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SPATIAL DISTRIBUTION OF MAJOR FOREST TYPES IN CROATIA AS A FUNCTION OF MACROCLIMATE

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The model of spatial distribution of major forest types in Croatia was developed as a function of macroclimatic variables (monthly mean temperature, monthly precipitation, monthly mean global solar irradiation and monthly potential evapotranspiration) and variables derived from digital elevation model (terrain aspect and slope). Neural networks were used as modelling tool. The model was developed within the frame of a raster geographic information system with a spatial resolution of 300 × 300 m, and it was based on a forest vegetation map (in scale of 1 : 500000) and interpolation macroclimatic models. The agreement between modelled and mapped forest types was very good, which suggests a strong correlation between macroclimate and the main forest types in Croatia and high model reliability. The model was applied to the entire area of Croatia, aiming at the construction of the potential spatial distribution of major forest types. The model could be useful for reforestation planning and for prediction of vegetation succession under assumed climatic changes.

Keywords: air temperature, DEM, GIS, neural networks, potential evapotranspiration, potential vegetation map, precipitation, solar irradiation

Antonić, O., Bukovec, D., Križan, J., Marki, A. & Hatić, D.: Prostorna razdioba glavnih tipova šuma u Hrvatskoj kao funkcija makroklime. Nat. Croat., Vol. 9, No. 1., 1–13, 2000, Zagreb.

Model prostorne razdiobe glavnih tipova šuma u Hrvatskoj razvijen je kao funkcija makroklimatskih varijabli (srednja mjesečna temperatura, mjesečna oborina, srednje mjesečno Sunčevo ozračenje i mjesečna potencijalna evapotranspiracija) te varijabli izvedenih iz digitalnog elevacijskog modela (orijentacija i nagib terena). Neuralne mreže korištene su kao oruđe za modeliranje. Model je razvijen u okviru rasterskog geografskog informacijskog sustava, uz prostornu razlučivost od 300 x 300 m i baziran je na karti šumske vegetacije (mjerila 1:500000) i interpolacijskih makroklimatskih modela. Podudaranje između modeliranih i kartiranih tipova šuma vrlo je dobro, što upućuje na jaku korelaciju između makroklime i glavnih tipova šuma u Hrvatskoj, te na visoku pouzdanost modela. Model je primjenjen na cijeli hrvatski teritorij s ciljem konstruiranja potencijalne prostorne razdiobe glavnih šumskih tipova. Model bi mogao biti koristan u planiranju pošumljavanja, kao i u predviđanju vegetacijske sukcesije pod utjecajem pretpostavljenih klimatskih promjena.

Ključne riječi: temperatura zraka, DEM, GIS, neuralne mreže, potencijalna evapotranspiracija, karta potencijalne vegetacije, oborina, Sunčevo ozračenje

INTRODUCTION

Macroclimatic variables are usually major environmental factors which influence the large-scale spatial variability of vegetation (WOODWARD, 1987). Correlation between forest types and macroclimatic variables was recognized early in Croatia (BECK-MANNAGETTA, 1901; ADAMOVIĆ, 1909) and examined in numerous studies (see review in BERTOVIĆ, 1975). This correlation is relatively strong, due to the fact that Croatia is a country with large macroclimatic variability, from a warm and dry Mediterranean to a cold and wet mountainous climate. BERTOVIĆ's important study (1975) provides general knowledge about the relation between macroclimate and major forest types in Croatia (defined according to the Braun-Blanquet approach), including statistics of ecologically relevant macroclimatic variables recorded at the meteorological stations situated within the particular forest type. The use of this knowledge in the management of the natural resources is limited by the fact that it is often hardly applicable in the real space. Thus, some important tasks, such as reforestation planning or the prediction of vegetation succession under assumed climatic changes, are solved arbitrarily.

The recent development of methods for the spatial interpolation of macroclimatic variables (see e.g. MITCHELL, 1991; LENNON & TURNER, 1995; THORNTON *et al.*, 1997), as well as raster modelling procedures within a framework of geographic information systems (GIS), enables spatially explicit implementation of the correlation between vegetation and climate over larger areas (see e.g. BRZEZIECKI *et al.*, 1995; LEATHWICK, 1998). It makes it possible to develop spatially explicit models, capable of predicting vegetation type as a function of macroclimatic variables, which are useful for the management of forest resources. The development and testing of such a model for Croatia, at the level of major forest types, were the basic aims of this research. The second aim was the construction of the spatial distribution of potential vegetation, using the mentioned model.

