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Paddy Soils in Tropical Asia

Part 4. Soil Material Classification

by

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As stated earlier in a preceding paper,[1] material characteristics of tropical Asian paddy soils are quite variable from one country to another, and even from one region to another in each country. This variability emerges from the very fact that most paddy soils are alluvial soils. The following two statements are relevant to the consideration of the nature of alluvial soils, and, accordingly, of paddy soils (Kyuma *et al.*[2])

1. Alluvial soils by definition, are those that are not markedly different from the most recent geological sediments laid down in the lowest part of a terrain by fluvial or marine action. As they have undergone little or no pedogenetical changes, no specific morphology has newly developed on their profiles other than that inherited from alluvial sediments. Thus, the nature of alluvial soils is directly governed by the nature of the parent sediments.

2. Variability of soil is by far the greatest in alluvial soils, among all the other soil groups. It is conditioned by the geology and the degree of weathering in the catchment and/or the milieu of sedimentation. At one extreme, fresh volcanic ejecta are laid down in alluvia (e.g., the island of Java), while at the other extreme there are such cases as the 7th Approximation notes where: "Chemically and mineralogically, the materials in an oxic horizon may be indistinguishable from materials at comparable depths in Entisols."[3] It should be further noted that the range of variability is wider in the tropics than in the temperate and cold regions.

In view of the above-stated, the soil material factor is of paramount importance in the classification of soils in alluvial lowlands in the tropics. This is especially true for such cultivated soils as paddy soil, because the soil material factor is directly connected with soil fertility.

In the present U.S. soil classification system,[4] the material factor, in such terms as mineralogy and texture, is used as a differentiating characteristic for the "family" category, and this differentia is carried over to the lowest category, "soil series". In the actual soil classification, however, "family" category is the least elaborated, and the soil material factor is often not taken into proper consideration. In the case of residual soils in uplands,

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the geology or petrology may be conveniently used instead of soil material. But this is not possible for the soils in alluvial lands. Therefore, the significance of the soil material factor in alluvial soil studies is even greater.

This problem must somehow be overcome, otherwise alluvial soil classification even at the lowest category would greatly reduce its value in relation to soil fertility evaluation. In this paper we deal with this problem of soil material classification as the prerequisite for more rational "soil series" separations.

Data and Methods

The data for the plow layer soil of the same 410 samples were used in this study. They were described in Part 1 and 2 and their correlations were analyzed in Part 3 of this series.[5]

In the classification of soil materials both chemical and mechanical characteristics should be taken into consideration. At the same time, for a method to be practically useful the number of data should not be too great. Therefore, we decided to take two sets of data, total chemical composition and mechanical composition.

A short account should be given on the method of total chemical analysis. An X-ray fluorescence spectrographic method proposed by Norrish *et al.*[6] was followed. The standard procedure finally adopted by us was as follows:

1. Ignition of air-dried fine soil (<2 mm) to remove organic matter and to destroy carbonates, followed by pulverization.
2. Fusion of the sample with a flux ($Li_2B_4O_7$-Li_2CO_3-La_2O_3 mixture) to prepare the sample glass.
3. Spectrographic analyses of 9 elements (Si, Fe, Al, Ca, Mg, Mn, Ti, K, P).
4. Calibration and calculation with a computer.

The fusion of the sample and the addition of La_2O_3 seem to have removed practically all the matrix effect and the linearity of the calibration curves was good for all the elements. As the sum of the contents of the 9 oxides usually fell in the range of 97–102%, the contents were recalculated so as to make the sum 100%, neglecting Na and other minor elements.

As given elsewhere,[2] the reproducibility and the precision of this method as compared to the wet-chemical method were satisfactory for the purpose of classification, in which many data are used collectively as a vector. By the fluorescence X-ray method average of 5 to 10 samples per day per person can be analyzed, thus the method can be used routinely for total chemical analysis in soil survey work.

The method of classification may be described under two headings; a) setting up of soil material classes, and b) placing a new sample in one of the classes.

a) Setting-Up of Soil Material Classes.

