Geotech Geol Eng
DOI 10.1007/s10706-017-0248-2

ORIGINAL PAPER

Evaluation of Pore-Pressure Monitoring Setup

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Received: 15 September 2016 / Accepted: 27 April 2017

Abstract In this study soil parameters are back analyzed by using the finite element method and two optimization algorithms, the Non Linear Least Squares (NLLS) and Coupled Local Minimizers (CLM) method. Soil permeability parameters are back analyzed to match the observed values of the variation of pore-water pressures at the Fosso S. Martino Landslide in Italy. Piezometer readings are used to back analyze the permeability coefficients of three soil layers and the left-hand side water level boundary. Furthermore, the performance of each piezometer is evaluated through neglecting the information of other points and performing the optimization analysis. It is found that both optimization algorithms determine soil parameters that represent the pore-water fluctuation of the study area, with their advantages and drawbacks. The NLLS computes values that represent the performance of the pore-water fluctuation in the piezometer readings however, the selection of the starting values is important in order to reduce the computational time. The CLM method was also able to compute adequate soil parameters however, the computational effort is much higher due to the fact that this method uses several search points in the process. For the minimum monitoring setup needed for the adequate determination of soil parameters, the piezometers in the middle of the slope provided the best information. These piezometers are essential to adequately back analyze the soil properties in this case study. Great attention has to be considered in maintain these piezometers in order to continue monitoring the slope.

Keywords Monitoring · Seepage · Back-analysis · Finite element

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1 Introduction

The performance of geotechnical modelling depends on the adequacy of obtaining quality data from monitoring, whereas, the successful performance of monitoring depends on the ability to judge the optimal positioning of instruments. Geotechnical monitoring can be used to check critical design assumptions, assess contractor's means and methods, inform stakeholders, and reduce litigation (Marr 2008). The two main goals of slope monitoring are to detect potential landslides and to identify the causes of the movements. In many cases slope movements develop gradually and the early detection of movements is critical for protecting against the hazard. The information gathered from monitoring systems is needed to perform adequate slope maintenance, to perform remedial measures, to reduce uncertainties, and to activate alarm systems. The monitoring of the rate of

Published online: 02 May 2017

movement, failure surface and pore pressures are important to understand the phenomenon. Furthermore, as soil parameters measured in situ or in laboratory have uncertainties, an adequate location of sensors may reduce some of them, helping to a better understanding of the problem under study. For most of the potentially unstable slopes, the cost of prevention is less than the cost of remediation. As a result, investigation may indicate possible failure helping to protect humans and avoiding expensive repairs (Simons et al. 2002). According to Kovári (1988) monitoring pore pressures and movements of a landslide may help to assess the following features: (1) detection of a slide before it can be recognized from morphological indications, (2) determination of the area on the ground surface belonging to the sliding mass, (3) investigation of the sliding mechanism including slip surfaces and creep zones, and (4) safety assessment and continuous safety surveillance.

Before a slope is instrumented, an adequate monitoring plan and design must be performed. Details on these aspects have been described in Peck (1988) and Turner and Schuster (1996). For the installation of monitoring systems, many types of sensors and data transmission systems are available. A monitoring system must collect data accurately, reliably, efficiently, and in a timely manner (Turner and Schuster 1996). The magnitude, rate, and distribution of slope movement are generally the most import measurements required. However, a set of sensors placed arbitrarily in and on a landslide will produce a series of measurements that are difficult to interpret. A simple rule to follow according to Peck (1988) is “every instrument installed on a project should be selected and placed to assist in answering a specific question.” In the first stage of implementation of a monitoring system, some advanced knowledge of what magnitude and expected location of pore pressures and deformation is needed. For example, Žlender et al. (2012) used adaptive network-based fuzzy inference system to optimize the number of investigation points, field and laboratory for planning geotechnical investigations.

Critical zones in the slope may be identified from a finite element analysis, which considers the material stress–strain constitutive relationship, expected loading, and other effects. Finite element analysis gives a predicted displacement and seepage field that can be used to select the proper sensors, and optimizes their location. Finite element methods can also be used to analyze active landslides (Conte et al. 2014). Once a monitoring program begins, any variations between the design and actual data could be an indication of unexpected behavior or incorrect modelling assumptions. In general, due to economic constraints it is not possible to implement an entire network of landslide monitoring that could include: inclinometers, tiltmeters, extensometers, and piezometers, among other devices. Complete monitoring systems have been seldom implemented with few exceptions for research purposes. In practical engineering, the restricted project budget limits the monitoring program to few instruments; thus, the correct location of the equipment on and in the slope is essential for obtaining adequate information that represents the complete mass performance.

