A Static Model of Abiotic Predictors and Forest Ecosystem Receptor Designed Using Dimensionality Reduction and Regression Analysis

PAVEL SAMEC[1,3*], PETRA RYCHTECKÁ[2], PAVEL TUČEK[1], JAN BOJKO[3], MILOŠ ZAPLETAL[4,5] AND PAVEL CUDLÍN[6]

[1]*Department of Geoinformatics, Faculty of Science, Palacký University, 17. listopadu 50, CZ-771 46 Olomouc, Czech Republic (www.geoinformatics.upol.cz)*

[2]*Faculty of Forestry and Wood Technology, Mendel University, Zemědělská 3, CZ-613 00 Brno, Czech Republic*

[3]*Forest Management Institute Brandýs nad Labem, Nábřežní 1326, CZ-250 01Brandýs nad Labem, Czech Republic*

[4]*Centre for Environment and Land Assessment – Ekotoxa, Otická 37, CZ-746 01Opava, Czech Republic*

[5]*Silesian University at Opava, Faculty of Philosophy and Science, Masarykova 37, CZ-746 01 Opava, Czech Republic*

[6]*Global Change Research Centre AS CR, v.v.i., Lipová 1789/9, CZ-370 05 České Budějovice, Czech Republic*

[*]*Corresponding author: Mr. Pavel Samec, Department of Geoinformatics, Faculty of Science, Palacký University Olomouc, 17. listopadu 50, Olomouc, CZ-771 46, E-mail: psamec@post.cz*

Samec, P.[*], Rychtecká, P., Tuček, P., Bojko, J., Zapletal, M. and Cudlín, P. 2016. A Static Model of Abiotic Predictors and Forest Ecosystem Receptor Designed Using Dimensionality Reduction and Regression Analysis. *Baltic Forestry* 22(2): 259-274.

Abstract

The closeness of dependence level between growth environment (abiotic predictors) and forest ecosystem (receptor) indicates accordance or discrepancy between site and forest state. Our forest ecosystem analysis was focused on static model approximation between abiotic predictors with the closest dependence and properties of the receptor at 1×1 km grid in the Czech Republic (Central Europe). The predictors have been selected from natural abiotic quantities sets of temperatures, precipitation, acid deposition, soil properties and relative site insolation. The receptor properties have been selected from remote sensing data, density and volume of above-ground biomass of forest stands according to the forest management plans, and from surface humus chemical properties. A selection of the most dependent quantities was made by combining factor analysis and cluster analysis. The static modelling of the dependences between selected predictors and receptor properties was conducted by canonical correlation analysis. Average temperature, annual precipitation, total potential acid deposition, soil base saturation, CEC, total acid elements and site insolation index closely corresponded to NDVI and surface humus base saturation, Corg and acid elements content at 30% of the analysed grid of forest soils and it indicated forest state within the confidence interval at 69% of the forest soil grid (r_{CCA} = 0.79; P < 0.00001). The forest ecosystem state that corresponds to the selected abiotic predictors was demonstrated in hilly altitudes. The tested procedure is inconvenient for forest state analysis in floodplains and moorlands. Based on approximation deviations, highland and mountain forests were divided into areas with non-optimum or more optimum ecosystem state than as corresponds to the values of the predictors.

Keywords: forest state monitoring; EMEP-LRTAP; floodplain; mountain forests; canonical correlation analysis.

Introduction

Forest ecosystems consist of predictors and the receptor. The classification of interacting predictors and receptor deviations may suggest trend of forest ecosystem state change (Noble et al. 2004). Abiotic predictors of growth environment and the receptor of vegetation define basic spatial relationships of terrestrial ecosystems (Keller et al. 1997). The receptor usually indicates the response of the joint action of numerous predictors. When one of the forest state predictors appears to be dominant, its manifestations result from the participation of other factors that cannot be omitted (Flückiger et al. 1986). The ecosystem acidification due to industrial pollution of atmosphere changed the closeness of dependence between abiotic predictors and the receptor. Acid deposition highlighted sensitivity of forests towards freeze and drought (Chappelka and Freer-Smith 1995). On one hand, acid

deposition, freeze and drought are stressors, on the other hand, they are integral part of the vegetation growth environment. Its impact on ecosystems is not definite all the time, but it is differentiated. A spatial differentiation of the abiotic stressors is the basic assumption for forest abiotic vulnerability simulations (Zapletal 2006). Acid deposition and non-optimum growth environment expose forests to decline. Different reactions of acid substances in the atmosphere and in the soil hamper the modelling of their partial effect on the ecosystems (Erisman et al. 2005). The various effect of acid deposition on different forest stands and soils is indicated by critical levels and loads (CLL) (Gauger et al. 2002). The measurements of critical loads in forest ecosystems are carried out in small forest basins of EMEP-LRTAP systems. The different relations of predictors in forest ecosystems makes itself felt by diversification of the ecological response of forests to stress (Purdon et al. 2004). Extrapolation of CLL from small forest basins up to landscape ecosystem scales linearizes local hot-spots and thereby decreases total heterogeneity of different forest ecosystem states (Smith and Fowler 2001).

The closeness of dependence between predictors and forest ecosystem receptor is a prerequisite for simulations of forest response on growth environment change. The feasibility of these simulations is conditioned, on one hand, by choice of suitable spatial platform of the modelling, on the other hand, by suitable selection of interacting forest ecosystem properties. The recent environmental change and commercial changes of forest tree-species composition most participate in change of European forest ecosystem functions (Lindner et al. 2010). The environmental change more affects managed forests than natural forests and may positively influence forests predominantly on unexposed nutrient-rich sites, while the predisposed forests are being affected negatively (Pietsch et al. 2014). The forest ecosystem functions are most influenced by environmental processes of climate change, increase of atmospherical contents of CO_2 and O_3 and by acidification (Schröter et al. 2005). The increase of CO_2 content, on one hand, stimulates bioproduction, on the other hand, it decreases plant tolerance on O_3 deposition (Karnosky et al. 2005). The forest soil acidification causes both forest decline and decreased ability of the ecosystem adaptation on climate change due to fine root length increment and forest biomass decrease (Cudlín et al. 2007). Nevertheless, joint action of nitrogen deposition and regional climate change will not afflict the Central-European forests unequivocally negative, but on different sites positively or negatively (Schröder et al. 2015).

The selection mode of variables in environmental modelling is either empirical, or statistical (Smith et al. 2011). The ecological classifications of vegetation are usually focused on analyses of spatial relations among empirically selected basic predictors, which may not influence all states of the receptor at the same signification level, thereby empirical selection allows obtain only generalized relationships between predictors and receptor (Hruška et al. 2001). Average temperature, annual precipitation, vegetation period, soil texture and topography are basic abiotic predictors of forest ecology (Barthlott et al. 1999). Nutrient balances, species composition or biomass are basic properties of the ecosystem receptor (Gaston and Spicer 2004). Seasonal or substance constituent parts of the basic predictors are specific abiotic predictors, which may potentially influence health status of the receptor. Basic predictors influence the receptor by the same rate in the whole interval of natural values, but different values of specific predictors may also influence the receptor contradictory (Smith and Herman 2004). The dynamics of the feedbacks between basic predictors and selected ecosystem properties indicates community response to climatic change, ecological disturbance or pollution (Foley et al. 1998). The empirical selection of variables is not component of the modelling, but the model is designed after inductance of quantities, which roles are known experimentally or theoretically. The statistical selection is based on indication of the most mutually correlating abiotic predictors and the receptor properties from the general matrix of many quantities. Statistical selection within suitable spatial environmental modelling platform allows to select predictors so that they can indicate specific receptor states (Csontos et al. 2007).

The aim of our study was distinction of close and deviated relations between the growth environment and forest ecosystem properties by multivariate selection and canonical correlation analysis. The equation $f(\boldsymbol{Y}) = f(\boldsymbol{X})$ expresses the basic relationship between predictors ($\boldsymbol{X}$) and the receptor ($\boldsymbol{Y}$) in ecosystems. The static model of $f(\boldsymbol{Y}) = f(\boldsymbol{X})$ is compiled only from identically approximated items in contrast to the extrapolated CLL landscape models. The differences between basic and specific forest ecosystem state predictor models were investigated by the comparison of statistical approximation deviations (Noble et al. 2004). Closely approximated statistical dependence between the selected predictors and the receptor properties may help in indication of equilibrium forest ecosystem state. Deviations between obtained and modelled receptor state may help to differentiate non-optimum or more optimum forest state than as corresponds to the correlation with predominant local growth conditions. The ecological disturbances are simultaneously manifested by a lower forest canopy and simplified ecosystem structure. Low values of NDVI, stand density and volume and alterations in the supply and a chemism of surface humus are basic empirically classifiable indicators of the forest disturbances (Keller et al. 1997). In order to be able to use the basic indicators of ecosystem disturbances for obtaining their relations with the growth environment of the man-

aged forests, we designed large-scale spatial modelling platform. The planned management changes of the forest canopy after main felling according to the normal forest concept potentially cover <10% of the management-plan area territory. The main fellings regulated by the normal forest concept may not significantly affect total potential character of forest canopy in the area, while unregulated fellings may (Smidt and Herman 2004, Gauger et al. 2002, Smith and Fowler 2001). Low values of the forest disturbance indicators in large-areal scale of the sustainably managed cultural landscape usually correspond only with abnormal forest dieback, where the unregulated fellings have been mainly concentrated (Pačes 1985). The permanent forest disturbances in Europe are namely concentrated along upper tree limit and on azonal sites, where marginal ecological gradients occur (Christensen et al. 2005). Among accidentally occurring natural disturbances, abiotic harmful agents are those that affect the forest state the most. However, their scope in the cultural landscape is, to a certain extent, implicated by alterations in the forest species composition and by the use of intensive silvicultural systems (Lochman et al. 2004).

