's method (Hosmer and Lemeshow, 2004).

LWR is an extension to the concept of general regression. The difference between LWR and Multiple Linear Regression is that in LWR the independent variables effect on the dependent one is weighted based on a weighted function in terms of their geographical location. Basically, LWR is a form of spatial data analysis that allows for the evaluation of a dependent variable based on one or more local independent variables (Cleveland and Devlin, 1988; Brunsdon et al., 1996; Fotheringham et al., 2002; Atkinson et al., 2003; Lall et al., 2006). LWR is used to improve the results obtained with simple LR, allowing for the coefficients β_k to vary for each estimation point. In this work, the exponential (Eq. 4) and the tri-cubic (Eq. 5) weighting functions are used to assign weights to the observation points. The first was applied in a similar work (Atkinson et al., 2003), while the latter is a common, efficient weighting function that is used with LWR.

$$w(d) = \exp\left(-d/a\right) \tag{4}$$

$$w(d) = \left[1 - \left|d/h\right|^3\right]^3, \ \left|d/h\right| \leq 1. \tag{5}$$

In Eqs. (4) and (5) above, w denotes the weights, a and h are nonlinear parameters which determine the spatial correlation distance of measurement points with respect to the estimation point for each function and d is the Euclidean distance between the estimation point and the measurement point.

3.2 Calculation of model deviance

The erosion occurrence probability can be calculated in conjunction with the model deviance. The reliability of both LR and LWLR is determined using the G-Statistic method. It is a simple and effective statistical approach to evaluate the model efficiency and the

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reliability of each of the independent variables tested. The model deviance is given by

$$D = -2\sum_{i=1}^{n}\left[y_i \ln\left(\frac{p(\boldsymbol{x}_i)}{y_i}\right) + (1-y_i)\ln\left(\frac{1-p(\boldsymbol{x}_i)}{1-y_i}\right)\right], \tag{6}$$

where y is a binary variable that indicates the result of an experiment. The conditional probability of the effect to be present is expressed as $P = \left(y = 1\,|\boldsymbol{x}\right) = p(\boldsymbol{x})$. Variable $\boldsymbol{x} = (x_1 x_2, \ldots, x_K)$ denotes a series of independent variables. Probability $p(\boldsymbol{x})$ is calculated as in Eq. (1),

$$p(\boldsymbol{x}_i) = \frac{\exp(\beta_0 + \beta_k x_k)}{1 + \exp(\beta_0 + \beta_k x_k)}. \tag{7}$$

The G-Statistic is given by

$$G = D_{\text{null}} - D_k, \tag{8}$$

where term D_{null} denotes the deviance when the model is applied without independent variables, i.e., when $p(\boldsymbol{x}) = [1 + \exp(\beta_0)]^{-1}$. Term D_k refers to the deviance for the model with k independent variables. The difference between these two terms is often cited as a sign of goodness of fit. The greater this difference, the more important is the influence of the estimation variables used. The optimal result for D is zero (Hosmer and Lemeshow, 2004). The process of the proposed statistical model described above was implemented with original code developed in the Matlab programming environment.

4 Results and discussion

The evaluation of the BSTEM model results involved the calculation of the percentiles used to categorize the calculated erosion area significance. The BSTEM model results are in very good agreement with the behaviour of the banks after the flood events.

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Of the twelve measurement points, four were identified with no or low erosion as the affected area was under or very close to the 25th percentile equal to 0.52 m^2 (Table 1). In addition, the inspection showed that the observed affected area at the four locations was limited considering that the bank form had not changed. The remaining eight points were identified as eroded and significantly eroded based on the model results for the affected area and, the bank form had changed at those locations. The affected area at the three significantly eroded locations ranges from 1.399 to 2.043 m^2, close and over the 75th percentile which is equal to 1.38 m^2.

The aforementioned results mean that the BSTEM outcome for the eight subsections of the first campaign can be also characterized as reliable. Therefore, they can be used as validation locations for the statistical model performance. The statistical model considers the twelve measurement locations as eroded or not eroded based on the BSTEM results and the observed bank formation (Table 2).

