DIGITAL SOIL MAPPING USING GEOMORPHOMETRIC ANALYSIS AND CASE-BASED FUZZY LOGIC APPROACH

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ABSTRACT:

In low relief region such as plains, applied digital soil mapping has a controvertible issue, therefore, this study was aimed to digital mapping of soil classes at family levels by appropriate Geomorphometric variables along with fuzzy logic with area of 16,600 hectares in Qazvin Plain. Based on the geomorphologic map, the plain and pen plain are dominant landscape units. In this regards, 61 soil profiles were dogged. According to the expert's opinion, covariates including diffuse insolation, standardized height, catchment area, valley depth and multiresolution valley bottom flatness (MrVBF) had the most important in order to generating soil map. Also, 19 fuzzy soil class maps were generated through using sample-based in ArcSIE software. Validation were carried out using achieved overall accuracy (OA) and Kappa index through error matrix. Subsequently, both ignorance and exaggerating uncertainty of hardened soil map were also done. The results showed that 19 soil families class were found. Accordingly, OA and the Kappa index were 54% and 46% respectively. The uncertainty of ignorance and exaggeration were obtained from 0 to 0.64 and 0 to 1, respectively. Moreover, the results indicated that exaggerated uncertainty was the highest in the northern and the lowest in the southern regions. Generally, applied geomorphometric parameters had the specific importance in the low relief areas for mapping of soils that have not been assessed properly so far.

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1. INTRODUCTION

The progressive of spatial information technology has created a great potential for digital soil mapping (DSM) paradigm. However, approaches based on DSM not considered continuously in soil class and boundary mapping (Minasny and McBratney 2016). Regarding to this issue, Fuzzy logic is one of the approach that preserved continuous nature of boundary and soil class within mapping units. This approach has been widely applied for mapping spatial soil distribution studies (Zhu et al.,2010). Almost all previous studies on digital soil mapping have used terrain as most important factor (McBratney et al., 2003). In low relief areas such as plains, soil forming factors variation generally do not differ along with soil conditions. Thus, mapping soil classes variation over this area remains a challenge (Liu et al,2012). The choice of effective auxiliary covariate should be thought to prevail soil mapping class in low relief area. However, some efforts have been made to predict the variation of soil class by using remote sensing data and using land surface dynamic feedback (LSDF) for digital soil mapping in such lands (Yang et al., 2016; Bui, 2017). Mirakzehi et al. (2018) in low relief deltaic soils in Sistan area reported that, although topographic attributes are very poor for modelling of soil in this condition but some Geomorphometry factors (i.e., channel networks, valley depth, convergence index, NDSI, and catchment area) were the most important covariates in soil classes mapping. Other studies revealed well results in using of case and sample-based approaches in soil mapping under fuzzy logic (Menezes,2016., Yang et al, 2017). This study aimed to modeling and mapping soil family class from case-based approach regards to compute the uncertainty in mapping units in studied plain.

2. PROPOSED METHOD

2.1. Study area and soil sampling

An area in the Qazvin plain of Iran, across 36° 1’ and 36° 9’ N, and 50° 14’ and 50° 21’ E was chosen (Fig. 1). It covers approximately 16660 ha. Piedmont (45%), Plain (44.58%), Peneplain (9.29%) and Hilland (1.13%) are the dominant landscape units in this area. In this context, 61 pedons with 750 m intervals and using the stratified random sampling method were excavated in various Geoform map units of studied area (Zink, 2016), and then the pedons were described (Schoeneberger et al. 2012). Subsequently, soil samples were taken from all identified genetic horizons. After the determination of physiochemical properties according to the standard methods, the pedons were eventually classified based on key to soil taxonomy (Soil Survey Staff, 2014) up to family level.

