THE IMPORTANCE OF SAMPLING FOR THE EFFICIENCY OF ARTIFICIAL NEURAL NETWORKS IN DIGITAL SOIL MAPPING

FREIRE, SÉRGIO
e-GEO, Centro de Estudos de Geografia e Planeamento Regional, Faculdade de
Ciências Sociais e Humanas da Universidade Nova de Lisboa.
sfreire@fcsh.unl.pt
FONSECA, INÊS
Centro de Estudos Geográficos, Universidade de Lisboa, Alameda da Universidade.
BRASIL, RICARDO
Centro de Estudos Geográficos, Universidade de Lisboa, Alameda da Universidade.
ROCHA, JORGE
Centro de Estudos Geográficos, Universidade de Lisboa, Alameda da Universidade.
TENEDÓRIO, JOSÉ A.
e-GEO, Centro de Estudos de Geografia e Planeamento Regional, Faculdade de
Ciências Sociais e Humanas da Universidade Nova de Lisboa.

Abstract

In Portugal, soil mapping remains incomplete, and there are also significant problems with the existing cartography. Digital Soil Mapping uses advanced computer-based techniques such as Artificial Neural Networks (ANN) for mapping soil classes in a cheaper, more consistent and flexible way, using surrogate landscape data. This work used five different training sets to evaluate the impact that sampling has on the predictive accuracy of ANNs. The testes were carried out in IDRISI Taiga for two catchments in northern Portugal, using an ANN method known as multi-layer perceptron. Results show that sampling design is very important for the accuracy of soil mapping with ANNs.

Keywords: Digital Soil Mapping, AutoMAPticS, IDRISI Taiga, Mondim de Basto, Vila Real

Resumo

A IMPORTÂNCIA DA AMOSTRAGEM NA EFICIÊNCIA DE REDES NEURONAIS ARTIFICIAIS EM CARTOGRAFIA DIGITAL DE SOLOS.

Portugal não dispõe ainda de uma cobertura completa e harmonizada de cartas de solos. A cartografia automática de solos utiliza técnicas digitais avançadas como as Redes Neuronais Artificiais (RNA) para prever a distribuição espacial de tipos de solos de forma mais económica e consistente, usando variáveis responsáveis pela formação e desenvolvimento dos solos. Neste trabalho são usadas cinco amostras para avaliar o impacto que diferentes métodos de amostragem têm na exactidão da modelação por uma RNA. O teste realizou-se em IDRISI Taiga para duas bacias no Norte de Portugal, com recurso ao método *multi-layer perceptron*. Verificou-se que a amostragem é determinante para a performance da RNA.

Palavras-chave: cartografia digital de solos, AutoMAPticS, IDRISI Taiga, Mondim de Basto, Vila Real

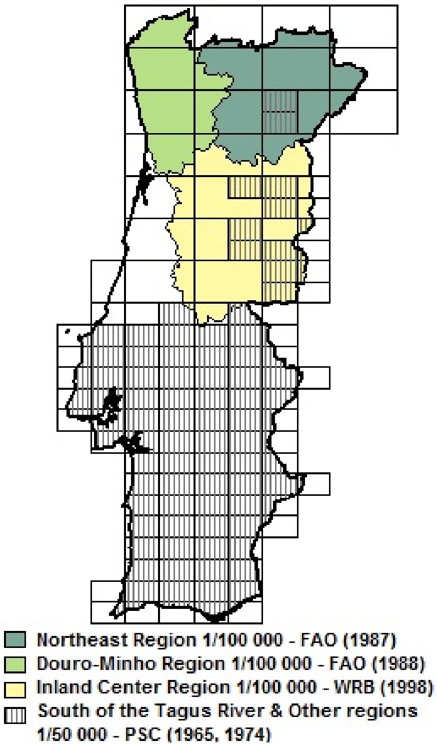
1. INTRODUCTION

Soils are an important non-renewable resource crucial for human activities (POTOCNIK & DIMAS, 2005). By supporting valuable services, such as food production, biodiversity, and pollution buffering, soils play a fundamental role in sustainable land use. The simple absence of soil information adds to the uncertainties of predicting food production, and lack of reliable and harmonized soil data has considerably hampered land degradation assessments, environmental impact studies and adapted sustainable land management interventions (MULLER & NILSSON, 2009).

Although soil surveys have been carried out in many countries, the scale and area coverage of resulting soil maps are not ideal for planning applications at national level (DOBOS et al., 2006). Additionally, there is a lack of consistency between soil classifications and legends across countries, which contributes towards a slow progression in integrating soil datasets, even in Europe (ESBN, 2005).

