PEDOTRANSFER FUNCTIONS FOR DIGITAL SOIL MAPPING IN TROPICAL REGION: A CASE STUDY OF DIGITAL SOIL MAPPING OF SOIL CARBON AND NITROGEN IN WEST JAVA, INDONESIA

FUNGSI PEDOTRANSFER UNTUK PEMETAAN TANAH DIGITAL DI DAERAH TROPIS: STUDI KASUS PEMETAAN KANDUNGAN KARBON DAN NITROGEN TANAH DI PROVINSI JAWA BARAT, INDONESIA

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Abstrak

Variasi kandungan karbon dan nitrogen di permukaan tanah dimodelkan dengan menggunakan fungsi pedotransfer yang memanfaatkan data dari Digital Elevation Model-DEM, Normalized Difference Vegetation Index-NDVI dan bioiklim. Data pengamatan tanah Puerto Rico, USA, digunakan untuk pengembangan model prediksi properti tanah, yang kemudian diaplikasikan di wilayah provinsi Jawa Barat, Indonesia. Fungsi pedotransfer yang disusun dengan menggunakan 22 parameter input derivasi dari tiga faktor pembentukan tanah (topografi, vegetasi, dan iklim) menghasilkan model dengan koefisien determinasi (R^2) 71% dan 66%, masing-masing untuk kandungan karbon dan nitrogen di permukaan tanah. Hasil yang sebanding juga diperoleh dengan mereduksi jumlah input parameter berdasarkan parameter yang signifikan (RMSE 3,12% dan 0,05% untuk masing-masing kandungan karbon dan nitrogen tanah). Hasil ini menunjukkan bahwa fungsi pedotransfer dapat digunakan sebagai alat bantu pengambilan keputusan untuk memetakan variasi properti tanah dalam mendukung penyusunan kebijakan di bidang peningkatan sumber daya lahan untuk mengidentifikasi masalah daya tahan pangan.

Kata kunci: Fungsi pedotransfer, Pemetaan tanah digital, Karbon, Pedometrik.

Keywords:

Pedotransfer function

Digital soil mapping

Soil carbon

Pedometrics

Abstract

Pedotransfer functions (PTFs) for the tropical region were developed to model topsoil total carbon and nitrogen variations, by using input parameters of Digital Elevation Model-DEM, Normalized Difference Vegetation Index-NDVI and bioclimatic variables. Puerto Rico dataset was used to develop the model, while West Java, Indonesia was chosen for the model application. Using 22 input parameters derived from the three soil forming factors (relief, vegetation, and climate), the PTF could explain 71% and 66% of the soil total carbon and nitrogen variations, while comparable results were obtained from reduced input parameters (RMSE 3.12% and 0.05% for topsoil total carbon and nitrogen, respectively). This result suggests that application of PTFs to model soil properties variation, especially in the tropical region, could be used to generate reliable pre-assessment information to support decision making in the land productivity improvement plan.

INTRODUCTION

Under the threatening of exponential population growth, food security becomes the fundamental problem for any nations around the world. Human population was projected to reach about 10 billion people in 2050 (Cohen 2003), while on the contrary, about 24% of land has been degrading in the last three decades (Bai et al. 2008) extent and severity are contested. We define land degradation as a long-term decline in ecosystem function and productivity, which may be assessed using long-term, remotely sensed normalized difference vegetation index (NDVI). In the developing countries where it mostly happens, this wicked environmental problem challenges the decision maker to make a correct policy to be addressed.

