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Geoderma 101 (2001) 31–48

GEODERMA

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High-resolution continuous soil classification using morphological soil profile descriptions

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Received 6 January 2000; received in revised form 28 June 2000; accepted 6 September 2000

Abstract

Soil grid data were gathered from 156 points in the 30-ha Muizen forest (Ranst, Belgium). At each grid point, soil profiles were examined morphologically by augering to 120-cm depth. In the laboratory, pH(KCl) was determined on samples from every horizon. To allow numerical analyses, all the morphological attributes were given ordinal scores. The analysis consisted of two parts. First, the master horizons were split up into subtypes using Principal Components Analysis and a non-hierarchical clustering technique. This was necessary to overcome the problem of the anisotropy of the soil profiles, which makes it impossible to pool the data of all the horizons and analyse them together. Next, the distinguished horizon subtypes were used as input for the continuous soil profile classification with the 'fuzzy *k*-means with extragrades' algorithm.

Five different soil classes plus an extragrade class were distinguished. The distinguished soil classes exhibited a fair degree of spatial autocorrelation and correlated well with the Belgian Soil Map.

The technique developed ensures the compatibility with national or global soil classification systems based on diagnostic horizons and properties on the one hand and the production of high-resolution soil classes for local use on the other. Furthermore, the developed technique allows reanalysis and optimisation of data from previous surveys. © 2001 Elsevier Science B.V. All rights reserved.

Keywords: Soil morphology; Multivariate statistical analysis; Fuzzy sets; Continuous soil map

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PII: S0016-7061(00)00088-4

1. Introduction

Due to the advancing technology (e.g. GPS), an increasing number of high-resolution data on the spatial distribution of yields, plants, pollutants, etc. is becoming available. However, most of the existing soil maps lack the appropriate level of detail to combine with these data (e.g. Bouma et al., 1999). The soil classes of many of the existing soil maps are defined in terms of only a limited number of attributes and furthermore, they are crisply delineated in the geographic space. The latter ignores the fact that soils are not a definite object but rather an ecological continuum (Burrough et al., 1997; de Gruijter et al., 1997; Duchaufour, 1998). Therefore, although these soil maps are constructed using point observations in the field, the information that can be retrieved from them is at a considerably higher level of aggregation, namely at the level of the mapping units.

Next to this aggregation mismatch (sensu de Gruijter et al., 1997) for certain applications, there is also a changing demand towards soil science. Traditionally, soil classification systems were oriented towards agriculture. However, there is a growing need for soil maps for other (e.g. ecological) applications, which implies that soil classification systems have to become more versatile and flexible (e.g. Klijn and de Waal, 1992; van den Brink et al., 1999). Therefore, soil geography needs a shift towards a new, more effective paradigm to fulfil the increasing demand for specific soil data at the pedon aggregation level or lower (de Gruijter et al., 1997). New paradigms for local soil classification have been proposed by FitzPatrick (1967, 1980, 1993) and by de Gruijter and McBratney (1988) and McBratney and de Gruijter (1992).

FitzPatrick introduced a coordinate system of soil properties to define so-called segments (virtual horizons) in a multidimensional attribute space. Soil horizons are assigned to these segments and subsequently each soil profile is described by means of a soil formula. Finally, soils are classified based on a successive simplification of this formula.

McBratney and de Gruijter (1992) argued that a system of discrete soil classes is not adequate for soil classification and proposed a numerical classification based on fuzzy sets. This technique still exploits the traditional concept of soil classes, but in a thoroughly widened sense (Ameskamp, 1997). Some 30 years ago, the first attempts at the numerical soil classification was made (e.g. Rayner, 1966; Norris, 1971; Moore et al., 1972; Webster and Burrough, 1972a,b). However, it never gained wide acceptance since the numerical taxa derived from local data sets were difficult to relate to soil classes at national and international scales (Burrough et al., 1997). The most important reason for this is the fact that only a few of these studies used the soil horizons as classification units (e.g. Rayner, 1966; Moore et al., 1972), while in soil science, it is widely accepted that diagnostic horizons are the fundamental units of soil classification. Since numerical classification of soils is impeded by the so-called anisotropy of the profiles (not all horizons occur everywhere; sensu Moore et al., 1972), most authors bypassed this problem using soil samples taken at fixed depths (Norris, 1971; Webster and Burrough, 1972a,b; Oliver and Webster, 1987a,b; Theocharopoulos et al., 1997). Furthermore, most of the numerical classification studies used quantitative chemical and physical soil properties, which makes them difficult to apply in the field.

Therefore, the aim of this study is to explore the possibilities of a numerical soil classification system which starts from morphological soil properties and uses soil horizons as the building bricks towards soil profile membership classification. With this classification system an attempt is made to produce high-resolution soil classes, which remain compatible to existing higher order frameworks for soil classification.

The onset of this research was an attempt at explaining detailed distribution patterns of the herbaceous ground flora of the Muizen Forest, Belgium (Verheyen and Hermy, 2000).

