ISSN 1995-4255, Contemporary Problems of Ecology, 2014, Vol. 7, No. 7, pp. 855–863. © Pleiades Publishing, Ltd., 2014.
Original Russian Text © P.A. Shary, L.S. Sharaya, 2014, published in Lesovedenie, 2014, No. 5, pp. 83–90.

Change in NDVI of Forest Ecosystems in Northern Caucasus as a Function of Topography and Climate

P. A. Shary[a] and L. S. Sharaya[b]

[a] *Institute of Physical Chemical and Biological Problems in Soil Science, Russian Academy of Science, ul. Institutskaya 2, Pushchino, Moscow oblast, 142292 Russia*
e-mail: p_shary@mail.ru

[b] *Institute of Ecology of the Volga River Basin, Russian Academy of Sciences, ul. Komzina 10, Togliatti, Samara oblast, 445003 Russia*

Received September 13, 2013

Abstract—A grid of long-term average July temperature (T_{JUL}) with a grid spacing 500 m was developed to analyze associations between the NDVI vegetation index of mountain forests and climate and topography in the Kuban river basin. The detail of a map obtained based on this grid is substantiated (validation is a special term also used in this paper) by the close association ($R^2 = 0.978$) of temperature on weather stations with topography. It was demonstrated that the long-term average July temperature is significantly determined not only by an altitude (above sea level) but also by the slope insolation (terminology) and valley characteristics. A close nonlinear association with $T_{\rm JUL}$ was detected for the NDVI of mountain forests in this basin. Samples of pine forests close to glaciers reveal close nonlinear associations between the summer NDVI and topography and distance from glaciers. Ecological optima of $T_{\rm JUL}$ were detected for broad-leaved, small-leaved, and pine types of forest in the basin; such an optimum was not established for dark coniferous forests. The average value of NDVI can decrease in predicted NDVI estimations of broad-leaved forests, according to the climatic E GISS scenario, by 2050, since the temperature optimum of forests will move to the area of high-altitude topography, which is characterized by less favorable topographical conditions for the development of forests.

Keywords: geomorphometry, climate and topography effect on NDVI of forests, ecological optima, nonlinearity of associations, Northern Caucasus

DOI: 10.1134/S1995425514070099

INTRODUCTION

Forest vegetation follows variables of the environment (such as topography and climate), and this association is especially clearly manifested in the mountains, where the climate itself is closely associated with topography. The association between air temperature and topography is not reduced only to its dependence on altitude and geographical latitude and longitude, which were used for the interpolation of data on weather stations during the development of grid of the WorldClim high (30″) resolution climate global model [16]. Exposure (terminology), slope steepness, and the special role of mountain ranges and valleys are no less important for vegetation. Therefore, one of aims of our work was to conduct interpolation of weather station data with proper accounting of these factors.

The Normalized Difference Vegetation Index (see definition and properties in [17] is associated with the content of chlorophyll in vegetation; therefore, it is quite often used for estimation of the functional activity of forests. Since vegetation in the mountains changes with altitude and at different slopes and landforms, the question of when this association is linear with topographic attributes (and when nonlinearity is significant) is of interest. A broadened set of 18 basic morphometric variables (MVs) [23], which makes it possible to statistically compare NDVI with a whole spectrum of quantitative topographic attributes with the use of multiple regression methods (including using nonlinear expressions for independent variables), was introduced in geomorphometry (the science of quantitative analysis of the Earth surface) [10, 20]. It was demonstrated in a number of studies that some properties of forest ecosystems are better described by previously unused MVs and with an account of nonlinear associations [6–9, 11].

Interference in the influence of such environmental factors as climate and topography on mountain massif forests was little studied by quantitative methods. However, this question was found to be important with respect to the prognosis of forest redistribution in conditions of changing climate. For example, forests are modeled as monotonically rising by ~500 m during warming in the prognosis of forest change in Swiss Alps [18], even though topography in a new altitude area (which has favorable temperature conditions) can have sharp gradients that complicate its mastering. The task of the work is to conduct simultaneous accounting of the climate and topography and to detect whether changes in the prognostic estimations of mountain forest transformation are considerable.

The program Analytic GIS Eco, developed by P. A. Shary, was used for calculations and map construction [24].

MATERIALS AND METHODS

SRTM30 grids [21] of high resolution 30″, which were transformed for mountain Caucasus into a grid with resolution 500 m in the Kavraisky projection for European Russia, were a source of data on topography. Measurements from 67 weather stations, averaged over 40 years, were a source of data on climate; 34 hydroposts were additionally used for precipitation.

A broadened system of basic MVs, the meaning of which is described in [23], was used for the land surface analysis. Several compound or transformed MVs described in [11] were added to them. For example, exposure of A_0 slopes for statistical comparison requires transformation, since this MV is circular and 0° and 360° is the same for it (northern slopes); A_0 sine and cosine values were used (northern and eastern components of exposure, respectively [12]). In addition, quadratic and cubic terms of Z altitude and GA steepness were tested. These terms were centered [19] for a decrease in effects of linear dependence between analyzed spatial factors (predictors); that is, Z^2 values were replaced with $(Z\text{-}Z_{CP})^2$, Z^3 with $(Z\text{-}Z_{CP})^3$, etc. Since the distribution of regression model remainders must be normal, nonlinear transformations of some MVs described in [11] were used; the transformed MVs were marked below by superscript "T."