The location of instruments for slope stability is far from trivial. However, when a priori critical zones are identified such as geostructural discontinuities, joints and faults, the instrumentation location is straightforward. Instruments should be placed where structurally weak zones, most heavily loaded zones, or zones where the highest pore-water pressures are anticipated (Dunnicliff 1993). Cracks appearing on the surface of a slope are an indication that large displacements have already taken place and that sliding surfaces have already been formed. In cases where no such critical zones are identified, the selected location should reflect the behavior of the whole body. Remote sensing techniques, such as aerial photography, satellite-, radar-, and LIDAR-derived images can be successfully used for both the detection of landslides and monitoring of landslide activity (Dewitte et al. 2008). The information derived from these techniques helps to define critical zones to guide the location of sensors.

Measurements of pore pressures within the slope are important in analyzing many landslide and other engineering problems. Back analysis of a seepage field is essential for control planning and implementation of safety measures (Ren et al. 2016). Such measurements are crucial when excess hydrostatic pressures may exist therefore, it is important to implement a pore-pressure monitoring. The knowledge of the groundwater flow is an important factor for slope stability analysis as well as for predicting critical zones (Pirone et al. 2015).

In order to understand the behavior of the groundwater flow in a slope, it is important to properly determine its soil parameters. In this document, Non Linear Least Squares (NLLS) and Coupled Local

Minimizers (CLM) method are used for back analysis of soil parameters (permeability coefficients) combining the FEM and optimization algorithms. A back analysis consists in finding the values of the parameters that, when used in the numerical or analytical model of the problem under study, leads to results as close as possible to the corresponding measurements. This approach is also called inverse modelling or inverse analysis. The inverse modelling is used to match the observed values of the variation of pore-water pressures at the Fosso S. Martino Landslide in Italy. Piezometer readings are used in the inverse modelling to compute the permeability coefficients of three soil layers and the left-hand side water level boundary. By combining the FEM with an optimization algorithm, the numerical procedure consists in solving an inverse problem in which the error function is a measure for the discrepancies between the measured and numerical data. Therefore, in an iterative process the unknown permeability coefficients are adjusted until the difference between the numerical and measured data are minimized. Here, the forward problem for the seepage analysis is solved in PlaxFlow (finite element package).

Additionally, due to the high costs of installing and maintain monitoring systems, a second objective of this paper was to identify the minimal setup of a pore-pressure monitoring. For this, the setup of observation points was evaluated based on the difference between the measured and computer pore-water pressures.

2 Back Analysis of Soil Parameters

Soil properties obtained from back analysis of geotechnical problems are more reliable than those obtained from laboratory or in situ tests (Duncan and Stark 1992). According to Cornforth (2005) back analysis provides confidence in ensuring the reliability of remedial work and allows the engineers to use less conservative factors of safety for landslides than for slope stability calculations where no failure has occurred. Actual geotechnical problems can be considered as a large-scale field test, where back analysis directly computes the soil parameters. By this large field test some restrictions and uncertainties may overcome, for example, the sample for laboratory testing. An extra benefit of the back analysis is that it allows simultaneous adjustment of multiple parameters.

The main features of an optimization problem are an objective function to be minimized, a set of variables (unknowns) that affect the value of the objective function, and a set of restraints which allow the variables to take on certain values. By this means, the optimization problem finds values of the variables that minimize the objective function, while filling the restraints. In this framework, the objective function is the difference between field or laboratory data and numerical computations of the forward problem (seepage analysis). The back analysis consists in determining the set of parameters that reduces the difference function leading to the best estimate of the field or lab data.

In this study, the objective function for the coupled local minimizers (CLM) and nonlinear least squares (NLLS) is represented as a least square problem with the objective function $f(\mathbf{x})$ been:

$$f(\mathrm{x}) = \frac{1}{2}\mathrm{e}(\mathrm{x})^T\mathrm{e}(\mathrm{x}) \tag{1}$$

$$\mathrm{e}(\mathrm{x}) = \begin{bmatrix} y_1^* - y_1(\mathbf{x}) \\ y_2^* - y_2(\mathbf{x}) \\ \vdots \\ y_m^* - y_m(x) \end{bmatrix} \tag{2}$$

where the error vector $\mathbf{e}(\mathbf{x})$ is of m-dimensions and depends of the n-dimensional vector ($\mathbf{x}$) with variables xj, (j = 1,…,n). The error vector contains the error between the measured data (yi*) and the computed values obtained from numerical analysis (yi($\mathbf{x}$)). For this seepage analysis, the measured values are the piezometric levels with the variables being the horizontal and vertical permeability parameters (kx and ky) of each layer.

Local gradient-based optimization methods like the NLLS-algorithm converge fast, but do not guarantee to find the global minimum of the objective function. If the objective function contains local minima, the result of the optimization will depend on the choice of the starting input parameters. Specific details on the NLLS algorithm can be found in (Madsen et al. 2004).