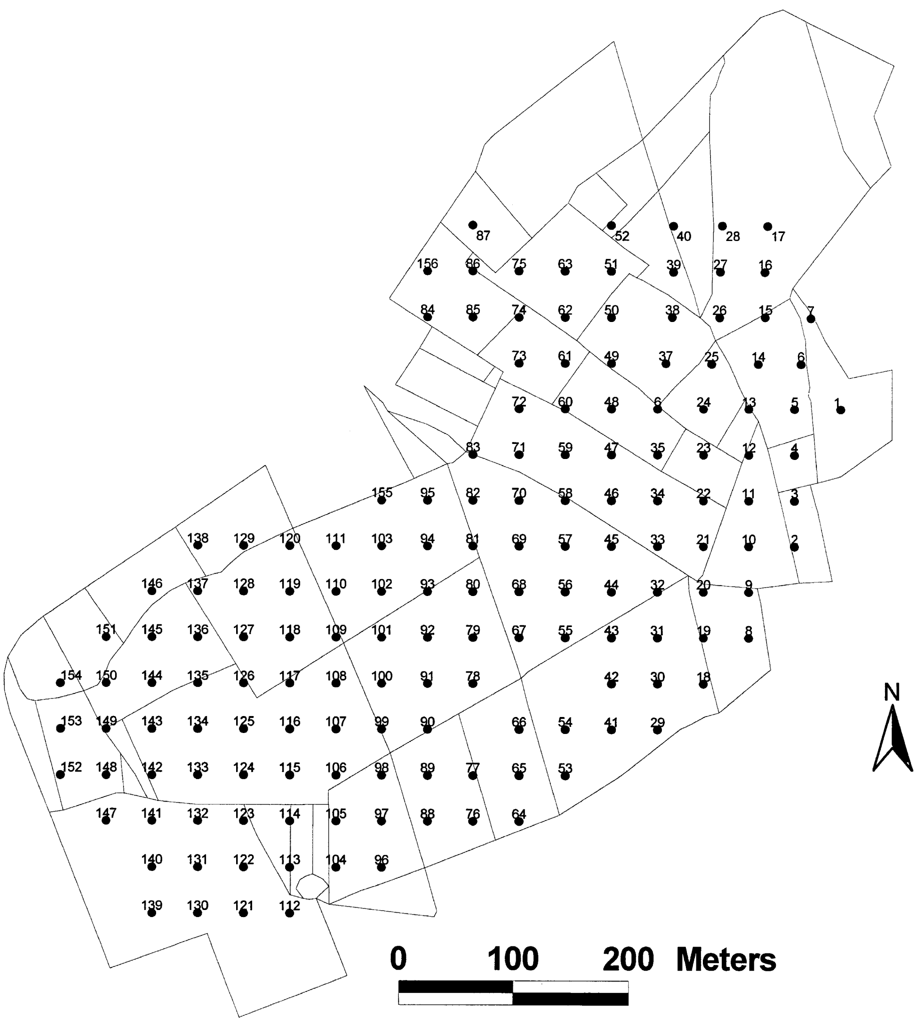

Fig. 1. Map of the Muizen forest and the location of the 156 augerings.

2. Materials and methods

2.1. Study area

The study was carried out in the 30-ha Muizen Forest (Fig. 1), a deciduous forest situated in a flat and low lying (10 m above sea level) region near Antwerp in the north of Belgium. The forest has a complex land-use history. Only its northern part has probably never been deforested. The southern part on the other hand was entirely reclaimed for agriculture during the first half of the 19th century. Due to the poor drainage, most of these fields were soon abandoned and reafforested. However, the drier

Table 1
Sample profile descriptions of the two soil types of the Muizen Forest (Vandamme and Van Hove, 1957)

Gleysol	
Altitude	9 m
Slope and aspect	Level
Land use	Meadow
Soil type	uLep[a] (strongly gleyic, silt loam soils without profile development with a clayey substratum within 80-cm depth)
Horizons	Ap 0–19 cm: silt loam; 10YR 3/2.5; moderate developed crumby structure; very friable; pH(KCl): 6.0; % clay: 11.6
	A–Cg 19–38 cm: heavy silt loam; 10YR 4/2; structureless; very friable; pH(KCl): 5.0; % clay: 13.4
	2C1g 38–60/65 cm: sandy-clay; 5Y 6/3; structureless; very firm; pH(KCl): 4.1; % clay: 24.1
	2C2g 60/65–85 cm: sandy-clay; 5Y 6/1; structureless; slightly sticky, firm; pH(KCl): 4.5; % clay 30.9
	2C3g 85–120 cm: sandy-clay; 5Y 6/1; structureless; slightly sticky, firm; pH(KCl): 4.6; % clay: 30.3
	2C4g 120–150 cm: sandy-clay; 2.5Y 5/0; structureless; sticky, firm; pH(KCl): 5.0; % clay: 18.1
Plaggic anthrosol	
Altitude	9 m
Slope and aspect	Level
Land use	Orchard
Soil type	Pcm[a] (medium dry to medium wet, sandy loam soils with thick, anthropogenic humus A horizon)
Horizons	Ap1 0–28 cm: sandy loam; 10YR 3/3; structureless; very friable; pH(KCl): 5.4; % clay: 5.5
	Ap2 28–70/76 cm: sandy loam; 10YR 4/3; structureless; very friable; pH(KCl): 4.2; % clay: 4.9
	A2 70/76–100 cm: sandy loam; 10YR 5/6; structureless; very friable; pH(KCl): 4.3; % clay: 8.7
	B2g 100–126 cm: clayey sand; structureless; slightly sticky, nonplastic; pH(KCl): 4.5; % clay: 12.3
	Cg 126–150 cm: sandy clay; structureless; slightly sticky, nonplastic; pH(KCl): 4.5; % clay: 20.2

[a] Series according to the Belgian soil classification system (IWONL, 1950).

