Heterogeneous farmland owners: two approaches for objective based classification

Eija Pouta
MTT Agrifood Research Finland,
Luutnantintie 13, 00410 Helsinki, FINLAND
e-mail: eija.pouta@mtt.fi

Sami Myyrä
MTT Agrifood Research Finland,
Luutnantintie 13, 00410 Helsinki, FINLAND
e-mail: eija.pouta@mtt.fi

Harri Hänninen
Finnish Forest Research Institute Metla,
Metsäntutkimuslaitos, PL 18, 01301 Vantaa, FINLAND
e-mail: harri.hanninen@metla.fi

Contributed Paper prepared for presentation at the International Association of Agricultural Economists Conference, Beijing, China, August 16-22, 2009

Abstract

Landowner classifications based on their objectives have been used to describe the heterogeneous group of landowners. As the accurate information on landowners preferences is essential in policy planning and evaluation of the effects of various policy instruments, there is a need to develop feasible methods for classifying land owners. In this study we apply objective based classification to farmland owners using the data of Finnish farmland owners. We compare two classification methods, traditional cluster analysis and latent class analysis, in terms of their criterion validity. The comparison of criterion validity, consisting from convergent, concurrent, discriminant and predictive components of validity, revealed that latent class analysis was superior method. The analysis showed that objective grouping of farmland owners was relevant predictor of landowner behavior, and is thus valuable information for agricultural policy makers.

Introduction

Land owners are heterogeneous band of people. In most western countries the diversity of landowners is increasing as primary production, i.e. agriculture and forestry, is decreasing. Many landowners have given up farming; some have left their fields to idle while others have leased them to active farmers. These changes in land use pattern have lead to many problems in both the productivity development of agriculture and in implementing environmental policies (Klemola et al. 2002, Fraser 2004, Myyrä et al. 2005, Lichtenberg 2007). In order to design and implement effective natural resource policies, or tailor extension and marketing services, there is a need to segment land owners according their values and objectives for land ownership.

Landowner classifications based on their objectives have been used particularly in the studies of private non industrial forest owners (Kurtz & Lewis 1981, Marty et al. 1988, Karppinen 1995, Kline et al. 2000a, Kline et al. 2000b, Kendra & Hull 2005, Boon et al. 2004, Ross-Davis & Broussard 2007, Majumdar et al. 2008). The classifications have been used to understand and predict timber selling behaviour (Kuuluvainen et al. 1996) and forest management (Ovaskainen ym. 2006), and reactions to policy alternatives such as protection of forests (Kline et al. 2000a, Kline et al. 2000b). The farmland ownership objectives, beyond farmers, are less studied, and owner classifications based on objectives have been constructed only in few studies (Koontz 2001, Maybery et al. 2005). Although, some classifications exists they have not been used to predict landowner behaviour or responses to policy programs, which would be valuable for increasing efficiency of these policies. From the policy point of view it is particularly valuable to compare how the classifications obtained using different methods relate to the landowner behaviour as the accurate information on landowners preferences is essential in policy planning and evaluation of the effects of various policy instruments. Farm land owners, with their versatile socioeconomic structure and behavioral opportunities, provide a new, virgin and policy relevant field to test the methods of classifying landowners based on their objectives.

The idea in classifying land owners is to define classes that are homogenous but differ from each other. The classification methods have developed in resent years as latent class analysis has established a foothold in applied social research (e.g. Scarpa & Thiene 2005, Ward et al. 2008 Aldrich et al. 2006, Morey et al. 2006). However, the prevailing method in forming landowner classes has been a cluster analysis, whereas applications of latent class analysis have been rare (Table 1).

The latent class method has, as a statistical approach more power than traditional cluster analysis to predict class membership (Magidson & Vermut 2002). The advantages of latent class approach contrast with traditional cluster analysis are more detailed output on predicted behavior and the wider selection of statistical tests available to test the validity of results (Aldrich et al. 2007). The traditional cluster analysis may, nevertheless, be preferred when the groups are identified based upon a large number of variables. In this study the focus is on the evaluation of the classification results of these two different methods based on validity concepts from social sciences.

