SPATIALISATION OF GRAPEVINE PHENOLOGICAL DATA AT DIFFERENT SCALES BY USING AN ARTIFICIAL NEURAL NETWORK

PROSTORSKI PRIKAZ FENOLOŠKIH PODATKOV ZA VINSKO TRTO V RAZLIČNIH SKALAH Z UPORABO NEVRONSKIH MREŽ

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POVZETEK

Znanje o fenologiji poljščin igra pomembno vlogo na različnih področjih človekovih aktivnosti (v kmetijstvu, alergologiji, agrometeorologiji...). Pri tem pa je pomembna tako časovna, kot prostorska variabilnost fenoloških podatkov. Pri časovnem spremljanju fenološkega razvoja rastlin gre za opazovanja različnih fenofaz na fenoloških postajah. V primeru, da pa nas zanima prostorska variabilnost fenoloških podatkov, pa potrebujemo mreže fenoloških opazovalnih postaj, ki pa jih je težko načrtovati in organizirati. Zato so nam lahko v veliko pomoč različne prostorske interpolacijske tehnike (kot na primer kriging, nevronske mreže, ...). Z njimi na podlagi omejenega števila podatkov iz fenoloških postaj, ki so razporejene na nekem območju, ocenimo vrednosti za celotno obravnavano območje. S tem dobimo bolj globalen pogled na prostorske vzorce razporeditve posameznih fenofaz. V našem primeru smo za oceno uporabnosti metode z nevronskimi mrežami uporabili opazovane in modelirane fenološke podatke za vinsko trto (*Vitis vinifera* L.) na dveh prostorsko kompleksnih ter različnih območjih - farma "Fattoria di Poggio Casciano", Firence - Italija (velikost približno 1 km^2) ter Toskanska regija - Italija (velikost približno 20.000 km^2). Poleg fenoloških podatkov so bili uporabljeni tudi klimatološki in geografski podatki. V primeru Toskanske regije je bil uporabljen digitalni relief z ločljivostjo 1,1 km, v primeru farme "Fattoria di Poggio Casciano" pa digitalizirani kartografski podatki z ločljivostjo 5 m. Od klimatoloških podatkov so bile za področje Toskane uporabljene dnevne vrednosti sledečih parametrov za 67 meteoroloških postaj: minimalna, maksimalna in povprečna temperatura zraka ter dnevna količina padavin in globalno obsevanje. V primeru fenoloških podatkov, je bil za simulacijo fenoloških faz vinske trte v regionalni skali (Toskanska regija) uporabljen fenološki model, v lokalni skali (farma "Fattoria di Poggio Casciano") pa podatki iz opazovanj. Rezultati kažejo, da nam modeli z nevronskimi mrežami lahko dajo dobre ocene fenološkega razvoja tako na lokalni, kot na regionalni skali, ter tako bolj globalen pogled na prostorsko porazdelitev fenoloških podatkov na določenem območju. V regionalni skali je korelacija med simuliranimi podatki ter podatki ocenjenimi z modelom, ki uporablja nevronske mreže, izredno visoka (r=0,89 do 0,96 pri 1% tveganju), v lokalni skali pa nekoliko manj (r=0,55 do 0,75). V splošnem lahko trdimo, da metoda, ki temelji na principu nevronskih mrež, predstavlja možnost za ocenjevanje prostorskih vzorcev v različnih prostorskih skalah. Seveda je možna razširitev metode tudi na druge kulturne rastline.

Ključne besede: fenologija, Italija, prostorska porazdelitev, regionalna skala

ABSTRACT

The knowledge of crop phenology is a very important step in many fields of human activity, such as agriculture, allergology, agrometeorology. To make a complete characterisation of phenophase trends, both the time and the spatial distribution of crop phenology are necessary. Unfortunately, while the time of phenological stages can be followed by means of local monitoring network, the spatial distribution requires an extension over the land surface of phenological measurements network that is extremely difficult to plan and organise. Thus interpolation techniques (such as kriging, fuzzy, neural network, etc.) can represent useful tools to extend over the land surface site phenological data. With this aim, observed and simulated phenological data of grapevine were used to evaluate the performances of neural network approach for extending site data at different spatial scales (farm and region). Finally the main problems and perspectives were discussed.

