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Additive biomass models for *Quercus* spp. single-trees sensitive to temperature and precipitation in Eurasia

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Abstract. The analysis of the biomass of oak (genus *Quercus* spp.) trees on the aboveground component composition based on regression equations having the additive biomass structure is fulfilled. Two trends of changes in the tree biomass structure are revealed: due to the mean January temperature and due to the mean annual precipitation. It was shown for the first time that both trends are mutually determined: the intensity of biomass trend in relation to the temperature is changing when depending on the level of precipitation, and the intensity of biomass trend in relation to precipitation level is changing during to a transition from the cold zone to the warm one and vice versa.

Key words: oak trees, tree biomass, allometric models, additive biomass equations, mean January temperature, mean annual precipitation.

1. Introduction

Information about forest tree biomass can easily be derived through allometric equations, as it is done for example for biomass stock per ha, especially in many-species forests (Dahlberg et al., 2004; Zeng et al., 2018; Usoltsev et al., 2019a), for greenhouse gas reporting (de Miguel et al., 2014), for analysis of national forest inventories data, in ecological studies (Marklund, 1987; Riedel & Kändler, 2017), as well as in gas-exchange, nutrient and energy flow studying, forest growth and biomass allocation models (Zianis et al., 2005; Vonderach et al., 2018).

All above mentioned equations are usually internally contradictory, they are not harmonized by the biomass structure, i.e. they do not provide the additivity of component composition, according to which the total biomass of components (stems, branches, needles, roots) obtained by "component" equations would be equal to the value of biomass obtained by the total biomass equation (Kozak, 1970). The additivity methods can be divided into aggregative (Parresol, 2001) and disaggregative (Dong et al., 2015) approaches. It was recently showed that having in mind the result correctness, both approaches differ only slightly (Affleck & Diéguez-Aranda, 2016). The development of regional allometric models

of tree biomass sensitive to climate variables has shown both negative (Forrester et al., 2017) and positive (Zeng et al., 2017) results. The influence of climatic changes on the biomass of a particular tree species in the format of additive models according to transcontinental hydrothermal gradients was not been studied, with some single exceptions (Usoltsev et al., 2019a, b).

In the present study, the first attempt is made to simulate the changes in the additive component composition of tree aboveground biomass in oak forests on Trans-Eurasian hydrothermal gradients. In the simulation we used the database of the biomass of 530 sample trees (genus *Quercus* spp.), the distribution of sample plots of which in the territory of Eurasia is shown in Figure 1 (Usoltsev, 2016; Lakida et al., 2017).



Figure 1. Distribution of sample plots with biomass measurements (kg) of 530 oak sample trees on the territory of Eurasia

2. Materials and methods

Of the above-mentioned two databases (Usoltsev, 2016; Lakida et al., 2017) containing data on biomass and dendrometric parameters, 530 trees were selected for the analysis, including 8 species-vicariants of the genus *Quercus* spp. Their distribution by regions, tree species and mensuration indices is presented in Table 1.

Each sample plot on which tree biomass estimating was performed is positioned relatively to the isolines of the mean January temperature (Fig. 2) and relatively to the isolines of mean annual precipitation (Fig. 3). The matrix of harvest data was compiled, in which the biomass component values and mensuration tree parameters were related with the corresponding values of mean January temperature and precipitation, then included in the regression analysis procedure.

Deciona	Species of the	Ranges:		Data
Regions	genus Quercus spp.	age, years	diameter, cm	number
Czech Republic, Switzerland	<i>Q. robur</i> L.	13÷104	4.0÷69.7	16
Bulgaria	 Q. rubra L., Q. robur subsp. pedunculiflora (K.Koch) Menitsky, Q. petraea (Mat.) Liebl., Q. frainetto Ten. 	17÷70	1.5÷29.5	49
Hungary	Q. petraea (Mat.) Liebl.	68	15.8÷23.8	9
The Ukraine	<i>Q. robur</i> L.	6÷128	2.5÷50.5	370
European part of Russia	<i>Q. robur</i> L.	12÷130	1.1÷46.9	66
Russian Far East	Q. mongolica Fisch. ex Ledeb.	56÷166	9.5÷34.5	7
Japan	<i>Q. serrata</i> Murray, <i>Q. mongolica</i> Fisch. <i>ex</i> Ledeb.	4÷40	1.1÷16.5	13

Table 1. Distribution of the 530 oak sample trees by countries, regions, tree species and mensuration indices



