

CONTINUOUS PREDICTION OF CREEP IN A SLOPE UTILIZING INCLINOMETER DATA

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Creep of natural slopes is difficult to quantify, especially with regard to variations due to seasonal changes. A quick clay slope in Norway was instrumented with 71 inclinometers. The inclinometers were also meant to monitor the influence of construction works taking place in the area. Distinguishing deformations due to creep and deformations due to construction works can be complex especially because of seasonal variations. Inclinometers were installed from 6 to 35 months before the construction works started, and results were used to develop a method for separating the influence of construction and creep on the measured deformation. Various types of prediction models were evaluated, from different curve fitting methods to more advanced machine learning models. A random forest machine learning algorithm utilizing meteorological data and historical measurements proved to give the most reliable prediction, reducing the mean absolute error of the predicted deformation by more than 50% compared to the conventional curve fitting methods.

Keywords: Geotechnical engineering, creep, deformation, inclinometers, machine learning, prediction model.

1. Introduction

A quick clay slope in Norway was extensively instrumented before construction works started in its vicinity. The slope was deemed unstable, with calculated safety factors around 1.0. The ground conditions consisted of a few meters of dry crust clay and fill material, covering 10-30 m of quick clay characterized by low plasticity ($I_p \sim 6\%$) and a water content of about 24%. Bedrock was between 10 to 30 m below the surface. Ground investigations and instrumentation were performed before construction work started. 71 biaxial In-Place-Inclinometers (IPI) with a measurement range of $\pm 15^\circ$ were installed in the slope. The inclinometer segments were connected with universal joints and were linked together in a string. The segment lengths varied between 0.5 to 2.0 m, for a total of 1258 gauges. The inclinometer strings were installed in an inclinometer channel, consisting of a customized casing pipe with slots. The inclinometer channel itself was installed using a drilling rig. Two sets of spring-loaded wheels roll along the vertical slots in the inclinometer channel to ensure the correct X-Y direction of the strings (Figure 1). The bottom of the inclinometer was fixed into the bedrock.

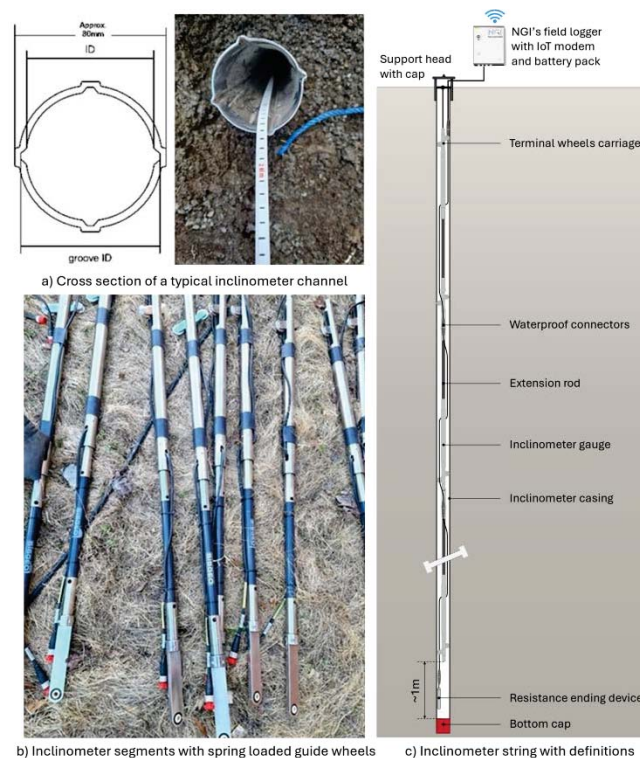


Fig. 1. a) Picture and cross section of inclinometer channel, b) Picture of inclinometer segments with spring loaded guide wheels and c) vertical cross section of inclinometer string with definitions of the different elements.