Food security problem is highly related to the soil (Bouma and McBratney 2013). Soil degradation decreases agricultural crops productivity and eventually decreases livestock production. In more than three centuries of mankind history, a human has been using more than 50% of the terrestrial land (Ellis et al. 2010) from 1700 to 2000. Location Global. Methods Anthropogenic biomes (anthromes). While the main purpose is to fulfill human needs, this anthropogenic factor has caused the soil to degrade which end up with the food security problem. In Indonesia, the example of the anthropogenic pressure on soils is the population increase from 88 million in 1961 to 254.5 million in 2014 that was not balanced by the expansion of the arable land area, which then reducing the ratio of the arable land to population from 0.20 to 0.09 ha/person (World Bank 2014). As the consequence, agricultural land was intensified to fulfill the food demand, marked by the increase of the irrigated agriculture from 130,000 to 530,000 hectares in the period of 2008-2012 (IDGAIF 2012) and the increasing of the total fertilizer

input per hectare of land, including Urea, Ammonium, Phosphate, NPK, and organic fertilizer, from about 390 to 500 kg/ha (national average) in the period of 2007-2014 (ICADI 2014; IDGAIF 2012; IFPA 2017). The latter increase could possibly due to inefficient fertilizer application that later increases the risk of environmental pollution and/or the sign of soil degradation due to intensification where more soil amendments are required to stabilize land productivity. Therefore, both risks need soil improvement strategies to be planned and applied to manage the agricultural soils to achieve sustainable food production.

Before a plan can be realized, however, pre-assessment is needed to ensure the applicability of the land management. In term of soil improvement, a map showing the current condition of the soil can be used as the base plan. However, the high heterogeneity of the soil makes the soil map preparation becomes costly, laborious, and time-consuming. The advance of computer and information technology, followed by the enhancement of digital soil mapping and pedometrics, however, can cut the cost and the time constraint to create a pre-assessment map for decision-making support (McBratney et al. 2003; S. Grunwald, Thompson, and Boettinger 2011; Finke 2012). Model can be developed to study the correlation between soil properties and its influencing environmental factors, using freely accessible global environmental dataset available on the world wide web, and the results have been proven to be reliable (Ross, Grunwald, and Myers 2013; Xiong et al. 2014; S. Grunwald 2009; Vasques, Grunwald, and Myers 2012)

Despite the advance in digital soil mapping and pedometrics, and the highly available global environmental dataset on the internet, the requirements of representative soil samples to generate soil model become more problematic especially in the

developing countries that lack supporting data availability. This problem can be addressed by developing pedotransfer function-PTF from the area, which has similar environmental conditions. Therefore, the objective of this article was to develop PTFs for the tropical region to assess current soil conditions. This article was intended to guide the decision maker to prepare a pre-assessment information to support their decision in land productivity improvement plan to address food security problem, particularly in the tropical region. The development of digital soil map of carbon, nitrogen, and soil CN ratio for West Java Province, Indonesia, was used for a case study. Soil model to assess these soil properties was developed based on the soil samples dataset of Puerto Rico, USA, using input data of downloadable global environmental data set from the internet. Puerto Rico was chosen because of its dominant soil orders and parent materials are similar with West Java Province. More than 75% of soils in both areas are Ultisols, Inceptisols, and Alfisols (NRCS 2005). Furthermore, both areas are dominated by sedimentary and volcanic rock parent materials, which cover more than 80% of each area (Hartmann and Moosdorf 2012).

METHODOLOGY

PTFs was developed using multiple linear regression analysis (MLRA), in which two models to assess soil carbon and nitrogen variations were developed based on the correlation of the soil properties and its soil forming factors (climate, topography, and vegetation). Soil profile data of Puerto Rico, USA, for model development, was downloaded from National Cooperative Soil Survey website (<http://ncsslabdatamart.sc.egov.usda.gov/>), while soil profile data of West Java, for model validation,

was obtained from ISRIC - World Soil Information website (<http://www.isric.org/>). Furthermore, three soil forming factor dataset including ASTER Global Digital Elevation Model-DEM (topography factor), Moderate Resolution Imaging Spectroradiometer (MODIS) Normalized Difference Vegetation Index-NDVI (vegetation factor), and Bioclimatic variables-Bioclim (climate factor), as independent variables for model input, were downloaded from Japan Space Systems GDEM website (product of Japan Ministry of Economy, Trade, and Industry METI and US National Aeronautics and Space Administration-NASA, <http://gdem.ersdac.jspacesystems.or.jp/>), NASA Land Processes Distributed Active Archive Center website (NASA-LPDAAC 2001), and World Clim - Global Climate Data website (Hijmans et al. 2005), respectively.