Four samples of 200 points were used for analysis of nonlinearities for pine and dark coniferous types of forests as determined on the Electronic Map of Russian Forests [2]; light forests (with crown cover < 40%) were not included; all areas with altitude less than 500 m were also excluded from consideration. S.A. Bartalev et al. calculated the corrected (on cloud borders etc.) NDVI values for summer 2001 with a resolution in terms of 250 m [3], as well as the matrices of types of forests [3, 13]. We transformed their data to resolution 500 m. As is known (for example, [15]), the NDVI distribution deviates from the normal distribution; therefore, the $(\mathrm{NDVI}/\mathrm{NDVI}_{\mathrm{AV}})^5$ variable, the distribution of which is closer to normal distribution ($\mathrm{NDVI}_{\mathrm{AV}}$ is an average in the sample), was used instead of the NDVI for the problem of nonlinearity. The topography, climate, latitude, longitude, and distance from glaciers were used as environmental factors for solving the problem of nonlinearity of associations. The latter means the lowest distance from the point of observation to the closest border of glaciers, the location of which was estimated according to topographic maps.

The significance of linear dependence between predictors (multicollinearity) was estimated by the maximal value of so-called "dispersion inflation factors" [19]. If this maximum was less than 5.15, multicollinearity was considered to be insignificant; otherwise, this combination of predictors or independent variables was excluded from consideration [11]; this was due to the fact that "independent" variables cannot be already considered as independent variables, which can result in a wrong result, manifesting as an increasingly higher determination coefficient. The normality of distribution of a dependent or analyzed variable (response) was estimated by graphs of normal probability [19]. The normality of distribution of the model residuals (errors) was checked by the same method. If the distribution of residuals significantly differed from the normal distribution, an appropriate nonlinear transformation of the response was conducted. In general, these regression models are some of the most currently popular ones, the so-called generalized linear models (in fact, nonlinear, see [11]).

The selection of predictors was conducted by a search for all combinations for a fixed amount of predictors (4 or 3); the combination of predictors with the largest values of the R^2 determination coefficient was selected; as opposed to approximate approaches of stepwise regression, this method is considered to be more correct [19].

RESULTS AND DISCUSSION

Generation of Climatic Grids Based on Associations of Weather Station Data and Hydroposts with Topography

The association of long-term average July temperature (T_{JUL}) in mountain Caucasus with topography was described by the regression equation

$$T_{JUL} = -0.05927Z_{-49.69} + 0.000006962(X+Y)/2^{1/2}_{+6.39}$$
$$+ 0.04256F(35°,225°)_{+2.93} + 0.2771kh^{\mathrm{T}}_{+2.53} + 26.00,$$
$$R^2 = 0.978(Degr = 0.7\%), \quad P < 10^{-6}, \tag{1}$$

where Z is the altitude; $(X+Y)/2^{1/2}$ is the distance to the northeast (X and Y, longitude and latitude in meters, respectively); F(35°,225°) is the relative insolation of slopes from southwest; kh is the horizontal curvature (branches are noted by the sign "+" for spurs and "–" for hollows). The equation can be read as follows: if an observer moves along the isoline of the altitude Z, he will register the highest temperatures on slopes that are well insolated from southwest slopes (+F(35°, 225°)) located on the branches (+kh), which are at extreme positions on the northeast of Northern Caucasus macroslope (+$(X + Y)/2^{1/2}$). Subscripts (Student's t-statistics) describe the significance of each predictor in the model, and the larger the t-statistics module, the higher the predictor significance. According to them, Z has the largest significance, but other predictors are also significant. Southwest azimuth 225° was obtained by a search for all values of the azimuth x (via 5°) in the insolated $F(35°,x)$. The largest heating of southwest slopes is caused by a delay in the heating of low soil layers. Since F depends on both exposure and slope steepness, as well as shade [23], this MV can be one of the reliable topographic attributes for a description of the temperature conditions of slopes (see more details in [12]); the association between R^2 and sun declination above the horizon (taken 35°) was very weak [11].

According to (1), T_{JUL} decreases by ~6°C when rising by 1 km. The found R^2 demonstrates that 98% of T_{JUL} spatial variability is explained by topography (Z, F, and kh) and geographic variable $(X+Y)/2^{1/2}$. Verification (checking) of the model was conducted according to Allen's cross-validation method [19]; a description of the *Degr* parameter and *Degr* < 50% criterion is given in [11]. During the model verification, it was found that the degradation of *Degr* in new observation points is small according to this criterion; that is, the model (1) has a good predictive power in new observation points (where there were no measurements).

Grids of long-term average January temperature and precipitations of warm and cold periods, as well as average annual precipitations, were also developed for the analysis of associations between NDVI and climate and topography. To construct the precipitation model, the northern macroslope was divided into several parts because of rain shades and similar phenomena [4]. In general, precipitation is less closely related to topography than temperatures.

Nonlinearities and Ecological Optima of NDVI

Four samples of coniferous forests in the Kuban basin were analyzed with 200 points. "Pines X" were located along the main divide, "Pines Y" were located across it, and "Pines" were in the intermediate location. The sample "Dark coniferous" was rather distant from glaciers, since spruce–fir forests do not grow close to them in the Kuban river basin. The following regression equations describing spatial NDVI variability for different coniferous forest samples were obtained:

1) "Pines-Y" sample (in the valley of Kuban river sources, the closest to Elbrus mountain)

$$(\mathrm{NDVI}/\mathrm{NDVI}_{\mathrm{AV}})^5 = 0.5692(D_{GLAC}/D_{\mathrm{AV}})^2_{+23.26} - 1.529 \times 10^{-6}(Z - Z_{\mathrm{AV}})^2_{-9.19} + 2.618 \times 10^{-9}(Z - Z_{\mathrm{AV}})^3_{+7.09} - 0.0004910\,Z_{-5.24} + 1.469; \tag{2}$$

$$R^2 = 0.813\ (Degr = 0.9\%),\ P < 10^{-6}.$$

2) "Pines" sample (moderately distant from glaciers)

$$(\mathrm{NDVI}/\mathrm{NDVI}_{\mathrm{AV}})^5 = 0.4060(D_{GLAC}/D_{\mathrm{AV}})^2_{+15.89} - 0.0009431Z_{-8.16} - 9.868 \times 10^{-7}(Z - Z_{\mathrm{AV}})^2_{-5.97} + 1.959 \times 10^{-9}(Z - Z_{\mathrm{AV}})^3_{+4.35} + 2.407; \tag{3}$$

$$R^2 = 0.707(Degr = 2.6\%),\ P < 10^{-6}.$$

3) "Pines-X" sample (located along the glaciers)

$$(\mathrm{NDVI}/\mathrm{NDVI}_{\mathrm{AV}})^5 = -0.00001163(X - Y)/2^{1/2}_{-17.02} + 0.1053\,T_{JUL\,+9.61} - 0.01823(T_{JUL} - T_{JUL,\,\mathrm{AV}})^2_{-4.29} - 0.2158khe^{\mathrm{T}}_{-3.21} + 11.13; \tag{4}$$

$$R^2 = 0.746(Degr = 1.8\%), \quad P < 10^{-6}.$$

4) "Dark coniferous" sample (distant from glaciers)

$$(\mathrm{NDVI}/\mathrm{NDVI}_{\mathrm{AV}})^5 = -0.001022Z_{-18.25} + 0.1377H^{\mathrm{T}}_{+8.61} + 0.008947F(35, 225)_{+6.67} - 0.0008245P_{YEAR-5.46} + 2.994; \tag{5}$$

$$R^2 = 0.759(Degr = 1.3\%), \quad P < 10^{-6}.$$

In the equations, D_{GLAC} is the distance from glaciers; $(X\text{-}Y)/2^{1/2}$ is the distance to southeast; *khe* is the MV describing the terrain dissection; H is the MV describing mean-convex and mean-concave landforms [23]; and P_{YEAR} is the average annual sum of precipitations. These environmental variables explained from 70 to 81% of spatial NDVI variability in the studied samples of coniferous forests.

The following can be seen from these equations. Associations between NDVI and environmental factors are nonlinear both by D_{GLAC} and Z altitude (the role of the quadratic by Z member prevails) for the "Pines-Y" sample located most closely to glaciers across the range. For the "Pines" sample, located not so close to glaciers, the associations with D_{GLAC} and Z are nonlinear but with a prevailing role of the member linear by Z. For the "Pines-X" sample, which is approximately more distant from glaciers are located along the range, an association with D_{GLAC} in an insignificant and linear association with Z prevails. All associations are linear for the "Dark coniferous" sample, which is located distant from the glaciers. Such results can be explained by the fact that the nonlinear character of the NDVI association with spatial factors arises close to marginal conditions (glacier borders or ecological niche).

We explain the latter in more detail. It is seen in Fig. 1 that the ecological optimum is observed in the dependence between NDVI and T_{JUL}, when NDVI has maximal and close values in a small temperature range. The falling low-temperature branch of this dependence is created by approaching the borders of fundamental ecological niche, which is determined by low July temperatures that decrease the functional activity of forests. The falling of the high-temperature branch is created by the realized ecological niche, that is, by competition with deciduous forests located lower along the slopes. We note that pines grow in much warmer conditions in the absence of competition than at the optimum observed here (close to 11°C). It is impossible to accept such an optimum as

