RESPONSE TO REVIEWERS’ COMMENTS

Manuscript: SOIL Discuss., 2, 647-674, 2015

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

Dear Editor,

We would like to thank you and the referees for the time that you have spent on reading and commenting on the above manuscript. The referees provided useful and constructive comments that helped to improve the manuscript overall.

The response to the comments are given in the revised manuscript (using track changes) and below in italic font.

We hope the changes listed have made the manuscript suitable for publication and we look forward to your response.

Sincerely,

Dr. Emmanouil Varouchakis

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Topical Editor Comment

The authors improve and complement the initial manuscript. They answer important issues raised by the reviewers. However, I have the impression that more information could be necessary and the conclusions must be completely rewritten. But it should be evaluated with the revised manuscript.

We would like to thank the topical editor for his review and for the time he devoted on reviewing this manuscript.

We have added in the revised manuscript the new information based on the reviewers suggestions and we have modify and enrich the conclusions section.

Anonymous Referee #1

1) The authors present a case study in which they combine the existing BSTEM model with existing regression models. As I am nor familiar with regression techniques, I recommend another reviewer after major revision.

Response#
First, we would like to thank the anonymous reviewer for the time he devoted on reviewing this manuscript and for his useful comments.

We believe that overall the main objective of our work has been misunderstood by the reviewer and is our responsibility to improve this part of the paper. The following paragraph can be added in the text to clarify the proposed methodology and the aim of this work (page 4 lines 12-29 at the end of the introduction section).

Overall, the concept of this work is to present a statistical model based on LR methodology for the estimation of the erosion probability at specific ungauged riverbank locations where independent secondary explanatory information is available. BSTEM has an auxiliary role to estimate/validate potential eroded riverbank locations by calculating the potential eroded area, using field measurements of hydraulic, hydrologic and geomorphologic variables. These estimations (dependent variables) are then used to set up and validate the statistical model which is then applied to ungauged riverbank points.

BSTEM is an existing deterministic model that can be used, among others, to predict eroded riverbank area. LR is also an existing statistical model that uses secondary information to calculate probability of an event to occur. Locally Weighted Logistic Regression (LWLR) is a new proposition that combines LR and LWR to create a local model that calculates the probability of erosion to occur, based on secondary information (e.g. bank slope, river cross section) that are spatially correlated. Therefore, the accuracy of the predictions is expected to improve compared to the global regression model LR. To the best of our knowledge, the combination of deterministic and stochastic models to predict river bank erosion appears for the first time in the scientific literature.

2) My own area of expertise regards bank erosion, and here I have major concerns that lead me to recommending major revision. The paper does not show any validation of the method by showing a comparison between predicted bank erosion and observed bank erosion. No maps of erosion predictions are given.

Response#

The aim and scope of this work is not to present a model that predicts bank erosion under the classical terms of volume or area removed but to predict the probability of a specific bank location to fail or not. Therefore, we cannot provide such maps. BSTEM is applied in order to produce reliable validation points for the statistical model.
We have included a methodology flowchart that fully explains the approach followed (Page 6 lines 5-6, Fig. 3) accompanied by a characteristic photo highlight of the riverbank location (KI) with the most intense observed erosion (Page 11 lines 12-17, Fig 4).

Regarding the BSTEM model: The BSTEM model was validated for the predicted erosion (m$^2$) after a field investigation that was performed at the end of the wet period of the hydrologic year of 2013-14. Photographs were taken at some locations where the 50 cm scaled stick was placed showing the eroded area. The eroded area at each location was successfully predicted as the observed affected area was quite similar. Especially at the location (KI) with the most significant effect, the predicted eroded area was equal to 2.043 m$^2$ and the affected area measured at the field (and represented in the modified photo, Fig. 4) was roughly 2.08 m$^2$. The situation is the same for the other locations. However, the purpose of this work was to use BSTEM results (at the twelve locations) together with field inspection to setup the statistical model and provide validation points (binary data, erosion and no erosion locations). Therefore, quantified measurements at those points were not performed but only field inspection to validate that the BSTEM results are consistent with reality. Therefore, only at the point with the most intense erosion, a close photo was taken and analyzed to quantify the erosion. (Page 11 lines 10-23).

