PREDICTION OF GROUNDWATER LEVEL FLUCTUATIONS ON GROHOVO LANDSLIDE USING RULE BASED REGRESSION

Goran Volf[1*] – Elvis Žic[1] – Nevenka Ožanić[1]

[1]Department of Hydraulic Engineering, Faculty of Civil Engineering, University of Rijeka, Radmile Matejčić 3, 51000 Rijeka, Croatia

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Abstract:

In order to contribute to understanding the effect of atmospheric conditions on the groundwater level fluctuations on Grohovo landslide, a machine learning tool for induction of models in form of the set of rules was applied on a dataset comprising daily atmospheric and groundwater level data measured in 2012. The atmospheric data comprises of an average daily air temperature, humidity, wind speed, pressure, total evapotranspiration, and precipitations. For the experiment independent variables i.e. atmospheric data and present groundwater level were used to model target variable i.e. predicted groundwater level for 24 and 48 hours in advance.

The presented models give predictions 24 (first model) and 48 (second model) hours in advance for groundwater level fluctuations on Grohovo landslide. The first model is consisted from seven, and the second model from five rules. Both models have very high correlation coefficients of 0.99 and 0.97, respectively. From the given models, it can be concluded that the most influence on the groundwater level fluctuations have sum of daily precipitations and average daily air temperature.

The obtained models are intended for use in the models for debris flow propagation on the Rječina River as a part of an Early Warning System.

1 Introduction

Groundwater level fluctuations are usually subjected to various variations such as differences between the supply and release of groundwater, gaining or loosing stream flow variations, tidal effects, urbanization, earthquakes, land subsidence, meteorological phenomenon, and nowadays global climate changes [1, 2]. The meteorological phenomena that are important for groundwater level fluctuations mainly include atmospheric pressure, wind blowing, frost/ice, evapotranspiration and precipitations (i.e. rainfalls) [2]. Rainfall causes minor or major fluctuations of groundwater. Where surface or subsurface losses of rainfall or travel time for vertical percolation are sizeable, fluctuations are minor, while in adequately permeable aquifers, the response of groundwater

* Corresponding author. Tel.: ++385-51-563-750
E-mail address: goran.volf@uniri.hr.

level to rainfall may be rapid, so rainfall can be considered as a good indicator for groundwater level fluctuations in such type of aquifers [1, 2].

The main tools which were used for description of hydrological parameters and understanding the physical processes in a given observed system are physical and conceptual based models. Many investigations and experiments have been made in predicting groundwater level fluctuations, where some of them are physically based numerical models which are used to explain the groundwater flow in aquifers and some are empirical applying models which are used to produce time series of water table depths [3, 4]. The physically based models mainly need a large quantity of accurate measured data since the physical properties of groundwater can never be ascertained with absolute accuracy. Unavoidable discrepancies between the model and the real world system reduce simulation accuracy hindering efforts to appropriately manage the groundwater resources [5]. Also, the empirical time series models have their own limitations, because they are not adequate when the dynamical behaviour of the hydrological system changes with time [6].

Nowadays, the use of Artificial Intelligence (AI) based approaches to build models like: Artificial Neural Networks (ANN), Adaptive Neuro-Fuzzy Inference System (ANFIS), Genetic Programming (GP), Support Vector Machine (SVM) techniques, etc. in water resources issues has become viable solutions [2]. Recently conducted research of groundwater level fluctuations modeling with AI approaches has been presented in: for ANN [2, 5, 7, 8, 10, 11, 12, 13, 14], GP [2, 15], ANFIS [2, 7, 8, 10, 11], SVM [2, 9].

In this research another kind of AI, Machine Learning (ML) was used, i.e. an algorithm for induction of rule based regression models from measured data on the Grohovo landslide. The rule based regression models for numeric prediction use regression equation in the terminal nodes which allow a more accurate prediction of the target attribute. The models are interpreted as a set of IF THEN rules where each rule is associated with a multivariate linear model. Unlike other AI methods which provide very good predictions, but sometimes are limited in terms of interpretability (black box models), the rule based regression models tend to be more descriptive and interpretable (white box models) [16]. The main purpose of this research is to apply the rule based regression model on a data set measured on Grohovo landslide to build reliable prediction models for groundwater level fluctuations. They will be used as a part of Early Warning System (EWS) in models for landslide movements and debris flow propagation on the Rječina River, downstream of the Grohovo landslide (see Fig. 1) [17].

The Grohovo landslide is a reactivated complex landslide near the City of Rijeka, Croatia. Several historical episodes of landslide movements and their consequences demonstrate the need for a landslide behavior forecasting and a EWS establishment in order to reduce the landslide risk and to protect human lives. An early warning can be defined as a timely advice before a potentially hazardous phenomenon occurs. An efficient EWS comprises of identification and estimation of hazardous processes, communication of warnings and adapted reaction of local population. Moreover, early warning systems have to be embedded into local communities to ensure effectiveness of the entire system [18].

In the last decades with the growth of computational capabilities, predictive hydrological models for establishing EWS are being developed. As a part of the EWS in areas where there is no possibility of minimizing human activities or mitigating risk prediction of flash floods, mud flows, debris flows and landslides movements becomes a crucial tool for preventing the consequences caused by the mentioned hazards.