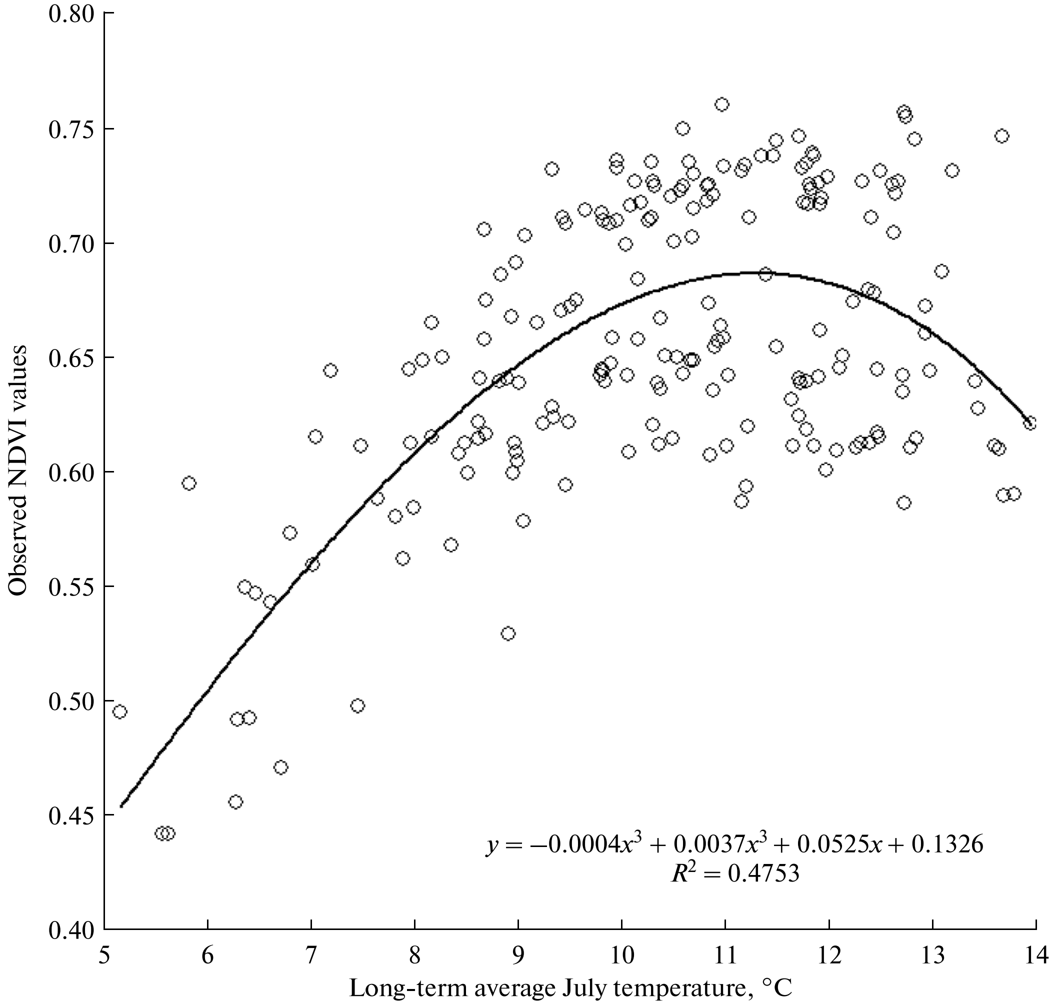

Fig. 1. Association between NDVI in summer 2001 and July temperature for the sample "Pines-Y". The curve shows a cubic trend.

physiologically caused; it is caused both by interaction of physiological limitations and competition.

We note that a similar optimum exists for broad-leaved and small-leaved forests for the forests in the Kuban river basin; however, it does not exist for dark coniferous forests (Fig. 2). A possible reason for this may be that spruce–fir forests in the basin are rarely located close to glaciers and that the fundamental ecological niche here can play much smaller role for them.

Predicted changes for 2050 in NDVI of mountain forests, including future ecological optima, are given in Fig. 2; this is discussed in the following part.

Cooperative Effect of Climate and Topography on Mountain Forests

In this part, all forests of mountain part of the Kuban river basin (altitudes > 500 m) are considered; data on forest types and NDVI obtained for more than 11000 plots are used. Broad-leaved forests occupy the largest area (approximately 8500 plots); the area of coniferous forests is nine times smaller (small-leaved forests are 4.5 times smaller). Three-predictor models were used for analysis of the associations between the forest NDVI and climate and topography (because of the larger amount of points) with estimation of the tightness of association by nonparametric rank Spearman's correlation coefficient (r_S) and without t-statistics calculation. The predictors (as above) are ordered by significance (the first one is the most significant) by approximate methods of standardization of regression equations [11, 19].

Out of all of the tested climatic characteristics for the NDVI of the entire mountain forest massif and for certain types of forest, the association was the strongest with July temperatures. Thus, its grid was used for estimation of forest transformation over time. The grid of a predictive model of July temperature was developed from data of the E GISS climatic scenario for 2050 [27] as follows. The initial planetary grid was transformed using the Delone triangulation method from a grid with a smaller spacing (0.5°C). The values