Key words: Vitis vinifera, spatial interpolation, macro and microscale

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1 INTRODUCTION

The knowledge of the temporal trend of the phenological phases (beginning, full, and conclusion) represents one of the basic topics helping human activity in many fields. For example, in agrometeorology, phenology allows to quantify the relationships between plants and environment, in allergology it allows to assess pollination production and thus to advise about the risks due to allergenic plants; while in agricultural activity, phenophase trends can strongly affect the efficiency of cultivation techniques, and thus their monitoring is one of the basis for improving farmer decision making.

Network of phenological measurements provides a continuos monitoring of crop development. Phenological scales and field technicians are generally the basis for a permanent and continuos evaluation and control of phenological conditions. These measurements must be carried out during the growing season and evaluated according to the meteorological conditions and the different characteristics of territory. Extension services are generally the most suitable organisation for this activity. Collected data are stored and elaborated and then they are diffused among the users by means of different communication techniques (such as phone, fax, radio, bulletin, post, Internet, etc.)

Two main consideration, however, must be pointed out: the variability of phenological trend over the land surface and the cost of monitoring management. As regards the first point, the phenological development of crops shows a high variability also at small spatial scale. This is generally due to many factors, such as macro-geographic (mountain, lake, sea, etc.) and micro-topographic (elevation, slope, distance from valley bottom, aspect, etc.) elements. In particular, in hilly areas, these elements vary consistently at very small scale thus causing strongly differences in the development of crop. These considerations confirm the need of a very localised monitoring of phenology, that however, it is limited by the high cost of monitoring management (staff of field technicians, elaboration and distribution of collected data, etc.).

To solve these problems, spatialisation techniques can represent a suitable alternative. Starting form a limited number of phenological observations, these techniques allow for an extension of phenological data to get a more global view of the distribution of phenophases in the studied area. In such a way, the effect of the territory can be evaluated and monitored with a limited employment of staff, and spatial pattern of phenophases can be distributed almost in real time.

Many are the approaches proposed for the spatialisation of data. Their suitability depends on the available data (weather, productivity, phenology, etc.) and the characteristics of the expected outputs. Recent works have demonstrated that data taken by the Advanced Very High Resolution Radiometer (AVHRR) mounted onboard of the National Oceanic and Atmospheric Administration (NOAA) satellites are useful for eco-climatic classification (Maselli et al., 1996). Other useful means that can be

used to explore the spatial distribution, are represented by semi-variance analysis and kriging, which are fundamental instruments of Geostatistics (Davis, 1973).
Artificial neural networks, which are capable of learning relationships in pattern of information, seems to be a very useful tool for the spatialisation of data. A neural network can be viewed as a computer system that is made up of several simple and highly interconnected processing elements similar to the neuron structure found in the human brain (McClelland et al., 1986 a, b). Problems which are normally not solvable by traditional algorithmic approaches can be solved with a neural network approach (Davidson and Lee, 1991). Neural network are suitable for problems which require the interpretation of large data sets. In addition they can also be used to solve problems in which the inputs and corresponding output values are known, but the relationship between inputs and outputs are not well understood. These conditions are commonly found in many environmental and agricultural applications. Specifically neural network models have successfully been used in biological applications to predict processes such as crop phenology (e.g. soybean), insect pest treatments threshold, weather forecast, optimum temperature in greenhouses, etc. (Crisci et al., 1998).

On the basis of these considerations the performances of neural network models to extend phenological observation of grapevine (Vitis vinifera L.) over land surface were evaluated. Specifically, two spatially complex areas with a different extension (1 Km^2 and 20,000 Km^2) located in Central Italy were selected, and the results were analysed considering the reliability of the up-scaling methodology and discussing the possibility of an operational application of this approach.

2 MATERIAL AND METHODS

2.1 STUDIED AREAS

Neural network were applied in two areas, with a different spatial scale. The first was an area of about 100 ha locates in the “Fattoria di Poggio Casciano” farm, Florence-Italy (11°20’ Long. East and 43°42’ Lat. North) in which the morphological characteristics are extremely complex (three main valleys East-West oriented, altitude between 150 to 260 m, slopes exposed towards South and North with an average slope of 12-13 %). The second area was the whole territory of Tuscany Region, Central Italy (20,000 Km^2), which is characterised, as well as the previous one, by a very complex morphology (the Appenine mountains on the North-East, several river valleys East-West oriented (Arno, Ombrone, Serchio rivers) and the sea on the West border).