Table 2
Overview of the attributes recorded for the different horizons and their scores

Variable	Measurement scale	Remarks
1. Horizon thickness (cm)	Continuous	In units of 5 cm
2. pH(KCl-1 M-1:5 suspension)	Continuous	
3. % Ferruginous mottling	0–4	0: none; 1: <2%; 2: 2–20%; 3: 20–50%; 4: >50%
4. Number of subhorizons[a]	0–2	Number of subhorizons distinguished on the basis of the percentage of ferruginous mottling
5. Texture (palpation)	0–4	0: sand; 1: loamy sand; 2: sandy loam; 3: silt loam; 4: sandy clay
6. Consistence (palpation)	0–4	0: loose; 1: very friable; 2: friable; 3: firm; 4: very firm
7. Cohesion grade[b]	0–3	0: no cohesion; 1: weak; 2: moderate; 3: strong
8. Cohesion type[b]	0–2	0: massive or single grain; 1: blocky; 2: crumb
9. Size of the blocks [b,c]	0–2	0: fine; 1: medium; 2: coarse
10. Carbonate content (HCl 10%)	0–3	0: no detectable effervescence; 1: very feeble effervescence; 2: visible effervescence; 3: strong effervescence
11. Value of the dominant colour (Munsell soil chart)	0–3	The Value scores are ranked and 0 is assigned to the minimum value for each horizon (Harden, 1982).
12. Hue of the dominant colour (Munsell soil chart)	0–5	The Hue scores were ranked (10Y/7.5Y/5Y/2.5Y/10YR/7.5YR/5YR/2.5YR) and 0 is assigned to the minimum value for each horizon (Harden, 1982).
13. Chroma of the dominant colour (Munsell soil chart)	0–5	The Chroma scores are ranked and 0 is assigned to the minimum value for each horizon (Harden, 1982).
14. No. of distinct colours within a horizon[a]	1–3	Number of other colours, other than the dominant colour, present in the horizon
15. Rubification (calculated)	0–10	Sum of Hue and Chroma (Harden, 1982)

For the size of the blocks, there is no pedogenetic trend for the C and 2C horizon.

[a]Only for the C and 2C horizons.

[b]Ranked on the basis of the pedogenetic development.

[c]Only for the A horizon.

parcels at the forest margins were only abandoned and reafforested during the second half of the 20th century (De Keersmaeker et al., 1999).

The soils of the Muizen Forest are developed in Quarternary niveo-aeolian sandy loam and silt loam deposits with a sandy-clay layer of Tertiary marine origin at approximately 1-m depth. This substratum has a variable fossil shell lime content. On the Belgian Soil Map (Fig. 7; De Coninck, 1963) the soils of the drier parts were classified as *Pcm* (Belgian soil classification system), which correlate with Plaggic Anthrosols in the World Reference Base of Soil Resources (W.R.B.; FAO et al., 1998). The soils of the wetter parcels were mapped as *uLep* which key out as Gleysols in W.R.B. (FAO et al., 1998). Sample soil profile descriptions are given in Table 1 (Vandamme and Van Hove, 1957). It should be noted that in both profiles the B horizon is absent or only weakly developed. This is due to presence of the sandy-clay substratum that slows down drainage and hence illuviatial accumulation of clay hardly occurs.

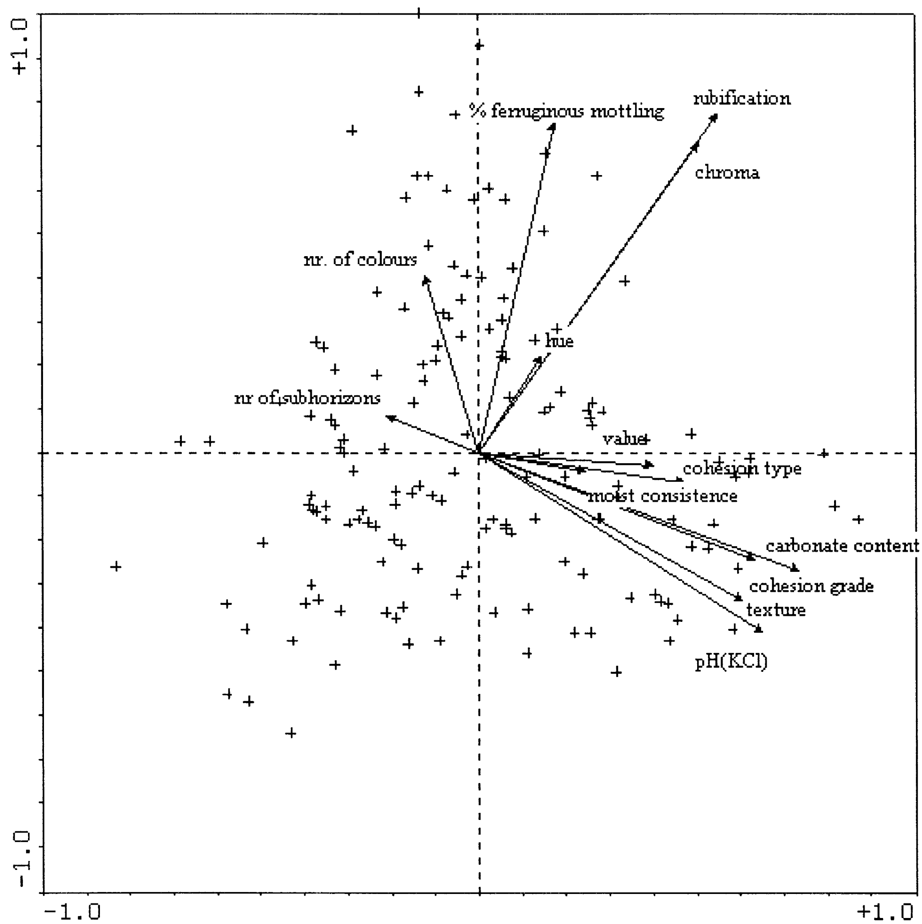

Fig. 2. Biplot of the first two Principal Components of the C1 horizon.