A numerical taxonomic method proposed by Sokal and Sneath[7] appears to be useful for this purpose. Numerical taxonomy may be defined as "the numerical evaluation of the affinity or similarity between taxonomic units and the ordering of these units into taxa on the basis of their affinities." It was originally proposed for general or natural classification of such objects as plants, insects, microbes, etc. In this study, however, the method is used for creating groups on the basis of similarity of a limited number of characters which are relevant to material features of the soil. The classification aimed at in this study is not the "natural" one, but the more specific or the practical one.

The actual procedure of numerical taxonomy consists of the following steps; 1) standardization of the data to make them dimensionless, 2) computation of between-sample similarity coefficients, 3) sorting or clustering, 4) formulation of a dendrogram.

As stated earlier, two sets of data, total chemical composition and mechanical composition, are used in this study. Since the twelve characters, i.e., contents of 9 elemental oxides and 3 textural separates, are correlated with each other at varying degrees (cf., Table 2 of Part 3[5]), the relative weights given to chemical and mechanical characteristics are not necessarily proportionate to the number of data used. In this condition it should be better to use a fewer number of mutually independent compound characters that can be extracted from the original characters by means of principal component analysis (PCA).*

Starting from the correlation matrix of the 12 characters for the 410 sample soils, principal components were extracted, the eigenvalues and eigenvectors of which are given in Table 1. The eigenvalues of the first 3 components are greater than 1 and the cumulative percentage of eigenvalues for the 3 components is about 70%. In Table 2 correlation coefficients (or factor loadings) between principal components and characters are given together with the communalities for the first 3 components. From the communality figures we can see that the greater part of the information possessed by the original data is represented by the 3 principal components, except in the cases of Silt, TiO_2, K_2O, and P_2O_5.

The first principal component represents the fundamental character of the material as determined by the 3 major elemental oxides, SiO_2, Fe_2O_3, and Al_2O_3, and texture. Alkaline earth bases, MnO_2, TiO_2, and P_2O_5 moderately contribute to this component. A high positive score** is due to clayey texture and/or low silica, high iron and alumina contents; a high negative score would indicate sandy and/or siliceous nature of the material.

The second principal component is related to texture and mineral reserve. A high positive score is expected when a soil contains a high amount of volcanic sands of basic composition, whereas a high negative score is due to a soil derived from silty to clayey sediments containing a high amount of illite and fine micas. But when soil texture is either extremely sandy or clayey and calcium, manganese, potash contents are moderate, the scores are almost solely determined by the texture.

* The method will be briefly explained in a paper to follow.

** Formulae for score computation are given in Appendix 1.

Table 1 Eigenvalues and Eigenvectors for the First Four Principal Components

Principal Component	1	2	3	4
Eigenvalue	4.981	1.737	1.508	0.908
Cumulative % of Total Variance	41.5	56.0	68.6	76.1
Eigenvector				
Sand	−0.338	0.420	0.153	0.230
Silt	0.132	−0.420	0.239	−0.413
Clay	0.325	−0.241	−0.334	−0.017
SiO_2	−0.433	0.002	−0.069	−0.124
Fe_2O_3	0.389	0.186	−0.135	−0.012
Al_2O_3	0.387	−0.179	−0.051	0.173
CaO	0.169	0.349	0.495	−0.301
MgO	0.289	0.108	0.447	−0.111
MnO_2	0.278	0.355	−0.123	−0.230
TiO_2	0.188	0.270	−0.347	0.247
K_2O	0.061	−0.352	0.425	0.597
P_2O_5	0.217	0.256	0.147	0.397

Table 2 Factor Loading Matrix and Communality for the First Three Principal Components

Principal Component	1	2	3	Communality
Sand	−0.754	0.554	0.188	0.910
Silt	0.294	−0.553	0.294	0.479
Clay	0.726	−0.318	−0.410	0.796
SiO_2	−0.965	0.002	−0.085	0.939
Fe_2O_3	0.868	0.245	−0.166	0.840
Al_2O_3	0.864	−0.236	−0.063	0.805
CaO	0.376	0.460	0.608	0.723
MgO	0.644	0.142	0.549	0.737
MnO_2	0.620	0.468	−0.151	0.625
TiO_2	0.419	0.356	−0.426	0.484
K_2O	0.137	−0.465	0.522	0.507
P_2O_5	0.484	0.338	0.180	0.381

The third principal component is mainly related to the base status of the soil. Clay and TiO_2 contents moderately contribute to this component. A high positive score results from high contents of alkaline earth bases and potash especially when clay and TiO_2 contents are low; conversely a high negative score is expected for a soil having high contents of unsaturated (base-poor) clays and/or TiO_2.