The paper is organized as following: In Section 2, study area and measured data are described. Section 3 gives the modeling methods used in this paper, while Section 4 describes the modeling experiment. Section 5 provides the results, i.e. the constructed models with discussion, and finally Section 6 contains the conclusions of this paper.

2 Materials and methods

2.1 Study area description

The Grohovo landslide (Fig. 1) is located on the north-eastern slope of the Rječina Valley near the City of Rijeka, Croatia. It is a complex and retrogressive landslide. Movements of mixed rocky and soil material in initial landslide body have characteristics of debris avalanches. The area in the vicinity of the landslide is geomechanically unstable. The rearrangements of the river beds due to slides of rock mass represent a significant risk of danger. The total size of the landslide is estimated at approximately 18 ha (see Fig. 1). Siliciclastic flysch or basic rocks are characterized by substantial lithological heterogeneity due to frequent vertical and lateral alternation of various lithological members, such as marls, siltstones, shales and fine-grained sandstones [19]. Flysch rock mass exhibits weak permeability, which causes susceptibility to decomposition and erosion. The entire area is characterized by a network of small streams that erode slopes and significantly enhance the production of sediment in the Rječina River watershed area.

Through the Croatian-Japanese bilateral scientific research project “Risk Identification and Land-Use Planning for Disaster Mitigation of Landslides and Floods in Croatia” the area of Grohovo landslide is monitored with the respect to the behaviors of landslide bodies, to the causes of and potential for sliding, hazard and risk assessments of potential surfaces, and to the establishment of a monitoring and EWS for new skating areas [20]. In the hydrological studies made by [21], continuously were collected meteorological, hydrological and geological data for the development of the 2D and 3D numerical models to simulate the propagation of flash floods and debris flow during landslides or rockslides, in which large quantities of debris accumulate in the river bed [17].

Also, it is very important to notice that groundwater level fluctuations influences on development and emergence of debris flows and landslides of rock mass [17].

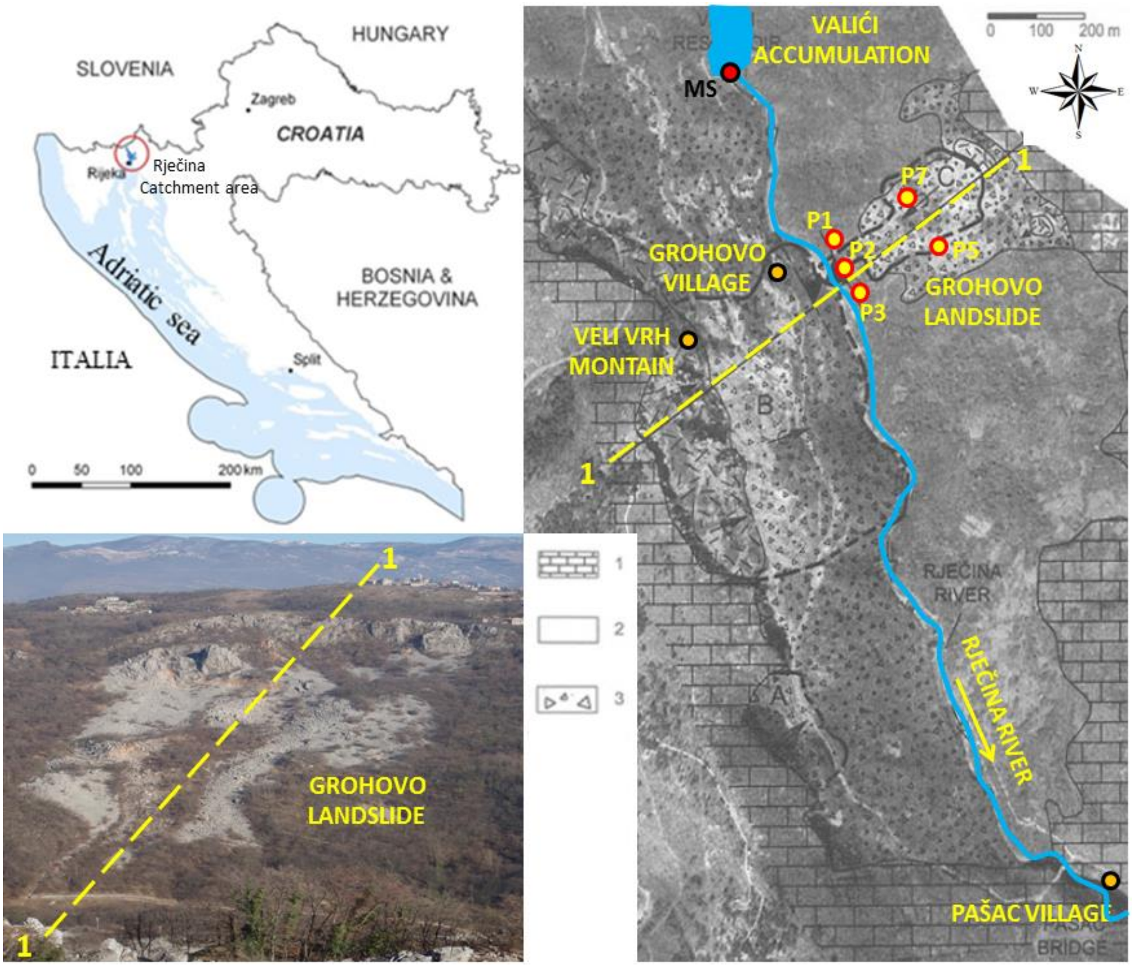

Figure 1. Grohovo landslide location with data sampling points: 1 - carbonate bedrock; 2 - flysch deposits covered by primarily fine-grained slope deposits; 3 - flysch deposits covered by rockfall talus; Pi - piezometers; MS - meteorological station [17].

