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Introduction

The state of land and building markets is, on a local level, a very sensitive gauge of both short- and long-term economic trends. Indeed, the real-estate market is "where" a multiplicity of economic, cultural, social and demographic factors are synthesised with respect to choices regarding the qualitative and locational aspects of a property (Fanning et al. 1994). This synthesis is strongly conditioned by choices in town planning made by the responsible public official. These may have a decisive influence on the amount and distribution of city revenue and connected real-estate market trends (Camagni 1993). Unlike what happens with other goods, the demand and supply of real estate seems to be strongly conditioned by its geographic position and so cannot be analysed independently of its location [2] .

The spatial analysis of the real-estate market and, in particular, of the factors which contribute to determining prices, is a very useful instrument both in outlining the geography of the economic development of vast areas (Di Pasquale, Wheaton 1995) and in attaining, with great precision, the standardisation of prices for taxation and city planning[3] .

The aim of the present paper is the construction of a simulation model, on a spatial level, of real-estate values with reference to the housing market in the urban area of the city of Treviso (I). The model was built using a neural network which gives one the possibility of analysing the marginal contribution of single real-estate characteristics independently of the a priori choice of the interpolation function; at the same time it works well even in the presence of statistical correlation among the explicative variables, a serious drawback in multiple regression models.

The work is divided into several parts.

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[1] Raimondo Amabile is a phd student in "Appraisal of Real Estate and Urban Economy" at the University of Padua. Paolo Rosato is researcher at the University of Padua.

[2] Besides, the effect of variables of localisation on real-estate market trends has been well known since the beginning of the last century when famous scholars like Von Thunen, starting with the economic use of land, developed value determining models which, with the necessary up-dating, are still very worthwhile. Moreover, the gravitational organisation models of urban areas developed by Hurd and Christaller find important empirical confirmation in the distribution of real-estate values.

[3] In this connection, please remember the last decree for the reformation of fiscal surveys, which leaves the important role of examining the close existing relationship between revenue and value of real estate up to a territorial analysis of the real-estate market.

First, a synthetic picture of the real-estate market of the area studied has been drawn up with reference to the main conditioning factors. This is followed by a brief illustration of the inquiry carried out and of the results obtained with special attention given to extrinsic characteristics, that is those which regard the environmental context in which the real estate is located.

Then the problem of the selection of a neural network model for the appraisal of property values is presented. To this end two different neural network models were tested, MLP (Multi Layer Perceptron) and RBF (Radial Basis Function), both calibrated for the analysis of unitary values as well as for total values.

Finally, there is the description of the procedure for the spatialization of obtained results from the neural model for the definition of a values map. For this purpose, spatial interpolation techniques were used on a database containing the geographic distribution of the environmental characteristics which most influence property values.

1. The main features of the real-estate market in the urban area of Treviso

The territory under inquiry is the urban area pertaining to the city of Treviso, situated in the eastern Veneto plain, 20 km north of Venice, which besides Treviso, includes ten towns from the surrounding belt [4]. The total surface area is of about 110 skm and the total number of inhabitants is 170.000, 47% of which are residents of Treviso (the capital of the province). From the social-economic point of view, Treviso represents the model of development in north-east Italy in its limited size, intense and widespread economic development and its high standard of living.

Research on the real-estate market of the area under study was planned in such a way so as to collect the necessary information to clarify the role of the local context, determined by environmental variables, in a broad sense, in determining real-estate values. To this end we took a sample in a segment of the market which was as homogeneous as possible with regard to variables other than those of location; at the same time, we tried to gather all the elements which condition the protagonists of the market by making reference to direct knowledge of the commercial reality and to the experience of real-estate agents (Shenkel 1978; Simonotti 1988).

As a general reference point, the inquiry assumed the residential housing units located in buildings representative of the prevailing building typology in the territory under consideration and

[4] As regards the city of Treviso, the inquiry only took the area outside the city walls into consideration; this area is characterised by a fluctuating market as far as both supply and demand are concerned, unlike the historic city centre where the supply is not elastic and the demand very steady. The neighbouring towns which were included are: Ponzano Veneto, Villorba, Carbonera, Silea, Casier, Preganziol, Quinto di Treviso.

homogeneous with respect to both intrinsic characteristics of the buildings and to legal-economic features [5] .