The CLM algorithm is a hybrid local/global optimization method that offers a valuable alternative as it combines the advantage of the local gradient-based algorithms with the global approach of genetic algorithms. This method can avoid local minima when searching complex multi-dimensional objective functions. Details on the CLM method can be found in (Teughels et al. 2003; Badsar et al. 2007).

The CLM method considers the minimization of an objective function f(x) with multiple local minima, among which the global minimum has to be found. In the CLM method, a number of N search points is assumed, at which an average objective function is evaluated and minimized. Instead of undertaking separate independent searches from each of the points, the set of optimizers are coupled in order to generate an interaction so that the population generates a minimum that should be better than the best result that would be obtained from all individual local runs. Therefore, a cooperative search mechanism is set up that is realized by minimizing the average objective function. During the minimization process the search points are pairwisely coupled by a synchronization constraints that force them to end at the same final point (Badsar et al. 2007).

3 Case Study of the Seepage Problem

In this section a back analysis is performed using the NLLS and CLM method as optimization algorithms for determining soil permeability parameters, and to assess the minimum setup of monitoring points in a seepage example. Soil parameters are back analyzed to match the observed values of the variation of pore-water pressures at the Fosso S. Martino Landslide in Italy. Piezometer readings are used to back analyze the permeability coefficients of three soil layers and the left-hand side water level boundary. Then, the performance of each piezometer (measurement point) is studied through neglecting the information of other points and performing the optimization. The seepage finite element analysis is calculated in PlaxFlow (PlaxFlow 2007).

The geometrical model, soil properties and measured data (rainfall, piezometers and inclinometers readings) are extracted from Calvello et al. (2008). In their study, a numerical model to predict the behavior of rainfall-induced movements is proposed. This model is validated using a transient seepage and a kinematic analysis.

3.1 Site Description Fosso S. Martino Landslide

The Fosso S. Martino Landslide in located in central Italy. The stratigraphy is presented in Fig. 1 where the location of the twelve piezometers (D8, A1, A2, F9, F10, B3, B4, B5, C6, C7, G11, and G12) and the two inclinometers (B and C) are show. The mesh discretization is shown in Fig. 2, where 950 triangular elements are used.

The landside moves along a narrow band of weathered bedrock which is covered by a clayey silt colluvial material. These movements are considered to be very slow (0.02 m/year). Details on geological morphological and geotechnical settings can be found in (Bertini et al. 1984), where the inclinometers readings are also discussed. The lab soil permeability assigned to the materials for the *k*x and *k*y of the Colluvium are 0.05 and 0.05 (m/days), for the Weathered bedrock 0.05 and 0.05 m/days and for the Rock Basement 5.00 and 0.10 m/days. These two datasets are used as starting parameters in the inverse modelling. A complete description of the soil characteristics including index properties and strength parameters are given in (Bertini et al. 1984; Calvello and Finno 2004). The seepage modelling is influenced by the quantity and the intensity of the rainfall. The monthly rainfall for a period of 3 years 1980–1983 (1095 days) is used in the model. The piezometric data used as observation points are presented in Fig. 2. This information is used in the inverse modelling as target (objective) (Fig. 3).

The transient 2D seepage flow using Darcy's law is governing by the following differential equation:

$$\frac{\partial}{\partial x}\left(-k_x\frac{\partial\varphi}{\partial x}\right)+\frac{\partial}{\partial y}\left(-k_y\frac{\partial\varphi}{\partial y}\right)+c_e\frac{\partial\varphi}{\partial t}=Q \tag{3}$$

where *k*x and *k*y are the effective permeability in the horizontal and vertical direction, respectively, φ is the total head composed of the elevation head and the pore pressure head. Q is any flow source (inflow) or sink (outflow), and c_e is the effective capacity. The transient seepage flow is solve in a finite element package (PlaxFlow).

3.2 Numerical Results from NLLS and CLM

The NLLS and CLM algorithms are used to compute the best fitting parameters needed to match the observed piezometric data (measured data from the twelve piezometers). The objective function is formulated with Eq. 1. The components of the error vector **ei**(**x**) contains the discrepancies in pore-water

