



## Modelling factors affecting litter mass components of pine stands

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**Abstract:** Litter mass represents a key factor in the process of carbon sequestration. Pine plantations are known to accumulate high amounts of litter, which may act as real carbon sink only if it persists for long time. Thus, predicting litter mass by means of robust and straightforward models which convey information from several ecological predictors become crucial in this framework. The aim of this paper was to test for relationships between environmental predictors and pine litter mass (total branch, needle and cone) by Generalized Linear Models, exploring the contribution of different environmental variables in describing patterns of pine litter mass. Different predictors accounting for seasonality, spatial and geomorphological variability, pine stand properties, remotely sensed derived biomass were taken into account. Considering total litter mass, observed vs. predicted values showed a statistically highly significant relation ( $p < 0.001$ ) by retaining four variables: elevation, latitude, stand age and season. Similar results were achieved for the needle litter mass, which represented anyway the largest fraction of the litter. Regarding branch litter mass, only stand age appeared to be a significant variable. For cone litter mass, no variables were statistically significant in explaining its variance. Potential ecological background processes responsible for the correlations between variables are discussed.

**Abbreviations:** GLM – Generalized Linear Model, NDVI – Normalized Difference Vegetation Index, NIR – Near Infrared, RMSE – Root Mean Squared Error, VIF – Variance Inflation Factor.

### Introduction

Dead biomass lying on ground drew intense attention of ecologists within the frame of the International Biological Program (Smith 1968). Under the umbrella of such a world-wide project, researchers targeted the quantitative description of biomass partitioning and energy flow throughout compartments of the Earth's major vegetation types (Newbould 1967). Studies on the productivity of terrestrial communities increased our understanding considerably about litter accumulation in various forest types (Ellenberg 1971, Andrzejewska and Petruszewicz 1975; Jakucs, 1985).

Few decades later, when evidences about global climate change became more evident, knowledge on dead biomass was brought into the centre of interest again, and importance of litter in the process of carbon sequestration

was highlighted (Dewar and Cannell 1992, Schlesinger and Lichter 2001, Paul et al. 2002). Pine plantations are known to accumulate high amounts of litter, which may act as real carbon sink only if it persists for long time. Pine monocultures of Southern and Central Europe often get fire owing to the large quantity of flammable dry biomass accumulating in them, thus carbon returns to the atmosphere (Moreno 1998, Schulze et al. 1999). For example, in Hungary, extensive afforestation took place with the alien *Pinus nigra* on shallow-soiled dolomite hills when the pastoral land use ceased during the middle decades of the 20th century (Tamás 2003). In 2002, an extensive survey in the pine stands of the same region has revealed 13.5-23 t/ha accumulated litter, that is much higher than the litter quantities in any of the corresponding natural vegetation types (Cseresnyés et al. 2006). Univariate regression between stand age and litter quantity was also

established (Cseresnyés et al. 2006). Flammability of these pine stands were analysed by McArthur's model (Noble et al. 1980), and considerable fire risks were predicted (Cseresnyés and Csontos 2004, 2006).

All the facts mentioned above inspired us to increase our understanding on relationships between litter quantities in *Pinus nigra* stands and environmental factors.

Least square regression analysis has long been used to investigate relationships between variables. In its simplest form, regression is based on a linear univariate relationship between one predictor and a response variable, such that

$$y = \alpha + \beta x + \varepsilon \quad (1)$$

where  $y$  is the response variable of interest,  $\alpha$  is the intercept of the regression model (a line in such a case),  $\beta$  is the regression coefficient (slope of the regression line in such a case),  $x$  is the predictor variable, and  $\varepsilon$  is the error generated both by measurement technique and any variation unexplained by the linear model.

Although univariate regression (i.e., based on single predictors) is the most widely used statistical technique, it is well known that univariate statistics are expected to reach only a part of the total variance of the system despite the complexness of the used fitting function (see Orlóci and Kenkel 1985, Legendre and Legendre 1998, Rocchini 2007b).