Material and Methods

The static modelling of dependences between abiotic predictors and the forest receptor was based on the statistical selection of the most mutually correlating quantities from the general matrix of variables and evaluation of their interrelationships (Borůvka et al. 2007). The modelling was conducted by multivariate exploratory data analysis (MEDA), canonical correlation analysis (CCA) and linear regression (LR). The modelling platform was a grid of 1×1 km covering forest lands on the territory of the Czech Republic (CR). The statistical selection of the abiotic predictors and receptor properties from the general matrix was conducted by MEDA. For the exploratory data analysis, we used basic multivariate methods because they preserved informational value of the selected quantities for potential forest management needs (Modrzyński 2003). CCA was used to verify the closeness of the dependence between the selected predictors and receptor. LR allowed us to distinguish areas with a sufficient correlation of predictors and receptor properties from another areas (Figure 1). The interpretation of the results was performed by discussion with regional studies on forest pollution load.

Input predictors and receptor quantities were collected according to the forest vulnerability classification concept in the CR such a manner that their relationship could be expressed using the $f(\boldsymbol{Y}) = f(\boldsymbol{X})$ approximation (Hruška et al. 2001). The CR and the neighbouring regions of Germany and southern Poland are the parts of Europe with the most seriously damaged environment by acid deposition (Akgöz et al. 1995). The comparison of differences

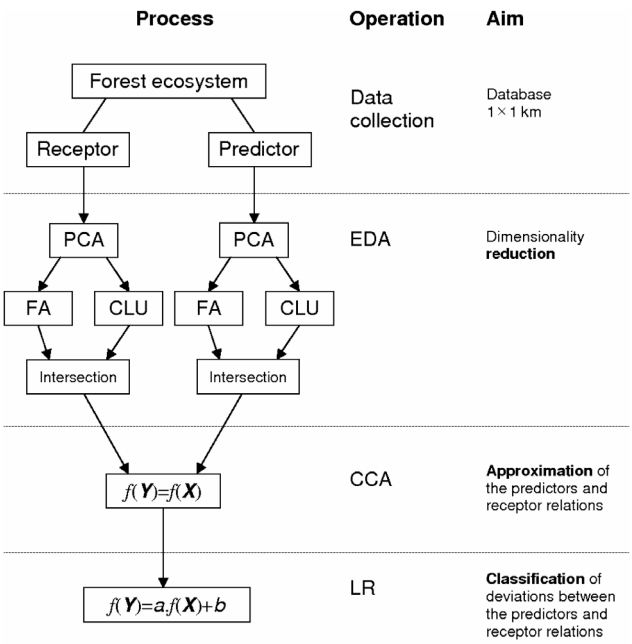

Figure 1. The flow chart of the ecosystem statistical analysis based on exploratory data analysis (EDA) of the predictors and receptor and their comparisons by canonical correlation analysis (CCA) and linear regression (LR)

between influences of forest ecosystem properties linear combinations and influences of seasonal values or compounds of other ecosystem properties is a specific feature of the introduced static modelling. This comparison was conducted by division of the general matrix to submatrices of cumulated and elementary forest ecosystem properties, which avoided unwanted auto-correlation between linear combinations of forest ecosystem specific properties and elementary specific ecosystem properties (Thalib et al. 1999). The predictors were defined as permanent site conditions that implicate production and natural forest composition (Purdon et al. 2004). The receptor was defined based on forest vegetation biomass parameters and chemical properties of surface humus (Emmer et al. 2000). We processed all the input data in a form of medium-term averages. The time period included in the calculation of average values differed in individual quantities depending on the methodical seriousness of data collection.

Modelling Platform

A regular square raster 1×1 km of a modelling platform was situated created in the national uniform trigonometric cadastral grid (Mervart and Cimbalnik 1997). The basic grid was created using 80,140 cells. The investigated cells with the actual forest representation ≥70% (16,266 cells; 20% of the total forest cover in the Czech Republic) were identified by the intersection with a vector model of the inventoried boundaries of forest and forestless land from the Information Data Centre of the For-

est Management Institute (FMI). Elevation median was identified for each investigated cell of the 1×1 km grid by intersection with DEM 25×25 m (Klimanek 2006).

Predictors

Basic climatic quantities, constituents of total potential acid deposition (*TPAD*), soil cation exchange capacity (*CEC*), base saturation (*BS*), aluminium – exchange base ratio (Bc/Al), organic carbon (C_{org}) and nitrogen (N_t), nutrient contents in the soil mantle (R_xO_y), content of soil clay (SC<2 µm) and orographic index of global radiation (OIGR) were all analyzed as predictors.

The normals (1971–2000) of average annual temperatures (*T*) and annual precipitation (*P*) and their spring (March–May), summer (June–August), autumn (September–November), winter (December–February), vegetation amounts (April–September) and out-of-vegetation amounts were used as the basic climatic quantities (D'Arrigo et al. 2003). The layers of climatic quantities in the 1×1 km grid were obtained by geographic interpolation from the dot data field of the data measured by the Czech Hydrometeorological Institute. IDW modification was used that includes the mean elevation of each cell as a co-variate in the calculation (Hadaš 2000).

The initial models of annual *TPAD* in the 1×1 km grid were approximated using the EMEP-LRTAP procedures according to the basic formula (Erisman et al. 1989):

$$TPAD = 2.SO_x + NO_y + NH_x ,$$

where SO_x is the total (wet and dry) deposition of sulphuric compounds (SO_2, SO_4^{2-} in the mist and in the precipitation); NO_y is the total deposition of oxidized nitrogen compounds (NO_x, NO_3^- in the mist and in the precipitation); NH_x is the total deposition of reduced nitrogen compounds (NH_3, NH_4^+ in the mist and in the precipitation) (Zapletal 2001, 2006). Medium-term average values of individual quantities in each cell were calculated from the models of 1998, 1999, 2000, 2003 and 2004.

The soil quantities were obtained from the diagnostic horizons in the 15,931 spot probes under the forestry explorations of the Department of Agriculture of the Czech Republic during 1979-2008. Location of these probes was characterized by elevation, management population of forest types (MP) and natural forest area ranges (NFAR) (Tomášková 2004). The spot probe elevation was identified from the 25×25 m raster DEM, where each pixel contains statistical elevation obtained by transforming the information from 3D projection of 1 m contour lines of the Basic Base of Geographical Data of the Czech Republic. Normals (1979–2008) of the selected soil quantities of diagnostic horizons were calculated within each MP in individual NFARs. The information on prevailing NFAR and representation of MP were inserted into the selected cells of 1×1 km grid from the database of regional plans of forest development and weighted averages of the selected quantities were calculated.

OIGR was used as an indicator of site insolation (Peedle et al. 2005). A set of SOLar POSition equations and intensities in GRASS GIS were used to insert the morphometrical characteristics of Sun declination, orientation, and position from DEM into each grid cell. The *r.sun* module was used to perform consequent calculation of OIGR values (Neteler and Mitasova 2002).

Receptor

The receptor properties were divided into quantities identified by the field survey and from the remote sensing. The quantities identified by field survey were expressed by standing volume per hectare (V_{ha}), mean forest density (ρ) and chemical composition of the surface humus on a cell area of 1×1 km grid. The data on V_{ha} and ρ were inserted into individual modelling grid cells through the sums and averages from the database of forest management plans of the CR administered by FMI.

To characterize the receptor, we used *CEC*, *BS*, C_{org}, N_t and R_xO_y of the organic horizons (OH) from the forest land work databases of the Ministry of Agriculture of the CR. The transformation of the humus chemical properties normals (1979–2008) from the probe set to modelling grid was carried out as a weighted average calculation in each cell by MP simplification, total composition of broad-leaved or conifer tree species and DEM. The information on MP was simplified to the sets of sites tending to a normal hydrologic model (IHN) and waterlogged sites (P). The prevailing composition of tree species was described as broad-leaved trees domination (≥ 50%) or conifer trees domination (> 50%) in the stand oldest storey from the FMI forest management plan database. The elevation was classified by altitudinal zones (Demek 1987).

Remote sensing data were represented by the generalized Landsat TM/ETM+ scenes from the period of 1997–2008. Pre-processing of the layers of individual channels and indices (NDVI and NDMI) included masking of original images in the forests as per FMI resources, exclusion of the cloud cover cells, orthorectification, coordinate system transformation, and resampling into the 1×1 km grid. Generalization was performed as a calculation of the arithmetic average of individual quantities from 28.5×28.5 m cells corresponding to the forest acreage inside of each 1×1 km cell. The medium-term averages were calculated for each quantity from the data of individual years from 1997 to 2008 in 1×1 km grid.

Static Modelling

The static modelling consisted of analysis of relations between basic predictors and receptor properties and analysis of relations between specific predictors and receptor

properties. Basic predictors and receptor properties have been selected at cumulated quantity submatrices. Specific predictors and receptor properties have been selected at elementary quantity submatrices. The cumulated quantity submatrices were formed from linear combinations of the elementary quantities. Individual quantities in all matrices were divided into natural sets by the physical and chemical essence, identification method, identical units, and standardization particulars (Smith et al. 2011). The sets were created for temperatures, precipitation, constituents of *TPAD*, soil nutrients, remote sensing quantities, forest mensuration field quantities, and surface humus nutrients.

The submatrix of specific predictors contained seasonal normal temperatures, seasonal precipitation amounts, SO_x, NH_x, NO_y, SC, *BS*, *CEC*, Bc/Al, C_{org}, N_t, oxides of individual soil macrobiogenous elements, and OIGR. The submatrix of specific receptor properties contained reflectances of the basebands of the secondary radiation of earth surface recorded by the Landsat carrier, NDVI and NDMI calculated from the basebands, chemical properties of the surface humus (*BS*, *CEC*, Bc/Al, C_{org}, N_t, R_xO_y), σ and V_{ha}. In the cumulated quantity submatrices, climatic quantities were grouped into *T* and *P*, acid atmospheric deposition constituents into *TPAD*, and oxides of individual soil macrobiogenous elements were summed to form a total content of acid elements ($TAE = Al_2O_3 + Fe_2O_3$) and a total content of alkaline elements ($TBE = CaO + MgO + K_2O$).