2.2 DIGITAL ELEVATION MODEL

Morphological and geographic data were collected for both areas. Specifically, a digital elevation model (DEM) of the Tuscany Region with a pixel size of 1.1x1.1 Km was generated by digitising and processing the contour lines every 100 m taken from 1:100000 geographic maps of the Istituto Geografico Militare Italiano (IGMI). Two digital images with North-South gradient and distance from the Tyrrhenian Sea were also produced by apposite Fortran programs. A DEM of Fattoria di Poggio Casciano farm was obtained by digitising and processing the contour lines every 5 m taken from 1:5000 Carta Tecnica Regionale of the Tuscany Region.

2.3 CLIMATIC DATA

A dataset of climatic data (1961-1990) of Tuscany was constructed. In particular, observed daily climatic data were collected for 67 stations evenly distributed over the region. The dataset consisted of five variables: minimum, maximum and mean air temperature, total precipitation and global radiation. All the data were error checked and transferred to a PC in a consistent format.

2.4 PHENOLOGY DATA

Data on grapevine phenology for the evaluation of the performances of the up-scaling methodology were obtained from different sources. A calibrated and validated model was used to simulate grapevine phenology at regional level. In the model crop ontogeny is divided in two periods: a development period between bud break and bloom and a fruit growth period between bloom and maturity. Duration of the period between bud break and bloom was calculated by setting the number of leaves on a shoot equal to 17 at bloom as a function of the rate of appearance of leaves[4]. The duration of the period between bloom and maturity was calculated as a function of cumulative degree days. This period is divided into two sub-phases which are the period between bloom and the veraison and the period between veraison and maturity. At local scale (Fattoria di Poggio Casciano farm), monitoring of crop development was made on cv. Sangiovese (the most representative cultivar of that area). In 13 different locations during 1997 and 1998, phenophases of grapevine (budbreak, bloom, onset of fruit growth, veraison and maturity) were monitored with weekly intervals on a sample of about 10 vines. To define and describe the phenological stages, the scale proposed by Eichorn and Lorenz was used.

[4] The rate of leaf appearance is calculated on the basis of the mean daily temperature assuming that the rate of leaf appearance declines during ontogeny with constant temperature (Miglietta et al. 1992)

2.5 NEURAL NETWORK UP-SCALING METHOD

In this study a neural network model was used for extending phenological observations over the land surface. In particular, means and coefficient of variations of model outputs computed for 31 years at ground stations were used to train and validate the neural network models at regional level. The input variables considered for the development of neural network models were longitude, latitude, altitude and distance from the sea corresponding to the ground stations. At the farm level, data observed over two years of experiment were used to develop neural network models. The input variables were mainly micro-topographic parameters, such as altitude, slope, aspect and difference in level from the valley bottom. Each of the above mentioned inputs of the neural network models were connected to a set of hidden nodes, and each of the hidden nodes was connected to all the output nodes, using three-layer feedforward neural networks.

3 METHODOLOGY PERFORMANCE

The performance of this methodology were tested dividing the study stations in two groups: the first for training (40 stations for Tuscany and 8 stations for the farm) and the second for testing (27 stations for Tuscany and 6 stations for the farm); and then comparing the estimated parameters obtained using the interpolation methodology with the observed phenological data by means of conventional statistics (correlation coefficient, MBE and RMSE).

4 RESULTS AND DISCUSSION

The application of neural network models provided a good estimation of phenological development both at regional or local scale. In the first case (table 1) the higher variability of phenological stages for the study area determined relative large deviance between estimated and simulated data (MBE = 3 to 10 days; RMSE = 8 to 30 days). However, the correlation coefficients (r= 0.89 to 0.96) obtained were statistically significant for all the phenological phases ($P<0.01$). Whilst, the application at local scale (table 2) showed lower deviances (MBE = -2 to 1.5 days; RMSE = 2.5 to 7 days), but at the same time, also the correlation coefficients were lower (r=0.55 to 0.75). Moreover, at regional scale a higher accuracy was achieved in the up-scaling of budbreak, bloom and veraison stages (table 1); while, at local scale higher accuracy was obtained for bloom, onset of fruit growth and veraison stages (table 2). In both studies however, the lowest accuracy was obtained for maturity stage (tables 1 and 2).

