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Application of Artificial Neural Network for assessing climate-induced changes in vegetation cover parameters

Gusev E.M.[a], Nasonova O.N.[b]
Water Problems Institute, Russian Academy of Sciences, Gubkina Street, 3, Moscow, Russia
sowaso@yndex.ru, olniknas@yandex.ru

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Abstract: A methodology for scenario projecting changes in vegetation parameters caused by climate change has been developed for the territory of the Russian Federation. Such parameters are widely used in Earth system parameterization schemes. The methodology is based on the artificial neural network technique generating relationships between vegetation parameters and climatic, edaphic, and orographic factors. For the projection period 2073–2100 and the SSP5-RCP8.5 climate scenario, changes in more than fifty vegetation parameters derived from the ECOCLIMAP dataset for the territory of Russia were modeled, and maps of the spatial distribution of these changes were constructed. It is shown that changes in the parameters under the selected climate scenario by the end of the 21st century are quite noticeable and differ in sign. Spatially averaged absolute values of the deviations of the projected values of different parameters from historical ones are in the range of 5–17%.

1 INTRODUCTION

One of the directions of long-term projecting changes in characteristics of thermal, hydrological and ecological regimes of large terrestrial objects (regions, river basins), which are needed for natural resources management, is application of regional Hydrological Models (HMs), Land Surface Models (LSMs), Soil – Vegetation – Atmosphere Transfer – schemes (SVAT), Soil and Water Assessment Tools (SWAT), etc.

Input data for these models represents meteorological forcing data and land surface parameters. For projecting- climate change impact on various systems, forcing data are usually simulated by Global Climate Models (GCMs). List of the land surface parameters is determined by the main block of the models, namely Land Surface Scheme (LSS) (Boone et al, 2004) and contains, as a rule, two groups. The first group includes parameters of soil and relief of the object under consideration, the second one contains vegetation parameters.

When projecting changes in thermal, hydrological and ecological regimes of terrestrial objects on a scale of several tens, and possibly even the first hundreds of years, the thermal and hydrophysical parameters of the soil (the main characteristics used in the aforementioned models) can be assumed to be constant, since time is far from being the main factor in soil formation. Vegetation parameters are also often assumed to be constant (Gelfan et al., 2020; Krysanova et al., 2017; Nadyozhina et al., 2023; Pechlivanidis et al., 2017). Their values are either taken from various datasets created for different ecosystems over the historical period or obtained as a result of calibration using the dynamics of thermal and/or water regime characteristics of the object under consideration over the historical period.

However, according to investigations in the field of Earth sciences, the ongoing anthropogenic increase in the content of greenhouse gases in the atmosphere (causing global climate change) leads to corresponding transformations of ecosystems, including terrestrial phytocenoses (IPCC, 2021),

[a] https://orcid.org/0000-0003-3886-2143
[b] https://orcid.org/0000-0002-3111-3337

which results in changes in the values of their parameters used in LSS. Therefore, it is necessary to develop a technique for projecting changes in the values of vegetation parameters, which largely determine heat and water exchange between the land surface and the atmosphere, in order to obtain more accurate estimates of the expected evolution of heat and water budgets of terrestrial objects.

The main way of projecting changes in such characteristics is based on the development of dynamic models of terrestrial vegetation (Dynamic Vegetation Models – DVMs) (Krinner et al., 2005), which allow one to describe numerous effects of interaction of vegetation with changing environment, including competition of different types of vegetation for resources (mainly radiation and water). However, despite significant advances in the development of DVMs (De Cáceres et al., 2023), the problem of their parameterization has not yet been solved (Hartig et al., 2012). In this regard, correlational, statistical, and empirical approaches to the analysis and projecting of vegetation response to climate change continue to be relevant (Anisimov et al., 2011; Ferrarini et al., 2022). For this reason, the aim of the present work is assessment of the capabilities of one of the empirical approaches to projecting the transformation of vegetation parameters due to possible climate change in the 21st century.

Projecting long-term dynamics of vegetation parameters is necessary for prognostic simulations of the components of heat and water balances of terrestrial objects by regional Earth system models, in particular, land surface model SWAP (Soil Water – Atmosphere – Plants) developed by the authors of this paper (Gusev and Nasonova, 2010).