More flexible methods for modelling response variables by considering several predictors are the Generalized Linear Models (GLMs; McCullagh and Nelder, 1989). GLMs represent straightforward models since they allow to: (i) consider several predictors within a single model, i.e. a vector  $(x_1, x_2, \dots, x_n)$ , by replacing slope of Eq.(1) with a vector of  $n$  regression coefficients  $(\beta_1, \beta_2, \dots, \beta_n)$ ; (ii) deal with many types of predictors such as continuous, binary, qualitative and ordinal (Engler et al. 2004); (iii) build a multiple regression model considering step-wise methods in selecting predictor variables, by directly estimating those predictors which lead to the highest amount of explained variance. Obviously data used as predictor variables must be adequate in the sense that they represent real factors determining the response variable pattern (Guisan and Zimmermann 2000). Reader is referred to Rushton et al. (2004) for a comprehensive review of statistical properties of GLMs.

The aim of this paper is to test for relationships between environmental predictors and pine litter mass by GLMs. More specifically, the contribution of different en-

vironmental variables in describing patterns of pine litter mass will be explored.

## Material and methods

### Field survey

Measurements of litter quantities were performed in 48 *Pinus nigra* stands, selected in Dunazug and Pilis Mountains (North Hungary). Each stand was larger (much larger in most cases) than 5 ha in area; thus, the stand size effect on litter decomposition reported by Wardle et al. (1997) can be excluded.

The stands ranged between 21 and 108 years, and we classified them into four age classes: 21-40, 41-60, 61-80 and older than 80 years. From each age class, 12 stands were sampled between May and October 2002. In all cases, 12 stands equally represented three exposition types: north-facing slopes, south-facing slopes and plateau position.

A sampling site of 20 m  $\times$  20 m size was marked in each stand and than its geographical coordinates, altitude and exposure were measured using a GPS instrument (Garmin-12). The slope angle was determined in the field by azimuth compass. The stand's basal areas were also calculated within the same 20 m  $\times$  20 m sampling sites (Newbould 1967).

For sampling forest floor litter, 2 m  $\times$  2 m quadrats were randomly selected in five replicates at each sampling site. Three litter fractions were collected from the quadrats: needles (including twigs with diameter less than 6 mm), branches (including twigs with diameter above 6 mm) and cones. The reason for dividing twig litter into two components was that the probability of fire initiation depends on the amount of litter with diameter less than 6 mm (Noble et al. 1980). The moist mass of collected litter fractions was weighed with springscales (50 g accuracy) in the field.

For all sampling sites, a subsample was separated from each collected litter fraction. The quantity of subsamples represented 10-20% of the total litter fractions. The subsamples were transported to the laboratory in a closed metal box and were weighed to 1 g accuracy. After this, the subsamples were dried to constant mass at 70 °C in a dry-heat oven (García-Plé et al. 1995, Kavvadias et al. 2001).

The dried subsamples were weighed again to 1 g accuracy and then (knowing the dry-substance content) the dry masses of accumulated litter fractions in the stands were calculated and expressed in kg/ha.

**Table 1.** Predictor variables used for the estimation of litter mass in *Pinus nigra* stands.

Predictor categories and variables	Measurement unit	Min	Max	Mean ( $\pm$ Standard Deviation)
1) Date				
Season	-	-	-	-
2) Spatial and geomorphological predictors				
X coordinate (UTM(WGS84), zone 34N)	m	337677	<b>352139</b>	343863 $\pm$ 4543
Y coordinate (UTM(WGS84), zone 34N)	m	5263124	5277121	5271166 $\pm$ 4970
Elevation	m	229	412	310 $\pm$ 51
Slope	°	0	40	16 $\pm$ 13
Aspect	-	-	-	-
3) Stand based predictors				
Stand age	years	21	108	59 $\pm$ 28
Stand basal area	m <sup>2</sup> /ha	19	102	55 $\pm$ 24
4) Spectral predictors				
Normalized Difference Vegetation Index (NDVI)	-	0.27	0.71	0.54 $\pm$ 0.13
Near Infrared (NIR) Digital Number	-	64	119	95 $\pm$ 13

### Spatial and geomorphological predictors

Spatial variables were taken into account considering both x and y coordinates (UTM(WGS84), zone 34N) and geomorphological predictors such as elevation, slope and aspect. Aspect was considered as a categorical variable considering flat, north and south facing (Table 1).