Table 1: Statistical analysis of the neural network predictions for a Three-Layer Feedforward NN with 40 Training and 27 Validation Scenarios. * Significant st $P<0.05$; ** Significant at $P<0.01$.

	Training			Validation		
	MBE	RMSE	r	MBE	RMSE	r
Budbreak	0.24	9.15	0.93**	3.14	8.79	0.96**
Bloom	0.15	6.77	0.95**	2.68	6.60	0.97**
Veraison	0.10	14.99	0.96**	2.39	10.82	0.99**
Maturity	0.61	27.71	0.88**	11.47	30.87	0.89**

Table 2: Statistical analysis of the neural network predictions for a Three-Layer Feedforward NN with 18 Training and 12 Validation Scenarios. * Significant at $P<0.05$; ** Significant at $P<0.01$.

	Training			Validation		
	MBE	RMSE	r	MBE	RMSE	R
Budbreak	0.01	4.96	0.71**	-0.86	4.04	0.55*
Bloom	-0.02	2.17	0.91**	1.57	3.91	0.64**
Onset of fruit growth	0.03	3.43	0.73**	0.66	4.09	0.61**
Veraison	0.02	1.17	0.95**	0.06	2.55	0.76**
Maturity	-0.10	6.74	0.60*	-2.11	6.80	0.54*

The spatial patterns of the phenological phases for both areas were reported in figures 1 and 2. As regards the regional pattern, the phenological development of grapevine was predicted to be faster in the areas located along coast and in the central areas, included the zones between Florence and Siena where the highest quality wine is produced. Whilst, most northern and eastern areas are unsuitable for grapevine cultivation due to the adverse climatic conditions (Figure 1).

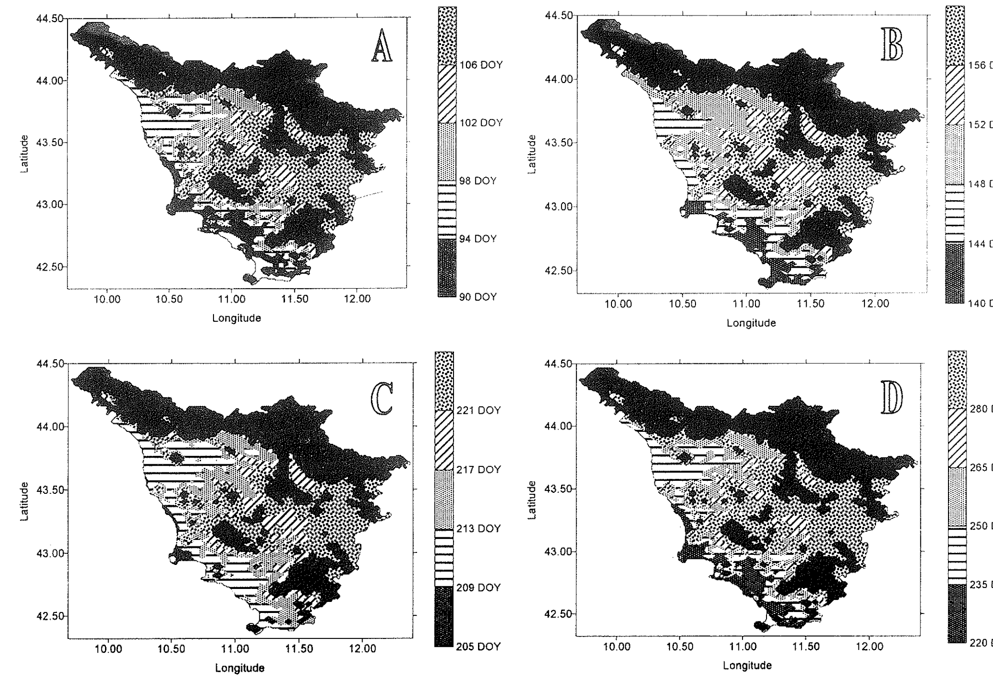

Figure 1: Neural Network prediction of means of budbreak (A), bloom (B), veraison (C) and maturity (D) dates for grapevine for Tuscany Region. Unsuitable areas are coloured in black.