2.2. Data collection

Between the beginning of August and the end of September 1998, data were collected from 156 points on a regular 40 m $\times$ 40 m grid (Fig. 1). At each grid point, soil profiles were examined morphologically by augering with an Edelman auger to 120-cm depth (cf. Bossuyt et al., 1999). The profiles were described using horizons for which 13 attributes (Table 2) were recorded in the field. This was done according to the FAO guidelines for Soil Profile Description (FAO, 1990). Additionaly, the pH(KCl) (1 M, 1:5 suspension) was determined on samples from every horizon in the laboratory and a rubification score was calculated by adding the colour hue and chroma scores (cf. Harden, 1982). Apart from these colour attributes, the other morphological attributes were assigned scores on an ordinal scale too (Table 2).

Nine horizon types were distinguished in the field: A1, A2, A3, A_b(buried), C1, C2, C3, 2C1 and 2C2.

2.3. Data analysis

The analysis consists of two parts: first, the above mentioned horizons were split up into horizon subtypes and next—using these subtypes—the soil profiles were continuously classified.

If anisotropy is absent, which means that all profiles have the same horizons, the first step becomes redundant. In that case, the attribute matrix with 156 (augerings) rows and N (the fixed number of horizons) $\times$ 15 (attributes) columns can be readily analysed using ordination and classification techniques (cf. Theocharopoulos et al., 1997).

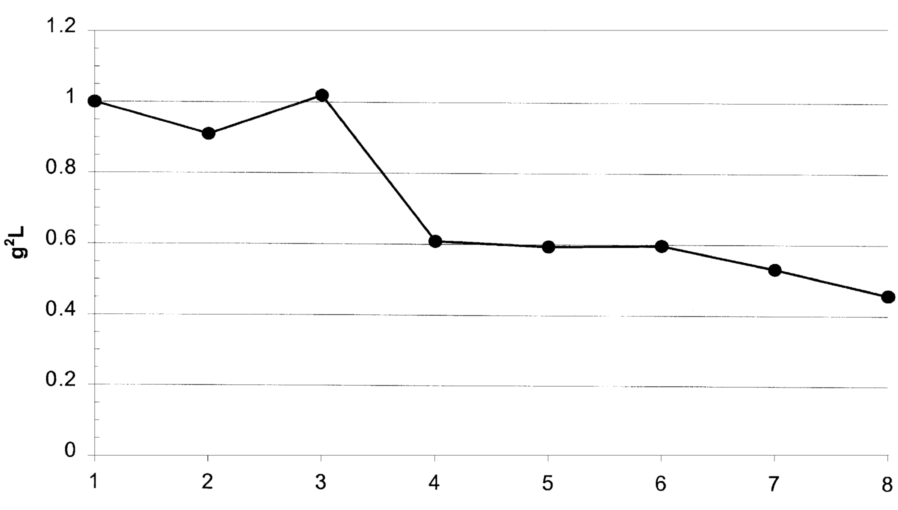

Fig. 3. Plot of g^2L (g is the number of subhorizons and L is the Wilk's criterion) as a funtion of g to determine the optimal number of subhorizons of C1.

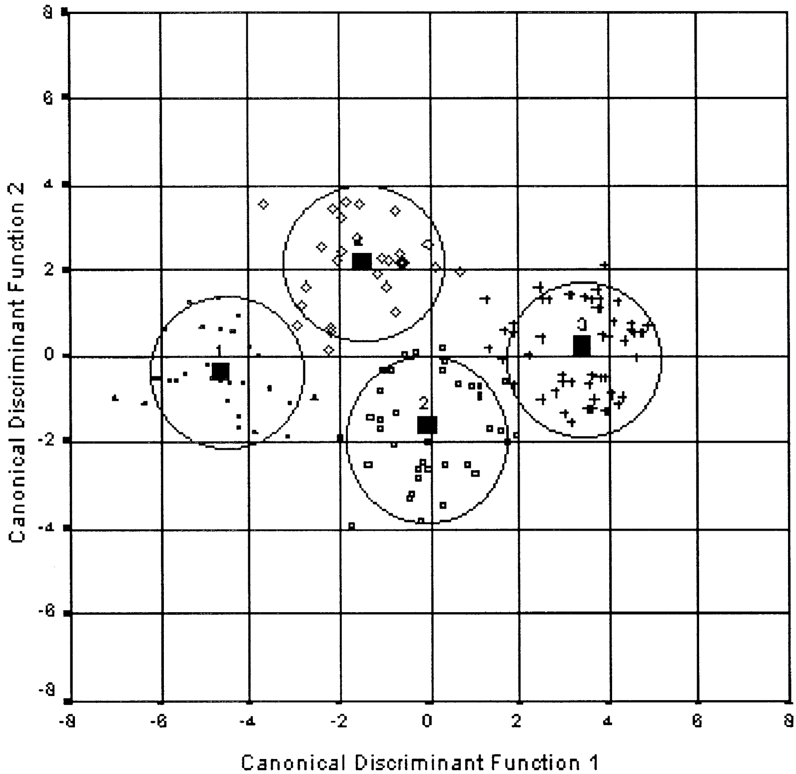

Fig. 4. Scatterplot of the first two discriminant functions for the four C1 subhorizons. The black squares are the group centroids and the circles with radius $r = \sqrt{\chi^2}$ (2 df) enclose the 90% confidence interval.

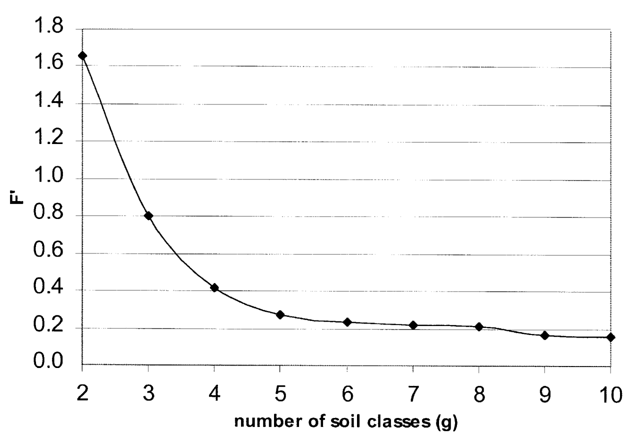

Fig. 5. Plot of the 'fuzziness performance index' (F') as a funtion of g to determine the optimal number of soil classes. The fuzziness exponent (φ) equals 1.3 and the extragrade exponent (α) equals 2×10^{-7}.