### Stand based predictors

Several authors demonstrated the relation between stand variables such as stand age, basal area or habitat quality and litter mass (Gower et al. 1996, Ågren and Knecht 2001, Kavvadias et al. 2001). Age effect was demonstrated for several conifer species, e.g., *Pinus sylvestris* and *Picea abies* (Bray and Gorham 1964), *Pinus patula* (Singh, 1984), *Pinus kesiya* (Das and Ramakrishnan 1985), *Pinus elliottii* (Wienand and William 1995), *Pinus nigra* (Filcheva et al. 2000), *Pinus strobus* (Peichl and Arain 2006). In this paper, stand age and stand basal area were taken into account (Table 1).

### Spectral predictors

Spectral predictors based on satellite image measures of biomass were derived from a 8-bit (0-255 Digital Numbers) Landsat ETM+ image (path 188, row 027, acquisition date June 8, 2000; spatial resolution 28.5 m), corrected both geometrically and radiometrically, covering the whole study area. Theoretically, a huge difference between the time of satellite image acquisition and survey period of the study plots could affect further analyses, since unknown disturbances like forest thinning, forest fire, etc. should be happened between the two types of surveys (litter vs. satellite). However, in this case, the temporal gap of 2 years between image and field data

should not threaten final results, since it is expected that disturbance should take some time to functionally act (see Rocchini, 2007a for an example on the matter).

Bands 4 (0.76 – 0.90  $\mu\text{m}$ , Near Infrared (NIR)) and 3 (0.63 – 0.69  $\mu\text{m}$ , Red) were linearly combined in order to calculate NDVI (Normalized Difference Vegetation Index), a proxy of cover biomass. NDVI is calculated as:

$$NDVI = \frac{\lambda_{NIR} - \lambda_R}{\lambda_{NIR} + \lambda_R}, \quad (2)$$

where  $\lambda_{NIR}$  is the reflectance in the NIR part of the spectrum (in such a case in the 0.76 – 0.90  $\mu\text{m}$  electromagnetic window) and  $\lambda_R$  is reflectance in the Red part of the spectrum (in such a case in the 0.63 – 0.69  $\mu\text{m}$  electromagnetic window), NDVI varying from a theoretical minimum of -1 (minimum reflectance in the NIR and maximum in the Red, low biomass) and a theoretical maximum of 1 (maximum reflectance in the NIR and minimum in the Red, high biomass). Strictly spoken, NDVI is based on (i) the high reflectance by vegetation in the NIR which is linked to scattering processes at the leaf scale, such that different types of vegetation show distinctive variability in leaf shape and size, water content, overall plant architecture, and density of vegetation cover, and (ii) the low reflectance in the Red due to the absorption by chloroplasts for photosynthesis. Original NIR Digital Number values were even considered within the model (Table 1).

### Response variables

Four different response variables were considered: (i) total litter mass, as the sum of the litter mass values partitioned into (ii) branch litter mass, (iii) cone litter mass and (iv) needle litter mass.

### Generalized linear models

In order to test for relationships between environmental predictors and the four litter mass types as response variables, a weighted analysis of deviance was used. Analysis of deviance is analogous to analysis of variance (ANOVA) but assuming non-normal error distribution (McCullagh and Nelder 1989, Pausas et al. 2003).

Starting from a full model, i.e., considering the entire predictor data set, an iterative stepwise model by exact Akaike Information Criterion (AIC; Hastie and Pregibon, 1992) was performed to derive a minimal adequate model: this model, composed by a restricted amount of predictors, explains a high proportion of variation for the response variable and contains the minimum number of variables for which no addition or deletion of any variable increases the explanatory power of the model.

Significance of each variable retained in the minimal adequate model was tested using the F-statistic (Crawley 1986, Ohlemüller et al. 2004). Moreover, an F-test was performed in order to check for statistical differences between Full and Minimal models.