Here, vegetation parameters for the territory of Russia are taken as a specific object of the study. The parameters are mainly derived from the global ECOCLIMAP dataset, which is widely used in regional and global LSSs incorporated in different classes of regional and global diagnostic and prognostic models and systems (Bessardon at al., 2024; Faroux et al., 2013; Gusev et al., 2024; Nasonova et al., 2021). In this paper, the Artificial Neural Network (ANN) method is used to create an empirical relationship between the values of vegetation parameters and climate characteristics (Gafarov and Galimyanov, 2018; Haykin, 1999).

It should be noted that application of the ECOCLIMAP is due to the authors' long-term experience of working with this dataset (Nasonova et al., 2021; Nasonova et al., 2023). In principle, the developed methodology for constructing an algorithm for projecting the climate-induced evolution of vegetation parameters can be applied to any other physiographic dataset whose parameters have a physical meaning.

2 METHODOLOGY

2.1 Global ECOCLIMAP dataset

ECOCLIMAP dataset was developed by the National Centre for Meteorological Research (CNRM/GAME, Meteo-France, Toulouse, France) (Faroux et al., 2013). It is based on information contained in vegetation, soil, relief, and climate maps; remote sensing data; results of international projects on land surface studies, and numerous literary sources.

ECOCLIMAP contains 215 ecosystems at 1 km spatial resolution. One set of parameters (soil depth, root depth, sand and clay fractions in the soil, etc.) is presented by average annual values, while the other set (Leaf Area Index - LAI, greenness fraction, roughness length, land surface albedo, etc.) reflects the intra-annual dynamics of the ecosystem structure and is described by mean monthly values. LSSs typically use parameter values aggregated for calculational grid cells of different size covering the Earth's surface, taking into accounting the fraction of each ecosystem in the cell. Here, the values of orographic, soil, and vegetation parameters were obtained for each half-degree grid cell.

Since ECOCLIMAP reflects land surface physiography during historical period, the values of vegetation parameters are more or less reliable for that period. This circumstance makes it possible to reveal the relationships between the values of vegetation parameters in the calculational grid cells and climatic characteristics for the region under consideration (in this case, Russia). To carry out this procedure, the fields of climatic characteristics covering the region and obtained for the historical period are required in addition to the fields of vegetation parameters.

2.2 Fields of climatic characteristics across the territory of Russia for the historical period

Since the ultimate goal of this study is to project changes in land surface parameter fields due to climate change while the dynamics of changes in climatic characteristics can be most reliably obtained by means of GCMs, the fields of climatic variables for the historical period were also derived from the

outputs of GCMs in order to maintain methodological homogeneity.

In this case, the territory of Russia was schematized as a set of 12639 regular grid cells with a spatial resolution of 0.5°×0.5° in latitude and longitude (Fig 1). Time series of meteorological data simulated by five GCMs (GFDL-ESM4, IPSL-SM6A-LR, MPI-ESM1-2-HR, MRI-ESM2-0, UKESM1-0-LL) participating in the international Inter-Sectoral Impact Model Intercomparison Project (ISIMIP3b) were used to obtain climatic characteristics for each calculational grid cell.

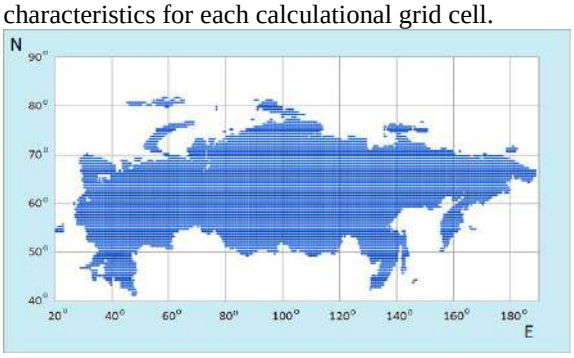


Figure 1: Schematisation of the territory of Russia with a half-degree spatial resolution.

The meteorological time series modeled by GCMs were subjected to so-called post-processing bias correction (Rasmussen, 2012) with the use of available observations and reanalysis products in order to reduce possible systematic errors of calculations.