The LR-based models provide the erosion probability P at the eight selected riverbank locations which is interpreted as *no erosion* for $0 \leq P < 0.5$ and as *presence of erosion* for $0.5 \leq P \leq 1$. Based on the erosion probability P, bank locations are characterized as stable (S) in the absence of erosion and unstable (U) otherwise. Unstable bank locations are vulnerable to erosion whereas stable bank locations are not.

The results derived from the application of the LR model, with uniform parameters for all estimation points, are presented in Table 3. The values of the independent variables and the BSTEM erosion estimates at the validation points are also presented in the same table. The model deviance was calculated equal to 6.14 and the G-Statistic equal to 7.23.

Results for the erosion probability at different ungauged locations along the Koiliaris' riverbanks obtained with the LR model are presented in Fig. 3. The values for the independent variables were obtained from a 3-D digital model of Koiliaris River developed based on a Digital Elevation Model.

Results for the erosion probability at the validation points derived by applying LWLR with the exponential and the tri-cubic weighting functions are presented in Table 4. The graphical representation of the results for the erosion probability at the ungauged locations is provided in Figs. 4 and 5 for the exponential and tri-cubic functions, respectively. In the case of the exponential weighting function the model deviance is equal to 6.27 and the G-statistic equal to 5.10, while in the case of the tri-cubic function the model deviance is equal to 5.12 and the G-statistic equal to 6.25.

Both LWLR models involve a nonlinear parameter in the weighting function that determines the correlation distance of the spatially correlated measurement points. The optimal distance in each case was calculated using a leave-one-out cross validation analysis involving the measurement locations. As a result, parameter *a* of the exponential weighting function was set to 600 m and parameter *h* of tri-cubic function was set to 400 m.

The results obtained with the LR method were in very close agreement with those of BSTEM as the erosion presence or absence was accurately predicted at six out of the eight locations, with one of the fail locations to have a narrow deviance from the set erosion presence limit. Next, to improve predictions, a method combining LR with the LWR, termed LWLR, was applied to account for the local spatial dependence of the independent variables at the measurement locations. Two spatial dependence functions were examined, the exponential and the tri-cubic. The LWLR model with the exponential function has, overall, similar performance to the LR model. The derived results are in agreement with the BSTEM estimates at seven out of the eight validation locations and the approach fails at only one validation location. The application of the LWLR model with the tri-cubic function leads to significant improvement of the estimates and to the accurate prediction of the erosion probability at all eight validation locations. The significant result for this model is the validation of a clearly unstable point (pin no. 7) which has independent variables that should provide a stable indication (as delivered by LR). Another point with similar characteristics (pin no. 4) was correctly identified as stable. Therefore, such performance is possible only when local spatial weighting functions are used.

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The only validation point indicated as stable (pin no. 4) belongs to the fourth river section (between pins no. 3 and 4, Fig. 1) which as a whole was determined by BSTEM as stable. However, two out of the three local measurements in the same section (pins KB and KC in Fig. 1) showed signs of erosion after the inspection. Generally though, apart from limited locations, the banks of that section did not show erosion signs due to the presence of dense seasonal riparian vegetation. The erosion probability estimation at this point is affected significantly, at local scale, by the spatially correlated measurement points with low vulnerability to erosion. Similarly, validation points 6 and 7 are also affected by the close presence of measurement locations with low vulnerability to erosion. This explains the difficulty in predicting erosion at these points. The model results may confirm the presence or absence of erosion at the validation points, but they are quite different from the targeted values of zero for no erosion and one for erosion presence. This is expected to improve when a larger dataset with greater variability of the independent variables effect on erosion becomes available.

The graphical representation of the LWLR model results at the discretized river section (Figs. 4 and 5) shows a significant difference in performance for the two weighting functions. The tri-cubic function (Fig. 5) delivers more reliable results as it is clearly considers the variability of the independent variables inside the correlation distance. This can be observed from the color variability in the graph of Fig. 5 that represents the variability of the erosion occurrence probability. On the other hand, the exponential function (Fig. 4) shows a smooth change in probability for the different pairs of independent variable values. This can be explained in terms of the function shape behaviour and the correlation distance. The tri-cubic function is herein applied in a shorter correlation distance according to the cross validation results which, can capture the local dependence of the explanatory variables that in longer distances are smoothed due to the presence of more data.