MATERIAL AND METHODS

Vegetation data

The study area was the entire land area of the Republic of Croatia. Approximately half of the area belongs to the Karst region with extremely rugged relief, which strongly affects local climate. Primarily due to this fact, the vegetation pattern in Croatia is very dissected.

The forest vegetation pattern examined in this research was based on the 1 : 500000 map provided by TRINAJSTIĆ *et al.* (1992). This data source was chosen because it is the only available representation of the real forest vegetation in Croatia, based on field surveys and generalised to a scale suitable for this research. Other available sources (e.g. BERTOVIĆ, 1975 or BERTOVIĆ & LOVRIĆ, 1992) were inappropriate, because they do not present real, but potential vegetation which prejudices correlation between macroclimate and vegetation. It has to be emphasised that the vegetation classification used in TRINAJSTIĆ *et al.* (1992) has an alternative, presented in the work of BERTOVIĆ & LOVRIĆ (1992). The differences between those two approaches, which are mainly related to the Mediterranean region, are not discussed in this paper.

The chosen map originally contains 14 main forest type classes and 43 subclasses mainly based on phytocoenoses in the sense of Braun-Blanquet (compare also TRINAJSTIĆ *et al.*, 1992 and RAUŠ *et al.*, 1992). The original map was digitised and rasterised in a spatial resolution of 300 x 300 m. For the purpose of this research, only main classes were used. Some modifications were made to avoid vegetation variability caused by other, non-climatic environmental influences (class number follows TRINAJSTIĆ *et al.*, 1992, syntaxonomy follows VUKELIĆ & RAUŠ, 1998):

1) class 4 (middle European flood-plain and swampy forests of *Salix* sp., *Populus* sp., *Fraxinus angustifolia* Vahl and *Alnus glutinosa* (L.) Gärtn.) was merged with class 5 (sub-Pannonian lowland forests of pedunculate oak, *Genisto elatae-Quercetum roboris* Ht. 1938 and *Carpino betuli-Quercetum roboris* (ANIĆ, 1959; RAUŠ, 1969),

2) class 7 (pubescent oak forest on an impermeable flysch lithological substratum, *Molinio-Quercetum pubescentis* Šugar 1981) was merged with class 3 (Mediterranean thermophilic deciduous forest, from *Quercetalia pubescentis* Br.-Bl. (1931) 1932),

3) class 11 (middle European montane and altimontane acidophilic coniferous forests, *Vaccinio-Piceion* Br.-Bl. 1939) was merged with class 10 (altimontane neutrophilic mixed forests, *'Abieti-Fagetum'* complex, see e.g. TRINAJSTIĆ, 1995),

4) class 14 (relic, edaphically conditioned pine forests, *Orno-Ericion* Ht. 1958) was omitted and

5) class 13 (subalpine coniferous forests, *Lonicero borbasianae-Pinetum mugi* (Ht. 1938) Borh. 1963 and *Listero-Piceetum abietis* Ht. 1969) was merged with class 12 (subalpine beech forest, *Homogyno sylvestris-Fagetum sylvaticae* (Ht. 1938) Borh. 1963.), because the total area of class 13 in Croatia is relatively small in the context of this research.

Thus, the final vegetation data set contains the nine major forest vegetation types listed in Tab. 1, which are similar to the 'seed regions' of Croatia, derived by GRAČAN *et al.* (1999) from the same vegetation data source. All of these types contain edaphically conditioned subtypes not examined in this paper. The spatial distribution of these types in Croatia is shown in Fig. 1.

