GIS-BASED AUTOMATED VALUATION MODELS (AVMs) FOR LAND CONSOLIDATION SCHEMES

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Abstract
Land consolidation is a powerful land management planning approach aiming for rural sustainable development. Land reallocation that involves the land tenure restructuring is the most important process in such schemes. The most critical parameter used in land reallocation is land value which in Cyprus is reflected by the market value. The conventional land valuation process is a type of mass appraisal carried out manually and empirically presenting several weaknesses regarding time, costs, transparency, accuracy, reliability and consistency. A solution to these problems is the employment of automated valuation models (AVMs) in the context of a proposed new framework for land valuation. Three models have been used based on linear, non-linear and artificial neural networks (ANN) methods combined with a GIS. Models have been tested for quality assurance based on international standards. Evaluation showed that AVMs are highly efficient compared to the conventional approach. In terms of models performance, ANN ranked first closely followed by the non-linear model and slightly worse the linear model.

Keywords: *Land consolidation, Land valuation, GIS, Automated valuation models (AVMs)*

1. INTRODUCTION

Land consolidation (Pašakarnis and Maliene, 2010) is an established multi-purpose land management and planning approach, which traditionally aims towards the sustainable development of rural areas (FAO, 2003a) with focus in agricultural efficiency. It is widely implemented in EU countries and in several other countries around the world (e.g. in Asia and Africa). The process involves the reconfiguring of space through land reallocation, both in terms of land ownership and land parcels boundaries to eliminate land fragmentation (Van Dijk, 2003). In addition, it provides the necessary infrastructure for rural development, i.e. road and irrigation networks in the case of agricultural-oriented projects. Land reallocation (Demetriou et al., 2012) is the core part of such a scheme, which aims to settle agricultural efficiency, costs of infrastructure, environmental impacts and the landowners' preferences. Land reallocation is based on land value because each landowner should receive after land consolidation a holding with approximately equal land value with that of his/her original property. If this value exceeds the original value, then the landowner must pay the extra cost to the Land Consolidation Corporation and vice-versa. Therefore, land value is a crucial metric in land consolidation (FAO, 2003b) and hence it should represent a reliable, accurate and fair measure so as to increase the acceptance of the land reallocation plan by landowners. This value can be the market value or the agronomic value. In contrast to other countries, the market value is utilized in Cyprus because rural land is attractive to both farmers and non-farmers for different development perspectives.

In Cyprus, land valuation is a mass appraisal process carried out manually and empirically by a five member Land Valuation Committee (LVC). It aims to assign the market value of each land parcel and its contents, i.e. the farmstead, wells, etc., by employing the sales comparison method, which is based on comparison with similar sales transactions that have occurred in the area concerned. Demetriou (2016a) has shown that this manual current procedure presents some weaknesses. In particular, the comparison of land parcel characteristics is mainly a result of an empirical analysis and subjective human judgment, which means the potential presence of inconsistencies across valuators, similar land parcels and the sub-regions of the study area and it is not the outcome of a robust, standardized analysis using appropriate tools such as a GIS. As a result, the process is not fully transparent and can lead to unfairness and bias against landowners. Based on this rationale, FAO (2002) emphasizes that the most important element of land valuation is not the method employed itself, but the method(s) of analysis utilized for estimating the scores of valuation factors involved. In other words, if analysis is reliable and accurate (e.g. through GIS spatial analysis), then it will positively influence the outcomes, irrespectively the valuation method used. Moreover, the process is not systematic because it does not involve a standard set of well-defined steps to reach the outcome and it does not rely on recognizing international or national standards. Furthermore, inevitably, the current process is time consuming, hence costly, because it is carried out manually and the LVC physically inspects parcel by parcel that may count some hundreds or more than one thousand for some study areas, suggesting that the process may take several weeks. Although the noted problems are occurred in other countries as well and they are recognized by land consolidation practitioners, the existing research work towards addressing those weaknesses is very rare (e.g. Yomralioglu et al., 2007) and it is focused on urban land consolidation schemes where the land value is represented by non-monetary terms. Similarly, although there is a huge literature about real estate for residential properties (houses, apartments and urban plots) it is very limited that focusing on agricultural land (e.g. Bastian et al., 2002; Madureira et al., 2007; Martinelli, 2014).