The climatic indicators of the historical period (mean annual values of incoming shortwave *SW* and longwave *LW* radiation, near-surface air temperature *T* and humidity *Hum*; the amplitude of mean monthly air temperature *AmpT*; annual sums of solid *Snowfall* and liquid *Rainfall* precipitation) were obtained by averaging meteorological data for the period 1981–2010. This period was taken as the base historical period (Commission for Climatology ..., 2014). Then the climate indicators were averaged over an ensemble of the five above-mentioned GCMs to obtain more reasonable values (ensemble averages are more reliable than individual model simulations, since structural differences between models are the dominant source of uncertainty in their products (Tebaldi et al., 2021)).

The constructed fields of vegetation parameters and climate indicators for the territory of Russia for the historical period make it possible to obtain a relationship between these two sets based on the ANN method.

2.3 Application of ANN to construct links between vegetation parameter fields and fields of climatic, edaphic, and orographic indicators on the territory of Russia

The type and features of vegetation are determined not only by climatic, but also by edaphic and orographic factors. Construction of such relationship was carried out with the help of ANN algorithm, which is a mathematical model based on the principle of organization of biological neural networks – networks of nerve cells of a living organism.

ANN is a system of simple processors (artificial neurons) connected and interacting with each other (Gafarov and Galimyanov, 2018; Haykin, 1999). Searching relationship between predictors (input variables for ANN; here, climatic, edaphic, and orographic characteristics) and output variables (in this case, vegetation characteristics) *Par* consists of determining optimal values of network parameters (by "training" ANN), which minimize the errors in the results of the network's operation on a sample of training data.

For this purpose, the *Par* values from the ECOCLIMAP dataset as well as the values of climatic, edaphic, and orographic predictors *X* were specified for each calculation grid cell on the territory of Russia. One part of this information served as the training set for the network, the second part served as a test set (also used in the process of training the ANN when optimizing its architecture), and the third part was a control set.

The ANN operator $\hat{A}$, which links vector of predictor values $\vec{X}_i$ with vector of vegetation parameter values $\overrightarrow{Par}_{m,i}$ for each computational grid cell, can be written as follows:

$$\overrightarrow{Par}_{m,i} = \hat{A}\left(lat_i, lon_i, \vec{X}_i\right) \qquad (1)$$

where i is the number of the computational grid cell; m is the index identifying a specific vegetation parameter (m=1, …, m_0; here, m_0 is the total number of parameters); lat_i and lon_i are the latitude and longitude of a cell center, respectively.

A set of input predictors $\vec{X}_i$ includes: (1) conservative (not changing or changing very slowly under climate change conditions) edaphic and orographic variables (such as soil depth $SoilDepth_i$,; $Sand_i$ и $Clay_i$ soil fractions; elevation of cell surface above sea level Alt_i; mean slopes of cell surface in meridional x_i and latitudinal y_i directions); (2) climatic variables (in particular, SW_i, LW_i, T_i, Hum_i, $AmpT_i$, $Snowfall_i$ и $Rainfall_i$), whose values change noticeably under climate change.

The main (explicit) input predictors that clearly determine the spatial patterns of land surface parameters are the coordinates of cells lat_i ~~и~~ and lon_i. The predictors $\vec{X}_i$ act as covariates, i.e. as variables that influence (often significantly) the relationship $\overrightarrow{Par}_{m,i} = f(lat_i, lon_i)$, but are not explicitly present in this relationship (as, for example, in the ECOCLIMAP dataset).

The training set $\overrightarrow{Par}_{m,i}$ used for training the ANN includes the following variables for each grid cell: mean annual values of soil root zone H_{root}, steam area index *SAI*, vegetation height H_{veg}, albedo of vegetation in the cold period α_{win}, extinction coefficient characterizing the transmission of radiation by vegetation η; as well as mean monthly values of leaf area index *LAI,* greenness fraction *Green*, roughness length of the land surface z_0, land surface albedo α. The total number of vegetation parameters for each grid cell was 53.

Investigation of possible options for constructing ANN allowed us to choose of the following topology of its architecture (Fig. 2).