The MEDA was focused on the dimensionality reduction made separately amongst predictors and separately amongst the receptor properties. The presumptions for the $f(\boldsymbol{Y}) = f(\boldsymbol{X})$ equation approximation were verified by linear correlations of the selected quantities. The MEDA was carried out using the sequence of principal component analysis (PCA), factor analysis (FA), and cluster analysis (CLU). PCA was used to detect correlations in individual sets. Those quantities were excluded from individual sets of quantities with identical units that were identified by component weights in a joint quadrant without having one markedly big vector of the component weights. The number of necessary component weights was identified by using the Cattel's index plot analysis from a number of influential factors that express >90 % of the total variability (Thalib et al. 1999).

The theoretical number of the included factors for determining the optimum number of the component weights was used to define the conditions for FA application. The input variables were standardized using a power or logarithmic transformation (Box and Cox 1964). The logarithmic transformation was used in those cases, where the power transformation failed to provide the values with normal distribution. Application of FA was aimed at finding the combinations of potentially correlating quantities from various sets of predictors and the receptor (Pollice 2011). With FA, those quantities were excluded that failed to reach $P > 0.60$. The similarities of quantities from the identical set were eliminated in FA merely to the variable with the higher absolute factor load value. The FA results were reviewed using the cluster analysis (CLU) with Euclidean metric. CLU allowed us to select from the identified combinations of potentially correlating quantities only those, which had close relationships only with quantities from other sets. The selection was carried out using the intersection of the FA and CLU results. CLU was carried out simultaneously by single linkage and using the Ward's approach (Rand 1971). Simultaneous application of both CLU methods took place in order to verify the robustness of relationships between the selected variables. With FA, the similarities of the variables from identical set were eliminated merely to the variable with a higher absolute factor load value. Dimensionality reduction was obtained based on intersection of FA and CLU under the conditions below: (1) so that all the sets remain represented; (2) so that each of the data sets is represented by a minimum of one variable; (3) so that those variables from one set are preferred that are close to the variables of different sets; and (4) so that the relatively outlying variables are excluded.

CCA was used to determine the $f(\boldsymbol{Y}) = f(\boldsymbol{X})$ formula relationships between the most significantly correlating matrices of the selected predictors and receptor (Johnson and Altman 1999):

$$f(\boldsymbol{Y}) = f(\boldsymbol{X}) = \sum_{j=1}^{n} \left(b_j . y_j\right) = \sum_{i=1}^{m} \left(a_i . x_i\right)$$

The canonical correlation $f(\boldsymbol{Y}) = f(\boldsymbol{X})$ formula was simplified by LR and tested by regression diagnostics (Zar 1994). The confidence interval belts of the modelled values and input quantities of the linear regression were used for the CCA models classification. The classification provided a comparison between the variable approximation quality from the elementary quantity matrices and cumulated quantities. The close approximation classification was made for the values in the model confidence interval. Classifications of the overestimated or underestimated approximation were done for the values outside of the model confidence interval as well as in the input data confidence interval. The other values were referred as outliers.

Results

Dimensionality Reduction

All the input data selections were typical of the impaired normality of distribution and residues, heteroscedasticity and residual correlation. Different input quantity intervals confirmed the need to carry out dimensionality reduction by a sequence of several MEDA techniques, on the one hand, while, on the other hand, they prefigured the need to perform selection of convenient quantities with

regard to the empirical approach. Autocorrelations, partly suppressed as early as individual specification variants were assembled, were manifested in the natural sets of individual quantities. Although PCA usually did indicated one significant component factor, the rest of the defined marginal factors were also manifested by non-parallel components of the compared quantities. The PCA application did not perform sufficient dimensionality reduction. Out-of-vegetation period temperatures (T_d), autumn temperatures (T_a) and winter temperatures (T_w), out-of-vegetation period precipitation (P_d) and summer precipitation (P_{su}), NH_x, Bc/Al, soil CaO and K_2O, green radiation reflectance (G), red radiation reflectance (R) and NIR were excluded during the PCA of elementary sets. The predictor dimensionality reduction using PCA excluded 9 variables (32%), 4 variables (18%) in the receptor properties.

The highest numbers of the separated influential scatter factors with FA reached 5–7 and included 68–86% of variability. The required amount of included variability of 90% was not reached, thus all the quantities with a load of $P > 0.60$ were taken into account. The most influential variability factors in the matrices of specified quantities mostly failed to cover even 40% of the data variability. More than 50% of variability was included by consideration of merely two factors only in predictors. The dimensionality reduction affected 7 variables (37%) in the FA specific predictors while reaching 9 variables (53%) in the FA receptor. FA of the basic predictors indicated inconvenient weights in one variable only (8%) while it included eight variables (53%) in the basic receptor properties (Figure 2). The similarity in distribution of the quantity values from different sets was a feature of the forest ecosystem potentially mutually correlating properties identification and elimination of superfluous quantities from identical sets.

The items selected from the specific predictors were spring temperatures (T_{sp}), precipitation amounts for a vegetation period (P_v) and winter (P_w), SO_x, while $NO_y + NH_x$ were eliminated, soil *BS* and SC content, and OIGR (Figure 3). The items selected from the basic predictors for modelling were *T*, *P*, *TPAD*, soil *BS* and *CEC*, content of *TAE* as well as OIGR (Table 1). Keeping the assumptions on the common action of numerous predictors from various sets of different natures on the forest ecosystem state, the monitoring of *TPAD* is more beneficial than the actual monitoring of SO_x. Both variables jointly indicated a synergy with soil *BS* and SC (Figures 2–3). The possible relationship between *TPAD* and soil C_{org} with N_t indicates that even the organic matter supply in forest soils was influenced by the air pollution load on the medium-term basis.

The quantities of forest biomasses identified on the land (σ a V_{ha}), NDMI as well as the surface humus properties of Bc/Al, *CEC* and N_t were excluded from the recep-

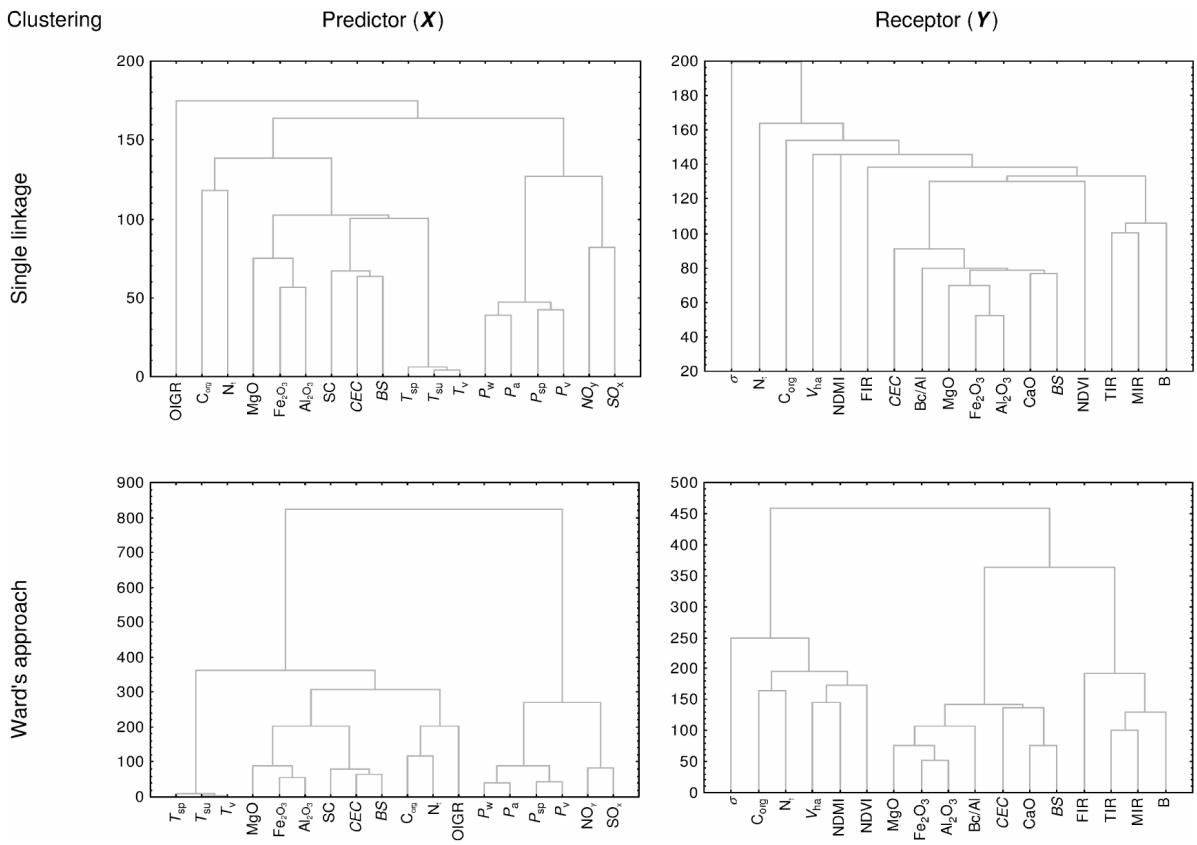

Figure 2. The single and Ward's clustering of the elementary predictors and receptor matrices

Table 1. Quantity selection according to the procedures of dimensionality reduction including maximal factor loads and explained variability (%) and the selection of properties for CCA: Light grey font indicates quantity eliminated by PCA; normal one indicates quantity preferred only by PCA; bold grey one indicates quantity selected by FA; bold black one indicates quantity verified by CLU