The first objective of the study is to apply landowner classifications to farmland owners, the landowner group that is less studied. Using the data of Finnish farmland owners we illustrate farmland owner classifications using traditional cluster analysis as well as latent class analysis. The second objective is to compare the two methods in terms of their criterion validity (Trochim 2006).

Table 1. Studies of land owner classifications and

Clustering method	***Study***
Cluster analysis in two phases	Ingemarson et al. 2006
Hierarchical clusterig and K-means clustering	Boon et al. 2004
Latent class method	Meilby & Boon 2004
Principal component analysis	Mayberry et al. 2005
Principal component analysis and Discriminant analysis	Selby et al. 2007
Principal component analysis and Five step cluster analysis (Punj Stewart 1983)	Kendra & Hull 2005
Principal component analysis and K-means clustering	Kuuluvainen et a. 1996 Karppinen 1998a Karppinen 1998b Kline et al. 2000b van Herzele & van Gossum 2008
Q-Technique (Stephenson 1953)	Kurtz & Lewis 1981
Two-step cluster analysis (motivations, soiciodemocraphics)	Ross-Davis & Boussard 2007

Classification approaches

The main focus is on the evaluation of the classification processes based on their results. Before explaining how the performance of the two methods, cluster analysis (CLA) and latent class analysis (LCA), can be evaluated from the classification results, we shortly describe the methods and possible differences in statistical procedures used in classifications.

Cluster analysis

The traditional approach to build homogenous groups of individuals based on their characteristics is cluster analysis. When a large amount of measurement scales is the basis of classification there are two ways to conduct the cluster analysis. First alternative is to use measurement items directly in two-step cluster analysis (e.g. Ross-Davis & Broussard 2007). Alternative approach is to use principal component analysis to summarize the measurement items and then apply component scores in the cluster analysis (K-means cluster) (e.g. Karppinen 1998a, 1998b, Kline et al. 2000, Majumdar 2008) or in the discriminant analysis (e.g. Selby et al. (2007). In this study we used principal component analysis combined with cluster analysis that is more widely used on ownership classifications.

First step in classification is reducing the number of items with principal component method (Hair ym. 2006). It transforms larger set of correlated variables to smaller set of uncorrelated variables i.e. orthogonal principal component scores without losing much information. The first step in the analysis is to select a direction, that collects for the most of the variation (the first principle component), then we define the direction, that collects the second best of the variation and so on. Analysis produces principal component scores that give the location of each observation in the space of common component. These variables are standardized and easily usable for further analysis such as clustering.

In K-means cluster analysis principal component scores are used to classify observations (similar approaches e.g. Karppinen et al. 1998, Kline et al. 2000, Majumdar 2008). The most common form of the algorithm uses an iterative refinement heuristic that starts by classifying the input points into *k* initial sets, either at random or using some heuristic data. It then calculates the mean point, or centroid, of each set. It constructs a new clustering by associating each point with the closest centroid. Then the centroids are recalculated for the new clusters, and algorithm repeated by alternate application of these two steps until convergence. The convergence is obtained when the points no longer switch clusters. In k-means algorithm the number of clusters *k* is an input parameter. Defining the number of clusters is often a subjective decision of researcher based on adequacy and interpretational interest of researcher.

Latent class approach

The idea of the latent class analysis is that behind the observed variables there may exist number of unobserved variables that may indicate the number of subpopulations, each of which having their own distribution of observed variables. In this the assumption is that behind objective measures there are latent objective classes. The goal is by studying observed statements i.e. answers on the questionnaire and individual characteristics to classify people to the classes. The estimation objective is to find response probabilities, i.e. probabilities that individual in a objective class gives a particular response, and unconditional class probabilities i.e. the probability that individual belongs to a objective class, given his / her individual characteristics that best explain the observed responses to the objective statements.

