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Forecasting landslide motion with machine learning models: the use case of Séchilienne landslide (French Alps) to identify the relevant predicting variables

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SUMMARY: The Séchilienne landslide is located in the Romanche valley, south-west of Belledonne massif and 20km south-east of Grenoble. The highly fractured nature of the landslide and the difference in hydraulic conductivity between fractured and micro-fissured rocks lead to the development of a perched aquifer located in the unstable zone. Pore water pressure variations of the perched aquifer led to a decrease in rock properties and are a key factor in landslide initiation. Thirty years of multi-parametric observations are available allowing to analyse the variation of terrain motion in relation to daily meteorological and hydrogeological conditions. These datasets are used to forecast landslide motion with supervised machine learning methods. The use of ensemble learning methods such as Random Forest and XGBoost allow to propose forecasting models while providing information about the most important predicting features. The features introduced in the model are described and discussed as well as the model calibration/validation strategy. We show that models combining meteorological and hydrogeological features obtained with a reservoir hydrological model have high predictive power.

Keywords: Landslide motion, Forecast, Machine Learning, Random Forest, Séchilienne landslide

Introduction

Recent works on landslide displacement forecasting using machine learning or deep learning models show relevant performance (Wang et al., 2022, Nava et al., 2023). However, these models 1) are mostly based on the use of past displacement information to forecast the futur displacement, 2) do not provide information on the most relevant predictive features in terms of meteorological and hydrogeological variables for the forecast, and thus the identification of possible precursory factors. Identifying these features is crucial as they could greatly improve the performance (reduction of false alarms) of early warning systems. In this context, the Séchilienne landslide is used as a use case to build a forecasting model based on Random Forest and XGBoost supervised models and to identify possible precursory factors.

I. Geological and hydrogeological context of the Séchilienne landslide

The Séchilienne landslide is located in the Romanche glacial valley, in the Belledonne massif on the southern slope of Mont Sec, 20km south-east of Grenoble (Fig. 1a). The unstable slope is composed of micaschist with unconformity Carboniferous to Lias sedimentary deposits as well as Würm glacial deposits. It extends from 450 to 1100m a.s.l. over an area of 1km² and involves a volume of 60 M m³. The measured surface velocity is in the range of 10 cm.yr⁻¹ for



most of the unstable slope to nearly 300 cm.yr^{-1} in the active part. The fracturation of the unstable slope leads to a dual-permeability behavior typical of fractured rock aquifers where conductive fractures play a major role in the drainage, while micro-fissured rocks ensure a slower flow (Vallet et al., 2015a, Nevers, 2021). The hydraulic conductivity gradient between fractured and micro-fissured rocks leads to a dual-aquifer layer system: the landslide-perched aquifer and the deep aquifer (Fig. 1c).