As these three principal components are mutually independent and represent different aspects of important material characteristics, such as siliceousness, texture, weatherable mineral reserve, and base status, their scores can be taken as the criteria of soil material classification, assigning each an equal weight. Taxonomic distances between all pairs of the samples were computed by the formula[7)]

$$d_{jk}=\left[\frac{\sum_{i=1}^{p}(x_{ij}-x_{ik})^2}{p}\right]^{1/2}$$

and adopted as the similarity coefficients for numerical taxonomy. In the above formula x_{ij} is the standardized ith principal component score of jth sample; p is the number of variables used, here $p=3$.

The weighted pair-group method is used for clustering, allowing two mutually nearest operational taxonomic units to join in one clustering cycle. The final result of clustering process is illustrated by a dendrogram.

b) Placing a New Sample in One of the Classes.

Based on the dendrogram we can set up soil material classes. Having the classes thus set up, the next step in classification is to place objectively a new sample possessing the required data in one of these classes. Discriminant functions appear to serve this purpose effectively.

For the purpose of illustration of the method let us consider a case of 2 variables and several groups (for detail see Okuno, T. *et al.*[8)]). Suppose a sample point is specified in two-dimensional space, X_1–X_2 plane. A general procedure of discrimination is first to compare the distances from the sample to the gravity centers of the classes (or groups), and then to put the sample into a class at the shortest distance. As a measure of distance, Mahalanobis' generalized distance is used, which is a squared distance in the principal component coordinates. Instead of computing the distances for each sample, a locus of equidistance points from the two groups to be compared is found. If the two groups have an equal variance-covariance matrix, the locus becomes a straight line, and a sample point on one side of the line belongs to the class whose center is on the same side. To simplify the procedure further, the sample point is projected on a straight line perpendicularly crossing the locus of equidistance points. The straight line is generally expressed as $z=a_0+a_1x_1+a_2x_2$, a linear combination of two variables, where a_0 is determined so as to make $z=0$ when x_1 and x_2 represent the points on the locus. The value of z assumes, therefore, a positive or a negative sign depending on which side of the locus the sample point is located. This straight line z is the discriminant function. If such discriminant functions are derived in advance for all pairs of the classes, classification of a new sample is an easy matter of checking the sign of z for each pair of classes.

Results and Discussions

Due to the restriction of the computer program of numerical taxonomy 50% of the samples were randomly selected by using the "Sample" program in SPSS (Statistical Package for Social Sciences).*

Based on the 3 principal component scores derived from the 12 data of mechanical and total chemical compositions, taxonomic distances were computed for all the pairs of 204 samples. By sorting with the weighted pair-group method a dendrogram as shown schematically in Fig. 1 was prepared.

On the dendrogram a straight line intersecting the distance axis at 0.60 was drawn and the clusters formulated before this threshold value were numbered as I through X in Roman numerals from the top to the bottom of the dendrogram. The value of 0.60 was chosen arbitrarily to produce an appropriate number of clusters. Only in the case of Class IX the