For example in our case, a unconditional class probability is the probability that a land owner living in urban area belongs to a specific objective class. The unconditional probability is not dependent on the responses in objective measures. In this manner all landowners that have similar characteristics have equal unconditional probability of belonging to a particular objective class. After estimating unconditional probabilities the conditional probabilities that landowner belongs to a objective class are calculated based on their responses to objective measures.

The probabilities are estimated by maximizing the likelihood function in the state of incomplete prior information of class membership or response probabilities (Arcidiacono and Jones 2003). In estimation unobserved information is replaced with its expected value and thereafter the maximum likelihood estimation is done as they where correct. The estimation results could then be used as to update the original expectations. This process is continued until the change in the log-likelihood function becomes very small. The estimation is done by assuming one class, then two classes, three classes and so on. On each step the explanatory power of the model is assessed to decide the optimal number of classes. For this purpose we used BIC and AIC information criteria that are log-likelihood scores with correction factors for number of observations and number of parameters.

Evaluation of classifications based on criterion validity comparisons

We evaluate the two owner classification methods utilizing the concept of criterion validity. In this study we use the approach of Trochim (2006) in which the criterion validity is described with several aspects, convergent, concurrent, discriminant and predictive validity, that are more easily assessed than the concept itself.

The *convergent validity* examines the degree to which the operationalization is similar to (converges on) other theoretically justified operationalizations. In the case of grouping landowners based on their objectives the question of interest is the similarity of different classifications. In our case the test is does the latent class analysis produce similar classifications as cluster analysis. We were also interested to see how these classifications might differ in terms of interpretation of the classes.

The second part of the criterion validity is concurrent validity. The *concurrent validity*, assesses the classifications ability to distinguish between groups that it should theoretically be able to distinguish between. In our case concurrent validity is crucial as the classes in landowner classification should be different from each other. This ability of the classification method to clearly separate groups includes two aspects: first, the intra-group homogeneity and the extra-group heterogeneity. This is especially interesting, because CLA concentrates on minimizing intra-group variance and solution in LCA is pinned from extra-croup heterogeneity. The classification method should produce landowner groups that differ from each other with regard to the original objective measures. However, each group itself should be as coherent as possible.

In *discriminant validity*, we examine the degree to which the operationalization diverges from other operationalizations that it theoretically should differe. In the case of land owner classifications, the landowner classification for one socioeconomic group or one region be different than the classification for other socioeconomic group or for other part of the country. In *predictive validity*, the classifications ability to predict something it should theoretically be able to predict is assessed. A strong association and logical causality between the variables of interest would provide evidence for predictive validity. In our case a landowner objective class should theoretically be associated with landowner behaviour.

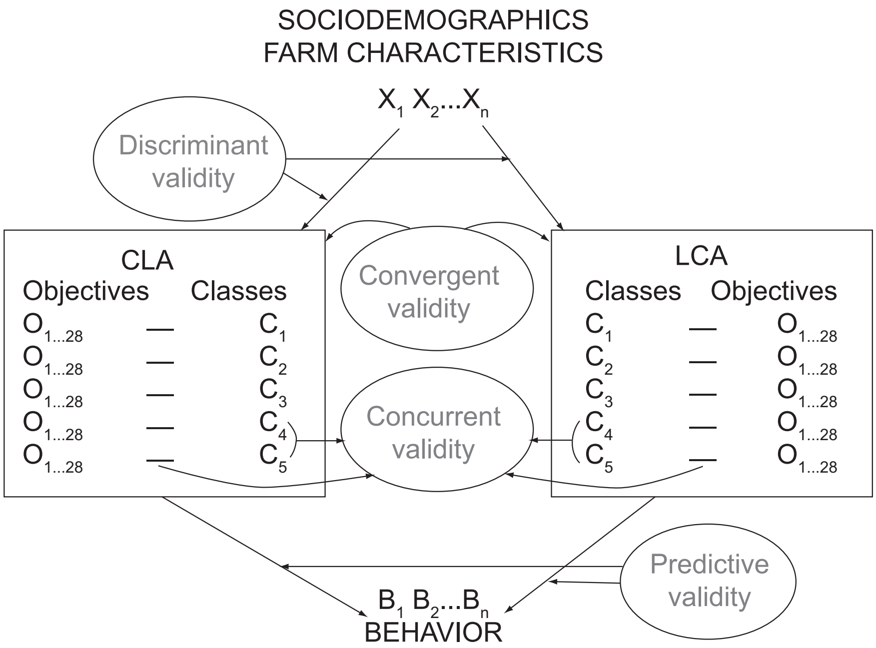

Figure 1. The approach of the study to evaluate the criterion validity of owner classifications.

