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SOIL PROPERTIES MAPPING USING A SOIL LAND INFERENCE MODEL (SoLIM) IN SOUTHERN VIETNAM: A CASE STUDY IN BINH PHUOC PROVINCE

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Abstract

Information of soil properties is critical for soil and environmental management. The spatial distribution of soil properties and its attribute is required for many environmental modelling and land monitoring applications. This study aims to generate maps of soil properties using the inference method provided by SoLIM (Soil Land Inference Model) program. The first case was implemented to generate continuous soil depth property in Suoi Rat catchment, Binh Phuoc. By using SoLIM model, the soil environment conditions over the study area are characterized using combination of GIS and remote sensing techniques. There are 9 environmental data layers were used as input data for estimating depths from the surface including parent materials, elevation, slope gradient, aspect, profile curvature, planform curvature, wetness index, vegetation cover and landform. The achieved results showed a relatively correlated between inferred depths and observed depths with R^2 *of 0.66. It demonstrates the efficiency of inference method for soil properties estimation which could help to overcome the limitation of soil surveys and improve accuracy of estimated maps*.

Keywords: *Soil properties, Soil depth, Landform, SoLIM.*

1. INTRODUCTION

SoLIM (Soil Land Inference Model) is a fuzzy inference scheme for estimating and representing the spatial distribution of soil types/soil properties in a landscape. It consists of three basis components: A knowledge acquisition process, a set of GIS techniques and a fuzzy inference engine. The knowledge acquisition process is used to extract the relationship between soils and their environmental conditions from a soil scientist. The GIS techniques are used to characterize soil formative environmental conditions. The fuzzy inference engine combines the extracted relationships with the environmental conditions to produce soil spatial information.

Because of the limitation of soil survey which is costly, time consuming and cannot provide the detailed soil information required by land monitoring applications and environmental modelling (Zhu, 1996). Soil depth is one of crucial input variables for modelling earth surface phenomena and it was defined as the depth from the surface to more or less consolidated material. However, there are few research has been conducted to develop an approach for estimating continuous spatial distribution of soil depth factor. In 1995, Dietrich et al. presented a method for estimating soil depths based on the mass balance between soil production and soil transport by erosion and this method was successfully applied in a sub catchment in California (Heimsath *et al.*, 1999). Geo-statistic methods of cokriging and regression kringing were used to predict soil depth in Murray Darling sub basin (Odeh *et al.*, 1995). An approach of inferential methods using indicators of plant species was implemented by Treiber and Krusinger (1979) but this method is applicable only in areas with a dominant species. The SoLIM approach is a new technique that allows reducing the disadvantages of traditional soil survey method for the purpose of estimating spatial distribution of soil properties. Under SoLIM technique, soil is considered as a result of integration among its formative environmental factors and time (Jenny, 1980). Soil information products devired through SoLIM are high quality on term of both level of spatial detail and degree of attribute accuracy (Zhu *et al.,* 2001).

This paper presents an application of SoLIM technique to predict soil depths in Suoi Rat catchment, Binh Phuoc province.

2. STUDY AREA

Suoi Rat catchment located in Dong Phu District - Binh Phuoc Province, Vietnam, covering about 62.3 km^2 (Figure 1). The rainy season is from May to December and dry season lasts from December to April next year. The average annual temperature from 25^0 – to 27^0 C and elevation ranges in 72 – 260 m.

