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Research article

ASSESSMENT OF CROP AND SOIL STATE USING SATELLITE REMOTE SENSING DATA

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ABSTRACT

For the first time in agricultural science represented the theoretical and methodological foundations of information and evaluating the state of crops and soil environment according to satellite sensing surface.

Keywords: crop and soil state, optimal estimation, satellite remote sensing, mathematical models, perennial grasses

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INTRODUCTION

One of the most important aims of satellite remote sensing is the monitoring of crop and soil state. Detailed information on the results of the monitoring can successfully help us to solve such important problems as: a prediction of crop yields; an evaluation of seed germination; an assessment of soil fertility and degradation as well as accounting, inventory, and classification of agricultural lands to develop the large-scale maps of agricultural soils. At an operative scale, typical tasks of the satellite remote sensing are to: (1) carry out the monitoring of crop and soil state, (2) predict the crop yields, (3) monitor the harvesting rates in large agricultural regions, (4) estimate of the grazing capacity and productivity of grasslands. All the tasks provide an effective support of decision-making in the agricultural management.

At the present time, there is a traditional solution of the most above-mentioned tasks on the basis of application of specific technologies for decoding the satellite images obtained by repeated remote sensing surveys. The images can provide useful results of satellite remote sensing of crop development's dynamics and of crop yields' prediction. The Normalized Difference Vegetation Index (NDVI) is most widely used for the decoding the satellite images [2, 8, 10]. A major shortcoming of this method is that the decoding the satellite images of landscape's physical elements is being carried out by tone, color, size, and other geometric features of the images. Therefore, many important natural processes can not be clearly distinguished on the satellite images.

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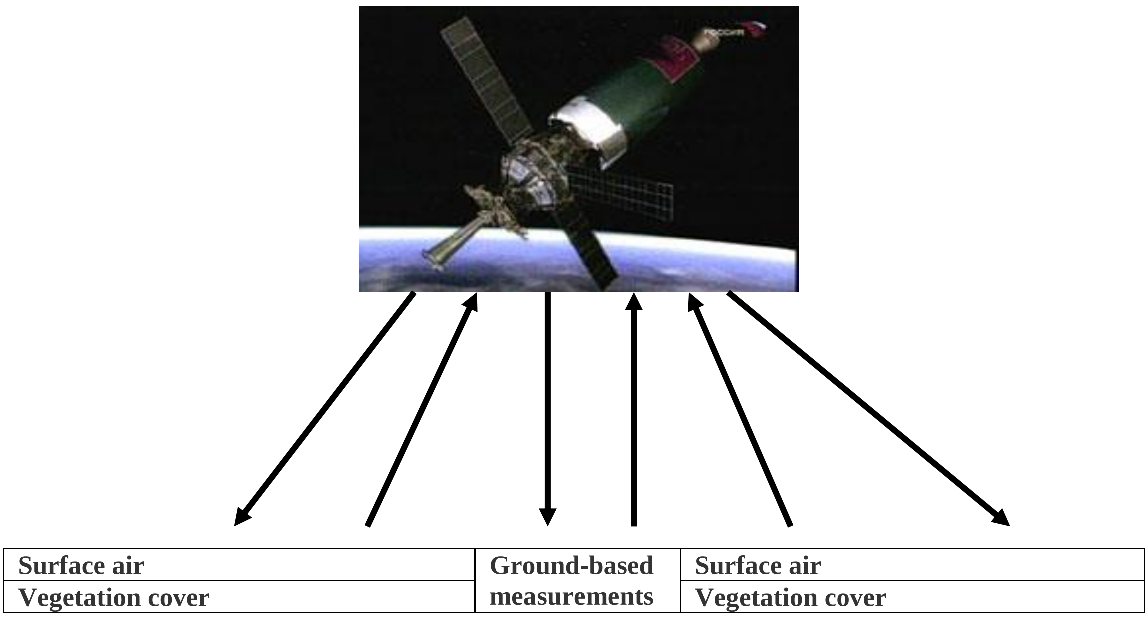
The only highly skilled specialists are able to: (1) fulfill the adequate interpretation and analysis of the satellite images, and, (2) make the predictions and recommendations.