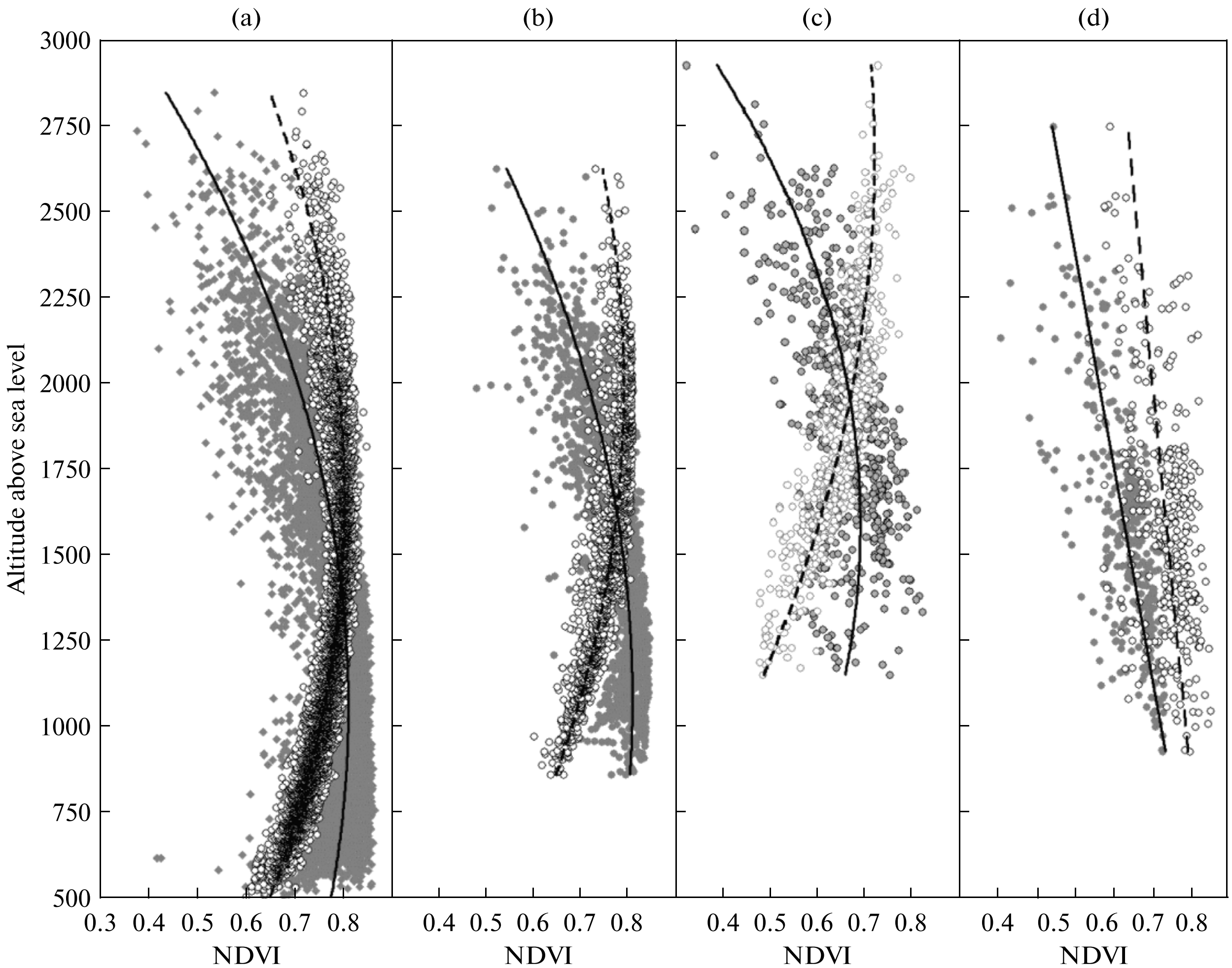

Fig. 2. Ecological optima for four types of mountain forests of Great Caucasus: broad-leaved (a), small-leaved (b), pine (c), and dark coniferous (d). Continuous trends refer to base period (2001); light circles and dashed lines refer to prognosis for 2050.

of temperature changes by 2050 were obtained using this grid for each weather station. The obtained measurements were summed with data on long-term average T_{JUL} values, and then the spatial model of the predicted temperature was formed by the method described above for the equation (1). The obtained model predicts an increase in July temperatures on average by 3.2°C by 2050 according to the E GISS scenario. The greatest change in temperature is expected to occur in the highland.

The prognosis for the spatial distribution of NDVI forests by 2050 was performed by replacing in the regression equation the temperature values of the base period by values predicted by E GISS scenario. The spatial distribution of the predicted NDVI of broad-leaved and coniferous broad-leaved forests (as this type of forest is determined in [2]) is described by the following regression equation

$$\mathrm{NDVI} = -0.365(T_{\mathrm{JUL}} - T_{JUL,AV})^2 + 0.138kv + 0.032T_{JUL} + 0.714; \quad (6)$$
$$r_{\mathrm{S}} = 0.67;\ P < 10^{-6}.$$

The temperature optimum of the base period for the NDVI of mountain broad-leaved forests described above was estimated as 14°C with altitude values appropriate to this optimum of approximately 1000 m (Fig. 2). Calculated according to the appropriate models, the modern and predicted NDVI maps for broad-leaved forests are shown in Fig. 3. In spite of an increase in T_{JUL} by 2050 for this type of forest by 3.2°C, model (6) provides a decrease in average NDVI value by 2050 of 7%. Since broad-leaved forests are thermophilic, the obtained result is an indication on the existence of factors that limit the use of the advantage of a temperature increase in the mountains by broad-leaved forests in the future.

For example, it was accepted in the forest models of Swiss Alps that all types of vegetation will go up the slopes as a result of expected warming by 1.5°C by 2050 and 3°C by 2100, which is predicted by the regional climatic model of mountain Alps [18]. However, the results of our modeling demonstrate that the altitude belt covering the optimum of climatic conditions of forests will move up, where