In order to tackle the noted deficiencies, Demetriou (2016a) has proposed a GIS-based new framework for land valuation in land consolidation schemes using automated valuation models (AVMs). AVMs (Downie and Robson, 2007; Schulz et al., 2013) are mathematically-based computer software programs employed in mass appraisal (e.g. Kilpatrick, 2011; IAAO, 2013a) that are able to estimate the market value of various types of properties based on market analysis and the attributes of properties (IAAO, 2003). The core process in developing an AVM is calibration that involves the testing of model structure and estimation of variable coefficients/parameters until statistical model performance indices are acceptable. Calibration is carried out by employing statistical techniques such as multiple regression analysis (MRA) (which is the most traditional) and newer methods as well, such as artificial neural networks (ANN) (e.g. Warzala et al., 1995; Nguyen, and Cripps, 2001; Kontrimas and Verikas, 2011) or other methods (e.g. adaptive estimation procedure and time series analysis) (IAAO, 2003). The noted framework has been applied in a case study land consolidation area in Cyprus by developing and evaluating three different calibration methods: a linear and a non-linear hedonic price model (Demetriou, 2016b) and an ANN model (Demetriou, 2016c), all combined with a GIS. Results showed that AVMs are highly efficient compared to the conventional land valuation method since it may considerably reduce time and resources used and provide a better reliability and transparency of the process.

In the light of the above, this paper aims to briefly present the proposed new framework, the three models employed to apply that framework and compare their outputs. Thus, the structure of the rest of the paper involves Section 2 that concisely describes the proposed new land valuation framework followed by an outline of the case study area (Section3). Afterwards, Section 4 provides a reference regarding AVMs and the calibration methods employed and then section 5 reports on results, focusing on the testing and quality assurance metrics for the three models. Eventually, conclusions are summed up in Section 6.

2. THE PROPOSED LAND VALUATION FRAMEWORK

The proposed by Demetriou (2016a) new land valuation framework is shown in Figure 1. The whole process is operationally based in a GIS environment. In particular, the basic input data involve sales transactions for land consolidation areas and the land valuation factors which can be represented by continuous and categorical maps. Both sales and factors data can be managed and explored using appropriate functions available in a GIS e.g. spatial analysis tools. Both data can be used to define a representative sample of land parcels to be manually appraised by the LVC (e.g. 10-20% of the population of parcels) so as to feed the AVMs to predict the land values of the rest of the parcels of a study area concerned. Whether the sample size is adequate or not will be revealed in the model evaluation that follows. AVMs can involve various basic types of land valuation modelling techniques used in real estate such as linear, non-linear regression and artificial neural networks (ANN) that employed in this research. Once the type of AVM is defined, then the three basic modelling steps, i.e. model specification, calibration and evaluation, follow (IAAO, 2013b). Peculiarly, model specification involves the definition of model type that reflects the valuation method i.e. the sales comparison approach (in the case of land consolidation in Cyprus) which in essence is transformed in an additive mathematical formula (hedonic price modelling) (IAAO, 2003). Specification also encompasses the selection of independent variables will be included in the model as predictors of the market value (depended variable). Both tasks are very important in order to develop an effective and accurate model. Calibration is the process of testing model structure to estimate factor coefficients using a different dataset employed in the evaluation. Calibration is carried out by utilizing the statistical technique already selected in the AVM step. In practice, specification and calibration are a common iterative process until statistical model performance indices are acceptable.