The use of other indices and optical indicators (criterions) does not help to solve this problem because other combinations of spectral optical channels are usually used without changing the traditional methodological framework. As a result, there are now circumstances when scientists do not have any effective automated systems for processing the remote sensing data and the reliable information on crop and soil states despite there is a high level of modern space technologies [11, 12]. The main reason of this problem is considered to be a lack of valid scientific approaches to its solving. The decoding the satellite images does not have a strictly scientific sense as it does not correspond to key scientific objectives of tasks to be solved. Many experts stressed this problem when they analyzed the only optical parameters of crops and soils not having direct ground-based information on the crop and soil state [8, 9].

Therefore the aim of this study was to develop new methods for estimating crop conditions from remote sensing data.

THE GENERAL SCHEME OF OPTIMAL ESTIMATION

Modern information theory considers the task of restoring information on indirect observations of system state as that of optimal estimation. Figure 1 shows a conceptual scheme of tasks for evaluating the crop and soil state using satellite remote sensing data. This conceptual scheme includes two key features. Firstly, a closed system includes a surface layer of atmosphere - vegetation - soil system All the components of the system should be considered as a single complex in order to achieve a sufficient accuracy and a reliability of assessment. Secondly, there are two different modes of the assessment of the crop and soil state on reference areas: (1) ground-based measurements on small reference plots, and (2) satellite remote sensing of large reference regions [13]. The satellite remote sensing system is equipped with multi-channel optical systems, and, therefore, there is a possibility to select the most suitable optical channels for effective remote sensing of the reference regions.



Soil cover		**Soil cover**
Reference region	***Reference plot***	***Reference region***

Figure 1: Conceptual scheme of tasks for estimating the state of crop and soil cover using satellite remote sensing data

Figure 2 shows a block diagram of measures for collection of information for optimal estimating the crop and soil state on the reference plots and in the reference regions. This scheme shows that the procedures for optimal evaluation of the crop and soil state include measures for processing (1) posterior informationobtaine by the satellite remote sensing and (2) prior information received by dynamic mathematical models.

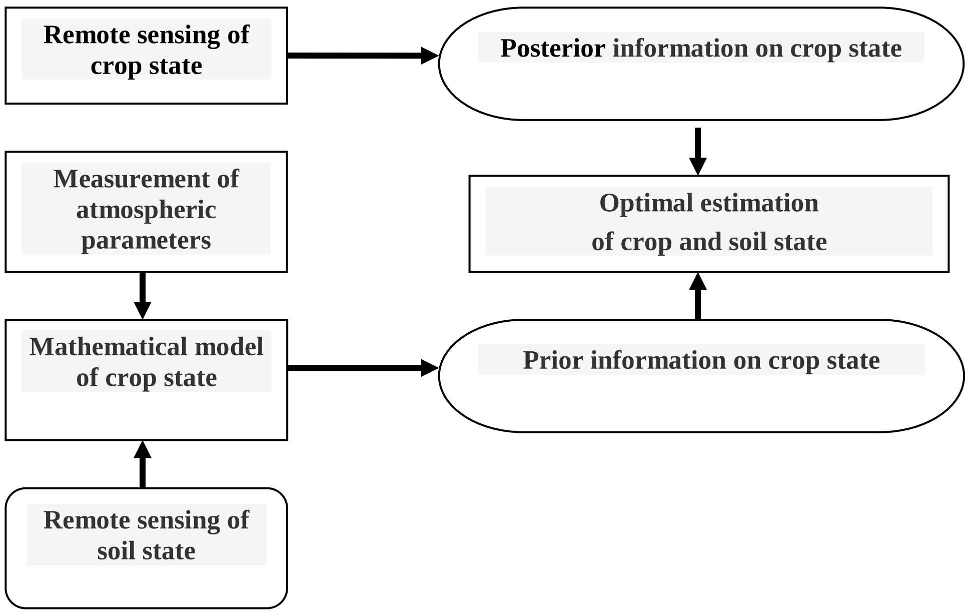


Figure 2: A block diagram of measures for collection of information for optimal evaluating the crop and soil state.

