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Alvaro Rocha
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Selecting a Set of Remote Indices for Comprehensive Monitoring of Acid Mine Drainages

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Abstract. Monitoring of acid mine drainage is an important ecological task. Remote sensing provides means of accurate operational observations of the Earth in a wide range of spectrum. Numerous remote indices of surface water state/quality have been developed based on remote sensing data. Monitoring of small-sized objects requires a fine spatial resolution which generally implies a coarser spectral resolution. Hence, only a qualitative knowledge of water optical features can be taken into account which makes it difficult to perform a quantitative analysis of water compounds. A possible approach is a comprehensive analysis of a numerous indicators, which can be sensitive not only to variations of water optical properties due to pollution but also to changes of the course of biological and sedimentation processes caused by it within next days. The aim of this work is selection and/or construction of a set of such indicators and presents the initial stage of the investigation. A list of used remote indicators (around 20 in total) is formed; an approach to their qualitative comparison is introduced and tested; the prospects of the future investigation are discussed; and some recommendations are given.

Keywords: Water quality · Acid mine drainages · Remote indices · Kizel coal basin

1 Introduction

Traditional methods of monitoring surface water pollution in mining areas are based on sampling, and their laboratory chemical analysis. The applied hydrochemical monitoring system has a number of fundamental drawbacks. The main ones are the spatial discretization and low temporal resolution of the data obtained, high labor costs and the complexity of sampling at remote, hard-to-reach or potentially life-threatening points, all of which determines their high cost [1]. As a result, monitoring data often do not provide representative estimates, do not reflect short-term fluctuations, and sometimes seasonal dynamics in the intensity of pollutant releases into the environment, including

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watercourses [1, 2]. At the same time, such fluctuations can be significant and have a substantial effect on the concentration of pollutants in surface waters and the range of their distribution [1, 3, 4].

All these problems fully relate to the Kizel coal basin (KCB), located in the east of the Perm Region (Russia) (Fig. 1), where acid mine waters with a chemical composition hazardous to the environment are flowed. The closure of mines and the termination of pumping of mine water since the 90s of the twentieth century led to a gradual restoration of the groundwater level and the formation of drainages of acid mine water through various mine workings. They form more than 90% of the release of pollutants into the environment, including surface water.