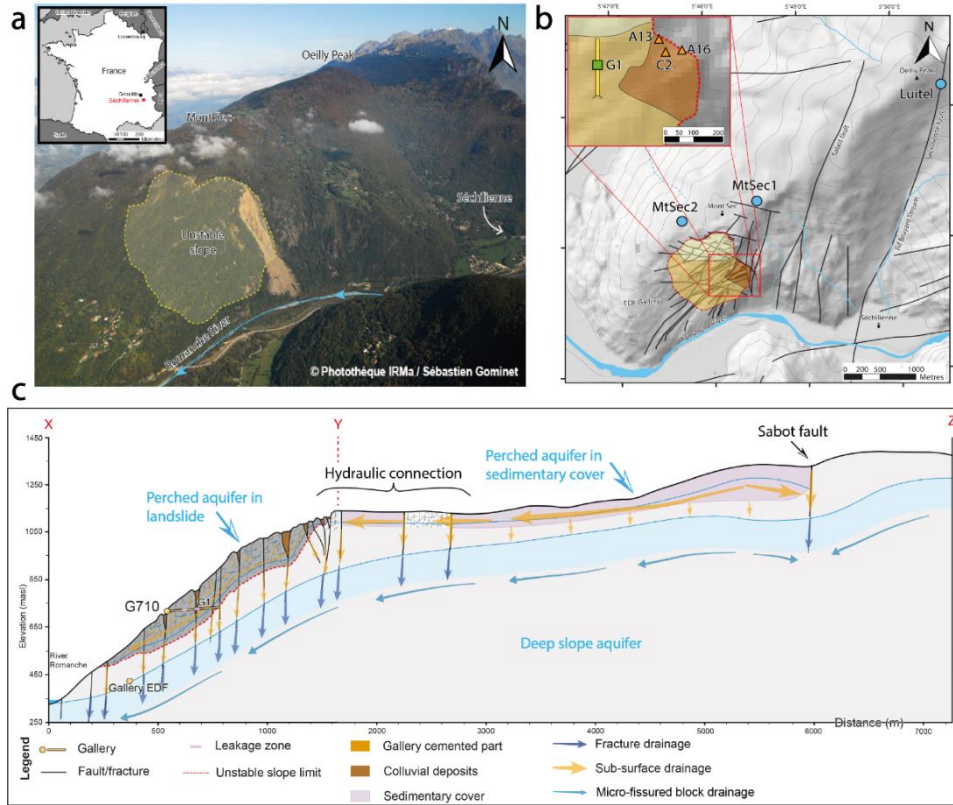


Figure 1. Aerial view of the Séchilienne landslide (a). Location of measurements stations (b). Hydrological cross-section of the instability (c) (modified from Nevers et al., 2021)

During low flow periods, the perched aquifer is structured as many saturated isolated zones which connect each other during high flow periods leading to an increase on the recharge area beyond the unstable slope limits (Vallet et al., 2015a, Nevers, 2021). Water levels fluctuation lead to pore pressure variations, resulting in a decrease in rock properties

II. Observation dataset

The Séchilienne landslide observation datasets consist in daily meteorological and displacement measurements over a period of thirty years (1992-2022). Temperature ($^{\circ}\text{C}$) and rainfall data (mm) are acquired from three weather stations (MTSEC1, MTSEC2 and LUITEL) located around the unstable slope in order to obtain a continuous series of data (Fig. 1b). Evapotranspiration (ETP) is determined using the Oudin's method in order to calculate effective rainfall values, assuming a maximum available water storage capacity value of 10 mm (Vallet et al., 2015a).



The surface displacement data (mm) are acquired at three locations with extensometers devices (A13, A16, C2) in the most active part of the landslide and characterised by measurement errors of ± 0.5 mm. Raw displacement data are filtered with a moving average (5 days) window by defining a lower and upper threshold. Displacement time-series exhibit seasonal fluctuations characterized by intermittent periods of acceleration and deceleration. A persistent and ascending trend is observed until 2008, followed by a phase of accelerated displacements and an amplification of seasonal amplitudes extending until 2013. Subsequent to this acceleration period, a reversal trend is observed together with a progressive decrease in seasonal amplitudes, leading to low amplitude seasonal variations since 2017 (Fig. 2a).