The procedure of optimal evaluation of the crop and soil state on the reference plots is shown in Figure 3. The dynamic mathematical models developed for predicting the crop and soil state are being indentified on the basis of combined data on ground-based and remote sensing assessments of the crop and soil state. It is not possible to effectively fulfill this procedure without using the dynamic mathematical models.

SELECTION OF SPECTRAL CHANNELS

A selection of structure of remote sensing system is related to: (1) a composition of obtained spectral information and (2) a selection of the most informative spectral optical channels and their wave lengths. There are two possible technical ways for a less or more effective application of spectrometric equipment. If there is already a given spectrometric equipment with a given set of the spectral optical channels, it is only possible to evaluate their informative valuability regarding each of the states of crops and soils. A result of this research will be a sorting out each optical channel for each of the crop and soil states with a lower accuracy [1]. If there is a possibility to undertake own selection of the spectrometric equipment, there is an opportunity to use an

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entire optical spectrum with a preliminary selected number of spectral optical channels. Afterwards, the valuability of the spectral optical channels is being also analysed for each of the crop and soil states in order to select the most informative spectral optical channel with a higher accuracy. The satellite remote sensing by this optical channel is recommended to repeat for achieving the highest accuracy and reliability of results. Hence, a key way for effective selection of optimal structure of remote sensing system is the analysis of information capability (informativeness) of spectral optical channels.

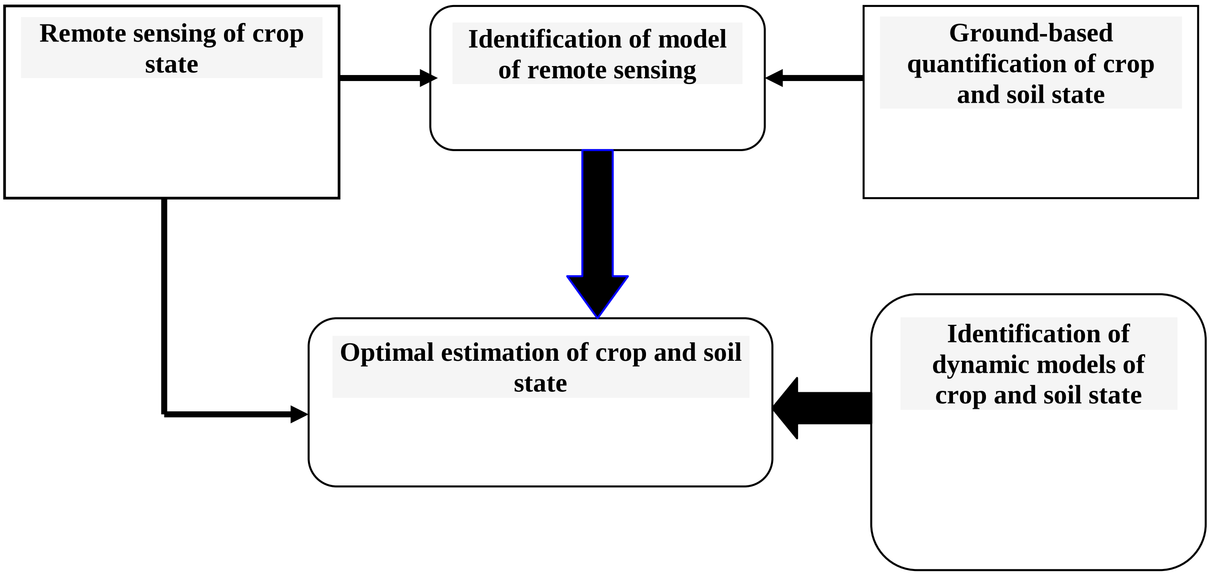

Figure 3: Stages of optimal estimation of crop and soil state on reference plots.