Data and analysis

Sample and survey procedure

The sample of land owners, covering active farmers and passive land owners, was selected from the register of tax administration. Mail survey was used to acquire data on land owners' objectives and behaviour. A survey was mailed out to the sample of 5 762 land owners. To guarantee a sufficient response rate, we used modification of Dillman's (Dillman 1978) total design method, including a reminder post card and re-mailing of the questionnaire. The mail survey yielded a total of 2 684 observations corresponding 47% from the sample. In addition to mail survey data the information from the register of agricultural taxation and income taxation was available for the respondents. In the comparison to population of farmland owners the data corresponded the population of farmland owners quite well.

The measurement

The land owner objectives for their landownership were measured with a 28 separate items in a five point scale from extremely important to totally irrelevant. The items were developed based on land owner objective items used in forest owner studies in Finland (e.g. Kuuluvainen et al.

1996, Karppinen 1998). The items related only to forests were removed and some new agricultural land related items were added. The items were related to leisure and recreation (5 items), to production and income (4 items), to nature and landscape (5 items), to economic security (5 items), to tradition and social values (7 items) and to economic investment (2 items). Also several variables related to landowner past and future choices, such as land use decisions, participation in environmental programs and participation in farmland improvements were measured in the survey. In addition to landowner objectives and behaviour, the questionnaire included information of farmland owners' socioeconomic background and information of farm property.

Statistical analysis

First step in the analysis was to conduct the land owner classifications with both cluster analysis and latent class analysis approaches. To avoid subjectivity in the various steps of statistical analysis the same dataset and scaling was used in both analyses. The methods we selected for comparison were the most commonly used way of classifying land owners: principal component analysis of objective measures and cluster analysis of principal components, and latent class analysis with socioeconomic covariates. As the CLA method involves the construction of principal components from objective variables, the objective variables are used as such in LCA with socioeconomic covariates.

After conducting the classifications the second step was to compare their criterion validity statistically. The first component of the criterion validity, the convergent validity was examined with contingency table of the two classifications. In contingency tables the association of the two classifications were tested with chi square test. The second component, the concurrent validity was evaluated with two analyses. The intra-group homogeneity was analysed with the standard deviation of original objective measures inside a class. The 28 inside class standard deviations were averaged to obtain the mean standard deviation per class per method.

These were averaged further to obtain a mean per classification method. The heterogeneity of groups within a classification method was tested with analysis of variance. The differences of means per each 28 objective measurement were analysed inside both classification methods and then compared between them.

The third component, discriminant validity, was evaluated with ability of the classification to differ along variation in the socio-demographic and farm variables. This association between background variables and clusters was tested by building multinomial regression models for both classifications and by comparing the goodness of fit of the models and the significance of independent sociodemographic variables between classifications.

The fourth evaluation was the evaluation of the predictive validity. Six behaviours relevant for land owners and measured in the questionnaire, cultivation, selling land, renting land, setting agricultural land aside, participation in environmental measures and participation in farmland improvements, were selected for the analysis. First, the strength of the association between a classification and behaviors were evaluated with contingency tables and Cramers' V statistic. Cramers V expresses the strength of the association with scale from no association (0) to full association (1). The Cramers V's were averaged inside both classification method to get general evaluation. Second approach was building logistic regression model for participation (0 no participation, 1 participation) in six behaviours. In these models classifications with both methods were used as the only independent variable beyond constant. The goodness of fits of the models and the significance of the coefficients of classes were compared between classification methods.