The statistical model proposed and applied in this work is a stochastic model that predicts the probability (0≤P≤1) of erosion to occur. Model validation is presented in the submitted (discussion) manuscript, Page 658 lines 14-18. A more detailed description of the validation method is given below and in the revised submission (Page 11 lines 31-32 and 12 lines 1-10).

The twelve measurements of the 2nd field campaign were used to apply LR and LWLR while the eight locations of the 1st campaign were employed as validation points. The first BSTEM application has provided a vulnerability assessment of the riverbank sections that these eight locations assign. The riverbank areas vulnerable to erosion, and therefore the associated locations are characterized as Unstable “U” and the non-vulnerable as Stable “S”. Correspondingly to the LR and LWLR that deliver probabilities of erosion to occur, P≥0.5 is interpreted as presence of erosion and is denoted as Unstable “U” and absence of erosion P<0.5 as “S”, Stable. Therefore, the different statistical model forms are validated based on the erosion vulnerability of the eight locations of the 1st field campaign (Tables 3 and 4). In addition, the proposed model is accompanied by a goodness of fit test estimation (G-statistic) which performs validation of predictions.
(G-statistic: Section 3.2 in the revised manuscript and in the discussion section page 12 lines 14-15 and lines 23-25).

Maps of riverbank erosion predictions cannot be produced using the BSTEM, since it can only deliver the potential erosion presented in a studied river cross section.

Similarly, spatial maps of riverbank erosion predictions cannot be produced by the statistical model since it predicts probability of erosion to occur when a specific couple of geomorphologic secondary variables apply based on the measurements in the specified correlation distance that the model has calculated. The produced 3D figures (fig. 5 of the revised manuscript) actually work as a probability map presenting the erosion probability when a specific couple of secondary variables is met (Added in text in Page 13 lines 6-7). The concept of the model is to present the probability variability of an event to occur considering secondary explanatory information. This is a new way of presenting the probability of bank failure.

3) The paper also does not provide any information about the values of the input data for BSTEM (flow parameters, bank material parameters, bank vegetation parameters, bank protection parameters). That makes the work irreproducible and unverifiable.

Response#

The paper is focused on the proposal of a statistical model for the estimation of riverbank erosion probability and that is the reason that the authors did not include extensive information on the BSTEM set up. BSTEM is applied in order to provide reliable validation points for the statistical model. However, we understand the reviewer’s concerns and we address the comment with the following information inserted at the methodology section (Page 6 of the revised manuscript to update the first paragraph lines 5-26).

The methodological steps of the proposed tool and of the overall process are briefly described by a flowchart presented in Figure 3. The riverbank erosion at selected sections and locations along the Koiliaris’ riverbanks was assessed using the BSTEM model. Bank geometry, channel and flow parameters, bank material and bank vegetation and protection parameters were used as input to the BSTEM model to calculate the bank eroded area ($L^2$). BSTEM was applied to address riverbank erosion at twelve selected monitoring locations along a river section. In addition, based on model’s efficiency and the quality of estimation, the reliability of BSTEM results is evaluated at eight sections of the same downstream area. Channel and bank geometry characteristics were measured during the field campaigns and are presented later in the text. As far as for the flow parameters, for the 1st BSTEM model application (eight river sections) river water elevation was set to 1.27 m for a 48h duration event based on field data. The 2nd BSTEM model application (twelve locations) estimates the cumulative riverbank erosion effect of three flash flood events (Fig. 2). The other parameters were similar for the two model
applications due to the fact that the same river section was employed. Therefore, reach slope varied between 0.0042 and 0.11 m/m and the bank material was set after field measurements analysis to “fine rounded sand” with an average medium grain size 0.3 (± 0.06) mm. The “geyer willow” was selected from the predefined list to describe the bank vegetation with the assumptions of the plants age of about 100 years and 100% contribution to assemblage. Finally, for the locations where the bank was protected the “boulders” choice was used to describe the bank material.

4) Three out of the five figures show predictions for three different regression methods without possibility of comparison with data or inter-comparison.

Response#

Inter-comparison of estimations is possible as the x and y axis of the plots are at the same scale for the results of the three methods tested and specific discussion is presented below. In addition, the validation points are shown on the plots for easier inter-comparison (Page 12 lines 26-29, Fig. 5).