After specification and calibration, the model output is provided and model evaluation takes place. Evaluation, i.e. model testing and quality assurance, involves the testing of the model performance with a property sample (called holdout sample) that has not been used before in model calibration to ensure that it meets the acceptable accuracy and reliability standards before its deployment. This process involves various statistical diagnostic tests such as exploratory data analysis e.g. the identification of outliers, normal distribution tests and ratio studies (Sipan et al., 2012) that compare in various ways the actual values against the predicted values of the model. Ratio studies are recognized as powerful tools for evaluating the performance of AVMs based on international standards provided by the International Association of Assessing Officers (IAAO, 2013b). If model evaluation produces acceptable results, then the land valuation map based on land value classification and the associated catalogue (providing information per holding and per landowner) can be prepared. Thereafter, both are subject to the approval of the LVC according to legislation, and which can afterwards proceed to the publication. On the other hand, if the model evaluation is not acceptable, then either the sample size needs to be increased or a different model type and/or model specification should be tried.

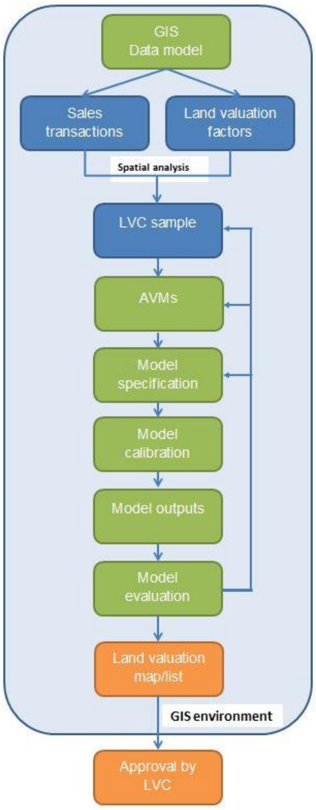

Figure 1. The proposed framework for a new land valuation process in land consolidation areas (Adapted from Demetriou 2016a)

This framework has been applied as a whole (apart from the last step) in a case study area in Cyprus which is described in the sequent section.

3. CASE STUDY AREA

The case study land consolidation area located in the village of Choirokoitia (Figure 2) which is administratively belongs to the District of Larnaca. The land consolidation area is located northwest of the settlement in lowland with few hills and it is included in an agricultural zone covering 266 hectares with 488 land parcels. The land use in this area is mainly citrus, olives, various fruit trees and cereals. Most of the land parcels are dry while others have irrigation via individual wells or from water reservoir connected via a network. The LVC completed land valuation in the study area in February 2009. The lowest value was defined at €2000 while the highest is €35000 per decare (1000 m^2). All the information regarding land valuation has been stored in ArcGIS and for each land parcel has been estimated (using either regular GIS functions or programming routines) a score representing fourteen land valuation factors classified in four categories: physical attributes, locational characteristics, economic conditions and legal factors. In particular, physical attributes involve: size (in square meters), shape (measured using the parcel shape index PSI developed by Demetriou et al., 2013), the mean slope (in percentage), mean elevation from sea level (in meters), aspect (measured clockwise in degrees), existence of a stream (yes or no) and soil type (that involves two geological types A and B). “A” represents Skeletic-calcaric-REGOSOLS/calcaric-lithic-LEPTOSOLS and “B” means calcaric-CAMBISOLS/calcaric–REGOSOLS. Locational characteristics encompass: access through a registered road (yes or no), access through a registered pathway (yes or no), the distance from residential zones (in meters), the distance from the main road (in meters) and the existence of sea view (yes or no). Economic conditions involve one factor, that is, land-use/productivity for the agricultural economic potential of a parcel, reflected by the expected net revenue per decare for various crops. Legal factors involve also only one factor, namely, the existence of irrigation rights (yes or no) for a parcel.