A further method for a valid quantification of informative efficiency of the selected spectral optical channels and their wavelenghts is dependent on a way of processing information for the state of surface air – vegetation - soil —system. An initial information on key parameters of the system can be contained in the above-mentoned dynamic models. The key parameters of the system's state in the dynamic models are:

X – a vector of crop state's parameters as follows: biomass per unit area, kg m^{-2}; moisture content of biomass, %; commodity portion,%, and other similar parameters.

G – a vector of soil state's parameters as follows, soil bulk density, kg m^{-3}; moisture content, kg m^{-3}; humus content,%; nutrient content, mg kg^{-1}.

Y – a vector of reflectance optical parameters of an arable field at a given spectral range.

Each measurable state (xi) is measured by optical parameter (y_{ki}), where i - indices of the states, $i = 1, 2, \ldots, I$; k - indices of spectral optical channels, $k = 1, 2, \ldots, K$. Among all the parameters of each state both minimum $x_{i,min}$ and maximum $x_{i,max}$ values of the state are being measured to determine a whole range (Di) of variations in the states: $Di = x_{i,max} - x_{i,min}$.

The whole range of each i^{th} state is divided into several sub-ranges $j_i=1,2,\ldots J_i$.

By the same way minimum ($y_{k,min}$) and maximum ($y_{k,max}$) values of optical quality and the whole range (D_k) of their variations ($D_k = y_{k,max} - y_{k,min}$) are being determined. The whole range of each spectral optical channel is divided into several sub-ranges l_k=1,2,... L_k.

Assessments of probabilities for the crop and soil states are being calculated as a number of measured points of i^{th} values within the j^{th} (sub)-range which are referred to a total number of points of spatial measurements. These assessments of probabilities are denoted as $p(x_{ij}) = n_{ij}/N$.

The assessments of conditional probabilities for the optical measurements are being calculated as a number of measured k^{th} values in the l^{th} (sub)-range for the j^{th} (sub)-range of i^{th} state which are referred to the total number of points of spatial measurements while the i^{th} state had the j^{th} level . The assessments of probabilities are denoted as $p(y_{lk}|x_{ij}) = n_{lk}/n_{ij}$.

A prior information on the measured i^{th} state is being evaluated on the basis of the above-mentioned assessments of probabilities for the crop and soil states:

$$H_i^x = -\sum_{j_i=1}^{J_i} p(x_{ij})\log p(x_{ij}) \tag{1}$$

A posterior information is being estimated by the same way after measurements of the i^{th} state using k^{th} spectral channel:

$$H_{k,i}^y = \sum_{j_i}^{J_i} p(x_{ij})[\sum_{l_k=1}^{L_k} p(y_{lk}|x_{ij})\log p(y_{lk}|x_{ij})] \tag{2}$$

A relative increase in information after measurements is used as an index of information capability (informativeness) of k^{th} channel to the i^{th} state:

$$IN_{ki} = \frac{H_i^x - H_{ki}^y}{H_i^x}100\% \tag{3}$$

According to these parameters an index of absolute information capability (informativeness) of k^{th} channel is being calculated for all the measured states:

$$IN_k = \sum_{i=1}^{I} IN_{ki} \tag{4}$$

If there is a need of more convinient use of spectral optical ranges and spectral optical channels in algorithms for the assessments of the state's soil - plant - atmosphere system and for the recognition of calculated states, all the above-mentioned indices of information capability (informativeness) (3, 4) are ranked according to their values for each of the spectral optical channels. The only spectral optical channels with maximum information capability (informativeness) are included into a strucrure of measuring system. As a result of such a selection, two combined sub-vectors, namely, Y_X – sub-vector of optical parameters of the crop state and Y_G – sub-vector of optical parameters of the soil state are being created from the above-mentioned Y vector. These sub-vectors

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can have the same components as many reflectance optical parameters are simultaneously related to to the crop and soil states.

If the given measuring system is applied, the analysis of information capability (informativeness) of measuring complexes of separate elements of soil - plant - atmosphere system is linked to the models of measurements. For instance, linear models of measurements of the soil state are:

$$Y_G = HG + E, \tag{5}$$

where Y_G – Y_G – sub-vector of optical parameters of the soil state at different optical ranges; G – vector of the soil state's parameters; H - matrix of parameters quantified on the basis of experimental results; E - vector of random errors of measurements of optical parameters at zero mathematical expectation and covariance matrix R.