2.2 Data sampling and analysis

As a part of the research activities in the Croatian Japanese Bilateral Project "Risk Identification and Land-Use Planning for Disaster Mitigation of Landslides and Floods in Croatia", a comprehensive integrated real-time monitoring system was installed at the Grohovo landslide.

To monitor the Grohovo landslide, several measuring instruments were installed to measure hydrologic and hydraulic parameters. Meteorological Station (MS) was installed in the middle of the crown of the Valići dam (Fig. 1) near the Grohovo landslide (approximately 200 m from the foot of the Grohovo landslide). The meteorological station measured 35 different meteorological parameters. The time steps (increments) used for the collection of the meteorological data consist of 10-minute intervals.

Also, five piezometers were installed in the area of the Grohovo landslide (P1, P2, P3, P5 and P7; see Fig. 1). Three piezometers were installed on the lower part of the landslide (at the landslide foot), and two piezometers were installed in the middle of the slide zone. The three lower piezometers (P1, P2 and P3) measure the groundwater levels, whereas groundwater levels (recharge to the Rječina River) are measured at the base of the upper piezometers (P5 and P7). Continuous monitoring of the groundwater levels began in December 2011 for piezometer P1 and in February 2012 for piezometer P3. In the groundwater data analysis, only piezometer P1 was used because other piezometers have gaps in measured data.

For better analysis, a 10-minute measured data from meteorological station and piezometers were converted into the daily data. Table 1 shows data used for modeling, while Fig. 2 shows time series of measured groundwater levels and precipitations during the study period. From Fig. 2, it can be seen that the highest groundwater level is observed in early autumn (15.10.2012.).

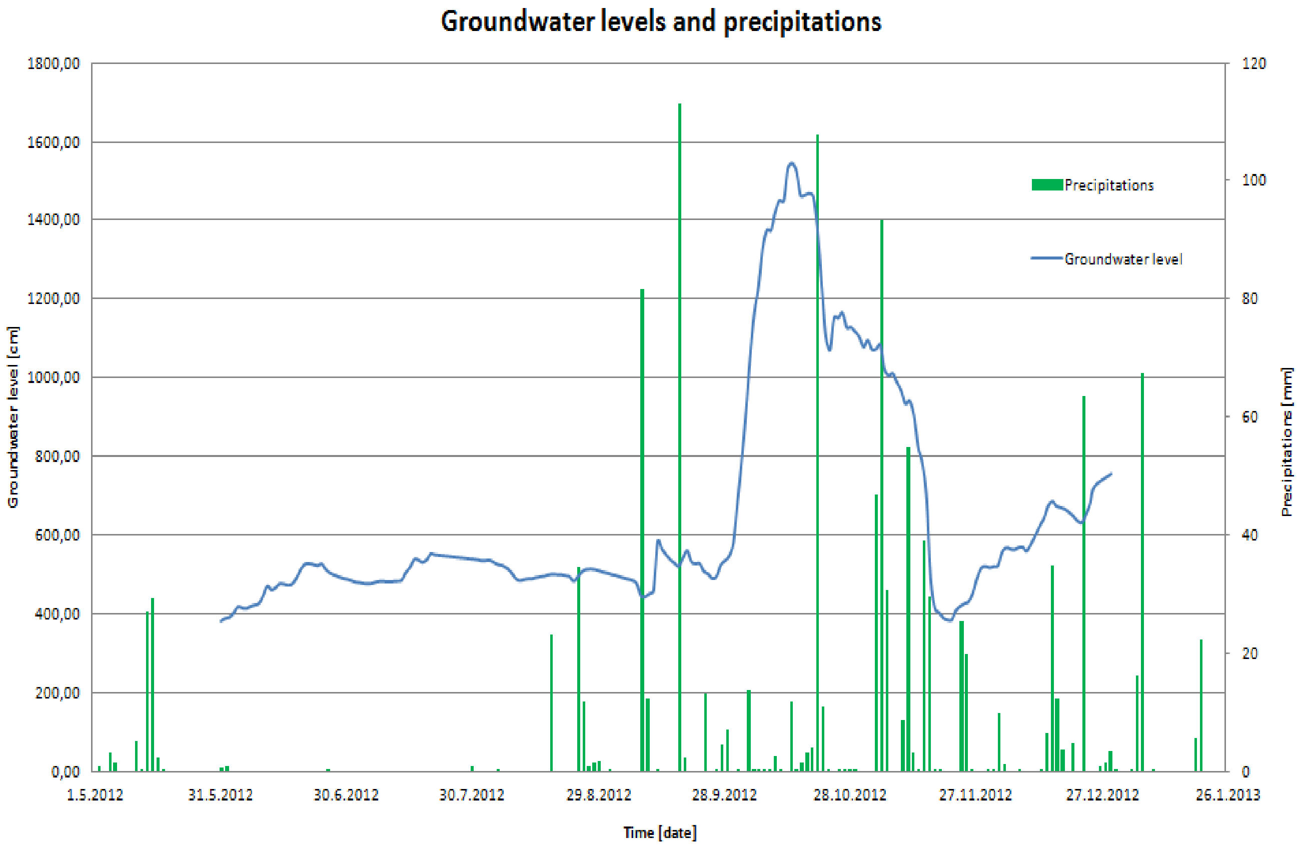

Figure 2. Time series plot of the measured groundwater levels and precipitations (rainfalls).