Figure 2. Distribution of biomass harvest data of 530 oak sample trees on the map of the mean January temperature, °C (World Weather Maps, 2007)



Figure 3. Distribution of biomass harvest data of 530 oak sample trees on the map of the mean annual precipitation, mm (World Weather Maps, 2007)

It is known that a stem diameter is a main predictor that most explains the variation of tree biomass, and their relationship as the most common and biologically determined is described by the allometric function. Allometry determines how tree shape and function scale with each other, related through size. Allometric relationships help scale processes from the individual to the global scale and constitute a core component of vegetation models. Allometric relationships have been expected to emerge from optimization theory, yet they do

not suitably predict empirical data (Fischer et al., 2019). On the allometry basis, several theories are proposed: the pipe model (Huber, 1925, 1927; Shinozaki et al., 1964a, b), the functional equilibrium model (Davidson, 1969), the fractal model (West et al., 1999), the metabolic scaling theory (when scaling exponent is constant) (West et al., 1997), the theory of adaptive mass distribution (when scaling exponent changes dynamically with size) (Poorter et al., 2015) and some of their modifications (Enquist & Niklas, 2001, 2002). However, when calculating allometric models of tree biomass there is always a residual variance, reflecting, in particular, the discrepancy between the annual dynamics of the crown mass, especially of the foliage, and the relative conservatism of a stem diameter, as an accumulator of its annual increments (Usoltsev, 1988), as well as differences of age status, soil and climatic conditions.

Total tree height is not always available in field measurements, and it may sometimes be better not to involve it in biomass estimation procedure (Williams & Schreuder, 2000). In this study, the task is to extract the climatic component from the residual dispersion of a model obtained during to calculation of tree biomass by stem diameter. To the share of climatic factors was predominant in this "information noise", it is necessary to take into account in the model in addition to the diameter, also the tree age, which is a factor largely determining the structure of tree biomass (Nikitin, 1965).

A negative relationship between the crown biomass of equal-sized trees and their age in forest stands is well known. Thus, the crown mass of the tree with a diameter of 12 cm at the age of 15 years exceeds that at the age of 35 years at the birch by 1.5-2.0 times, and at the aspen – by 2.4-4.4 times (Usoltsev, 1972) due to the age shift of the cenotic position of equal-sized trees: at the age of 15 years such tree is the leader, and at the age of 35 years it is the depressed tree, a candidate for dying. The influence of age on stem biomass in comparison with other components is minimal due to the relative stability of the stem shape: with the same stem shape and the corresponding volume, its biomass changes with age mainly due to age-related changes in the basic density related to a decrease in the proportion of sapwood having a reduced dry matter content compared to the heartwood (Usoltsev, 1988). Tree age, all other conditions being equal, also affects the mass of roots in terms of root-shoot relationships (Kazaryan, 1969).

We have in our database only 47 trees having both aboveground biomass and root one, represented by Central Europe, European part of Russia and Japan. Because of small root experimental data, we do not involve the biomass of roots into our additive biomass system. Root biomass data are high labour-consuming, and therefore they determined by researchers not at all sample plots, often without specifying the method of their estimation. The analysis

of the world data of underground tree biomass has showed that due to the imperfection of methods to estimate fine root biomass, the total underground biomass of trees and stands may be underestimated two to five times (Usoltsev, 2018).

We limited ourselves to the calculation of the coefficient of determination and the standard error. We have not calculated additional characteristics of the equation adequacy, such as the mean prediction error, the relative mean prediction error, the mean absolute error, and the relative mean absolute error, since they all are derived from the determination coefficient.

The disaggregation method of two-step proportional weighing, based on the principle "from general to particular" is developed as an alternative to the independent (without additivity) fitting approach. It has been implemented in two versions: as a sequential (Zheng et al., 2015) and parallel (Zhang et al., 2016) disaggregating additive systems of equations for aboveground biomass (Fig. 4). According to the structure of the disaggregation model of a two-step additive equation system (Zheng et al., 2015), the aboveground biomass P_a , estimated by an initial equation, is divided into biomass components by means of proportional weighting the corresponding component initial equations (see: Dong et al., 2015; Usoltsev et al., 2019a, b).

The coefficients of the regression equations of all two steps are evaluated simultaneously, that ensures the additivity of the biomass of all components (Dong et al., 2015). Since the regression coefficients in the designed model were calculated on the log-transformed data, a corresponding correction is introduced in the equations to eliminate the displacements caused by the logarithmic transformation of the variables (Baskerville, 1972).