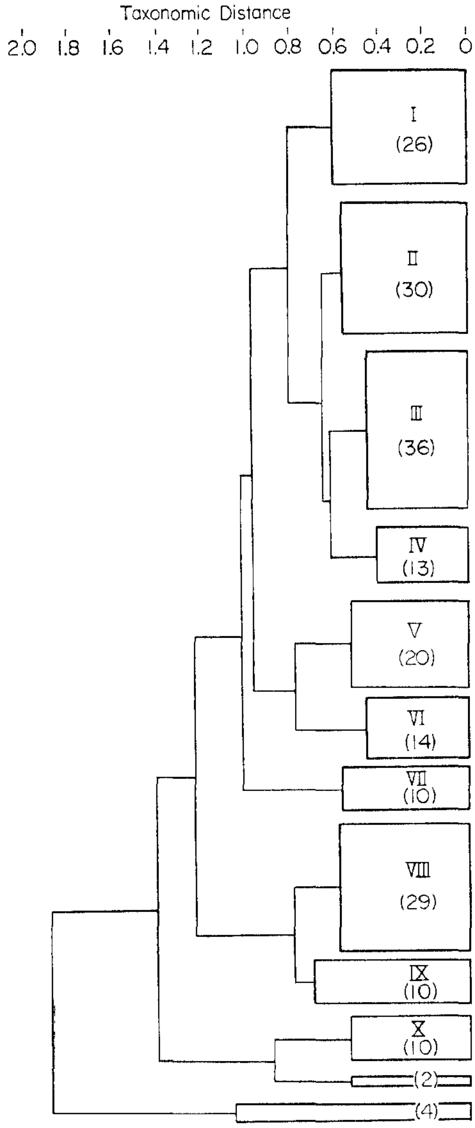

Fig. 1 Schematic Dendrogram Showing the Relation of the 10 Soil Material Classes

* SPSS-Kyoto Version, Data Processing Center of Kyoto University

threshold distance value was shifted to 0.79 to save a group of 10 members and in consideration of the relatively great distance of the group from the adjacent Classes. As six samples appearing at the bottom of the dendrogram were left out of the classes, the number of samples that fell into the 10 Classes was 198.

The means and standard deviations of the 3 principal component scores (PCS) were calculated for each of the 10 Classes, as shown in Table 3. Standard deviations are generally small, indicating a fair homogeneity of the Classes. Only in a few cases does it exceed 0.5, or a half of the standard deviation for the whole sample.

In order to see the basis of differentiation of the 10 Classes, the pattern of the 3 mean scroes are shown in Fig. 2. The characteristics of each group can be described with respect to each of the PCS's, but this will be done later when we have all the 410 samples classified into different Classes.

Having thus established 10 Soil Material Classes, we can now proceed to derive the discriminant functions. In order to derive linear discriminant functions, we have to assume

Table 3 Means and Standard Deviations of the 3 Principal Component Scores for the 10 Soil Material Classes

class	PCS(1)		PCS(2)		PCS(3)	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
I	0.807	0.356	0.126	0.703	−1.029	0.353
II	−0.674	0.354	−0.614	0.365	−0.177	0.514
III	0.402	0.325	−1.204	0.340	−0.021	0.497
IV	0.449	0.376	−0.196	0.243	0.196	0.271
V	−0.385	0.668	0.495	0.401	0.717	0.378
VI	1.283	0.328	0.971	0.402	0.006	0.372
VII	0.648	0.637	−1.025	0.238	1.380	0.270
VIII	−1.946	0.351	0.554	0.465	−0.326	0.254
IX	−0.505	0.335	1.370	0.535	−0.581	0.560
X	0.473	0.416	1.782	0.462	1.693	0.443

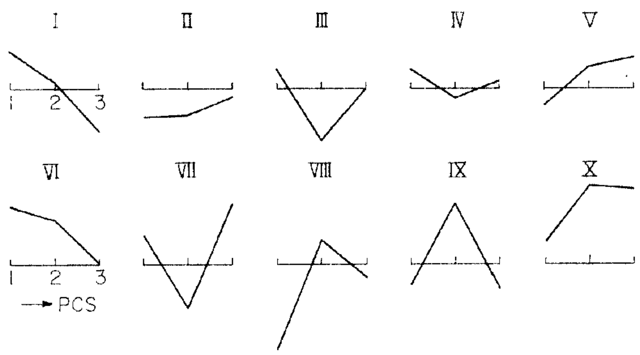

Fig. 2 Patterns of the Mean Principal Component Scores (PCS) for the 10 Soil Material Classes (I∼X)

equality of variance-covariance matrices for the 10 Classes, though usually this assumption is not strictly held.

The coefficients for discriminant function for each of $\binom{10}{2}=45$ pairs and the discriminant efficiency (i.e., the Mahalanobis' distance D^2 between the two groups concerned) are given in Appendix 2. The probability of error, that is, misclassification, can be computed by $E=D/2$, which is compared with a certain probability point of normal distribution; for example, where $E=2.00$, the probability of error is expected to be 2.28%.