2.2. Environmental covariates

The used environmental variables in this research including three datasets as following 1) Local scale morphometry (Elevation, Plan curvature, Profile curvature, Slope, Slope length factor, Terrain ruggedness index, Multi-resolution ridge top flatness index, Multi-resolution valley bottom flatness index; 2) Landscape scale morphometry (Mid-slope position, Normalized height, Standardized height, Valley depth, catchment area; 3) Hydrologic parameters such

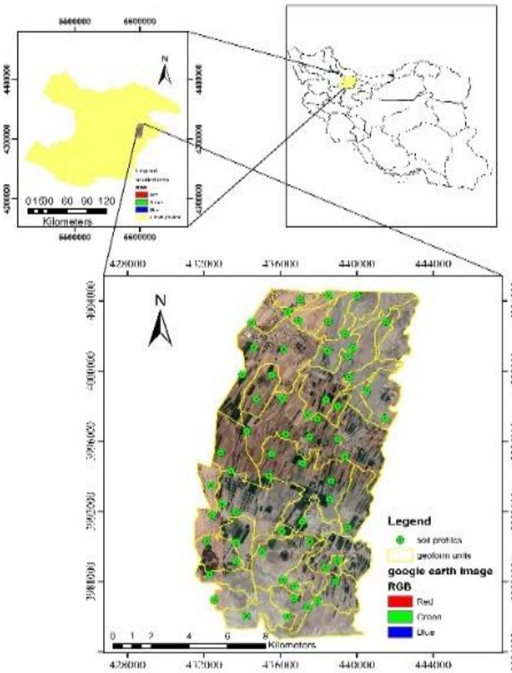

Figure1. Location of the study area with Pedon observation

as SAGA wetness index, and diffusion insolation that derived from DEM with 10-meters resolution were obtained from SAGAGIS software v.7.2. Multiresolution valley bottom flatness (MRVBF), standardized Height, diffusion insolation, valley depth, and catchment area were selected as the most important variables according to the local soil expert’s knowledge and the priority of Gini index analysis of random forest modeling in R Studio v.1.0.136.

2.3. Description of Case-based model

The technical details of computing the fuzzy membership value for a certain soil at a specific location can be represented as following generic equation:

$$S_{ij}^{k} = Tijk_{t=1}^{n}\left\{Pijt_{v=1}^{m}\left[E_{IJ}^{v,t}(e_{ij}^{v}.e^{v.t})\right]\right\} \quad (1)$$

All parameters are introduced in Shi,2004. For soil landscape modelling, ArcSIE as an extension in ArcGIS v.10.4.1 was applied in the studied area. In the first step, selected ancillary covariates (i.e., catchment area, diffuse inclusion, standardized height, MRVBF, and, valley depth) were imported as ".img" format. Subsequently, 70 % of soil pedons (43 points) as ".shp" format with text header were as the calibration dataset. Afterwards, continuous membership functions (bell shape default) were implemented to identify

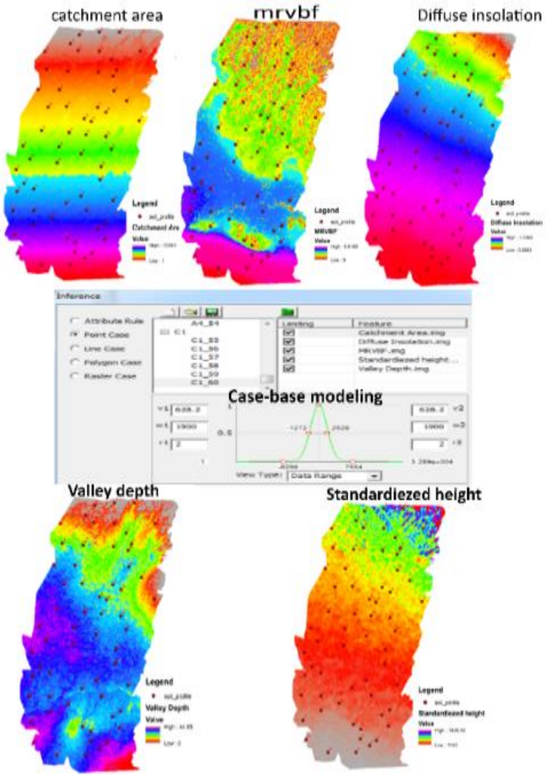

Figure 2. selected covariates and modeling in ArcSIE10.4

relationship between soil family class and axillary covariate. Finally, 23 fuzzy map were generated for each soil class and those hardened as the categorical raster map for validation with 30 percent of pedons were not used in calibration stage. The accuracy assessment of generated maps was computed by overall accuracy and kappa index that derived from confusion matrix.