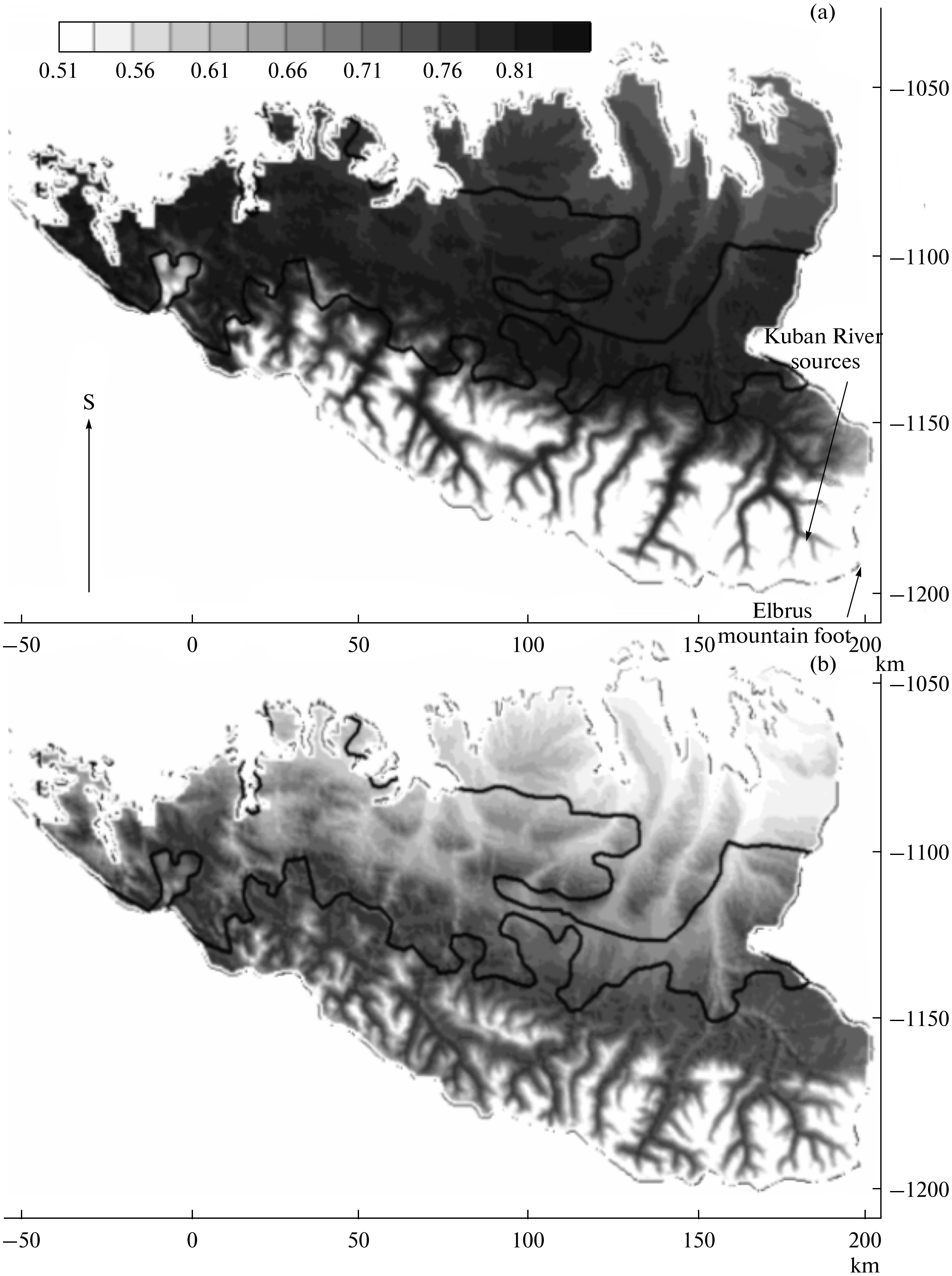

Fig. 3. NDVI maps of broad-leaved forests for base period (a) and for 2050 according to E GISS model (b) for the Kuban River basin. Dark line is the border of modern area of broad-leaved forests. The legend (single for a and b) describes NDVI values.

topography is characterized by steeper slopes and more pronounced ridges and valleys. These new (apparently, less suitable) topographic conditions for the growth of broad-leaved forests can induce a decrease in the functional activity of forests.

Figure 4 can provide definitive confirmation of this; for the territory of Kuban River basin, the following was shown: a) an increase in the values of slope steepness with an increase of altitude, and b) a decrease in NDVI values with an increase in steepness.

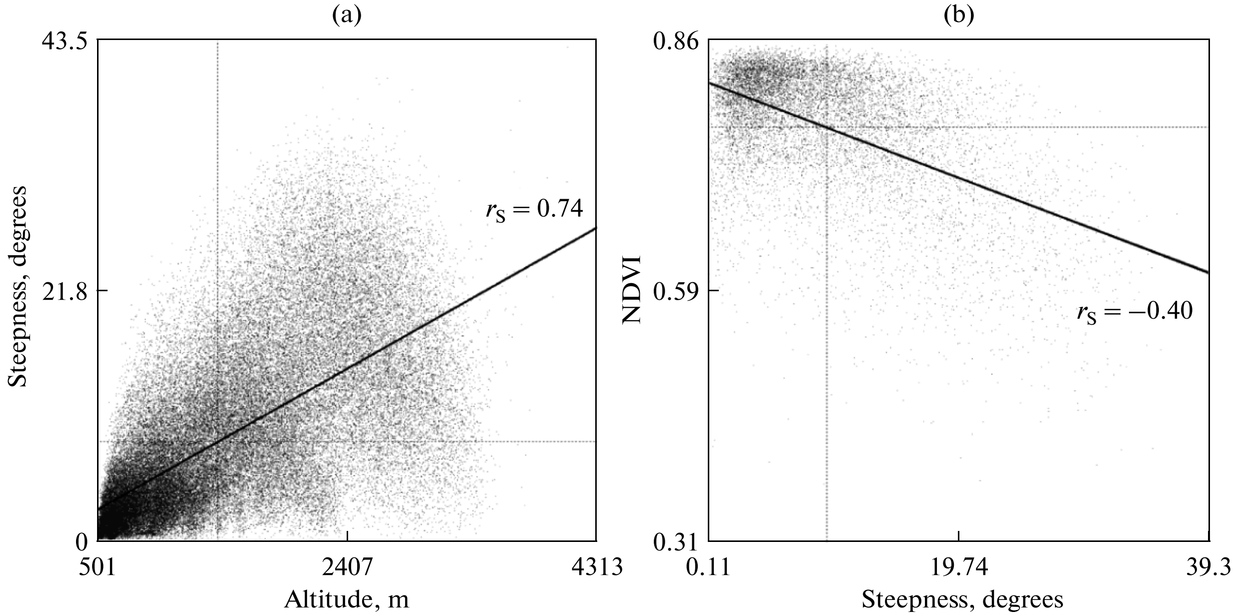

Fig. 4. Graphs of the association of *GA* incline with altitude and NDVI, illustrating how the relief specifics results in a decrease in NDVI in the upper parts of the mountains. *GA* increases with altitude (a), while NDVI decreases with *GA* (b) in mountains of the Kuban river basin.