Comparison with data is not possible as the model predicts probability of presence or absence of erosion at unmeasured locations. The plots present the probability of bank erosion to occur (z axis) for a specific couple of secondary variables (x and y axes). The model’s accuracy has been tested as previously described.

5) The main correlation found, i.e. the correlation between new bank erosion and recent bank erosion (= bank angle), is not much more than prediction by extrapolating ongoing trends.

Response#: The following response addresses the comment and parts of it have been added, if necessary, to different parts of the revised manuscript (as indicated next to each paragraph) based on the text flow.

Regarding “correlation between new bank erosion and recent bank erosion (= bank angle),” This work does not intend to correlate new with recent bank erosion; it predicts the erosion probability at ungauged locations and validation points, in between of the first and last measurement points, based on the characteristics of the riverbank at the eroded or not measurement locations. Furthermore, correlation is identified on the variability of the secondary information trend and on the predicted erosion probability (page 15 lines 31-32).

LR is a non-linear method. The method’s concept is to model binary primary variables that describe the presence or absence of an event and secondary variables to calculate the model’s parameters in order to predict the probability of the event to occur when more secondary information becomes available. Therefore, the predictions of LR are “extrapolation” at ungauged river location where the cross river section and bank slope is available based on the parameters calculated from the measurements. This work applies
"extrapolation" using two secondary variables that affect significantly the presence or absence of erosion.

However, in LWLR locality is important; the location of the new couple of secondary variables was used to identify and weight the effect of spatially correlated measurement points in order to calculate the model parameters. The proposed methodology, LWLR, exploits the local information of independent variables and translates it successfully to bank erosion probability. This is not a typical regression estimation (or "extrapolation") based on global parameters but herein the model parameters are calculated iteratively for the new couples of secondary variables (Page 15 lines 19-25. Revised manuscript).

“Extrapolation” though is useful and optimal when the model can successfully describe the real event, as it occurs herein with low model deviance and successful validation”.

The three plots (Fig. 5) present the probability of erosion to occur (z axis) at the specific riverbank locations when a couple of independent values is met (x and y axes). These couples of independent variables are randomly selected from locations among the measurement points based on a 3D model of the downstream part of River Koiliaris. In a similar work recently published (Vozinaki et al., 2015), the simple LR model was applied on predicting crop damage curves based on measurements of river flood depth and velocity (secondary data). The secondary data required to develop the probability curves (predictions) were produced by a Monte Carlo simulation in the absence of sufficient measurement data. Herein, the selected secondary values come from the 3D river structure model which was developed based on a 5m DEM (Page 12 lines 29-33 and page 13 lines 1-7).

Therefore, probability of erosion to occur at ungauged riverbank locations when significant secondary variables become available, “extrapolation”, through an efficient statistical model based on LR principles is a proposition that can aid riverbank erosion management. A similar model had been developed to identify the most appropriate secondary variables (Atkinson 2003).

6) The introduction mixes the problems of surficial soil erosion with bank erosion, and fails to list the beneficial effects of bank erosion for fluvial ecosystems.

Response#

The first paragraph of the introduction referred to surficial soil erosion will be removed in order to avoid confusion of the two topics. In addition the following paragraph can be added in the introduction to address the reviewer comment. (Page 2 lines 24-33).
On the other hand, riverbank erosion constitutes a significant factor to the functioning of river dependent ecosystems and provides a sediment source that creates riparian habitat. Bank erosion is a key geomorphological mechanism for the fluvial ecosystems since it regulates the diversity of habitats, species and vegetal units. The process provides riparian vegetation succession and develops dynamic habitats vital for fluvial plants and animals. For small scale bank erosion or for local extent there is no significant influence on the aquatic ecosystem and it is contributing to the ecosystem sustainability. In the opposite case, the ecosystem is significantly affected while riparian land losses and damages are caused providing areas vulnerable to flooding (Piégay et al., 1997; Piégay et al., 2005; Florsheim, 2008).

The downstream area of River Koiliaris has been characterised as zone of high agricultural productivity while lately the residential development has been increased. Therefore, the protection from floods is a major concern for the local authorities. The latter requires the protection of riverbanks from significant erosion by identifying highly vulnerable areas.

7) A few minor points: (1) Bridge (2009) is referenced but the list of references lists Bridge (2003); (2) At several locations: "the vulnerable to erosion locations" must be "the locations vulnerable to erosion" (similarly for areas vulnerable to erosion); (3) Page 4, line 27: "principals" must be "principles"; (4) Page 8, lines 17-18: This sentence is unintelligible; please rephrase.