Results

Convergent validity: similarities of classifications

The results of cluster analysis suggest that farmland owners can be divided into five groups based on their objectives for landownership. Also in the latent class analysis we ended up to five classes. Based on the interpretation of the classification from both methods it was plausible to name the landowner groups from the two methods using the same names. The first group was *Agricultural earners* who emphasized objectives that were associated with income, but also with economic security. For *Multiobjective owners* almost all objectives got importance, agricultural income, economic security as well as objectives linked to environment and traditions. *Family oriented owners* emphasized leisure and traditions related objectives. *Passionless amenity owners* valued objectives related to traditions, recreation and nature, however, these objectives were not perceived very strongly among these landowners. None of the objectives were important for *Indifferent owners*.

Both methods classified about 46% of the land owners into the same group (the diagonal in Table 2). Nevertheless, the two methods revealed some differences in group sizes as the cluster analysis produced more equal size groups than the latent class analysis. With latent class method the group sizes varied from 7 % to 30% as with cluster analysis the sizes were from 16% to 22%. The biggest differences (9%) were in the groups of agricultural earners and indifferent owners which both are very policy relevant owner classes. The biggest displacements between the two methods were among agricultural earners and multiobjective owners, but also among family oriented owners and passionless owners.

Table 2. Landowner groups based on latent class analysis (LCA) and cluster analysis (CLA).

LCA	CLA agricultural earners	multi-objective owners	family oriented owners	passionless amenity owners	indifferent owners	Total # (%)
agricultural earners	**254**	178	71	20	29	552 (30)
multiobjective owners	122	**154**	41	7	0	324 (18)
family oriented owners	6	48	**110**	163	1	328 (18)
passionless amenity owners	4	22	141	**204**	137	508 (28)
indifferent owners	0	0	2	3	**121**	126 (7)
Total # (%)	386 (21)	402 (22)	365 (20)	397 (22)	288 (16)	1838
Pearson Chi-Square	1,772E3					
Sig.	0.000					

Concurrent validity: internal homogeneity and external heterogenity

The comparison of results revealed differences in classifications, however these differences do not reveal the superiority of either method. In evaluation of the classifications we were interested did the classifications produce groups that differed significantly from each others with respect the original objective variables. The analysis of variance showed that both methods produced classifications that differed with respect all original objective measures significantly (Table 3). When pared comparisons were included in the analysis some differences were observed. There were all together 28x 10 comparisons in the analysis. From these 280 comparisons between groups, 271 comparisons showed significant difference in the LCA. The CLA results were considerably weaker as number of significantly different comparisons were 56 (20%) lower than in the LCA.

Table 3. Classifications ability to produce different groups in terms of original objective variables.

Measure	CLA	LCA
Objective measures that differ between classes / total number of measure (Analysis of variance F-test, $p<0.01$)	28/28	28/28
Class pares that differ in objective measurements / all class pares (Test for multiple comparisons Tamhane, $p<0.01$)	215/280	271/280

Second approach to evaluate the classifications was to analyse the variation in objective measures inside the classes using the means of the standard deviations of objective measures within each owner group (Table 4). The lower the deviation the more homogenous were the owner groups. Three groups of five were more homogenous in LCA, one group were equally homogenous with both methods and one group were slightly more homogenous with cluster analysis. To receive general evaluation of the homogeneity of clusters these means of deviations were once more averaged over the classes in both methods. These over all averages reveal the advantage of LCA with respect the homogeneity of clusters, even if the target in CLA is to minimize intra-cluster variance.

Table 4. Mean of Standard deviation of objective measures within the clusters and average over the clusters in method.