Table 1. Data set used for modeling purpose

Parameter	Description	Unit
Temp	Average daily air temperature	°C
Hum	Humidity	%
WS	Wind speed	m/s
AP	Atmospheric pressure	hPa
Tot. Evap	Total evapotranspiration	mm
Rain	Precipitations	mm
Rain 5	5 day sum of precipitations	mm
Rain 10	10 day sum of precipitations	mm
Rain 15	15 day sum of precipitations	mm
Rain 20	20 day sum of precipitations	mm
Rain 25	25 day sum of precipitations	mm
Rain 30	30 day sum of precipitations	mm
Rain 35	35 day sum of precipitations	mm
Rain 40	40 day sum of precipitations	mm
Rain 45	45 day sum of precipitations	mm
P1	Groundwater level on piezometer P1	cm
P1_pred 24	Groundwater level shifted for 24 hours (First model)	cm
P1_pred 48	Groundwater level shifted for 48 hours (Second model)	cm

3 Modeling method: rule based regression model

ML is a branch of AI concerned with the design and development of algorithms that allow computers to evolve behaviors based on empirical data, such as from sensor data or databases. A learner can take advantage of examples (data) to capture characteristics of interest of their unknown underlying probability distribution. Data can be seen as examples that illustrate relations between observed variables. A major focus of machine learning research is to automatically learn to recognize complex patterns and make intelligent decisions based on data; the difficulty lies in the fact that the set of all possible behaviors given all possible input is too large to be covered by the set of observed examples (training data). Hence, the learner must generalize from the given examples, in order to produce a useful output in new cases [22]. Kompare [23] in his PhD thesis gives some advantages of ML tools:

- ML generalizes the data and presents their knowledge in a more compact, easier to understand,
- build new knowledge about the observed domain,
- identify the system structure and parameter values, and with it automatically build the model,
- search space for possible model behavior with the use of qualitative modeling.

The tools of ML build models independently, or help experts from certain areas in a way to mediate him information in a more compact form. With these new "views" expert can easily build a better model [23].

3.1 Cubist

Cubist is a powerful software/tool for generating rule based models that balance the need for accurate prediction against the requirements of intelligibility. The Cubist models generally give better results than those produced by simple techniques such as multivariate linear regression, while also being easier to understand (more interpretable) than ANN and similar techniques of AI [24].

The rule based regression models for numeric prediction use regression equation in the terminal nodes which allow a more accurate prediction of the target attribute. The models are interpreted as a set of IF THEN rules where each rule is associated with a multivariate linear model [24]. A rule indicates that, whenever a case satisfies all the conditions, the linear model is appropriate for predicting the value of the target attribute. The algorithms for rule induction mostly represent different variations of the M5 algorithm. The algorithm implemented in a software package Cubist (See5/C5.0) was applied for modeling, in which the basic M5 algorithm was enhanced by combining the model-based and instance-based learning [25].

The accuracy of predictions can be done by simulating the model on a testing set of data and comparing the predicted values of the target with

the actual values. Another option is to employ cross-validation. The given (training) data set is partitioned on a chosen number of folds (n). In turn, each fold is used for testing, while the remainder (n-1 folds) is used for training. The final error is the averaged error of all the models throughout the procedure.
The size of the error between the actual and the predicted values can be calculated by:

1) Average error (AE),

$$AE = \sum_{i=1}^{N} \left| X \; - Y_i \right| \cdot \tag{1}$$

2) Relative error (RE),

$$RE = \frac{AE}{X_i} \; , \tag{2}$$

and correlation coefficient (R),

$$R = \frac{\sum_{i=1}^{N} (X_i - \overline{X}) \cdot \left(Y_i - \overline{Y}\right)}{\sqrt{\sum_{i=1}^{N} (X_i - \overline{X})^2 \cdot \sum_{i=1}^{N} (Y_i - \overline{Y})^2}} \; , \tag{3}$$

where, X is the observed/actual values, Y is the predicted/computed values, $\overline{X}$ is the mean of actual data, $\overline{Y}$ is the mean of computed data and N is the total number of data.
The average error magnitude is straightforward enough. The relative error magnitude is the ratio of the average error magnitude to the error magnitude that would result from always predicting the mean value; for useful models, this is less than 1. The correlation coefficient measures the agreement between the cases' actual values of the target attribute and those values predicted by the model.

4 Modeling experiment

For the experiment the ML algorithm See5/C5.0 for induction of rules, integrated in the Cubist modeling software was employed. The experiment was designed to elaborate a prediction models for groundwater levels 24 and 48 hours in advance. 24 and 48 hours predictions have been selected because these predictions will be used in numerical model to simulate the propagation of flash floods and debris flow during landslides or rockslides which is incorporated into EWS.

The groundwater level shifted for 24 hours was set as dependant variable in the first model and for 48 hours in the second model, while the average daily air temperature, humidity, wind speed, pressure, total evapotranspiration, precipitations and sum of 5, 10, 15, 20, 25, 30, 35, 40, 45 day precipitations and groundwater level in piezometer P1 were given as independent variables (see Table 1).
Model performance was done using 10-fods cross validation, while maximum number of set to 10 in the Cubist modeling software. The results of modeling experiments done by Cubist are given in Section 5.