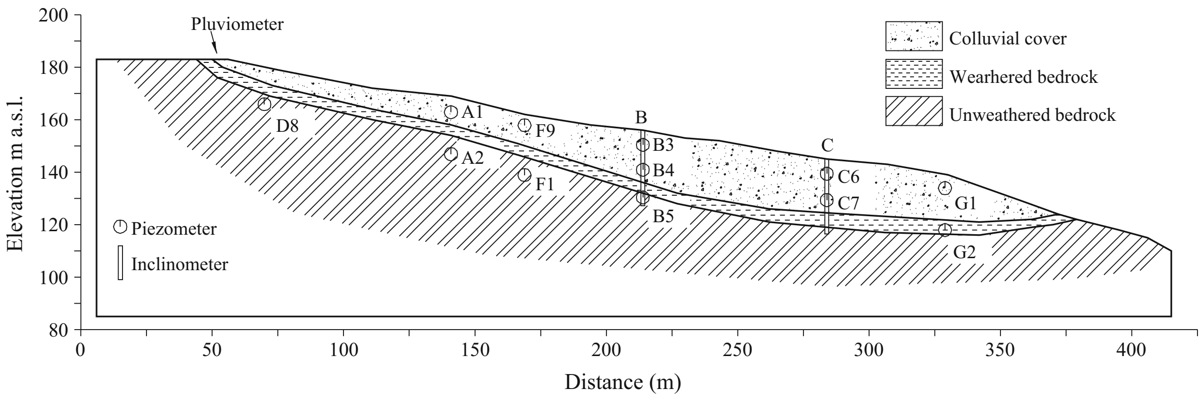


Fig. 1 Study site at Fosso S. Martino landslide (modified after Calvello et al. 2008)

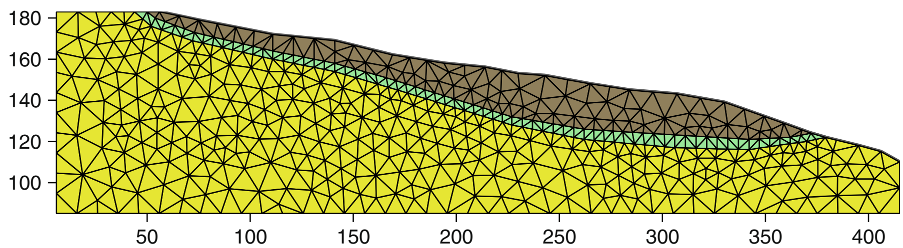
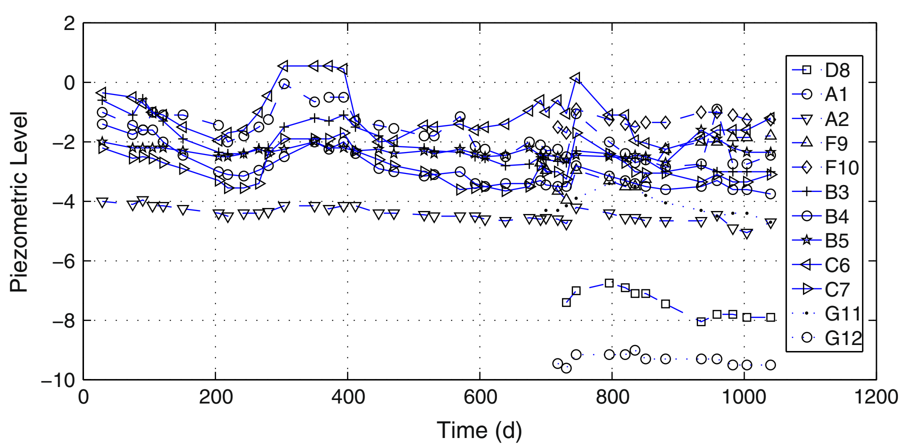


Fig. 2 Mesh discretization used in the finite element analysis

Fig. 3 Data of piezometric level used in the optimization analysis (modified after Calvello et al. 2008)



pressures (total elevation head). The dimension **m** of error vector **e** is 347 (12 observation points), and the dimension **n** of the parameter vector **x** is 7 (six permeability coefficients in three strata and left-hand side water level).

Since local optimizers are sensitive to the starting point, two sets of starting parameters are tested. The first set corresponds to the lab values (NLLS-LAB) and the second to that calibrated by Calvello et al. (2008) (NLLS-C08). For the CLM, the number of search point N = 5 and the starting value, for these points, are chosen randomly. The value of N = 5 has been chosen in order to have adequate convergence of the results and not to significant increase the computational time. The range of values for the permeability coefficients has been chosen from the in situ estimations presented in Calvello et al. (2008). Table 1 shows the results obtained for the three sets. When