Portugal, like most European Union member states, only has a fraction of its territory covered with soil maps at semi-detailed or reconnaissance scales (MCBRATNEY et al., 2003). While 55% of continental Portugal has soil maps at 1:50 000 produced by traditional methods of soil survey before the 1970s, only about 40% of the territory has more recent soil map coverage at 1:100 000 with some degree of overlap (Figure 1). Thus, not only the published coverage remains incomplete, but there are also significant problems with the existing cartography. There is a lack of cartographic uniformity between the different regions: (1) scales are different, (2) four different taxonomic systems were used, and (3) the framework behind the mapping of soil units at the two scales is different: the 1:100 000 maps have a physiographic basis whereas the 1:50 000 maps have a taxonomic basis. Moreover, using taxonomy as the basis of map design often results in high intra-unit variability of soil properties (MULLA & MCBRATNEY, 2000) and limited correlation between soil type and soil hydrologic parameters (WESTERN & GRAYSON, 2000). Therefore, only 43% of the area of Portugal has high standards of soil cartography.

Figure 1. Scale and legends of regional soil maps of continental Portugal.


Northeast Region 1/100 000 - FAO (1987)
Douro-Minho Region 1/100 000 - FAO (1988)
Inland Center Region 1/100 000 - WRB (1998)
South of the Tagus River & Other regions 1/50 000 - PSC (1965, 1974)

In order to bridge the gap between existing soil maps based on traditional soil survey and the increasing demand for soil information, the technique of Digital Soil Mapping (DSM) has been developed for mapping soil classes and/or soil properties (DOBOS et al., 2006). By combining computer-based technologies such as Geographical Information Systems (GIS) with advanced techniques such as Artificial Neural Networks (ANN) and Fuzzy Logic (FL), DSM has enabled mapping the spatial distribution of soils in a cheaper, more consistent and flexible way, using surrogate landscape data. Thus, ANN models provide the means to predict soil types at locations without soil spatial data by combining existing soil maps with landscape features known to be responsible for the spatial variation of soils (MCBRATNEY et al., 2003). The process uses a set of variables related to soil forming factors and the respective soil type as training data for the ANN, which constructs rules (TSO & MATHER, 2001) that can be extended to the unmapped areas.

Whilst the literature provides a number of examples where DSM is presented as an efficient mapping technique (e.g., ZHU, 2000; BEHRENS et al., 2005; CARVALHO JÚNIOR et al., 2011) and soil spatial variation is shown to be induced by a limited number of soil forming factors (MORA-VALLEJO et al., 2008), still little is known about the impact that the training sites have on the predictive accuracy of the models.

The sampling method and location of training sites appears particularly important for ANNs because their rate of learning, convergence to a solution, network performance and ability to generalize depend on the efficiency of the layout of the sampling pattern which, in turn, depends on the presence of spatial periodicity of the phenomena. Despite the fact that all environmental variables exhibit spatial autocorrelation at some scale (ENGLUND, 1988), high values found in the spatial distribution of the variables used to train an ANN is likely to affect is performance.

Therefore, in applying ANN for DSM, the likelihood that the sampling design used to select training areas has a relevant effect on the classification effectiveness is our main hypothesis. Hence, some of the main objectives of AutoMAPticS (Automatic Mapping of Soils), a research project carried out at national level and based on the development of artificial neural network (ANN) models, are to (i) predict soil classes in currently unmapped areas of mainland Portugal, and (ii) harmonize soil legends across regions with distinct soil mapping classifications, using Portuguese and Spanish soil spatial datasets to a) improve the level of transnational data integration and b) assess existing data.