The ANN is a multilayer perceptron (Gafarov and Galimyanov, 2018; Haykin, 1999) with two explicit layers of neurons (input and output) and two intermediate (hidden) layers. The input layer is formed by neurons that receive incoming signals and transmit them to the next first hidden layer. The signals in this case are the values of lat_i and lon_i, as well as predictors $\vec{X}_i$. To increase the flexibility of the ANN, a second hidden layer is used. The last layer in the network is the output layer receiving signals from the second hidden layer and consisting of neurons that form the values of the output vectors $\overrightarrow{Par}_{m,i}$. The optimal number of neurons in the first hidden layer was 17, in the second – 12.

The signal-transmitting bridges between neurons of adjacent layers (synapses) are characterized by transfer weight functions (activation functions, for which the hyperbolic tangent was used), whose weights were determined during the network training process. In so doing, an analysis of sensitivity of the output parameter vector to the input predictors was also carried out on the basis of a special procedure. After that the relative importance of each predictor was calculated for the created ANN. Data from training and testing samples were used for this analysis.

The result of synaptic learning and obtaining activation function weights is an algorithm for calculating vegetation parameters at any point on the territory of the Russia based on available values of climatic, edaphic, and orographic predictors.

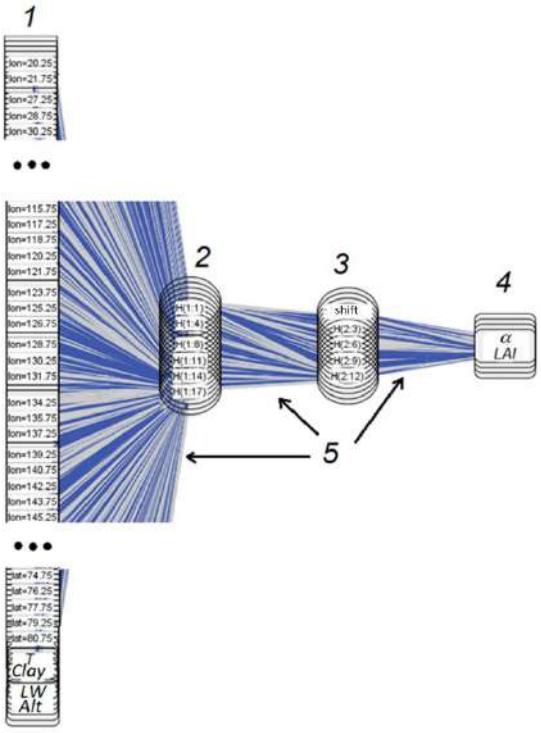


Figure 2: Architecture of the artificial neural network used.
1. An input (explicit) layer of neurons including latitude and longitude of grid cells, as well as values of corresponding climatic, edaphic, and orographic predictors.
2 and 3. Hidden layers of neurons with virtual values H(l:n), where l is the number of hidden layers and n is the number of neurons in each layer.
4. An output (explicit) layer of neurons containing vegetation parameters.
5. Signal-transmitting synapses.

3 RESULTS AND DISCUSSION

3.1 Calculating vegetation parameter fields for the territory of Russia in the historical period on the basis of ANN

The constructed ANN was trained on 50% of the values of the total sample of the climatic, edaphic and orographic characteristics. The resulting average final relative error in assessing the output vegetation parameters, calculated on their control sample, was equal to 2%. In addition, the importance of predictors allowing us to analyze the sensitivity of output function to input variables was determined (Kuvykin and Kuvykina, 2020). The analysis showed that the main contribution to formation of vegetation parameter values *Par* is made by the group of edaphic

predictors (~50%), the group of climatic characteristics is in the second place (~28%), the geographic location of the area is in the third place (~13%), and the group of orographic indicators is in the fourth place (~9%).