In the linear model of measurements (5) the conditional conjugate probability density of the optical parameters' vector with respect to the measured optical states (conditional likelihood function) is presented as:

$$f(Y|G,H) = (2\pi)^{-1}|R|^{-1/2}\exp\{-(Y-H^TG)^T R^{-1}(Y-H^TG)\} \tag{6}$$

Most of the soil state parameters are independent and their prior densities of distribution are defined as:

$$f(g_i) = \frac{1}{\sqrt{2\pi\sigma_i}}\exp\left(-\frac{(g_i-\mu_{gi})^2}{\sigma_i^2}\right), \tag{7}$$

where i = 1, 2, 3, ... I - are indices of soil state parameters; is a total dimension of the vector (G) of soil state parameters.

The posterior conjugate densities of distribution of the soil state parameters are presented as follows:

$$f(G|Y_G,H) = \frac{f(Y_G|G,H)\times\prod_{i=1}^{I} f(g_i)}{I(g,\omega)}, \tag{8}$$

$$I(G) = \int_{\Omega_G} f(Y_G|G,H)\times\prod_{i=1}^{I} f(g_i)\,dg_i$$

where - $\prod_{i=1}^{I}$ - multiplying the probability density operator, Ω_G - multidimensional integration domain in the parameter space of the soil

A criterion of information capability (informativeness) of measurements showes how much those increase the posterior information on the soil state compared with the prior information:

$$I(Y_G|G,H) = \int_{\Omega_G}\left[\frac{f(G|Y,H)-\prod_{i=1}^{I} f(g_i)}{\prod_{i=1}^{I} f(g_i)}\right]dg_i * 100\%. \tag{9}$$

ASSESSMENT OF CROP AND SOIL STATE

The assessment of the measured soil state for the model (5) is defined as follows [4]:

$$\hat{G}(t) = M_G(t) + [HR^{-1}H^T + R^{-1}]^{-1} HR^{-1}[Y_G(t) - H^T\hat{G}(t)], \tag{10}$$

where - $M_G(t)$ a vector of the mathematical expectation of the soil state.

To obtain the required estimates (10), there are several possible ways to set the vector of the mathematical expectation of the soil state - $M_G(t)$: 1) to calculate a dynamics of the measured soil state by the model; 2) to set a constant average value; 3) to use asymptotic estimates:

$$\hat{G}(t) = [R^{-1/2}H^T]^{-1} R^{-1/2} Y_G(t) \tag{11}$$

Perennial grasses will be used as an example to consider the methodology for the assessment of information capability (informativeness) of optical channels for the crops. The state of the perennial grasses is described by the dynamic model (5):

$$\begin{bmatrix} \dot{x}_{1m} \\ \dot{x}_{2m} \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \begin{bmatrix} x(t)_{1m} \\ x(t)_{2m} \end{bmatrix} + \begin{bmatrix} c_{11} & c_{12} & c_{13} & c_{14} \\ c_{21} & c_{22} & c_{23} & c_{24} \end{bmatrix} \begin{bmatrix} f_1(t) \\ f_2(t) \\ f_3(t) \\ f_4(t) \end{bmatrix} + \begin{bmatrix} \zeta_1(t) \\ \zeta_2(t) \end{bmatrix} \tag{12}$$