The direct method was used by consulting 10 brokers of proven experience and knowledge of the market. The collected data refer to transactions which took place between June and September 1995 and refer to homogeneous market dynamics.

The risk of inaccurate answers was reduced, as much as possible, by guaranteeing anonymity to those interviewed, buyers and sellers. The inquiry monitored nearly 100 transactions and for each a questionnaire containing the most important information on the intrinsic and extrinsic characteristics of the real estate in question was filled out. Greater attention was obviously given to the information that, with good reason, conditions the determining of market prices.

2. The data pre-processing

In order to guarantee accuracy at the information base and, at the same time, to obtain data that could be elaborated with the usual instruments of statistical analysis, quantitative and qualitative information gathered during the inquiry was recodified in continuous explicative dichotomous variables of the collected housing characteristics. The selection of the most explicative variables was done with principal components analysis (Jollife 1986). This analysis began with the sample (98 cases) made up of dimensional 18 vectors representative of housing characteristics and of market prices (see table 1).

At the same time a features extraction was drawn up (Fukunaga 1982; Bishop 1995), starting with the identified main components. The variables associated with the characteristics of each property sold, and taken into consideration for the construction of the model, are those contained in tables 2 and 3. These tables, for each variable, give the frequency and the relative percentage rate out of the total of the sample.

From the above-mentioned tables, it seems that the sample used is quite representative of the market segment in question. Indeed, the distribution of the cases with respect to the variables seems quite similar to the real situation, that is, substantially equal-distribution with respect to variables like the state of maintenance, giving onto a busy road and the vicinity of the historic city centre. The more particular characteristics, such as elegant finishings, location in run-down areas, giving onto the railway, find a more limited correspondence.

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[5] The inquiry was directed mostly towards blocks of flats, of a surface area equal to 100-120 sm and located in small buildings of three or four floors above ground, with supporting structure in reinforced cement, curtain walls in fired brick. Besides, housing was free of rental obligations and of real rights (servants, usufruet, etc.) and of guarantees (mortgages and securities).

Table 1 – The variables.

Variable	Description	0	1
Accaut	Independent entrance	Absent	Present
Affffss	Gives onto railway	Absent	Present
Affpreg	Presence of view	Absent	Present
Affstratraff	Gives onto busy road	Absent	Present
Ascensore	Presence of lift	Absent	Present
Conbu	State of repair and maintenance	Ordinary	Good
Degrado	Location in a run-down area	No	Yes
Distcomex	Distance from the closest extraurban centre	Cardinal variable	
Distmur	Distance from the historical centre of Treviso	> 1000 m	< 1000 m
Eta	Date of construction	Cardinal variable	
Finsig	Level of finishings	Ordinary	Exclusive
Garage	Independent garage	Absent	Present
Piano	Floor level	Cardinal variable	
Postosco	Open-air parking space	Absent	Present
Prztot	Total price	Cardinal variable	
Riscaut	Independent heating system	Absent	Present
Servizi	Number of bathrooms	Cardinal variable	
Supcom	Commercial surface area	Cardinal variable	
Vicbus	Vicinity of public transport	> 500 m	< 500 m

Table 2 – The sample characteristics (%) according to the variables expressed on a dichotomous scale.

Variable	0	1	Total
Affffss	71.4	28.6	100
Affpreg	81.6	18.4	100
Affstratraff	42.9	57.1	100
Conbu	59.2	40.8	100
Degrado	78.4	27.3	100
Distmur	45.9	54.1	100
Finsig	86.7	13.3	100
Vicbus	5.1	94.9	100

Table 3 – The characteristics of the sample according to cardinal variables (continuous)

Variable	Average	S.D.	Minimum	Maximum	N.
Prztot (millions of lire)	234.12	99.37	89.99	636.44	98
Supcom (sm)	115.60	43.50	40.46	342.83	98
Price (milions of lire/sm)	2.03	.46	1.150	3.858	98

3. The neural network model

The problem of the characterisation of the econometric function of real-estate prices, as also that of the estimation of the marginal contribution of single real-estate characteristics (implicit marginal price), finds a rational and logical solution in statistical models of multiple regression used for appraisal purposes (Shenkel 1978; Smith 1978; Mark, Goldberg 1988; Simonotti 1988; Murphy 1989; Brotman 1990).