Response#

Regarding the minor points referred by the reviewer, the authors have made the appropriate changes to the revised manuscript to address those comments.

(1) Bridge (2009) is referenced but the list of references lists Bridge (2003); Bridge 2003 is the correct, so we have corrected the year.
(2) At several locations: "the vulnerable to erosion locations" must be "the locations vulnerable to erosion" (similarly for areas vulnerable to erosion); The authors have corrected the corresponding sentences in the text
(3) Page 4, line 27: "principals" must be "principles"; The authors have corrected the sentence in the text (page 3 line 32)
(4) Page 8, lines 17-18: This sentence is unintelligible; please rephrase. The sentence is modified as follows, (Page 8 lines 9-10)

"Therefore, the proposed statistical model is extended to predict the erosion probability based on spatially correlated independent variables.”
The manuscript predicts the probable presence or absence of erosion by combining a physically-based bank erosion model and regression analysis. The bank erosion model computes the eroded area at 12 location using bank material properties and fluvial conditions at specific times. The regression model correlated the simulated bank eroded area and two independent variables, channel width and bank slope. The article is well written and has presented a unique approach in identifying vulnerable areas for erosion. However, I would like the authors to address the following issues:

We would like to thank the anonymous reviewer for his positive comments and for the time he devoted on reviewing this manuscript in order to provide useful suggestions.

1) Although BSTEM is considered a physically-based model, simulated values are still subjected to a huge amount of uncertainty brought about by several assumptions for instance the material property. I would like the author to show a comparison of the simulated and measured eroded areas. Quantification of the error in the simulated area vs the measured will give readers an idea of the uncertainties in the predictions. Stating that BSTEM’s results are "reliable" (page 10; lines 5-9) is not sufficient especially if results are used for prediction. "Reliable" has to be expressed in terms of some measure or metrics.

Response#

The BSTEM model was validated for the predicted erosion (m$^2$) after a field investigation that was performed at the end of the wet period of the hydrologic year of 2013-14 (revised manuscript Page, 7 lines 22-28, page 10-11 lines 28-29 and 1-7).

In more detail:

The BSTEM model was validated for the predicted erosion (m$^2$) after a field investigation that was performed at the end of the wet period of the hydrologic year of 2013-14. Photographs were taken at some locations where the 50 cm scaled stick was placed showing the eroded area. The eroded area at each location was successfully predicted as the observed affected area was quite similar. Especially at the location (KI) with the most significant effect, the predicted eroded area was equal to 2.043 m$^2$ and the affected area measured at the field (and represented in the modified photo, Fig. 4) was roughly 2.08 m$^2$. The situation is the same for the other locations. However, the purpose of this work was to use BSTEM results (at the twelve locations) together with field inspection to setup the statistical model and provide validation points (binary data, erosion and no erosion locations). Therefore, quantified measurements at those points were not performed but only field inspection to validate that the BSTEM results
are consistent with reality. Therefore, only at the point with the most intense erosion, a close photo was taken and analyzed to quantify the erosion. (Page 11 lines 10-23).

The BSTEM predictions at the 8 validation points were then characterized as reliable because they are located in between of the 12 points that were successfully validated by the field inspection. (Page 11 lines 25-28)

2) One of the most important factors affecting streambank erosion aside from channel geometry are bank materials (soil texture, geotechnical properties, roughness etc.). These should have been included as independent variables in LWLR. I suggest the authors perform additional analysis that at least consider a representative of the bank material as independent variables.

Response#

This work presents the framework of a methodology that can be applied in order to estimate the probability of erosion at specific riverbank locations considering explanatory and easy to determine secondary variables. Channel geomorphological characteristics such as cross section and bank slope are relatively easy to be determined at unmeasured locations by using a digital elevation model. On the other hand, bank material requires extensive field measurements in order characteristic bank material variables to be considered as secondary information. Such measurements did not take place during the field campaigns as it was not in the context of this work. (Page 16 lines 6-14)

(The last sentence has been added after a little modification in the text to cover hydrological variables too)

Such measurements did not take place during our field campaigns but only at the 8 specific locations during the 1st campaign to set up the BSTEM model. However, the grain size was only determined. Considering the location of the 12 measurement points, which was at the same river section and the similar grain size measured at the 8 locations, the 2nd BSTEM model was set with soil characteristics similar to the 1st one. Therefore, estimation with LWLR in different riverbank locations cannot be applied. However, this is an idea to be applied in a future campaign as the primary aim of this work was to present the methodology and to test its efficiency only using geomorphologic variables. Furthermore, a second aim was to present the methodological framework so others with similar data or with bank material data to test it at their study basin.