Figure 4. The pattern of the disaggregating two-step proportional weighting additive model of sequential (left) and parallel (right) schemes. The schemes show relationship between each biomass component, where lines from left to right indicate disaggregation and from right to left indicate summation (Zheng et al., 2015; Zhang et al., 2016)

We adhered to the concept that there is only one definite variant of stand (and tree) biomass structure corresponding to a given structure of taxonometric parameters (morphological structure) of a tree stand, determined by local forest growth conditions

(Usoltsev, 2007). If in some region we find a forest stand of the same morphological structure, then the structure of its biomass is likely to be the same, provided there were no anthropogenous and other abiotic influences. But as the range of expansion of woody species (genus), this compliance will be increasingly violated as a result of increasing the diversity of forest growth conditions. This change in the diversity of forest environment has geographical causes and in the regression multiple model is expressed by an increase in residual dispersion ("information noise"). In terms of biogeography, the increase of variability of this residual variance as a consequence of increasing diversity of forest environment, is most likely due to climate variables, such as temperature and precipitation, which are included in our models as additional independent variables.

3. Results

Based on the above, the following structure of the regression model is suggested:

$$\ln P_i = a_{0i} + a_{1i} (\ln A) + a_{2i} (\ln D) + a_{3i} (\ln D)^2 + a_{4i} [\ln(T+20)] + a_{5i} (\ln PR) + a_{6i} [\ln(T+20)] (\ln PR), \quad (1)$$

where P_i is biomass in dry condition of *i*-th component, kg; A is tree age, yrs; D is stem diameter at breast height, cm; *i* is the index of biomass component: aboveground (*a*), crown (*c*), foliage (*f*), branches (*b*), stem above bark (*s*), stem wood (*w*) and stem bark (*bk*); T is mean January temperature, °C; *PR* is mean annual precipitation, mm.

According to the theory of adaptive mass distribution, the scaling exponent (or exponent at the stem diameter in the allometric model) is not a constant, and in log-log coordinates the relationship has the nonlinear form (Poorter et al., 2015). To account for this nonlinearity, the stem diameter in the model (1) is introduced in the form of a second-order logarithmic polynomial:

$$\ln P_{i} = f [(\ln D), (\ln D)^{2}].$$
(2)

Since the mean January temperature in the northern part of Eurasia has negative values, the corresponding independent variable is modified to the form (T+20) to be subjected to logarithmic procedure. The schematic map of the isolines of mean January temperature, rather than the mean annual temperature, is used, since climate warming is most pronounced in the cold half of the year (Golubyatnikov & Denisenko, 2009; Laing & Binyamin, 2013; Felton et al., 2016). In this regard, a similar parallel trend of another level is interesting: according to the report of National Oceanic and Atmospheric Administration (2017), warming in the Arctic is twice as fast as in other parts of the Earth, and "the Arctic is on the front lines of climate change" (https://www.noaa.gov/explainers/changing-arctic-greener-warmer-and-increasingly-accessible-region) (Blunden et al., 2018).

Characteristic of equations (1) is obtained by regression analysis, and after correcting on logarithmic transformation by Baskerville (1972) and anti-log transforming is given in Table 2.

Biomass component	Regression coefficients of the model					adjR ² *	SE*		
P_a	3.49E-09	$A^{0.1098}$	$D^{1.9591}$	$D^{0.0823(\ln D)}$	$(T+20)^{5.6803}$	PR ^{2.6737}	$(T+20)^{-0.8555(\ln PR)}$	0.989	1.22
P_c	2.10E-11	$A^{-0.3144}$	$D^{1.7957}$	$D^{0.1310(\ln D)}$	$(T+20)^{6.5197}$	PR ^{3.5835}	$(T+20)^{-1.0249(\ln PR)}$	0.911	1.71
P_s	3.32E-08	$A^{0.2115}$	$D^{1.9960}$	$D^{0.0733 (\ln D)}$	$(T+20)^{4.8111}$	$PR^{2.2139}$	$(T+20)^{-0.7165(\ln PR)}$	0.987	1.25
P_f	9.41E-07	$A^{-0.5925}$	$D^{1.6748}$	$D^{0.0862 (\ln D)}$	$(T+20)^{4.3379}$	PR ^{1.8895}	$(T+20)^{-0.6925(\ln PR)}$	0.871	1.67
P_b	3.47E-13	$A^{-0.1857}$	$D^{2.0212}$	$D^{0.0966 (\ln D)}$	$(T+20)^{6.9935}$	$PR^{4.0371}$	$(T+20)^{-1.0841(\ln PR)}$	0.901	1.84
P_{w}	4.00E-08	$A^{0.3001}$	$D^{2.2722}$	$D^{0.01875(\ln D)}$	$(T+20)^{4.4532}$	$PR^{2.0392}$	$(T+20)^{-0.6545(\ln PR)}$	0.984	1.28
P_{bk}	2.17E-13	$A^{0.1331}$	$D^{1.3506}$	$D^{0.1655 (\ln D)}$	$(T+20)^{8.7348}$	PR ^{3.9457}	$(T+20)^{-1.3086(\ln PR)}$	0.960	1.40