The basic principle of the analysis of multiple regression consists in the interpolation of a theoretic function (parametric approach) among observed data, selected so that it approximates the data more so than any other. The result is that the parametric approach works when the property price function upholds the functional forms typically used in the drawing up of statistical models of multiple regression (linear, log-linear, Box-Cox, etc.). This generally happens when observation, even if limited, is not affected by noise and refers to intervals of small variation, where the function of the price can reasonably be approximated to a linear- or exponential-type trend.

When, on the other hand, the informative base is not very numerous and there is the presence of noise and note-worthy variability, the use of a nonparametric statistical approach is desirable.

Among the nonparametric regressive approaches there are the so-called connectionistic models, among which neural networks are particularly important (model free approach) (Hinton 1989; Haykin 1994).

From a statistical point of view of pattern recognition, neural networks are instruments capable of approximating non-linear arbitrary functions [6] by using non-linear mapping among multi-dimensional spaces, where the shape of the mapping depends on a number of parameters to be adjusted (Duda and Hart 1973; Fukunaga 1990).

From an appraisal point of view, a neural network is an alternative technique to multiple regression analysis in carrying out pluriparametric comparative synthetic assessments. The logic

[6] Kolmogorov's theorem demonstrated that every continuous function of several variables (for a closed and bounded input domain) can be pictured as a superposition of a small number of functions on a variable. For further information on interpretation in terms of neural networks of said theorem see Bishop (1996).

which governs the working mechanism of the neural network, and that of the operative mathematical algorithms which permit their expression, has, in fact, in the comparison its main referent.

Through neural networks there is a true, direct pluriparametric comparison among the properties which make up the learning set [7] and each property of the test set which is the object of appraisal. The neural network is therefore comparable to a sort of "virtual appraiser" of which the logic of evaluation is well known (learning algorithms), which in the learning phase of real-estate patterns creates a scale of potential prices in the hyperspace to n dimensions, representative of real-estate characteristics, and subsequently, in the prediction phase, places the real estate, which is object of appraisal, in the most appropriate slot.

Model selection took place by comparing the results produced by models belonging to two different families of neural networks, namely Multy Layer Perceptron (MLP) and Radial Basis Function (RBF). The selection criteria adopted was that of identifying the model with an optimal equilibrium between the capacity of approximation of the function of the total real-estate price and the capacity to estimate the implicit marginal prices measured by the estimated variance of the same marginal price (Amabile, Del Giudice 1997). And this with reference to both the calibrated analysis of prices per sm and that regarding total prices.

The neural-network model with the best results was the RBF type [8] (Radial Basis Function) (Girosi, Poggio 1990) with Gaussian-type radial functions. Unlike the MLP network [9] (Multi Layer Perceptron), characterised by the presence of one or more hidden layers, the RBF is made up on a single layer of separation between the input and output levels which in the case in question represent, respectively, the variables associated with the characteristics of the property and the property value.

As is known, the training phase must be preceded by the selection of learning, validation and test sets. For this purpose a non-repetitive sampling was carried out by means of random extraction from a uniform distribution of whole values, using a programme which transforms a stochastic

[7] The learning set is the sub-grouping of the data set with which the network learns the invariant characteristics using specific learning algorithms; the test set is the sub-grouping of the data set which is not used for model characterisation, with which the generalization capacity of the network is tested.

[8] Girosi and Poggio (1990) demonstrated that radial basis function networks possess the property of best approximation. "MLP and RBF networks are often contrasted in terms of the support of the basis functions that compose them. MLP networks are often referred to as "global", given that linear-logistic basis functions are bounded away from zero over a significant fraction of the input space. RBF networks, on the other hand, are referred to as "local", due to the fact that their Gaussian basis functions typically have support over a local region of the input space" (Jordan, Bishop 1996). In the case examined here, local mapping of the space for characteristics evidently better approximates data set distribution.

[9] The best model of MLP-type neural network turned out to be composed of a single hidden layer made up of 25 neurons with sigmoidal-type activation functions, and linear-type activation function for the output layer made up, as is known, in the case of real-estate appraisal by a single neuron. Learning took place on the basis of the same sets chosen for the RBF, using the back-propagation algorithm optimised with the term of momentum.

variable in [0.1] into a uniform variable [a, b], with a and b as whole numbers. And so, the initial data set was divided into three sub-groups of which the test set made up 20% of the entire sampling (18 transactions), the learning set 66% of the remaining part (54 transactions) consequently, the validation set was composed of 26 transactions.