Climate data

Four variables were selected as macroclimatic estimators of great importance for the spatial distribution of vegetation (see e.g. LANDSBERG, 1986 or ZIMMERMANN & KIENAST, 1999): 1) monthly mean air temperature, 2) monthly precipitation, 3)

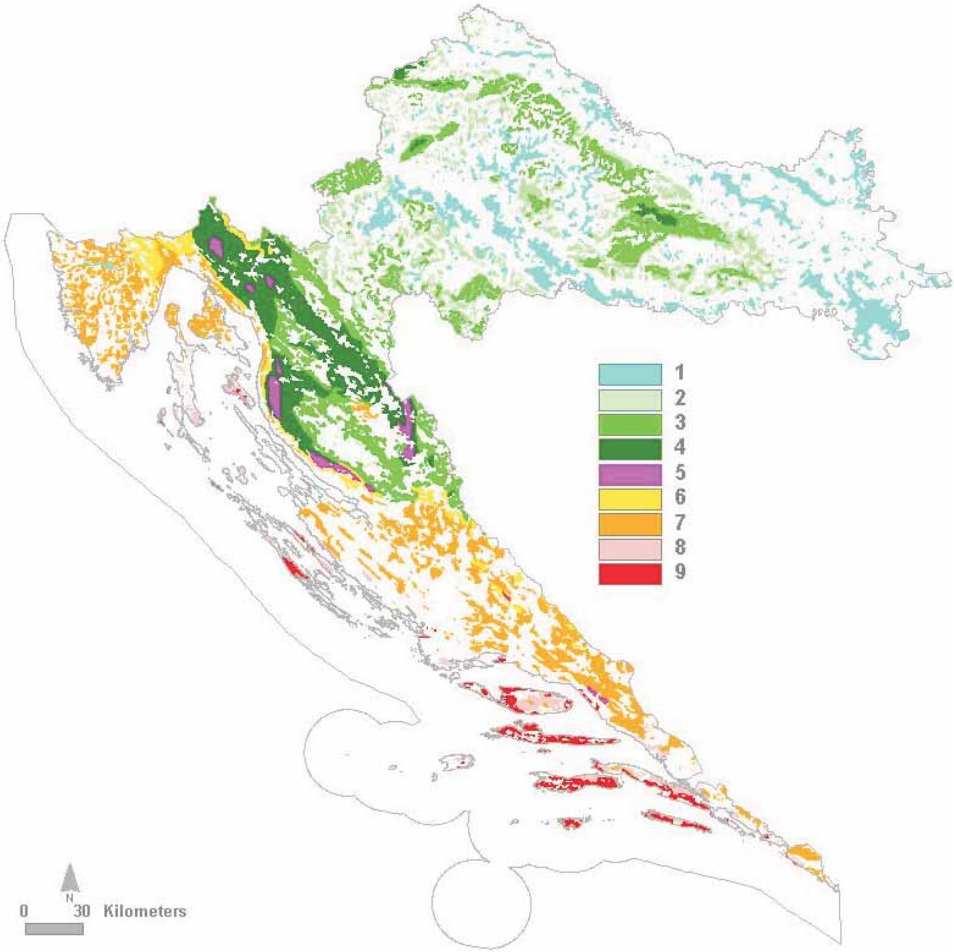

Fig. 1. Observed spatial distribution of major forest types used in analysis (simplified from TRINAJSTIĆ *et al.* (1992), see text for further explanation and Tab. 1 for legend). White area is non-forested.

monthly mean global solar irradiation on a horizontal surface at ground level and 4) monthly potential evapotranspiration on a horizontal surface. The first two climatic variables were taken directly from weather station chronicles. The last two were modelled for each weather station as a function of relevant climatic variables observed at the respective station, using the NIKOLOV & ZELLER model (1992) for global solar irradiation and the PRIESTLY & TAYLOR model (1972, see also BONAN, 1989) for potential evapotranspiration. Spatial distributions of climatic variables were averaged for the period of 1956–1995, with a spatial resolution of 300 × 300 m, using very accurate interpolation models presented in ANTONIĆ *et al.* (in press).