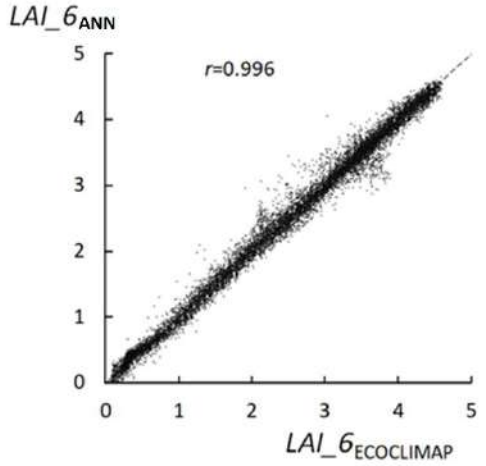
Figure 3 shows examples of comparison of vegetation parameter values generated by the ANN and derived from the ECOCLIMAP dataset for all calculational grid cells covering the Russian territory. Figure 4 shows examples of comparison of spatial patterns of a number of parameters generated by the ANN and taken from ECOCLIMAP. A similar comparison was carried out for all vegetation parameters and showed the same agreement as shown in Figs. 3 and 4.

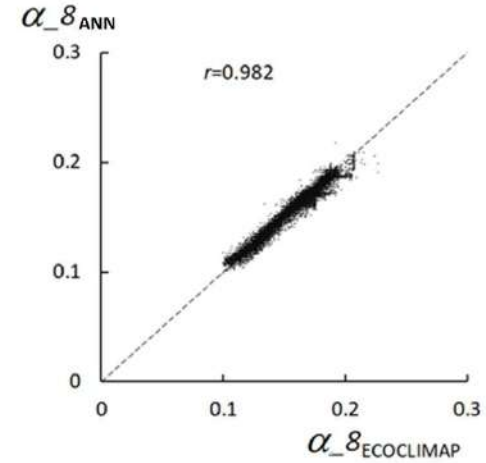
The analysis of the obtained results allows us to conclude that the vegetation parameters generated by the developed ANN for the territory of Russia practically duplicate their values derived from ECOCLIMAP. The only difference is that the sample of *Par* values generated by the ANN was supplemented with an algorithm for calculating *Par* using information on the spatial distribution of climatic, edaphic, and orographic characteristics across the territory of Russia.

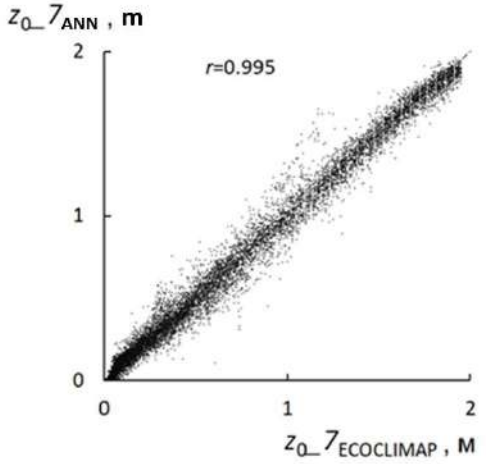
This algorithm allows generating *Par* fields for any other more or less plausible combinations of a set of specified predictors. And if noticeable changes in the values of edaphic and orographic indicators (at least those used in this study) are unlikely to be expected on the territory of Russia in the 21st century, then this is not the case with climatic characteristics. The developed algorithm makes it possible to conduct a scenario assessment of the impact of climate change on the evolution of vegetation parameters on the territory of Russia, which largely determine the heat and water exchange between the land surface and the atmosphere.

3.2 An example of calculating changes in vegetation parameter fields using climate change scenario assessments on the territory of Russia by the end of the 21st century

Let us consider an example of using the developed algorithm to assess changes in vegetation parameters in Russia by the end of the 21st century due to realization of one of climate change scenarios caused by projected socio-economic changes on the planet up to 2100 (IPCC, 2021).