Subsequently, with the intention of examining the homogeneity of the sub-groups, not guaranteed by a random extraction carried out starting from a sampling of reduced size, some statistical analyses were conducted (analyses of variance, cluster analysis) which prompted slight modifications in the learning set.

Of particular importance is the selection of the validation set to be used for the tuning of parameters in order to identify the best trade-off between bias and variance [10] (Johnston 1984; Bishop 1996) and so check the phenomenon of overfitting data which could invalidate the generalization capacity of the neural network. In this way the test set was only used to verify network prediction capacity with respect to completely unknown patterns, in harmony with the assertion that "the kindness of a model is seen by how it predicts data which are not used to estimate the model itself" (Simonotti 1988).

Normalisation was obviously only carried out for the dependent variable of price by square metre (Przmq) by dividing each amount by the order of size.

The training procedure [11] was carried out in two phases. The first phase, the so-called non-supervised one, enabled us, starting from the data set vectors, to determine the parameters of the base functions. In the second phase the optimisation of the spreading constant was carried out; this is representative of the width of the entrance interval to which each network neuron responds, the tuning of which can be carried out relatively quickly. The spreading parameter is usually included between the minimum Euclidean distance and the maximum of network training vectors.

The learning was carried out with non-linear optimisation algorithms[12]; in the first phase, to avoid overfitting phenomena, learning was stopped since the value of the quadratic function of the

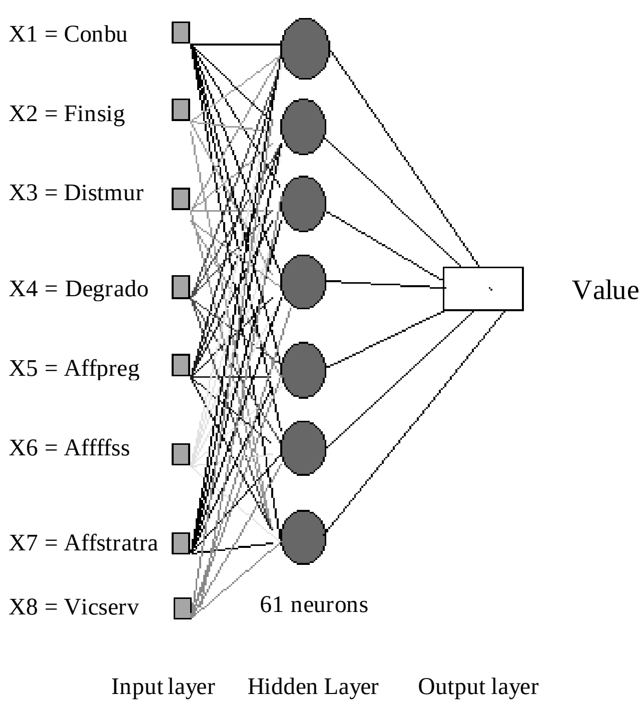
[10] "The bias measures the extent to which the average over-all data sets of the network function differs from the desired function. Conversely the variance measures the extent to which the network function is sensitive to the particular choice of data set""(Bishop 1996). A function which is closely fitted to the data set will tend to have a large variance and hence give a large expected error. A method to reduce the variance is smoothing the function, but if this is taken too far then the bias becomes large and the expected error is again large.

[11] The Matlab 4.2 neural networks package was used for processing the model. Matlab 4.2 has been developed by Mathworks Inc., Natik, MA.