The LWLR method with the tri-cubic function yields the highest value for the G-Statistic for the selected independent variables. Therefore, it can be viewed as the optimum approach to calculate the erosion presence probability at local scale. The G-

Statistic can be also used to assess the impact and importance of each independent variable on the estimates. Each variable was separately applied both in LR and LWLR. The G-Statistic obtained its highest values when the cross section width was applied. The results of the statistical term improved by 12 and 20 %, respectively, compared to the bank slope application.

The proposed statistical model is a useful, fast, efficient and fairly easy to apply tool that requires information from easy to determine geomorphological and/or hydrological variables. This tool provides a quantified measure of the erosion probability along the riverbanks and could be used to assist managing erosion and flooding events.

The two models applied in this work are not directly comparable. They have the same scope but deliver different results. The BSTEM model delivers the potential riverbank eroded area (L^2) while the LR-based models deliver the probability of a bank location to erode. Both are useful, depending on data and software availability, in providing information regarding the vulnerability of riverbanks to erosion. They can supplement each other by delivering the erosion probability of a riverbank location and the extent of the eroded area (L^2).

5 Conclusions

A combined deterministic and statistical methodology is proposed in this work to predict the probability of erosion presence or absence in a river section. The BSTEM model, set up with the appropriate geomorphologic, hydrologic and hydraulic variables, can provide reliable results regarding the potential erosion vulnerability of the riverbanks. It can provide large-scale estimates (river sections) as well as local-scale estimates (specific locations). However, the large number of variables essential for the model set up requires an appropriate knowledge of the hydrology, hydraulics and geomorphology of the study area. On the other hand, the proposed LR-based statistical model is flexible and can take into account a variety of explanatory variables in the estimation of erosion probability at the riverbanks.

The LR method performs satisfactorily in the plain form where uniform parameters are considered for all estimation points. Difference from the BSTEM results is observed only at two of the eight validation points. The LWLR method with the exponential weighting function gives results similar to those of LR. The LWLR method with the tri-cubic function provides significantly improved estimates which coincide with the BSTEM results at all validation points. The graphical presentation of the results in the discretized river section shows that the erosion probability increases with bank slope and decreases with cross section width. This is also confirmed by the positive sign of the bank slope coefficients and the negative sign of the cross section width coefficients in all LR applications. The deviance and the G-Statistic results show that the cross section width parameter is more important than bank slope for the estimation of erosion probability at the banks of the Koiliaris River.

The developed statistical tool provides an alternative proposition for the estimation of vulnerable to erosion riverbank locations which requires limited information on explanatory variables, yet can provide vulnerable location estimates with increased reliability. It is, therefore, considered as a very promising approach for the estimation of riverbank erosion probability. The tool is proposed as a supplementary solution to the riverbank erosion identification issue.

Author contributions. E. A. Varouchakis developed the statistical model, the model code and performed the simulations. Along with G. V. Giannakis, M. A. Lilli and N. P. Nikolaidis they designed and carried out the field campaigns while, with the aid of G. P. Karatzas, they analysed the collected data and the model results. E. Ioannidou performed part of the model simulations. M. A. Lilli and N. P. Nikolaidis applied the BSTEM model. Finally, E. A. Varouchakis prepared the manuscript with the contribution of all co-authors.

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Table 1. Amount of bank erosion at the measurement locations (Fig. 1) – Modelling results obtained by BSTEM.

	Eroded area (m^2)			
Map location	1st flood	2nd flood	3rd flood	Cumulative effect
KA	0.440	0.404	0.349	1.193
KB	0.566	0.510	0.394	1.470
KC	0.498	0.512	0.389	1.399
KD	0.411	0.410	0.328	1.149
KE	0.459	0.437	0.320	1.216
KG	0.258	0.255	0.213	0.726
KZ	0	0	0	0
KH	0.207	0.187	0.145	0.539
KJ	0.368	0.421	0.357	1.146
KI	0.741	0.728	0.574	2.043
KK	0	0	0	0
KL	0.167	0.162	0.132	0.461

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Table 2. Presence (1) or absence (0) of erosion at measurement locations using a binary indication for the statistical model (LR and LWLR) set up based on inspection and BSTEM results. Columns 3 and 4 present the measured independent geomorphological variables.