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


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

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

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 areas vulnerable to erosion 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 locations vulnerable to erosion by quantifying the potential eroded area. The derived results are used to determine validation locations for the evaluation of the statistical tool performance. 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 tool is easy to use, accurate and can be applied to any region and river.
1 Introduction

Riverbank erosion is a complex phenomenon resulting from various factors which affect the balance of ecosystems. It is also important from the geomorphological aspect as it also induces changes in the river channel course and in the development of the floodplain (Hooke, 1979; Bridge, 2003). 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 geomorphic 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 which are vulnerable to erosion is of utmost importance either for their protection or restoration.

On the other hand, riverbank erosion constitutes a significant factor to the functioning of river dependent ecosystems and provides a sediment source that creates riparian habitat. Bank erosion is a key geomorphological mechanism for the fluvial ecosystems since it regulates the diversity of habitats, species and vegetal units. The process provides riparian vegetation succession and develops dynamic habitats vital for fluvial plants and animals. For small scale bank erosion or for local extent there is no significant influence on the aquatic ecosystem and it is contributing to the ecosystem sustainability. In the opposite case, the ecosystem is significantly affected while riparian land losses and damages are caused providing areas vulnerable to flooding (Piégay et al., 1997; Piégay et al., 2005; Florsheim, 2008).
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 have been developed and tested. The most important issue concerning riverbank erosion is the identification of the areas vulnerable to bank erosion, 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 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.

Herein, a statistical tool is proposed for the determination of riverbank erosion probability. This work also involves the application of the Bank-Stability and Toe-Erosion Model (BSTEM 5.2) in order to provide data for the validation of the proposed tool. 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 principles of Logistic Regression (LR) and Locally Weighted Regression (LWR) 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 areas vulnerable to erosion. 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.

Overall, the concept of this work is to present a statistical model based on LR methodology for the estimation of the erosion probability at specific ungauged riverbank locations where independent secondary explanatory information is available. BSTEM has an auxiliary role to estimate/validate potential eroded riverbank locations by calculating the potential eroded area, using field measurements of hydraulic, hydrologic and geomorphologic variables. These estimations (dependent variables) are then used to set up and validate the statistical model which is then applied to ungauged riverbank points.

BSTEM is an existing deterministic model that can be used, among others, to predict eroded riverbank area. LR is also an existing statistical model that uses secondary information to calculate probability of an event to occur. Locally Weighted Logistic Regression (LWLR) is a new proposition that combines LR and LWR to create a local model that calculates the probability of erosion to occur, based on secondary information (e.g. bank slope, river cross section) that are spatially correlated. Therefore, the accuracy of the predictions is expected to improve compared to the global regression model LR. To the best of our knowledge, the combination of deterministic and stochastic models to predict river bank erosion appears for the first time in the scientific literature.
2 Case Study

The Koiliaris River Basin is situated 25 km east of Chania (005-12-489E, 039-22-112N) and occupies an area of about 130 km². 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, transferring 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 2013-14, 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 2013-14 hydrological year, the erosion sticks were
inspected on February 2014 during a field trip to identify potential erosion at the riverbanks.