5 Results and discussion

The goal of the presented models is to give a 24 and 48 hours prediction of groundwater level in the piezometer P1 at Grohovo landslide (see Fig. 1). The results of the models will be used as part of EWS in the model for landslide movements and debris flow propagation on the Rječina River, downstream of the Grohovo landslide [17].

5.1 First model-24 hours prediction

From the collected data (see Table 1), a model for prediction of groundwater level 24 hours in advance presented in Table 2 was constructed. The model contains seven rules where each rule has equation for calculation of predicted groundwater level. The accuracy of the model is given by the correlation coefficient (R) between the modeled and measured values of the groundwater levels, average and relative error. The correlation coefficient for the presented model (Fig. 2) using 10 fold cross-validation method is 0.99 with average and relative error of 18.196 and 0.08, respectively. How good the model is can also be seen from Fig. 3 where time series of measured and modeled data are presented. With visual inspection, it can be seen that the peak values are very well hit.

From Table 2, it can be seen that for the prediction of groundwater levels, the model is mostly used for rule induction groundwater levels on piezometer P1, sum of 5 and 10 day precipitations. In equations which describe target variable (predicted groundwater levels) are mostly used present groundwater level on piezometer P1, sum of 10, 35 and 45 day precipitations.

Table 2. Rule based model for predicting groundwater level 24 hours in advance

Rule No.	Rule	Equation
Rule 1	P1 <= 675.62	P1pred24 = -45.607 + 1.011 P1 + 0.06 Rain45 - 0.06 Rain35 - 0.07 Rain25+ 0.6 Hum
Rule 2	Rain10 > 39.6 Rain5 > 21.6 P1 > 675.62	P1pred24 = -20.494 + 1.00 P1 - 0.19 Rain35 + 0.07 Rain45 + 0.5 Hum
Rule 3	ET > 0.47 Rain10 <= 39.6 Rain > 0 P1 > 675.62	P1pred24 = 308.338 + 0.856 P1 - 34 ET - 3.2 Rain
Rule 4	WS > 7.46 Rain10 > 39.6 Rain5 <= 21.6	P1pred24 = 283.389 + 0.754 P1 - 0.04 Rain35 + 0.02 Rain45
Rule 5	Rain10 <= 39.6 Rain <= 0 P1 > 675.62	P1pred24 = 32.291 + 0.944 P1 + 2.45 Rain10
Rule 6	WS <= 7.46 Rain10 > 39.6 Rain5 <= 21.6 P1 > 675.62	P1pred24 = 118.286 + 0.948 P1 - 0.47 Rain40
Rule 7	ET <= 0.47 Rain10 <= 39.6 P1 > 675.62	P1pred24 = 121.249 + 0.893 P1 + 2.13 Rain10 - 3.2 Rain

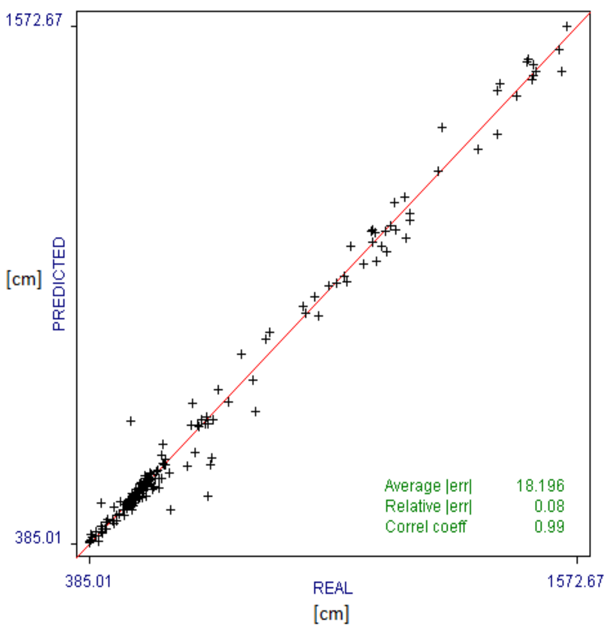

Figure 2. Measured and predicted (modeled) values of groundwater level in cm on piezometer P1 for the first model-24 hours prediction.

5.2 Second model-48 hours predictions

From the collected data (Table 1), a model for prediction of groundwater level 48 hours in advance presented in Table 3 was constructed. The model contains five rules where each rule has equation for calculation of predicted groundwater level. The accuracy of the model is given by the correlation coefficient (R) between the modeled and measured values of the groundwater levels average and relative error. The correlation coefficient for the selected model (Fig. 4) using 10 fold cross-validation method is 0.97 with an average and relative error of 35.676 and 0.15, respectively. How good the model is can also be seen from Fig. 5 where time series of measured and modeled data are presented. With visual inspection, it can be seen that the peak values are very well hit, as in the first model.

Table 3 shows that for prediction of groundwater level, the model mostly used for rule induction groundwater level on piezometer P1, sum of 5 and

10 day precipitations, like in the first model. In equations which describes target variable (predicted groundwater level) almost all modeling parameters are used.