As a “goodness of fit” measure for the final estimated minimal GLM, the  $D^2$  adjusted was calculated (we refer

to Weisberg 1980 or Guissan and Zimmermann 2000 for  $D^2$  adjusted calculation). Like the celebrated  $R^2$  adjusted used in multiple regression techniques, the  $D^2$  adjusted ranges from 0 to 1, with values of 1 indicating a perfect fit. The software for GLM was the R package (R Development Core Team 2007).

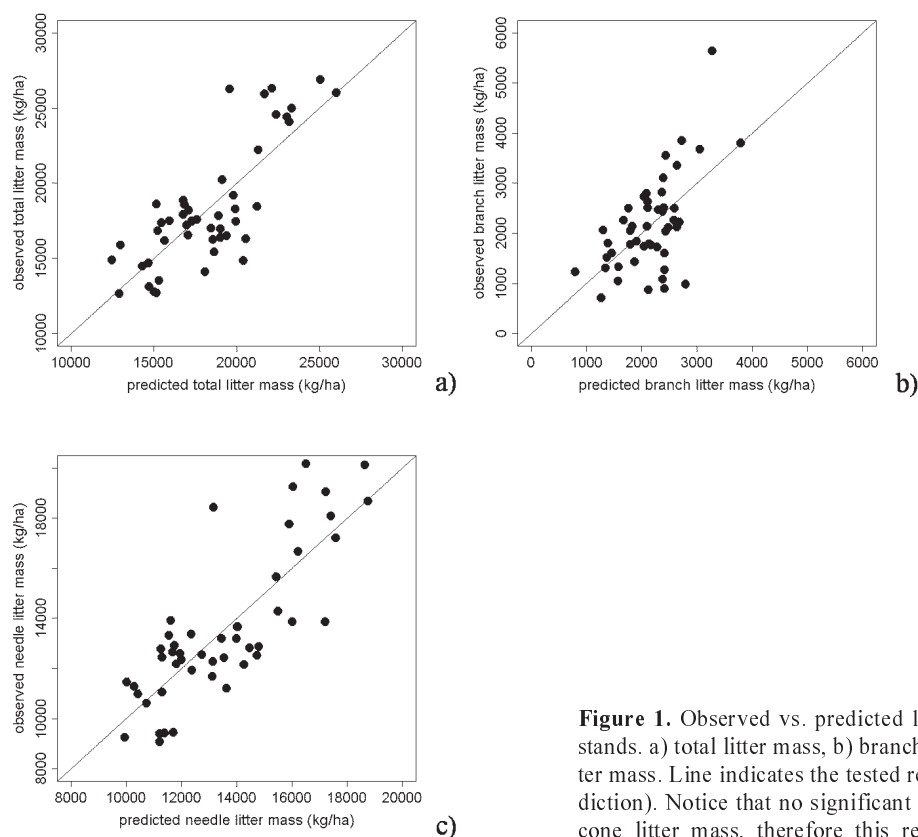
Finally an analysis of residuals was performed by plotting the observed vs. predicted values and calculating the Root Mean Squared Error (RMSE) as:

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n u^2}, \quad (3)$$

where  $n$  is the number of cases (in such a case  $n = 48$ );  $u$  designates residuals.

### Results

Considering total litter mass (ranging from 12879 to 26887 kg/ha), an explained variance of 0.502 was achieved by the minimal GLM, retaining four variables: elevation, latitude, stand age and season (Table 2). Observed vs. predicted values showed a statistically highly significant relation ( $R^2=0.63$ ,  $p < 0.001$ ) with an RMSE of 2410 kg/ha (Fig. 1, Table 2).



**Figure 1.** Observed vs. predicted litter mass in *Pinus nigra* stands. a) total litter mass, b) branch litter mass, c) needle litter mass. Line indicates the tested relation  $y = x$  (perfect prediction). Notice that no significant results were achieved for cone litter mass, therefore this response variable was removed from the figure.