Three pathways of meta soil models (Sabine Grunwald, Vasques, and River 2015) were used to guide the model development processes. These pathways include (1) spatial integrative analysis through geoprocessing, (2) soil predictions through functional fit methods and/or empirical-based soil-factorial modeling, and (3) transfer of soil models with the assumption of natural behavior and relationships similarity. The first pathway was used for data preparation and map production processes, using QGIS Desktop 2.8.1 (WIEN) with GRASS and SAGA plugins (QGIS 2015). These processes include basic raster data processing (data projection, merging, clipping, extractions, interpolation, and calculation); generating topographic primary and secondary attributes, i.e., slope and topographic wetness index (TWI), respectively; performing basic statistical summary of raster data; calculation of mean annual NDVI for Puerto Rico (data year 2002-2003) and West Java (data year

2012-2014); and application of PTFs for digital soil mapping. In total, around 22 independent environmental variables were prepared from this process, including three topographic data (elevation, slope, and topographic wetness index), one vegetation data (NDVI), 10 temperature data (annual mean temperature-bioclim1, mean diurnal range-bioclim2, isothermality-bioclim3, temperature seasonality-bioclim4, coldest month minimum temperature-bioclim6, annual temperature range-bioclim7, wettest annual quarter mean temperature-bioclim8, driest annual quarter mean temperature-bioclim9, warmest annual quarter mean temperature-bioclim4, and coldest annual quarter mean temperature-bioclim11), and eight precipitation data (annual precipitation-bioclim12, wettest month precipitation-bioclim13, driest month precipitation-bioclim14, precipitation seasonality-bioclim15, wettest annual quarter precipitation-bioclim16, driest annual quarter precipitation-bioclim17, warmest annual quarter precipitation-bioclim18, and coldest annual quarter precipitation-bioclim19). The statistical summary comparing the distribution of elevation, NDVI, mean annual temperature, and annual precipitation for Puerto Rico and West Java is presented in Table 1, while the samples point distribution for model development is depicted in Figure 1.

Moreover, the second pathway was used to develop PTFs, in which R statistical software was used for this purposes (R Development Core Team 2008). At first, the model was developed based on all input parameters. The parsimonious model was then formulated by subsequently reducing the input parameters until only statistically significant parameters were included in the model. The third pathway was used to apply the resulted PTFs to create digital soil

maps of carbon, nitrogen, and CN ratio for West Java, Indonesia.

Table 1. Statistical summary of elevation, NDVI, mean annual temperature, and annual precipitation for both Puerto Rico, USA and West Java Province, Indonesia.

Statistical Summaries	Puerto Rico, USA	West Java, ID
Elevation (m)		
Max.	1280.00	3055.00
Mean	244.16	437.98
Min	1.00	-4.00
Std. Dev.	229.63	451.17
Normalized Difference Vegetation Index (NDVI)		
Max.	0.91	0.88
Mean	0.63	0.60
Min	-0.14	-0.05
Std. Dev.	0.16	0.12
Mean annual temperature (°C)		
Max.	26.80	27.50
Mean	24.20	24.56
Min	17.50	9.80
Std. Dev.	1.60	2.81
Annual precipitation (mm)		
Max.	3361.00	4234.00
Mean	1831.16	2817.65
Min	752.00	1239.00
Std. Dev.	441.80	583.83

Figure 1. Puerto Rico soil sample distribution (total 110 sample profiles) for model development

RESULT AND DISCUSSION

The result of MLRA for soil carbon and nitrogen are presented in Table 2 to Table 5. Table 2 shows that 71% of soil carbon variation can be explained by the model using all (22) input parameters, with the RMSE value 5.11% to the model output. Furthermore, subsequence run was performed by eliminating the non-significant parameters resulted in only five significant

input parameters in the third run. Although having less multiple correlation values (multiple $R^2=44\%$), the reduced parameters model has comparable RMSE and p-value, i.e., 4.97% and 2.1E-9, respectively. This result shows that comparable output can be produced by using only five parameters input which was generated from two datasets (DEM and precipitation).