However, when not all horizons occur at every location, it is impossible to pool the data of all the horizons and analyse them together. To overcome this problem, the horizons were first split up into more homogeneous horizon subtypes on the basis of their attributes. Subsequently, these horizon subtypes were used to create an augering × horizon subtypes matrix, which is filled with the horizon subtypes thicknesses (in cm) for each augering and 0s if subtypes were absent. This matrix allowed to perform the continuous classification of the soil profiles.

2.3.1. The delineation of horizon subtypes

Only six horizons were split up into more homogeneous subtypes. The A3 ($n=20$), A_b ($n=4$),C3 ($n=10$) and 2C2 ($n=15$) horizons were not split up since there were too few observations.

First, six Principal Component Analyses were performed on the attributes of the horizons using CANOCO 4 (Ter Braak and Smilauer, 1998). To simplify the final interpretation of the distinguished horizon subtypes, it was decided to select only the most important attributes for the deliniation of the subtypes instead of using all the

Table 3
Class centres of the five distinguished soil classes; the horizon sub-type thicknesses are in centimeters

Horizon (sub-)type	Soil class				
	1	2	3	4	5
A1-I	1	0	1	1	1
A1-II	3	3	3	3	2
A1-III	1	1	0	1	0
A1[a]	5	4	4	5	3
A2-I	5	6	17	14	2
A2-II	9	9	3	2	1
A2-III	6	8	5	6	28
A2[a]	20	23	25	22	31
A3	2	3	1	3	7
C1-I	1	4	1	32	2
C1-II	1	7	39	1	1
C1-III	40	10	2	3	2
C1-IV	1	4	1	1	35
C1[a]	43	25	43	37	40
Ab	0	0	1	3	0
C2-I	4	9	3	5	8
C2-II	5	4	1	2	1
C2-III	4	4	4	1	1
C2-IV	2	5	1	6	12
C2[a]	15	22	9	14	22
C3	0	3	0	1	5
2C1-I	0	1	0	9	2
2C1-II	5	3	35	20	3
2C1-III	25	30	1	2	6
2C1[a]	30	34	36	31	11
2C2	4	3	1	3	1

[a] Thickness equals the sum of the distinguished horizon subtypes.

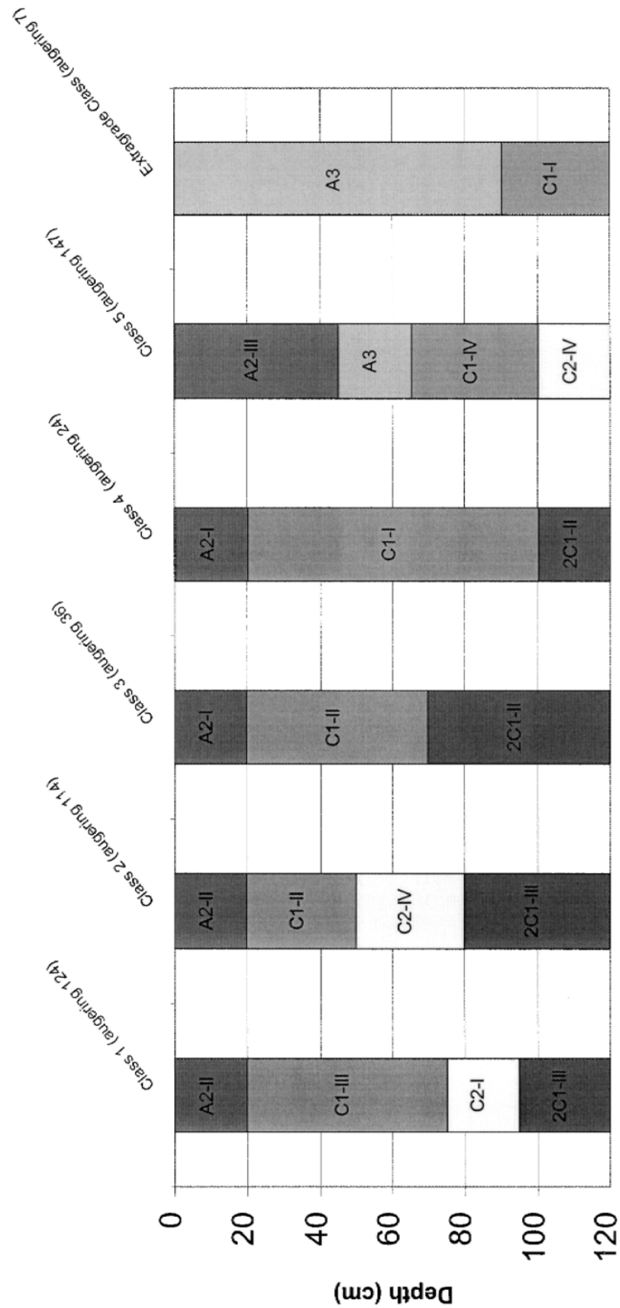

Fig. 6. Exemplars of the five soil classes.

attributes or the principal component scores. When selecting the attributes, it was controlled for that the exclusion of horizon attributes did not significantly alter the configuration of the grid points in the space of the resulting principal axes.