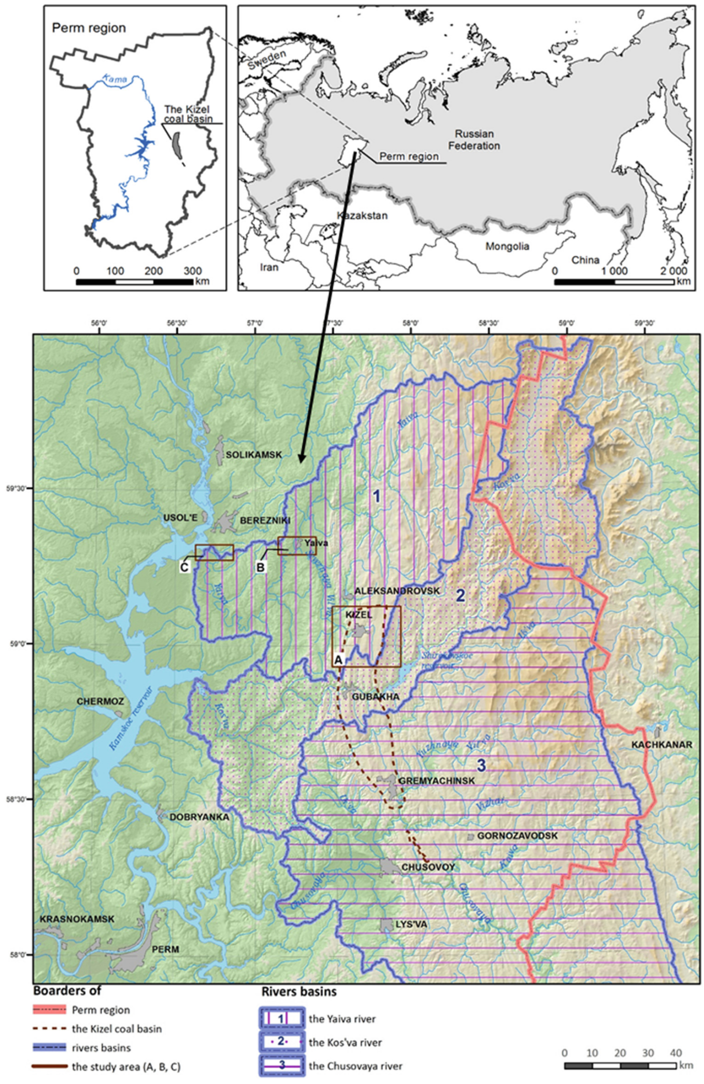

Fig. 1. The Kizel coal basin and surface water

There are 19 acid mine drainages (AMD) sources in the KCB currently, with an average annual discharge of about 25,000 m^3/year. The AMD has pH 2.3–5 and total mineralization up to 35,000 mg/L and extremely high concentrations of Fe_{total} (up to 3500 mg/L), Al (up to 190 mg/L) and several trace elements.

The pollution of the surface hydrosphere occurs within four large river basins of the region: the Yaiva, the Kosva, the Chusovaya and the Severnaya Vilva. The total length of polluted watercourses is over 500 km, flowing within 380 settlements. Along the river bed, as well as within the floodplains, significant volumes of technogenic deposits have been accumulated, containing high concentrations of pollutants, which are the secondary source of pollution of river ecosystems.

The monitoring of pollution of water bodies in this area has been carried out by the Ministry of Energy of the Russian Federation since 2000 to the present. Surface water was sampled during the warm period up to 6 times a year, the interval between sampling is about a month. We suppose that this frequency of measurements does not allow to estimate short-term fluctuations in the intensity of acid mine water inflow into the river network [5–7]. In addition, the existing monitoring system does not allow to promptly inform the authorities and the population about environmental hazards. Moreover, the data lose their relevance in the process of making environmental management decisions [5].

So, there is a need for additional sources of information about the state of the environment, for example, remote sensing data. Satellite monitoring has a number of significant advantages: the ability to simultaneously monitor the entire territory of the area under consideration, including hard-to-reach areas, and increase the monitoring frequency up to 1–2 times a month (taking into account cloudiness).

When analyzing the possibilities of remote monitoring of surface water pollution, two fundamental mechanisms of pollution manifestations should be considered. First, the spread of pollution can directly change the observable waters characteristics (i.e., transparency, color, temperature). Second, the course of biological and sedimentation processes can change under the influence of pollution, which will have an effect extended in time, possibly manifesting itself in a number of remotely measured parameters. Therefore, a comprehensive approach to remote monitoring of pollution is promising, combining a large set of characteristic indices. It is especially effective when research is focused on specific, pre-selected areas of interest. Then, on the basis of the collected statistics, it is possible to track even small perturbations in indicators against the background of known mean values and seasonal variations with greater reliability.

As an initial step in the investigation, it seems logical to study the sensitivity of various indices, to the emergence and spread of pollution. Due to the small size of the regions of interest, a high spatial resolution of remote sensing data is required; therefore, the work will study the indices calculated on the basis of measurements in the visible and infrared ranges of the spectrum. The effectiveness of these indices using will be verified on the example of observing the known events of pollution of the Yaiva river with mine wastewater from the KCB, which have been already studied by contact methods [7].

These considerations determined the structure of the work. Section 1 justifies the choice of the region of interest and observation dates. Section 2 contains a brief overview of the surface water characteristic indices known from the literature, calculated from the Earth remote sensing data (remote indices hereafter). Section 3 describes the used remote sensing data and methods of their analysis. Section 4 summarizes the results of the analysis; results are discussed in Sect. 5. Finally, conclusions are drawn on the described initial stage of the investigation and the prospects for its development are indicated.

2 Region of Interest and Observation Dates

The Kizel coal basin (the Western Urals, Russia) occupies area of 200 km^2. Folds have meridional and close to meridional orientation, they are elongated for tens of kilometers and complicated by numerous disjunctive dislocations. The KCB territory is within the drain area of the West Ural rivers that belongs to the Kama river basin. All rivers are greatly influenced by the KCB. Coal mining makes ecological situation worse that is determined by lithologic-and-geochemical characteristics of coal-bearing formations. More than 50 elements have been found in coal, 12 of which have 10–1,000 times higher concentration in coal than in background strata.