	CLA	LCA
	Mean of standard deviations of objective measures	
agricultural earners	1.03	1.03
multiobjective owners	0.99	0.84
family oriented owners	1.12	1.01
passionless amenity owners	1.09	1.11
indifferent owners	1.15	0.87
Mean over means	1.07	0.95

Discriminant validity: association with owner and farm characteristics

Next aspect in evaluation was to analyse how well clusters were associated with the variables that they can be hypothesised to be associated with. These variables were landowner sociodemographics and farm characteristics. With the multinomial logit analysis the membership in objective groups was connected to farmland owners' socioeconomic profile particularly on professional status, education and urban-rural dimension (Table 5). Also farm characteristic profiled the groups. These were geographical location and field hectares. Social psychological variables like attitudes toward farm locality and attachment to the place were used in the models.

Based on the goodness of fit statistics we got evidence of higher discriminant validity of LCA based classification, however, this was expected as in LCA the socioeconomic variables were used in classification as covariates (Table 5). The clustering based on LCA was more closely associated with sociodemographic variables as the pseudo R^2's as well as prediction correct statistics were higher. The individual variables were included in the models if significant in either of them. From ten variables all were significantly connected to classification based on CLA. However, there explanation power was still lower than in the LCA where only seven of these variables were significant.

Table 5. Association of classification with socio-demographic variables, goodness of fit of multinomial logit model and significance of individual sociodemographics.

Measures in multinomial logit		**CLA**	**LCA**
Likelihood Ratio Tests for model fit:	Chi square	1040	1218
	significance	0.000	0.000
Pseudo R^2	Cox and Snell	0.423	0.492
	Nagelkerke	0.440	0.517
Prediction correct		41.1 %	48.9 %
Variables in final model and their significance (p-value)			
living on the farm		0.002	0.170
employed		0.000	0.000
pensioner		0.000	0.000
owner type		0.019	0.076
forest entrepreneuer		0.000	0.343
education		0.000	0.000
field area		0.000	0.000
region		0.021	0.000
attachment to community		0.000	0.000
community environment attitude		0.000	0.000

Predictive validity: association with behavioural variables

As the landowner classes based on their objectives are often utilized in modelling landowner behaviour, the most interesting test to evaluate these classifications is to analyse how strongly they were associated with a set of landowner behaviours. The behaviours used in evaluation were decision to cultivate, previous land sales, land rentals, decisions to set aside the agricultural land, participation in environmental measures and participation in farmland improvements. The association were analysed with cross-tabulations and the strength of the association was measured with Cramers V. From these tested landowner behaviours all related significantly to CLA-classification and all except selling behaviour to LCA-classification. The association between behaviours and classifications were in four cases of seven stronger in LCA-classification and in three cases of seven in CLA-classifications (Table 6). Mean of the Cramers V's for both methods gave a general picture for comparison of the classifications. The mean was slightly higher for LCA revealing that the method worked better in forming classifications that were in connection to landowner behaviour.

Table 6. Association between landowner classification to landowner behaviour (cross tabs and Cramers V, all significant).

	CLA	LCA
	Cramers V	
Cultivated	0.488	0.574
Sold	0.084	0.043 NS
Rented	0.377	0.347
Set aside	0.246	0.300
Participation in environmental measures	0.181	0.216
Participation in farmland improvements	0.397	0.418
Mean of Cramers V's	0.30	0.32

Other approach to analyse the classifications ability to explain landowner behaviour was to build logit models of the dichotomous behaviour variables using classes in a dummy form as an only explanatory variables in the model. The interest was to see if the classes were significant explanators of the behaviours and also how high the goodness of fit of the models were with the two classification methods (Table 7). The goodness of fit of the models were in four of the six behaviours higher with LCA-classification and in two of the six behaviours when CLA were used. Higher goodness of fit of LCA based models was visible also in the mean of the R^2's over behavioral models, 0.18 in LCA based models and 0.15 in CLA-models. The only considerable difference in the significance of classes, was in the model explaining land selling behaviour where neither of the LCA-based classes was significant but three of five classes based on CLA were.

Table 7. Classifications ability to predict landowner behaviour, diagnostics from the models where classification as an only exogenous variable.

