underestimates the soil depth less than 10 cm and overestimates for 10-40 cm, but soil depth estimate above 50 cm has a normal dispersal. Unlike the other two models, predictions of different soil depths were consistent using the ANN model. RF and SVM models testing data could not estimate soil depths of more than about 100 cm. It can be concluded that RF and SVM models are appropriate for the mountainous watershed areas that are limited in the depth of the soil and ANN model is more suitable for watershed with agricultural fields and high soil depth. Mean error in both model calibration and model test of RF model is less than with the other two models. This is in line with the result of the study by Tesfa *et al*. (2009). Statistical prediction models were applied to predict soil depth over a mountainous watershed using different environmental variables derived from DEM and satellite image. These variables included 10 topographic variables: specific catchment area (*sca*), Aspect (*asp*), slope (*slp*), wetness inverse index (wii), wetness index (wi), sediment transport index (sti), D8 Slope averaged (D8SA), elevation, plan curvature, D8 Longest Upslope Length (D8 LUL) and general curvature. Three variables extracted from satellite image are landuse map (lum), NDVI, and first principal component analysis (pca1). Six most important variables for predicting soil depth were landuse map (lum), *specific catchment area*, wetness index, NDVI, aspect and slope gradient. Results indicated that topographic variables were generally more important than satellite extracted variables in predicting and mapping of soil depth in our study of the mountainous watersheds in west of Iran. The importance of the top 3 variables landuse, slope, and D8 Slope averaged (D8SA) in estimating the depth of the soil reveals the impact of human intervention and management on this parameter, and have negative correlation with soil depth. Because of proximity to villages and residential areas, class3 rangelands are destructed due to the negative factors such as grazing livestock, foliage harvesting, fires and change to rainfed landuse. Therefore the depth of the soil is low in comparison with class2 rangelands, which have greater distance from these areas. Rangelands class1 is much further away from residential areas and due to the topographical situation, it is hard to access them. For this reason, the soil depth is protected and

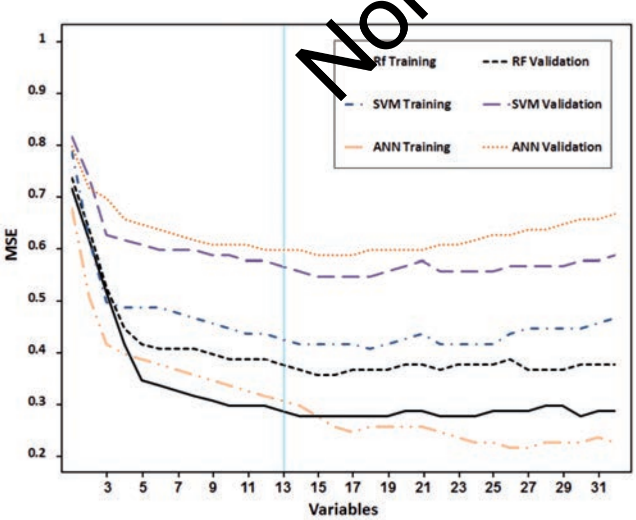

Figure 4. Model complexity (number of input variables) against mean square error. RF, random forests; SVM, support vector machine; ANN, artificial neural network.