Tab. 1. Description of major forest types used in the analysis. The order of forest types implies a natural vegetation zoning from inland low areas, over the mountainous region, to the coastal vegetation. A map class follows the numbers of main classes on the original map of TRINAJSTIĆ *et al.* (1992), which is modified for this purpose (see text). For the syntaxonomic aspect of classes see TRINAJSTIĆ *et al.* (1992) and VUKELIĆ & RAUŠ (1998). For species compositions see e.g. RAUŠ *et al.* (1992) or VUKELIĆ & RAUŠ (1998).

type	map class	general physiognomic and ecological description	main tree species
1	4+5	lowland deciduous forests including flood-plains and swamps	*Quercus robur* L.
2	6	colline and submontane deciduous forests	*Quercus petraea* Liebl.
3	8	montane deciduous mesophilic forests	*Fagus sylvatica* L.
4	10+11	altimontane mixed (coniferous/deciduous) forests	*Abies alba* L. and *Fagus sylvatica* L.
5	12+13	subalpine deciduous and coniferous forests	*Fagus sylvatica* L. and *Pinus mugo* Turra
6	9	montane deciduous thermophilic forests	*Fagus sylvatica* L.
7	3+7	Mediterranean deciduous forests	*Quercus pubescens* Willd.
8	2	Mediterranean mixed (evergreen/deciduous) forests	*Quercus ilex* L.
9	1	Mediterranean evergreen forests	*Pinus halepensis* Mill.

These models are based on data from 127 weather stations and on elevation data from a digital elevation model (DEM, spatial resolution of 300 × 300 m) and were developed using neural networks (NN).

The basic set of 48 independent estimators (4 climatic variables by 12 months) is reduced in this research to 5 composite estimators (non-linear analogues of principal components) using five-layered autoassociative NN (see BISHOP, 1995), which have 48 neurons in the first and last layer (48 basic estimators), 15 neurons in the second and the fourth layer and 5 neurons in the central layer. The logistic function was used as the activation function. Using this NN architecture, 99.79% of total macroclimatic variability was explained. After the last two layers were cut, this autoassociative NN was used as input for the development of forest type prediction model. Consequently, the forest type prediction model was actually driven by all 48 independent macroclimatic estimators, which were only filtered through the autoassociative NN.

To describe the basic topoclimatic variability, the same DEM is used for the calculation of terrain aspect and slope, which were used as additional independent estimators. The terrain aspect is a circular variable and it is consequently transformed into a northness and eastness by the cosine and sine transformation, respectively (GUISAN *et al.*, 1998, 1999). The northness is general estimator of the local thermics, while eastness was adopted in this research as a general estimator of being leeward to the major cyclones (PANDŽIĆ, 1989), which influence local precipitation (see PENZAR, 1959). Terrain slope was included as a general estimator of soil wetness. We think that more precise DEM-based topoclimatic variables (see ANTONIĆ, 1996 for review), such as topographic solar irradiation (DUBAYAH & RICH, 1995; ANTONIĆ, 1998), soil moisture potential and snow accumulation potential (e.g. BROWN, 1994), or exposure to wind (ANTONIĆ & LEGOVIĆ, 1999), are not suitable estimators for this research because they relate to a finer spatial scale.

Data analysis

Vegetation and climatic spatial distributions were overlaid and sampled for the final data matrix within the frame of a raster geographic information system (GIS). The initial data set of 253447 pixels was split into three approximately even-sized sets (training, verification and test set). The first set was used for the finding of the NN parameters, the second was used to check for overfitting (see e.g. LAWRENCE, 1997), and the third contained fully independent data used for the testing of different NNs and for the evaluation of a final model. The total data set used for model development was unbalanced, i.e. a particular forest type was represented with a different number of cases (pixels) according to its proportion in vegetation cover. The use of a balanced data set, performed in a separate control analysis, did not significantly improve model reliability.

The prediction model was derived using the feedforward NN with multilayer perceptrons (MLP) which is appropriate for classification problems (see e.g. BISHOP, 1995 or PATTERSON, 1996). The logistic function was used as the activation function. During the preliminary research, a number of NN architectures was tested. Each tested architecture had an input layer with 8 independent estimators (5 composite macroclimatic estimators, northness, eastness and terrain slope) and an output layer with 9 vegetation classes, but a number of hidden layers (1–2) and its neurons (5–40) varied. The NN architecture finally chosen had two hidden layers with 25 neurons. A further increase in NN architecture complexity did not yield significant model improvement in a reasonable model training time. However, the architecture of the final model illustrates the complexity of correlation between vegetation and climate in the real space.