Next, the different horizons were split up into subtypes using the selected attributes. Webster and Oliver (1990) and McBratney and de Gruijter (1992) recommend the use of non-hierarchical clustering techniques for soils. Therefore, it was opted to apply a partitioning method with the Wilk' s criterion (L), which seeks the minimise the determinant of the within group sums of squares matrix. To determine the optimal number of subtypes (g) within each horizon, g^2L was used as criterion: a sudden drop of g^2L in function of g indicates the optimal number of clusters (Marriott, 1971; see also Webster and Burrough, 1972a; Oliver and Webster, 1987a). The clustering was performed with GENSTAT 5/4.1 (1997). To simplify the interpretation of the distinguished horizon subtypes, canonical discriminant functions were calculated for each horizon using SPSS 8.0 (1998).

Finally, the augering $\times$ horizon (sub)type matrix was created, using the distinguished horizon subtypes together with the A3, A_b, C3 and 2C2 horizons and their respective thicknesses. The resulting matrix was sparse (82% 0s), as most horizon subtypes were often absent.

2.3.2. Continuous soil profile classification

Continuous classification was done with the 'fuzzy k-means with extragrades' algorithm (de Gruijter and McBratney, 1988; McBratney and de Gruijter, 1992; de

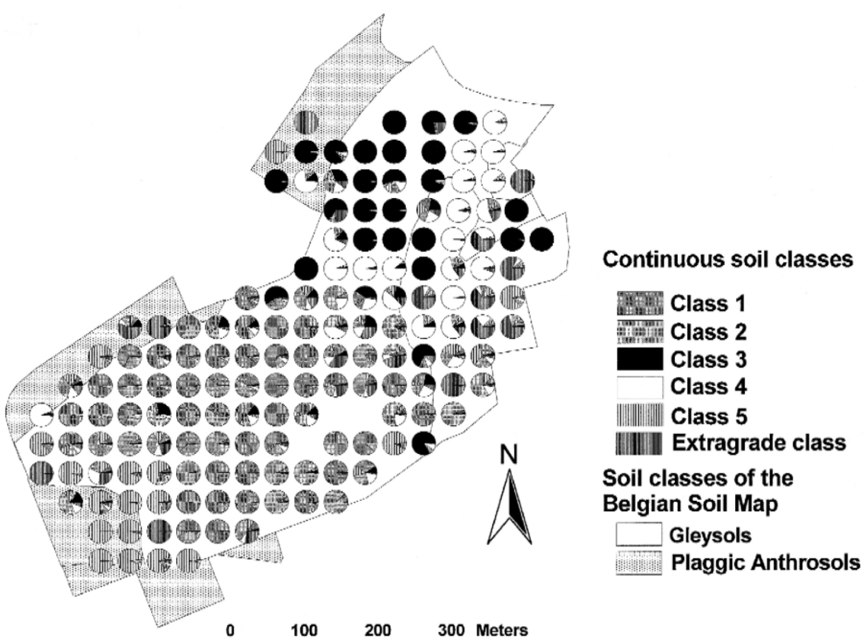

Fig. 7. Geographical representation of the memberships of the five continuous soil classes plus the extragrade class superimposed on the soil classes of the Belgian Soil Map (De Coninck, 1963).

Gruijter et al., 1997) using the FuzME software (ACPA, 1999). The Fuzzy k-means clustering algorithm (Dunn, 1974; Bezdek, 1975) is a generalization of the classical 'hard' k-means clustering algorithm. Later on, de Gruijter and McBratney (1988) extended the 'fuzzy k-means' algorithm to allow dicrimination between 'extragrades' or outliers and 'intergrades'.

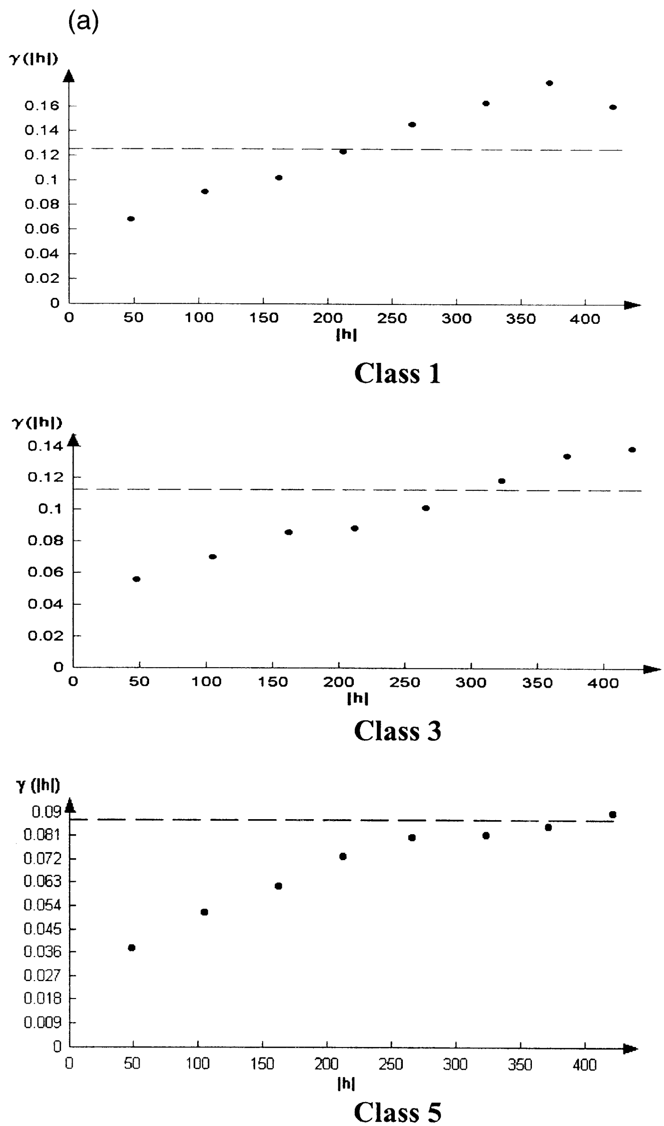

Fig. 8. Omnidirectional semivariograms of the five continuous soil classes plus the extragrade class (lag distances are in meters).