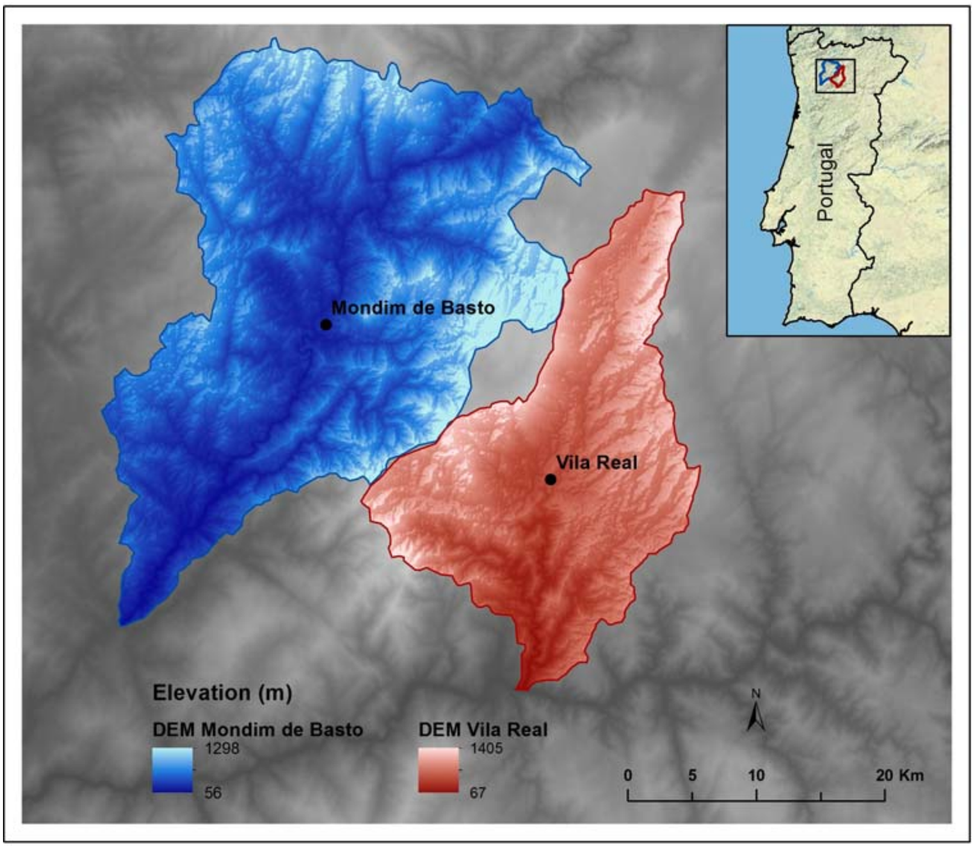
The present work aims at evaluating the impact that different sampling approaches used to select training areas for an ANN have on their predictive accuracy.

2. STUDY AREA

In order to assess the impact of sampling, two study areas in northern Portugal were selected: a catchment in Mondim de Basto (Rio Tâmega), in the Douro-Minho region (911 km^2), and another in Vila Real (Rio Corgo) in the Northeast region (468 km^2) as shown in Figure 2.

These catchments were chosen because they present diverse geomorphological and ecological characteristics and include soil types that are well representative of those found in each respective region. Soil types occurring in Mondim include Anthrosols, Fluvisols, Leptosols, and Regosols, while those in Vila Real include Anthrosols, Cambisols, Fluvisols, and Leptosols.

Figure 2. Location and Digital Elevation Model (DEM) of the study areas.



3. DATA AND METHODS

Independent variables used for training the ANN included both continuous terrain data and categorical (thematic) maps. The terrain surrogate data were derived from the Shuttle Radar Topography Mission (SRTM) digital elevation data (www2.jpl.nasa.gov/srtm) with a 90 m resolution and selected after multicollinearity tests showed little data redundancy. Seven morphometric variables, which are frequently used in DSM, were extracted from the terrain data: slope steepness, plan and profile curvatures, upslope catchment area, dispersal area, wetness index and potential solar radiation. These continuous variables were rescaled to a 0-255 value range.

In addition to altitude, land use from Corine Land Cover 2006 (CLC2006) and geological data were also included, as well as digital soil data at 1:100000 provided by DRAEM, the regional agriculture department of Northwest Portugal. All layers were clipped to the study area and converted to a raster structure with a 90-m cell size, using the ETRS1989-TM06 projection system.

In order to account for the possible effects of autocorrelation, the coordinates (latitude and longitude) were also included in the input set to indicate location. A formal assessment of spatial autocorrelation of variables was performed for both catchments. Measured through Moran´s I, the test indicated that both in Mondim and Vila Real autocorrelation is significantly high for slope steepness (0.76/0.82) and very high for potential solar radiation (0.88/0.88) and altitude (0.99/0.98).