At local scale the spatial pattern of the phenological development of cultivar Sangiovese showed that the growing season (budbreak dates) starts earlier in the fields South-West oriented, while Northern aspects and valleys seemed to show later budbreak dates. This spatial distribution pattern remained quite constant during all the season, independently from the considered phenophase (figure 2).

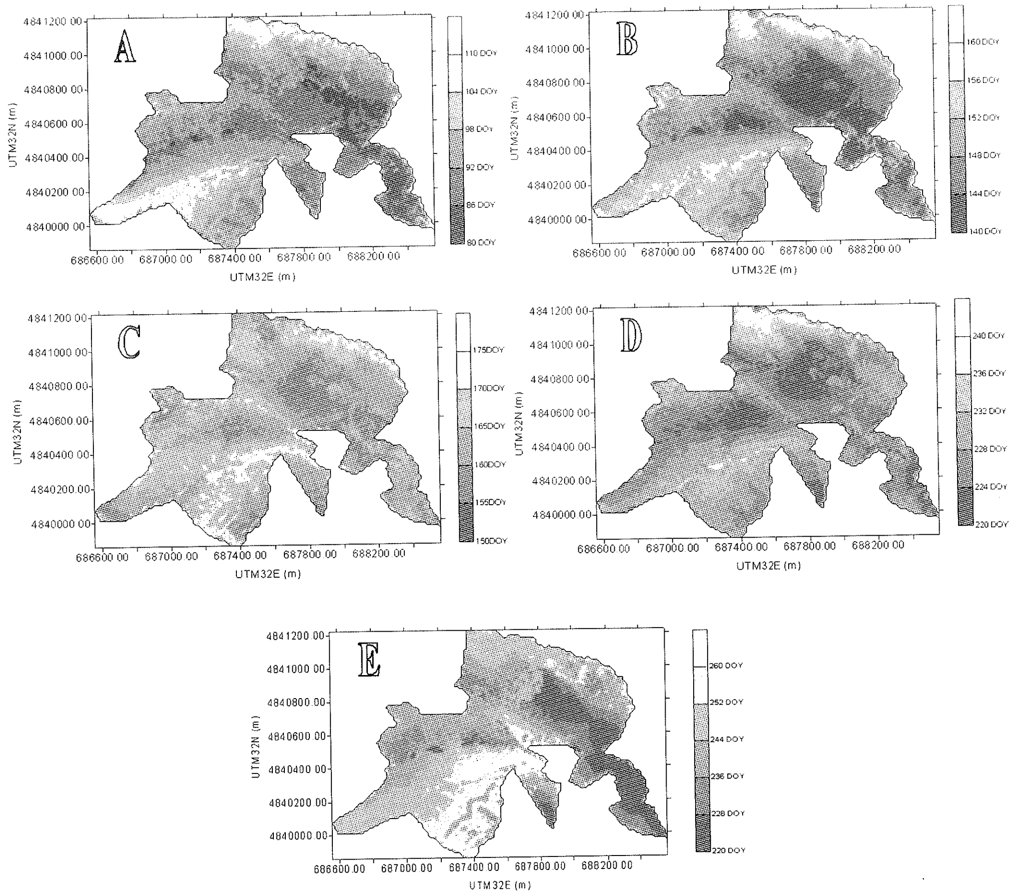

Figure 2: Neural network prediction of budbreak (A), bloom (B), onset of fruit growth (C) veraison (D) and maturity (E) dates for grapevine at local scale.

5 CONCLUSION

These results show that the up-scaling method based on neural network approach provides quite satisfactory estimates for both scales and a good accuracy in the representation of spatial patterns. This allows to describe the differences among areas and to emphasise the suitability of specific areas for high quality production.
Concerning the practical applications of this approach, it could be used to classify the different characteristics of environments for regional planning, or to improve cultivation techniques considering the actual phenophase variability of grapevine determined by topographic and geographic factors. Moreover the proposed methodology could be extended also for other crops, thus increasing the possible fields of operational application, such as agrometeorology, allergology, etc.

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