**Table 2.** GLM output for total litter mass subdivided into: univariate statistics of the total litter mass response variable, characteristics of the Full GLM, variables retained in the Minimal GLM and relation between observed and predicted total litter mass. The reader is referred to the main text for explanation. VIF is the acronym for Variance Inflation Factor (Fox 1997).

<i>Response Variable</i>	<i>Mean</i>	<i>Max</i>	<i>Min</i>	<i>N° Variables involved in Full GLM</i>			<i>Model Features</i>
Total litter mass (kg/ha)	18288	26887	12879	9			Gaussian distribution, "identity" link function
<i>Variables Retained in Minimal GLM</i>							
<i>Variable</i>	<i>Deviance Reduction</i>	<i>Coefficient Value</i>	<i>VIF</i>	<i>p(F)</i>	<i>D²adj</i>	<i>r</i>	<i>Statistical differences Full and Minimal GLM p(F)</i>
Elevation	138249024	-	1.77	***			
Y (latitude)	136759939	+	2.10	***			
Stand age	80657087	+	1.87	**	0.502	0.793	0.7806
Season	66029826	(+ spring -summer)	1.74	*			
<i>Linear relation of observed vs. predicted total litter mass</i>							
	<i>Tested relation</i>	<i>R²</i>	<i>p</i>	<i>RMSE (kg/ha)</i>			
	y=x	0.63	***	2410			

**Table 3.** GLM output for branch litter mass, subdivided into: univariate statistics of the branch litter mass response variable, characteristics of the Full GLM, variables retained in the Minimal GLM and relation between observed and predicted branch litter mass.

<i>Response Variable</i>	<i>Mean</i>	<i>Max</i>	<i>Min</i>	<i>N° Variables involved in Full GLM</i>			<i>Model Features</i>
Branch litter mass (kg/ha)	2159	5633	706	9			Gaussian distribution, "identity" link function
<i>Variables Retained in Minimal GLM</i>							
<i>Variable</i>	<i>Deviance Reduction</i>	<i>Coefficient Value</i>	<i>VIF</i>	<i>p(F)</i>	<i>D²adj</i>	<i>r</i>	<i>Statistical differences Full and Minimal GLM p(F)</i>
Stand age	6619533	+	1.05	**	0.263	0.598	0.9882
<i>Linear relation of observed vs. predicted branch litter mass</i>							
	<i>Tested relation</i>	<i>R²</i>	<i>p</i>	<i>RMSE (kg/ha)</i>			
	y=x	0.36	***	741			

**Table 4.** GLM output for cone litter mass, subdivided into: univariate statistics of the cone litter mass response variable and characteristics of the Full GLM. Notice that no variables were retained as significant in the Minimal GLM.

<i>Response Variable</i>	<i>Mean</i>	<i>Max</i>	<i>Min</i>	<i>N° Variables involved in Full GLM</i>			<i>Model Features</i>
Cone litter mass (kg/ha)	2593	5469	1183	9			Gaussian distribution, "identity" link function
<i>Variables Retained in Minimal GLM</i>							
<i>Variable</i>	<i>Deviance Reduction</i>	<i>Coefficient Value</i>	<i>VIF</i>	<i>p(F)</i>	<i>D²adj</i>	<i>r</i>	<i>Statistical differences Full and Minimal GLM p(F)</i>
None	None	None	None	none	None	none	none

**Table 5.** GLM output for needle litter mass, subdivided into: univariate statistics of the needle litter mass response variable, characteristics of the Full GLM, variables retained in the Minimal GLM and relation between observed and predicted needle litter mass.