The mines closure in the 1990s did not resolve the environmental problems. After a gradual restoration of ground water level, the mine water discharged during several years and according to several scientists the quality of the mine water discharge may worsen or become stable during 2–40 years. When acid mine and drainage waters enter natural waterways, changes in pH and the formation of ochreous precipitates can have devastating effects on aquatic ecosystems. The basins of three large rivers – the Yaiva, the Kosva and the Chusovaya rivers were significantly affected by the anthropogenic load after the coal mines closure. The Yaiva river basin is typical for the KCB territory that is why it has been taken as a model to verify the research algorithms. Further these algorithms will be applied for the investigation of other rivers running on the KCB territory.

The Yaiva river starts in the North Ural Mountains, 879 km from its mouth the river flows into the Kama reservoir making the Yaivinskii bay. The Severnaya Vilva river, being the first-order tributary of the Yaiva river, is in the immediate region of the early developed coal field. Almost all pollution sources connected to coal production are located on the catchment area of the right tributary of the Severnaya Vilva river – the Bolshoi Kizel river. The Bolshoi Kizel river and its tributaries are polluted as a result of the long-term influence of mine waters. There are no pollution sources among the Bolshoi Kizel's tributaries except the Severnyi Kizel river catchment – the reason why the hydrochemical composition of the Severnyi Kizel's waters were not observed. The Bolshoi Kizel river when flowing into the Severnaya Vilva river has a negative impact on it (Fig. 2). There are three main pollution sources of surface water at the Yaiva river catchment area: mine water discharge, polluted springs and tailingspiles' drainage water. 7 acid mine drainages, 13 springs (7 of them are polluted) and 24 tailingspiles were discovered on the Yaiva river basin [6].

Fig. 2. Region of interest: synthesized RGB satellite images (Landsat-5 TM surface reflectivities in 3, 2, 1 bands). Arrows point to: 1 – the Yaiva river before flowing of the Severnaya Vilva river. 2 – the Yaiva river after flowing of the Severnaya Vilva river. 3 – the Severnaya Vilva river

We analyzed satellite images for the summer period, when the content of pollutants is maximum, but for periods of different water content. According to hydrochemical analyzes, the Fe_{total} content at the points before and after the inflow of the Northern Vilva river with the Yaiva river in 2011 is twice as high as in 2010.

3 Remote Indices of Surface Water Quality

The variety of remote indices proposed in the literature can be divided into three main categories according to the method of calculation. The first includes indices constructed as linear combinations of spectral surface reflectance (SSR) in various channels, and more often – the ratios of such linear combinations. We will denote the SSR by the letter ρ with a subscript corresponding to the measuring channel. Another category of indices uses, quantities proportional to the measured brightness in individual channels (after radiometric and geometric calibration, but without atmospheric correction). These values will be denoted by the letter I with the corresponding channel subscript. As a rule, this approach is taken for the sake of simplicity. Since the introduction of such indices is based on qualitative considerations regarding the optical properties of water with impurities contained in it, we assume it is possible in some cases to replace the values of I by the values of ρ in calculation. Some indices of both these categories can have a clearer "spectral referencing" due to the introduction of coefficients describing the proximity of the center line of the measuring channel to a certain wavelength, λ. This description makes it possible to adapt the calculation of indices developed for some devices to the measurement data of other devices. Finally, the third category of indices uses a preliminary color space transformation such as RGB → HSV, RGB → LBV [8, 9] to construct an index in new color coordinates or to select coefficients in linear combinations of SSRs.

The list of indices found in the literature is given in Table 1. It should be noted that due to the general methodology of indices construction, in a number of cases the same indices could be proposed independently by several authors, and some of the proposed ones could escape our attention. Therefore, the presented list is not claimed to be complete. At the same time, it aggregates information from a few previous reviews, in particular [10–13].

A number of indices characterizing the content of *chlorophyll a* and suspended particles have been excluded from this list, since these indices are constructed for narrow spectral channels, for example, for the MODIS (Terra/Aqua) instrument. Unfortunately, a narrow spectral channel has a poorer spatial resolution under all other equal conditions, which makes it difficult to use the corresponding indices when observing small-sized objects.

Such indices as *NDVI* and $NDWI_{Gao}$ [14], while not being inherently water indices, can be used as characteristics of phytoplankton content also.