The discriminant efficiency is lowest between the Classes III and IV, followed by the ones between IV and V, II and III, and II and IV, the error probability for these pairs being 12.3, 7.6, and 6.6%, respectively. When the same 198 samples that make up the 10 Classes were reclassified by means of the discriminant functions, 22 samples or about 11% of the total were misclassified. Discriminant scroes, however, indicated that many of the misclassification cases occurred right at the margin. Since this much and this kind of errors is invitable in view of the discriminant efficiency, we decide to use the discriminant functions

Table 4 Distribution of the Samples from Each Country among the 10 Soil Material Classes

Soil material class	I	II	III	IV	V	VI	VII	VIII	IX	X	Sum
Bangladesh	1	14	12	0	6	0	18	2	0	0	53
%	1.9	26.4	22.6	0	11.3	0	34.0	3.8	0	0	
Burma	2	1	3	3	4	0	2	0	0	1	16
%	12.5	6.2	18.8	18.8	25.0	0	12.5	0	0	6.2	
Cambodia	4	3	2	0	0	0	0	6	1	0	16
%	25.0	18.8	12.5	0	0	0	0	37.5	6.2	0	
India	7	9	6	8	16	10	4	5	6	2	73
%	9.6	12.3	8.2	11.0	21.9	13.7	5.5	6.8	8.2	2.7	
Indonesia	19	2	0	0	3	14	0	0	0	6	44
%	43.1	4.5	0	0	6.8	31.8	0	0	0	13.6	
Malaysia	0	16	22	0	0	0	0	3	0	0	41
%	0	39.0	53.7	0	0	0	0	7.3	0	0	
Philippines	16	1	1	15	6	3	1	0	3	8	54
%	29.6	1.8	1.8	27.8	11.1	5.6	1.8	0	5.6	14.8	
Sri Lanka	3	1	0	2	6	1	0	4	14	2	33
%	9.1	3.0	0	6.1	18.2	3.0	0	12.1	42.4	6.1	
Thailand	9	21	20	1	1	3	0	24	1	0	80
%	11.2	26.2	25.0	1.2	1.2	3.8	0	30.0	1.2	0	
Sum	61	68	66	29	42	31	25	44	25	19	410

for farther steps.

By means of the discriminant functions all the rest of the soil samples including those unclassified in the dendrogram, were classified into one of the 10 Classes. The result is summarized as in Table 4 which shows the distribution of the samples from each country among the different Classes. The overall distribution of the samples among the Classes is generally parallel with that of the selected samples. The greatest number of samples is concentrated in Class II and III and the smallest number occurs in Class X.

It is known from the table that the number of Classes into which more than 10% of the total samples from each country fall is only 2 in case of Malaysia, 3 in case of Indonesia, and 4 in case of most other countries. The highest concentration is 54% of Malayan soils occurring in Class III, followed by more than 40% in Class I and IX in case of Indonesia and Sri Lanka, respectively. Thus certain regionalities are seen in the characters of soil materials.

The mean mechanical as well as total chemical compositions for the samples falling into each group are given in Table 5 together with the means of such characters related to soil material as pH, percentage base saturation (PBS), CEC, and clay mineralogical composition. Referring to Table 3, 4 and 5 we can characterize each of the 10 Classes as follows:

Table 5 Mean Mechanical and Total Chemical Compositions and Some Other Related Properties of the Samples Belonging to Each Material Class