Table 1 Optimized soil parameters for seepage analysis by NLLS and CLM

Soil parameters	NLLS-LAB		NLLS-C08		CLM	
	kx (m/days)	kx (m/days)	kx (m/days)	kx (m/days)	kx (m/days)	ky (m/days)
Colluvium	0.320	0.100	0.356	0.182	0.228	0.247
Weathered bedrock	0.026	0.019	0.010	0.022	0.208	0.251
Rock basement	2.608	0.581	1.154	0.296	1.055	0.504
Water level (m)	174.45		175.50		175.56	

comparing the lab values against the computed values, it can be seen that for the colluvial stratum the permeability coefficient *k*x is significantly increased passing from 0.05 to 0.320 m/days (NLLS-LAB) and 0.228 m/days (CLM), which correspond to an increase of 540 and 357%, respectively. The *k*y in this stratum increases 100 and 400% with values of 0.100 and 0.247 m/days. For the weathered clay the NLLS algorithm determines permeability coefficients that are around 50% lower than the lab values. The CLM method computes coefficients that are 300% higher. For the *k*x − rock the value is reduced from 5.0 to 2.6 m/days for the NLLS-LAB set and to 1.0 m/days for the CLM set. The *k*y − rock is increased by a factor of 5 for both cases, passing form 0.1 to 0.58 and 0.50 m/days, respectively.

When the optimization is performed with the NLLS-C08 values as starting parameters, the differences are drastically reduced, showing that the NLLS algorithm closely agree with the optimization algorithm, used in Calvello et al. (2008). Nevertheless, the colluvium coefficients which mainly control the seepage analysis differ, e.g., *k*x − colluvium differs in 80%. These differences are attributed to the numerical model used in the forward problem and the optimization algorithm codes. Note that for all the analyses the water level at the left-hand side of the model remains around 175 m a.s.l. To visualize the results obtained from the NLLS-LAB set, the total pressure head at each piezometer are compared against those measured and computed with the lab values.

The value of the objective function $f(x)$ computed for the lab values is 8390, whereas the values of $f(\mathbf{x})$ for the optimized parameters, NLLS-LAB, is 275 using 72 runs of the forward problem. For NLLS-C08, $f(x) = 285$ (88 runs) and for the CLM is 376 (608 runs). In the cases for the comparison presented in Table 1 all methods use equal number of fitness (objective function) evaluations. For all the runs, a tolerance of 1e−4 is used. The tolerance is a lower bound on the change in the value of the objective function during a step.

Figure 4 shows the measured pressure heads and the computed PlaxFlow pressure heads; one from the lab values and the second the optimized values. Note that the PlaxFlow results using the lab values give high discrepancies with respect the observed values. These differences are significant especially for the upper slope piezometers (D, A, F and B). A significant improvement is obtained by using the optimized values from the NLLS method. For this case, the computed values are in close agreement with the observed measurements. Nevertheless, these optimized values cannot completely capture the pattern of piezometers D8, A1 and F9. No clear explanation for this situation is encountered, however, it is believed that the proximity of these points to the boundaries (input rainfall and left water-level) influences these results. On the other locations, the observed and measured heads coincide, indicating the adequate determination of soil parameters.

As expected the number of calls is much higher in the CLM method than those in the NLLS algorithm. However, surprisingly, the $f(\mathbf{x})$ value for the CLM is higher than that of the NLLS, which due to the number of search points N = 5 and number of calls for the forward problem 608, is expected to be similar. No clear explanation is found for this discrepancy, nevertheless, the number of search points, tuning parameters, and computation of the gradient, may influence the results. The computed pressure heads derived from the numerical analysis using the optimized CLM parameters are comparable with the observations, except for some variations in piezometers D8, A1, F9 and C6, similar to the values derived from NLLS.