The graphs that we constructed, similar to the graph in Fig. 4, demonstrate that the maximal and minimal curvatures describing pronounced ridge and valley landforms increase along the module with altitude and decrease the NDVI of broad-leaved forests. In general, instead of an increase in NDVI due to warming (as is predicted in the Alps [18]), model (typo) (6) predicts a 7% decrease in NDVI due to these effects of the interaction of changing climate and invariable topography; according to model (6) in 2001, the average NDVI was 0.71 for this type of forest; it will be 0.66 by 2050. Modeling demonstrated that these effects are different for different types of forests. The average NDVI for pine forests will not significantly change by 2050; it will decrease by 3% for small-leaved forests and increase by 13% for spruce forests.

An "inhibitory" role of topography arises, because steep slopes (an incline of 20°–40° is usual in the upper reaches of Caucasus [6]) are unfavorable for the growth of forests. Tembotova et al. [5] noted a decrease of 22–23% in the area of mountain beech and hornbeam on very steep slopes (20°–40°) in Kabardino-Balkaria over last 20 years.

CONCLUSIONS

1. It is necessary to use a proportionate amount data on environment variables when analyzing the associations of these variables with forest ecosystem characteristics (which are represented by a considerable amount of satellite data). Detailed planetary data on climate with a spatial resolution of 600 m in moderate latitudes are available in WorldClim models [16]. These models interpolate climate in the mountains by altitude, latitude, and longitude; however, they do not take into account variables that are important for vegetation (slope insolation, role of ridges and valleys). Such variables were used in the presented work; their inclusion is based on the very close statistical associations of climate and topography (R^2 = 0.978), as well as on their significance. The obtained model was successfully verified according to accepted criteria, which confirms its reliability. Insufficient attention is paid to landscapes in climatologic models (and most of all to mountain landscapes) as argued by B. Beckage et al. [14], who used daily measurements of temperatures and precipitations from two weather stations for an analysis of forest changes over 40 years in time and space. Real measurements differed considerably from data on climatic models.

2. The more nonlinear the association of mountain forest NDVI with environmental factors is, the closer the growth conditions to marginal conditions are (proximity of glaciers and competition with other types of vegetation).

3. It should be noted that the results of the forest state prognosis for a particular time period depend on the accounting of ecological inertia (the delay of functional and structural forest transformations after climatic changes). In our predictive model, we use a type of association between forests and climate and topography developed for a long period of relatively steady climate, without taking into account the time required

for both internal reorganization of ecosystems and a change of their borders. In addition, events are not included in the described models (such as mass invasion of pest insects, sharp weather deviations from climatic scenarios, fires, etc). The NDVI prognosis for forests of the Kuban river basin by 2050, according to the selected scenario (without taking into account topography), leads to a result in which the growing conditions of broad-leaved forests become more favorable because of warming. Another result is manifested during simultaneous accounting of climate changes and topography (which remains practically invariable over the predictive period). The temperature optimum of forests moves up the slopes by almost 500 m, but the forests can't maintain primarily the same photosynthetic activity as in the base period in new forest area because of increased slope steepness and more frequent, sharply pronounced landforms. In other words, topography will "inhibit" the mastering by forests of new altitude belts, in which the predicted temperature optima will be located; therefore, its action will result in a decrease in NDVI in general. These peculiarities are true for cases of nonlinear associations between the photosynthetic activity of forests and climate. With linear associations, the result will be opposite (as with spruce–fir forests). The predicted estimations of forest change depend on the specific models and climatic scenarios used, but the general conclusion regarding the importance of accounting for the effect of interaction between climate and topography remains valid.