<i>Response Variable</i>	<i>Mean</i>	<i>Max</i>	<i>Min</i>	<i>N° Variables involved in Full GLM</i>			<i>Model Features</i>
Needle litter mass (kg/ha)	13536	20171	9083	9			Gaussian distribution, "identity" link function
<i>Variables Retained in Minimal GLM</i>							
<i>Variable</i>	<i>Deviance Reduction</i>	<i>Coefficient Value</i>	<i>VIF</i>	<i>p(F)</i>	<i>D<sup>2</sup>adj</i>	<i>r</i>	<i>Statistical differences Full and Minimal GLM p(F)</i>
NIR	84321484	-	2.22	***			
Elevation	79171208	-	1.59	***			
Slope	51337301	+	8.91	***	0.585	0.809	0.7806
X (longitude)	40276568	-	1.89	**			
<i>Linear relation of observed vs. predicted needle litter mass</i>							
	<i>Tested relation</i>	<i>R<sup>2</sup></i>	<i>p</i>	<i>RMSE (kg/ha)</i>			
	y=x	0.66	***	1723			

Considering branch litter mass (ranging from 706 to 5633 kg/ha), an explained variance of 0.263 was achieved by minimal GLM with only stand age as significant variable (Table 3). Observed vs. predicted values showed a statistically highly significant relation ( $R^2 = 0.36$ ,  $p < 0.001$ ) with an RMSE of 741 kg/ha (Fig. 1, Table 3).

No fitting was possible for cone litter mass (ranging from 1183 to 5469 kg/ha), i.e. no variables were statistically significant in explaining its variance (Table 4).

Finally, considering needle litter mass (ranging from 9083 to 20171 kg/ha), an explained variance of 0.585 was achieved by the minimal GLM, retaining four variables: NIR, elevation, slope and X coordinate (Table 5). Observed vs. predicted values showed a statistically highly significant relation ( $R^2 = 0.66$ ,  $p < 0.001$ ) with an RMSE of 1723 kg/ha (Fig. 1, Table 5).

## Discussion

Ecologists are nowadays using different explanatory techniques to seek insights on ecological processes producing patterns (Guisan et al. 2002) and generally to investigate correlations between response variables and sets of predictor variables. In our results nine correlations of that kind were statistically supported, and in the next paragraphs we would like to discuss explanatory ecological background processes.

Our results showed a negative correlation between the total litter mass values and the elevation (altitude) of the sites. Generally speaking, more elevated sites should receive more precipitation than lower elevated ones. It is

known that higher moisture content of the litter increases its decomposition rate via increased fungal activity (Fioretto et al. 1998, De Santo et al. 2002, Osono et al. 2003), thus, elevation as directly related to the increase in precipitation may have considerable effect on the litter mass as a result of accelerated fungal decomposition (Pausas 1997). Another factor contributing to the reduced total litter mass at high altitude sites could be linked to the shallow soil that often characterizes higher ridges (Zólyomi 1942), thus causing a reduced litter production.

Regarding the effect of latitude on total litter mass it is difficult to adopt an ecological interpretation. Most probably latitudinal change coincided with one or more environmental gradients not yet studied in our project.

Considering the relationship between stand age and total litter mass positive correlation was proved regarding stand ages of 20 to 80 years in an earlier study (Cseresnyés et al. 2006). Background processes are: (a) increased total biomass of stands with age (Gower et al. 1996, Law et al. 2001) and (b) longer time of accumulation of various litter fractions on the forest floor. Though total litter mass somewhat decreased in stands above 80 years old (Cseresnyés et al. 2006), this phenomenon does not prevent the detection of an overall positive correlation between stand age and total litter mass.

In our survey, spring time sampling resulted in higher amount of total litter mass than summer sampling. Two background phenomena can be encountered behind it. The first one is low temperature during winter time, that slows down or stops microbial decomposition. Mean an-

nual number of frost days range from 100 to 110 in the studied region (Pécsi 1999). This effect could have led to litter accumulation by spring time. However, as a second effect, litter accumulation by spring time is amplified by a pulse of needle litter fall during late winter (Roig et al. 2005).

Regarding the positive correlation between branch litter mass and stand age the accelerated self-pruning in older stands (Makinen and Colin, 1999) may contribute as additional effect to the obvious fact that larger trees drop larger branches.

In case of cone litter mass the lack of correlation with any of the studied environmental variables can be a consequence of the relatively stable size of assimilating crown surface of pine specimens grown in closed stands. That is, at about stand age of 15 years when canopy closure of an ageing stand happens, the intraspecific competition of pine individuals for light inhibits further growth of individual tree crowns, thus the cone producing surface of the stand remains constant, meanwhile the height growth of trees continues via formation of new whorles on the apical part of the crown simultaneously with the dieback of branches at the basal part of the crown. Additionally, cones are the most mobile component of the litter and their post-falling spatial relocation may mask correlations with environmental variables.