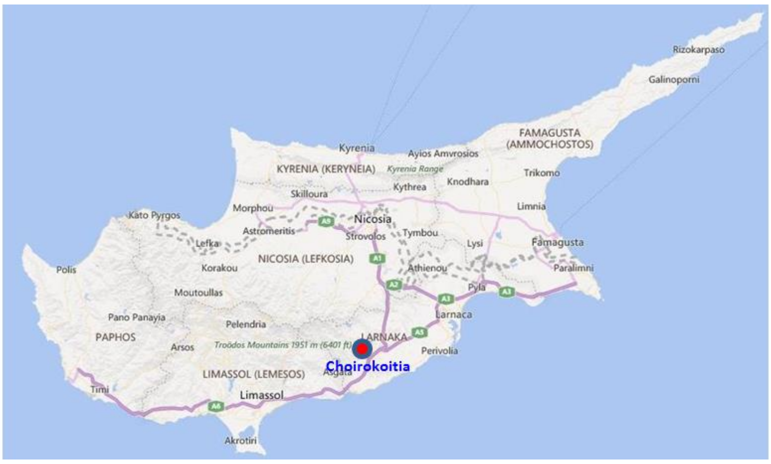

Figure 2. The location of Choirokitia village where is situated the case study area

4. AUTOMATED VALUATION MODELS (AVMS) AND THEIR EVALUATION

AVMs are mathematically based computer software programs used in real estate that are able to estimate the market value of various types of properties based on market analysis of a specified area and the characteristics of a certain group of properties (IAAO, 2003). AVMs that may involve different valuation statistical and mathematical modelling methodologies are employed by the private sector for automated valuation of isolated properties for a variety of purposes (e.g. imposing property taxes by governments, mortgage financing by banks and insurance estimations) and they are applied in a limited number of countries. Especially, AVMs are well established in Australia, Canada, Sweden and USA (Downie and Robson, 2007) and are developing in some other countries (e.g. UK and South Africa). In addition, AVMs are in essence parts of broader systems called Computer Assisted Mass Appraisal (CAMA) (Eckert, 2006; Gallagher et al., 2006) that used for automated mass valuation by public authorities in several countries, including Cyprus (Pashoulis, 2011). Although the advantages of AVMs over the traditional process of land valuation are clear in terms of consistency, objectivity, reduced cost and faster delivery time (IAAO, 2003), critical aspects are: how reliable, accurate and cost-effective is the outcome and the need for updated and accurate data. Furthermore, there is an uncertainty about AVMs outcomes in the case of special socioeconomic conditions in a country such as recession and financial crisis as currently occurred in several countries. Thus, for the development process of AVMs have been defined standards and specifications by the IAAO (2003). The core process in developing AVMs is calibration, which in this research it is carried out by three methods, namely, linear and non-linear MRA and ANN which are outlined below. All the three models have been developed within the IBM SPSS21 software.

Linear multiple regression analysis (MRA) (or hedonic regression modelling) is the oldest statistical calibration methodology has been utilized for estimating property values (Smith, 1971) which is very popular until nowadays (Milla et al., 2005; Eckert, 2006; Schulz et al., 2013). It is well-known that MRA involves the estimations of relationship among a dependent variable (Y) and one or more independent variables (X) and the unknown parameters, denoted as β, which may represent a scalar or a vector, namely expressed as a function $Y \approx f(X, \beta)$. In this study the dependent variable is land value (in Euros per decare) and the independent variables remained in the final model (among the fourteen noted earlier) are: access through a registered road, size, slope, access through a registered path, the existence of irrigation rights and the distance from residential zone. When fitting a regression line, four main assumptions required for testing hypothesis (Norusis, 2005): *normality* of the distribution of each value of the independent variables against the values of the dependent variable, *constant variance* (or homoscedasticity) between the dependent variable and all values of the independent variables, *independence* of observations and, *linearity* of the relationship between the depended variable and all independent variables. Examining the satisfaction of these assumptions is important since many regression tests such significant levels, confidence intervals and others are sensitive to certain types of violations. All the four assumptions can be checked by examining residuals and were met by this model.

In order to enhance the MRA process, new tools and methods were sought mainly from GIS field to involve a spatial analysis component in the process. In particular, efforts to use GIS in valuations appear to have begun with the boom of GIS, i.e. at the beginning of 1990 (e.g. Higgs et al., 1992; Longley et al., 1994; Wyatt, 1997; Zeng and Zhou, 2001; Sipan et al., 2012). Moreover, GIS facilitates the consideration of new concepts such as spatial autocorrelation and spatial heterogeneity (Jahanshiri et al., 2011) which could not be involved in the traditional MRA method. Therefore, modified versions of MRA so as to integrate spatial data have been arisen, such as: Spatial Lag Model (SLM), Spatial Error Model (SEM), General Spatial Model (GSM), Spatial Durbin Model (SDM), Spatial hedonic model and Geographically Weighted Regression (GWR) (Wang and Ready, 2005; Jahanshiri et al., 2011).