Predictor	Elementary	Cumulated	Transformation	λ	Load	Variability
Climate		***T***	Box-Cox	2.11	-0.71	46.72
	T_v		Box-Cox	2.06	-0.90	48.80
	T_d		Box-Cox	2.15	-	-
	$\boldsymbol{T_{sp}}$		Box-Cox	2.05	-0.90	48.80
	T_{su}		Box-Cox	2.09	-0.90	48.80
	T_a		Box-Cox	1.96	-	-
	T_w		Exp	2.27	-	-
		P	Box-Cox	-1.35	0.60	46.72
	$\boldsymbol{P_v}$		Box-Cox	-1.49	0.76	48.80
	P_d		Box-Cox	-1.41	-	-
	$\boldsymbol{P_{sp}}$		Box-Cox	-1.17	0.86	48.80
	P_{su}		Box-Cox	-1.64	-	-
	$\boldsymbol{P_a}$		Box-Cox	-1.43	0.88	48.80
	$\boldsymbol{P_w}$		Box-Cox	-1.35	0.89	48.80
Pollution		***TPAD***	Box-Cox	0.67	-0.65	11.30
	$\boldsymbol{SO_x}$		Box-Cox	0.93	-0.81	10.48
	NO_y		Box-Cox	0.07	-0.69	10.48
	NH_x		Box-Cox	0.14	-	-
Soil	***BS***	***BS***	Box-Cox	0.42	-0.75	48.80
	SC	**SC**	Box-Cox	1.31	-0.82	48.80
	CEC	***CEC***	Box-Cox	-0.28	-0.63	48.80
	Bc/Al	**Bc/Al**	Box-Cox	-3.13	-0.83	46.72
		TAE	Box-Cox	3.09	-0.75	46.72
	Al_2O_3		Box-Cox	2.69	-0.64	48.80
	Fe_2O_3		Box-Cox	3.09	-0.69	48.80
		TBE	Box-Cox	0.68	-0.91	46.72
	CaO		Box-Cox	-2.73	-	-
	K_2O		Box-Cox	1.57	-	-
	MgO		Box-Cox	1.93	-0.70	48.80
	N_t	$\mathbf{N_t}$	Box-Cox	-9.15	0.70	7.45
	C_{org}	$\mathbf{C_{org}}$	Box-Cox	-0.94	-0.69	16.07
Terrain	**OIGR**	**OIGR**	Ln	-	0.63	11.30

Receptor	Elementary	Cumulated	Transformation	λ	Load	Variability
Remote sensing	B	**B**	Box-Cox	0.39	-0.65	15.99
	G	G	Box-Cox	0.34	-	-
	R	R	Box-Cox	-0.58	-	-
	NIR	NIR	Box-Cox	0.07	-	-
	MIR	**MIR**	Box-Cox	0.35	-0.73	27.86
	FIR	FIR	Box-Cox	2.77	-0.59	6.49
	TIR	TIR	Box-Cox	-1.32	-0.55	27.86
	NDVI	**NDVI**	Box-Cox	1.09	-0.70	12.00
	NDMI	NDMI	Box-Cox	1.58	0.40	12.00
Surface humus	***BS***	***BS***	Box-Cox	0.83	-0.74	23.82
	CEC	*CEC*	Box-Cox	-1.31	-0.60	18.19
	Bc/Al	Bc/Al	Box-Cox	-8.58	-0.52	6.49
		TAE	Ln	-	-0.76	27.86
	$\mathbf{Al_2O_3}$		Box-Cox	-0.49	0.74	18.19
	$\mathbf{Fe_2O_3}$		Box-Cox	-0.05	-0.83	23.82
		TBE	Box-Cox	-0.50	-0.81	27.86
	CaO		Box-Cox	-0.25	-0.86	23.82
	K_2O		Box-Cox	-0.92	-	-
	MgO		Box-Cox	-1.14	-0.77	18.19
	N_t	N_t	Box-Cox	-14.78	-0.44	7.24
	C_{org}	$\mathbf{C_{org}}$	Ln	-	0.79	27.86
Forest biomass	σ	σ	Ln	-	-0.52	6.94
	V_{ha}	V_{ha}	Box-Cox	1.29	0.50	6.94

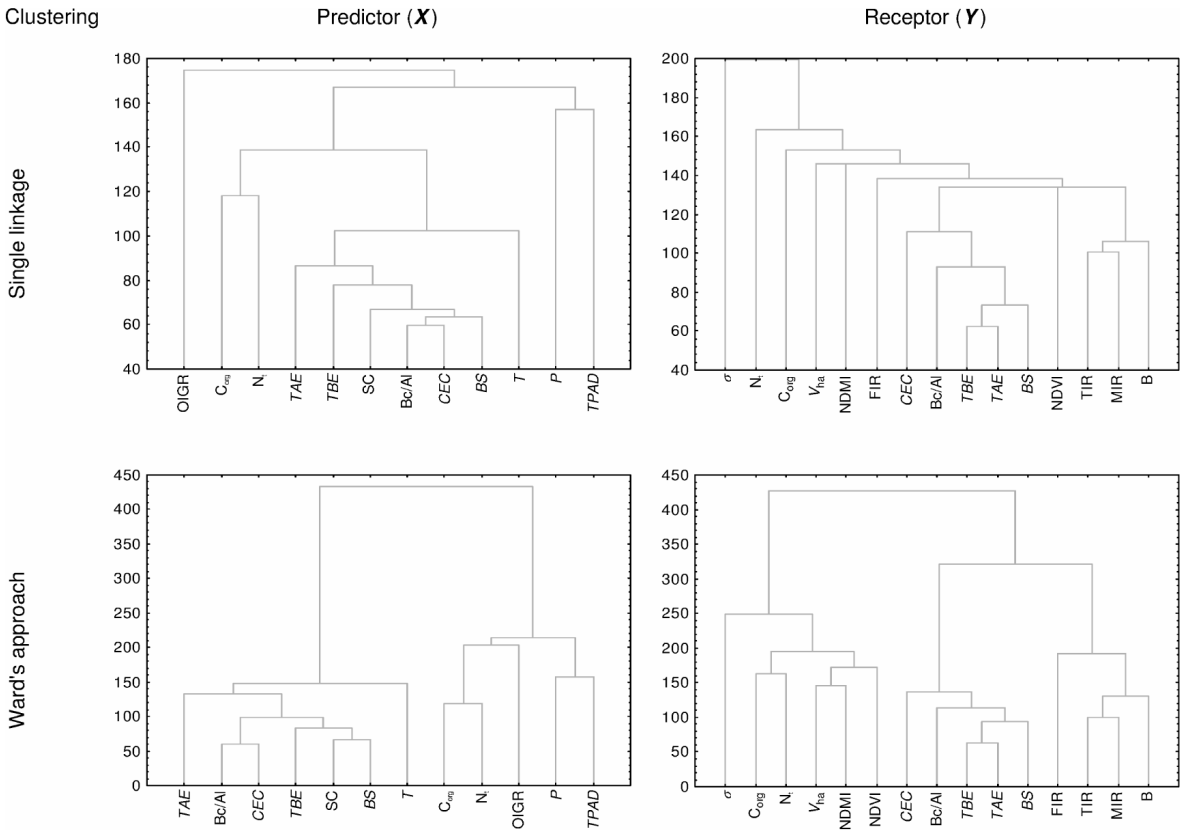

Figure 3. The single and Ward's clustering of the cumulated predictors and receptor matrices

tor properties. NDVI was selected as the basic indicator of forest biomass. *BS*, *TAE* and C_{org} were selected from the surface humus properties. NDVI takes the values > 0 in forested landscape and > 1 in richly structured forests.

Linear Correlations

Statistically significant level of correlation was documented amongst the selected abiotic predictors and receptor properties. It was mainly MIR and *BS* surface humus that correlated with most of predictors, thereby supporting the optimization of the CCA model. The carbon content in surface humus correlated negatively with the clay content, cation exchange capacity, base saturation and *TAE* in the mineral soil horizons while the *TAE* surface humus correlated positively with the other soil properties. Similarly, NDVI correlated positively with the soil clay content, base saturation, cation exchange capacity and *TAE*. In the proposed static models, the carbon content in surface humus correlated negatively with the distribution of average annual temperatures and marginally with *TPAD,* as well. Base saturation of the surface humus showed statistically significant correlation with all predictors, but also with C_{org} and *TAE* of the surface humus and, marginally, also with the MgO content in humus. *BS* of the surface humus correlated positively with the distribution of temperatures, acid deposition and other soil properties, and it correlated negatively with precipitation. Positive correlation dependencies in the soil *BS* were documented only for temperatures and other soil properties only while closer, but negative correlations with regard to the precipitation characteristics and acid deposition were identified.

The spatial distribution of *TPAD* constituents is directly proportional to the generalized distribution of soil *BS* values in the 1×1 km grid. On one hand, soil *BS* appears to be dependent on the permanent soil conditions expressed using SC and *CEC* while, on the other hand, its distribution also corresponds statistically more significantly with the distribution of SO_x in *TPAD* than in humus. The acid deposition influence on soil *BS* values is statistically higher than the actual influence of total supplies of the base substances. No linear correlations were identified between the precipitation characteristics and *TPAD*; nevertheless, the distribution of SO_x correlated significantly with P_v and P_w and it was found correlated negatively with the distribution of soil *BS* values and clay content. The closer positive correlation of SO_x and P_w implies that its input into forest ecosystems is still relatively significant namely in the winter season (Table 2).

The negative correlations of C_{org} content in surface humus provide evidence that raw humus forms usually occur on poor soils accompanied by the occurrence of conifer stands or in the mountains in the territory of the CR.

Table 2. The Pearson correlation coefficients (**bold** P <0.0001) between particular quantities of predictors and receptor

Quantity	MIR	NDVI	BS_{humus}	MgO	C_{org}	TAE_{humus}
T	**0.42**	-0.04	**0.60**	-	**-0.71**	**0.49**
T_{sp}	**0.42**	-0.03	**0.60**	0.03	-	-
P	**-0.36**	**0.05**	**-0.45**	-0.02	**0.53**	**-0.39**
P_v	**-0.40**	0.04	**-0.47**	-0.02	-	-
P_w	**-0.32**	**0.06**	**-0.42**	-0.02	-	-
$TPAD$	0.00	**-0.07**	**0.08**	-	**-0.05**	0.00
SO_x	0.03	0.00	**0.06**	0.00	-	-
SC	**0.25**	**0.11**	**0.52**	0.03	**-0.51**	**0.54**
BS_{soil}	**0.20**	**0.15**	**0.55**	0.02	**-0.51**	**0.54**
CEC	**0.10**	**0.18**	**0.41**	-	**-0.28**	**0.43**
TAE_{soil}	**0.17**	**0.29**	**0.37**	-	**-0.19**	**0.37**
OIGR	**-0.10**	**-0.21**	**-0.24**	0.00	**0.13**	**-0.08**

Nevertheless, the positive correlation between the *BS* of surface humus and in the mineral soil horizons provides evidence that the humus receptor properties are, to a certain level, permanently dependent on a persistent potential of the site fertility capacity characterized by several soil properties.