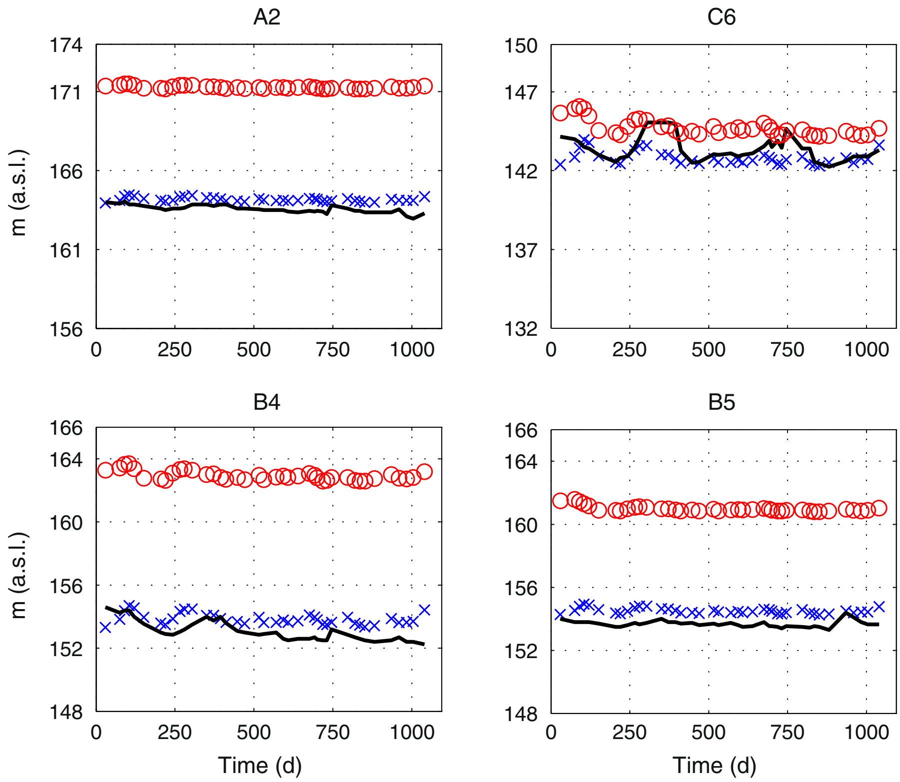


Fig. 4 Comparative analysis for total head between measured level (*line*), computed with lab parameters (*open circle*) and computed by optimized parameters NLLS-LAB (*times*)

3.3 Optimization Based on Selected Piezometers

The importance of each observation point is analyzed by optimizing the soil parameters without considering a ‘selected’ piezometer. Two analyses are carried out. The first removes the data of the selected piezometer from the target function and then the optimization is performed. In the second analysis, only the data from the selected piezometer is used as target function. For the two analyses, the optimized parameters are then used to obtain the value of the objective function considering all the data of the 12 piezometers as observed records. Additionally, two sets of starting values are used, NLLS-LAB and NLLS-C08. The objective function remain the same, however, the dimension **m** of error vector and observation points used in each analysis vary. In Table 2 the number of observation points and residual dimension **m** for each analysis is shown.

Figure 5 shows the values of the objective function for the first analysis. For the first set using the lab values as starting parameters, the lab set gives a $f(\mathbf{x}) = 8390$ and the optimized values using all the data gives a $f(\mathrm{x}) = 275$ (ALL), as mentioned early. By ignoring the data of piezometer D8 and after performing the optimization, the computed values are used to obtain the $f(\mathbf{x})$, which is equal to 277. Therefore, the data of piezometer D8 is not essential in order to obtain a good estimation of the parameters. The same is true for piezometers A_S, F_S, and G_S, where neglecting their data do not highly increase the value of the objective function. The subscript S is used to indicated that all the piezometers in the location are considered, e.g., A_S covers piezometers A1 and A2. The worst case is found when the data of piezometers in C_S are ignored, giving a $f(\mathbf{x}) = 397$.

In Table 3 the results of the back analyzed parameters of each layer without considering the data from a selected piezometer are presented. It is included the value of the objective function $f(\mathrm{x})$ and the number of runs need for the back analysis.

For the second set using C08’s parameters as starting values serve to find adequate parameters—in terms of the value of $f(\mathbf{x})$. Even when seven of the piezometers are ignored, i.e., D_S, C_S, F_S, and G_S (DCFG), the value of $f(\mathbf{x}) = 280$. This analysis shows that an adequate selection of the starting values is

Table 2 Analyzed cases for monitoring seepage setup optimization

First analysis			Second analysis		
'Without' piezometer	Observation point	Residual dimension	Only piezometer	Observation point	Residual dimension
ALL (reference)	12	347	D8	1	12
Ds (D8)	11	335	A1	1	40
As (A1, A2)	10	267	A2	1	40
Fs (F9, F10)	10	319	F9	1	15
Bs (B3, B4, B5)	9	227	F10	1	13
Cs (C6, C7)	10	267	B3	1	40
Gs (G11, G12)	10	320	B4	1	40
DCFG (D, C, F, Gs)	5	200	B5	1	40
G11	11	333	C6	1	40
G12	11	334	C7	1	40
			G11	1	14
			G12	1	13

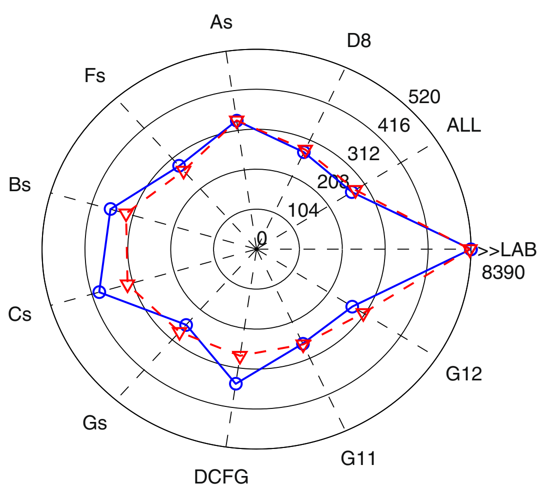


Fig. 5 Value of the objective function determined without considering some piezometers NLLS. Optimized from lab values (*solid line—circle*), optimized from C08 values (*dashed line—triangle*)

necessary to warranty good values when using the NLLS method.