Unlike to the linear functions, nonlinear regression can estimate models with arbitrary relationships between independent and dependent variables by employing iterative estimation algorithms. As a result, the process is more demanding than linear MRA, and if the initial values of independent parameters are poor, then the algorithm may not converge or it may converge on a local optimum. Another disadvantage is that variable selection methods are not possible with non-linear functions, and hence many trials are needed to find the best fit. Therefore, in our case, various non-linear function forms were attempted and it was revealed that best fit is provided by a simple exponential form of the linear model: $Y = e^{f(X,\beta)}$. A simple form of an exponential function is almost exclusively used as a shortcut for the natural exponential function e^x where e is Euler's number such that the function is its own derivative. The exponential function is used to model a relationship in which a constant change in the independent variable gives the same proportional change in the dependent variable. The independent variables used in the final model are those used in the linear model.

Further to the regression based methods, the employment of AI methods for valuations began after 1990. In particular, ANNs (Fausett, 1994) have been the most widely used AI technique for valuation during this period (e.g. Kathmann, 1993; Garcia et al., 2008; Kontrimas and Verikas, 2011) as an alternative to the MRA model. ANNs try to loosely simulate the functioning the way human brain cells or natural neurons produce a certain activity, as a reaction to inputs from other brain cells or sense organs and the way that outputs can be transferred through other neurons (Kathmann, 1993). Technically speaking, ANNs are non-conventional computer programs that are typically organized in three layers, i.e. input, hidden and output layers as illustrated in Figure 3. Layers are made up of a number of interconnected 'nodes' which contain an 'activation function'. Patterns are presented to the network via the 'input layer' (that consists of the independent variables noted in rectangles), which communicates to one or more 'hidden layers' where the actual processing is done via a system of weighted 'connections'. The hidden layers, then link to an 'output layer' that provides the predicted land value. ANNs contain some form of 'learning rule' which modifies the weights of the connections (noted within parentheses) according to the input patterns that iteratively change. In essence, ANNs learn by example as they fed new information and process it based on previous training examples.

Input **Hidden** **Output**

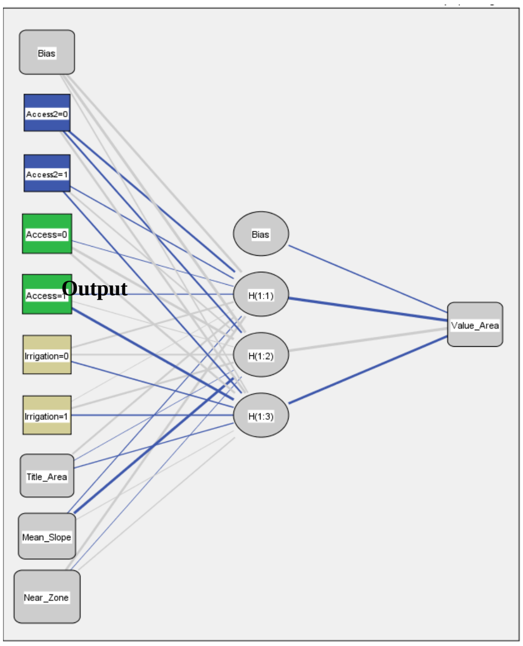

Figure 3. The structure of the ANN employed in this research

After the development of three AVMs the last step involves their evaluation. This process involves the model testing and quality assurance which is carried out using ratio studies and involve four basic measures: (i) appraisal level (mean, median, weighted mean) representing accuracy (ii) variability-uniformity (coefficient of dispersion-COD), reflecting consistency (iii) reliability (confidence interval) and (iv) vertical inequities (price-related differential-PRD, price related bias-PRB), also reflecting both accuracy and consistency. All the acceptable numerical limits of the above metrics, which are noted below, are defined by the international standards (IAAO, 2013b) depending on the type of property.