Table 2. MLRA result for soil carbon model using all input parameters.

Coefficients	All Parameters (22)			Reduced Parameters (5)		
	Est.	Pr (> t)	Sig	Est.	Pr (> t)	Sig
(Intercept)	82.870	3.6E-01		12.581	7.4E-09	***
DEM	0.031	2.2E-04	***	0.018	3.2E-10	***
TWI	-0.187	4.0E-01				
Slope	-0.068	2.6E-02	*			
NDVI ^a	0.001	1.3E-01				
bioclim19	-0.222	1.3E-01				
bioclim18	0.010	3.4E-01				
bioclim17	0.363	3.4E-02	*	0.082	9.4E-03	**
bioclim16	0.064	2.3E-02	*	0.038	1.3E-02	*
bioclim15	-0.011	9.3E-01				
bioclim14	-0.326	3.9E-02	*	-0.265	2.0E-02	*
bioclim13	-0.268	1.6E-06	***	-0.165	7.5E-04	***
bioclim12	-0.004	7.4E-01				
bioclim11 ^b	2.434	7.8E-02	.			
bioclim10 ^b	-0.942	3.0E-01				
bioclim9 ^b	0.251	8.6E-01				
bioclim8 ^b	0.151	4.8E-01				
bioclim7 ^b	-0.847	3.3E-01				
bioclim6 ^b	-0.258	7.1E-01				
bioclim4 ^b	0.008	7.0E-01				
bioclim3 ^b	-0.984	3.7E-01				
bioclim2 ^b	1.201	1.9E-01				
bioclim1 ^b	-1.564	1.5E-01				
Dependent variable	Total C	(%)		Total C	(%)	
Multiple R ²	0.71			0.44		
p-value		1.6E-10	***		2.1E-09	***
RMSE	5.11			4.97		

Sig. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

^a x10000

^b x10

Table 3. Statistical distribution of soil carbon values (%) from soil profiles, and from model outputs of all and reduced parameters

Statistics	Soil Profiles	All Parameters	Reduced Parameters
Min.	0.32	0.32	0.32
Max.	46.67	19.84	14.49
1Q	1.77	1.80	2.02
Median	2.57	2.71	3.45
3Q	3.90	4.37	4.30
Mean	3.96	3.59	3.57

Table 4. MLRA result for soil nitrogen model using all input parameters.

Coefficients	All Parameters (22)			Reduced Parameters (4)		
	Est	Pr (> t)	Sig	Est	Pr (> t)	Sig
(Intercept)	-5.036	6.1E-01		-8.833	6.1E-06	***
DEM	0.003	1.9E-03	**	0.003	7.0E-08	***
TWI	-0.002	9.2E-01				
Slope	-0.002	5.1E-01				
NDVI ^a	0.000	2.3E-02	*			
bioclim19	-0.030	6.6E-02	.			
bioclim18	0.002	1.0E-01				
bioclim17	0.016	3.4E-01				
bioclim16	0.002	5.7E-01				
bioclim15	0.002	9.0E-01				
bioclim14	0.017	3.6E-01				
bioclim13	-0.021	4.0E-03	**			
bioclim12	0.002	1.9E-01				
bioclim11 ^b	0.504	2.6E-03	**	0.4564	5.5E-04	***
bioclim10 ^b	0.049	6.1E-01				
bioclim9 ^b	-0.594	1.1E-03	**	-0.4452	6.9E-04	***
bioclim8 ^b	-0.004	8.7E-01				
bioclim7 ^b	0.086	3.7E-01				
bioclim6 ^b	-0.141	1.2E-01				
bioclim4 ^b	-0.004	9.4E-02	.			
bioclim3 ^b	0.200	8.3E-02	.	0.0818	1.4E-04	***
bioclim2 ^b	-0.199	5.1E-02	.			
bioclim1 ^b	0.158	1.9E-01				
Dependent variable	Total N	(%)		Total N	(%)	
Multiple R ²	0.66			0.48		
p-value		1.6E-08	***		4.3E-11	***
RMSE	0.61			0.38		