The results of the second analysis, where only the selected piezometer is used in the optimization, are presented in Table 4. For the first set, the best results are obtained for piezometers A1, F_S, and B_S, for example, the best result is observed for piezometer F10 giving a $f(\mathbf{x}) = 362$. The worst results are obtained for piezometers C_S and G_S, for example, G12 gives an $f(\mathbf{x}) = 5000$. When using the C08 values as starting parameters, the optimization is improved and the worst case, now D8, gives a $f(\mathbf{x}) = 1900$. The best results are again obtained for piezometers F_S and B_S, with the minimal in B3 giving a $f(\mathbf{x}) = 315$. Based on these results, the locations of piezometers B_S (B3, B4, B5) and F_S (F9, F10) are the most important to back analyze adequately the soil parameters in the present seepage analysis.

Figure 6 shows the computed horizontal permeability (kx), vertical permeability (ky), and left-side water level. These results correspond to the optimization using only one selected piezometer. For comparative proposes the lab values (LAB) and the optimized values using the entire data (ALL) are displayed. For the colluvial stratum and for all the optimized analyses (Fig. 6a), the lab kx parameter is increased. This pattern indicates that the lab value of 0.05 m/days cannot produce comparable results with respect to the observations.

It can be observed, that piezometers A2, F10 and B_S compute values similar than those in the reference value (ALL), which are close to the 0.30 m/days contour. The pattern of ky shows that piezometers F9, B3, B4 and C7 compute values that are higher than those of the reference value.

For the weathered clay stratum (Fig. 6b), the kx parameter is only similar to the reference value (ALL = 0.026 m/days) in locations A1 and B3. On

Table 3 Back analyzed permeability coefficients without data from selected piezometer

Selected	*k*x_col	*k*y_col	*k*x_wea	*k*y_wea	*k*x_rock	*k*y_rock	Water level	*f*(**x**)	Runs
Ds	0.337	0.119	0.034	0.018	2.863	0.542	175.21	277	72
As	0.338	0.077	0.030	0.013	2.570	0.651	175.03	338	88
Fs	0.355	0.087	0.030	0.024	3.301	0.551	175.12	286	72
Bs	0.259	0.054	0.030	0.048	2.366	0.550	175.92	369	64
Cs	0.216	0.198	0.052	0.092	2.254	0.601	175.21	397	64
Gs	0.486	0.107	0.022	0.031	1.818	0.298	175.45	260	96
DCFG	0.409	0.360	0.091	0.067	2.509	0.352	174.61	354	112
G11	0.457	0.122	0.056	0.028	2.264	0.428	175.46	270	104
G12	0.369	0.101	0.035	0.020	2.450	0.487	175.43	276	96

Table 4 Back analyzed permeability coefficients only with data from selected piezometer

Selected	*k*x_col	*k*y_col	*k*x_wea	*k*y_wea	*k*x_rock	*k*y_rock	Water level	*f*(**x**)	Runs
D8	0.131	0.096	0.078	0.259	4.268	0.256	175.55	1936	72
A1	0.096	0.081	0.025	0.108	3.374	0.392	175.41	802	96
A2	0.202	0.101	0.258	0.001	2.242	0.540	175.18	1091	72
F9	0.443	0.210	0.069	0.080	1.276	0.767	174.33	739	72
F10	0.259	0.050	0.236	0.115	2.308	0.560	174.76	362	80
B3	0.263	0.149	0.028	0.100	1.979	0.692	174.71	488	80
B4	0.343	0.231	0.077	0.070	2.014	0.725	174.27	618	80
B5	0.263	0.014	0.229	0.102	2.715	0.596	174.61	762	64
C6	0.072	0.067	0.041	0.075	5.008	0.174	175.97	4693	72
C7	0.047	0.170	0.043	0.062	3.982	0.203	175.61	2414	80
G11	0.044	0.063	0.058	0.047	4.863	0.208	176.01	3899	40
G12	0.059	0.064	0.055	0.073	4.612	0.153	175.99	4997	56

locations A2, F10 and B5 the computed values are much higher than those obtained using the entire data. Note that these piezometers are located in the weathered bedrock indicating that if only the readings in the rock are used, important information is ignored. For *k*y, the worst result is obtained for piezometer D8, where the other values are below the 0.13 m/days contour. However, none of the analyses compute values close to the reference value of 0.02 m/days. The closer is piezometer G11 with value of 0.047 m/days.