Especially, appraisal level measures how close are predicted values to real market values by utilizing basic metrics of central tendency. While ideally the perfect appraisal level for any metric is 1.0, an appraisal level between 0.90 and 1.10 is considered acceptable for any type of property. These measures are point estimates reflecting an indication of the appraisal level; hence they need to be combined with confidence intervals providing indicators of the sample statistics. Similarly, variability-uniformity quantifies the dispersion of ratios, hence the smaller the measure the better, but extremely low measures may due to a poor calibration as a result of sales chasing or a non-representative sample. According the standards, the COD acceptable range of vacant land (selected because it is the closest category to agricultural land that is not included in the list) is between 5.0-25.0.

The third measure, i.e. reliability which is represented by the confidence intervals, reflects the degree of confidence can be placed in an estimated statistic for a sample of appraised properties. Especially, the upper and lower limits of a certain measure of central tendency are 0.9-1.0 for a confidence interval 95% for any kind of property. The measure of dispersion i.e. COD is a "horizontal" metric regardless of the value of individual properties. In contrast, vertical inequities provide evidence about the accuracy of appraised individual properties. An index for measuring vertical inequality is called price-related differential (PRD), which is calculated by dividing the mean ratio by the weighted mean ratio and it should be between 0.98 and 1.03 Measures significantly above 1.0 show regressivity i.e. low-value properties are appraised at a greater percentage market value than high-value properties and; metrics significantly lower than 1.0 suggest a progressivity, that is, low-value properties are appraised at smaller percentages of market value than high-value properties. Furthermore, IAAO (2013b) suggests carrying out a statistical test for price related bias (PRB) as well, because it provides a more meaningful and easily interpreted index than PRD. When PRBs scores with 95% confidence interval fall outside the range of -0.10 to +0.10, indicate unacceptable vertical inequities. In addition to the above metrics included in the ratio studies standards, they have been also used the root mean squared error (RMSE) and the mean absolute percentage error (MAPE) which are widely used (Ahn et al., 2012; Schulz et al., 2013). The former measures the discrepancies between the predicted values and the actual observations whilst the latter measures scaled discrepancies. Furthermore, it has been used in evaluation the forecasting error (FE) introduced by Nguyen and Cripps (2001), that measures how many land parcels from the whole population have been assigned a predicted value that differs compared to the market value, less than a certain percentage (e.g. 10-20%).

5. RESULTS

The detailed analysis and discussion of the outputs of the linear/non-linear models and the ANN is provided by Demetriou (2016b and 2016c), respectively. Models ran using three different stratified samples of 10%, 15% and 20% of the population of land parcels included in the study area. Both papers showed that a sample of 15% is the most efficient because it produces significantly better results than the 10% sample and very similar outputs with those produced by the 20% sample with much less effort. Thus, Table 1 summarizes the quality assurance metrics for the three models for the 15% sample. Results show that all the appraisal level statistics, that is, the three main measures of central tendency the mean, median and the weighted mean of ratios for all models are within the acceptable standards (i.e. between 0.9 and 1.10) revealing that predicted land values are quite close to those defined by the LVC. The best appraisal level resulted from the ANN model with a value very close to 1.0 while the linear and non-linear models present very similar values, slightly higher, than those of the ANN. A stronger relevant indication is the estimation of appraisal levels based on 95% confidence interval to determine whether it can be reasonably concluded that they differ from the established performance standards in a particular instance. Thus, based on the calculated scores that fall within the range 0.9-1.10 for all three models, the relevant standard has been met suggesting reliability evidence.