Table 2. Characteristics of equations (1)

* $adjR^2$ – coefficient of determination adjusted for the number of parameters; SE – equation standard error.

All regression coefficients of equations (1) are characterized by the Student's significance level of 0.05 and better [including at variables (ln*D*) and (ln*D*)²], and the resulting equations are adequate to the original values presented in the available database. Unlike of our previous result on larch tree biomass (Usoltsev et al., 2019a), where the combined effect of temperature and precipitation was not statistically significant (Student's test t_{akt} is from 0.08 to 1.33, which is below the standard value $t_{05} = 1.96$), this model includes synergism [ln(*T*+20)](ln*PR*), which is significant (t_{akt} is from 2.04 to 6.49, which is higher than the standard value $t_{05} = 1.96$) for all biomass components. When using a 3D-interpretation, this means a «propeller-shaped» surface of biomass in dependence upon temperature and precipitation, which was previously confirmed by the example of tree biomass of two-needled pines (Usoltsev et al., 2019b).

The designed initial equations (1) are then modified to the additive form according to the early published algorithm (see: Dong et al., 2015; Usoltsev et al., 2019a, b), structure of which is shown in Figure 4 (left), and the final form of the transcontinental additive model of the component composition of oak tree biomass is shown in Table 3.

Table 3. Final three-step additive model of oak tree biomass

	$P_a = 3$	$3.49E-09 A^{0.1098} D^{1.9591} D^{0.0823 (lnD)} (T+20)^{5.6803} PR^{2.6737} (T+20)^{-0.8555 (lnPR)}$
Step	D _	1 <i>D</i>
1	Γ_c –	$\frac{1303.6 A^{0.5259} D^{0.2003} D^{-0.0577(\ln D)} (T+20)^{-1.70867} PR^{-1.3696} (T+20)^{-0.3084(\ln PR)} \times \Gamma_a}{1000}$

	$P_{s} = \frac{1}{0.0008 A^{-0.5259} D^{-0.2003} D^{0.0577(\ln D)} (T+20)^{1.70867} PR^{1.3696} (T+20)^{0.3084(\ln PR)}}$	$\times P_a$
Step 2a	$P_{f} = \frac{1}{30.038 A^{0.4068} D^{0.3464} D^{0.0104(\ln D)} (T+20)^{2.6556} PR^{2.1476} (T+20)^{-0.33916(\ln PR)}}$	$\times P_c$
	$P_b = \frac{1}{-0.0333 A^{-0.4068} D^{-0.3464} D^{-0.0104(\ln D)} (T+20)^{-2.6556} PR^{-2.1476} (T+20)^{-0.33916(\ln PR)}}$	$\times P_c$
Step 2b	$P_{w} = \frac{1}{230.8 A^{-0.1669} D^{-0.9216} D^{0.1468(\ln D)} (T+20)^{4.2816} PR^{1.9065} (T+20)^{-0.6541(\ln PR)}}$	$\times P_s$
	$P_{bk} = \frac{1}{-0.0043 A^{0.1669} D^{0.9216} D^{-0.1468(\ln D)} (T+20)^{-4.2816} PR^{-1.9065} (T+20)^{0.6541(\ln PR)}}$	$\times P_s$

Next, it is necessary to find out whether the additive model obtained is enough adequate and how its characteristics relate to the adequacy of initial equations. To do this, the first and the second models are tabulated on the empirical measurement data and the calculated values of biomass are compared with the empirical ones using the coefficient of determination. The comparison results shown in Figure 5, indicate that the adequacy of the two systems of equations are close to each other.