	I (61)	II (68)	III (66)	IV (29)	V (42)	VI (31)	VII (25)	VIII (44)	IX (25)	X (19)	whole (410)
Sand	12.40	34.43	8.64	21.83	58.72	20.33	18.82	73.78	68.38	54.63	33.81
Silt	22.73	34.05	35.21	33.93	19.84	25.92	49.76	15.54	10.05	25.70	27.60
Clay	64.87	31.52	56.15	44.20	21.43	53.76	31.43	10.68	21.56	19.68	38.59
SiO_2	62.85	80.45	67.40	66.55	73.81	59.00	66.65	94.62	77.55	62.70	72.12
Fe_2O_3	9.90	3.07	5.71	7.69	4.51	11.95	6.71	0.82	5.41	6.89	5.96
Al_2O_3	22.12	12.78	21.53	19.25	14.58	20.98	18.31	3.45	11.87	18.41	16.38
CaO	1.31	0.39	0.46	1.95	2.03	3.22	1.58	0.22	0.98	6.89	1.42
MgO	0.90	0.38	0.94	1.23	0.95	1.57	1.98	0.05	0.68	2.28	0.92
MnO_2	0.22	0.06	0.06	0.18	0.11	0.31	0.10	0.02	0.14	0.16	0.12
TiO_2	1.54	0.99	1.11	1.04	0.86	1.59	0.96	0.64	1.98	0.94	1.14
K_2O	1.04	1.85	2.67	1.96	2.99	1.16	3.59	0.40	1.31	1.49	1.83
P_2O_5	0.12	0.09	0.13	0.15	0.15	0.22	0.13	0.06	0.12	0.24	0.13
pH	6.1	5.3	5.2	6.5	6.8	7.0	6.6	5.3	6.0	6.9	6.0
PBS	94.2	59.1	81.5	100.0	103.2	106.2	98.9	65.0	83.0	105.8	85.6
CEC	31.1	12.3	20.4	26.7	13.9	34.4	15.4	4.2	10.3	15.5	18.6
7Å	43.1	52.4	46.7	32.6	36.8	37.3	32.4	70.1	63.0	29.3*	46.4*
10Å	5.0	19.2	20.9	12.4	20.2	3.9	28.2	5.1	8.2	12.3*	13.9*
14Å	51.9	28.5	32.4	55.0	43.0	58.9	39.4	24.8	28.8	58.4*	39.7*

* As 4 samples falling into Group X have no crystalline minerals, the means were taken for the rest of the samples concerned.

Class I Fine-textured material with moderate base status (some are of pyroclastic origin); 14–7 clay with very little 10 Å minerals.*

Class II Medium-textured material with low base status (typically low humic gley soils on terraces); highly siliceous; 7 Å-clay dominant with moderate 14 and 10 Å minerals.

Class III Fine-textured material with low base status (many are derived from deltaic sediments); slightly siliceous; $MgO > CaO$; 7–14 clay with moderate 10 Å minerals.

Class IV Medium-textured material with high base status (some are of pyroclastic origin); 14–7 clay with little 10 Å minerals.

Class V Coarse-textured material with moderate base status (often occurring on river-levees); moderately siliceous; high potash; 14–7 clay with moderate 10 Å minerals.

Class VI Fine-textured material with high base status (typically calcareous alluvial soils and grumusols; many are of pyroclastic origin); 14–7 clay with very little 10 Å minerals.

Class VII Medium-textured (silty) material with moderate base status (mostly of Ganges-Brahmaputra sediments origin); very high potash; 7–10–14 clay.

Class VIII Very coarse-textured material with very low base status (strongly weathered sandy terrace or plateau materials); very highly siliceous, 7 Å-clay dominant with little 14 Å and very little 10 Å minerals.

Class IX Coarse-textured (low silt) material with low base status (typically local alluvial sediments in acidic rock area); moderately siliceous; 7 Å-clay dominant with moderate 14 Å and very little 10 Å minerals.

Class X Coarse-textured material with high base status (almost exclusively of pyroclastic origin); very high alkaline earth bases; 14–7 clay with little 10 Å minerals or amorphous clay (allophane).

As evident in the above discussions, the material classification established in this study clearly reflects fertility differences among the sample soils. For example, the soils having Class VI material are base-saturated and contain a high amount of better-quality clay. Their mineral nutrient reserves are moderate to high and nutrient holding capacity is also high. On the contrary, the poorest soils are those having Class VIII material, in which nothing but silica is abundant.

We have established in a study yet to be published the correlation between the soil fertility rating and soil material composition in a more quantitative manner. Because of this correlation we can expect that if the soil material classes are set up as the basis of "family" classification, and therefore of "soil series" separation, in the course of soil surveys, the interpretation of the latter would become much easier and its usefulness in relation to the assessment of soil capability greatly enhanced.

* See, Part 2[1], for the way of expressing clay mineralogical composition.

Summary

In view of the importance of soil material characteristics in determining paddy soil capability, a method of classification for soil materials is proposed. Special attention was paid to make it as practically applicable as possible because of the great need for such a method of ready applicability, especially in the alluvial soil areas of tropical Asia.