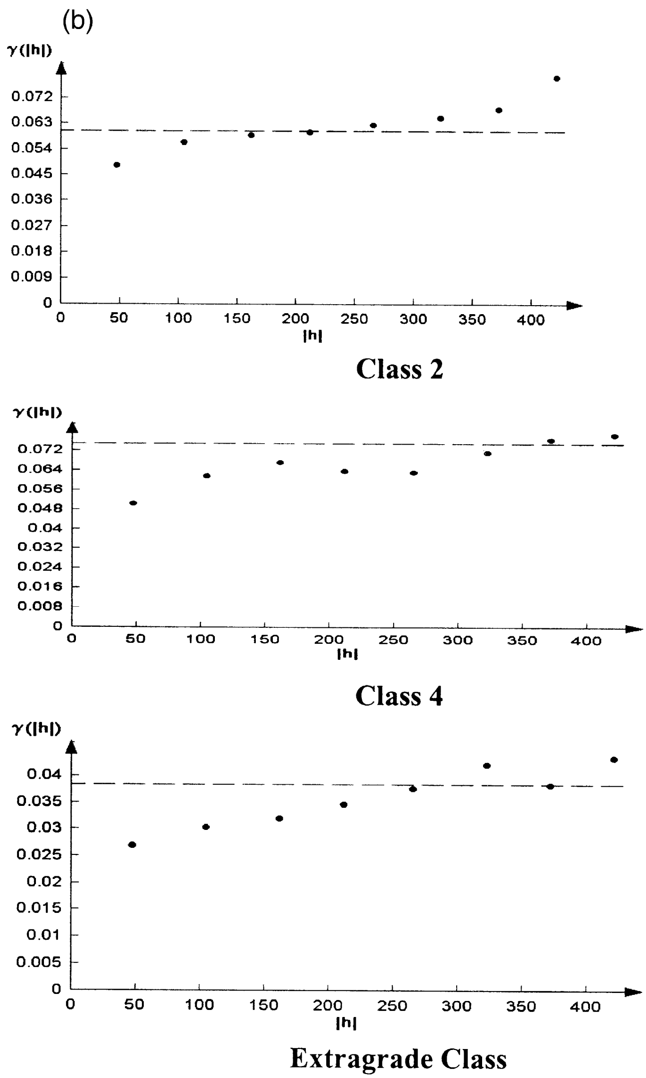

Fig. 8 (*continued*).

The ‘fuzzy k-means with extragrades’ algorithm requires two parameters to be chosen: the fuzziness exponent (φ) and the extragrade exponent (α). For φ, which determines the fuzziness of the output, Odeh et al. (1992) proposed a value between 1.12 and 2 (1 corresponds with the classical ‘hard’ *k*-means clustering). With φ set to 1.3, memberships that were neither too fuzzy nor too hard were obtained. The extragrade exponent determines the outlier or extragrade group. In this case, an alpha value as small as 2×10^{-7} was necessary to obtain an average extragrade membership of $1/(k+1)$, as was proposed by McBratney and de Gruijter (1992).

To determine the optimal number of classes, the ‘fuzziness performance index’ (Odeh et al., 1992) was used.

The results of the continuous classification were plotted on a map and an overlay with the Belgian Soil Map was made using ArcView 3.1 (ESRI, 1998). Finally, to demonstrate the spatial autocorrelation of the distinguished soil classes, omnidirectional semivariograms were computed from the profile memberships. Calculations were done with VARIOWIN (Pannatier, 1996).

3. Results

3.1. The delineation of horizon subtypes

Since the procedure for all the horizons is the same, only the results for the C1 horizon are shown.

Principal components 1 and 2 explain 21.9% and 17.7% of the total variance, respectively. The biplot (Fig. 2) reveals three groups of correlated attributes: a “colour group” with rubification,% ferruginous mottling and chroma; a “pH group” with the pH(KCl); carbonate content; cohesion grade and texture and finally, a lesser important group of colour value and cohesion type. Given this correlation structure, the configuration of the grid points in the space of the first two principal axes was not significantly altered when the rubification, colour value, cohesion grade and pH(KCl) were selected for further analysis.

Marriott’s criterion (Fig. 3) indicated an optimal division in four C1 subtypes. The scatterplot of the canonical discriminant functions (Fig. 4) shows a clear separation of the groups along the two axes. The pH(KCl) on axis one and rubification on axis two appeared to be the most important discriminating attributes:

subtype C1-1 has the lowest pH and a relatively high degree of rubication
subtype C1-2 has a relatively high pH and the lowest degree of rubification
subtype C1-3 has the highest pH and a relatively high degree of rubification
subtype C1-4 has a relatively low pH and the highest degree of rubification.

Similarly, the A1, A2, C2 and 2C1 horizon were split up in three, three, four and three types, respectively. So, together with the A3, Ab, C3 and 2C2 horizons, a total of 21 horizon types and subtypes were distinguished.