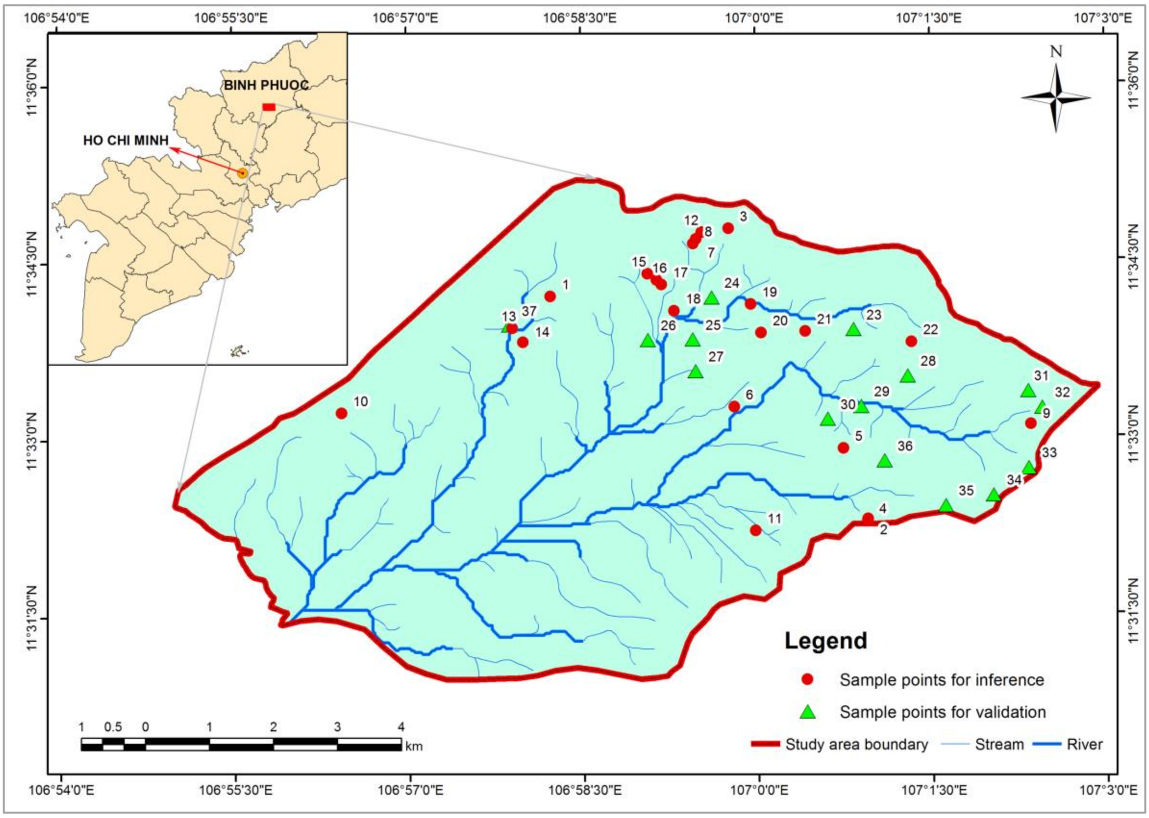

Figure 1. Location of the study area

3. DATA

The data used in this study including:

(a) **Environmental layers**: parent materials, elevation, slope gradient, aspect, profile curvature, planform curvature, wetness index, vegetation cover and landform. The ASTER DEM with spatial resolution of 30m over the study area has downloaded to generate environmental layer: elevation, slope gradient, aspect, profile curvature, planform curvature, and wetness index using a SoLIM Solutions. The landform map of the study area was also derived from ASTER DEM and landform elements of ridge (or mountain peak), slope shoulder, back slope, foot slope, and were then extracted from DEM using fuzzy k-mean classification method using a Python program (Song et al, 2012) . A LandUse/LandCover map in 2012 was used as vegetation cover layer.

(b) **Soil samples**: Totally, 37 soil samples taken from the field in 2012 were used with its attribute of XY location and measured depths. Among these 37 soil sampling points, 22 points were used for modelling and 15 points for validation.

4. METHODOLOGY

A SoLIM application has been applied to estimate soil depths in the study area. It was implemented through two main steps:

(1) Data preparation: It is required to create a "GIS-database" including all environmental layers and they are generated using provided tool by SoLIM software. Data must be converted to native file format of *3dr for SoLIM solution. Once the data preparation is finished, they are imported to SoLIM program the same time with soil samples.

(2) Run an inference using the GIS database and field sample points to produce a soil depth map. In this step, the similarity between environmental layers and soil will be compute and establish, the fuzzy inference engine will then applied to infer soil property/type based on **similarity** between an unknown position and existing field samples based on the environmental conditions. The following flowchart shows the procedure for estimating soil depth using SoLIM application (Figure 2).