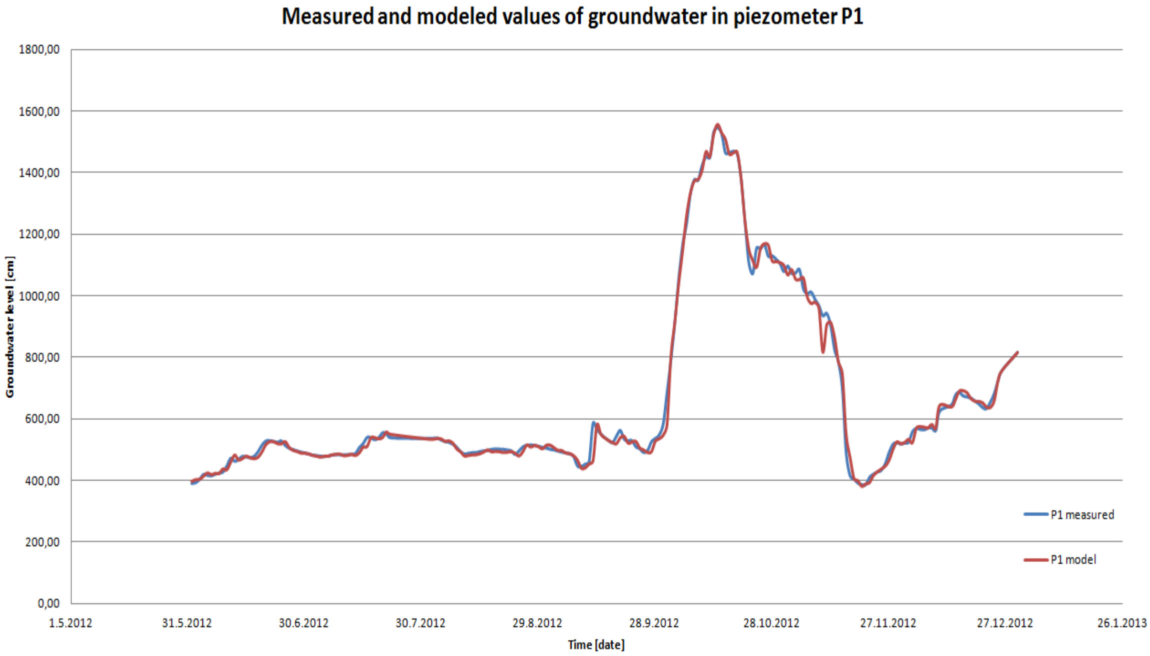

Figure 3. Measured and modeled groundwater level data on piezometer P1-time series for the first model-24 hours prediction.

Table 3. Rule based model for predicting groundwater level 48 hours in advance

Rule No.	Rule	Equation
Rule 1	P1 <= 569.53	P1pred48 = -17.644 + 0.949 P1 - 0.37 Rain25 + 0.2 Rain20 + 0.11 Rain40 - 0.33 Rain5 + 0.7 Hum + 0.15 Rain10 - 0.05 Rain35 + 0.02 Rain45
Rule 2	Rain5 > 45.4	P1pred48 = -4.697 + 0.977 P1 - 0.13 Rain35 + 0.05 Rain45 + 0.06 Rain30 - 0.05 Rain15 + 0.3 Hum - 0.08 Rain5 – 1.00 ET
Rule 3	Rain10 <= 39.6 P1 > 569.53	P1pred48 = 311.69 + 4.94 Rain10 + 0.775 P1 - 0.75 Rain15 - 0.05 Rain40 + 0.9 Temp
Rule 4	ET > 0.29 Rain10 > 39.6 Rain5 <= 45.4 P1 > 569.53	P1pred48 = 108.021 + 4.12 Rain10 + 0.459 P1 + 61 ET - 0.51 Rain40
Rule 5	ET <= 0.29 Rain5 <= 45.4 P1 > 569.53	P1pred48 = 298.826 + 0.725 P1 - 0.41 Rain40 + 7.1 Temp - 0.07 Rain35 + 0.03 Rain45 + 0.03 Rain30

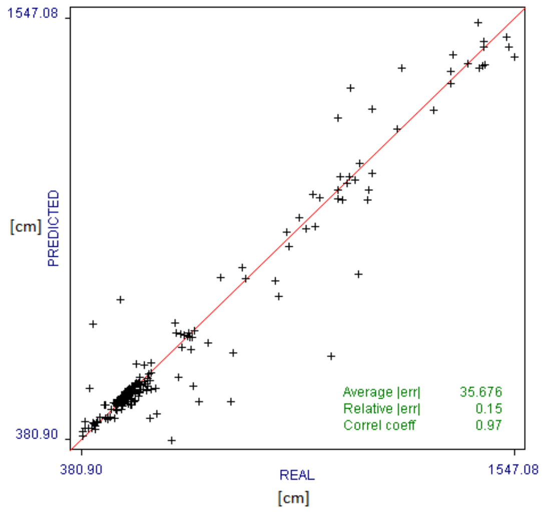

Figure 4. Measured and predicted (modeled) values of groundwater level in cm on piezometer P1 for the second model-48 hours prediction.

By comparing models, it can be seen that the first model (24 hours prediction) has seven rules and correlation coefficient of 0.99. The second model (48 hours prediction) has 5 rules and correlation coefficient of 0.97 which is insignificantly lower than correlation coefficient for the first model. In both models peak values are very well hit (see Figs. 3 and 5).