Regression Models

Generalization of predictors influenced directly the credibility of the estimated forest ecosystem state. The confidence intervals of linear approximations between the predictors and receptor divided 1×1 km grid into areas of dense, optimum or scarce forest biomass, and into outliers of azonal ecosystems. The investigated forest biomass characteristics correspond largely to the abiotic conditions from lowlands to uplands. Even a lower number of quantities sufficed to describe the forest biomass receptor better than the forest growth environment using a higher number of selected predictors. The receptor state was best characterized by NDVI, *BS* and C_{org} of surface humus. Specific predictors included almost 70% of variability, basic predictors 84% of variability. Also the total redundancy of the canonical correlation function indicating higher uncertainties in the elementary quantity model was related to the amount of variability extraction (Table 3).

The linear regression models of both elementary and cumulated quantities were loaded with heteroscedasticity (Figure 4). Both models had direct proportion of ***X*** and ***Y*** values. The regression equation of the elementary quantity model had lower correlation coefficient than the equation of the cumulated quantity model, and was characterized by parameter -0.088. The sum of the *z*-scores corresponding to the cumulated predictor averages ($\Sigma z_i = 0$) indicates the average receptor properties, but the sum of the elementary predictor *z*-score averages indicates potential improvement/aggravation of the forest state. The slopes of both equations were similarly lower than 1.

Table 3. Canonical weights of identified canonical roots (r_u) in generated regression functions (P <0.00001)

Population	Fun-tion	Quality	r_1	r_2	r_3	r_4	r_5
Elementary	Predictor	T_{sp}	-0.61	-0.69	0.50	-0.90	
(r_{CCA}=0.73)		P_v	0.30	-0.15	0.83	-0.69	
		P_w	-0.08	0.52	-0.19	-0.67	
		SO_x	-0.25	-0.26	0.33	0.64	
		BS_{soil}	-0.34	1.06	1.02	1.05	
		SC	0.07	0.02	-0.75	-1.42	
		$OIGR_{172}$	0.19	-0.40	0.80	-0.17	
	Receptor	MIR	-0.18	-0.65	-0.90	-0.02	
		NDVI	0.27	0.76	-0.70	-0.03	
		BS_{humus}	-0.97	0.34	0.61	0.05	
		MgO	-0.10	0.01	0.08	-1.00	
Cumulated	Predictor	T	-0.84	-0.52	-0.66	-0.01	0.45
(r_{CCA}=0.79)		P	0.02	-0.09	0.06	0.42	0.90
		$TPAD$	-0.16	0.02	0.02	0.17	-0.83
		SC	0.06	0.20	0.61	-1.05	0.63
		BS_{soil}	-0.38	-0.23	0.54	1.76	0.22
		CEC	0.17	0.50	0.24	-0.26	-0.75
		TAE_{soil}	0.06	0.68	-0.48	-0.50	-0.05
		$OIGR_{172}$	0.12	-0.34	0.69	-0.24	-0.23
	Recep-tor	MIR	-0.03	-0.02	-0.57	-1.01	-0.07
		NDVI	0.28	0.56	-0.31	0.07	0.82
		BS_{humus}	-0.33	0.68	-0.67	0.84	-1.23
		C_{org}	0.66	0.80	-0.11	-0.35	-1.05
		TAE_{humus}	-0.12	0.33	1.13	-0.77	0.10

Both canonical correlation models incline collectively to underestimation of the receptor values in 46% of the cases. Nevertheless, the elementary quantity model also overestimated the forest receptor values estimated values in more than 47% of the cases. In approximately 30% of the cases the cumulated quantity model assessed the forest biomass in the model confidence interval and provided the overestimation in 24% of the cases only. The receptor was characterized by quite an extracted scatter in both specifications. Both canonical correlation models were characterized by low proportions of outlying estimates (Figure 5). All the physical sets of the compared predictors and receptor properties remained preserved naturally in the model of elementary quantities while the growth environment characteristics in the model of cumulated quantities were simplified. The model of cumulated quantities expressed well the relationship of forest density and abiotic predictors in all the lowlands and highlands including the topography of sandstone rock cities (Table 4).

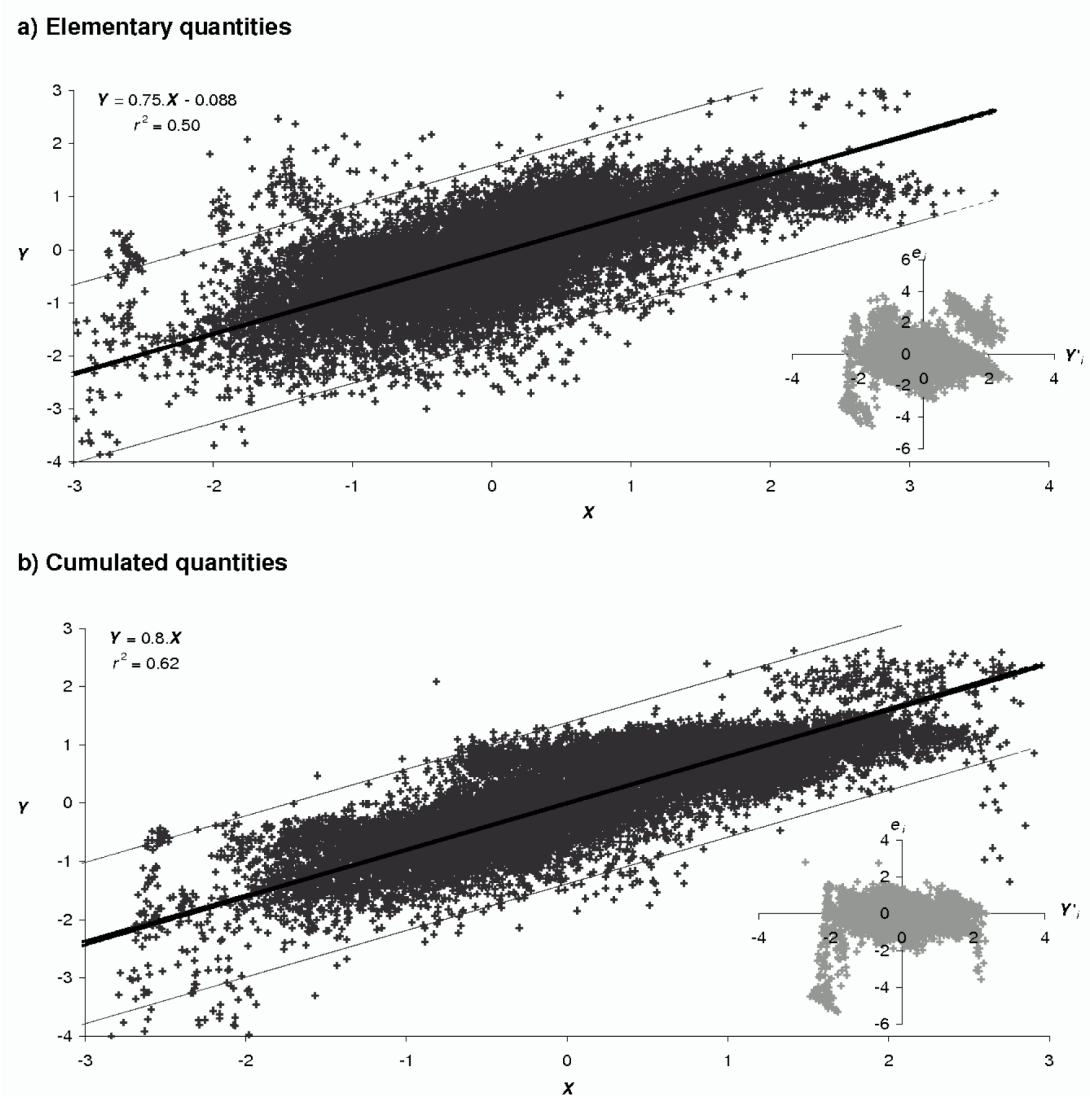

Figure 4. Linear regressions between weighted averages of predictors (***X***) and receptor (***Y***) with graphs of residuum's analyses. Y'_i is approximation of ***Y***; e_i is residuum from difference (Y'_i - Y_i)

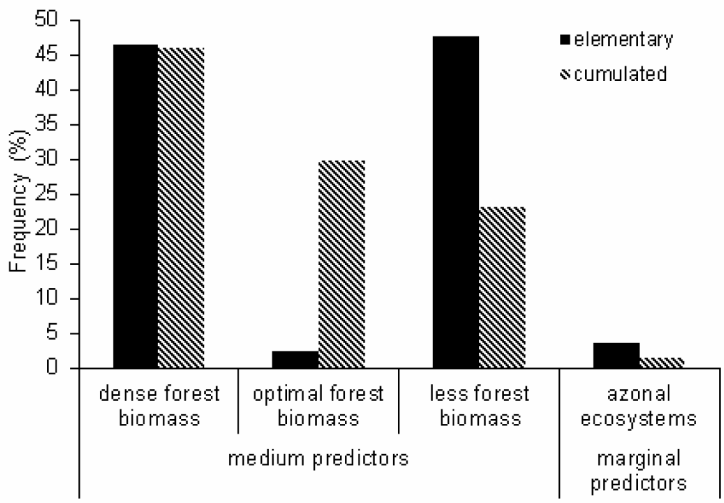

Figure 5. Compositions of the forest state classification based on confidence intervals of the linear regression between canonical functions of selected predictors and receptor