RESULTS AND DISCUSSION

The NN model originally calculates the probability of incidence of each forest type for a given set of input values. Thus, the model returns nine probabilities for each pixel. The class with largest probability is used for the classification of the given pixel into the forest type. Classification results for ten NNs, independently initialised and trained by thousand epochs, are presented in Tab. 2. All of NNs classify major forest types with a correctness between 78 % and 79 % in total. Classification correctness for particular vegetation classes varies for different NNs (Tab. 2). Due to this fact, the final model combines the results of these ten NNs, with each pixel being finally classified into that forest type that is most frequent in ten independent classifications. If two or more forest types have equal frequency, the selection between them is done randomly.

Tab. 2. Classification correctness for ten independent NNs. All values are in percentages. Numbers of forest types follow Tab. 1.

forest type	1	2	3	4	5	6	7	8	9	total
NN 1	88.1	63.7	77.6	92.3	34.7	34.5	94.2	52.1	94.1	79.3
NN 2	87.2	55.4	82.6	90.6	24.7	39.9	92.6	64.9	91.5	78.6
NN 3	90.5	54.4	84.5	90.3	21.5	41.2	90.6	51.3	94.7	78.6
NN 4	87.5	59.9	80.3	91.6	27.4	30.6	94.6	48.0	91.9	78.6
NN 5	83.8	61.8	81.9	89.1	16.5	37.6	91.4	61.7	90.9	78.2
NN 6	87.9	48.3	83.6	91.8	35.3	36.1	92.7	58.2	89.9	77.7
NN 7	85.1	62.8	82.5	90.8	25.7	40.4	90.9	62.3	87.7	79.1
NN 8	90.6	61.2	77.2	90.6	30.0	35.1	92.0	46.2	96.2	78.3
NN 9	88.2	50.0	86.9	87.7	27.0	39.2	93.3	65.3	90.1	78.5
NN 10	91.7	51.7	82.4	89.4	38.0	35.7	93.4	64.4	90.0	78.6

The final model has a total classification correctness of 79.5 % and overall Kappa statistics (MONSERUD & LEEMANS, 1992) of 0.75 (see Tab. 3 for detailed classification results). Consequently, the total agreement between observed and modelled forest types could be characterised as 'very good' (LANDIS & KOCH, 1977). Moreover, the total portion of correctly classified pixels together with pixels misclassified to the adjacent forest type (Fig. 2) is 96.8 % (see also Fig. 3). These results suggest: 1) a strong correlation between macroclimate and the spatial distribution of main forest types in Croatia and 2) high model accuracy. However, the spatial pattern of misclassified pixels is clearly non-random (Fig. 3), which suggests the additional influence of topoclimatic factors. The final model was applied to the entire land area of the Republic of Croatia, aiming at the construction of a potential spatial distribution of nine major forest types (Fig. 4).

A lower agreement (according to LANDIS & KOCH, 1977, it could be assigned the value 'fair') between the observed and modelled pixels for type 5 (subalpine deciduous and coniferous forests; Tab. 3) could be explained by the hypothesis that the incidence of this type in Croatia, which frequently occupies the ridges of the

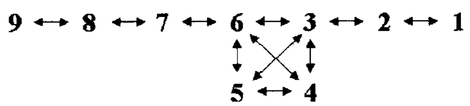

Fig. 2. The scheme of spatial arrangement of adjacent forest types arising from the original map of TRINAJSTIĆ *et al.* (1992). Numbers of types follow Tab. 1. Arrows indicate the existence of spatial contact between types. Types 3, 4, 5 and 6 belong to the complex of beech forests (monodominant or mixed).

highest mountains, is probably additionally conditioned by topography (especially by terrain exposure to wind). This assumption could be supported by the classification results for type 4 (altimontane mixed forests): in Gorski kotar, where this type is widely spread, our model predicts its incidence well, while on the Pannonian mountains, where this type mainly occupies ridges, it almost disappears from the modelled forest cover.