3.2. Continuous soil profile classification

The ‘fuzziness performance index’ stabilised between four and five soil classes (Fig. 5). However, a better interpretation of the extragrade class was possible when five continuous soil classes were distinguished. The centres of the five soil classes (Table 3) were calculated as the average of the horizon (sub-)type thickness, weighted by the profile membership to the respective soil class. The five continuous soil classes can be considered as variants of Gleysols (FAO et al., 1998). From Table 3 it appears that the discrimination among the five soil classes is mainly due to differences between the A2, C1 and 2C1 horizons. Since class 2 only differs from class 1 by a more variable C1 horizon, soil class 2 can be regarded as a phase of class 1. Class 1 and its phase differ from class 3, 4 and 5 by their highly variable A2 horizon and their different C1 and 2C1 horizons. Class 3 compared to class 4 has a different C1 horizon and a less variable 2C1 horizon. Finally, class 5 differs from the other classes by a different and thicker A2 horizon, a different C1 horizon and a thin 2C1 horizon. Due to the presence of artefacts (bits of brick and pottery) in the A horizon, this class can be regarded as a Plaggic Gleysol (FAO et al., 1998). Most profiles that were classified as extragrades had a very thick (more than 50 cm) A horizon rich in artefacts. Hence, the extragrade class consists mainly of Plaggic Anthrosols (FAO et al., 1998). In Fig. 6, exemplary profiles of the five classes plus the extragrade class are visualised.

The spatial distribution of the different soil types (Fig. 7) reveals that most of the distinguished soil classes exhibit a fair degree of spatial dependency. This is confirmed by their respective semivariograms (Fig. 8) from which it appears that notably classes 1, 3 and 5 exhibit a high degree of spatial autocorrelation. On the other hand, the phase of class 1, class 4 and the extragrade class are not strongly spatially autocorrelated. For class 4, this is probably due the presence of spatial anisotropy (Fig. 7).

Finally, Fig. 7 also illustrates that the distinction between Plaggic Anthrosols and Gleysols on the Belgian Soil Map coincides relatively well with the distinction between soils with Plaggic properties (class 5 and the extragrade class) and Gleysols in our continuous classification.

4. Discussion

The numerical soil classification system developed can be regarded as a solution for what Duchaufour (1982, pp. 159) called the dilemma of soil classification: there has to be a framework to group the major soil classes of the world but at the same time, soil classification has to provide a means of making large-scale maps for practical purposes, which often necessitates detailed characteristics that are only of local importance. In our study, the fit in existing frameworks for soil classification (in this case the Belgian Soil Classification System and the W.R.B. for Soil Resources) was assured by using horizon types and subtypes to classify the soils. This allowed us to identify both Plaggic Anthrosols and Gleysols as was already done on the Belgian Soil Map. However, at the same time, it was also possible to distinguish five local variants of the latter soil type.

Furthermore, while in most conventional classification systems a choice between the soil properties and their relative importance is made (Duchaufour, 1998), this is not the case with the developed system. The use of numerical techniques allows the selection of those soil properties that maximally account for the in-situ variation of the soils which is of relevance for land use assessment. In this case, the combination of the pH, substratum type, moisture regime and thickness of the A horizon were the most important attributes for the discrimination among the soil classes. Since the distinguished soil classes explain the distribution of the herbaceous woodland flora very well (Verheyen and Hermy, 2000), it can be concluded that a major part of the in situ variation of the Muizen Forest soil is indeed covered by these soil classes.

Finally, evidence for the appropriateness of the applied method comes also from the spatial autocorrelation of the distinguished soil classes. While strong spatial autocorrelation of the soil classes does not necessarily imply the presence of well-defined classes in the attribute space and vice versa (Burrough et al., 1997), spatial autocorrelation does mean that the augerings are not allocated to the classes by chance alone. Furthermore, it suggests that some spatially correlated physical processes caused the differentiation among the soil classes.

Although above-mentioned arguments illustrate the aptness of the applied technique, some remarks are nevertheless warranted.

First of all, it is recognised that the use of morphological attributes like colour variation, consistence, ... derived from augerings may add an additional 'vagueness' to the data set (Burrough, 1989; McBratney and de Gruijter, 1992). However, since morphological descriptions of augerings are cheap and not labour-intensive, it is possible to perform augerings at many locations and, consequently, to maximise detail in the geographical space.

Next, the use of horizons as building bricks towards soil profile membership classification and therefore, the incorporation of the soil profile anisotropy, makes the analysis very complex and consequently, many choices had to be made. For instance, it was decided to use 'crisp' clustering techniques for the delineation of the horizon subtypes, while McBratney (1993) feels it would be more fruitful to have continuous gradation between horizon classes, better reflecting the intergrading nature of soil horizons. However, since the profiles are also continuously classified, this would result in double fuzzy soil classes (e.g. Ameskamp, 1997). Although practically possible and probably conceptually more sound, it would have been very difficult to interpret the double fuzzy soil classes. After all, the ultimate goal of soil classification is to find an optimal compromise between effective soil data structuring and limited loss of detail (de Gruijter et al., 1997).

Finally, concerning the fuzzy clustering algorithm, McBratney and de Gruijter (1992) already pointed out that the choice of the fuzziness and the extragrade exponent, as well as the determination of the optimal number of classes, is rather subjective. Since for the determination of the optimal number of classes one disposes over some objective criteria (Odeh et al., 1992) and for the fuzziness exponent one is guided by common sense (the results may not be too diffuse, neither too discrete), only the choice of the extragrade exponent remains highly subjective.

5. Conclusions

In this paper, the aptness of semi-quantitative morphological soil profile descriptions for numerical soil classification is explored. The use of horizons combined with the delineation of horizon subtypes ensures the compatibility with national or global soil classification systems based on diagnostic horizons and properties on the one hand and the production of high-resolution soil classes for local use on the other. Furthermore, the developed technique allows reanalysis and optimisation of data from previous surveys.

Acknowledgements

The authors thank Roel Van de Moortel for his assistance during the field work and Bea Bossuyt and two referees for their comments on the manuscript. We are also grateful to Alex McBratney, Australian Centre for Precision Agriculture, for putting the FuzME software at our disposal. The paper was written while the first author held a grant from the Flemish Institute for the Encouragement of Scientific and Technological Research (IWT).

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