Table 1. Remote indices of surface waters

Index	Equation	Reference
NDWI	$(\rho_G - \rho_{NIR})/(\rho_G + \rho_{NIR})$	[15]
MNDWI	$(\rho_G - \rho_{SWIR1})/(\rho_G + \rho_{SWIR1})$	[16]
NDPI	$(I_{SWIR1} - I_G)/(I_{SWIR1} + I_G)$	[10]
EWI	$(I_G - I_{NIR} - I_{SWIR1})/(I_G + I_{NIR} + I_{SWIR1})$	[17]
NWI	$(I_B - (I_{NIR} + I_{SWIR1} + I_{SWIR2}))/(I_B + (I_{NIR} + I_{SWIR1} + I_{SWIR2}))$	[18]
FAI	$\rho_{NIR} - \rho_R - (\rho_{SWIR} - \rho_R) \times (\lambda_{NIR} - \lambda_R)/(\lambda_{SWIR} - \lambda_R)$	[19]
NEW	$(I_B - I_{SWIR2})/(I_B + I_{SWIR2})$	[20]
WRI	$(\rho_G + \rho_R)/(\rho_{NIR} + \rho_{SWIR1})$	[21]
NDWI-B	$(I_B - I_{NIR})/(I_B + I_{NIR})$	[22]
TWI	$\rho_R - \rho_{SWIR}$	[23]
SWI	$(Sat - V)/(Sat + V)$	[8]
$AWEI_{nsh}AWEI_{sh}$	$4(\rho_G - \rho_{SWIR1}) - (0.25\rho_{NIR} + 0.75\rho_{SWIR2})$ $\rho_B + 2.5\rho_G - 1.5(\rho_{NIR} + \rho_{SWIR1}) - 0.25\rho_{SWIR2}$	[24]
NDWI-DB	$(I_{DB} - I_{SWIR2})/(I_{DB} + I_{SWIR2})$	[11]
WI_{2015}	$1.7204 + 171\rho_G + 3\rho_R - 70\rho_{NIR} - 45\rho_{SWIR1} - 71\rho_{SWIR2}$	[25]
WE-LBV	$-0.290\rho_G + 1.716\rho_R - 0.544\rho_{NIR} - 0.981\rho_{SWIR1}$	[9]
CMI	$\rho_G - \rho_B - (\rho_{SWIR} - \rho_B) \times (\lambda_G - \lambda_B)/(\lambda_{SWIR} - \lambda_B)$	[12]
ABI	$(\rho_R - \rho_B) \times (\lambda_G - \lambda_B)/(\lambda_R - \lambda_B)-$ $-(\rho_{NIR} - \rho_B) \times (\lambda_G - \lambda_B)/(\lambda_{NIR} - \lambda_B)$	[13]
AMWI	$(\rho_R - \rho_B)/(\rho_R + \rho_B)$	[7]

Most of the listed indices take into account the optical properties of surface waters (features of scattering and absorption of electromagnetic radiation) at a qualitative mode. They do not require the referencing of the measured quantities included in them to narrow spectral bands, but operate with the general concepts of change of scattering (absorption) with a decrease (increase) of the length of an electromagnetic wave. It is sufficient to indicate that the measurements refer, e.g., to the dark blue, blue, green, red, near infrared or short-wave infrared bands of the spectrum, see Table 2 (the channels directly used in the development of the listed indices are shown in bold, their analogs in other devices – in italics). The advantage of this approach is that the indices can be easily adapted to the data of various instruments. An obvious drawback, it is impossible to sharply adjust the indices for direct quantitative account of the characteristic features in the scattering or absorption spectra of the water components of interest.

Table 2. Corresponding of spectral bands of remote indices to the measuring channels

Index	Channel number, central wave length (nm)			Font size and style	
	Landsat-5 TM	Landsat-7 ETM +	Landsat-8 OLI	Terra MODIS	Sentinel-2A MSI
DB	–	–	**1 (443)**	*9 (443)*	*1 (443)*
B	**1 (480)**	**1 (480)**	**2 (482)**	**3 (469)**	*2 (490)*
G	**2 (560)**	**2 (560)**	**3 (565)**	**4 (555)**	*3 (560)*
R	**3 (660)**	**3 (660)**	**4 (660)**	**1 (645)**	*4 (665)*
NIR	**4 (830)**	**4 (830)**	**5 (867)**	**2 (858)**	*8a (865)*
SWIR	–	–	–	**5 (1240)**	–
SWIR1	**5 (1650)**	**5 (1650)**	**6 (1650)**	*6 (1640)*	*11 (1610)*
SWIR2	**7 (2200)**	**7 (2200)**	**7 (2215)**	*7 (2130)*	*12 (2190)*

Apparently, the first proposed "water" index was the *NDWI* by McFeeters [15]. He took into account the fact that the water column scatters sunlight in the visible range more strongly, while infrared radiation is weakly scattered back and, as a result, is almost completely absorbed by water. This feature is less typical for land objects, which makes it possible to highlight areas of open water. The presence of large suspended particles in the water increases the scattering of longer infrared waves, thus the index is sensitive to water "turbidity" and can potentially be used to analyze the spatial structure of currents. The turbidity water index *TWI* uses the same properties of interaction of light with water [23].