3 Methodology

The methodological steps of the proposed tool and of the overall process are briefly described by a flowchart presented in Figure 3. The riverbank erosion at selected sections and locations along the Koiliaris’ riverbanks was assessed using the BSTEM model. Bank geometry, channel and flow parameters, bank material and bank vegetation and protection parameters were used as input to the BSTEM model to calculate the bank eroded area ($L^2$). BSTEM was applied to address riverbank erosion at twelve selected monitoring locations along a river section. In addition, based on model’s efficiency and the quality of estimation, the reliability of BSTEM results is evaluated at eight sections of the same downstream area. Channel and bank geometry characteristics were measured during the field campaigns and are presented later in the text. As far as for the flow parameters, for the 1st BSTEM model application (eight river sections) river water elevation was set to 1.27 m for a 48h duration event based on field data. The 2nd BSTEM model application (twelve locations) estimates the cumulative riverbank erosion effect of three flash flood events (Fig. 2). The other parameters were similar for the two model applications due to the fact that the same river section was employed. Therefore, reach slope varied between 0.0042 and 0.11 m/m and the bank material was set after field measurements analysis to “fine rounded sand” with an average medium grain size 0.3 ($\pm$ 0.06) mm. The “geyer willow” was selected from the predefined list to describe the bank vegetation with the assumptions of the plants age of about 100 years and 100% contribution to assemblage. Finally, for the locations where the bank was protected the “boulders” choice was used to describe the bank material.

The bank erosion vulnerability of the Koiliaris’ riverbanks was first studied during hydrological period 2010-11. 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 2013-14, a second field campaign was designed to identify at this time the locations vulnerable to erosion. 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 2013-14 were considered to assess the cumulative effect on bank erosion. It has to be mentioned here that during the inspection, end of the wet period of hydrological year 2013-14, 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 (L²). 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 based on spatially correlated independent variables.

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:

\[ p(\mathbf{x}) = \frac{1}{1 + \exp(-\mathbf{x})}, \]  
\[ \mathbf{x} = \beta_0 + \sum_{k=1}^{K} \beta_k x_k, \quad k = 1, \ldots, K, \]  
where \( p(\mathbf{x}) \) is the probability of the dependent variable, \( 0 \leq p(\mathbf{x}) \leq 1 \), associated with a given location, \( K \) is the number of the respective independent variables, \( \beta_0, \beta_k, k = 1, \ldots, K \) 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):

\[ L(\beta|y_1, \ldots, y_n) = \prod_{i=1}^{n} (p(x_i)^{y_i}(1-p(x_i))^{1-y_i}), \]  
where \( n \) is the sample size, \( x_i \) represents the values of the independent variables for the \( i^{th} \) sample (Eq. 2), \( p(x_i) \) is determined by Eq. (1) and \( y_i \) is the value of the dependent variable for the \( i^{th} \) 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 \( \beta_k \) 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.

\[ w(d) = \exp(-d/a), \]  
\[ w(d) = [1 - |d/h|^2]^3, |d/h| \leq 1. \]
In Eqs. (4) and (5) above, w denotes the weights, \( \alpha \) 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 reliability of each of the independent variables tested. The model deviance is given by

\[
D = -2 \sum_{i=1}^{n} \left[ y_i \ln \left( \frac{p(x_i)}{y_i} \right) + (1 - y_i) \ln \left( \frac{1-p(x_i)}{1-y_i} \right) \right],
\]

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 \( P = (y = 1|x) = p(x) \). Variable \( x = (x_1, x_2, ..., x_K) \) denotes a series of independent variables. Probability \( p(x) \) is calculated as in Eq. (1).

\[
p(x_i) = \frac{\exp(\beta_0 + \beta_kx_k)}{1 + \exp(\beta_0 + \beta_kx_k)}
\]

(7)

The G-Statistic is given by

\[
G = D_{null} - D_k,
\]

where term \( D_{null} \) denotes the deviance when the model is applied without independent variables, i.e., when \( p(x) = [1 + \exp(\beta_0)]^{-1} \). 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. 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 BSTEM model was validated for the predicted erosion (m$^2$) after a field investigation that was performed at the end of the wet period of the hydrologic year of 2013-14. Photographs were taken at some locations where the 50 cm scaled stick was placed showing the eroded area. The eroded area at each location was successfully predicted as the observed affected area was quite similar. Especially at the location (KI) with the most significant effect, the predicted eroded area was equal to 2.043 m$^2$ and the affected area measured at the field (and represented in the modified photo, Fig. 4) was roughly 2.08 m$^2$. The situation is the same for the other locations. However, the purpose of this work was to use BSTEM results (at the twelve locations) together with field inspection to setup the statistical model and provide validation points (binary data, erosion and no erosion locations). Therefore, quantified measurements at those points were not performed but only field inspection to validate that the BSTEM results are consistent with reality. Therefore, only at the point with the most intense erosion, a close photo was taken and analyzed to quantify the erosion.

