Regional Research Network

„Water in Central Asia“

CAWa

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Contents

Resume

Given the final year 2019 of the CAWa project, this report is to summarize on operability of the WUEMoCA tool for monitoring and assessment of irrigated land in Central Asia. Developed as a means for RS-based assessment of irrigated crops, their development dynamics and their water availability, consequently WUEMoCA showed new potential that was used by SIC's team in the analysis of water use efficiency and for development of new tools. The latter further transformed into an online advising system for irrigated land fertility improvement could help to improve efficiency of irrigated agriculture as a whole. This system combines the yield programming methodology developed in the Soviet period and the usage of different spectra of satellite images to catch deviations in crop growing process and give recommendations for removal of deficiencies in crop growth.

The report consists of a few parts:

1. Part 1 – collection of ground data and statistics by district and province of the republics (countries) in the region and their comparison with RS-based data (validation) – Muminov Sh., Sorokin D.
2. Assessment of available water supply for irrigated land since 2012 and irrigated land productivity – Sorokin A., Sorokin D., including development of a mechanism for water use efficiency assessment – Sorokin D.
3. Study by Solodkiy G., Stulina G., and Kenjabayev Sh. of a possibility to use RS-based data for the improvement of farming technology.
4. Usability of RS-based methods for the improvement of yield programming methods to the benefit of extension services.

Chapter 1. Data collection and validation

The data were collected by the candidate of economic sciences Sh. Muminov in 183 districts and towns of Uzbekistan, 25 districts and cities of Turkistan and Kzylorda provinces of Kazakhstan, 55 districts and towns of Kyrgyzstan, and 68 districts and towns of Tajikistan on crop acreage, yields, gross harvest, total and for the following crop (since 2014 to 2018):

- wheat
- maize (corn)
- rice
- oil crops
- cotton
- tobacco
- sugar beet
- potato
- vegetables
- cucurbits
- fruits and berries
- grapes
- fodder crops

1.1. Validation of land use indicators

Validation was done on the data from 156 districts and provinces of Uzbekistan over 2000-2017 to show that the requirements of potential users of WUEMoCA for land and water use indicators are met, i.e. the remote sensing results correspond to actual water-related situation (deviations are within admissible limits).

1. Net irrigated area (Fir_n), thousand ha – area equipped with irrigation infrastructure linked with water sources (excluding the area under canals, structures, roads, and buildings).
2. Irrigated crop acreage (Fir_f), thousand ha – irrigated area under crops during the reporting period, double usage is counted twice.

1.2. Results

1. The difference between the WUEMoCA results and statistics on irrigated crop acreage (dFir_f) was 12 % in 2015, 5.8 % in 2016, 8.4 % in 2017, and 2.5 % in 2018. Thus, there is visual downward trend indicating to growing accuracy of RS-results in WUEMoCA. Table 1.1 shows the crop acreage average over 2000-2018 by WUEMoCA against statistics and the data from the Uzbek Ministry for Water Management (received from Basin Irrigation System Authorities).

2. WUEMoCA shows irregular pattern of Fir_f in time and in the territory of Uzbekistan. The comparison of land use indicators (WUEMoCA results and statistics) was made on irrigated crop acreage, including double season crops, between provinces of Uzbekistan over 2000-2018. The resulting deviation was assessed as the difference between remote sensing results and statistics in % of statistics.

On average over 2000-2018, the deviation of RS-results from statistics in the sum of all crop acreages in Uzbekistan is estimated at 18 %. This means that the total irrigated crop acreage calculated by WUEMoCA is 18 % lower than that shown in statistics. There is a trend of decreasing deviation over 2000-2018 (Fig. 1). Minimal deviations are observed in: 2002 (-5%), 2009 (-2%), 2016 (7%), and 2018 (-3%). Maximal deviations are observed in dry years: 2000 (-40%), 2001 (-32 %), and 2008 (-34 %).