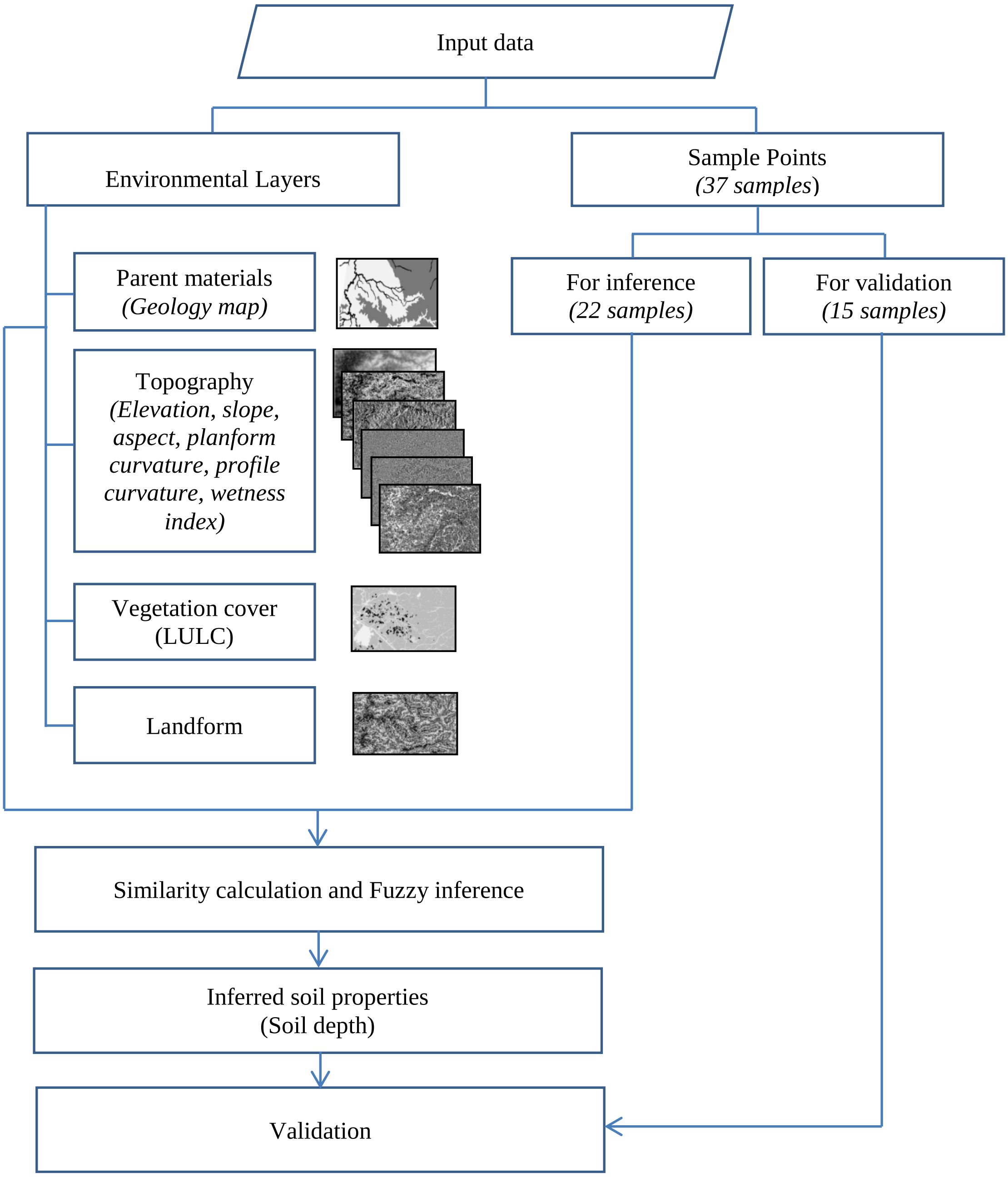

Figure 2: The procedure for soil depth estimation using SoLIM

In order to evaluate the estimated map, the Root Mean Square Error (RMSE) was used in this study. RMSE is one of the most commonly used error measures and it gives the weighted variation in errors (residuals) between the predicted and observed values. It is calculated using formula as following:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i' - y_i)} \qquad (1)$$

Where n is number of districts used for validation, y_i' is the inferred depths, and y_i is the observed depths.

5. RESULT

The spatial distribution of estimated soil depths is shown in Figure 3 as below. It is clear to be seen that the depth map inferred from SoLIM was represented with continuous spatial variation in whole study area. The depths are ranged from 40 to 285 cm; lower depths (from 40 to 150 cm) are shown in dark yellow color and located in valley area. The higher depths (> 150 cm) are represented in blue and bright blue and located in higher elevation (footslope). The white color indicated NoData areas; in case of the study area, NoData pixels located in streams and roads. According to SoLIM rules in the inference process, SoLIM Solutions does not only predict soil property value for every location but also provides the uncertainty associated with the prediction at each location. If the uncertainty is too high (higher than the uncertainty threshold of 0.5), SoLIM Solutions will assign NoData to that position in the final soil property map.

The inferred depths were compared to observed depths to evaluate the estimated map accuracy. The results showed a good correlation between these two data sets with R^2 of 0.66 and RMSE (Root Mean Square Error) is 61.6 cm (Figure 4). The differences between estimated depths and observed depths are showed in Table 1.