	CLA		LCA	
	Model R2 (Nagelkerke)	significant classes / all classes (p<0.05)	Model R2 (Nagelkerke)	significant classes / all classes (p<0.05)
Cultivated	0.321	4/5	0.403	5/5
Sold	0.018	3/5	0.005	0/5
Rented	0.188	4/5	0.155	5/5
Set aside	0.137	5/5	0.153	4/5
Participation in environmental measures	0.079	3/5	0.142	3/5
Participation in farmland improvements	0.201	4/5	0.227	4/5
Mean R^2	0.15		0.18	

Discussion and conclusions

This study produced validity comparison of farm landowner classifications between cluster analysis and latent class analysis based on the concept of criterion validity, consisting from convergent, concurrent, discriminant and predictive validity. Generally we can conclude that LCA was better in all validity comparisons. However, there are also other factors affecting the choice of the method, like learning effort of a new method and computationally intensity. Tools for CLA could be found in most of the econometrical or statistical packages. However, the availability of software for LCA has also increased and the current high-speed pc's can easily handle computationally intensive LCA tasks.

CLA as it is conducted with two steps, first principal component analysis of objective measures and then cluster analysis of principal components, provide on all these steps more opportunities for subjective evaluation of the results and opportunities to subjectively affect on final classification. In some occasions the researcher's subjective evaluation may be an advantage.

Analysis showed that farmland owner objective groups were relevant predictor of landowner behavior. This is valuable information for researcher looking for methods to be applied to policy evaluations. The accuracy of targeting the policy programs for the heterogeneous landowner population could be increased especially in EU. Grouping of farmland owner is also a cost efficient way to interpret agricultural policy in US, because transaction costs related to auctioning could be decreased.

References:

Aldrich, G. Grimsrud, K. Thacher, J. & Kotchen, M. 2007. Relating environmental attitudes and contingent values: how robust are methods for identifying preference heterogeneity?, Environmental and Resource Economics 374: 757–775.

Arcidiacono, P. & Jones, J. 2003. Finite Mixture Distributions, Sequential Likelihood and the EM Algorithm. Econometrica 71(3):933-946.

Boon T. E., Meilby H., Thorsen B. & Jellesmark, O. 2004. An empirically based typology of private forest owners in Denmark: Improving communication between authorities and owners. Scandinavian Journal of Forest Research 19, 4: 45-55.

Dillman, D. 1978. Mail and Telephone Surveys: The Total Design Method. New York: John Wiley & Sons.

Fraser, E. 2004. Land tenure and agricultural management: Soil conservation on rented and owned fields in southwest British Columbia. Agricultural and Human Values 21 (1): 73–79.

Hair J.F.Jr., Black, W.C., Babin, B.J., Anderson, R.E. & Tatham, R.L. 2006. Multivariate Data Analysis (sixth ed), Prentice-Hall, Upper Saddle River, NJ.

Hirsch, F., Korotkov, A. & Wilnhammer, M. 2007. Private forest ownership in Europe. Unasylva 2132, 554: 23–25.

Ingmarson, F., Lindhagen, A. & Eriksson, L. 2006. A typology of small-scale private forest owners in Sweden. Scandinavian Journal of Forest Research 21: 249-259.

Karppinen, H. 1998a. Values and objectives of non-industrial private forest owners in Finland. Silva Fennica 32(1): 43-59.

Karppinen, H. 1998b. Objectives of non-industrial private forest owners: differences and future trends in southern and northern Finland. Journal of Forest Economics 4(2): 147-173.

Kendra, A; & Hull, R. B 2005. Motivations and Behaviors of New Forest Owners in Virginia. Forest Science, 51, 2: 142-154.

Klemola, E., J. Karttunen, E. Kaila, K. Laaksonen, & A-M. Kirkkari. 2002. Lohkon koon ja muodon taloudelliset vaikutukset. In English: Economic effects of parcel size and shape. Helsinki: TTS (Work Efficiency Institute) Publications No. 386.

Kline, J.D. Alig, R.J. & Johnson, R.L. 2000a. Forest owner incentives to protect riparian habitat, Ecological. Economics 33: 29–43.

Kline J. D., Alig R. J., & Johnson, R.L. 2000b Fostering the production of nontimber services among forest owners with heterogeneous objectives. Forest Science 46, 2: 302-311.