Tab. 3. Classification matrix for the final model (see text for further explanation). Numbers of forest types follow Tab. 1. Bold values indicate correctly classified pixels. N is a number of pixels for each forest type in the test set (84468 pixels in total). Kappa statistics indicates agreement between observed and modelled map for each forest type, without agreement expected by chance (see MONSERUD & LEEMANS, 1992).

forest type	1	2	3	4	5	6	7	8	9
1	**11056**	328	150	0	0	0	0	0	0
2	902	**8304**	1182	0	0	0	0	0	0
3	429	5821	**15664**	973	99	463	395	2	0
4	0	0	1797	**10972**	988	706	130	0	0
5	0	0	8	23	**493**	117	0	0	0
6	0	0	14	10	10	**1224**	444	0	0
7	80	0	17	1	111	677	**14936**	398	26
8	0	0	0	0	0	0	132	**1656**	150
9	0	0	0	0	0	0	34	721	**2825**
N	12467	14453	18832	11979	1701	3187	16071	2777	3001
correct (%)	88.7	57.5	83.2	91.6	29.0	38.4	92.9	59.6	94.1
Kappa	0.91	0.61	0.65	0.79	0.41	0.49	0.91	0.69	0.85

Fair agreement for type 6 (montane deciduous thermophilic forests) suggest that this type, although relatively widespread in Croatia, has a less defined self-specific macroclimate. Consequently, it could be understood as a widely spread ecotone between adjacent forest types (compare Tab. 1 and Fig. 2). Agreements for other forest types are 'good' (types 2, 3 and 8), 'very good' (type 4) or 'excellent' (types 1, 7 and 9).

Total unexplained variability could be ascribed to: 1) vegetation mapping errors related to the scale used (1 : 500000), 2) the use of spatially discrete vegetation classes, while nature boundaries between classes are often blurred, 3) remaining local influences (such as in Motovun forest, Istria, where lowland pedunculate oak forest in the valley of the Mirna River is an enclave within the Mediterranean vegetation) and 4) model error (e.g. as on some patches in the Kvarner area, where the model unrealistically predicts montane deciduous mesophilic forest; Fig. 4).

The presented model could be suitable for general reforestation planning and for the prediction of regional vegetation succession under assumed climatic changes. Besides, the model could be a macroclimatic frame for more detailed local models of the