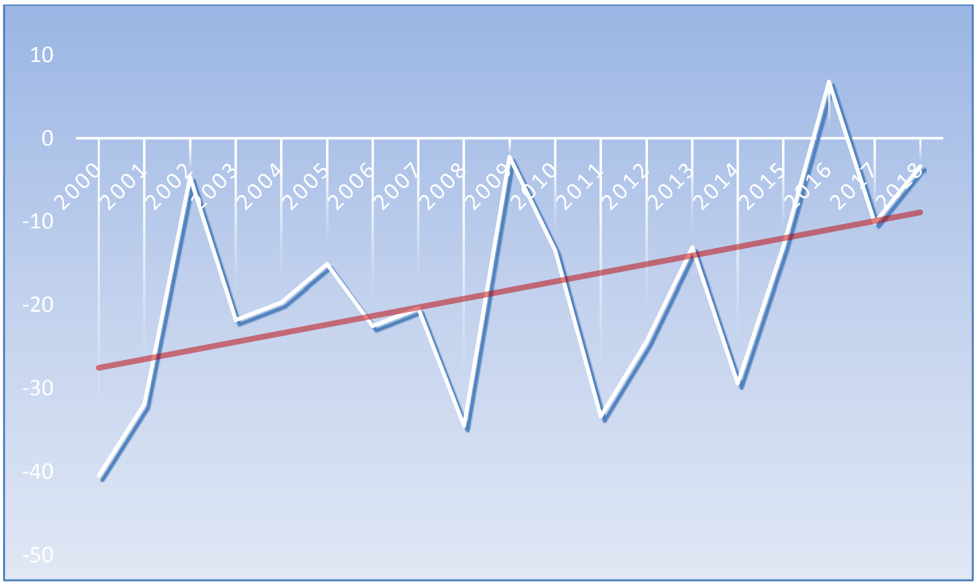


Figure 1.0 Dynamics of deviations of RS results from statistics on crop acreage in Uzbekistan (%)

The analysis of deviations shows irregular pattern of this indicator both in time and space in Uzbekistan. The lowest negative deviations were observed in the following provinces on average over 2000-2018: Andijan province – 8 %, Fergana province – 4 %, Khorezm province – 5 %. The highest negative deviations were observed in: Surkhandarya - 42 %, Djizakh – 41 %, Kashkadarya – 29 %. For other provinces, deviations were as follows: Tashkent province – 14 %, Navoi province – 15 %, Samarkand province – 20 %, Namangan province -21 %, Bukhara and Syrdarya provinces -21 %.

The opposite situation was observed in the Republic of Karakalpakstan, i.e. the irrigated crop acreage by RS was higher than statistics (27 %). In recent years (2016, 2017, 2018), positive deviations were also observed in Khorezm province (16%), Fergana province (14%), and Andijan province (3%). Thus, these years the irrigated crop acreage derived by RS is higher than statistics.

WUEMoCA shows that on average over 2000-2018 the irrigated crop acreage is estimated at 3.2 Mha in Uzbekistan, while the irrigated area (4.2 Mha) exceeds crop acreage by 1.0 Mha or 24 % of irrigated area. Available non-used irrigated land demonstrates the low water availability for irrigated land and the poor water use (huge losses on the way from intake point at district boundary to field). The largest shares of unused land (up to 40 %) were observed in the dry years 2000, 2001, and 2008.

3. Exceedance of Fir_n (net irrigated area) over Fir_f (irrigated crop acreage) in WUEMoCA demonstrates the availability of non-used irrigated land. According to WUEMoCA data, this exceedance (dFir = Fir_n – Fir_f) varied from 9 to 25 % over last 5 years. The possible causes are: poor water availability of irrigated land and low water use efficiency (huge losses on the way from intake point at district boundary to field). Table 1.2 gives the data on non-used irrigated land in Uzbekistan over 2015–2017. As a whole, statistics show lower values of non-used land than WUEMoCA, although in some years (e.g. 2016) the statistics data is higher than the results in WUEMoCA.