It was established that the variety of land features (in particular, the presence of buildings and asphalt roads) and lighting conditions (the influence of shading) does not always allow for the reliable identification of water bodies using *NDWI*. The search for its more optimal varieties led to the emergence of a number of indices that are close in meaning: *MNDWI* [16], *NDPI* [10], *NEW* [20], *NDWI-B* [22], *NDWI-DB* [11]. The next natural development step was the use of multispectral indices: *EWI* [17], *NWI* [18], *WRI* [21]. Attempts to take into account the relative significance of measurements in different spectral channels led to the introduction of additional weight coefficients, as well as the construction of indices based on color space transformations: *SWI* [8], $AWEI_{nsh}$, $AWEI_{sh}$ [24], WI_{2015} [25], *WE-LBV* [9].

At the same time, attempts were made to introduce indices for describing the intensity of biogeochemical processes in water bodies: *FAI* [19], *CMI* [12], *ABI* [13]. The possibility of using *NDVI* and $NDWI_{Gao}$ for this purpose was mentioned above. Specifically, mention should be made of *AMWI* [7], built on the *NDWI* principle, but aimed at detecting increased concentrations of iron oxides caused by the intrusion of acidic mine waste waters into surface waters.

4 Data and Methods

In this work we used Landsat-5 TM data, atmospherically corrected and preprocessed to SSRs. The data set was accessed through Google Earth Engine (GEE), [26] and is indicated there as "LANDSAT/LT05/C01/T1_SR". We also used the "GLCF: Landsat Global Inland Water" collection ("GLCF/GLS_WATER") from GEE as a mask for open surface water.

SSRs in Landsat-5 TM bands B1 – B5, B7 ($\rho_{B1} - \rho_{B5}$, ρ_{B7}) were used to calculate spatial distributions of the following indices: *NDWI, MNDWI, FAI, WRI, TWI, AWEI$_{nsh}$, AWEI$_{sh}$, WI$_{2015}$, WE-LBV, ABI, AMWI, NDWI$_{Gao}$*. We assumed following equalities: $\rho_B = \rho_{B1}$, $\rho_G = \rho_{B2}$, $\rho_R = \rho_{B3}$, $\rho_{NIR} = \rho_{B4}$, $\rho_{SWIR} = \rho_{SWIR1} = \rho_{B5}$, $\rho_{SWIR2} = \rho_{B7}$, $\lambda_B = 480$ nm, $\lambda_G = 560$ nm, $\lambda_R = 660$ nm, $\lambda_{NIR} = 830$ nm, $\lambda_{SWIR} = 1650$ nm. This assumption is most appropriate for all indices but *FAI*, which uses *MODIS SWIR* band different from *TM SWIR1* band. Notice, *ABI* was originally developed for narrow *MODIS* spectral bands, but in this work, we formally apply TM data to evaluate its "wider-band" analogue. We emphasize the main purpose was a preliminary qualitative analysis of the sensitivity of different possible indices to the observed pollutions.

As a spatial distribution of each index was calculated for the both observation dates, we applied a water mask obtained from the GEE GLCF/GLS_WATER dataset to select the regions of open water. We then manually inspect index values and establish color scale limits, same for both dates, in order to get maximum contrast (without saturation) within open-water regions. Then spatial distributions of the index were re-calculated for the whole territory and both dates with the corresponding color scale applied for the further comparison. This procedure was repeated for each index individually. All data processing was performed in GEE environment.

5 Results and Interpretation

In this preliminary analysis we restricted our study with a qualitative comparison of spatial distribution and relative change of the selected remote indices. The spatial distributions of the indices for the same region of interest and the two dates (August, 5, 2010, and July, 14, 2011) were built as described in the previous section. The results are shown in the Fig. 3.

The values of the calculated indices for the same regions of open water for the two dates differ markedly (Fig. 3), but these differences are not necessarily caused by the occurrence and spread of pollution. Additional factors of variability can be: the state of the atmosphere (despite the atmospheric correction procedure), change of the water level, and seasonal variability. For this reason, we applied the comparison with the reference values when interpreting the spatial distributions of remote indices (hereafter, for simplicity – maps of indices).