[12] The algorithms work by minimising the average quadratic error function $E = \frac{1}{2}\sum_{n=1}^{N}\left\| y\left(x^{n};w\right) - t^{n}\right\|$ expressed as the difference between the function to be fitted $y\left(x^{n};w\right)$ dependent on input vectors and on synaptical weights and on the target function expressed as deterministic function with the addition of Gaussian noise with normal distribution with zero mean and standard deviation which does not depend on the data set. (For further mathematical statistical information see Jordan, Bishop 1996; Bishop 1996). When it is not reasonable to assume the Gaussian distribution

sum of errors calculated on the validation set was beginning to increase. In the second phase, in order to inquire into whether the network had reached a local minimum, which is quite frequent when the error function presents complex trends, the learning was pushed up to the maximum values of the spreading constant (maximum distance among the values of the whole data set) then registering the error on the validation set for the iterative phase. At the end of the tuning, the spreading constant, in correspondence to which the quadratic error function, with reference to the validation set, had a minimum value, was taken as optimum. Finally the chosen neural network, characterised by a layer made up of 61 neurons, was trained with the learning and validation set (Flexer 1996) to which a uniform noise was added in (0, 0.05) (Bishop 1996; Lin, Lee 1996) and proportional to the spreading constant in order to obtain a regularisation effect of the regression function [13]. The addition of noise generally prevents the network from interpolating data too precisely, therefore, contributing to diminishing the risk of overfitting.

Figure 2 – The RBF model



hypothesis of the target data, the use of a sum-of-square error can lead to modest results. In these cases the Gaussian mixture model can be used.

[13] It has been demonstrated that in the hypotheses of 1) sufficiently large target data; 2) sufficiently large number of adaptive weights; 3) optimisation of the network so as to reach minimum cost function; the outputs of a network trained by minimising a sum-of-squares function approximate the conditional averages of the target data (Bishop 1996).

The generalisation capacity of the network was evaluated with the help of the test set made up of a pattern which was completely unknown to the model. As is clear from table 4, the average absolute relative percentage error (2.3%) is based on values well under the appraisal threshold (10%) considered admissible for the use of the regression model for appraisal purposes, while the RMS (Root Mean Squared) error which has the advantage of being independent of the size of the test is quite low (0.05) [14] and this confirms the excellent generalisation capacity of the RBF neural network.

Table 4 – Performance of the RBF network (price per sm).

Actual house price	Predicted value	Relative % Error
1.832	1.803	-1.6
2.181	2.123	-2.7
1.766	1.765	-0.05
3.005	3.006	0.03
2.303	2.303	0
1.730	1.714	-0.9
2.096	2.096	0
2.754	2.754	0
2.009	2.077	3.4
1.976	1.976	0
2.597	2.601	0.1
2.394	2.394	0
2.471	2.682	8.5
1.995	1.803	-9.6
2.192	2.180	-0.5
1.772	1.801	1.6
1.600	1.652	3.2
1.829	1.652	-9.7
	Average error	**2.3%**
	RMS error	**0.05**

Real-estate characteristics are not all of equal importance. The surface area variable is, as is well known, the most important because the transaction is based on it (just think of contract terms) and because it usually presents obvious relationships of complementarity (flat and garage) and of substitution (interior surface area and balcony). Usually though, multiple regression models are gauged with reference to prices per square metre, so as to cover up the effects of multi-collinearity which nearly always involve the commercial surface variable. This circumstance should be kept in mind when interpreting results.

[14] RMS values near to one indicate that the prediction model is behaving like an average agent, while the null value indicates perfect prediction of test set patterns.

In order to examine how the neural network behaves regarding the problem connected to the difficulty of expressing the commercial surface as an independent variable, a neural network model was calibrated, analogous to the one examined previously, this time however the surface was also taken as an independent variable.

And so all of the phases, previously studied in detail, were repeated which led to the choice of an RBF type neural network characterised by a hidden layer composed of 71 neurons, each of which with Gaussian-type radial function.

The generalization capacity of the neural network, also in this case tested on a test set which was not used to calibrate the model, appears to be particularly satisfying with an average absolute relative error percentage of 1.3% and a RMS error of 0.0011 (tab. 5).

Table 5 - Performance of the RBF network (total price).