Measured deformations were in general gradually increasing in the direction parallel to the slope, confirming that the slope was creeping gradually downwards. However, the deformation magnitude and direction varied with the inclinometers and were affected by seasonal changes. There was also significant noise in the measured data. Finally, the role of the construction works on deformation was unclear and difficult to assess using only direct measurements. The objective of this project was therefore to predict deformation due to creep, utilizing machine learning algorithms. Such approaches have previously shown promising results, especially for reservoir landslides (Huang et al. 2017; Yang et al. 2019), but is not commonly used for quick clay slopes. Different prediction models, including curve fitting functions and machine learning models, were calibrated/trained on the deformations measured by the inclinometers and their performance to predict displacement were compared.

2. Prediction models

In total, twelve mathematical functions and four machine learning algorithms were fitted/trained on measured data. Inclinometer data were preprocessed before training, by calculating the resultant vector of the biaxial tilt, and removing the first 60 days of the data due to installation effect of the channel. The data used for training the models consisted of creep measurements only, with no influence from the construction works. The dataset was then divided into a training period and a test/validation period. Different splits of training and testing (from 80/20 to 20/80%) were tested.

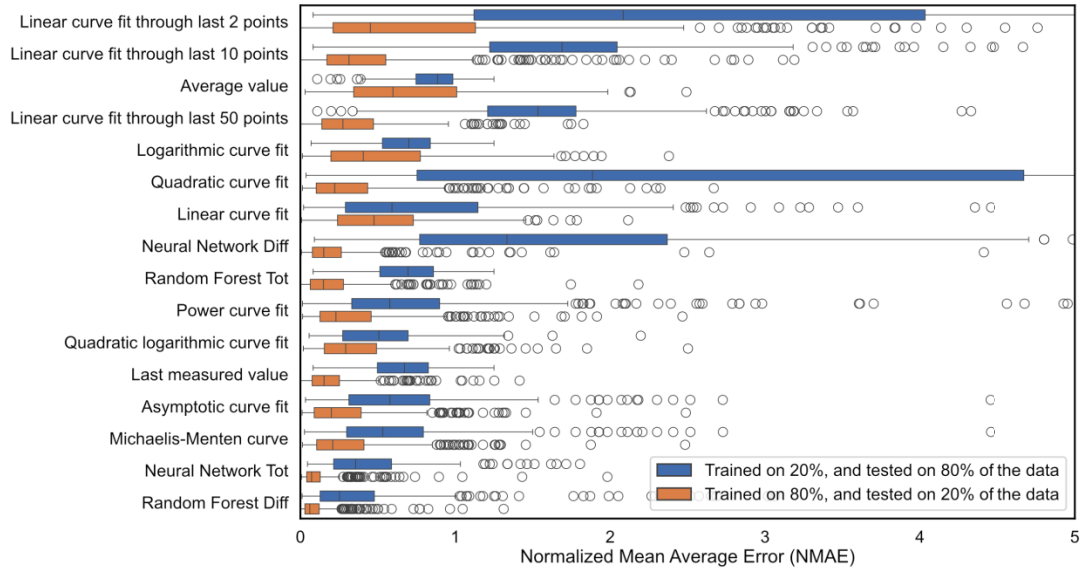
The mathematical functions tested included the linear function (ax), quadratic function (ax^2+bx), semi-logarithmic linear function ($a\log(x)$), semi-logarithmic quadratic function ($a\log^2(x)+b\log(x)$), power function (ax^b), asymptotic function ($a(1-e^{-bx})$), Michaelis-Menten function ($ax/(b+x)$). All functions were constrained to pass through the origin (zero initial deformation). The fitting process is performed in Python utilizing the SciPy library and the curve fit function (Virtanen et al. 2020). In addition, the final measurements in the training period and the average value of the training period are included as simple base case predictions.

The machine learning model uses meteorological data and previous measurements from the inclinometers, to predict the expected deformation due to creep. Python and the Skforecast library were used (Rodrigo and Ortiz 2024) to conduct supervised learning. Skforecast is based on the scikit learn library but includes proper handling of time-dependent data. Two algorithms were tested: Random Forest Regressor (Breiman 2001 and Geurts et al. 2006) and Neural Network MLP Regressor (He et al. 2015 and Kingma and Ba 2014). The variables used in the training of the machine learning algorithms included temperature, precipitation, number of days since installation of the inclinometer, freezing degree-days and snowmelt. Cumulated precipitation and snowmelt over 3, 7, 14, 30, 60 and 90 days were also included. Snowmelt was calculated using the model of NVE and seNorge (Saloranta 2012). The snow water equivalent (SWE) model for snowpack water balance was based on the HBV model (Sælthun 1996). The hyperparameters of the machine learning algorithms have been optimized utilizing Bayesian search combined with backtesting (Rodrigo and Ortiz 2024).