Table 4. Basic characteristics of the discussed forestland regions in the Czech Republic

No	Investigated region	Total area (km²)	Forest cover (%)	Geomorphology	Discussed results
1	Děčín Upland	80.0	97.0	broken plateau	Zapletal (2006)
2	Lužice Mts.	212.0	63.0	broken plateau	Zapletal (2006)
3	Jizera Mts.	536.8	74.0	mountains	Borůvka et al. (2007)
4	Jičín Upland	2187.6	39.0	upland	Zapletal (2006)
5	Giant Mts.	407.5	79.0	mountains	Purdon et al. (2004)
6	Orlické hory Mts.	385.9	55.0	mountains	Lochman et al. (2004)
7	Králický Sněžník Mts.	76.0	78.0	mountains	Reininger et al. (2011)
8	Rychleby Mts.	276.0	69.0	upland	Hédl (2004)
9	Hrubý Jeseník Mts.	612.0	82.0	mountains	Reininger et al. (2011)
10	Nízký Jeseník Mts.	2714.7	35.6	upland	unpublished data by FMI
11	Moravian-Silesian Beskids	8243.2	75.2	upland	Purdon et al. (2004)
12	Ore Mts.	1800.2	66.9	mountains	Bridges et al. (2002)
13	Doupov Mts.	697.1	25.9	upland	Hruška et al. (2001)
14	Křivoklát Hillycountry	1549.9	38.7	hillycountry	unpublished data by FMI
15	Svatojiřský forest	18.5	92.0	hillycountry	unpublished data by FMI
16	Třebechovice plateau	374.0	54.0	hillycountry	unpublished data by FMI
17	Iron Mts.	580.0	51.0	upland	Hruška et al. (2001)
18	Žďár Hills	709.0	46.0	upland	Zapletal (2006)
19	Drahany Upland	1579.1	55.4	upland	Drápelová et al. (2010)
20	Hostýnsko-vsetínské vrchy Hills	1339.6	52.3	upland	Erisman et al. (2005)
21	Český les Mts.	1082.4	60.2	upland	Fiala et al. (2009)
22	Brdy Mts.	982.9	65.8	upland	Keller et al. (1997)
23	Tábor Hillycountry	1599.0	41.0	hillycountry	Evans et al. (2001)
24	Bohemian-Moravian Upland	7823.7	33.7	upland	Mauer et al. (2007)
25	Chřiby Mts.	1249.1	30.8	upland	unpublished data by FMI
26	Šumava Mts.	2113.0	66.4	mountains	Purdon et al. (2004)
27	Novohradské hory Mts.	144.5	81.4	upland	Smidt and Herman (2004)
28	Pošumaví Hills	2809.2	35.2	upland	Evans et al. (2001)
29	Javořice Upland	374.0	52.0	upland	Lochman et al. (2002)
30	Libín Mt.	80.1	88.0	mountains	Evans et al. (2001)
31	Dyje-Morava plain	2945.5	13.9	lowland	Smidt and Herman (2004)

Discussion

Forest ecosystem state indication

The proposed static canonical correlation models either underestimated, or overestimated and/or closely approximated the forest ecosystem state. Close $f(\boldsymbol{Y}) = f(\boldsymbol{X})$ approximation indicated a forest state corresponding to basic abiotic predictors. Underestimated forest state approximation indicated a denser forest biomass than the modelled estimation of relation between the selected abiotic predictors and receptor properties in areas with preserved refugia of natural vegetation. Overestimated forest state approximation indicated scarcer forest biomass than the modelled estimation of relation between the selected abiotic predictors and receptor properties in areas with prevailing unnatural stands.

The underestimated approximation meant that the model revealed scarcer biomass of forest stands than the submatrix of the receptor properties. The forest ecosystem state in these territories is more optimum than that indicated by the predictors. A coherent underestimated approximation in the specific forest ecosystem properties occurred in the Šumava Mts., Tábor Hillycountry, Křivoklát Hillycountry, Doupov Mts., Ore Mts., in the western half of the Lužice Mts., in the Jizera Mts., Rychleby Mts., in the western parts of Hrubý Jeseník Mts., in the eastern Drahany Upland, in the central part of Chřiby Mts., Hostýnsko-vsetínské vrchy Hills, and along the Radhošť Plateau of the Moravian-Silesian Beskids continually. The underestimated approximation in the forest ecosystem basic properties was very similar, more continuous on the North-Eastern slopes of the Ore Mts., in the Děčín

Upland, along the entire Lužice Mts. as well in the Giant Mts. and Orlické hory Mts. (Figure 6). These regions were repeatedly affected by air pollution or gale disasters that disrupted the cultivated, poorly structured forest plantations even more (Modrzyński 2003, Bridges et al. 2002; Borůvka et al. 2007, Fiala et al. 2009). Local large-areal closed young-growth stands on the restored clearing after unregulated fellings and continuous natural forests con-

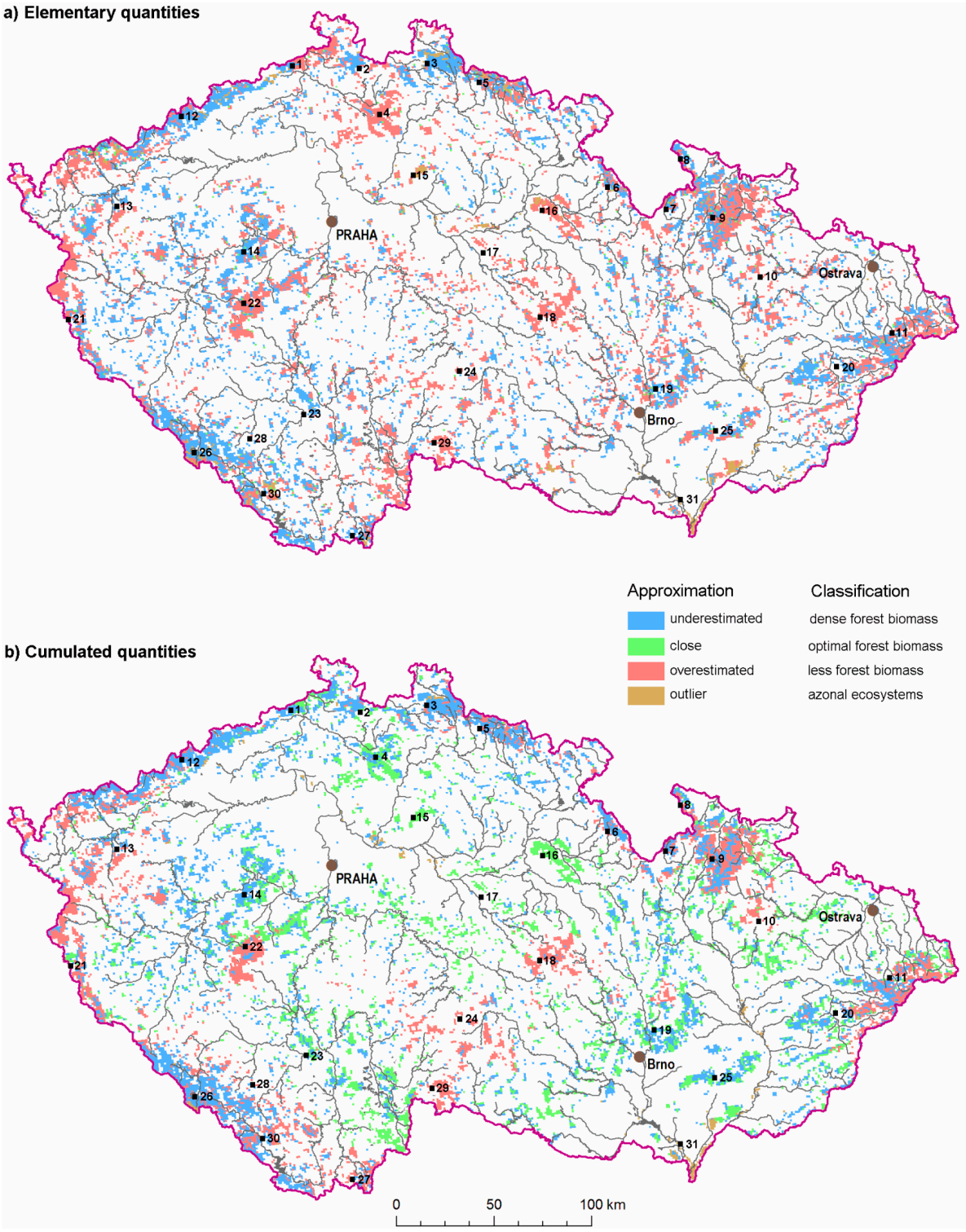

Figure 6. The mapped forest state classification and selected discussed regions in the Czech Republic. For information about the regions see Table 4

tributed to indication of the more optimum state of other stands in the wider surroundings (Hédl 2004, Purdon et al. 2004, Reininger et al. 2011).

The overestimated approximation meant that the model showed denser biomass of forest stands than the submatrix of the receptor properties. The forest ecosystem state in these territories is less optimum than that indicated by the predictors. Overestimated approximation in the forest ecosystem specific properties occurred namely in the Český les Mts., the southern edge of the Ore Mts., in the Brdy Mts., in a wide range from the Novohradské hory Mts., in the south through the Bohemian-Moravian Upland, Iron Mts. and Třebechovice plateau up to the Děčín Upland, Jičín Upland, Hrubý Jeseník and Králický Sněžník Mts. on the north, and up to the central parts of the Beskids in the eastern territory of the CR. The overestimated approximation of the forest ecosystem basic properties was limited to the Beskids, Hrubý Jeseník Mts., Český les Mts., southern Brdy, Žďár Hills, Javořice Upland, and Pošumaví Hills. Managed spruce or pine stands dominate in these regions (Keller et al. 1997, Hruška et al. 2001, Mauer et al. 2007).

