Towards the Generation of a Spatial Hydrological Soil Group Map Based on the Radial Basis Network Model and Spectral Reflectance Band Recognition

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ABSTRACT

Hydrological soil group is essential to soil information for several fields of modeling and applications. This information can affect suitable environmental, agricultural, and hydrological development. Laboratory analysis for soil sampling cannot efficiently provide the needed information because these analyses are commonly costly, time-consuming, and limited in retrieving the temporal and spatial variability. In this context, remote sensing is now solid to offer meaningful spatial data for studying soil characteristics on various spatial scales utilizing the different spectral reflectance. For this study, the integration of Geographic Information System (GIS) remote sensing data and survey data with the Artificial Neural Network (ANN) were used to generate a hydrological soil group map and to infer spatial patterns of soils across complete area converges for Alghadaf Wadi in the Western Desert of Iraq. The generated soil information was tested based on the sand, silt, and clay content. The testing result indicated that the differences between actual and predicted values to determine soil classes are agreed well. Therefore, this method is vital for mapping and monitoring soil texture by providing timely, fast repetitive data and relatively cheap.

1. INTRODUCTION

Soil type is essential information for managing and planning water resources and monitoring the environmental impact of development. A thorough comprehensive of soil information can positively affect the application of sustainable ecological, hydrological, and agricultural development. The statement of soil characteristics in spatial and temporal form is essential for several fields of modeling and application, such as farming, forestry, runoff, and erosion simulation [1, 2]. The rate of runoff to the infiltration of rainfall depends on the soil texture, which is considered the main parameter that affects the runoff of the catchment. Hence, the soil texture is an essential factor in selecting the type and the location of structures in terms of stability and potentiality of surface runoff [3-5].

Soil Conservation Service (SCS) is efficient modeling; it is widely applied in many types of research to determine the surface runoff from an inevitable occurrence of rainfall [6-9]. This type of modeling relies on providing the Curve Number (CN). Curve Number is derived from the land use/cover and the soil texture where the soil texture is classified into subgroups. The United State Geology Survey (USGS) classified the hydrological soil groups into four classes [10, 11]. CN is a critical factor for starting modeling to estimate the storm runoff in many hydrological models such as Environmental Policy Integrated Climate (EPIC) [12], Soil and Water Assessment Tool (SWAT) [13, 14], and Agricultural Non-Point Source Pollution (AGNPS) [15, 16].

Identifying the soil type based on laboratory tests is costly and time-consuming. Remote sensing is one of the access methods and the best alternatives that can be applied to offer valuable information for soil investigation and monitoring. Where this information can be used for site designing and planning construction activities. Indeed, remote sensing is a powerful method of predicting soil characteristics on different spatial scales based on different electromagnetic spectrum ranges [17, 18].

The difference in spectral reflectance, which is the ratio of radiant energy reflected that incident on a body, is a function of several important properties of soil [19-21]. The physical and chemical characteristics of materials define the spectral reflectance utilized to recognize them.

Five specific soil spectral reflectance curves have been developed by Salisbury et al. [22, 23]. These curves were used to identify organic matter, iron, and soil texture based on the relationship between reflectance and soil type. Many researchers used laboratory spectral analysis to recognize some soil characteristics [24-26]. The correlation between laboratory analysis and image data of Landsat TM and SPOT are used to define various soil texture categories [27, 28].

The component image with band two and band 8 of the Advanced Spaceborne Thermal Emission and Reflection (ASTER), were used to predict the soil texture categories by Apan et al. [27]. They found that soil absorption features can recognize the changes between clay soil and quartz on the map. Bands 5 and 6, representing a short wave of ASTER, can be detected in the clay soil, while the thermal bands (10-14) can be used for quartz index [29]. The short and thermal could see the dark clayey soil and sandy, but the results are fluctuated depending on the organic substance [22, 30].

Soil reflectance is quite a complex phenomenon. Consequently, it is hard to estimate the soil characteristics
based on the physical model [31]. The theoretical approach is always not valid for soil properties assessment and does not agree with reality [19]. Thus, to tackle the complex relationship between soil properties and spectral reflectance, there is a need for a method that can handle the nonlinearity in this task.

The Western desert of Iraq is a vast area, and soil data are scarce [32-35]. Remote sensing is an efficient tool to provide a database of soil maps in digital form. These maps are generated based on the interpolation of the primary data source. The traditional interpolation consists of a severe issue to handle the complexity of reflectance with soil texture, especially in the broad areas. Hence, the following study presents an intelligible methodology for soil texture recognition. This methodology combines Artificial Neural networks (ANN) with remote sensing data and the Geographic Information System (GIS). Using Artificial Intelligence (AI) will improve the perspectives of digital soil mapping and integrate it with GIS to accomplish complete region coverage.

2. CASE STUDY

Anbar province is the study area in this research. It is the western desert of Iraq. It has the geographic coordinates between 30°36'01" to 35°09'32' N and 38°47'35" to 44°09'38" E, and has a total area of 138,500 km², as shown in Figure 1. The climate is arid, with superb in winter and dry in summer. The variation in day temperature is around 36°C [36-38]. Under these conditions, the land surface is heated in the daytime and cool at night. The evaporation rate is 3200 mm, and the average annual rainfall is 115 mm. These conditions with a high infiltration rate caused scarce water resources for the region. The study area is a flat region, rising in elevation westwards—generally, the topographic incline of the part from east to west. The western desert of Iraq belongs to the Inner Platform of the Arabian Platform [39-42]. The landform of the case study is a consequence of a complex interaction between lithology, structure, and climate. The central plateau of the study area was rocky [43-45]. Topographically, the studied area is described by a regular increase in elevation from east to west [46, 47]. The drainage is chiefly easterly and northeasterly. The general characteristics of the study area are thick soil cover and the absence of vegetation. Based on the supervised classification by Arc-GIS as shown in Figure 2, most of the study area was covered by bare soil (72.5%) flowed by open grass (22.1%), farmland (2.81%), water body (1.28%), built-up (1.33%) of the total area.