For the parameters in the bedrock (Fig. 6c), the pattern of *k*x is similar to the colluvium, showing the closer agreement for piezometers A2, F10 and BS, however, for the other locations, the optimized values are higher than the one for the reference case. The pattern of *k*y − rock for all cases are similar, showing values around the reference case of 0.6 m/days, exceptions are piezometers C_S and G_S which give values lower than 0.2 m/days.

The water level (Fig. 6d) at the reference value is 174.5 m, this value varies from a minimum of 173.3 m in piezometer F9 and B4 to a maximum of 175 m in piezometers C6 and G_S. Taking the optimized parameters for the entire data as the best estimation of the actual soil properties, it is observed that the piezometers F10 and B_S give the best results, this is in concordance with the observations of the values of the objective function.

4 Conclusions

In this study the soil permeability of three soil layers in the Fosso S. Martino Landslide is inferred from the back analysis of the monitored soil pore-water pressure using the finite element method and two optimization algorithms, respectively the Nonlinear Least Squares (NLLS) and Coupled Local Minimizers (CLM) method. The advantages of obtaining soil

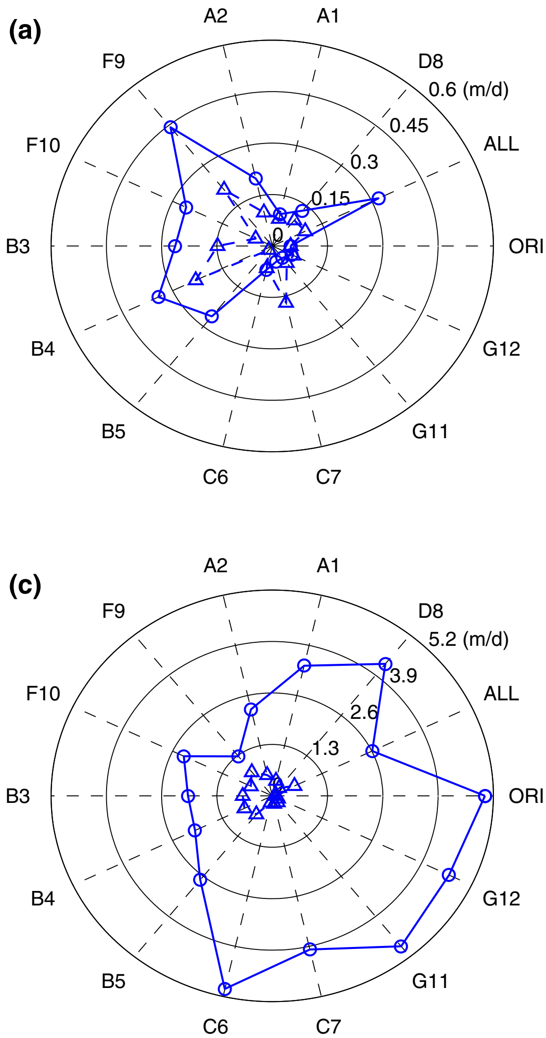


Fig. 6 Parameter optimization values of NLLS. Original parameters (ORI), calibrated parameters considering all piezometers (ALL), calibrated parameters considering only selected piezometer; horizontal permeability *kx* (*solid line—circle*), vertical permeability *ky* (*dashed line—triangle*): **a** colluvium stratum; **b** weathered clay; **c** rock basement; and, **d** left-side water level (*solid line circle*)

parameters from back analysis are presented and discussed. Back analysis helps to overcome some limitations and uncertainties in the use of laboratory and in situ tests.

It is found that the NLLS method is capable of determining the set of parameters that represent the pore pressure variation within the slope. These results are in close agreement to those presented in the literature and those obtained by the CLM method. Negligible differences are found due to the numerical model used in the forward problem and the optimization algorithm codes. The NLLS computes values that represent the performance of the pore-water fluctuation in the piezometer readings however, the selection of the starting values are important in order to reduce the computational time. The CLM method was able to compute adequate soil parameters however, the computational effort is much higher due to the fact that this method uses several search points in the process. Although several search points are desirable, a high number will drastically increase the computational time.

Based on the results of the presented problem, the plausible use of inverse modelling combined with finite element analysis to obtain soil parameters from piezometric readings is demonstrated. The main advantage of the inverse modelling is that simultaneously allows the calibration of multiple parameters. Additionally, the full extent of finite element analysis can be exploited by combining this method and optimization algorithms.

The effectivity of the number and setup of the piezometers in the experimental site was verified by reducing successively in the optimization analysis the information of piezometers. For the minimum monitoring setup needed for the adequate determination of soil parameters, it is observed that based on the calibrated values, the piezometers in the middle of the slope provided the best information. These piezometers are essential to adequately back analyze the soil properties in this seepage analysis.

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