An X-ray fluorescence spectrographic method for the total chemical analysis of soil materials was proved satisfactory for routine use in terms of accuracy and time. The total chemical nature of soil material was described in terms of nine major elements (Si, Fe, Al, Ca, Mg, Mn, Ti, K, P) analyzed. Total chemical composition and mechanical composition data were subjected to data processing.

To avoid redundance in information, 3 mutually independent principal components were extracted, which appear to represent different aspects of soil material features. From the 3 principal component scores taxonomic distance was computed as a similarity coefficient for use in numerical taxonomy.

By means of numerical taxonomy 10 soil material classes were set up, each of which was characterized in terms of texture, base status, mineral composition, etc. In order to facilitate objective placement of a new sample in one of the classes, discriminant functions were derived for all pairs of the 10 material classes.

The 10 soil material classes appear to represent the major varieties of paddy soil materials in tropical Asia. Since the correlation between the soil fertility rating and the soil material composition has been confirmed, the use of the 10 material classes as the basis of "soil family" separation in soil surveys would improve homogeneity of the lower taxonomic units ("soil series") and make their interpretation easier and more correct in relation to soil capability assessment.

Appendix 1 Formulae for Computation of Principal Component Scores (PCS) for the Use in Soil Material Classification

$$PCS(1)=1/\sqrt{4.98}\times(-0.34X_1+0.13X_2+0.33X_3-0.43X_4+0.39X_5+0.39X_6+0.17X_7+0.29X_8+0.28X_9+0.19X_{10}+0.06X_{11}+0.22X_{12})$$

$$PCS(2)=1/\sqrt{1.74}\times(0.42X_1-0.42X_2-0.24X_3+0.00X_4+0.19X_5-0.18X_6+0.35X_7+0.11X_8+0.36X_9+0.27X_{10}-0.35X_{11}+0.26X_{12})$$

$$PCS(3)=1/\sqrt{1.51}\times(0.15X_1+0.24X_2-0.33X_3-0.07X_4-0.14X_5-0.05X_6+0.50X_7+0.45X_8-0.12X_9-0.35X_{10}+0.43X_{11}+0.15X_{12})$$

where

$X_1=(x_1-33.88)/25.99$	$X_2=(x_2-27.67)/13.66$
$X_3=(x_3-38.44)/21.65$	$X_4=(x_4-72.13)/11.49$
$X_5=(x_5-5.96)/3.73$	$X_6=(x_6-16.38)/6.97$
$X_7=(x_7-1.42)/1.96$	$X_8=(x_8-0.92)/0.77$
$X_9=(x_9-0.13)/0.12$	$X_{10}=(x_{10}-1.15)/0.60$
$X_{11}=(x_{11}-1.83)/1.27$	$X_{12}=(x_{12}-0.13)/0.08$

x_1-x_{12} are the original variables used for extracting the principal components (cf., Table 1, for the variable numbers).

Appendix 2 Coefficients and Discriminant Efficiency (D.E.) of the Discriminant Function for Each Pair of the 10 Soil Material Classes

	I～II	I～III	I～IV	I～V	I～VI	I～VII	I～VIII	I～IX	I～X
a_0	−2.698	−0.949	−4.281	−2.513	2.158	4.421	7.207	1.404	12.028
a_1	8.764	2.390	2.118	7.059	−2.813	0.940	16.294	7.768	1.984
a_2	3.738	6.715	1.628	−1.862	−4.265	5.816	−2.165	−6.285	−8.358
a_3	−5.025	−5.947	−7.225	−10.298	−6.101	−14.205	−4.151	−2.643	−16.046
D.E.	20.025	15.888	10.133	27.080	11.257	41.054	48.692	19.190	58.164

	II～III	II～IV	II～V	II～VI	II～VII	II～VIII	II～IX	II～X	III～IV
a_0	1.749	−1.583	0.185	4.856	7.119	9.905	4.102	14.726	−3.332
a_1	−6.374	−6.646	−1.705	−11.576	−7.824	7.530	−0.996	−6.780	−0.272
a_2	2.978	−2.109	−5.599	−8.002	2.078	−5.903	−10.022	−12.095	−5.087
a_3	−0.921	−2.200	−5.272	−1.076	−9.180	0.875	2.383	−11.020	−1.279
D.E.	8.760	9.169	11.418	35.538	25.488	16.600	21.018	57.364	5.415