Actual house price	**Predicted value**	**Relative % error**
636.4	636.6	0.02
280.0	274.7	-1.9
315.0	314.8	-0.07
171.0	169.2	-1.0
380.1	379.1	-0.3
400.0	399.6	-0.1
152.0	149.8	-0.1
110.0	109.7	-0.2
175.7	185.0	5.3
235.0	235.0	-0.01
427.5	427.5	0
340.0	334.4	-1.6
210.0	215.1	2.4
190.0	178.0	-6.3
175.7	176.7	0.5
215.0	211.2	-1.8
135.0	135.1	0.09
142.5	142.3	-0.1
	Average error	**1.3%**
	RMS error	**0.0011**

The result is that the RBF neural model, at least as far as predictions of the total price of real estate is concerned is tolerant towards the problem of statistical multi-collinearity between esplicative variables of the studied phenomenon, which often can invalidates the possibility of using regression models for the purpose of total price prediction. Besides, the neural model seems suitable to work with real-estate characteristics expressed on a dichotomous scale since the coverage and separation of the space for characteristics, most probably, is facilitated by the use of input vectors with dichotomous values.

4. The mapping of real-estate values

With the aim of assessing the joint impact of the location variables on real-estate values in the city of Treviso, we proceeded by drawing up the geographic situation of real estate value. The mapping was done by integrating the real-estate value model given with the neural network and illustrated in the preceding paragraphs with a geographic informative system on the environmental characteristics of the urban area of Treviso[15].

Integration took place by means of the following phases:

1. Definition of a "standard" type of real estate based on building characteristics;
2. Identification of the significant environmental characteristics in order to determine real estate values;
3. Identification and mapping of the environmental variables of the area under consideration;
4. Assessment of the value of the "standard" real estate in the various parts of the territory taken into consideration;
5. Mapping of the fluctuation of value.

The "standard" real estate hypothesised for the evaluation on a territorial level of the effect of the local and environmental variables of real-estate values is made up of a flat of 100-120 sm, with average finishings, in an ordinary state of repair. In other words, the reference is to a piece of real estate which is most frequently found on the local residential market with respect to which the inquiry was designed. This condition is represented by assuming the value 0 for all the intrinsic variables in the previously illustrated model (*conbu* and *finsig*).

Having stated this, it is clear that real-estate value is conditioned exclusively by extrinsic variables, that is, by its social and environmental context and so, by the quality of the view (*affpreg*), by the distance from the city centre (*distmur*), from its being located in a run-down area from a social or urban point of view (*degrado*), by the vicinity of busy roads (*affstratraff*) or railways (*affffss*) and accessibility to public transport (*vicbus*).

The selection of the variables to be taken into account in the simulation of value was done on a map with the scale of 1:20.000 and concerned a square of 10.5 km per side, with its centre at the very centre of the historical centre of Treviso. This square, which includes the whole area under study, was subdivided into 441 square cells, the side of each equal to 0.5 km, each of which was considered homogeneous with regard to assumed extrinsic variables. Subsequently, a database containing the prevailing state of context variables of each cell was drawn up.

[15] About GIS techniques on real estate research see Weber (1990, 1997).

The database was compiled by collecting information, of primary importance, on environment, history and urbanistic linear-like details (motorways, busy main roads, railways, water ways, etc.) as well as precise data (valuable buildings, parks, picnic areas, abandoned areas, cemeteries, etc.).

The above-mentioned database constitutes the link between neural network and territorial arrangement since, by applying the model, it is possible to reconstruct the fluctuation of the potential value of the standard real estate in each elementary mapped unit. Said value, even though found within quite a wide interval, is quite homogeneous in the territory under consideration (see tab. 6). Indeed, standard deviation is a modest entity with respect to the average, with variation coefficient equal to about 12%.