LAI_6ANN
r=0.996
LAI_6ECOCLIMAP


α_8ANN
r=0.982
α_8ECOCLIMAP


z0_7ANN , m
r=0.995
z0_7ECOCLIMAP , M

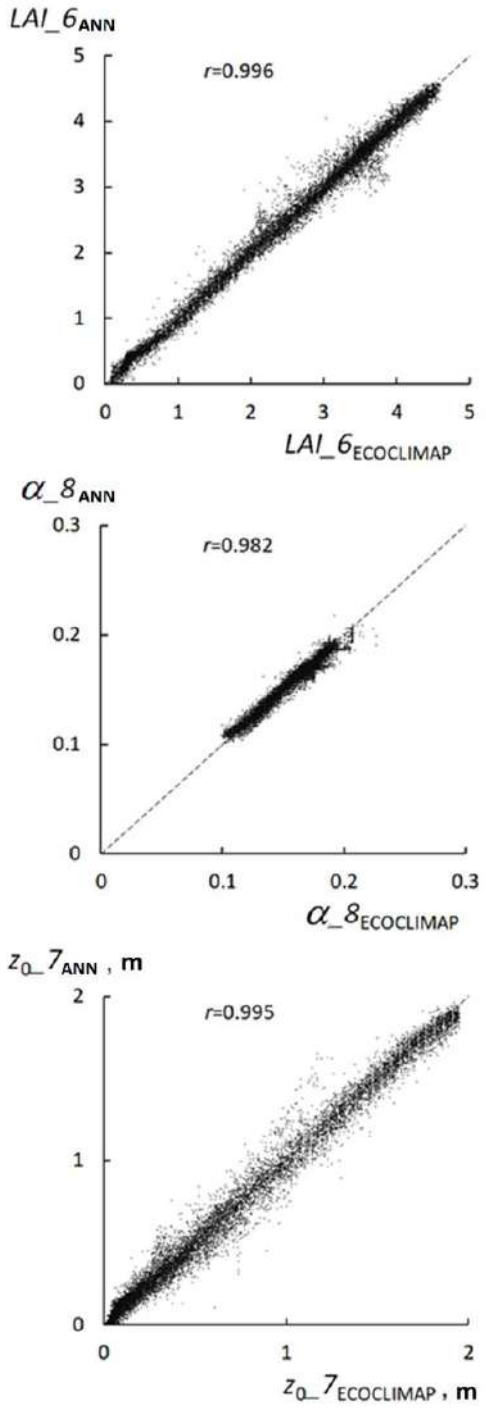


Figure 3: Comparison of vegetation parameter values generated by the ANN and derived from ECOCLIMAP for all grid cells of the Russian territory (the variables are labelled with ANN and ECOCLIMAP indices, respectively), as well as the correlation coefficient *r* between them. *LAI_6* is the leaf area index averaged over June, α_8 is the land surface albedo in August, z_0_7 is the land surface roughness length in July.

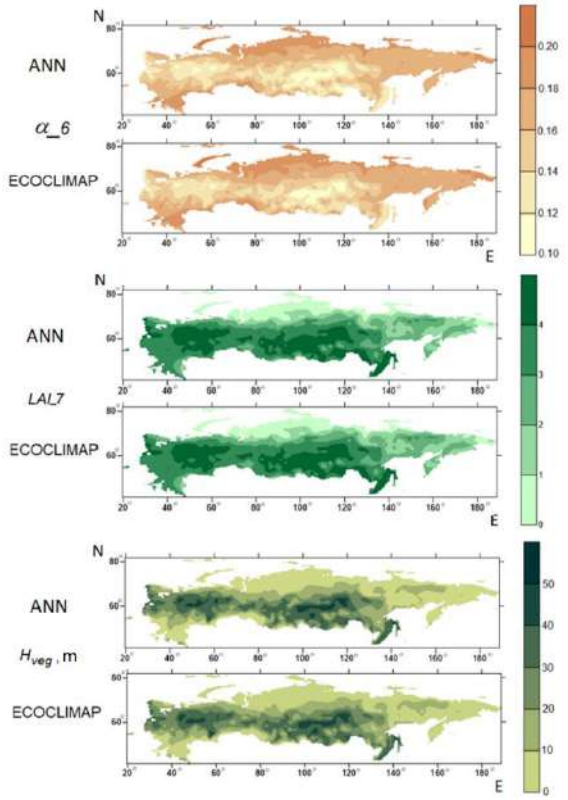


Figure 4: Spatial distribution of the land surface albedo in June α_6, leaf area index in July *LAI_7*, and mean annual height of vegetation H_{veg} generated by the ANN and derived from ECOCLIMAP for the territory of Russia in the historical period.

