The use of digital filters in the calculation of indicators of natural systems in geomodeling

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Abstract. The use of digital filters is ubiquitous, but their use for predicting data from natural systems has always caused dubious results. This paper discusses the possibility of using the Kalman filter for predictive activities when processing geodata. Large amounts of accumulated information can open up new horizons for human activities, including when using geospatial data referencing. The results of the study are presented and conclusions are drawn about the possibility of using digital filters in the calculation of natural indicators.

1. Introduction
The forestry sector of the economy is an invaluable source of renewable energy, a participant in the process of maintaining the environment and a resource with a rich variety of food products. Forests cover about 30 percent of the entire globe, but urbanization processes reduce this number over time. One of the challenges that must face humanity is the preservation and protection of forests.

In an age of technological progress, we can expect the introduction of new information technologies in the process of tracking, regulation and management of forestry. A lot has already been done on this path, from the introduction of specialized tree growth sensors to satellite monitoring of the formation of forest fires.

Forest fires and illegal logging do the most harm to the forest ecosystem and the state as a whole. Information and geographic information systems existing in this area are mainly aimed at detecting and tracking fires or illegal activities, but do not take into account the further development of events, do not calculate possible risks. For this purpose, it is first necessary to determine the possibility of using digital filters when calculating a forecast based on data from natural systems, and then apply them when predicting the behavior of a forest fire, depending on the wind, the degree of moisture in the earth, or other indicators.

The use of spatial data simplifies many management processes and carries a large amount of information.

Research of natural systems is currently acquiring new technological aspects. The interrelation of the earth sciences with the sciences that develop information progress contributes to the understanding of natural processes and their interaction. Natural phenomena can take on various states, therefore, to assess them, various criteria are used, which, first of all, need to be systematized for further work with them.

Processing and rational use of geodata is currently an urgent task for researchers. One of the mathematical solutions applicable to solving the problem is the Kalman filter, which, without exaggeration, can be called the most powerful tool for filtering data.
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2. Methods and Materials
The Kalman filter is designed to simulate the response of a system with an unknown transfer function [1].

The essence of this filter is to form a state indicator by means of calculating predictions, and then adjust it by comparing it with the incoming new information (figure 1) [2, 3].

To check the performance of this filter with geodata, information was taken on the moisture indicators of the earth's surface at a specific point in the Khanty-Mansi Autonomous Okrug for six months. The data were taken from the website of the laboratory of satellite oceanography of the Russian State Hydrometeorological University in the SATIN system, by converting satellite sensing data using the PYTHON programming language.

The mathematical toolkit of the Kalman filter consists of two phases. The first phase is the extrapolation or prediction of the value of the system at the next point in time. In mathematical form, the first phase is an equation of matrix form, which in turn is divided into two equations: the equation for directly predicting the state of the system (1) and the equation for predicting the covariance error (2).

\[ \hat{x}_k = F_k \hat{x}_{k-1} + B_k u_{k-1}, \]

where, \( \hat{x}_k \) — the predicted state on \( k \) step; \( F_k \) — dynamic transition matrix system state; \( \hat{x}_{k-1} \) — the value of the system in the previous step; \( B_k \) — matrix of managing influence; \( u_{k-1} \) — managing influence on the previous step.

\[ P_k = F_k P_{k-1} F_k^T + Q_k, \]

where, \( P_k \) — error prediction covariance matrix; \( F_k \) — dynamic matrix transition state of the system; \( P_{k-1} \) — covariance matrix that displays the error in the previous step; \( Q_k \) — the covariance matrix of the noise value.

Due to the fact that in our research managing influences are not defined, that is, they are absent, their value will be zero (\( B_k = 0 \)), or managing influence can be referred to noise.

The second phase — the phase of correction of the system. At this stage actual data are compared with received predicted, after which the values are adjusted. In the same way as in the first phase, the equations are a matrix form that can be represented in several stages [2].

As the first stage, we consider the Kalman gain equation (3):

\[ K_k = P_k H^T \left( H P_k H^T + R \right)^{-1}, \]

where, \( K_k \) — Kalman gain coefficient; \( P_k \) — covariance matrix of error prediction; \( H^T \) — state matrix of the obtained values in relation to the actual data; \( R \) — covariance matrix for measuring noise.

