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Research Paper

The role of observations in the inverse analysis of landslide propagation

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ABSTRACT

Model calibration is usually based on trial-and-error procedures that, in turn, rely on expert judgment or previously acquired experiences for similar phenomena. Efficient and reliable procedures for model calibration of the propagation stage of landslides are still needed. This paper addresses this issue by proposing an inverse analysis procedure and applying it to the case history of a short run-out landslide triggered by a rising perched water table after a heavy rainfall. It focuses on the key role played by the field observations used to set up the inverse analysis, and evaluating the reliability of the numerical simulations. It also investigates the effect of different types of optimization parameters on the inverse analysis results, referring to a mixed-phase model or to a two-phase model for the propagating soil. Several sets of observations are used; all of them refer to the soil deposit thickness at the end of propagation, but differ in both location and number of the adopted values. The numerical analysis of the case history is performed through the academic "GeoFlow_SPH" model, and model calibration by inverse analysis is conducted using the "UCODE" software. The results obtained are discussed with the aim to provide practical criteria to identify the minimum amount of information required for a satisfactory model calibration.

1. Introduction

Back-analyses of boundary-value problems are commonly used in geotechnical engineering to calibrate relevant soil properties for modelling purposes. Slope stability was among the first geotechnical problems initially tackled by back-analysis [7,13]. This issue is becoming more and more important for landslides with potentially long run-out. In the literature, there are many articles that discuss the shortcomings of back-analysis in slope stability applications [30,20,12]. Yet, the increasing use of sophisticated mathematical models currently prompts the geotechnical community to use back-analyses of reported case studies to properly identify the corresponding model parameters. Although the interpretation of laboratory tests is commonly used to this aim, the specimens being tested are unlikely to represent real site conditions of the soil [20,28]. In addition, regular trial-and-error methods might be grueling processes for calibrating and validating complex constitutive models. In these cases, the use of automatic inverse modelling algorithms is surely advantageous. Calvello [2] recently coined the expression "observational modelling approach" to indicate any method or procedure that employs inverse analysis techniques to update, with time, the design predictions of a geotechnical boundary value problem using available monitoring data.

Inverse modelling has been employed for different slope stability and landslide simulations [36,3,33,32]. The majority of the research conducted on this topic has focused on landslide triggering employing the hydraulic response of the slope, such as measures from piezometers, as observations to identify the model soil properties [37,1]. Landslide propagation behaviour, although a subject of broad and current interest (e.g., [9,14,15], has rarely been coupled with inverse analysis algorithms explicitly considering the geometric characteristics of the slope as observation values, which may include ground displacements and run-out soil heights (e.g., [10]). This kind of data is particularly useful for the simulation of the propagation stage of landslides. Concerning that, for a well-posed inverse analysis problem, it is very important to choose proper sets of observations-not always an easy task to perform.

The study presented herein deals with the key role played by field observations when they are used to set up an inverse analysis. To this aim, the paper proposes an original procedure to optimize the calibration of a landslide propagation model when observations of the deposition heights are available. The procedure is organised in two sequential steps and it includes both parametric and optimisation analyses, wherein the results of the first ones provide relevant information for the second ones. The observation sets employed in the definition of the inverse problem always refer to the values of soil deposit thickness, yet they differ for both the

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location and the number of adopted field values. During the first step of the procedure, when the analyses are conducted using a simpler rheology to model the propagating soil, many observation sets are tested with the aim of defining the ones that are most suitable to be used for the back-analysis of the landslide. Those sets are then used, in the second step of the procedure, to calibrate the model parameters of a more complex two-phase soil model.

The proposed procedure is tested for a landslide case history that occurred in Hong Kong and for which detailed information is available [21]. The inverse modelling algorithm used in the study is "UCODE" [27,26], which employs a modified Gauss-Newton non-linear regression to minimise a user-defined weighted least-squares objective function. Landslide propagation is simulated using the "GeoFlow_SPH" model [25,11], which schematises the propagating mass as a mixture of a solid skeleton saturated with water, the unknowns being the velocity of the solid skeleton and the pore water pressure.

2. Methods

2.1. SPH modelling of landslide propagation

In this paper, the propagation simulation is performed through the "GeoFlow_SPH" model, which is a depth-integrated hydro-mechanical coupled model proposed by Pastor et al. [25], based on the fundamental contributions of Hutchinson [19] and Pastor et al. [23]. This model incorporates the coupling between pore pressures and the solid skeleton inside the propagating mass. In particular, a depth-integrated, coupled, mathematical model has been derived from the velocity–pressure version of the Biot–Zienkiewicz model [23]. The equations are complemented with simple rheological equations describing soil behaviour and are discretised using Smooth Particle Hydrodynamics (SPH), which is a meshless method introduced independently by Lucy [22] and Gingold and Monaghan [16] for astrophysical modelling applications. GeoFlow_SPH was recently used to successfully simulate different case studies of landslide propagation involving mixtures of coarse-grained soils saturated with water, also showing bifurcation of the soil mass [24] or soil entrainment during the inception of debris avalanches [11]. In most cases, a frictional-type rheology has been effectively used to schematise these case studies.