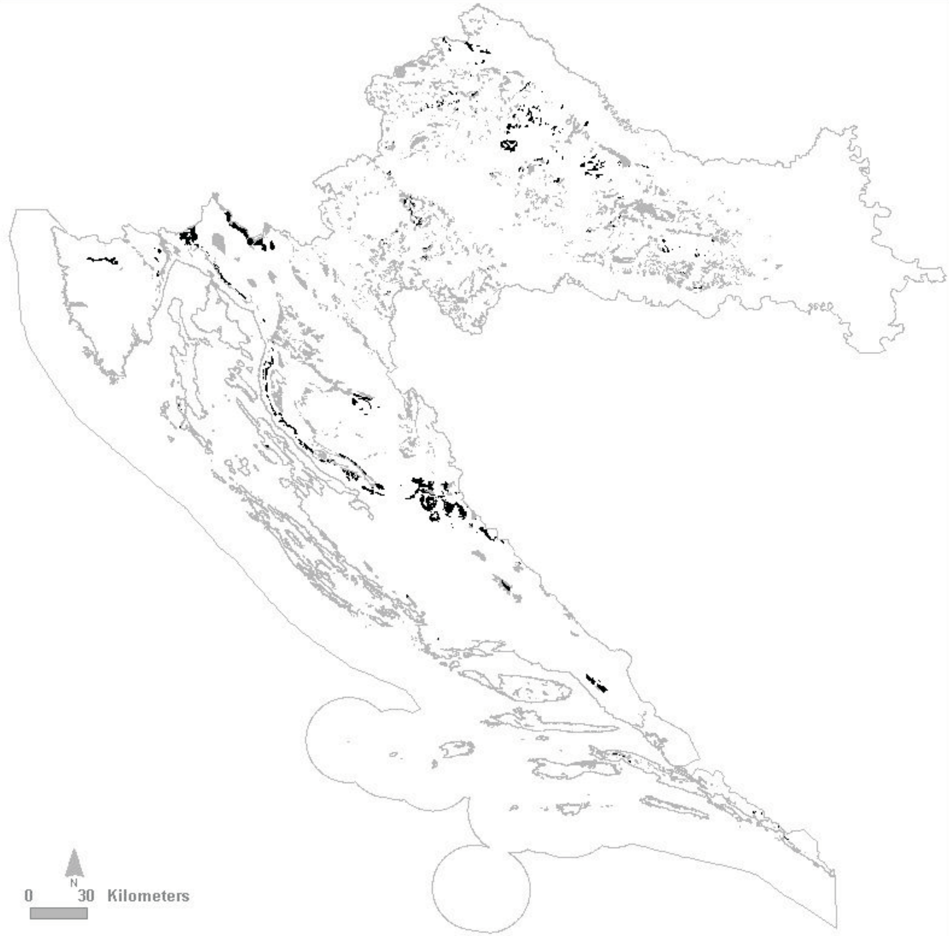

Fig. 3. Spatial distribution of correctly classified pixels (white) and misclassified pixels (grey – misclassifed into adjacent forest type, black – misclassified out of adjacent forest type, see Fig. 2 and text for further explanation). Non-forested area is also white.

spatial distribution of vegetation types (see e.g. BROWN, 1994; BRZEZIECKI, 1995; VAN DE RIJT, 1996; TAPPEINER, 1998; ZIMMERMAN & KIENAST, 1999) as well as the distribution of particular species (e.g. FRANKLIN, 1998; GOTTFRIED *et al.*, 1998; LEATHWICK, 1998, GUISAN *et al.*, 1998, 1999; ZIMMERMAN & KIENAST, 1999). These local models, especially supported by remote sensing (see e.g. BROWN, 1994 or MICHAELSEN *et al.*, 1994) and by other relevant environmental variables (lithological substratum, soil properties, local topoclimate, human impact), could have a crucial role in the inventory and mapping of data needed for optimal management of forest resources and protected areas in Croatia. These points will be the objects of future research.