Further using the calculated data, we correct the system taking into account the actual state of \( z_k \) and obtain an equation of the following type (formula 4):

\[ \hat{x} = \hat{x}_k + K_k \left( z_k - H \hat{x}_k \right), \]
where, $z_k$ — measurement of actual state at the moment.

At the last stage, the equation of the covariance matrix of the updated state of the system (5):

$$P_k = (I - K_k H) P_{\hat{x}} ,$$  \hspace{1cm} (5)

where, $I$ — identity matrix.

In order to apply the filter to our analyzed system, it is necessary to determine the matrices (values of scalar coefficients) that determine the dynamics of the system and the measurements of $F$, $B$ and $H$ [4, 5]:

- $F$ is a matrix describing the dynamics of the system, in our case with a natural system, the dynamics has a stochastic character, so we take this variable equal to 1 (that is, we indicate that the predicted value will be equal to the previous state).
- $B$ is a matrix that determines the application of the control action. Since we do not have the ability to influence the natural process, we take $B = 0$.
- $H$ is a matrix that defines the relationship between measurements and system state. In our case (a natural process), we assume that the measurement fully reflects the state of the system, therefore, we take this variable also equal to 1.

To correct the predicted state, it is necessary to define the following matrices (moved to the filter settings):

- $R$ - measurement error. It can be determined by testing measuring instruments and determining the error of their measurement, the absolute value is set.
- $Q$ - Determining the process noise is more difficult because it is required to determine the variance of the process, which is not always possible. In any case, you can choose this parameter to provide the required level of filtration.

Thus, taking into account the above, the calculation at step $k$ is carried out according to the formulas [6]:

- Prediction

$$\hat{x} = F x_{k-1} ,$$  \hspace{1cm} (6)

$$\hat{P}_k = F^2 P_{\hat{x}} + Q$$  \hspace{1cm} (7)

- Correction:

$$K_k = \frac{H \hat{P}_k}{H^2 \hat{P}_k + R}$$  \hspace{1cm} (8)

$$x_k = \hat{x}_k + K_k (z_k - H \hat{\hat{x}}_k)$$  \hspace{1cm} (9)

$$P_k = (1 - K_k H) \hat{P}_k$$  \hspace{1cm} (10)

where $K_k$ is an auxiliary coefficient, $x_k$ is the corrected forecast of the system state, $P_k$ is the corrected forecast error, $z_k$ is the value of the current measurement of the system state.

Based on the above, it can be argued that the Kalman filter is essentially an IIR filter with a dynamic adjustment of the transfer function [7, 8].

3. Results and Discussion

To confirm the adequacy of the chosen model, it is necessary to reproduce it at the application level, we implement the filter in the C# programming language (figure 1).
Figure 1. Block diagram of the algorithm implemented in the C# programming language.

As a result of the work of the application program implemented by the Kalman filter for predicting the natural parameter at a given point, a graph was built showing the level of deviation of the calculated data from their real indicator. (figure 2) [9].
Figure 2. The results of the program implemented by the Kalman filter.

On the graph, the initial data is shown in blue, the data arising from the forecast of the Kalman filter are shown in yellow, and the difference is shown in red.

The graph shows that there is an insignificant difference between the a priori and the calculated data by the Kalman filter. These discrepancies are caused by the absence of coefficients of controlling influencing factors in the equation of the Kalman algorithm. This is due to the fact that during the experimental part in the course of the study, the data taken are stochastic and have a natural origin [10]. There are many external interdependent factors in relation to this kind of data. Accordingly, taking into account all natural influencing factors is an extremely difficult task, since when calculating one external factor, new interdependent factors appear [11, 12]. It should also be borne in mind that if a parameter with a zero characteristic is encountered in the data, then the filter measurement matrix degenerates with an erroneous value, which in turn is reflected in the graph as a series of deviations.

4. Conclusions
The use of digital filters in the calculation of indicators of natural systems is a rather unexplored area. Based on the results obtained, there is a very insignificant discrepancy between the obtained data and the initial ones. Further development of this approach is relevant, in particular, if the work of external influencing factors is realized with a certain average statistical characteristic, which in turn will greatly increase the results of the filter and its use when working with geodata. This is especially true when studying natural phenomena, in particular those occurring in remote forest areas, where fires, illegal felling and spontaneous felling of trees are possible. Here we can talk about predicting the level of temperatures, humidity, adding to the calculation of external influencing factors, such as wind, etc. More accurate forecasts can not only improve the process of managing the region, but also bring significant economic benefits.

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