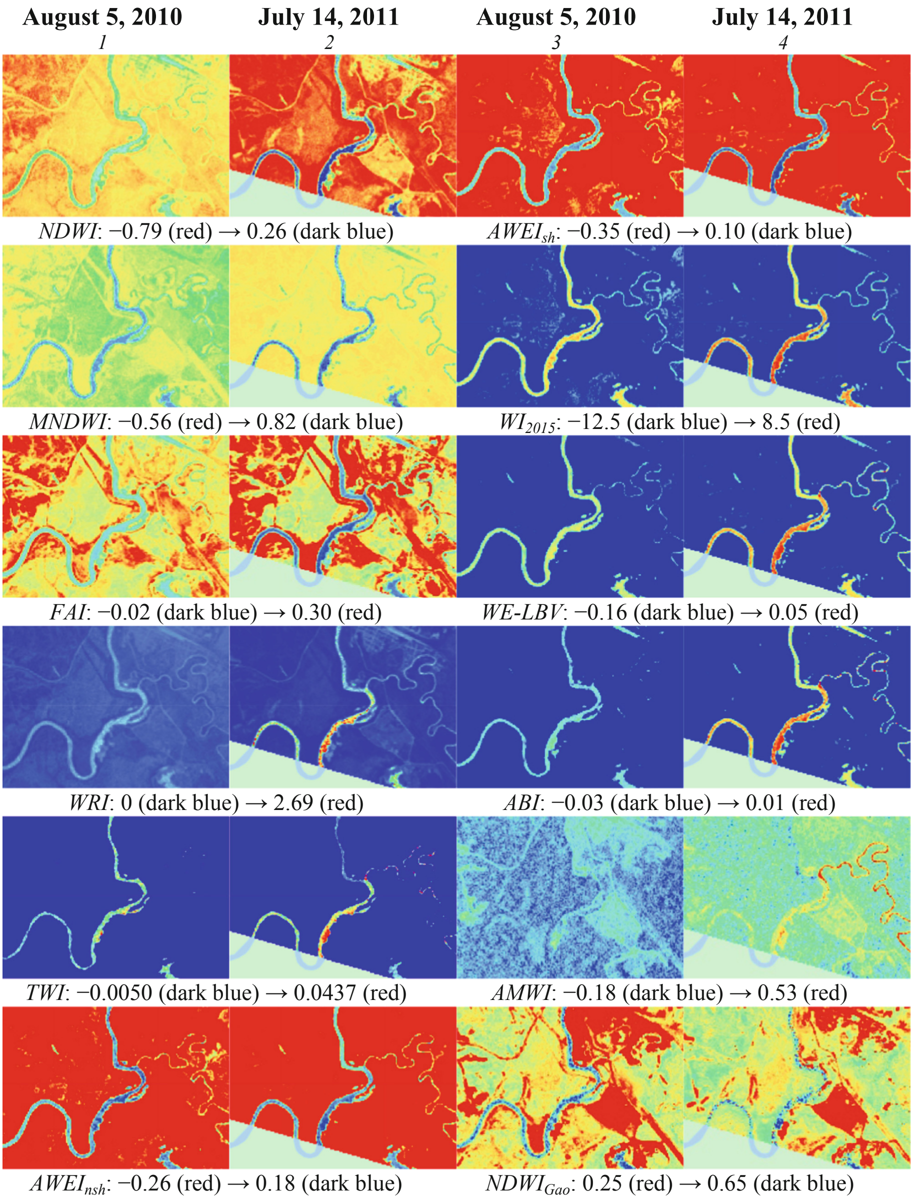

Fig. 3. Maps of selected indices for Aug, 5, 2010 (columns 1 & 3), and Jul, 14, 2011 (columns 2 & 4). Ranges of values are given under each map

We proceeded from the fact that the water composition of the Yaiva river above the inflow of the Severnaya Vilva river was to its norm, and the corresponding values of the indices can be used as indicators of the "normal state". By their contrast with the values calculated below the inflow of the Severnaya Vilva river, one can judge the sensitivity of the studied index to the occurrence and spread of pollution.