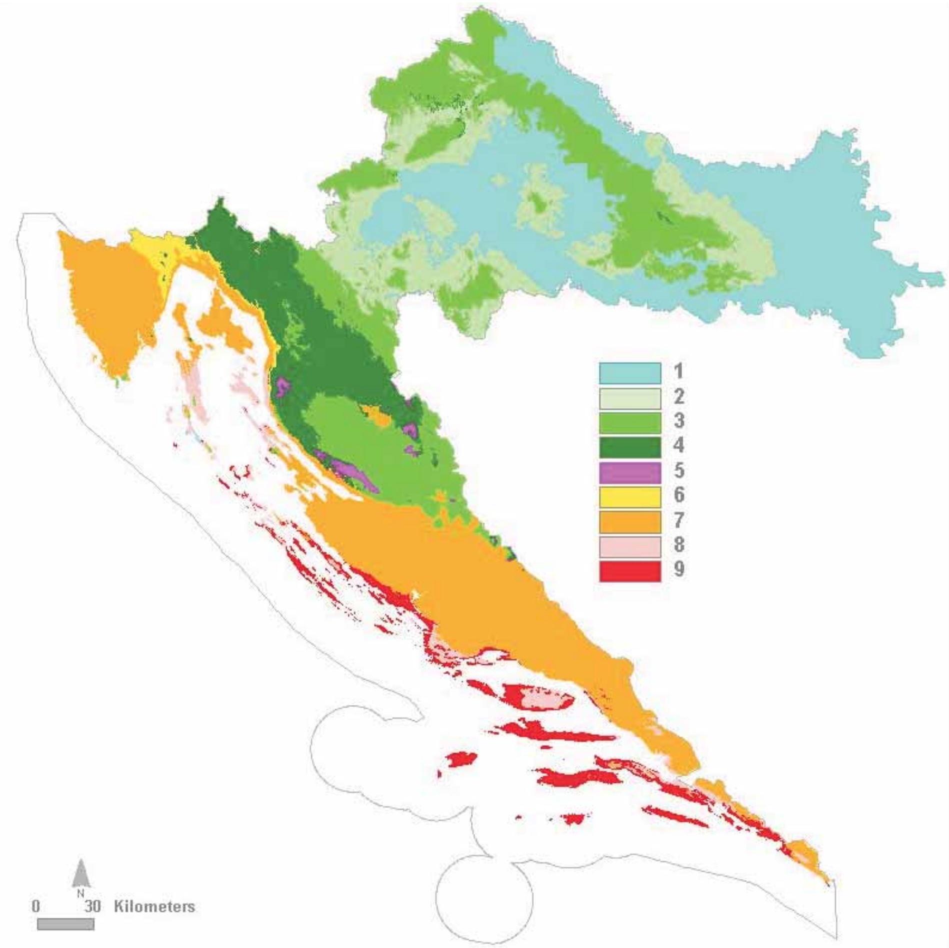

Fig. 4. Spatial distribution of major forest types predicted by the model (see Tab. 1 for legend) for the entire territory of Republic of Croatia (modelled potential vegetation).

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SAŽETAK

Prostorna razdioba glavnih tipova šuma u Hrvatskoj kao funkcija makroklime

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U radu je prikazan razvoj i testiranje modela prostorne razdiobe glavnih tipova šuma u Hrvatskoj. Model je razvijen kao funkcija makroklimatskih varijabli (srednja mjesečna temperatura, mjesečna oborina, srednje mjesečno Sunčevo ozračenje i mjesečna potencijalna evapotranspiracija) i varijabli izvedenih iz digitalnog elevacijskog modela (orijentacija i nagib terena). Kao izvor vegetacijskih podataka korištena je karta realne šumske vegetacije mjerila 1:500000, koja je za potrebe ovog istraživanja svedena na devet glavnih tipova šuma (Tab. 1 i Fig. 1). Kao izvor podataka o makroklimi korišteni su modeli visoke pouzdanosti, izrađeni u prostornoj razlučivosti 300 × 300 m.

Model je razvijen u okviru rasterskog geografskog informacijskog sustava, u prostornoj razlučivosti 300 × 300, te uz korištenje neuralnih mreža kao oruđa za modeliranje. Upotrijebljene su višeslojne neuralne mreže bez povratnih veza. Tijekom modeliranja testirane su različite arhitekture neuralnih mreža. Konačna arhitektura ilustrira složenost korelacije između šumske vegetacije i makroklime u realnom prostoru. Testiranje modela provedeno je na nezavisnom uzorku. Deset nezavisnih inicijalizacija odabrane neuralne mreže rezultiralo je ukupnom točnošću klasifikacije između 78 % i 79 % (Tab. 2). Kako je točnost klasifikacije varirala za pojedine šumske tipove (Tab. 2), konačni model kombinira rezultate svih deset međusobno nezavisnih mreža. Taj konačni model klasificira šumsku vegetaciju s ukupnom točnošću od 79.5 %. Ukupna Kappa statistika iznosi 0.75 što se označava kao 'vrlo dobro'. Osim toga, udio točno klasificiranih piksela zajedno s pikselima klasificiranim u susjedni tip šume (Figs. 2 i 3) iznosi 96.8 %. Svi ti rezultati upućuju na jaku korelaciju između makroklime i prostorne razdiobe šumske vegetacije u Hrvatskoj, te istovremeno na visoku pouzdanost modela. U radu su prikazani i komentirani rezultati klasifikacije modelom za svaki šumski tip posebno (Tab. 3).

Prostorna vegetacijska varijabilnost neobjašnjena modelom može se tumačiti pogreškom vegetacijskog kartiranja u sitnom mjerilu, korištenju diskretnih tipova koje omogućuju kartiranje dok su prirodne granice između tipova često nejasne, lokalnim utjecajima i pogreškom modela. Model je primijenjen na cijeli hrvatski teritorij s ciljem konstruiranja potencijalne prostorne razdiobe glavnih šumskih tipova (Fig. 4).

Model bi mogao biti koristan u planiranju pošumljavanja, kao i u predviđanju vegetacijske sukcesije pod utjecajem pretpostavljenih klimatskih promjena. Nadalje, model bi mogao biti prikladan makroklimatski okvir za detaljnije, lokalne modele prostorne razdiobe vegetacijskih tipova, kao i posebnih biljnih vrsta, uz korištenje dodatnih okolišnih procjenitelja kao što su litološka podloga, značajke tla, topoklimatski procjenitelji, te antropogeni utjecaji.