Due to the high complexity of obtaining the age of trees in comparison with the stem diameter measuring, one use specially designed equation or table that reflects the relationship of the tree age with the stem diameter. To this end, the equation (3) is calculated:

$$A = \exp\{-1,6598+0,6774(\ln D)+2,2621[\ln(T+20)]+0,9003(\ln PR)-0,4865[\ln(T+20)](\ln PR)\};$$

$$adjR^{2} = 0,747; SE = 1,42.$$
 (3)

Using the result of tabulating eq. (1) by the given values A, D, T and PR, 3Ddependences of biomass components on temperature T and precipitation PR for trees aged 100 years with D = 24 cm and H = 22 m were designed (Fig. 6).

To estimate climate-related changes in the total biological productivity of oak stands, the above equations, calculated only for aboveground tree biomass, are not sufficient. Because of the small experimental data of root biomass, we calculated the roots-to-shoot ratio in dependence upon the defining variables, having in mind the available 47 data. Of the morphology-caused variables, only age is statistically significant, and the following equation is obtained

$$P_{r}/P_{a} = \exp\{-21,6606-0,8536(\ln A)-2,7020[\ln(T+20)]+4,7564(\ln PR)\};$$

adj $R^{2} = 0,856; SE = 1,20,$ (4)

where P_r is tree root biomass, kg. Equation (4) may be used in a rough estimation of underground biomass on tree and forest levels.



Figure 5. The ratio of the harvest biomass and its values obtained by calculating the initial (*a*) and additive (*b*) models of the larch tree biomass



Figure 6. Dependence of oak tree biomass upon the January mean temperature (*T*) and precipitation (*PR*). Designations: P_a , P_s , P_b and P_b are correspondingly biomass: aboveground, stems, foliage, and branches, kg

The obtained models of oak tree biomass make them possible to establish quantitative changes in the structure of tree biomass due to climatic changes, in particular, the mean temperature of January and mean annual precipitation. The percentage change in the structure of biomass is associated with the ratio of these two climatic variables.

In Figure 7 it is shown the change in the tree biomass (Δ , %) with an increase in temperature by 1°C in different ecoregions, characterized by different values of temperature and precipitation. It is assumed that climate change does not affect precipitation, which changes only geographically (by regions), and the temperature as a result of the expected climate change increases by 1°C at different territorial (zonal) temperature levels, designated as -15 Δ ...0 Δ . Figure 7 shows the general pattern of increase of all the biomass components in moderate dry areas (PR = 400 mm) and decrease in water-rich areas (PR = 700-900 mm) with an increase in temperature by 1°C in all temperature zones of Eurasia.

In Figure 8 it is shown the change of tree biomass (Δ , %) with the increase in precipitation by 100 mm in areas characterized by different values of temperature and precipitation. It is assumed that the January temperature changes only geographically, and precipitation as a result of the expected climate change increases by 100 mm at different

territorial levels of precipitation, designated as 400Δ ... 900Δ . Figure 8 shows the common pattern of increase of the all biomass components with an increase in annual precipitation by 100 mm in all temperature zones of Eurasia and in all regions that differ in precipitation, with exception of foliage biomass that is decreasing in the regions of warm and moderate temperatures (from 0°C to -1°C).



Figure 7. Change of tree biomass with (+) (surface 1) and (-) (surface 2) when temperature increasing by 1°C due to the expected climate change at different territorial levels of temperature and precipitation. Symbols Δ_a , Δ_s , Δ_f and Δ_b on the ordinate axes mean the change (± %) of biomass of aboveground, stems, foliage and branches, respectively, with the temperature increase by 1°C and at the constant precipitation





Figure 8. Change of tree biomass with (+) (surface 1) and (-) (surface 2) when precipitation increasing by 100 mm due to the expected climate change at different territorial levels of temperature and precipitation. The symbols Δa , Δs , Δf and Δb along the ordinate axes represent the change (\pm %) of aboveground, stems, needles and branches biomass, respectively, with precipitation increase by 100 mm and at the constant mean temperatures of January

4. Discussion

Analysis of the 3D-surfaces in Figure 6 allows us to draw some nontrivial conclusions. As we can see there, all of the biomass components vary according to approximately one overall scheme, but in different proportions. The dependence, common to all of the components: in cold climatic zones ($T = -15^{\circ}$ C), any increase in rainfall leads to corresponding increase in the biomass value, and in moderate warm zones ($T = 0^{\circ}$ C), leads to a decrease in foliage biomass value, to a slight decrease in branch biomass and remains unchanged in the aboveground and stem biomass.