The scenarios considered in (IPCC, 2021) represent a combination of Shared Socioeconomic Pathways (SSPs) and Representative Concentration Pathways (RCPs) scenarios. The RCP family of scenarios prepared for the Fifth Assessment Report (AR5) of the Intergovernmental Panel on Climate Change (IPCC) represent anthropogenically induced trajectories of greenhouse gas concentrations in the atmosphere that lead to changes in radiation at the land surface due to the greenhouse effect by the end of the 21st century.

By the IPCC Sixth Assessment Report (AR6) (Eyring et al., 2021), the RCP scenarios were updated with SSP scenarios that took into account possible ways of global socioeconomic development that influence climate change (in particular, SSP1 – sustainable development – "Taking the Green Road"; SSP3 – inequality between countries, regional rivalry – "A Rocky Road"; SSP5 – development based on the use of fossil fuels – "Taking the Highway") (Riahi et al., 2017).

The volumes of carbon dioxide emissions in SSP scenarios and land use that affect climate change on the planet vary depending on the path of the expected socioeconomic development. In this paper, the most severe scenario SSP5-RCP8.5 characterized by high greenhouse gas emissions that will grow rapidly until the end of the 21st century was used. This makes it possible to demonstrate in the most contrasting way the amplitude of the climate-induced transformation of *Par* by the end of the 21st century.

To obtain climatic characteristics for each calculational grid cell of the territory of Russia for the projection period of 2073–2100, time series of daily values of meteorological data projected by the aforementioned five GCMs and subjected to post-processing bias-correction were used. Daily values of meteorological data were averaged over the projection period and over an ensemble of five GCMs. The obtained values represent a field of climatic predictors for the developed ANN, which allowed us to project the values of vegetation parameters for the territory of Russia for 2073–2100 and to assess their changes compared to the historical period.

Before analyzing the obtained results, it is necessary to discuss a number of methodological aspects that clarify interpretation and possible application of the results.

Let us consider the first aspect. The long-term dynamics of the parameters of terrestrial vegetation is associated both with evolution of species structure of ecosystems and with changes in biomass of plants, their photosynthetic activity and productivity, which change the habitus of plants. These changes are largely due to changes in the rate of carbon absorption by terrestrial ecosystems, which is associated with the direct and indirect impacts of increasing atmospheric carbon dioxide CO_2 concentrations on the planet's carbon cycle.

The direct impact is determined by the so-called effect of fertilization of phytocenoses by atmospheric CO_2 (an increase in the rate of photosynthesis and plant productivity due to an increase in the concentration of CO_2 in the surrounding space) (Eliseev, 2017). The indirect impact is determined by climate change caused by the greenhouse effect of the atmosphere due to an increase in the concentration of CO_2 and other greenhouse gases (IPCC, 2021).

The developed methodology for projecting changes in vegetation parameters takes into account only the last effect (the impact of climate change) and does not consider the effect of fertilization, since all information about the vegetation parameters used for training the ANN was obtained for the current concentration of CO_2 in the atmosphere.

The second aspect is related to the fact that the methodology does not take into account the non-equilibrium structure of terrestrial ecosystems under the long-term evolution of climatic indicators. At the same time, transformation of ecosystems associated with succession processes (introduction of new species, replacement of some dominants by others, etc.) occurs with relaxation processes rather than instantly. Therefore, the assumption about quasi-equilibrium correspondence of vegetation parameters to climatic indicators is an approximation. At the moment it is difficult to answer how this effects the results because of poor development of models of competitive struggle of species in ecosystems and lack of necessary information.

Finally, the third aspect concerns change in vegetation parameters due to changes in the share of agroecosystems in terrestrial ecosystems. The developed ANN assumes that the shares of agroecosystems in the considered territory correspond to climatic conditions. This assumption is generally quite plausible and is contained in the trained ANN. However, this correspondence can be changed to suit the socioeconomic policy pursued in the region. Such changes, naturally, are not reflected in the proposed methodology.

Now, let us consider the results of the assessment of climate driven changes in vegetation parameters $\Delta Par_{\mathrm{proj}}$ on the territory of ~~the~~ Russia in the projection period 2073–2100 under realization of climate scenario SSP5-RCP8.5 in comparison with their values Par_{hist} averaged over the historical period 1981–2010.