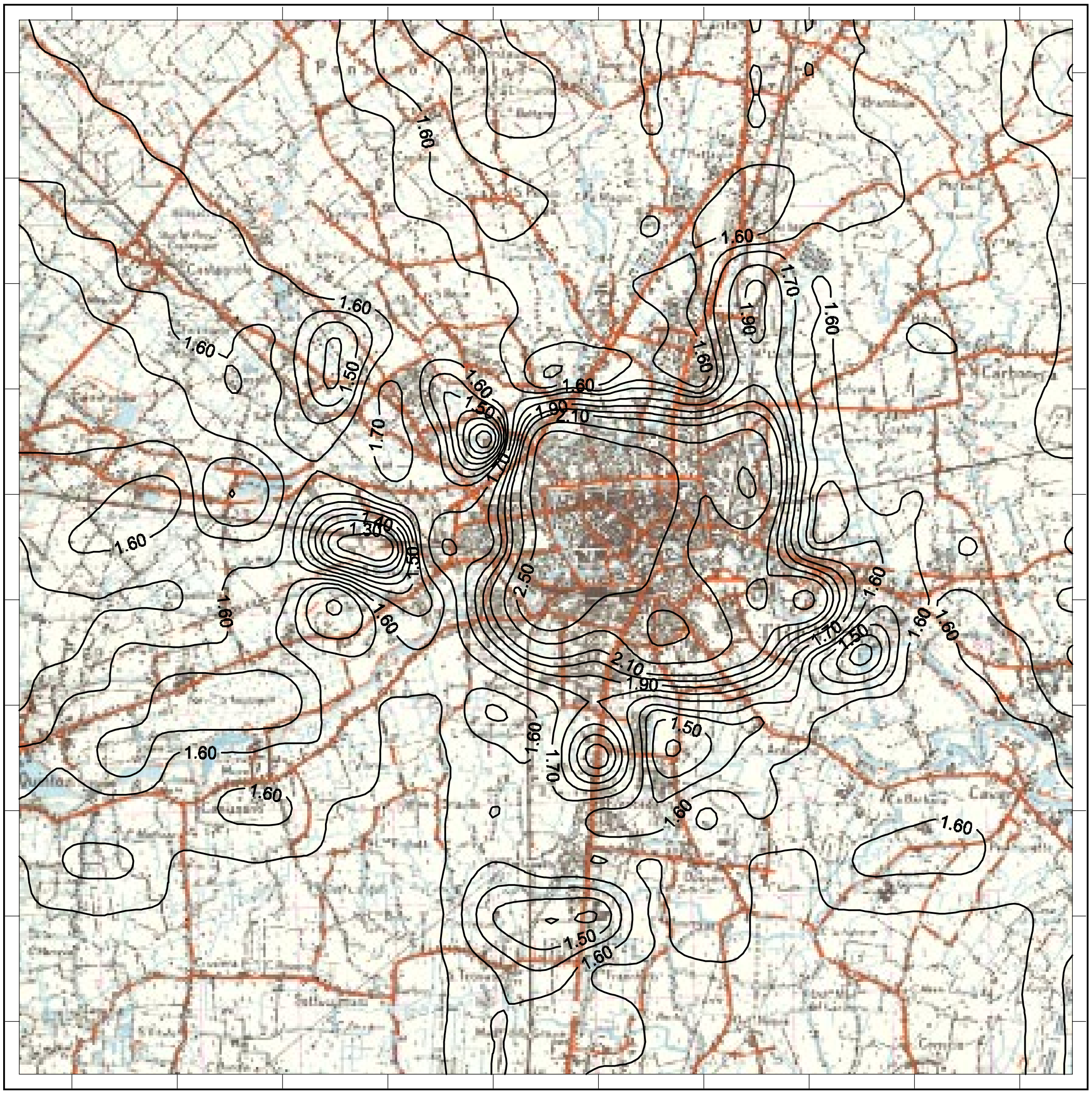
Table 6 – Estimated potential value

	Average	**Minimum**	**Maximum**	**S. D.**	**Skewness**
Potential value (millions of lire/ sm)	1.67	1.21	2.90	0.201	3.66

Obviously, this does not mean that real real-estate values are so homogenous, but that potential fluctuation of the unitary value of residential property on the territory is constant in extended areas. The distribution is slightly asymmetrical towards the higher values. This is because of the relative distribution of environmental variables considered in the territory which, even if homogenous, includes various circumscribing precincts which have penalising elements regarding value, and others, a bit more numerous, which contain elements of environmental worth. Finally, certain important differences from market-price distribution reported in tab. 3 are worth noting. The main differences are: a) average values appear to be decidedly inferior (1.67 by 2.03 million lire per sm); b) variability is much more contained (12% versus 23% in the variation coefficient). The differences are essentially due to the fact that reconstruction of value on a territorial level took a property in average condition as a reference point (from inferior to good) and without high-quality finishings. The sample, on the other hand, was made up of real estate of 40.8% in good state of repair and 13.3% with high-quality finishings. The different average intrinsic characteristics justify the differences between the averages. The minor variability is also due to the lack of influence of the intrinsic characteristics since in the sampling they vary from case to case while in the value assessment on a territorial level they were hypothesised as constant.