Outlier classifications of the regression functions usually occurred at isolated points only in the Libín Mt., in the Svatojiřský forest, on the northern hillside of the Jizera Mts., and in the Dyje-Morava plain. Outliers $f(\boldsymbol{Y}) = f(\boldsymbol{X})$ occurred in azonal floodplain forests or pine forests, large-areal ravine forests, waterlogged forests and moorlands, which are ecological hot spots at the same time (Evans et al. 2001, Smidt and Herman 2004). The CCA of forest ecosystem basic properties was used to distinction of concentrated disrupted forests on the Jizera Massif in the Jizera Mts. (Borůvka et al. 2007), on the plateau of the Ore Mts. (Bridges et al. 2002), the windthrown region of Trojmezí in the Šumava Mts. (Fiala et al. 2009) as well as the spruce decline epicentres in the Drahany Upland, Nízký Jeseník Mts., and in the Beskids (Akgöz et al. 1995, Purdon et al. 2004, Drápelová et al. 2010).

Advantages of the static modelling

The main advantage of the proposed static modelling by CCA is the transparent analysis of the relationships between the selected predictors and receptor. The specific features of the proposed model consist in the equal probability of the forest ecosystem state estimation in each 1×1 km cell, the inclusion of variables manifested in large areas with relatively low spatial gradients, and *TPAD* monitoring in synergy with other abiotic predictors differentiating it from the conventional critical load models by EMEP-LRTAP. The forest ecosystem critical load models in the territory of the CR are extrapolated predominantly from unnatural spruce stands, where levels of the critical loads are adapted to spruce response but not to another tree species (Purdon et al. 2004, Smidt and Herman 2004, Erisman et al. 2005). On the contrary, the static CCA model used the characteristics of total forest biomass including all the occurring tree species. It was the forests in the mountain altitudes that usually tended to interpretation errors. In the mountain conditions of the CR, most of the forest area as well as natural forests with dense biomass stock in rugged reliefs, and loose spruce groves and shrubbery with naturally low biomass along the upper tree limit, are preserved. Therefore, a mosaic of cells indicating more optimum forest state together with cells indicating non-optimum forest state appeared in the mountain locations.

The selected abiotic predictors may be stable in short time intervals on a small scale, but on the large scale included in the 1×1 km grid, slight differences of properties prevail among adjacent grid cells. Chemical interactions of *TPAD* constituents with atmospheric water were the cause of low spatial gradients of the selected predictors. Presence of SO_x in the forest growth environment appears to be more medium-term significant than nitrogen deposition. Although nitrogen critical loads are exceeded on a regular basis, they were not manifested with the necessary factor loads in the multivariate selection. Also *TPAD* was not indicated by FA as significantly correlating with the other quantities, but CLU failed to confirm this result. The distribution of *TPAD* in the territory of the CR is close to the distribution of annual precipitation or, if the Ward's method is applied, it is also similar to the distribution of C_{org} and N_t. Considering the indication of environmental pollution hot spots will single out localities with significantly different ecological conditions from the generalized model potentially better than the indication of outliers using quantities with low space gradients.

Disadvantages of the static modelling

The main disadvantage of the used approach of static modelling consists in the uncertainty of the forest ecosystem state in areas with close $f(\boldsymbol{Y}) = f(\boldsymbol{X})$ equation approximation, when the CCA model from cumulated quantities is compared with the CCA model from elementary quantities. The model uncertainties were caused by the overestimation of conifer stand occurrences in the modelling grid and ignoring the error matrix. Assignment of the theoretically corresponding average values of the humus properties emphasized artificially the relationship of conifers with the soil surface. Generalization of the remote sensing data may not have corresponded with this forest state generalization in numerous cases. While the generalization of the information on stand density and forest volume led to schematization and pronounced simplification of the tree species composition of forests, the remote sensing data generalization conversely resulted in the acquisition of compound values. This gave rise to inaccuracies in the receptor indication. These inaccuracies caused exclusion

of the forest vegetation biomass parameters identified by a field survey from the receptor specification.

The generalization executed from the data transformation into the 1×1 km grid as well as LR caused a loss of certain anomalies that could indicate the non-repeatable and ecologically important local extremes (Thalib et al. 1999). The proposed CCA models do not work with directions of predictor actions, so they fail to determine sources of forest damage. Hot spots in critical ecosystem load models comprise pollutants which do not travel far from the source or which encounter high terrain elevations. The statistical distinction of hot spot emission sources from critical deposits outside these sources requires stable source production and stable conditions in the environment. Under such conditions, hot spots with stable occurrence are the sources of pollution at the same time (Pollice 2011). Heavy metals with locally high concentration gradients have a distribution close to normal only on the small scale, while on the large scale the distribution has a sharp sinistral slope, therefore, the large-scale model concept in the 1×1 km grid is better described by *TPAD* constituents according to EMEP-LRTAP (Gauger et al. 2002).

The model of the forest ecosystem specific properties indicated trend of forest ecosystem state change in 94% of evaluated cells, although the model of the basic properties indicated trend in the 69% of cells only. Although linear correlations between elementary quantity assignments were more significant, they also included higher uncertainties, which the CCA model of cumulated quantities expressed in a higher number of weights. The biggest differences between both CCA models were due to the weights of atmospheric precipitation, temperatures, acid deposit constituents and soil *BS* (Table 4). Although the calculation of multiple weights of the $f(\boldsymbol{Y}) = f(\boldsymbol{X})$ function extracted more uncertainties, the weight with the highest achieved confidence still contained an uncertain component, the omission of which led to various deviations in further analyses (Smith et al. 2011). Despite the described deficiencies the statistical approximations appear to provide a convenient supporting means that allow estimation of the occurrence of functional dependencies between individual forest ecosystem constituents.

Conclusion

The multivariate static modelling characterizes trend of forest ecosystem change and it provides base for sustainable forest management. The forest ecosystem state was closely approximated by canonical correlation analysis in the lowlands and uplands. The CCA indicates potential deviations between optimum forest state and disturbances in altitudinal differentiated areas. Slight deviations to the function were mainly concentrated in the highland and main mountain systems of the CR. Outliers occurred separately in the territories with concentrated occurrences of floodplains, ravine forests and moorlands. Overestimation of the function is indicative of a non-optimum forest state, while underestimation of the function is indicative of a more optimum forest state. The CCA models allow basic static simulations of the forest ecosystem response to growth conditions change. The specific predictors of spring temperatures, annual precipitation during vegetation period and during winter, SO_x, and soil *BS* indicated forest ecosystem state deviation in 1×1 km grid better than basic predictors. The basic predictors of average temperatures, annual precipitation, total potential acid deposition, soil *BS*, *CEC* and total content of acid elements indicated distinctly more equilibrium forest ecosystem state and lower contribution of outliers. The static modelling provides base for formulation of objectives of the measures necessary for receptor state change to make it more responsive to abiotic predictors of growth conditions. Reduction of *TPAD* and altered tree species compositions that will increase the values of NDVI, surface humus and soil base saturation and C_{org} content may contribute to the indication of correspondence in environmental influences on forest state.

Acknowledgement

The authors gratefully acknowledge the support by the Operational Program Education for Competitiveness – European Social Fund (CZ.1.07/2.3.00/20.0170) and the National Sustainability Program I (NPU I), grant No. LO1415 of the Ministry of Education, Youth and Sports of the Czech Republic and the Internal Grant Agency of Palacký University in Olomouc (PrF 2013 024).

References

Akgöz, E., Häusler, T., Henžlík, V., Jaakola, S., Kenneweg, H., Reuther, M., Rock, B., Schardt, M., Stoklasa, M. and Zawila-Niedzwiecki, T. 1995. Forest Damage in Central European Mountains – Final Report of a Large Area Experiment for Forest Damage Monitoring in Europe Using Satellite Remote Sensing. UNEP, Geneva, 97 pp.

Barthlott, W., Biedinger, N., Braun, G., Feig, F., Kier, G. and Mutke, J. 1999. Terminological and methodological aspects of the mapping and analysis of global biodiversity. *Acta Botanica Fennica* 162: 103–110.

Borůvka, L., Mládková, L., Penížek, V., Drábek, O. and Vašát, R. 2007. Forest soil acidification assessment using principal component analysis and geostatistics. *Geoderma* 140:374–382.

Box, G. E. P. and Cox, D. R. 1964. An analysis of transformations. Journal of Royal Statistical Society Series B 26: 211–246.

Bridges, K.S., Jickells, T.D., Davies, T.D., Zeman, Z. and Hůnová, I. 2002. Aerosol, precipitation and cloud water chemistry observations on the Czech Krusne hory plateau adjacent to a heavily industrialised valley. *Atmospheric Environment* 36: 353–360.

Chappelka, A.H. and Freer-Smith, P.H. 1995. Predisposition of trees by air pollutants to low temperatures and moisture stress. *Environmental Pollution* 87: 105–117.

Christensen, M., Hahn, K., Mountford, E.P., Ódor, P., Standovár, T., Rozenbergar, D., Diaci, J., Wijdeven, S., Meyer, P., Winter, S. and Vrška, T. 2005. Dead wood in European beech (*Fagus sylvatica*) forest reserves. *Forest Ecology and Management* 210: 267 – 282.

Csontos, P., Roccini, D. and Bacalo, G. 2007. Modelling factors affecting litter mass components of pine stands. *Community Ecology* 8: 247–255.

Cudlín, P., Kieliszewska-Rokicka, B., Rudawska, M., Grebenc, T., Alberton, O., Lehk,o T., Bakker, M.R., Børja, I., Konôpka, B., Leski, T., Kraigher, H. and Kuyper, T.W. 2007. Fine root and ectomycorrhizas as indicators of environmental change. *Plant Biosystems* 141: 406–425.

D'Arrigo, R.D., Cook, E.R., Mann, M.E. and Jacobs, G.C. 2003. Tree-ring reconstructions of temperature and sea-level pressure variability associated with the warm-season Arctic Oscillation since AD 1650. *Geophysical Research Letters* 30: 1549.