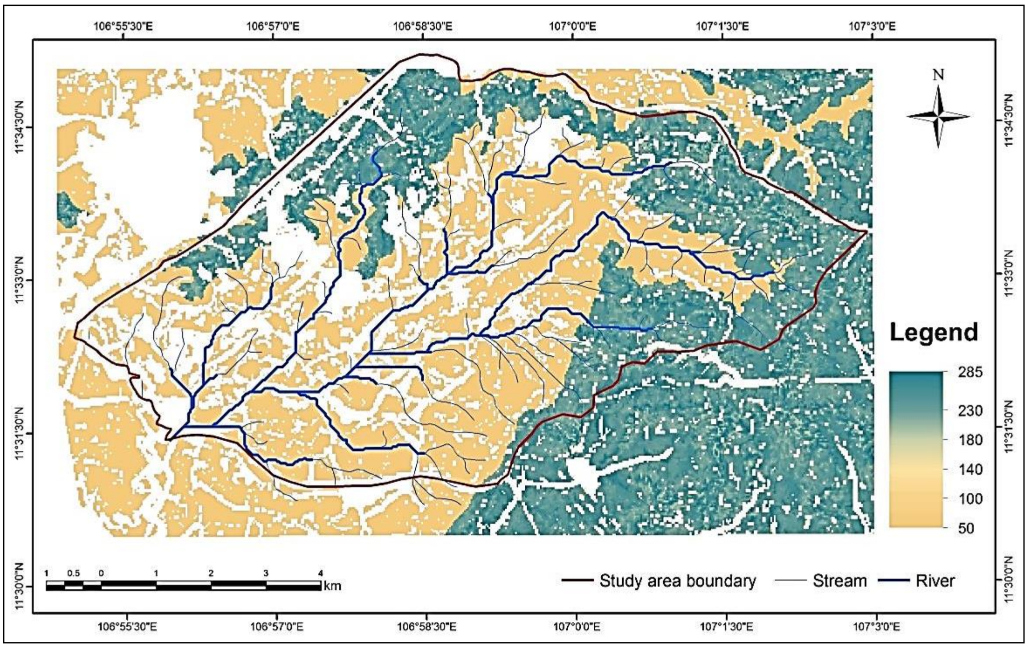

Figure 3: The inferred soil depth map over the study area

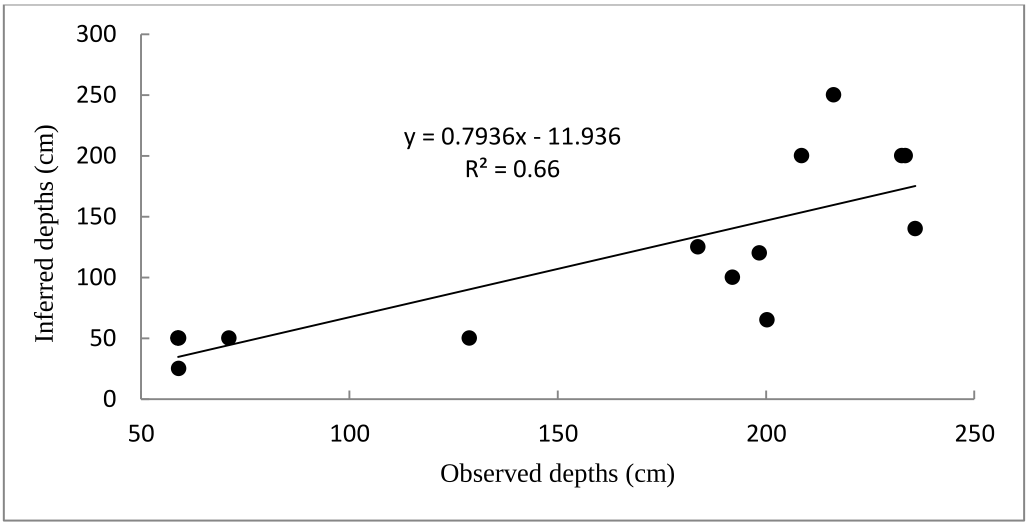

Figure 4. Correlation between inferred depths from SoLIM and observed depths

Table 1. The difference between inferred and observed depths

Point ID	Coordinate (UTM-WGS 84)		Inferred	Observed	Residuals
	X	Y	(cm)	(cm)	(cm)
23	719620	1279240	200.2	65	135.2
24	717400	1279735	59.0	50	9.0
25	717106	1279078	58.9	50	8.9
26	716405	1279069	59.0	25	34.0
27	717151	1278584	58.9	50	8.9
28	720466	1278516	183.6	125	58.6
29	719739	1278039	71.1	50	21.1
30	719214	1277838	128.8	50	78.8
31	722576	1278318	198.4	120	78.4
32	722565	1278030	232.6	200	32.6
33	722359	1277085	233.4	200	33.4
34	721811	1276659	191.9	100	91.9
35	721062	1276490	235.8	140	95.8
36	720105	1277190	216.2	250	-33.8
37	714284	1279277	208.5	200	8.5
RMSE					**61.6**

6. CONCLUSION

This study aims to generate soil properties using a developed approach of SoLIM solution. A test case was first implemented for soil depth prediction in Suoi Rat catchment, Binh Phuoc, Vietnam. The obtained depths was relatively correlated with observed depths (R^2 of 0.66) indicating the usefulness of fuzzy inference for soil properties mapping. This result pointed out that the SoLIM application worked well in this study area and successfully produces a continuous soil depth. It also gave a promise to generate other soil properties/soil type with high accuracy. This paper presented an initial result of soil depth estimation using fuzzy inference engine approach. The applicability of SoLIM application will be more explored for other soil types/properties in different landscape characteristic in future works.

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