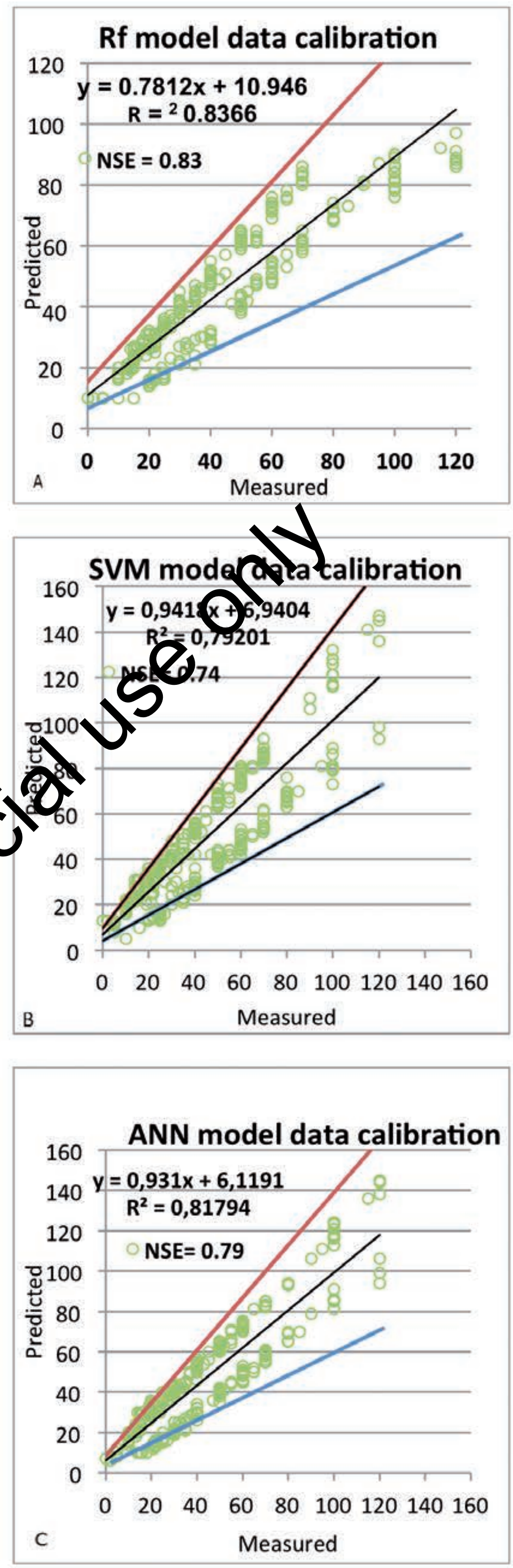

Figure 5. Predicted and measured soil depth data calibration with 5 SD: A) random forests (RF); B) artificial neural network (ANN); C) support vector machine (SVM).

enclosure areas is also significant. A large part of class2 rangelands has been converted to rainfed. But due to plough in the direction of the steep slope and thus an increased soil erosion rate, these areas have lost their soil depth. In the course of a few years, these areas have been abandoned due to their reduced production capability, and classified as bare lands. Therefore, the effects of human intervention variable (landuse) in relation to the depth of the soil indicate that abandoned rainfed located on gradient more than 50% have the second lowest value of the soil depth after the edges and rocks. This is consistent with the literature (Kuriakose *et al*., 2009; Sarkar *et al*., 2014; Yang *et al*., 2014). Slope and D8 Slope averaged (D8SA) quantify relationships between soil depths and slope. The importance of the variables *sca*, *wi*, plan curvature, and wetness inverse index reveals the role of flat and concave areas in preservation of surface runoff due to the higher soil depth in these areas. Similar result was also reported by other authors (Tesfa *et al*., 2009; Mehnatkesh *et al*., 2013; Sarkar *et al*., 2014; Yang *et al*., 2014). The depth of the soil in the northern slope is more than other directions due to having more moisture and less sunny hours. Minimum depth of soil is at the southern slope. This is consistent with the results reported by Penížek and Borůvka (2006) and Tesfa *et al*. (2009). The three major indices extracted from satellite images: landuse map, NDVI and pca1 are among the important variables to estimate the depth of the soil. This shows that the importance of vegetation in forecasting soil depth in the study area, which has also been reported by previous researchers (Tesfa *et al*., 2009; Gastaldi *et al*., 2012; Seid *et al*., 2013). Carriero *et al*. (2005) showed that there was a fairly good correlation between soil depth and slope gradient, wetness index and mean annual precipitation for the study basin. They showed that this correlation can be improved, if information about vegetation characteristics is added.