According to the features of spatial contrasts, index maps can be divided into several types. Denote by G, LY, UY, and SV the characteristic (median) values of the indices for the land areas, upstream and downstream after the inflow of the Severnaya Vilva river currents of the Yaiva river, and the Severnaya Vilva river, respectively. Taking the UY values for each index as a "standard" of unpolluted water, the characterization the most general patterns of the spatial distribution of this index values could be done qualitatively comparing the G, LY, and SV values with UY on each map. For this purpose, we construct new index maps of the form $index' = index - UY$, where index is each of the indices calculated above, and UY is its median value for the region of the upstream the Yaiva river. Then we paint the areas of positive values in red, negative ones in blue, and those close to zero in white. The calculation results are shown in the Fig. 4.

In most cases, the indices give a positive contrast between open water and land. The exceptions are *FAI* and, in part, *AMWI* (in low pollution conditions). A much more complex scheme is provided by the contrasts of the indices over different regions of open water under different pollution conditions on August 5, 2010 and July 14, 2011. This scheme is visualized in Table 3, where all the considered indices are listed in the cells in accordance with the conditions set by the top row and left columns of the table.

Table 3. General scheme of the pattern of spatial contrasts of indices

Criteria	Date	$LY \approx UY$	$LY > UY$
$SV < UY$	08/05/2010	$NDWI$, $MNDWI$, WRI, TWI, $AWEI_{nsh}$, $AWEI_{sh}$, WI_{2015}, $WE\text{-}LBV$, ABI, $NDVI$, $NDWI_{Gao}$	–
	07/14/2011	$AWEI_{nsh}$, $AWEI_{sh}$	$NDWI$, $MNDWI$, TWI, WI_{2015}, $WE\text{-}LBV$, ABI
$SV \approx UY$	08/05/2010	$AMWI$	
	07/14/2011	FAI	WRI, $NDVI$, $NDWI_{Gao}$
$SV > UY$	08/05/2010	FAI	–
	07/14/2011		$AMWI$