3. MATERIALS AND METHODS

The following methodology consists of several steps of data collection, preparing, and modeling to achieve the aim of this study, as shown in Figure 2. The methodology is represented in the following steps:

First steps: Unsupervised classification has been performed on the satellite image of the case study (Landsat 8, August 2014). The classification process is based on the unsupervised algorithm and rectified with the spot heights and ground points. The unsupervised classification is a significant stage for preparing the primitive maps for soil sample collection and survey.

4. RESULTS AND DISCUSSION

The unsupervised map gives a good representation of some classes. These classes are categorized based only on the natural grouping in the image value. Thus, the unsupervised classification is a suitable technique to prepare a primitive map for soil survey to collect soil samples. This process will reduce the effort, cost, and time. To accurately estimate soil type, selecting soil sample location is performed based on specific criteria. Therefore, the unsupervised classification will be accomplished. Figure 3 shows the selected part of the study region where the unsupervised classification is performed. Flat surface, bare soil, and consistency of all types of classification were recommended to choose this part of the study area with a suitable scale for reconnaissance. In addition, the surveillance according to the primitive map will reduce the errors of the pixel vegetation cover, which is recommended...
not covering over 20%, as well as the mistakes of spectral signatures of water, urban areas, roads, soil roughness topography, and slope for each location selected. These conditions are suggested to provide an accurate classification [48, 49]. In this figure, six classes are available, which represent the land cover classes; each class is given specific color. The number and location of each sample are shown in this figure, which has been taken into different categories for sieve analysis. There are 19 samples in and out of the selected region to cover the study area using a GPS device. By using ERDAS software, spectral reflectance has been recorded for each position. Nine bands were used while two thermal bands were reduced.

Sensitivity analysis has been applied to express and assure the complicity relation of soil type with reflectance. Figure 4 illustrates the sensitivity of clay, sand, and silt to the bands. It is obvious that Figure 4 shows that the soil type undetectable by band 2. In contrast, band 7 and band 9 are the greatest sensitive with the soil type, especially sand and silt while clayey soil can be estimated by band 1, band seven, and band 6. The spectral reflectance of soil type and bands are very complex where all bands are participating in detecting specific but in different weights. Indeed, reflectance variation over bands can be a good platform for building a highly accurate model for soil type estimation. Thus, it is essential to containing all the bands in the ANN model.

The actual and estimated values of the ANN model are illustrated in Figure 5. This figure shows that the soil type of the study region is sandy with the highest percentage compared with clay and silt. Also, this figure demonstrated that the estimated values of clay are more accurate than silt and sand, while a considerable fluctuation between estimated and actual values of sandy soil. Indeed, the performance of the ANN model is constant therefore the total percentage for the estimated output of the ANN model is 100%. Thus, it can be concluded that a low percentage estimation is more accurate than a high percentage.

For evaluating the modeling performance, where Table 1 presents the performance for each type of soil. Obviously, there is a noticeable variation in the accuracies of estimation values of the three types of soil. The clay prediction has superior results among other classes in all performance criteria were the lowest RMSE, NRMSE, and $r$ (3.811, 0.1002, and $r = 0.8565$ respectively). By comparing the accuracies of sand and silt, some fluctuation in results can be seen. Based on NRMSE, sand has more minor errors than silt. In contrast, silt estimation performs better than sand estimation depending on RMSE and $r$.

<table>
<thead>
<tr>
<th>Performance</th>
<th>Clay</th>
<th>Silt</th>
<th>Sand</th>
</tr>
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<tbody>
<tr>
<td>RMSE</td>
<td>3.811</td>
<td>7.209</td>
<td>9.034</td>
</tr>
<tr>
<td>NRMSE</td>
<td>0.1002</td>
<td>0.2301</td>
<td>0.252</td>
</tr>
<tr>
<td>$r$</td>
<td>0.86</td>
<td>0.64</td>
<td>0.49</td>
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As mentioned previously, this paper's main objective is to develop a Curve Number (CN) map for Anbar province, where
Figure 6 represents the soil type of this study. By simulating the reflectance of 3000 points in different locations in the ANN model, the percentage of soil types is integrated with GIS. This map shows the distribution of hydrological soil type (Figure 7) over the study area which is an important parameter for a variety of types of investigation. Land cover and hydrological soil group maps were used to generate Curve Number (CN) for the study area as shown in Figure 8.

**Figure 7.** Hydrological soil group map of the study area

**Figure 8.** Curve number map of the study area

5. CONCLUSIONS

Remote sensing is a significant tool for monitoring, detecting, and mapping soil texture by providing repetitive data and relatively cheap as well as fast, and timely. Prediction of soil classes based on the use of the relationship between soil type and spectral reflectance was attempted in this study. The hydrological soil group represents as a platform for several fields of modeling and applications. This calls for generating hydrological soil group maps to support timely decision making on land management and planning of water resources. The combined procedure of Geographic Information System and Remote Sensing data with Artificial Neural Network were used to generate a hydrological soil group. The performance of this methodology was tested according to the difference between actual and predicted values. The results show that the clay prediction has superior results among other types in all performance criteria were the lowest RMSE, NRMSE, and r (3.811, 0.1002, and r =0.8565) respectively. By comparing the accuracies of sand and silt, it can be seen some fluctuation in results. Based on NRMSE sand has less errors than silt. In contrast, silt estimation performs better than sand estimation depending on RMSE, and r.

**REFERENCES**