Figure 5 shows spatial distribution of the projected changes in some vegetation parameters over the territory of Russia as compared to their historical values. Fig. 5 provides information on localization of areas with different amplitudes and signs of changes. For fifty other vegetation parameters studied in the work, the patterns of their changes are similar.

The obtained results show that spatially averaged changes in various parameters are in the range of 5–17%, while for individual areas they are even greater. Besides, changes in the same parameter in different areas may differ in sign.

Thus, this example of assessing changes in vegetation parameters under climate changes projected by the end of the 21st century according to the SSP5-RCP8.5 scenario demonstrates that noticeable changes of different sign in vegetation

parameters can be observed in different places on the territory of Russia

The next step in the general theme of the study outlined in the Introduction should be an assessment of impact of the obtained changes in vegetation parameters on the components of heat and water balances of the territory, since quite noticeable deviations of the projected values of the parameters from their historical values under climate change do not guarantee the same noticeable response of the components of heat and water balances controlled by these parameters. Moreover, numerous negative feedbacks of biosphere processes, making the biosphere stable, neutralize the reaction of natural structures to changes in both external factors and parameters of these structures. The indicated response can be noticeable only in the case of (1) sufficient sensitivity of the characteristics of water and thermal regimes of ecosystems and, accordingly, sensitivity of models reproducing these regimes to the values of corresponding parameters, (2) sufficient coherence of the contribution of parameter changes. In addition, the response of heat and water balance components of the territory to the dynamics of vegetation parameters also depends on the climate change scenario.

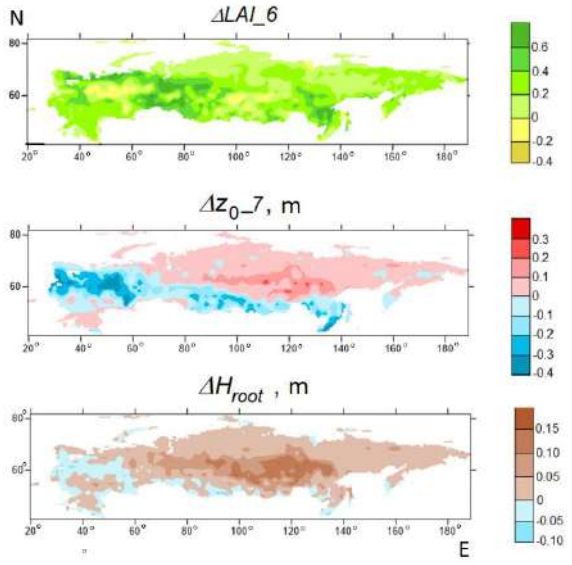


Figure 5: The spatial patterns of the projected changes in vegetation parameters in 2073-2100 for the SSP5-RCP8.5 climate scenario compared to the historical period. *ΔLAI_6* is change in mean leaf area index in June, Δz_{0}_7 is change in mean roughness length in July, ΔH_{root} is change in the root zone depth.

4 CONCLUSIONS

1. A methodology for scenario projecting climate-induced changes in vegetation parameters used in the Earth system parameterization schemes has been developed for the territory of Russia.

2. The methodology is based on the application of the artificial neural network and reproduces the dependence of vegetation parameters on climatic, edaphic and orographic factors for the territory of the Russian Federation.

3. For the projection period of 2073–2100 and the climate scenario SSP5-RCP8.5, changes (relative to the historical period of 1981–2010) in more than fifty vegetation parameters derived from the ECOCLIMAP dataset were calculated across the country. Maps of spatial distribution of these changes by the end of the 21st century were constructed.

4. It is shown that changes in the considered vegetation parameters by the end of the 21st century under the selected climate scenario are quite noticeable and multidirectional (in sign) across the territory of Russia. Mean absolute values of these changes are in the range of 5–17% as compared to the historical period.

5. The obtained changes in vegetation parameters can serve as input data for modeling the dynamics of heat and water balance components in the territory of Russia. This is necessary to reveal whether such changes should be taken into account when projecting heat and water exchange at the land surface – atmosphere interface.

6. The developed methodology can be applied to assess changes in vegetation parameters derived not only from ECOCLIMAP, but also from any other dataset, provided that the parameters have physical meaning.

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