Table 1.1. Comparison of irrigated crop acreage in Uzbekistan, average over 2000-2018, between different data sources

Net irrigated area, Fir_n, Mha	Irrigated crop acreage, Fir_f, Mha		
	WUEMoCA	BISA	Statistics
4.2	3.2	3.4	3.5

Table 1.2. Non-used irrigated land in Uzbekistan as the difference between net irrigated area and irrigated crop acreage (Fir_n – Fir_f)

Year	Unit	WUEMoCA	Statistics
2015	Mha	0.8	0.3
	%	19	7
2016	Mha	0.4	0.6
	%	10	14
2017	Mha	1.0	0.7
	%	24	17

Figures 1.1 and 1.2 show dynamics of crop acreage for two zones located in different river basins and river reaches: the Amu Darya lower reaches and Fergana province, Uzbekistan (Syr Darya River basin). The comparison between WUEMoCA and statistics is made for the data from 2000 to 2018. In general, the irrigated crop acreage values calculated by WUEMoCA exceed the statistics (e.g. the difference is 4 % on average for Fergana province). At the same time, statistics exceeds the results in WUEMoCA in some years. It is noticeable that in particularly dry years (2000, 2001, 2008) the non-used land areas by WUEMoCA were higher than those shown in statistical books.

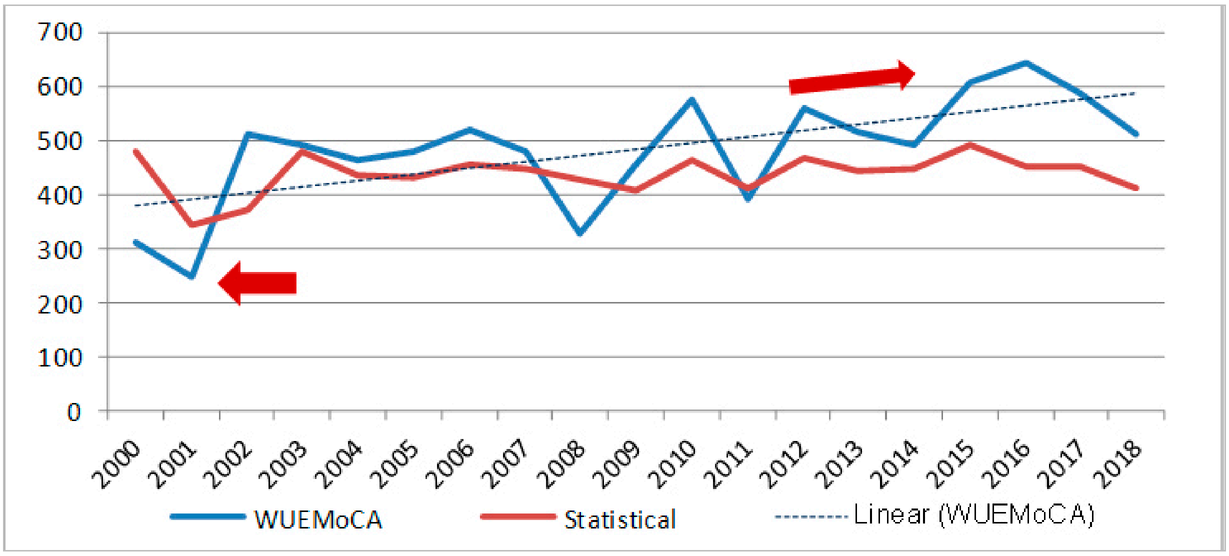


Figure 1.1. Dynamics of irrigated crop acreage (Fir_f) in the Amu Darya lower reaches (Khorezm province, Uzbekistan and Karakalpakstan) over 2000-2018, comparison of WUEMoCA data and statistics, thousand ha

