IMPROVING THE ACCURACY OF MEASURING SOIL MOISTURE FOR EARLY WARNING OF RISKS ASSOCIATED WITH EXCESSIVE WATER CONTENT IN THE SOIL

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Abstract

Early warning of the risks associated with excessive soil moisture is important for various areas of production. For example, during the construction of multi-storey buildings, a hydrophysical examination of the soil is necessarily carried out, its water content is measured. In the field of flood forecasting, the sites of previous floods and the residual water content and water capacity of the soil are necessarily investigated. In agriculture, in order to avoid water stress of cultivated plants, the water content of the soil is examined before irrigation. All these examples show that in order to reduce risks, it is necessary to investigate the factors that create these risks and, if possible, more accurately assess the current values of these factors. The article is devoted to the issues of improving the accuracy of determining the spectral indices used to determine soil moisture. The main disadvantage of such indices is that they use the spectral absorption lines of water vapor. Consequently, the use of these indices requires adequate compensation for the influence of the atmosphere. The solution of this problem was carried out on the basis of the following provisions (a) for seven classes of soils, a model expression for the dependence of the reflection spectrum on the moisture content in the soil is known; (b) they have experimentally taken curves of the indicated dependence; (c) a function of the dependence of the experimentally measured value of soil reflection on the degree of soil moisture is introduced; (d) the search for the optimal form of the introduced function is carried out at which the square of the difference between the experimentally measured reflection value and the known model function reaches a minimum value. In this case, this search is carried out by the method of variational optimization, subject to the introduction of some restrictive condition on the desired function, using the form of continuous recording of discrete sums; (e) by equating the calculated optimal function with the experimentally obtained reflection value at a particular wavelength, calculate the water content of the soil. Use the wavelength where the estimate of water content is minimal is recommended.

Keywords: soil, water content, spectral indices, water vapor, risks, early warning

I. Introduction

Early warning of the risks associated with excessive soil moisture is important for various areas of production. For example, during the construction of multi-storey buildings, a hydrophysical examination of the soil is necessarily carried out, its water content is measured. In the field of flood forecasting, the sites of previous floods and the residual water content and water capacity of the soil are necessarily investigated. In agriculture, in order to avoid water stress of

cultivated plants, the water content of the soil is examined before irrigation. All these examples show that in order to reduce risks, it is necessary to investigate the factors that create these risks and, if possible, more accurately assess the current values of these factors. The moisture content of the surface layer of the soil is an important factor influencing the energy exchange between the earth's surface and the atmosphere. Soil water content (hereinafter referred to as SMC) can currently be determined by three spectral methods:

- 1. The method of combining spectral bands $[1 \div 3]$;
- 2. Spectral Model Method: Exponential or Gaussian Model [4,5];
- 3. Geostatistical methods [6-8].

The first method includes the use of such well-known indices as the Water Index of Soil (WISOIL) [9]; shortwave angular slope index (SASI) [3]; Normalized Soil Moisture Index (NSMI) [1].

The main disadvantage of these indices is that they use the spectral absorption lines of water vapor. Hence, the use of these indices requires adequate compensation for the influence of the atmosphere.

The second method includes the spectral exponential model, which is most suitable in the short-wave infrared range [5]. The same method applies to the model of the inverted Gaussian function in the range (1.8÷2.8 μ m), denoted as SMGM. The main disadvantage of this method is the deterioration of its accuracy at high SMC.

With regard to geostatistical methods, these methods require data on the spatial distribution of soil moisture and use interpolation methods to determine the moisture in a given area $[6\div8]$. This method depends entirely on the reliability of data on the distribution of SMC in the study area.

In [10], a semi-empirical soil model was proposed, in which the relationship between the reflective characteristic of the soil and the SMC index was determined in relation to a priori formed soil classes.

According to [10], for each of these classes, the following analytic formula is true

$$\rho_i(\lambda) = a_i(\lambda) \cdot SMC^2 + b_i(\lambda)SMC + c_i(\lambda)$$

where *i* is an index indicating the number of the class; **a**, **b**, **c** are the spectral coefficients.

In [11], a method was proposed for determining SMC based on model (1), as applied to one of the seven above classes.

According to this method, for a certain soil class, the actual value of SMC should minimize the sum below

$$E = \sum_{i=0}^{q} [\rho_i - (a_i \cdot SMC^2 + b_i \cdot SMC + c_i)]^2$$
(2)

(1)

where i – indicates a specific wavelength; q – the number of such wavelengths; ϱ_i – experimentally taken reflective characteristics.

The disadvantage of this method lies in the need to carry out relatively more calculations to determine the actual value of SMC.