Overall, both models accurately predict the time when the groundwater level starts increasing. Additionally, the model's response is more important for the development of the EWS than precise groundwater level prediction when considering the short time of the response of water level to rainfall in the small watersheds, like Rječina River watershed.

Also, the results of the experiments show that it is useful to use different approaches during modeling, as in this case ML. As for any modeling method where measured data is used, it is essential that the database consists of sufficiently different situations from which the ML algorithm can learn to predict the dependent variable. Also, for better model results, it would be useful to have more measured parameters that affect the dependent variable. However, the resulting models behave in line with expectations and yields satisfactory results.
Regarding very high predictions of both models, they can be used as a part of EWS in model for landslide movements and debris flow propagation on the Rječina River.

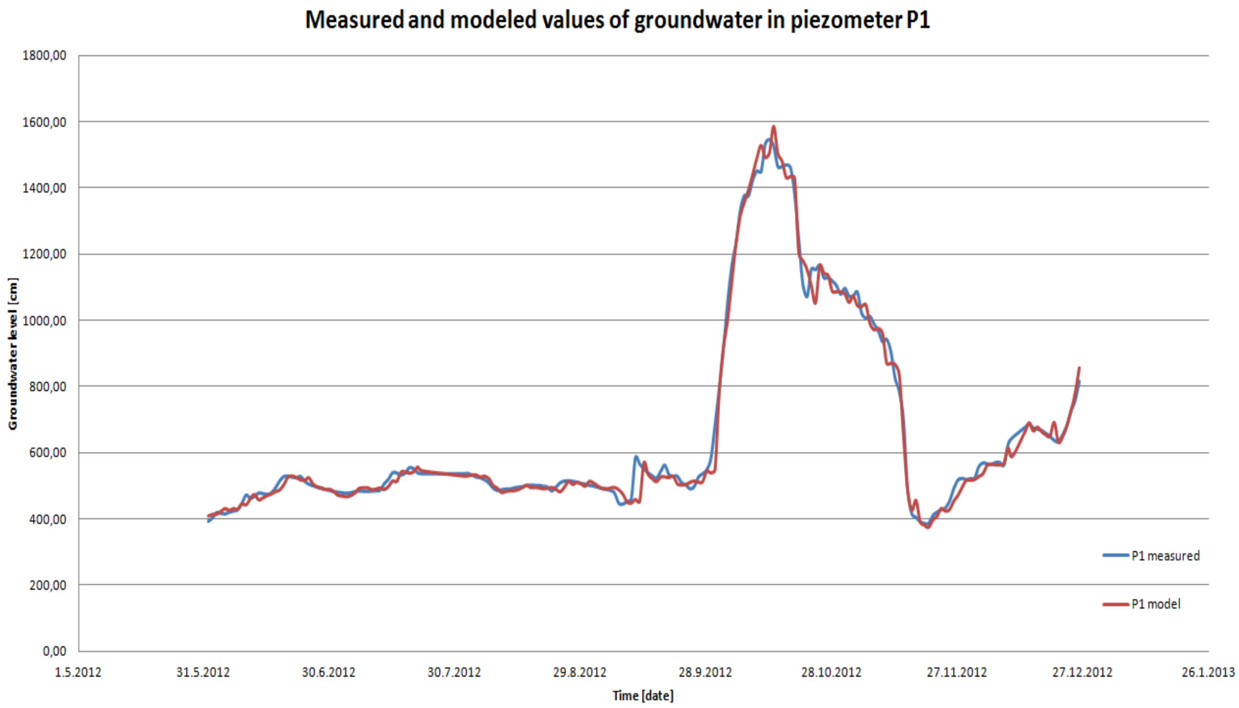

Figure 5. Measured and modeled groundwater level data on piezometer P1-time series for the second model-48 hours prediction.

6 Conclusion

In this research rule based regression using the Cubist modeling software was applied on measured data at the Grohovo landslide to induce predictive models for 24 and 48 hours groundwater level. The models have very good predictive power and have proven that rule based regression models can be an extremely useful method for predicting groundwater levels. With this method different view on data was obtained than from other analysis (AI techniques) because these models are presented in a set of descriptive IF-THEN rules which give a useful insight in modeling parameters that affect the groundwater levels.

Overall, the models accurately predict the time when the water level starts increasing. Additionally, the model's response is more important for the development of the EWS than precise water level prediction when considering the short time of the response of water level to rainfall in the small watersheds like Rječina River watershed.

Therefore, some of the advantages of using ML tools in modeling can be highlighted, namely building descriptive models, or a white box models, which makes it easier to interpret the models themselves. Therefore, the models are more appropriate, enabling them to see their functioning, i.e. the functioning of the system that is modeled.

Overall, it is especially important to emphasize the use of ML tools for easier and more efficient modeling of hydrological process, as shown in this paper.

The ongoing research is focused on the implementation of the model results in models for landslide movements and debris flow propagation as a part of EWS.

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References

[1] Todd, D. K., Mays, L. W.: *Groundwater Hydrology*, Third revision by John Wiley and Sons Inc., 636p, 2005.

[2] Shiri, J., Kisi, O., Yoon, H., Lee, K-K., Nazemi, A. H.: *Predicting groundwater level fluctuations with meteorological effects implications-A comparative study among soft computing techniques*, Computers and Geosciences, 2013, 56, 32-44.