$$t \in (0,T),\ x_{1m}(0) = x_{1m,0},\ x_{2m}(0) = x_{2m,0},$$

supplemented by the model of measurements

$$y_{1i}(t) = p_1 e^{-p_2(x_1(t) + x_2(t))} + \varepsilon_1(t), \tag{13}$$

$$y_{2i}(t) = p_3 e^{-p_4 x_2(t)} + \varepsilon_2(t).$$

where: x_{1m}, x_{2m} - dry and wet weight of above-ground plant biomass in a given area (kg m^{-2}); f_1 - daily air temperature (^oC); f_2 - daily radiation (W $m^{-2} \cdot h^{-1}$); f_3 – daily precipitation (mm) affecting soil moisture content; f_4 = t - time of Day ; ζ_1 (t), ζ_2 (t) - random noise in the model with zero mean and variance of d_1, d_2; a_{11} - a_{44}, c_{11} - c_{24} - model parameters; $t \in (0,T)$ - growing season, $x_{1m}(0) = x_{1m,0}$, $x_{2m}(0) = x_{2m,0}$ - the initial conditions of the vegetation; y_{1m} - optical parameter from the first optical channel of measurements (in the video range) y_{2m} - optical rate obtained on the second optical channel measurements (in the infrared range); p_1-p_4 - parameters of the optical measurement system which are estimated by experimental data; ε_1(t), ε_2(t) - random noise in the model of measuring probe with zero mean and variance.

Models (12) and (13) can be represented in vector-matrix form:

$$\begin{aligned} \dot{X} &= AX + CF(t) + Z(t), \\ Y_X &= F(X) + E(t), \end{aligned} \tag{14}$$

$$F(X) = \begin{bmatrix} p_1 e^{-p_2(x_1(t) + x_2(t))} \\ p_3 e^{-p_4 x_2(t)} \end{bmatrix},$$

$$X(0) = X_0,$$
$$M[E(t)] = 0,\ \mathrm{cov}[E(t)] = S,$$
$$M[Z] = 0,\ \mathrm{cov}[Z(t)] = D.$$

where: $M[E(t)] = 0$ - vector of expectation errors of optical measurements; $\mathrm{cov}[E(t)] = S$ - covariance matrix of the errors of optical measurements: $M[Z] = 0$ - vector expectations modeling errors, $\mathrm{cov}[Z(t)] = D$ - covariance matrix of the modeling errors.

The models (14) enable to fulfill a simultaneous use of prior and posterior information about the measured state and the measuring probes, respectively. The use of information can be achieved in the dynamic systems called as optimal filters [6]:

$$\begin{aligned} &\dot{\hat{X}} = A\hat{X} + CF(t) + R(t)\frac{\partial F^T(\hat{X})}{\partial \hat{X}} S^{-1}(Y_X(t) - F(\hat{X})) \\ &\dot{R} = D + R(t)A^T + AR(t) - R(t)\frac{\partial F^T(\hat{X})}{\partial \hat{X}} S^{-1} \frac{\partial F(\hat{X})}{\partial \hat{X}} R(t), \\ &\hat{X}(0) = M[X_0],\ R(0) = \mathrm{cov}[X_0], \end{aligned} \tag{15}$$

where: $\hat{X}$ - optimal estimate of the state vector of biomass, R - covariance matrix of the estimation errors.

PERCULIARITIES OF ASSESSMENT OF CROP AND SOIL STATE WITHIN REFERCE PLOTS

Procedures for assessing the crop (15) and soil (10, 11) states of are similar for the reference and experimental plots. If there is detailed information on satellite remote sensing data for the reference plots a question is: how to effectively use additional information on the crop and soil state on the basis of direct ground-based measurements of its parameters? According to the scheme in Figure 5.4 this additional information is usually used to identify: (i) the models of measurements of parameters of the soil (5) and crop (13) states, and, (ii) the dynamic models of the states (14).

If we: (i) indicate the directly measured parameters of the crop state as:

$$Z_X = X + J \tag{16}$$

where: J - vector measurement errors,

and of the soil state as:

$$Z_G = G + q \tag{17}$$

where: q - vector measurement errors,

(ii) integrate all the parameters of the models of measurements into the vector H, and, all the parameters of dynamic models into the vector P, we can define the following procedures of identification:

- for the models of measurements of the states:

$$\hat{H} = \arg\min_{H}[(Z_G - HG)^T g_G (Z_G - HG)] \quad (18)$$

- for the dynamic models of the states:

$$\hat{P} = \arg\min_{P\hat{I}(A,C)} [(Z_X - (AX + CF))^T g_X (Z_X - (AX + CF))], \quad (19)$$

where g_G, g_X - weighted matrices which are used to control the ratios of identification errors,

$\hat{H}$, $\hat{P}$ - estimates of model parameters, which are generated by the procedures of identification (18), (19).