An even number of training sites (500 pixels) were selected, whenever possible, for each soil type. However, not all soil types covered areas sufficiently large to allow the selection of the same number of pixels. Thus, 1689 pixels (out of 112 416) were selected in Mondim and 2040 (out of 57 788) were selected in Vila Real. For their selection, two different sampling strategies were implemented. The ANN was trained by presenting it a number of different examples of the same soil type drawn either (i) randomly (RS), or (ii) in a stratified fashion (SS). For the latter, training pixel vectors were located by choosing (a) random coordinates within soil types strata (SRS), (b) random coordinates within soil types and chosen evenly in the frequency space (SRPS), (c) nearest coordinates within soil types and chosen evenly in the frequency space (SNPS), and (d) farthest coordinates within soil types and chosen evenly in the frequency space (SFPS).

The neural network was trained in IDRISI Taiga (Clark Labs), using a highly popular supervised method known as multi-layer perceptron (MLP), run in hard classification mode. The MLP classifier is based on the back-propagation algorithm (HAYKIN, 1999). The experimental setup for each training set used the default specifications presented in Table 1 as initial values.

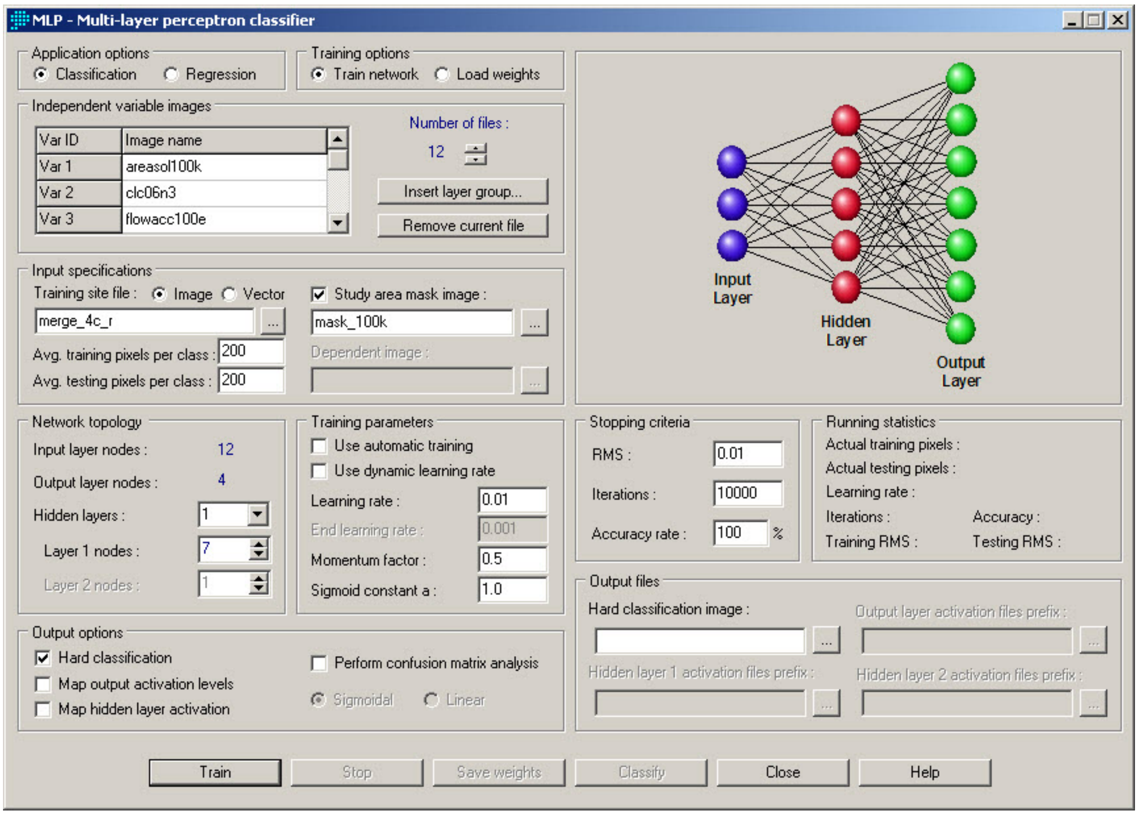
Table 1. Characteristics and parameters of the ANN MLP in IDRISI Taiga.