Correspondingly, in water-rich areas (PR = 900 mm), the rise in temperature causes a decrease of biomass values, and in moderate dry areas (PR = 400 mm), in their increase. This pattern is opposite to the previously constructed analogous models for the aboveground biomass of two-needled pines (Usoltsev et al., 2019b) and larches (Usoltsev et al., 2019a). Perhaps this contradiction is due to the smaller ranges of temperature and precipitation in the areas occupied by oak stands, compared with pine and especially with larch ones, as well as due to biological features of coniferous and deciduous species. The regularities for pines and larches were previously confirmed by other authors on the local level (Glebov & Litvinenko, 1976) and some regional levels (Molchanov, 1976; Polikarpov & Chebakova, 1982).

Using the data of above- and underground biomass of 600 sample trees of eight larch species (genus *Larix* spp.) growing throughout China, the allometric model including the stem diameter and height as independent variables, was developed. After introduction into the allometric model the indices of the mean annual temperature and precipitation, as additional independent variables, it was established that the temperature increase by 1°C leads to an increase in the aboveground biomass of equal-sized trees by 0.9% and to a decrease in the underground one by 2.3%, and an increase in precipitation by 100 mm causes a decrease in the above- and underground phytomass by 1.5 and 1.1%, respectively (Zeng et al., 2017). Our results confirm the data by Zeng et al. (2017) related to the change in the aboveground biomass of larch trees with the increase in temperature by 1°C, but only partly, namely in the areas of low precipitations. With the increase in precipitation by 100 mm, we obtain the opposite result from Zeng's conclusion, namely an increase rather than a decrease in aboveground tree biomass. As had been mentioned above, this contradiction may be due to

the smaller ranges of temperature and precipitation in the areas occupied by oak stands, as well as due to biological features of coniferous and deciduous species.

In another study devoted to European forests (Forrester et al., 2017), there was no statistically significant effect of temperature and precipitation on the tree biomass of the most components. The reasons may be the following: a small range of temperature and precipitation variations within Europe, a study of species groups instead of a single species, the introduction of too many variables and their combined effects into the model, and the use of meta-data instead of harvest biomass indices.

The study of the regional variability of the allometric models of aboveground biomass of trees of Masson pine in southern China showed that diameter at breast height, together with the long-term average of growing season temperature, total growing season precipitation, mean temperature of wettest quarter, and precipitation of wettest quarter, had significant effects on values of aboveground biomass. Excessive precipitation during the growing season and high mean temperature in the wettest quarter reduced the aboveground biomass, while a warm growing season and abundant precipitation in the wettest quarter increased it (Fu et al., 2017). Thus, the reaction of pine biomass to the increase in precipitation in the subtropical conditions of China in the wettest quarter is negative, and in the wettest quarter at extremely high temperatures is positive. A similar differentiated reaction of biomass and net primary production to temperature and precipitation was shown earlier on the example of stands of two-needled pines in Eurasia (Usoltsev et al., 2019c). Apparently, any response of forests to climate change is species-specific and reflects the biological and ecological specificities of each tree species.

Our model obtained and the patterns shown are hypothetical: they reflect the long-term adaptive responses of forest stands to regional climatic conditions and do not take into account the rapid trends of current environmental changes, which place serious constraints on the ability of forests to adapt to new climatic conditions (Alcamo et al., 2007). Although modelling at the global level shows that the productivity of forest cover is mainly determined by temperature, other factors (salt stress, length of vegetative period, imbalance between air and soil temperatures, frost drought) limit the productivity to a much larger extent than just temperature. Besides, some experiments show clearly that the water status affects stomata opening and closing in very much degree, and our understanding of the adaptation to water shortage is still patchy (Schulze et al., 2005).

5. Conclusions

Thus, we have made the first attempt to simulate changes in the component composition of the aboveground biomass of oak trees by trans-Eurasian hydrothermal gradients, that revealed the presence of non-trivial regularities. The analysis of the aboveground biomass of oak trees on the basis of the component composition, using regression model method, showed changes in the structure of the biomass of trees, both in connection with the average temperature of January and average annual precipitation, namely: the intensity of changes in biomass due to temperature varies depending on the level of site moisture, and the intensity of changes in biomass due to the level of moisture changes during the transition from cold to warm temperature belts. The adequacy of the obtained regularities is determined by the level of variability 87-99 % explained by the proposed regression models.

The obtained model of oak tree biomass make it possible to establish quantitative changes in the biomass structure due to climatic changes, in particular, the mean temperature of January and mean annual precipitation. The proposed additive model, adapted for use in the forest area of Eurasia, is designed for a more accurate assessment of the carbon-depositing ability of oak forests. However, this is a solution to the problem only in the first approximation, because it is based on a limited amount of harvest data.

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