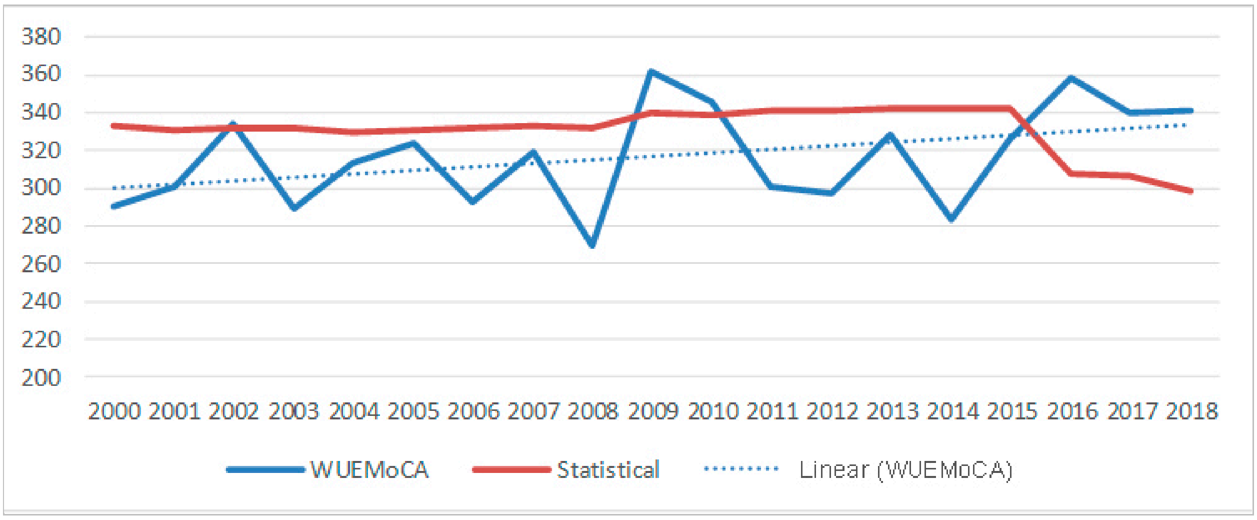


Figure 1.2. Dynamics of irrigated crop acreage (Fir_f) in the Fergana Valley, Uzbekistan over 2000-2018, comparison of WUEMoCA data and statistics, thousand ha

1.3. Water data validation

Initially, WUEMoCA was intended as a tool to demonstrate potentials of satellites for detection of irrigated areas under crops and assessment of crop yields of cotton, wheat and rice. The SIC's team was to ensure information support of the project and make it close to user's needs as much as possible. In this context, we have organized questioning and workshops and, consequently, made a proposal to extend WUEMoCA functionalities by adding the 'water factor' and the user input option. To this end, our experts and programmers have developed the "User polygon", which allowed calculating water and land use efficiency and productivity on the base of processed satellite data and user inputted actual data (drawing area of interest, input of statistics).

For validation of water indicators, the data on irrigation water intake during growing seasons (April-September) was collected on 154 districts of Uzbekistan (by I. Ergashev) and analyzed. The data was analyzed on possible errors, updated (if errors are found) and added to DB for further use in WUEMoCA, in particular, for calculation of water use efficiency.

Figures 1.3-1.4 show dynamics of water intake from the Amu Darya and the Syr Darya basin in the territory of Uzbekistan during the growing seasons (April-September) 2000-2016. The low-water period in the Amu Darya basin in 2001, 2008 and 2011 is interesting: heavy drop in amounts of water intake in the lower reaches against a minor decrease of intake in other zones of the area under consideration.