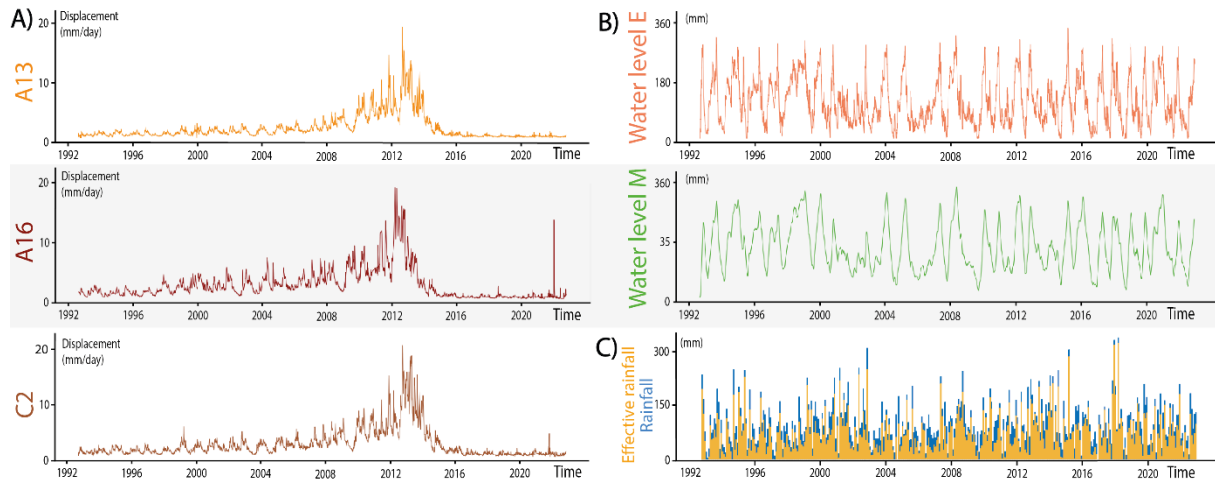


Figure 2 : Data from extensometers A13, A16 and C2 (a). Simulated water levels in reservoirs E and M (b). Monthly cumulated rainfall and effective rainfall data (c).

The dynamic of the perched aquifer is modelled using a reservoir model implemented in the Karstmod software (Mazzilli et al., 2019). This model consists of an upper reservoir (E), a matrix reservoir (M) and a hysteresis flow component, designed to represent slow and fast flow components of the fractured system. The input data for this model includes net rainfall, evapotranspiration (ETP) and groundwater flow measurements in gallery G710. The model simulates the water flow signal and water levels in the reservoirs E and M.

The water level time-series in reservoirs E and M do not show any significant trends but exhibit strong seasonality. Furthermore, they present strong responsiveness to precipitation for reservoir E, while reservoir M exhibits a long memory of precipitation with a more prolonged time response (Fig. 2b).

Net rainfall shows low seasonal variation, characterized by less rainy winters and summers compared to the rest of the year. Conversely, effective rainfall shows high seasonal contrast with dry summer and wet winters. The recharge signal is clearly influenced by air temperature variations through ETP processes. Both rainfall and effective rainfall time-series do not show any trend, and the amplitude of the seasonal variations remains constant over the whole period (Fig. 2c).

III. Methods

The surface displacement data were decomposed into three components (respectively trend, seasonality and random) using a multiplicative analysis over a 365-day period. In this study, the seasonal and random components are both assumed to be linked to the rainfall triggering



factors (Vallet et al., 2014). These two signals were aggregated into a single detrended displacement signal time-series.

We used supervised machine learning models (Random Forest / XGBoost) to simulate, in forecasting mode, landslide displacement for the three measurements points (A13, A16 and C2). We defined a list of 441 hydro-meteorological features derived from the observed net and effective rainfall and the simulated groundwater levels in the reservoirs E and M. The features consist of attributes derived from classical and advanced statistical descriptors (Tab. 1). The features are computed over moving temporal windows from 5 to 90 days in order to observe long-term forcing effects.

Table 1. Subset of predicting hydro-meteorological features (among 441 features)

Time series data	Features name	Features significance
Rainfall	R_sd_5	5-day rainfall standard deviation
	R_max_10	10-day rainfall maximum value
	R_rainyday_30	30-day number of rainy days
	R_rainyday_10mm_90	90-day number of days with rainfall exceeding 10mm
Effective Rainfall	ER_min_15	15-day effective rainfall minimum value
	ER_cumul_20	20-day cumulated effective rainfall
	ER_3rainyday_30mm_60	60-day number of 3 consecutive days with effective rainfall exceeding 30mm
Water level E and M	hE_diff_20	20-day difference in water level in reservoir E
	hM_diff_mean_30	30-day difference in the average water level of reservoir M compared to the overall average

Several strategies were employed to train and test the model performances, either on displacement time-series, either on detrended displacement time-series. For displacement data with trend, we selected three validation periods (1999, 2005 and 2012) that are representative of average displacement amplitudes. For each validation periods, we adjusted the length of the model training period

from one to several years. Regarding the detrended displacement data, we also adjusted the duration of the training period. Moreover, due to the absence of trends in the signal, we were able to train and test the models over much longer periods.

IV. Results

For each extensometers and validation periods, the displacement predictions from the Random Forest and XGBoost models exhibit relatively close results. These observations are the same for detrended displacements forecasts. Therefore, we subsequently chose to present only the results of displacement forecast for extensometer A13 for the year 2005, as well as detrended displacement forecasts for the period 2005-2010 generated using the Random Forest model.