The highest accuracy of assessment of the crop and soil state can be achieved if the procedures of identification (18), (19) will be performed only within the reference plots. If the procedures of identification are being carried out on the experimental plots (or beyond the reference plots), the accuracy of the assessment of the crop and soil state becomes lower as the parameters of the above-mentioned models for these experemental plots will differ from those for the reference plots.

APPROBATION

Figure 5 shows a dynamics of perennial grasses between cuttings. Shaped points indicate the measured values of parameters' actual state of crop biomass, whereas solid lines reflect a process of adaptation of the model of measurement (13) to the measured values. As shown in Figure 5 the algorithm of the adaptation provides an 1% accuracy of the model's justification to the actual processes.

Figure 6 shows a dynamics of the optimal filter's (15) operation. The optimal filter estimates the biomass state of perennial crops on the basis of their measured optical parameters and of the meteorological data without measuring the ground-based, relevant parameters of crops. The shaped points also indicate the measured values of parameters' actual state of crops, while the solid lines reflect the crop biomass state's estimates obtained by the optimal filter. The filter provides a 2-3% accuracy of assessment, which is sufficient for an effective development of technological impacts on crops on the basis of information from the remote sensing facilities.

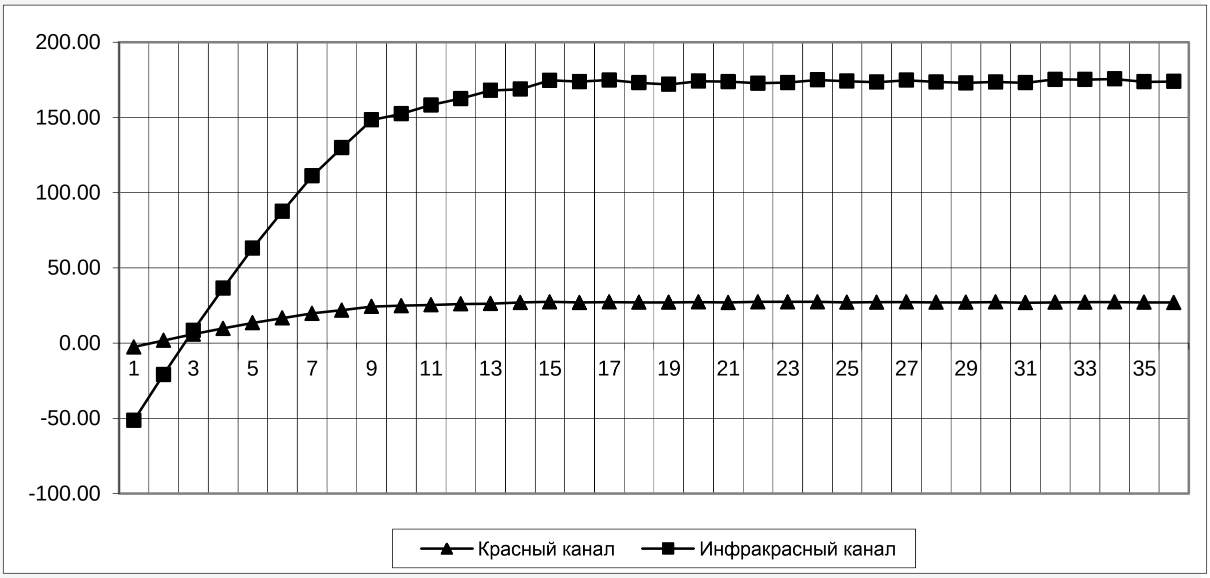

Figure 4: Information from optical channels for remote sensing

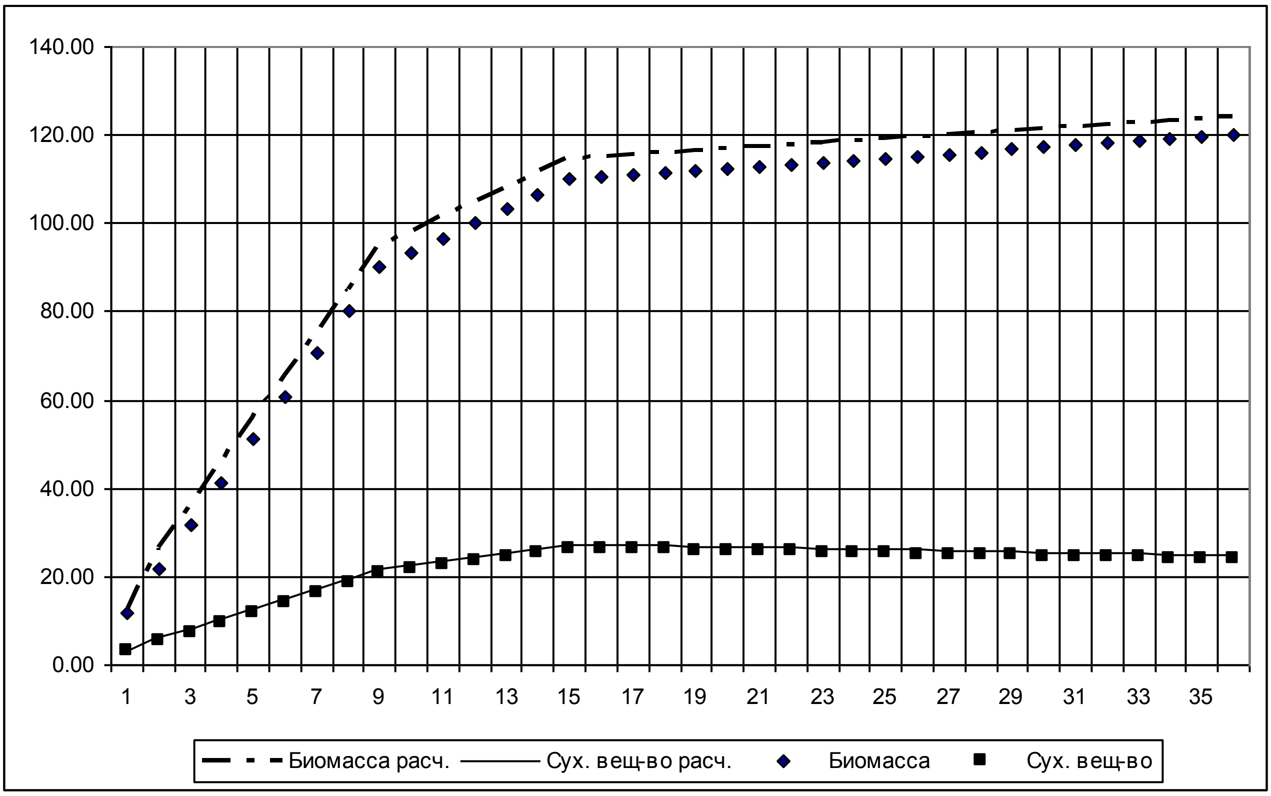

Figure 5: Estimating the state of crop biomass on the basis of information from optical channels for remote sensing.

CONCLUSIONS

To fulfill all the procedures of authomated monitoring and optimal assessment of the crop and soil state by satellite remote sensing tools the following stages of research and development are to:

1. create the set of key parameters of the crop and soil state which are relevant to the main aims of studies;

2. fulfill the analysis of informativenes of all the optical channels and to select the most effective optical channels regarding the optimal assessment of the key parameters of the crop and soil state;

3. range the most effective optical channels into three subvectors of measurements of the parameters' crop and soil state;

4. select the relevant models of measurements for the most effective optical channels;

5. identify the selected models of measurements on the basis of data obtained by simultaneous ground-based measurements and satellite remote sensing, and to estimate the efficiency of the model's ideintification;

6. develop the current and predicted assessments of the crop and soil state on the basis of results of satellite remote sensing and modelling.

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