Sig. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

^a x10000^b x10

Table 4 shows the resulted model from all (22) input parameters could explain 66% of soil nitrogen variation, with the RMSE value is 0.61%. However, only five out of 22 input parameters were significant to the model output, with 95% of confidence interval. Moreover, consecutive MLRA were run by removing the non-significant parameters resulted in only four significant input parameters in the third analysis. The reduced parameters model has lower multiple correlation values (multiple $R^2 = 48\%$) compared to the all parameters model, but having lower RMSE and p-value, i.e., 0.38% and 4.3E-11 respectively. This result shows that comparable output can be produced by using only four parameters input which was generated from two data sets (DEM and temperature).

Table 5. Statistical distribution of soil nitrogen values from soil profiles and from model outputs of all and reduced parameters

Statistics	Soil Profiles	All Parameters	Reduced Parameters
Min.	0.03	0.03	0.06
Max.	3.00	3.87	2.13
1Q	0.14	0.14	0.15
Median	0.21	0.27	0.21
3Q	0.37	0.45	0.46
Mean	0.32	0.46	0.39

Table 6. The statistical summary of the soil carbon and nitrogen raster data generated from the soil models, and its comparison to another published result (Soil C only)

Parameters	Soil C (%)	Soil N (%)	Soil C (%)*
Validation points	15	5	157
Min.	0.32	0.02	0.24
1Q	1.13	0.11	0.95
Median	1.51	1.24	1.18
3Q	4.97	2.29	1.67
Max.	47.75	9.01	7.82
Mean	4.15	1.47	-
RMSE	3.32	0.05	-

*(Minasny, Sulaeman, and Mcbratney 2011)

Furthermore, the resulted PTFs with reduced input parameters then were applied to West Java. The statistical summary of the soil carbon and nitrogen raster data generated from the corresponding soil models, and its corresponding maps, are presented in Table 6 and Figure 2. The statistical summary from Table 6 shows that the RMSE value for soil total carbon model is 3.32%. Although having less soil profile data for validation purposes ($n=15$), but the distribution of the validation points represents the zones with low to high soil total carbon content (Figure 2A). Furthermore, RMSE value for soil total nitrogen model is 0.05. However, this value was calculated based on only five available validation data points which do not represent the overall range of total soil nitrogen (Figure 2B).

Both regression models show that tropical soil carbon and nitrogen variations are correlated with topography, vegetation, temperature, and precipitation gradients, with a coefficient of determination 71% and 66%, respectively. However, the parsimonious models show different significant stressors for both soil carbon and nitrogen.

Previous studies of soil properties in tropical region have shown strong relationship between soil carbon and nitrogen and topographic gradients, in which soil carbon and nitrogen dynamics were mainly driven by different behavior of soil water movement and soil respiration found in different topographic positions (Epron et al. 2006; de Castilho et al. 2006; Spain 1990; Luizão et al. 2004). However, in the case of Puerto Rico site, only elevation variation has a significant correlation with soil carbon and nitrogen. Complex topographic setting resulted from unique soil formation in the mountainous island, especially in the upland area, causing the correlation between soil properties and topographic

gradients in this area are mostly driven by its elevation variations. Furthermore, in the tropical mountainous island, elevation also regulates precipitation and temperature, in which higher rainfall with lower temperature is mostly experienced in the upland area compared to its lowland counterpart (Hijmans et al. 2005).