Map location	Presence/Absence of erosion	Bank slope (degrees)	Cross section width (m)
KA	1	60	9.00
KB	1	75	9.25
KC	1	65	8.75
KD	1	55	9.00
KE	1	85	10.76
KG	1	60	11.55
KZ	0	75	10.00
KH	0	65	13.50
KJ	1	60	13.35
KI	1	75	7.60
KK	0	70	13.00
KL	0	50	9.00

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Table 3. Result of LR application at the eight validation locations (Fig. 1). The independent variables used and the BSTEM estimates are also presented. In column 4, S denotes stable and U unstable bank locations.

Validation points	Bank slope (degrees)	Cross section width (m)	BSTEM erosion estimates	Erosion (P) LR
1	84	9.25	U	0.84
2	58	9.05	U	0.64
3	81	9.35	U	0.82
4	33	9.00	S	0.38
5	82.5	8.75	U	0.85
6	44	9.00	U	0.49
7	27	9.26	U	0.30
8	57	9.25	U	0.62

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Table 4. Result of LWLR application at the eight validation locations (Fig. 1). The LR estimates, the independent variables used and the BSTEM estimates are also presented. With bold face the diverged values are indicated. In column 4, S denotes stable and U unstable bank locations.

Validation point	Bank slope (degrees)	Cross section width (m)	BSTEM Erosion estimates	Erosion (*P*) LR	Erosion (*P*) LWLR (exp. model)	Erosion (*P*) LWLR (tri-cubic model)
1	84	9.25	U	0.84	0.85	0.86
2	58	9.05	U	0.64	0.58	0.74
3	81	9.35	U	0.82	0.75	0.87
4	33	9.00	S	0.38	0.27	0.25
5	82.5	8.75	U	0.85	0.81	0.82
6	44	9.00	U	**0.49**	0.54	0.53
7	27	9.26	U	**0.30**	**0.21**	0.52
8	57	9.25	U	0.62	0.64	0.73

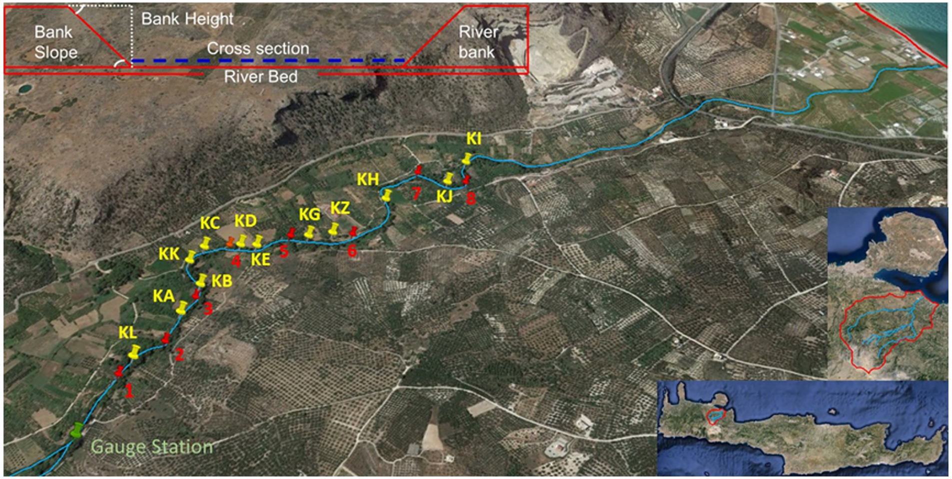

Figure 1. The downsream part of the Koiliaris River located in the western part of the island of Crete. The yellow pins represent the measurement locations, the red pins the validation locations and the green pin the Gauge Station located at the intersection of the the Koiliaris River with the Keramianos tributary. A representation of the measured geomorphological values is provided in the upper left corner.