MLP parameters		
Group	Parameter	Default value
Input specifications	Avrg. training pixels per class	200 / 250
	Avrg. testing pixels per class	200 / 250
Network topology	Hidden layers	1
	Layer 1 nodes	7
Training parameters	Automatic training	no
	Dynamic learning rate	no
	Learning rate	0.01
	End learning rate	0.001
	Momentum factor	0.5
	Sigmoid constant “a”	1
Stopping criteria	RMS	0.01
	Iterations	10000
	Accuracy rate	100%

In the Mondim catchment, an average of 200 pixels per class were used for training and testing, while 250 were used for Vila Real, due to constraints in the total area covered by some soil types. Some of these parameters were progressively changed and the network performance monitored, namely: number of layer 1 nodes, use of automatic training, use of dynamic learning rate, and number of iterations (maximum of 100 000). Training ended when one of the stopping criteria was achieved: either a RMSE ≤ 0.01, an accuracy of 100%, or the defined maximum number of iterations. Therefore the default neural network included 12 input layer nodes, 4 output layer nodes, and one hidden layer with 7 nodes (see Figure 3).

In a study area, for a given combination of sampling method and parameters, results of different runs can vary due to different seeding of training pixels. Thus, five model runs were performed for each combination, in order to average their accuracies, as calculated by IDRISI.

Figure 3. View of MLP interface and initial training parameters used in IDRISI Taiga.



MLP - Multi-layer perceptron classifier

Application options
● Classification ○ Regression

Training options
● Train network ○ Load weights

Independent variable images

Var ID	Image name
Var 1	areasol100k
Var 2	clc06n3
Var 3	flowacc100e

Number of files : 12

Insert layer group...
Remove current file

Input specifications
Training site file : ● Image ○ Vector
merge_4c_r
☑ Study area mask image :
mask_100k
Avg. training pixels per class : 200
Avg. testing pixels per class : 200
Dependent image :

Network topology
Input layer nodes : 12
Output layer nodes : 4
Hidden layers : 1
Layer 1 nodes : 7
Layer 2 nodes : 1

Training parameters
□ Use automatic training
□ Use dynamic learning rate
Learning rate : 0.01
End learning rate : 0.001
Momentum factor : 0.5
Sigmoid constant a : 1.0

Stopping criteria
RMS : 0.01
Iterations : 10000
Accuracy rate : 100 %

Running statistics
Actual training pixels :
Actual testing pixels :
Learning rate :
Iterations :
Accuracy :
Training RMS :
Testing RMS :

Output options
☑ Hard classification
□ Map output activation levels
□ Map hidden layer activation
□ Perform confusion matrix analysis
● Sigmoidal ○ Linear

Output files
Hard classification image :
Output layer activation files prefix :
Hidden layer 1 activation files prefix :
Hidden layer 2 activation files prefix :

4. RESULTS AND DISCUSSION

The results of ANN training for both catchments are presented in Table 2, where for each sampling method, the main parameters and respective values are shown only for the combination obtaining the highest averaged accuracy, as computed by IDRISI.

In Mondim, the best performance of the ANN was obtained with SRS (73%), by adding one node to the hidden layer. This result was closely followed by SNPS (72%), with SFPS showing the worst performance (51%). Whilst random sampling did not achieve as good predictive accuracy results as the one possible to obtain with stratified sampling (65% vs. 73%), it is clear that spatial autocorrelation causes an outstanding drop-off in the number of iterations required to achieve similar levels of accuracy (72% and 73%). Thus, accounting for spatial autocorrelation by choosing pixels that are as close as possible to each other (SNPS) resulted in only 5000 iterations being required (as opposed to 50 000) to achieve similar accuracy levels. This effect was also observed in the results obtained for Vila Real. Here SNPS clearly performed better (87%) and SRS, SRPS, and SFPS the worst (66%), with accuracies being generally higher than in Mondim. While in Mondim best performances in all sampling methods are obtained using dynamic learning rate, in Vila Real highest accuracy was reached with automatic training and without dynamic learning rate. The difference being that automatic training automatically adjusts the learning rate during training, re-starting the iteration process with new random beginning weights, whilst in dynamic learning rate, the rate is lowered progressively.

Table 2. Impact of sampling method on the performance of ANN models.

Sampling Method	Iterations	Layer 1 nodes	Automatic training	Dynamic learning rate	Accuracy (%)
Mondim de Basto					
RS	100000	8	N	Y	64.9
SRS	50000	8	N	Y	73.3
SRPS	100000	7	N	Y	58.9
SNPS	5000	7	N	Y	71.8
SFPS	90000	7	N	Y	51.3
Vila Real					
RS	90000	7	N	N	74.4
SRS	90000	7	N	N	65.5
SRPS	50000	7	N	Y	65.7
SNPS	30000	7	Y	N	86.9
SFPS	90000	8	N	Y	66.4

Although results are slightly different for each catchment, they show that the predictive accuracy of the ANN models in supervised mode is highly dependent on the sampling method used to select training sites.