The result from Table 2 showed that only extreme climatic events have a significant correlation with soil carbon and nitrogen dynamics. Extreme rainfall events significantly correlated with soil carbon variation, in which soil carbon had a positive correlation with precipitation of driest (bioclim14) and wettest months (bioclim13), and negative correlation with precipitation of the driest (bioclim17) and wettest quarters (bioclim16). Moreover, Table 4 showed that soil nitrogen has a significant correlation with temperature dynamics within a year, in which soil nitrogen content had a positive correlation with the mean temperature of the coldest quarter (bioclim11) and isothermally (bioclim3), but having a negative correlation with a mean temperature of driest quarter (bioclim9). This result confirmed previous studies that showed the effect of the magnitude and frequency of rainfall and temperature sensitivity of soil microbial activities to biogeochemical cycle of soil carbon and nitrogen (Austin et al. 2004; Fierer and Schimel 2002; Mikha, Rice, and Milliken 2005; Islam, Khan, and Islam 2015). Furthermore, a low variation of NDVI values from the MODIS images (Table 1), which resulted in no significant correlation with soil carbon and nitrogen variation, suggested that high-resolution vegetation imageries might be able to improve the model results.

Table 4 shows the statistical summary of the raster data of soil carbon and nitrogen, which were generated from the corresponding PTF for West Java region. These

results show that 75% of the region has soil carbon less than 5%, which most of them are located in a lowland area, i.e., northern and southern coast of West Java (Figure 2A). Higher soil carbon is mostly located in the upland area, that is the mid-horizontal region of the West Java (Figure 2A).

Figure 2. Map of soil total carbon (A), nitrogen (B), and CN ratio (C) of West Java, Indonesia, generated from the corresponding PTFs

A recent study of soil carbon dynamics in Java Island showed comparable results of topsoil carbon content, i.e., ranging from 0.24 - 7.82% (the data year 2000-2010), with the majority of the soil sampling data were located on the northern coast of Java (Minasny, Sulaeman, and Mcbratney, 2011) Indonesia, from 1930 to 2010. We used 2002 soil profile observations containing organic carbon (C). Furthermore, the map of soil nitrogen (Figure 2B) also shows a similar trend with soil carbon map, in which 75% of the region has a low percentage of topsoil total nitrogen, i.e., 0.02 – 2.29% (Table 6), which mostly are on the northern coast of West Java. These low values are related to the higher mean temperature of the annual driest quarter in lowland area which has a negative correlation with the percentage of topsoil total nitrogen (bioclim9 variable in Table 4). Furthermore, the ratio between soil carbon and nitrogen contents is depicted in the CN ratio map (Figure 2C), in which higher CN ratio in the northern coast of West Java is mostly due to very low percentage of total soil nitrogen, lower CN ratio in upland area is influenced by higher soil carbon and nitrogen content.

CONCLUSION

PTFs for the tropical region to generate soil carbon, nitrogen, and CN ratio maps in West Java, Indonesia, were generated from soil profiles dataset of Puerto Rico, USA, using multiple linear regression methods. Using 22 input parameters derived from freely accessible climate, topography, and vegetation dataset, the resulted PTF could explain 71% and 66% of soil total carbon and nitrogen variation, respectively. The

comparable result was obtained by using reduced input parameters, using only statistically significant parameters. Soil total carbon variation could be modeled by using five input parameters from DEM and bioclimatic precipitation dataset, including elevation, precipitation of driest month, wettest month, driest quarter and wettest quarter (RMSE = 3.32%), while soil total nitrogen variation was modeled using four input parameters from DEM and bioclimatic temperature dataset, including elevation, mean temperature of coldest quarter, driest quarter, and isothermality (RMSE = 0.05%). The generated maps of soil carbon, nitrogen, and CN ratio of West Java region from the PTFs showed the comparable result with the previous study, suggested this digital soil mapping technique could be used to generate a reliable pre-assessment map to support decision making in land productivity improvement plan to address the food security problem.

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