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Riverbank erosion probability tool

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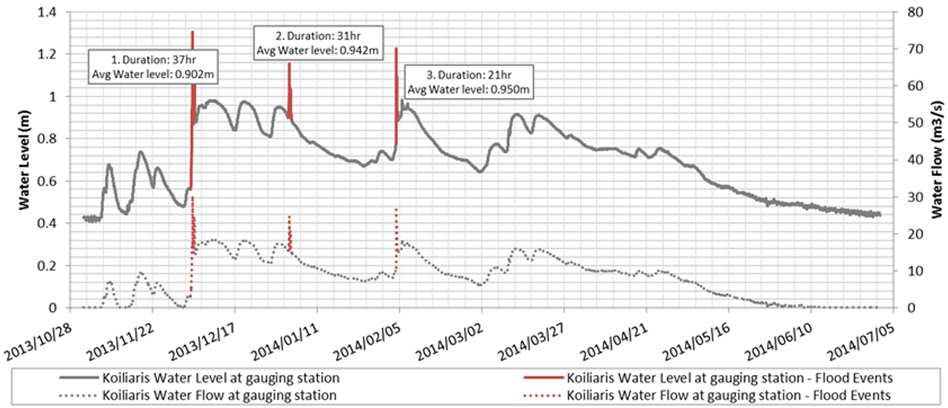

Figure 2. Typical hydrograph of the Koiliaris River at the Gauge Station (November 2013–June 2014).

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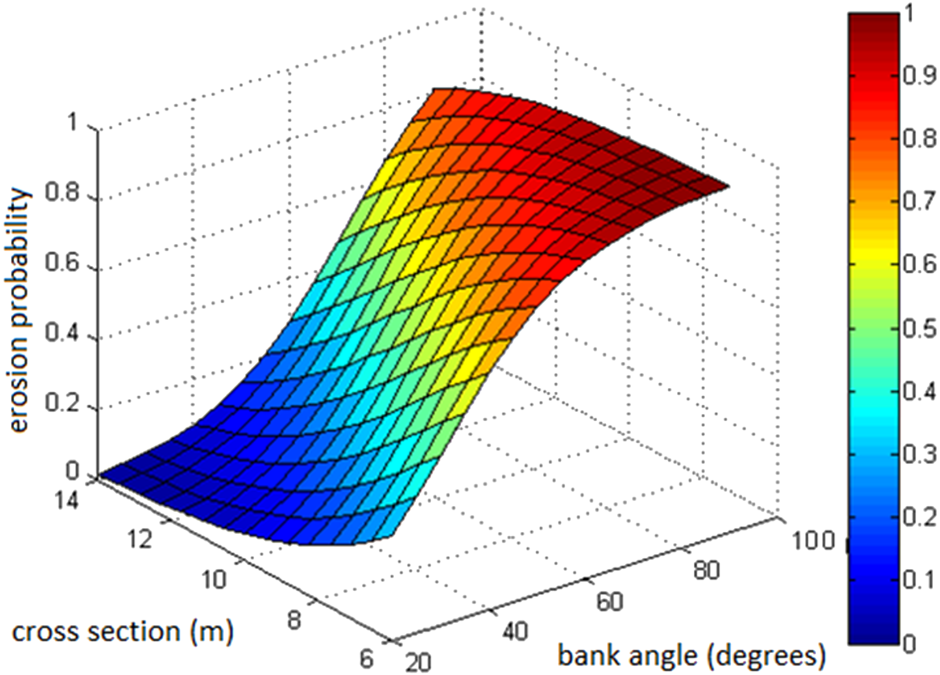

Figure 3. Erosion probability predictions using LR as a function of the independent variable values of ungauged Koiliaris' riverbank locations.