Conclusions

In this study, RF, ANN and SVM models were developed using environmental variables derived from DEM and satellite image in order to soil depth prediction. Because of the topography of the study area, RF model has the best performance than other two models. The results showed that landuse is the most important variable in soil depth prediction for the case study. Optimum quantity (point sample number) and quality (method of sampling and point samples distribution on study area) of field data are significant parameters for accuracy of soil prediction models. In comparison with prior researches, a large number of field data with adequate distribution on study area was used in order to improve the accuracy of prediction in this study. The study was performed on mountainous areas with an area of 270 square kilometres. 336 samples were used for calibration and 93 were used for testing the models. On average, one sample was picked per 0.63 km^2, which means that the number of samples per area unit is higher in comparison to previous studies with similar study areas (Mehnatkesh *et al*., 2013; Sarkar *et al*., 2014). For sampling, profile drilled method and metal bar as an ancillary tool were used. This increased the accuracy of the results in comparison with previous studies (Tesfa *et al*., 2009; Mehnatkesh *et al*., 2013). In our study, variable selection for all the models was performed based on the RF model. Therefore, a possibility for further work is to perform specialised variable selection for the other two models. In addition, the models developed in this study should be used and validated in other mountainous watersheds with similar environmental conditions to evaluate its overall accuracy for model transportability.

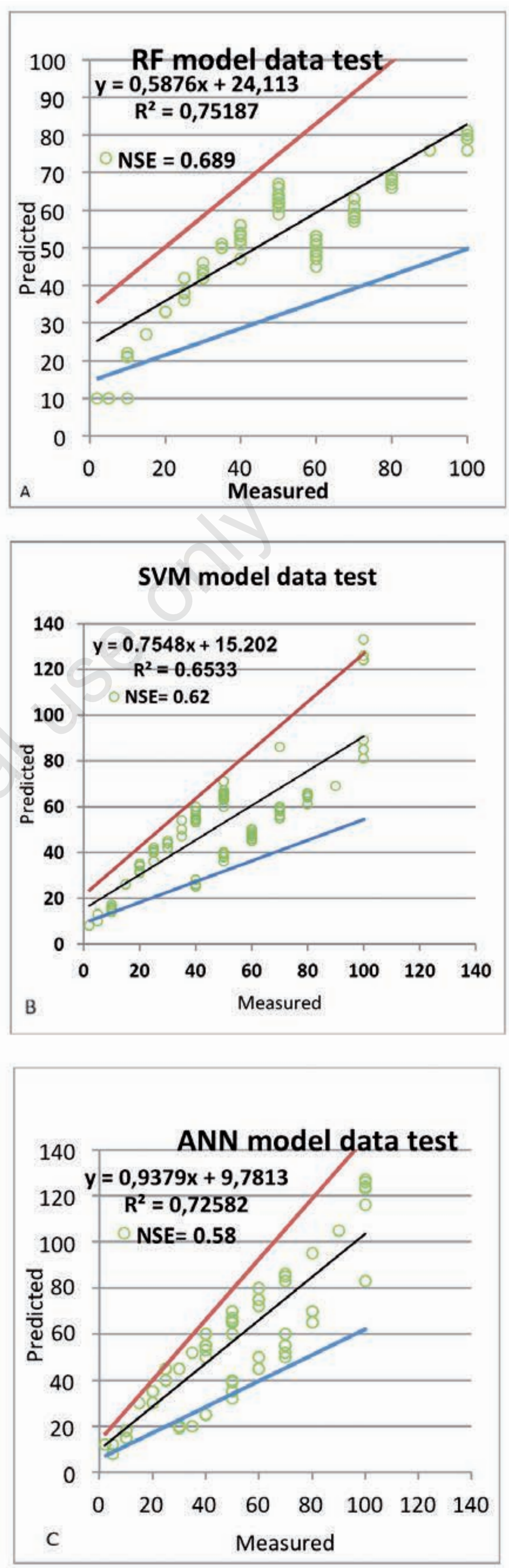

Figure 6. Predicted and measured soil depth data test with 5 SD: A) random forests (RF); B) artificial neural network (ANN); C) support vector machine (SVM).

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