The aforementioned results mean that the BSTEM outcome for the eight subsections of the first campaign can be also characterized as reliable because they are located between of the twelve points that were successfully validated by the field inspection. 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 twelve measurements of the 2nd field campaign were used to apply LR and LWLR while the eight locations of the 1st campaign were employed as validation points. The
first BSTEM application has provided a vulnerability assessment of the riverbank sections that these eight locations assign. The riverbank areas vulnerable to erosion, and therefore the associated locations are characterized as Unstable “U” and the non-vulnerable as Stable “S”. Correspondingly to the LR and LWLR that deliver probabilities of erosion to occur, $P\geq 0.5$ is interpreted as presence of erosion and is denoted as Unstable “U” and absence of erosion $P<0.5$ as “S”, Stable. Therefore, the different statistical model forms are validated based on the erosion vulnerability of the eight locations of the 1st field campaign (Tables 3 and 4). In addition, the proposed model is accompanied by a goodness of fit test estimation (G-statistic) which performs validation of predictions.

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 Table 3. The values for the independent variables were obtained from a 3D digital model of Koiliaris River developed based on a Digital Elevation Model (DEM).

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. 5b and 5c 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.

Inter-comparison of estimations is possible as the x and y axis of the plots are at the same scale for the results of the three methods tested and specific discussion is presented below. In addition, the validation points are shown on the plots for easier inter-comparison. The three plots (Fig. 5) present the probability of erosion to occur ($z$ axis) at the specific riverbank locations when a couple of independent values is met (x and y axes). These couples of independent variables are randomly selected from locations among the measurement points based on a 3D model of the downstream part of River Koiliaris. In a similar work recently published (Vozinaki et al., 2015), the
A simple LR model was applied on predicting crop damage curves based on measurements of river flood depth and velocity (secondary data). The secondary data required to develop the probability curves (predictions) were produced by a Monte Carlo simulation in the absence of sufficient measurement data. Herein, the selected secondary values come from the 3D river structure model which was developed based on a 5 m DEM. The produced 3D figures (Fig. 5) actually work as a probability map presenting the erosion probability when a specific couple of secondary variables is met.

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 $\alpha$ 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.

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. 5b and 5c) shows a significant difference in performance for the two weighting functions. The tri-cubic function (Fig. 5c) delivers more reliable results as it 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. 5c that represents the variability of the erosion occurrence probability. On the other hand, the exponential function (Fig. 5b) 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

The BSTEM model set up provides reliable results regarding the potential erosion vulnerability of the riverbanks that can be used to validate the estimations of the proposed statistical model. On the other hand, the proposed LR based statistical model estimates efficiently the erosion probability at the riverbanks using two secondary variables that affect significantly the presence or absence of erosion. However, in LWLR locality is important; the location of the new couple of secondary variables was used to identify and weight the effect of spatially correlated measurement points in order to calculate the model parameters. The proposed methodology, LWLR, exploits the local information of independent variables and translates it successfully to bank erosion probability. This is not a typical regression estimation based on global parameters but herein the model parameters are calculated iteratively for the new couples of secondary variables.

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 Koliaris River.

This work presents the framework of a methodology that can be applied in order to estimate the probability of erosion at specific riverbank locations considering explanatory and easy to determine secondary variables. Channel geomorphological characteristics, such as cross section and bank slope, are relatively easy to be determined at unmeasured locations by using a digital elevation model. On the other hand, hydrological variables or bank material requires extensive field measurements in order characteristic variables to be considered as secondary information. Such measurements did not take place during the field campaigns as it was not in the context of this work. The developed statistical tool provides an alternative proposition for the estimation of riverbank locations vulnerable to erosion 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 contribution

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.

Acknowledgements

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Learning" of the National Strategic Reference Framework (NSRF) - Research Funding Program: Thales. Investing in knowledge society through the European Social Fund.