For the analyses to be performed herein, two different mathematical models will be used: (i) the mixed-phase model, and (ii) the two-phase model.

The first schematisation can be profitably used when water and soil can be effectively approximated as a single-phase material with averaged physical and rheological properties. Pastor et al. [23] states that the following two are the limit cases: (i) flow of granular materials with high permeability, for which the consolidation time is much smaller than propagation time, hence the material behaves as "drained"; (ii) flow of slurries with high water content, for which the dissipation time for pore water pressures is much higher than the propagation time, hence the behaviour of the material can be assumed as "undrained". In both cases, the material behaviour can be approximated as mixed-phase material, for instance, by using the following frictional law:

$$\tau_b = -\rho g h \cdot \tan\phi_b \cdot \mathrm{sgn}(\overline{v}) \quad (1)$$

where τ_b is the basal shear stress, g is the gravity acceleration, h is the propagating soil depth computed as perpendicular to the ground surface, ϕ_b is the basal friction angle, $\overline{v}$ is the depth-averaged flow velocity and *sgn* is the sign function.

The two-phase model considers pore water pressure changes in time and space within the propagating mass during the propagation time, and two unknown variables, the velocity of the soil skeleton (v) and the pore water pressure (p_w). Both variables are defined as the sum of two components related to propagation and consolidation along the normal direction to the ground surface. The governing equations are discussed in previous papers [25,24,6,11]. It is worth recalling that the vertical distribution of pore water pressure is approximated using a quarter-cosinus shape function, with a zero value at the surface and zero gradient at the basal surface [25], while the time evolution of pore water pressure is then given by Eq. (2). In case of a frictional law, the basal tangential stress is now given by Eq. (3).

$$\frac{dp_w^b}{dt} = \frac{\pi^2}{4h^2} c_v p_w^b \quad (2)$$

$$\tau_b = -(\rho g h - p_w^b) \cdot \tan\phi_b \cdot \mathrm{sgn}(\overline{v}) \quad (3)$$

where c_v is the consolidation coefficient, τ_b is the basal shear stress, g is the gravity acceleration, h is the propagating soil depth, ϕ_b is the basal friction angle, p_w^b is the basal pore water pressure, *sgn* is the sign function, and $\overline{v}$ is the depth-averaged flow velocity. The use of the two-phase model implies that the initial pore water pressures must be assigned. This can be done by assigning the initial height of water table relative to soil thickness (h_w^{rel}), and the ratio between the initial basal pore-water pressure and the liquefaction pressure at base of the flow (p_w^{rel}).

The importance of pore pressure dissipation during landslide propagation has been demonstrated in the literature [25,35,31]. In the model considered herein, it is worth noting that the value of the consolidation coefficient (c_v) affects basal pore water pressure (p_w^b); the latter influences the basal shear stress (τ_b) and, in turn, both affect flow velocity ($\overline{v}$) and flow depth (h). Another important process, i.e. bed entrainment, will be not included in the analyses of the selected case history. This choice was because the landslide propagated over an urbanized area a paved road, both not erodible for such volume of landslide mass.

2.2. Inverse analysis by non-linear regression

Inverse analysis algorithms work in the same way as trial-and-error calibration approaches: model input parameters are adjusted until the model's computed results match the observed behaviour of the system. Herein, model calibration by inverse analysis is conducted using UCODE [27], a computer code designed to allow inverse modelling posed as a parameter estimation problem. In UCODE, the parameters are optimised by minimising, using a modified Gauss-Newton non-linear regression algorithm, a weighted least-squares objective function, S(b):

$$S(b) = [\underline{y} - \underline{y}'(b)]^T \underline{w}[\underline{y} - \underline{y}'(\underline{b})] = \underline{e}^T \underline{we} \quad (4)$$

where b is the vector of the parameters being estimated, y is the vector of the observations being matched by the model, y′ (b) is the vector of the corresponding computed values, ω is a diagonal weight matrix, e is the vector of residuals.

The regression implies, at any given iteration, multiple runs of the numerical model to update the chosen input parameters. The sensitivity matrix employed is, indeed, computed using a perturbation method, either by forward or central differences approximations. Two convergence criteria are used to close the optimisation: maximum parameter change lower than a user-defined percentage of the value of the parameter at the previous iteration; objective function change lower than a user-defined amount for three consecutive iterations. Weights are assigned to the observations, by means of a diagonal weight matrix, for two purposes: to reduce or increase the influence of some observations in relation to the other ones; to produce weighted residuals that