In addition, the coefficient of dispersion-COD is best for the ANN followed closely by the non-linear model and slightly increased in the linear model. It is remarkable that all metrics are very far from the highest acceptable value i.e. 25. Furthermore, the price-related differential-PRD is the same for all three models which is close to the best i.e. 1.0 and within the acceptable range 0.98-1.03, although is closer to the maximum limit. This potentially shows a slight regressive tend i.e. low-value properties are appraised at a greater percentages market value than high-value properties. Similarly, the estimated price related bias-PRB is around -0.08 for all models that is, within the acceptable limits i.e. -0.10 to 0.10, showing a trend towards the lower limit. Therefore, PRB shows that for 95% confidence interval, assessment levels do not change by more than 10% when values are halved or doubled. Also, RMSE and MAPE are both the best for the ANN model followed by the non-linear and then the linear model with a difference between best and worst from 5-10%. The maximum FE for 10% i.e. the difference between the predicted and true values is less than 10% for 59% of land parcels as resulted by both non-linear and ANN models with very close result by the linear model (around 57%). Similarly, for around 90% of the predictions, the difference from actual values is less than 20%, which is an acceptable inaccuracy for the purposes of land consolidation. Based on the fact that the required sample for achieving the above accurate and reliable results is 15% (i.e.73 land parcels out of 488 of the whole study area) the LVC could provide this sample in about 5 days compared to the 25 working days took the whole land valuation in terms of site visits, suggesting a time and cost savings around 80%, assuming that the data processing time is roughly similar in both cases.

Table 1. Testing and quality assurance for the three models

Appraisal level					
	Mean	Median	W. mean	RSME	MAPE
Linear	1.059	1.023	1.02	2524.00	12.94
Non-linear	1.06	1.03	1.02	2406.41	12.55
ANN	1.028	1.00	0.99	2398.62	11.71
	Uniformity	**Vertical inequalities**			
	COD	PRD	PRB		
Liner	11.99	1.03	-0.079		
Non-linear	11.57	1.03	-0.08		
ANN	11.38	1.03	-0.07		
Reliability					
	95% c.i. (mean)	95% c.i. (median)	FE<=10%	10%>FE<=20%	FE>20%
Linear	1.03-1.09	0.99-1.05	57.00	30.92	12.08
Non-linear	1.03-1.09	0.99-1.06	58.94	30.43	10.63
ANN	1.00-1.06	0.97-1.04	58.45	29.95	11.59

Further to these time and cost savings, the quality of land valuation is enhanced since the AVM comprises fourteen land valuation factors compared to the LVC that takes into account around six factors, suggesting a more integrated consideration of the aspects involved. It is also interesting noting that the most important factors (based on significance levels) for each model (with a slightly different order in each case) are: the distance from residential zones, slope, size, access through a registered road, access through a pathway, the availability of irrigation and then the other factors follow. In addition, the precise calculation of variable scores through spatial analysis and comparison through modelling process, indicates a consistency that would be difficult to be achieved by the LVC using the traditional method. Moreover, the reliability of outputs, which is checked through international standards, and the potential for an analytical explanation of the outputs through this standardized modelling process, provides transparency, which is required for such planning processes.

6. CONCLUSIONS

This paper showed that the AVMs presented in this research are considerably more efficient in terms of time, costs, reliability, consistency and transparency compared with the traditional empirical process followed by the LVC. Therefore, the authorities involved in land consolidation schemes should consider introducing AVMs combined with the adoption of international appraisal standards and integrate them within the relevant legislation and practices. Also, the combination and even the full integration of these methods within a GIS is currently common best practice for land valuation. In terms of performance, the ANN method ranked best closely followed by the non-linear model and then slightly worse the linear model.

The contribution of this research is both scientific and practical. In terms of the former, it extends the knowledge about an important and still a very limited area of research, i.e. land valuation of agricultural land for a popular and widely implemented in EU planning approach, i.e. land consolidation. Regarding the latter, the models may have practical full implementation in Cyprus and in other countries that use market value in land reallocation. Especially, models are timely very valuable because the current financial crisis rapidly changed land values, hence a revision of land values for several land consolidation schemes is required. Moreover, models may have considerable impact regarding the acceptance of the land consolidation plan by landowners since the empirical process has been transformed in a systemic, analytical and transparent operation.

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