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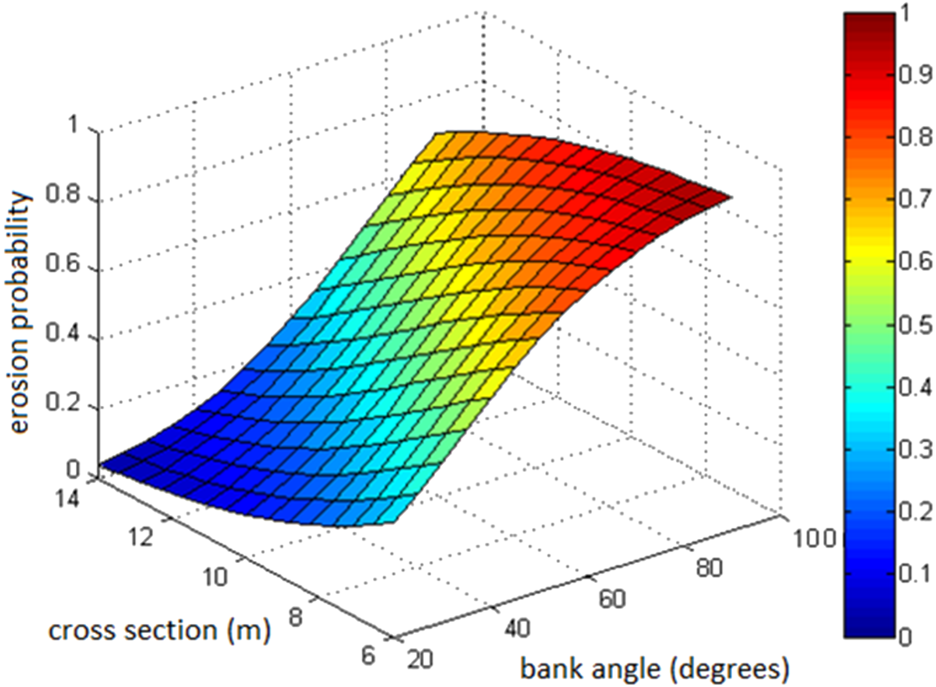

Figure 4. Erosion probability predictions using LWLR with the exponential weighting function versus independent variable values of ungauged Koiliaris' riverbank locations.

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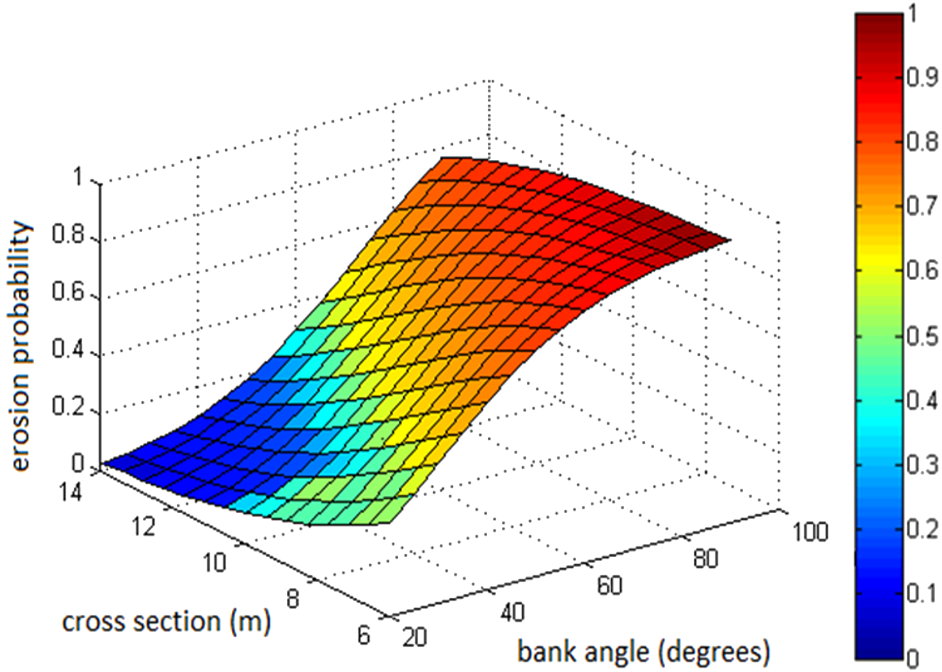

Figure 5. Erosion probability predictions using LWLR with the tri-cubic weighting function versus independent variable values of ungauged Koiliaris' riverbank locations.

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