Recursive machine learning algorithms were used, which means it utilizes the last predicted value when predicting the next value. Both algorithms have been trained to predict the change in deformation (i.e. the difference from yesterday's predicted value) and the absolute value of the deformation. The mean average error (MAE) was used as the optimization parameter. MAE provides better resilience against the distortions introduced by outliers than mean squared error (Willmott and Matsuura 2005). MAE is also more resilient to values close to zero than mean absolute percentage error (Myttenaere 2016). To provide a more balanced measure of accuracy, MAE was normalized by the average measured deformation. Each of the models were fitted to the 1258 inclinometer gauges/sensors and a normalized mean average error was calculated for each sensor, and for each fitted model.

3. Results

The machine learning algorithms provided the most precise prediction of deformation, both with a 20/80% and an 80/20% training/test split (Figure 2). The Michaelis-Menten curve gives the lowest estimation error on average of the mathematical functions for both splits. Among the machine learning algorithms, the Random Forest Regressor, trained on predicting the difference or change in deformation (Random Forest diff), performed best reducing the mean NMAE by more than 50% compared to the curve fitting methods, for both splits. This proves that the meteorological data have an impact on the measured deformation and that the prediction method should be a function of these variables. Looking at the different shapes of the curves fitted, it is easy to understand that there is a huge difference between having a training/test split of 80/20% compared to 20/80% (Figure 3). With an 80/20% training/test split, simply using the last measured value as prediction results in a relatively low estimation error. But this prediction performs quite bad for the 20/80% split. This means that using the last value as prediction is a good prediction for a short period of time, but the quality of the prediction decreases quickly. Checking both an 80/20 and 20/80% train/test split means you can compare how the model performs for both short and long time periods. The Random Forest machine learning algorithm gives the lowest estimation error on average for both short and long time periods.



Boxplot explanation:

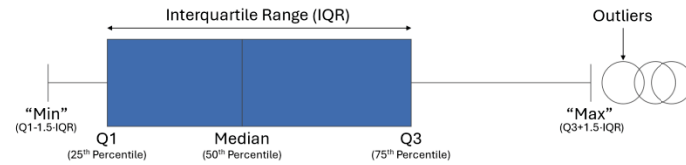


Fig. 2.Box plot of Normalized Mean Average Error (NMAE) for each inclinometer gauge/sensor and the different prediction models.Blue boxes show the NMAE when the models are trained on 20% and tested/validated on 80% of the data. Orange boxes show the NMAE when the models are trained on 80% and tested on 20% of the data.