5. CONCLUSIONS

There is a growing demand for high-resolution spatial soil information for environmental planning and modelling. Portugal does not have complete soil-map coverage because soil surveys are field and labour intensive, and therefore very expensive.

Digital Soil Mapping approaches are based on emerging powerful techniques such as ANN which can provide high-quality digital soil maps in a fast and cost-effective way. However, not much is known about the impact that the selection of training sites have on the accuracy of the models. This work evaluated that impact for two catchments in northern Portugal, and conclusions are that (1) sampling strategy has a very important impact on the accuracy of soil predictive maps developed using ANNs and (2) sampling strategy benefits from reflecting high autocorrelation of factors of soil formation because the ANN learns faster that close neighbouring positions are more likely to have similar soil types, allowing the model to converge faster to a better solution. Therefore different sampling strategies should be assessed and tested prior to using ANN for modeling the spatial distribution of soils classes.

Subsequent work will involve the testing of different types of ANNs applied in the same catchment areas and the comparison with the MLP results presented here. Classification of soils using ANNs will also be tested at different spatial resolutions, and additional study areas will be included.

Future work will also explore the hybridization power of using Fuzzy Logic for DSM, and results obtained using both methodologies will be compared and validated using existing maps and soil profile data. The best model will be used to map soil classes across areas which are currently lacking spatial soil data, ultimately enabling the completion of the Portuguese soil map coverage at 1:100000.

REFERENCES

BEHRENS T., FORSTER H., SCHOLTEN T., STEINRUCKEN U., SPIES E., GOLDSCHMITT M. (2005): "Digital soil mapping using artificial neural networks", *J. Plant. Nutr. Soil Sci.* 168: 1-13.

CARVALHO JUNIOR, W. et al . (2011): "Digital soilscape mapping of tropical hillslope areas by neural networks", *Sci. Agric. (Piracicaba, Braz.)*, 68(6): 691-696.

DOBOS E., CARRÉ F., HENGL T., REUTER H.I. & TÓTH G. (2006): "Digital Soil Mapping as a Support to Production of Functional Maps", EUR 22123 EN. Office for Official Publications of the European Communities, Luxemburg, 68 p.

ENGLUND E.J. (1988): "Spatial Autocorrelation: Implications for Sampling and Estimation", in LIGGETT W. (Ed.) *Proceedings of the ASA/EPA Conferences on Interpretation of Environmental Data, III Sampling and Site Selection in Environmental Studies*, EPA 230/8-88/035, 31-39

ESBN (European Soil Bureau Network) (2005): "Soil Atlas of Europe". European Commission, Office for Official Publications of the European Communities, L-2995 Luxemburg, 128 p.

HAYKIN S. (1999): *Neural Networks – a Comprehensive Foundation*. Prentice Hall, New Jersey, 842 p.

MCBRATNEY A.B., MENDONÇA SANTOS M.L., MINASNY B. (2003): "On digital soil mapping", *Geoderma*, 117, 3-52.

MORA-VALLEJO A., CLAESSENS L., STOONVOGEL J. & HEUVELINK G.B.M. (2008): "Small scale digital soil mapping in southeastern Kenya", *Catena*, 76, 44-53.

MULLA D.J. & MCBRATNEY A.B. (2000): "Soil spatial variability", in M.E. SUMNER (Ed.) *Handbook of Soil Science*, A 321-352. CRC Press, Boca Raton.

MULLER A.J., NILSSON S., (2009): "Foreword to FAO/IIASA/ISRIC/ISS-CAS/JRC, Harmonized World Soil Database (version 1.1)". FAO, Rome, Italy and IIASA, Laxenburg, Austria, 43 p.

POTOCNIK J. & DIMAS S. (2005): Preface. In Soil Atlas of Europe. European Soil Bureau Network. European Commission, Office for Official Publications of the European Communities, L-2995 Luxemburg, 128 p.

TSO B. & MATHER P.M. (2001): *Classification Methods for Remotely Sensed Data*. Taylor and Francis, London, 332 p.

WESTERN A. & GRAYSON R. (2000): "Soil moisture and runoff processes at Tarrawarra", in R. GRAYSON & G. BLÖSCHL (Eds.) *Spatial Patterns in Catchment Hydrology: Observations and Modelling*. Cambridge University Press, Cambridge, 209-246.

ZHU A.-X. (2000): "Mapping soil landscape as spatial continua: The neural network approach", *Water Resources Research*, 36(3): 663-677.

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