3. RESULTS

The majority of soil family class in the studied area was"Fine loamy, mixed, active, thermic Fluventic Haploxerepts" with 26% equal with 4306 ha. Fuzzy soil map of this family has a highest membership degree with white tone that distributed in the central of predicted map (Fig. 4). However, the membership degree has been preserved across the landscape because of fuzzy logic ability to retain the continuous nature in soil mapping units (Fig. 3).

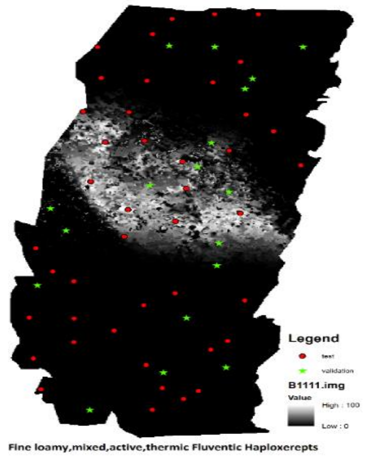

Figure 3. Predicted fuzzy soil family of B1111

Result of categorical raster map validation illustrated that OA and kappa index obtained 54% and 44%, respectively. As shown in Fig. 4, the highest producer accuracy (PA) and user accuracy (UA) of soil family class B1111 were evaluated 100%.

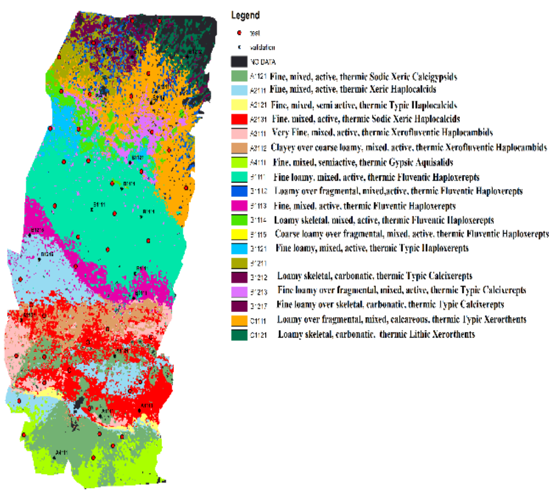

Figure 4. Categorical raster soil map of family level

Furthermore, PA and UA of soil family class C1111 were determined 100% and 50%, respectively, vice versa both PA and UA of soil family A1121 were determined 50% and 100%, respectively. It can be concluded that applied model for C1111 and A1121represented overestimate and underestimate, respectively. (Lacoste,2011).

The results of the ignorance and exaggeration uncertainty in the family level were obtained from 0 to 0.64 and 0 to 1, respectively. In this regard, the amount of ignorance uncertainty in the southern regions is the highest due to the diversity of soil classes and the high degree of membership associated with each soil class, whereas in the northern region it was the lowest due to the less diversity of soil classes and the higher purity of the soil map units (Fig. 5a). The results of exaggerated uncertainty content indicated that in the northern regions of the studied area its content was the highest because of the less diversity classes besides the less a number of pedons, whereas the amount of uncertainty is lowest in the southern regions (Fig. 5b).

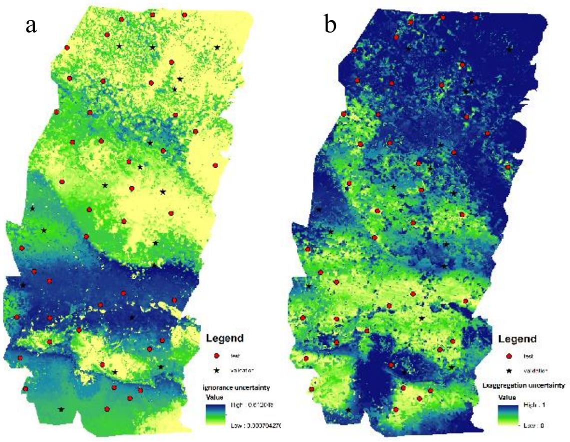

Figure 5.a)-ignorance uncertainty b)- exaggeration uncertaintv

4. CONCLUSION

All in all, using of the appropriate Geomorphometric covariates along with fuzzy logic approach can generate the digital map of soils with acceptable accuracy in the family level in low relief areas.

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