Koontz, T.M. 2001. Money talks—but to whom? Financial versus non-monetary motivations in land use decisions, Soc. Nat. Resource 14: 51–65.

Kurtz, W.B & Lewis, B.J. 1981. Decision-making framework for nonindustrial private forest owners: an application in the Missouri Ozarks. Journal of Forestry 79(5): 285-288.

Kuuluvainen, J. Karppinen, H. &d Ovaskainen, V. 1996. Landowner objectives and non-industrial private timber supply. Forest Sci. 42, 3: 300–309.

Latacz-Lohmann, U., & C. VanderHamsvoort, 1997. Auctioning conservation contracts: A theoretical analysis and an application. American Journal of Agricultural Economics 79: 407-18.

Lichtenberg, E. 2007. Tenants, Landlords and Soil Conservation. American Journal of Agricultural Economics 89 2: 294–307.

Magidson, J. & Vermut, J. 2002. Latent class model for clustering: a comparison with K-means. Canadian Journal of Marketing Research 20: 37-44.

Majumdar, I., Teeter, L. & Butler, B. 2008. Characterizing Family Forest Owners: A Cluster Analysis Approach. Forest Science, 54, 2: 176-184

Marty TD, Kurtz WB, & Gramann JH. 1988. PNIF owner attitudes in the Midwest: a case study in Missouri and Wisconsin. North J Appl For 5, 3:194–197

Maybery D, Crase L, & Gullifer C. 2005. Categorizing farming values as economic, conservation and lifestyle. Journal of Economic Psychology 26:59–72

Meilby, H. & Boon, T. E. 2004. Comparison of forest owner typologies : based on latent class analysis and cluster analysis: Scandinavian Forest Economics. (in) Proceedings of the biennial meeting of the Scandinavian Society of Forest Economics Vantaa, Finland, 12th-15th may, 2004 / Pajuoja, H.; Karppinen, H. Volume: 40: 179-188.

Morey E., Thacher, J. & Breffle, B. 2006. Using angler characteristics and attitudinal data to identify environmental preference classes: A latent class model. Environmental and Resource Economics 34, 1: 91-115.

Myyrä, S., Ketoja, E. Yli-Halla, M. & Pietola, K. 2005. Land Improvements under Land Tenure Insecurity: The Case of pH and Phosphate in Finland. Land Economics 81, 4: 557–569.

Ovaskainen, V., Hänninen, H., Mikkola, J. & Lehtonen, E. 2006. Cost-sharing and private timber stand improvements: A two-step estimation approach. Forest Science 52, 1: 44-54.

Ross-Davis A.L., & S.R. Broussard. 2007. A Typology of Family Forest Owners in North-Central Indiana. Northern Journal of Applied Forestry 24(4): 282-289.

Scarpa, R. & Thiene, M. 2005. Destination choice models for rock climbing in the Northeastern Alps: A latent-class approach based on intensity of preferences. Land Economics 81, 3:426-444.

Selby, A., Koskela, T. & Petäjistö, L. 2007. Evidence of lay and professional forest-based development discourses in three contrasting regions of Finland. Forest Policy and Economics 9: 633-646.

Stephenson, W. 1953. The study of behavior: Q-Technique and its methodology. University of Chicago Press (Midway reprint). Chicago, Illinois. 376 p.

Trochim, W. M. 2006. The Research Methods Knowledge Base, 2nd Edition. Internet WWW page, at URL: <http://www.socialresearchmethods.net/kb/> (version current as of 20. October 2006).

van Herzele & van Gossum 2008. Typology building for owner-specific policies and communications to advance forest conversion in small pine plantations. Landscape and Urban Planning 87, 3: 201-20

Ward, K.J., Stedman, R.C., Luloff, A.E. Shortle, J.S. & Finley, J.C. 2008. Categorizing Deer Hunters by Typologies Useful to Game Managers: A Latent-Class Model . Society & Natural Resources, 21, 3: 215 – 229.