REFERENCES

1. Bartalev, S.A., Ershov, D.V., Lupyan, E.A., and Tolpin, V.A., Possibilities of satellite service VEGA use for different tasks of terrestrial ecosystems monitoring, *Sovrem. Probl. Distantsionnogo Zondirovaniya Zemli Kosmosa*, 2012, vol. 9, no. 1, pp. 49–56.
2. Bartalev, S.A., Ershov, D.V., Isaev, A.S., Potapov, P.V., Turubanova, S.A., and Yaroshenko, A.Yu., *Karta lesov Rossiskoi Federatsii okrashennaya po preobladayushchim gruppam porod derev'ev i somknutosti drevesnogo pologa. Masshtaba 1 : 14000000* (Map of the Forests of Russian Federation Stained by Prevailing Groups of Trees and Solidity of Woods, Scale 1 : 14000000), Moscow: Inst. Kosm. Issled., Ross. Akad. Nauk, 2004.
3. Bartalev, S.A., Egorov, V.A., Ershov, D.V., Isaev, A.S., Lupyan, E.A., Plotnikov, D.E., and Uvarov, I.A., Satellite mapping of Russia's vegetation cover using MODIS satellite spectroradiometer data, *Sovrem. Probl. Distantsionnogo Zondirovaniya Zemli Kosmosa,* 2011, vol. 8, no. 4, pp. 285–302.
4. Zalikhanov, M.Ch., Kolomyts, E.G., Sharaya, L.S., Tsepkova, N.L., and Surova, N.A., *Vysokogornaya ekologiya v modelyakh* (Models of High-Altitude Ecology), Moscow: Nauka, 2010.
5. Tembotova, F.A., Pshegusov, R.Kh., Tlupova, Yu.M., Tembotov, R.Kh., and Akhomgotov, A.Z., Assessment of condition of forest ecosystem of mountainous region of Kabardino-Balkaria using remote sounding data, *Izv. Ross. Akad. Nauk, Ser. Geogr.*, 2012, no. 6, pp. 89–97.
6. Tkhazaplizheva, L.K. and Shkhagapsoev, S.K., The state of cenopopulations and survival strategy of *Lilium monadelphum* Bieb. in a stressful environment (the Elbrus region), *Russ. J. Ecol.*, 2010, vol. 41, no. 2, pp. 129–138.
7. Sharaya, L.S., Predictive mapping of forest ecosystems in geoecology, *Povolzh. Ekol. Zh.*, 2009, no. 3, pp. 249–257.
8. Sharaya, L.S., Predictive mapping of forest ecosystems by landscape-ecological approach, *Izv. Samar. Nauchn. Tsentra, Ross. Akad. Nauk*, 2013, vol. 15, no. 3, pp. 38–47.
9. Sharaya, L.S. and Shary, P.A., Relation of abiotic and biotic characteristics of Zhiguli forest ecosystems, *Izv. Samar. Nauchn. Tsentra, Ross. Akad. Nauk*, 2009, vol. 11, no. 1, pp. 22–30.
10. Sharaya, L.S. and Sharyi, P.A., Geomorphometric study of the spatial organization of forest ecosystems, *Russ. J. Ecol.*, 2011, vol. 42, no. 1, pp. 1-8.
11. Shary, P.A., Rukhovich, O.V., and Sharaya, L.S., Analysis of the spatial variation in wheat yield depending on agricultural landscape conditions, *Agrokhimiya*, 2011, no. 2, pp. 57–81.
12. Shary, P.A. and Smirnov, N.S., Mechanisms of the effects of solar radiation and terrain anisotropy on the vegetation of dark conifer forests in the Pechora-Ilych state biosphere reserve, *Russ. J. Ecol.*, 2013, vol. 44, no. 1, pp. 9–17.
13. Bartalev, S.A., Belward, A.S., Ershov, D.V., and Isaev, A.S., A new SPOT4-VEGETATION derived land cover map of Northern Eurasia, *Int. J. Remote Sens.*, 2003, vol. 24, no. 9, pp. 1977–1982.
14. Beckage, B., Osborne, B., Pucko, C., Gavin, D.G., Siccama, T., and Perkins, T., A rapid upward shift of a forest ecotone during 40 years of warming in the Green Mountains of Vermont, *Proc. Natl. Acad. Sci. U.S.A.*, 2008, vol. 105, pp. 4197–4202.
15. Fisher, J.I., Mustard, J.F., and Vadeboncoeur, M.A., Green leaf phenology at Landsat resolution: scaling from the field to the satellite, *Remote Sens. Environ.*, 2006, vol. 100, pp. 265–279.
16. Hijmans, R.J., Cameron, S.E., Parra, J.L., Jones, P.J., and Jarvis, A., Very high resolution interpolated climate surfaces for global land areas, *Int. J. Climatol.,* 2005, vol. 25, pp. 1965–1978.
17. Huete, A., Justice, C., and van Leeuwen, W., *MODIS Vegetation Index (MOD13). Algorithm Theoretical Basis Document, Ver. 3*, Arizona: Univ. of Arizona and Virginia, April 1999.
18. Lischke, H., Guisan, A., Fischlin, A., and Bugmann, H., Vegetation responses to climate change in the Alps — modeling studies, in *A View from the Alps: Regional Perspectives on Climate Change*, Cebon, P., Dahinden, U., Davies, H., Imboden, D., and Jaeger, C., Eds., Boston: MIT Press, 1998, ch. 6, pp. 309–350.

19. Montgomery, D.C. and Peck, E.A., *Introduction to Linear Regression Analysis*, New York: Wiley, 1982.
20. Pike, R.J., Evans, I.S., and Hengl, T., Geomorphometry: a brief guide, in *Geomorphometry: Concepts, Software, Applications. Developments in Soil Science*, Hengl, T. and Reuter, H.I., Eds., Amsterdam: Elsevier, 2009, vol. 33, ch. 1, pp. 3–30.
21. Rodriguez, E., Morris, C.S., Belz, J.E., Chapin, E.C., Martin, J.M., Daffer, W., and Hensley, S., *An Assessment of the SRTM Topographic Products, Technical Report JPL D-31639*, Pasadena, California: Jet Propulsion Lab., 2005.
22. Schmidt, G.A., Ruedy, R., Hansen, J.E., Aleinov, I., Bell, N., Bauer, M., Bauer, S., Cairns, B., Canuto, V., Cheng, Y., Del Genio, A., Faluvegi, G., Friend, A.D., Hall, T.M., Hu, Y., Kelley, M., Kiang, N.Y., Koch, D., Lacis, A.A., Lerner, J., Lo, K.K., Miller, R.L., Nazarenko, L., Oinas, V., Perlwitz, J.P., Perlwitz, Ju., Rind, D., Romanou, A., Russell, G.L., Sato, M., Shindell, D.T., Stone, P.H., Sun, S., Tausnev, N., Thresher, D., and Yao, M.-S., Present day atmospheric simulations using GISS Model E: comparison to insitu, satellite and reanalysis data, *J. Clim.*, 2006, vol. 19, pp. 153–192.
23. Shary, P.A., Sharaya, L.S., and Mitusov, A.V., Fundamental quantitative methods of land surface analysis, *Geoderma*, 2002, vol. 107, pp. 1–32.
24. Wood, J., Overview of software packages used in geomorphometry, in *Geomorphometry: Concepts, Software, Applications. Developments in Soil Science*, Hengl, T. and Reuter, H.I., Eds., Amsterdam: Elsevier, 2009, vol. 33, part 10, pp. 257–267.

Translated by A. Barkhash