The variations and amplitudes of the predicted displacements show only partial with the measured data. These observations can be attributed to (1) a training period that is too short to establish significant relationships between the displacements and the features, and (2) the influence of the increasing trend of displacement associated with larger amplitudes, which can prevent the model's ability to identify lasting relationships.

Conversely, applying forecast model to the detrended displacement time-series yields results that are closer to the observed signal with a correlation coefficient of 0,45. This improvement in accuracy can be attributed to the ability to use longer training periods and the absence of trend, resulting in nearly constant displacement amplitudes over time.

In both cases, the principal used features by the models exhibit a consistent ranking of importance. The most significant features are hydrogeology features, particularly the variations and maximum water levels in reservoirs E and M over windows of 5 to 30 days, with importance ranging from 10 to 30%. Features related to effective rainfall are also prominent (with importance below 10%) and are mainly associated with the number of rainy days and/or the number of consecutive rainy days over windows 15 to 90 days.

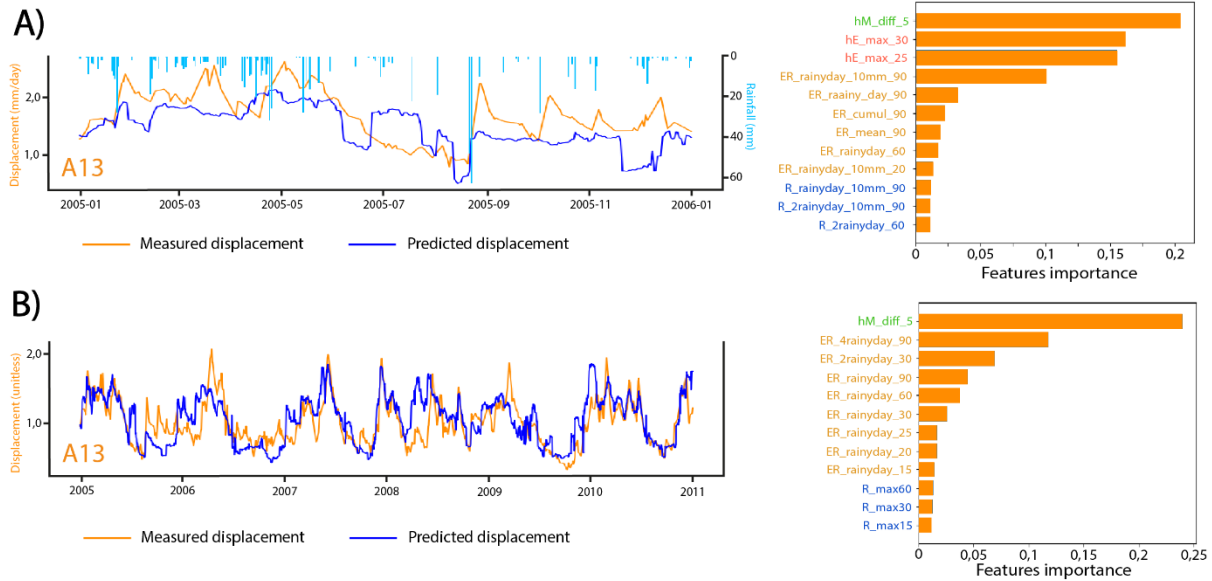


Figure 3. Forecasts and feature classifications of the Random Forest model on extensometer A13 for displacement time-series (a) and for detrended displacement time-series (b)

Conclusion

Random Forest and XGBoost algorithms are used to simulate terrain displacement at three locations for the Séchilienne landslide from a series of specifically calculated hydro-meteorological features. The results of predicted displacements is significantly closer to observed data on detrended displacements with an accuracy of 0,45 than on raw displacement signals. This can be attributed to (1) the potential to use larger training periods for the models and (2) constant displacement amplitudes over the time unaffected by the signal trend. The most predictive features are those derived from slope hydrogeological observations (eg. Variations of groundwater levels in the reservoirs) and from effective rainfall. Considering that the most promising results are associated with detrended displacements, it suggests the need to develop solutions to incorporate the prediction of displacement trends, in order to establish a comprehensive predictive model.

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