[3] Box, G.E.P., Jenkins, G.M.: *Time series analysis: Forecasting and control*, Holden Day, Boca Raton, Florida, 1976.

[4] Hipel, K.W., Mc Leod, A.I.: *Time series modelling of water resources and environmental systems*, Development of Water Science, vol. 45, Elsevier Science, New York, 1994.

[5] Coppola, E., Rana, A., Poulton, M., Szidarovsky, F., Uhl, V.: *A neural network model for predicting aquifer water level elevations*, Ground Water, 2005, 43 (2), 231-241.

[6] Bierkens, M. F. P.: *Modeling water table fluctuations by means of a stochastic differential equations*, Water Resources Research, 1998, 34 (10), 2485-2499.

[7] Barzegar, R., Adamowski, J., Moghaddam, A.A.: *Application of wavelet-artificial intelligence hybrid models for water quality prediction: a case study in Aji-Chay River, Iran*, Stochastic Environmental Research and Risk Assessment, 2016, 30, 1797-1819.

[8] Barzegar, R., Moghaddam, A. A., Baghban, H.: *A supervised committee machine artificial intelligent for improving DRASTIC method to assess groundwater contamination risk: a case study from Tabriz plain aquifer, Iran*, Stochastic Environmental Research and Risk Assessment, 2016, 30, 883-899.

[9] Raghavendra, S., Deka, P.C.: *Forecasting monthly groundwater level fluctuations in coastal aquifers using hybrid Wavelet packed-Support vector regression*, Civil and Environmental Engineering, 2015, 2:999414.

[10] Djurovic, N., Domazet, M., Stricevic, R., Pocuca, V., Spalevic, V., Pivic, R., Gregoric, E., Domazet, U.: *Comparation of groundwater level models based on artificial neural networks and ANFIS, 2015*, The Scientific

World Journal,742138, http://dx.doi.org/10.1155/2015/742138.

[11] Jalalkamali, A., Sedghi, H., Manshouri, M.: *Monthly groundwater level prediction using ANN and neuro-fuzzy models: a case study on Kerman plain, Iran*, Journal of Hydroinformatics, 2011, 13 (4) 867-876.

[12] Daliakopoulos, I. N., Coulibaly, P., Tsanis, I. K.: *Groundwater level forecasting using artificial neural networks*, Journal of Hydrology, 2012, 309, 229-240.

[13] Kumar, S., Indian, A., Khan, Z.: *Neural network model for prediction of groundwater level in Metropolitan considering rainfall-runoff as a parameter*, International Journal of Soft computing and Engineering, 2013, 3 (3), 195-198.

[14] Sušanj, I., Ožanić, N., Marović, I.: *Methodology for developing hydrological models based on an artificial neural network to establish an early warning system in small catchments*, Advances in Meteorology, 2015, Article ID 430217.

[15] Shiri, J., Kisi, O.: *Comparation of genetic programming with neuro-fuzzy systems for predicting short-term water table depth fluctuations*, Computers and Geosciences, 2011, 37 (10), 1692-1701.

[16] Volf, G., Atanasova, N., Kompare, B., Precali, R., Ožanić, N.: *Descriptive and prediction models of phytoplankton in the northern Adriatic*, Ecological Modelling, 2011, 222, 2502-2511.

[17] Žic, E., Arbanas, Ž., Bićanić, N., Ožanić, N.: *A model of mudflow propagation downstream from the Grohovo landslide near the city of Rijeka (Croatia)*, Natural Hazards and Earth System Sciences (NHESS), 2015, 15, 293-313.

[18] Thiebes, B.: *Landslide Analysis and Early Warning Systems*, Ph.D Thesis, 2012, The University of Vienna, Austria, Springer, Heidelberg.

[19] Benac, Č., Jurak, V., Oštrić, M.: *Qualitative assessment of geohazard in the Rječina Valley, Croatia*, Proceedings of the 10th IAEG International Congress: IAEG Engineering geology for tomorrow's cities, The Geological Society of London, 2006, 658, 1-7.

[20] Arbanas, Ž., Mihalić, S.: *Progress in the Croatian-Japanese joint research project on landslides*, Proceedings of the IPL Symposium, Sassa, K.; Takara, K.; He, B. (ed.). Kyoto: ICL, 2012, 38-46.

[21] Ožanić, N., Arbanas, Ž., Mihalić, S., Sušanj, I., Žic, E., Ružić, I., Dragičević, N.: *Hrvatsko-japanski projekt o poplavama i klizištima: znanstvene aktivnosti i primjena rezultata*, Zaštita od poplava u Hrvatskoj, Okrugli stol, Biondić, D.; Holjević, D. (ur.), Hrvatske vode, Vukovar, 2012a, 171-188.

[22] Witten, I.H., Frank, E.: *Data Mining - Practical Machine Learning Tools and Techniques with Java Implementations*, 2000, Academic Press, USA.

[23] Kompare, B.: *The use of artificial intelligence in ecological modelling*, Ph.D. Thesis, 1995, FGG, Ljubljana, Royal Danish School of Pharmacy, Copenhagen, Ljubljana.

[24] Cubist, modeling tool, web address: http://www.rulequest.com/cubist-info.html.

[25] Quinlan, J. R.: *Learning with continuous classes*, In: Proceedings of the AI'92, 5th Australian Joint Conference on Artificial Intelligence, Adams & Sterling, Singapore, World Scientific, 1992, 343-348.