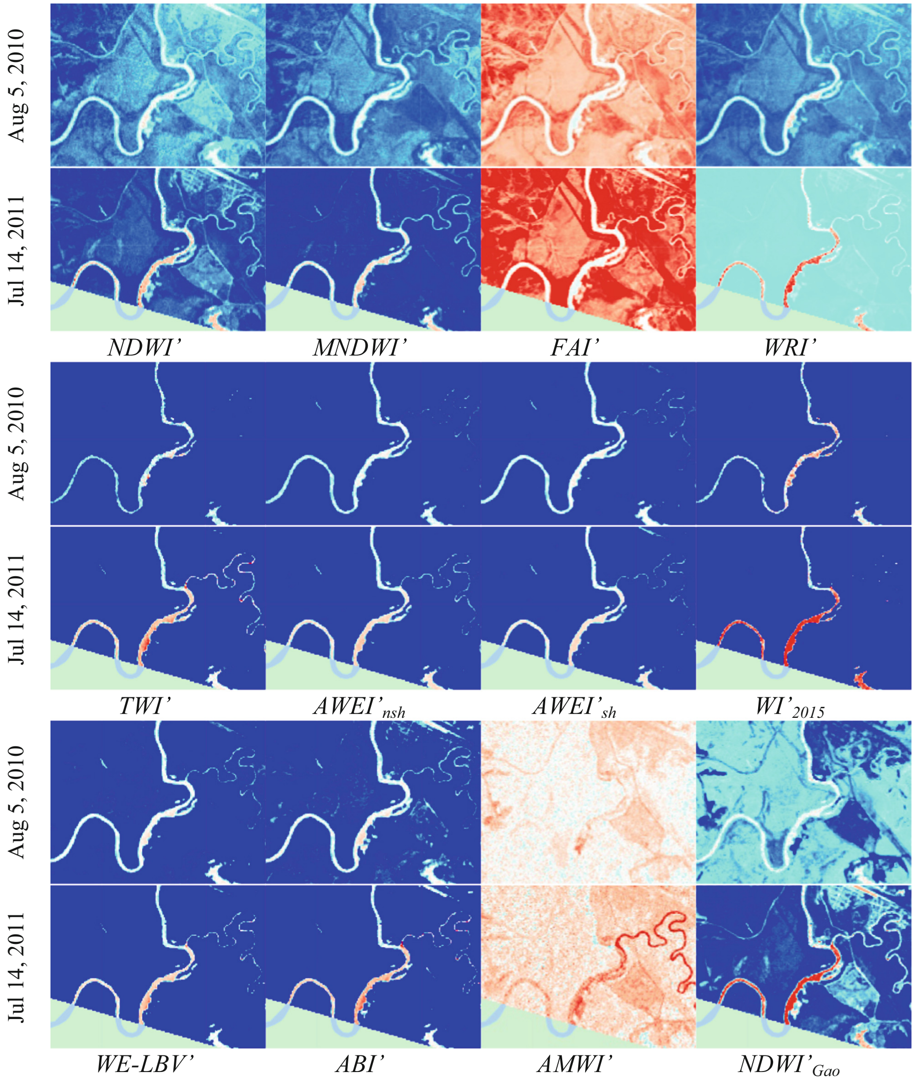

Fig. 4. Patterns of spatial contrasts of indices for the selected dates with respect to the reference values *UY* (red – above *UY*; blue – below *UY*)

6 Discussion

The territory investigation was made during 2006 to 2018 by the Ural Center for social-ecological monitoring of coal-mining territories. The results of the hydrochemical analyzes indicate that the pollution on 14.07.2011 was stronger than that of 05.08.2010. Concentrations of Fe_{total} in the Yaiva river upstream and downstream after the inflow of the Severnaya Vilva are 0.22 and 0.46 mg/l in 2010, 0.11 and 0.8 mg/l in 2011. At the same time, the source of pollution in the Yaiva river was its left tributary, the Severnaya

Vilva river. Satellite images (Fig. 2) confirm this fact and indicate that pollution in the Yaiva river spread mainly downstream of the inflow of the Severnaya Vilva river.

First of all, it should be noted that river channels are sharply manifested in the maps of most of the indices. The Yaiva riverbed is clearly visible practically on all the maps, and the channel of the Severnaya Vilva river is on many. This is expected for *NDWI*, *MNDWI*, and some others but much less obvious for *FAI* and *ABI*. A special case is *AMWI* that will be discussed below.

As can be seen from Fig. 4 and Table 3, all considered indices can be grouped into the following five categories according to the pattern of spatial contrasts they form: 1) (*NDWI*, *MNDWI*, *TWI*, WI_{2015}, *WE-LBV*, *ABI*); 2) (*WRI*, *NDVI*, $NDWI_{Gao}$); 3) ($AWEI_{nsh}$, $AWEI_{sh}$); 4) *AMWI*; 5) *FAI*.

By choosing the most informative indices from each category, it is possible to form a five-dimensional feature space for diagnostics and monitoring of pollutions. At the same time, the role of each of the features will obviously be different. For example, *FAI* can be informative at the initial stage of pollution, because sharply changes the contrast in comparison with the "normal state" only in the inflow area. *AMWI* is probably the most effective for direct quantitative assessments and tracking the dynamics of pollution: the highest values correspond to the maximum concentration of pollutants, the lowest – to the minimum. The indices of the *AWEI* group turned out to be practically insensitive to the intensity of pollution and can be used to form (refine) the mask of open water, demonstrating the maximum robustness to observation conditions and water pollution. As representatives of the first and second groups *TWI* and *WRI* can be selected, respectively. They provide the most contrasting maps without saturation in the ranges of minimum or maximum values, which gives the possibility for a detailed study of the spatial structure and pathways of pollution.

This research was of a qualitative nature. Its results can be used as guidelines for constructing the feature space in more complex, multidimensional schemes for multispectral and hyperspectral monitoring of surface water pollution. The study was limited to considering pollution cases for two specific dates. One of the promising areas of further work, is the analysis of the temporal dynamics of indices reflecting various aspects of the course of processes in surface waters that change under the pollution.

7 Conclusion

A qualitative analysis of the sensitivity of various remote indices of surface water quality/state to the occurrence of pollution was carried out. Based on the literature review, a list of the most frequently used indices was compiled, calculated from the data of satellite scanners operating in visible and infrared spectral ranges. Due to the small sizes of the studied objects (widths of river beds), one of the limiting requirements was a relatively high spatial resolution of the source remote data. Therefore, some indices developed for high spectral/low spatial resolution were excluded from consideration.

The sensitivity of various indices to the occurrence and spread of pollution was analyzed based on the case study of the Yaiva river pollutions on 08/05/2010 and 07/14/2011. Thus, the indices can be grouped into five categories reflecting different aspects and stages of pollution. The results obtained will be demanded in further work for the formation of an optimal feature space when implementing an approach of monitoring surface water pollution based on remote data of multispectral and hyperspectral satellite imagery.

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