The solution to this problem, in our opinion, lies in the transition to a conditionally continuous form of model (2) as applied to a certain fixed wavelength.

II. Methods

For some fixed wavelength λ_i we have

$$E(\lambda_i) = [\rho_i - (a_i \cdot SMC^2 + b_i \cdot SMC + c_i)]^2$$
(3)

Let us introduce for consideration the following functional dependence

$$\rho_i = \varphi(SMC) \tag{4}$$

Obviously, function (4) is a decreasing function. We impose the following integral constraint on function (4):

$$\int_{0}^{SMC_{max}} \varphi(SMC) dSMC = C; C = const$$
(5)

The geometric form of some functions that satisfy condition (5) is shown in Fig. 2.

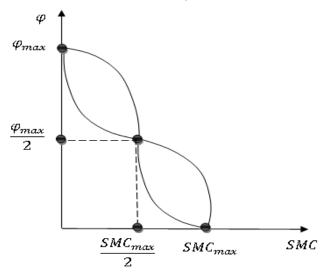


Fig. 2: Geometric interpretation of the restrictive condition (4) as applied to the function $\varphi(SMC)$

On the basis of expressions (3) and (4), we form the following quadratic target functional F $F = \int_{0}^{SMC_{max}} [\varphi(SMC) - (a_i \cdot SMC^2 + b_i \cdot SMC + c_i)]^2 \, dSMC \tag{6}$

Taking into account expressions (5) and (6), we form the problem of unconstrained variational optimization

$$F_1 = \int_0^{SMC_{max}} [\varphi(SMC) - (a_i \cdot SMC^2 + b_i \cdot SMC + c_i)]^2 \, dSMC + \int_0^{SMC_{max}} [\varphi(SMC)dSMC - C]$$
(7)

where, γ – Lagrange multiplier.

Obviously, the solution of problem (7), i.e. calculation of such a function $\varphi(SMC)_{opt}$ at which F₁→min at the chosen wavelength will open the way to determining the SMC at that wavelength by solving the following equation

$$\rho(SMC)_{opt} = a_i \cdot SMC^2 + b_i \cdot SMC + C_i \tag{8}$$

III. Results

We give a model solution of the optimization problem (7). According to [12], the solution of the problem must satisfy the condition

$$\frac{d\left\{\left[\varphi(SMC) - \left(a_i \cdot SMC^2 + b_i \cdot SMC + C_i\right)\right]^2 + \gamma \cdot \varphi(SMC)\right\}}{d\varphi(SMC)} = 0$$
(9)

From (9) we get

$$2[\varphi(SMC) - (a_i \cdot SMC^2 + b_i \cdot SMC + c_i) + \gamma = 0]$$
⁽¹⁰⁾

From (10) we find

$$\varphi(SMC) = \left(a_i \cdot SMC^2 + b_i(SMC) + c_i - \frac{\gamma}{2}\right)$$
(11)

Calculate the value γ . From expressions (5) and (11) we obtain $\int_{\alpha}^{SMC_{max}} \left[\alpha SMC^{2} + b (SMC) - c - \frac{\gamma}{2} \right] dSMC = C$

$$\int_{0}^{SMC_{max}} \left[a_i SMC^2 + b_i (SMC) - c_i - \frac{\gamma}{2} \right] dSMC = C$$
(12)

From (12) we get

or

$$C + \frac{\gamma}{2} \cdot SMC_{max} = a_1 \frac{SMC_{max}^3}{3} + b_i \frac{SMC_{max}^2}{2} - c_i \cdot SMC_{max}$$
(13)

$$\gamma = \frac{2a_1 SMC_{max}^2}{3} + b_i SMC_{max} - 2c_i - \frac{2C}{SMC_{max}}$$
(14)

Taking into account (11) and (14), we get

$$\varphi(SMC)_{opt} = a_1 \left(SMC^2 + \frac{SMC_{max}^2}{3} \right) + b_i \left(SMC + \frac{SMC_{max}}{2} \right) + \frac{C}{SMC_{max}}$$
(15)

It can be shown that with the obtained solution (15), the target functional (7) reaches a minimum, because SMC_{max} is always a positive value.

IV. Discussion

Based on the solution that we got (13), we can propose the following method for determining SMC:

1. To find SMC in all wavelengths, the equation is solved:

$$\rho_i = \varphi(SMC)_{opt}$$

with respect to SMC.

2. The wavelength at which SMC has the smallest value is fixed.

3. The resulting SMC value is determined at this wavelength.

Accuracy Increase of measuring of SMC make it possible to construct more reliable early warning systems designated for prediction of flooding events.

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