	III～V	III～VI	III～VII	III～VIII	III～IX	III～X	IV～V	IV～VI	IV～VII
a_0	−1.565	3.107	5.369	8.155	2.352	12.976	1.767	6.439	8.701
a_1	4.669	−5.203	−1.450	13.904	5.378	−0.406	4.942	−4.930	−1.178
a_2	−8.577	−10.980	−0.900	−8.881	−13.000	−15.073	−3.490	−5.893	4.188
a_3	−4.351	−0.154	−8.259	1.796	3.304	−10.099	−3.072	1.124	−6.980
D.E.	21.456	28.462	12.083	48.801	40.185	62.328	8.134	11.202	11.965

	IV～VIII	IV～IX	IV～X	V～VI	V～VII	V～VIII	V～IX	V～X	VI～VII
a_0	11.487	5.684	16.308	4.672	6.934	9.720	3.917	14.541	2.263
a_1	14.176	5.650	−0.133	−9.872	−6.119	9.235	0.709	−5.075	3.753
a_2	−3.793	−7.913	−9.986	−2.403	7.678	−0.303	−4.423	−6.496	10.081
a_3	3.075	4.583	−8.821	4.197	−3.908	6.147	7.655	−5.748	−8.104
D.E.	38.397	21.342	32.951	20.594	20.577	20.838	13.890	18.322	33.634

	VI～VIII	VI～IX	VI～X	VII～VIII	VII～IX	VII～X	VIII～IX	VIII～X	IX～X
a_0	5.049	−0.755	9.869	2.786	−3.017	7.607	−5.803	4.821	10.624
a_1	19.106	10.581	4.797	15.354	6.828	1.044	−8.526	−14.310	−5.784
a_2	2.100	−2.020	−4.093	−7.981	−12.100	−14.173	−4.119	−6.192	−2.073
a_3	1.950	3.458	−9.945	10.055	11.563	−1.841	1.508	−11.895	−13.403
D.E.	63.206	21.748	23.971	69.565	59.515	40.536	16.032	66.222	36.977

Note: A general formula of discriminant function is

$$Z(\mathrm{A}\sim\mathrm{B}) = a_0 + a_1 \cdot \mathrm{PCS}(1) + a_2 \cdot \mathrm{PCS}(2) + a_3 \cdot \mathrm{PCS}(3)$$

where PCS(1)～PCS(3) are the values computed as in Appendix 1.

The model is designed so as that positive Z indicates the sample belonging to class A and negative Z to class B.

References

1. Kawaguchi, K. and Kyuma, K., "Paddy Soils in Tropical Asia, Part 2. Description of Material Characteristics," *Tonan Ajia Kenkyu,* Vol. 12, No. 2, pp. 177–192 (1974).
2. Kyuma, K., Okagawa, N. and Kawaguchi, K., "A Numerical Approach to the Classification of Alluvial Soil Materials," *Trans. 10th Int. Congr. Soil Sci., Moscow,* Vol. VI, pp. 543–551 (1974).
3. Soil Survey Staff, *Soil Classification: A Comprehensive System, 7th Approximation,* USDA, Washington, D. C., 1960.
4. Soil Survey Staff, *Ditto, 1967 Supplement,* USDA, Washington, D. C., 1967.
5. Kawaguchi, K. and Kyuma, K., "Paddy Soils in Tropical Asia, Part 3, Correlation and Regression Analyses of the Soil Data," *Tonan Ajia Kenkyu,* Vol. 13, No. 1, pp. 45–57 (1975).
6. Norrish, K. and Chappel, B. W., "X-ray Fluorescence Spectrography," In Zussman, J. ed. *Physical Method in Determinative Mineralogy,* Academic Press, N. Y., 1967.
7. Sokal, R. R. and Sneath, P. H. A., *Principles of Numerical Taxonomy,* Freeman & Co., San Francisco, 1963.
8. Okuno, T. *et al., Tahenryo Kaisekiho* (*Multivariate Statistical Methods*), Nikka-Giren, Tokyo, 1971.