The following map (fig. 2) illustrates the fluctuation of assessed value on a territorial level by the neural network in the urban area of the city of Treviso.

Figure 2 – Real estate value map (millions per sm).



The predominant uniformity of value in most of the territorial precincts under consideration is confirmed by the map. The highest values, superior to 2.5 million per sm, are found in the proximity of the city walls, where the vicinity to the historic centre disguises the effect of busy roads and the vicinity of railway infrastructures which, however, check growth of urban revenue in various contexts, as is shown by the drastic fall of values outside said infrastructures (for example to the south of the railway station and to the north-west of the city centre). To the north-east of the city wall, on the other hand, where there are historic and environmental treasures, together with the absence of heavy transportation infrastructures, the potential value is kept high and superior to 2 million.

The area to the south and to the south-east is more varied. Here elements of value (parks, rivers, etc.) coexist with penalising factors (southern ring-road, industry, abandoned areas, and popular housing) and so the value fluctuation is quite differentiated, and oscillates between 1.5 and 2 million per sm.

As regards the areas furthest from the city centre, the valorising elements (buildings of historic worth, parks, rivers, schools, etc.) and elements of depreciation (abandoned areas, cemeteries, prison, run-down areas, etc.), play a very important role. In particular, the areas to the north-west and west of the city centre seem to be strongly influenced by the presence of numerous penalising infrastructures (railways, busy roads, general market, airport, prison, run-down areas, etc.) and by the absence of elements of value, with values often inferior to 1.5 million per sm.

Conclusion

This work is an attempt to build a model capable of simulating the mechanisms involved in the determination of housing prices in the urban area of the city of Treviso; special attention was given to the effect produced by variables of location. The model was built starting from samplings of transactions and using a neural network. The results obtained were then used to reconstruct real-estate market trends from a geographic point of view. As regards appraisal of the econometric function of real-estate prices, with special emphasis on environmental and infrastructural characteristics, the approach adopted has proved to be both rational and consistent. An analysis of the results shows notable interpretative and predictive capacity on the part of the neural model. Besides, the network has an elevated tolerance with regard to “noisy” data and to the presence of outliers; both these circumstances are particularly frequent when territorial or appraisal-type problems are examined with little information available. This prerogative makes the model very useful in appraisals.

The possibility of further examining marginal contributions of the single characteristics of property values, also in the presence of multi-collinearity among these same characteristics, is very interesting. Finally, the mapping of value fluctuations enables first-hand verification of the “goodness” of the assessed model and its capacity to portray the real situation.

The general approach presented here seems, therefore, useful both as an instrument of support for urban and territorial planning, as well as a permanent monitoring system of the real-estate market with the aim of creating an informative system of support for the analysis of real-estate investment. In this regard, it is important to emphasise that the potentiality for continuous adaptation of neural networks (adaptive systems) to the changing situation of the market enables quite easily to maintain the model and, anyway, one able to adjust on-line its simulation capacity. This opens innovative scenarios regarding the construction of dynamic-type appraisal models.

However, the model does present certain evident limitations. In the first place, it represents only a segment of the real-estate market and, therefore, is of limited use. Then, it was built with reference to rather a limited database since the sampling used was made up of only 98 cases. Besides, the value-mapping procedure is based on a database of 441 data regarding elementary mapping units of about 0.25 skm. This level of detail seems to be adequate only for areas which are more peripheral, homogenous and of recent expansion. Vice versa, in areas with older buildings where properties put to the most varied uses are mixed (commercial, residential and industrial), where areas of different states of social and urban decline co-exist, and where building density is highest, the analysis of territorial characteristics should be far more detailed.

Therefore, the approach, is susceptible to notable improvements both from the point of view of data to be assumed and from that of techniques to be employed in their elaboration. From the information point of view, there is a particular need to improve flexibility and precision in appraisal, so as to increase information on the market with which to calibrate models, despite the fact that neural networks work well even when few data are available. Furthermore, territorial description should be more precise in order to enable adequate reconstruction of value tendencies even in very complex areas from an urbanistic point of view. This need should be dealt with with proper GIS capable of managing all available information on the territory.

As far as model-like aspects are concerned, the use of resampling and bootstrap techniques seem interesting in analysing the variability of value curves of geographic analysis, especially when these are based on imprecise territorial data.

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