References


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

<table>
<thead>
<tr>
<th>Map location</th>
<th>1st flood</th>
<th>2nd flood</th>
<th>3rd flood</th>
<th>Cumulative effect</th>
</tr>
</thead>
<tbody>
<tr>
<td>KA</td>
<td>0.440</td>
<td>0.404</td>
<td>0.349</td>
<td>1.193</td>
</tr>
<tr>
<td>KB</td>
<td>0.566</td>
<td>0.510</td>
<td>0.394</td>
<td>1.470</td>
</tr>
<tr>
<td>KC</td>
<td>0.498</td>
<td>0.512</td>
<td>0.389</td>
<td>1.399</td>
</tr>
<tr>
<td>KD</td>
<td>0.411</td>
<td>0.410</td>
<td>0.328</td>
<td>1.149</td>
</tr>
<tr>
<td>KE</td>
<td>0.459</td>
<td>0.437</td>
<td>0.320</td>
<td>1.216</td>
</tr>
<tr>
<td>KG</td>
<td>0.258</td>
<td>0.255</td>
<td>0.213</td>
<td>0.726</td>
</tr>
<tr>
<td>KZ</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>KH</td>
<td>0.207</td>
<td>0.187</td>
<td>0.145</td>
<td>0.539</td>
</tr>
<tr>
<td>KJ</td>
<td>0.368</td>
<td>0.421</td>
<td>0.357</td>
<td>1.146</td>
</tr>
<tr>
<td>KI</td>
<td>0.741</td>
<td>0.728</td>
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</tr>
<tr>
<td>KK</td>
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<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>KL</td>
<td>0.167</td>
<td>0.162</td>
<td>0.132</td>
<td>0.461</td>
</tr>
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</table>
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.

<table>
<thead>
<tr>
<th>Map location</th>
<th>Presence/Absence of erosion</th>
<th>Bank slope (degrees)</th>
<th>Cross section width (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>KA</td>
<td>1</td>
<td>60</td>
<td>9.00</td>
</tr>
<tr>
<td>KB</td>
<td>1</td>
<td>75</td>
<td>9.25</td>
</tr>
<tr>
<td>KC</td>
<td>1</td>
<td>65</td>
<td>8.75</td>
</tr>
<tr>
<td>KD</td>
<td>1</td>
<td>55</td>
<td>9.00</td>
</tr>
<tr>
<td>KE</td>
<td>1</td>
<td>85</td>
<td>10.76</td>
</tr>
<tr>
<td>KG</td>
<td>1</td>
<td>60</td>
<td>11.55</td>
</tr>
<tr>
<td>KZ</td>
<td>0</td>
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<td>10.00</td>
</tr>
<tr>
<td>KH</td>
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</tr>
<tr>
<td>KJ</td>
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<td>60</td>
<td>13.35</td>
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<td>7.60</td>
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<td>70</td>
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</tr>
<tr>
<td>KL</td>
<td>0</td>
<td>50</td>
<td>9.00</td>
</tr>
</tbody>
</table>
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.

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

<table>
<thead>
<tr>
<th>Validation point</th>
<th>Bank slope (degrees)</th>
<th>Cross section width (m)</th>
<th>BSTEM Erosion estimates</th>
<th>Erosion (P) LR</th>
<th>Erosion (P) LWLR (exp. model)</th>
<th>Erosion (P) LWLR (tri-cubic model)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>84</td>
<td>9.25</td>
<td>U</td>
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</tr>
<tr>
<td>4</td>
<td>33</td>
<td>9.00</td>
<td>S</td>
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<td>0.25</td>
</tr>
<tr>
<td>5</td>
<td>82.5</td>
<td>8.75</td>
<td>U</td>
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<td>0.81</td>
<td>0.82</td>
</tr>
<tr>
<td>6</td>
<td>44</td>
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<td>U</td>
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<td>0.54</td>
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<tr>
<td>7</td>
<td>27</td>
<td>9.26</td>
<td>U</td>
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<td>U</td>
<td>0.62</td>
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<td>0.73</td>
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</table>
Figure 1. The downstream 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.
Figure 2. Typical hydrograph of the Koiliaris River at the Gauge Station (November 2013 – June 2014).
Figure 3. Process flowchart that presents the combined application of the BSTEM and of the proposed statistical model (SMODEL) based on LR principles. The notation “S” and “U” correspond to Stable and Unstable riverbanks respectively.
Figure 4. Photo highlight of the riverbank location (KJ) with the most intense observed erosion accompanied by the appropriate scaled tools to provide a rough estimate of the eroded area.
Figure 5. Erosion probability predictions using a) LR, b) LWLR with the exponential weighting function and c) LWLR with the tri-cubic weighting function versus variable independent values at random ungauged Koiliaris' riverbank locations. The black dots indicate the eight validation points.