Demek, J. 1987. Obecná geomorfologie [General geomorphology]. Academia, Praha, 476 pp. (in Czech).

Drápelová, I., Menšík, L., Kulhavý, J. and Marková, I. 2010. Sulphur and nitrogen concentrations and fluxes in bulk precipitation and throughfall in the mountain and highland spruce stands in the Czech Republic. *Journal of Forest Science* 56:429–441.

Emmer, I.M., Wessel, W.W., Kooilman, A., Sevink, J. and Fanta, J. 2000. Restoration of Degraded Central-Europen Mountain Forest Soils under Changing Environmental Circumstages. In: Klimo, E., Hager, H., Kulhavý, J. (Editors), Spruce Monocultures in Central Europe – Problems and Prospects. EFI Proceedings No. 33, Brno, p. 81–92.

Erisman, J.W., de Leeuw, F.A.A.M. and van Aalst, R.M. 1989. Deposition of the Most Acidifying Components in the Netherlands During the Period 1980–1986. *Atmospheric Environment* 23: 1051–1062.

Erisman, J.W., Vermeulen, A., Hensen, A., Flechard, C., Dämmgen, U., Fowler, D., Sutton, M., Grünhage, L. and Tuovinen, J.-P. 2005. Monitoring and modelling of biosphere/atmosphere exchange of gases and aerosols in Europe. *Environmental Pollution* 133: 403–413.

Evans, C.D., Cullen, J.M., Alewell, C., Kopáček, J., Marchetto, A., Moldan, F., Prechtel, A., Rogora, M., Veselý, J. and Wright, R. 2001. Recovery from acidification in European surface waters. *Hydrology and Earth System Science* 5: 283–297.

Fiala, P., Materna, J., Reininger, D. and Samek, T. 2009. Conditions of surface soil layers and mineral nutrition of Norway spruce stands in the natural forest area Bohemian *Forest. Reports of Forestry Research* 54: 1–11.

Flückiger, W., Braun, S., Leonardi, S., Asche, N. and Flückiger-Keller, H. 1986. Factors contributing to forest decline in northwestern Switzerland. *Tree Physiology* 1:177–184.

Foley, J.A., Levis, S., Prentice J.C., Pollard, D., Thompson, S.L. 1998. Coupling dynamic models of climate and vegetation. *Global Change Biology* 4: 561–579.

Gauger, T., Anshelm, F., Schuster, H., Erisman, J.W., Vermeulen, A.T., Draaijers, G.P.J., Bleeker, A. and Nagel, H.D. 2002. Mapping of ecosystem specific long-term trends in deposition loads and concentrations of air pollutants in Germany and their comparison with Critical Loads and Critical Levels. Umweltbundesamt, Berlin, 108 pp.

Hadaš, P. 2000. Analysis of the climate as a stress factor to forest ecosystems. *Ekológia* (*Bratislava*) 19 Supplement: 162–176.

Hédl, R. 2004. Vegetation of beech forests in the Rychlebské Mountains, Czech Republic, re-inspected after 60 years with assessment of environmental changes. *Plant Ecology* 170: 243–265.

Hruška, J., Cudlín P. and Krám, P. 2001. Relationship between Norway spruce status and soil water base cations/aluminium rations in the Czech Republic. *Water, Air, and Soil Pollution* 130: 983–988.

Gaston, K.J. and Spicer, J.I. 2004. Biodiversity: An Introduction. Blackwell Publishing, Malden – Oxford – Carlton, 191 pp.

Johnson, K.W. and Altman, N.S. 1999. Canonical correspondence analysis as an approximation to Gaussian ordination. *Environmetrics* 10: 39–52.

Karnosky, D.F., Pregitzer, K.S., Zak, DR., Kubiske, M.E., Hendrey, G.R., Weinstein, D., Nosal, M. and Percy, K.E. 2005. Scaling ozone responses of forest trees to the ecosystem level in a changing climate. *Plant, Cell and Environment* 28: 965–981.

Keller, K., Černý, M., Bytnerowitz, A., Smith, L., Šesták, M., Michalec, M., Pernegr, V. and Kučera, J. 1997. Air Pollution Status of a Representative Site in the Czech Republic Brdy Mountains. *Environmental Pollution* 98: 291–297.

Lindner, M., Maroschek, M., Netherer, S., Kremer, A., Barbati, A., Garcia-Gonzalo, J., Seidl, R., Delzon, S., Corona, P., Kolström, M., Lexer, M.J. and Marchetti, M. 2010. Climate change impacts, adaptive capacity, and vulnerability of European forest ecosystems. *Forest Ecology and Management* 259: 698–709.

Lochman, V., Bíba, M. and Fadrhonská, V. 2002. Air pollution load of forest stands in Vojířov and the impact on soil and runoff water chemistry. *Journal of Forest Science* 48: 292–309.

Lochman, V., Mareš, V. and Fadrhonská, V. 2004. Development of air polutant deposition, soil water chemistry and soil on Šerlich research plots, and water chemistry in a surface water source. *Journal of Forest Science* 50: 263–283.

Mauer, O., Bagár, R. and Palátová, E. 2007. Response of Norway spruce (*Picea abies* /L./ Karst.) at lower elevations of the Bohemian-Moravian upland to the changing climatic conditions and to the weather course. In: Střelcová, K., Škvarenina, J. and Blaženec M. (Editors), Proceedings of International Scientific Conference Bioclimatology and Natural Hazards. Slovak Bioclimatology Society at the Slovak Academy of Science, Poľana nad Detvou, p. 1–9.

Mervart, L. and Cimbálník, M. 1997. Vyšší geodézie 2 [Higher geodesy 2]. Vydavatelství ČVUT, Praha, 178 pp. (in Czech).

Modrzyński, J. 2003. Defoliation of older Norway spruce (*Picea abies* /L./ Karst.) stands in the Polish Sudety and Carpathian Mountains. *Forest Ecology & Management* 181: 289–299.

Neteler, M. and Mitasova, H. 2002. Open source GIS: A GRASS GIS Approach. Kluwer Academic Publishers/Springer Verlag, Oxford – Amsterdam, 426 pp.

Noble, R., Smith, E.P. and Ye, K. 2004. Model selection in canonical correlation analysis (CCA) using Bayesian model averanging. *Environmetrics* 15: 291–311.

Peedle, D.R., Rabe, N.J., Soenen, S.A. and Johnson, D.L. 2005. Derivation of Topoclimatic Indices for Alpine Snowpack Analysis in Alberta Rocky Mountain Watersheds. In: 62th Eastern Snow Conference. Waterloo, Ontario, p. 173–190.

Pietsch, K.A., Ogle, K., Cornelissen, J.H.C., Cornwell, W.K., Bonisch, G. Craine, J.M., Jackson, B.G., Kattge, J., Peltzer, D.A. Penuelas, J. Reich P.B. Wardle, D.A., Weedon, J.T., Wright, I.J. Zanne, A.E. and Wirth, C. 2014. Global relationship of wood and leaf litter decomposability: the role of functional traits within and across plant organs. *Global Ecology and Biogeography* 23: 1046–1057.

Pollice, A. 2011. Recent statistical issues in multivariate receptor models. *Environmetrics* 22: 35–41.

Purdon, M., Cienciala, E., Metelka, V., Beranová, J., Hunová, I. and Černý, M. 2004. Regional variation in forest health under long-term air pollution mitigated by lithological conditions. *Forest Ecology and Management* 195: 355–371.

Rand, W.M. 1971. Objective criteria for the evaluation of clustering methods. *Journal of the American Statistical Association* 66: 846–850.

Reininger, D., Fiala, P. and Samek, T. 2011. Acidification of forest soil in the Hrubý Jeseník region. *Soil and Water Research* 6: 83–90.

Schröder, W., Nickel, S., Jenssen, M. and Riediger, J. 2015. Methodology to assess and map the potential development of forest ecosystems exposed to climate change and atmospheric nitrogen deposition: A pilot study in Germany. *Science ot the Total Environment* 521: 108–122.

Schröter, D., Cramer, W., Leemans, R., Prentice, I.C., Araújo, M.B., Arnell, N.W., Bondeau, A., Bugmann, H., Carter, T.R., G.A., de la Vega-Leinert, A.C., Erhard, M., Ewert, F., Glendining, M., House, J.I., Kankaanpää, S., Klein, R.J.T., Lavorel, S., Lindner, M., Metzger, M.J., Meyer, J., Mitchel, T.D., Reginster, I., Rounsevell, M., Sabaté, S., Sitch, S., Smith, B., Smith, J., Smith, P., Sykes, M.T., Thonicke, K., Thuiller, W., Tuck, G., Zaehle, S. and Zierl, B. 2005. Ecosystem Service Supply and Vulnerability to Global Change in Europe. *Science* 310: 1333–1337.

Smidt, S. and Herman, F. 2004. Evaluation of air pollution-related risks for Austrian mountain forests. *Environmental Pollution* 130: 99–112.

Smith, R.I., Dick, J. McP. and Scott, E.M. 2011. The role of statistics in the analysis of ecosystem services. *Environmetrics* 22: 608–617.

Smith, R.I and Fowler, D. 2001. Uncertainty in estimation of wet deposition of sulphur. Water, Air and Soil Pollution Focus 1: 341–354.

Thalib, L., Kitching, R.L. and Bhatti, M.I. 1999. Principal component analysis for grouped data–a case study. *Environmetrics* 10: 565–574.

Tomášková, I. 2004. Evaluation of changes in the tree species composition of Czech forests. *Journal of Forest Science* 50: 31–37.

Zapletal, M. 2001. Atmospheric deposition of nitrogen and sulphur compounds in the Czech Republic. *The Scientific World* 1: 294–303.

Zapletal, M. 2006. Atmospheric deposition of nitrogen and sulphur in relation to critical loads of nitrogen and acidity in the Czech Republic. *Journal of Forest Science* 52: 92–100.

Zar, J. 1994. Biostatistical Analysis. Prentice Hall Int., New Jersey, 944 pp.

Received 17 December 2014
Accepted 30 September 2016