Throughout the survey needles formed the largest part of the litter mass (reader is referred to Cseresnyés et al. 2006 for a major description of the used dataset). Berg and Meentemeyer (2001) found strong correlation between total and needle biomass for conifers. Thus, as expected, the strong negative correlation between elevation and litter mass observed for the total litter mass is also valid for the needle fraction alone. Reasons of the correlation are the same as it was discussed for the total litter mass, probably with an additional effect of wind removal that may cause litter loss at high elevation hilltops more easily for needles than branches.

Another interesting correlation was detected for needles between slope angle and litter mass. To understand this we must consider that the acting surface ( $AS$ ) capturing rain on a slope decreases as the slope angle  $\alpha$  increases according to the following equation:

$$AS = \cos(\alpha) \times RS, \quad (4)$$

where  $RS$  is the real surface of the slope. Thus, a slope of  $45^\circ$  captures 71% of rain if compared to the plain ground. That is why extreme steep slopes may function as orographic deserts in a more humid landscape, as it was perfectly demonstrated by Pócs (1999) detecting desert

specialist cryptogams on steep loess cliffs of Hungary. Hence the reduced precipitation input together with the increased loss of water due to surface run-off results in a more dry litter layer with reduced microbial activity on slopes compared to the plain ground. Therefore, the steeper the slope the higher the amount of needle litter will be found.

NIR provided for negative correlation with needle litter mass. In fact, it is well known that the high reflectance of vegetation in the NIR part of the electromagnetic spectrum is directly related to scattering processes at the leaf scale, thus promoting NIR as a direct estimator of biomass (see e.g., Lillesand et al. 2003, Koetz et al. 2005). On the other hand it should be stressed that higher values of litter mass should be related to humus presence, i.e., high humidity content. Empirically speaking, the considered soils should bring low water holding capacity, mainly due to their high stoniness and steep slopes in absolute terms (Cseresnyés et al. 2006). However, from a relative point of view, it is worth remembering that the relative presence of water (or simply humidity) should tend to have a saturating effect on brightness values, and likely all sensors may be affected (Rees 2001, Coppin et al. 2004, Rocchini 2007b). Strictly spoken, the higher the humus (humidity content) the lower the NIR value. NDVI did not provide any positive outcomes as a predictor of litter even if related to biomass, since from a statistical viewpoint using NDVI would reduce the values' dynamic range by rescaling original data (see e.g., Rocchini et al. 2007).

Finally, the effect of longitude on needle litter mass may receive a similar discussion as it was written about the correlation between latitude and total litter mass, with the conclusion that ecological interpretation cannot be done at the moment.

## Conclusions

In this paper, we demonstrated the powerfulness of using GLMs for predicting litter mass values by using environmental variables. Obviously, since this is one of the first tests on the matter, the amount of explained variance in terms of  $D^2$  adjusted did not exceed ca. 60%. However, this paper represents a primer for further investigating the effect of additional environmental variables.

Replacing field collected litter mass raw data by data collection based on remote sensing techniques is proposed because of the obvious advantage of the latter in overcoming the disadvantages of field collection, such as: time costs, the necessity of different sampling designs for the different litter types and the need of additional laboratory measurements to ensure the accuracy of the data.

As far as we know, to date only univariate models based mainly on stand age, basal area and slope/aspect exist (Bray and Gorham 1964, Gower et al. 1996, Cseresnyés et al. 2006). We demonstrated that using more complex models should allow to evaluate the relative weights of predictors on the whole predicting model, leading to robustly estimate complex variables such as litter mass. Moreover, they should allow to distinguish simultaneous influences of environmental variables on single components of litter mass, such as branch, needle and cone litter. Knowledge of determinants of litter mass will favour the understanding of the underlying processes promoting suited environmental policy and forest management practices.

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