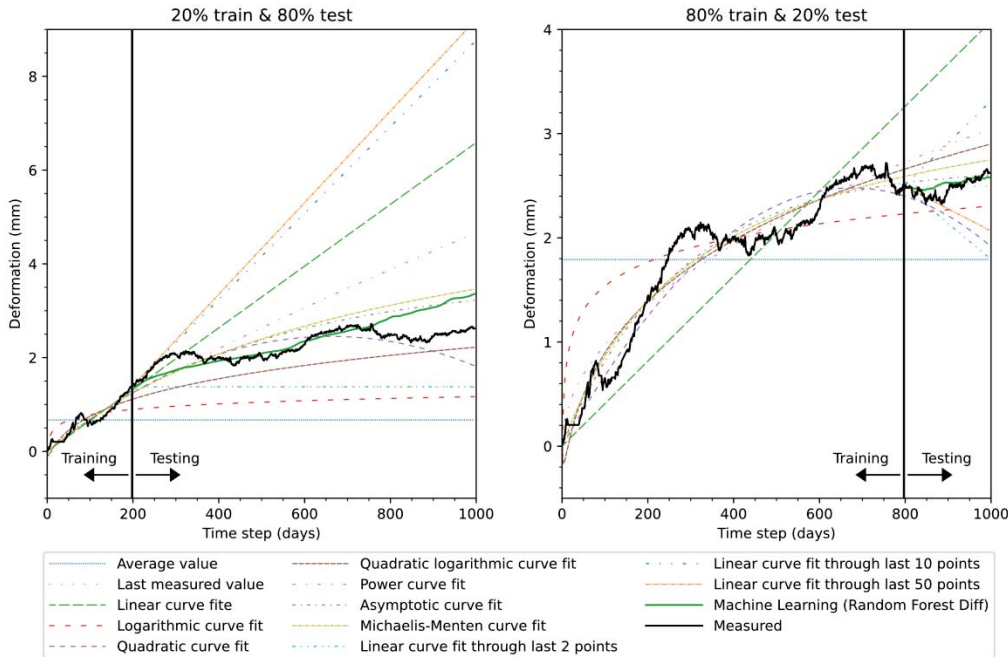


Fig. 3.Deformation measured by inclinometer34 sensor nr. 2, shown with the different prediction models and different training/test splits.The figures illustrate the shapes of the prediction models and indicate visually issues/upside of the models and different train/test splits. Keep in mind that this is only data from one of the 1258 inclinometer gauges/sensors which the models are trained and tested on.

The influence of the different variables was determined using the Shapley values (Lundberg et al. 2020) of each variable for each sensor. The ten most important variables for each sensor were determined, and the weighted number of appearances was calculated (Figure 3). Given that the machine learning model is recursive, it is expected that the last prediction is a significant variable. Additionally, the number of days since the inclinometer's installation is

crucial, likely because deformation accumulates from the installation day, linking any general increasing trend to the elapsed time since installation. The last three most important variables are the precipitation, snowmelt and temperature.

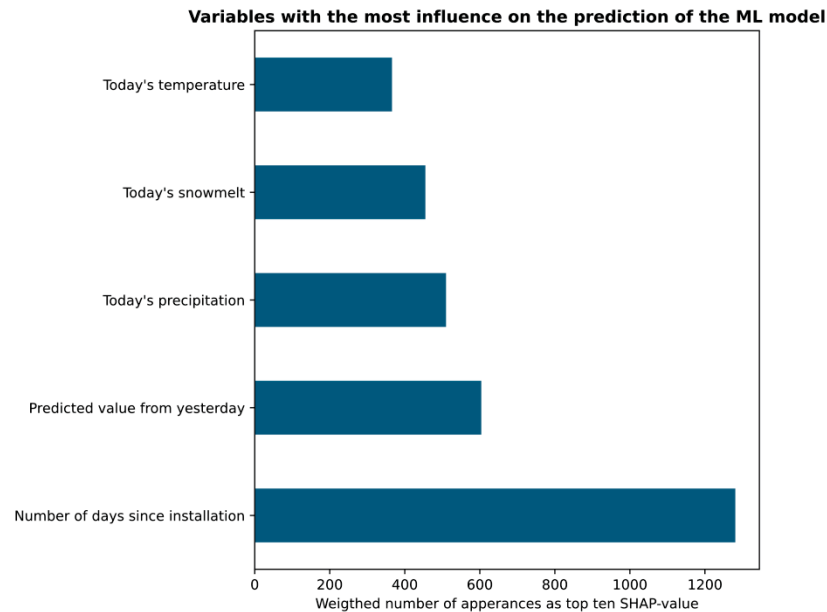


Fig. 4. Variables with the most influence on the prediction of the Machine Learning model (Random Forest Diff).

4. Conclusions

The machine learning models, particularly the Random Forest Regressor trained on the differences between consecutive observations rather than the total value, have shown greater performance, reducing the average estimation error with more than 50% compared to the curve fitting methods. The five most important variables that influence the performance of the machine learning algorithm are the number of days since the inclinometer was installed, the predicted value from yesterday, and today's precipitation, snowmelt, and temperature. Weather variables influenced the measured deformation of the slope, and machine learning contribute to improve the prediction of the natural deformation.

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