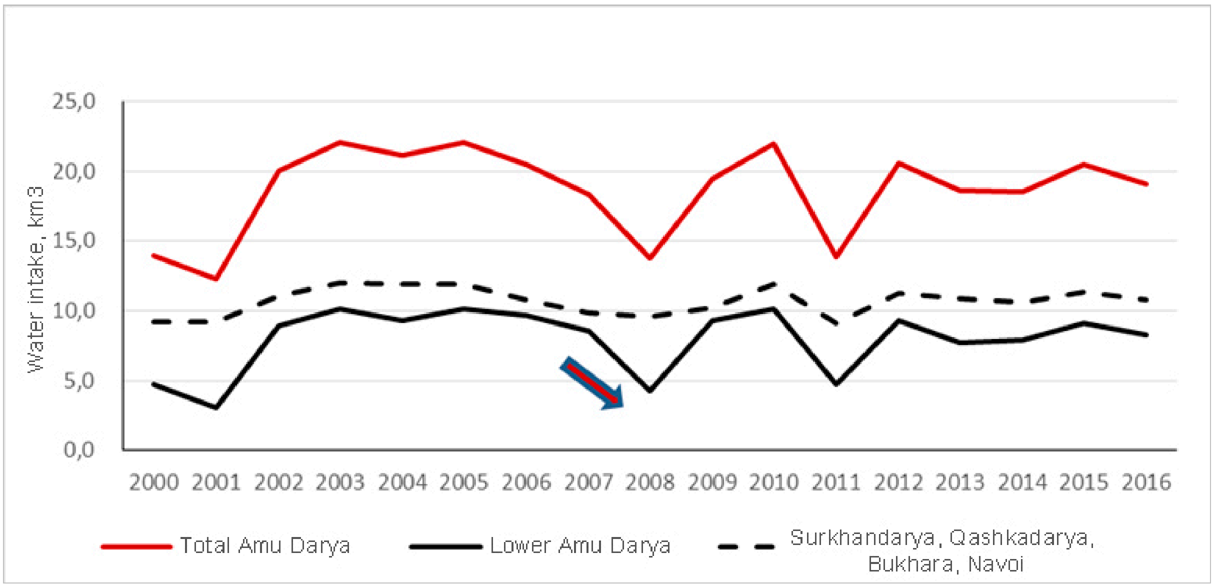


Figure 1.3. Dynamics of water intake from the Amu Darya basin in Uzbekistan during growing seasons (April-September) 2000-2016

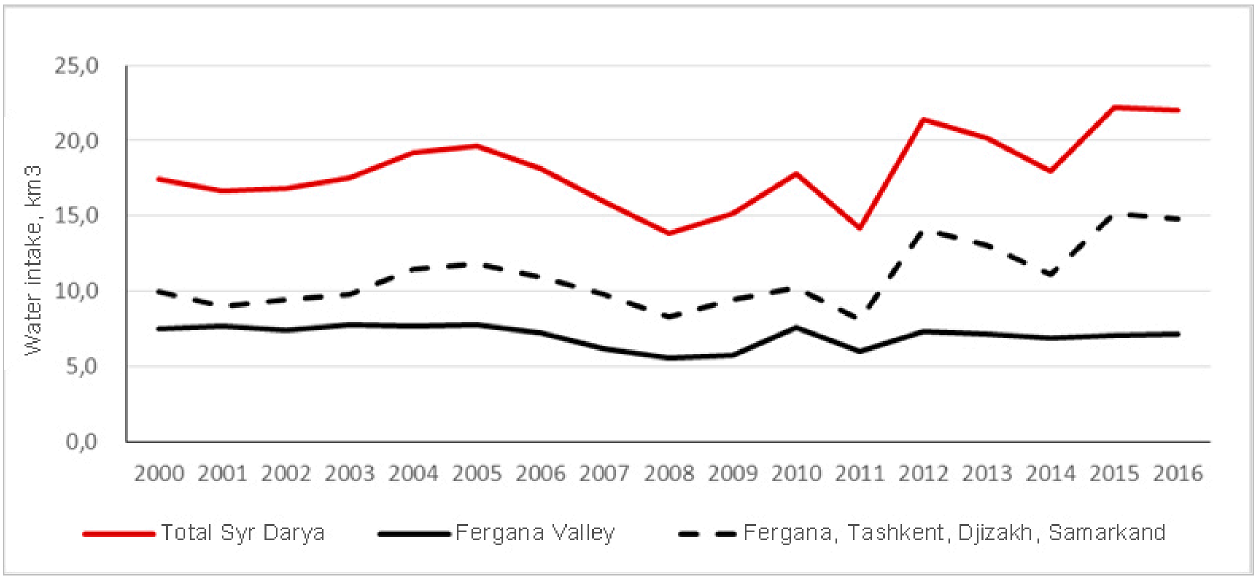


Figure 1.4. Dynamics of water intake from the Syr Darya basin in Uzbekistan during growing seasons (April-September) 2000-2016

Crop acreages were compared for all provinces in the Aral Sea basin from 2000 to 2018 (Figures 1.5 – 1.10).

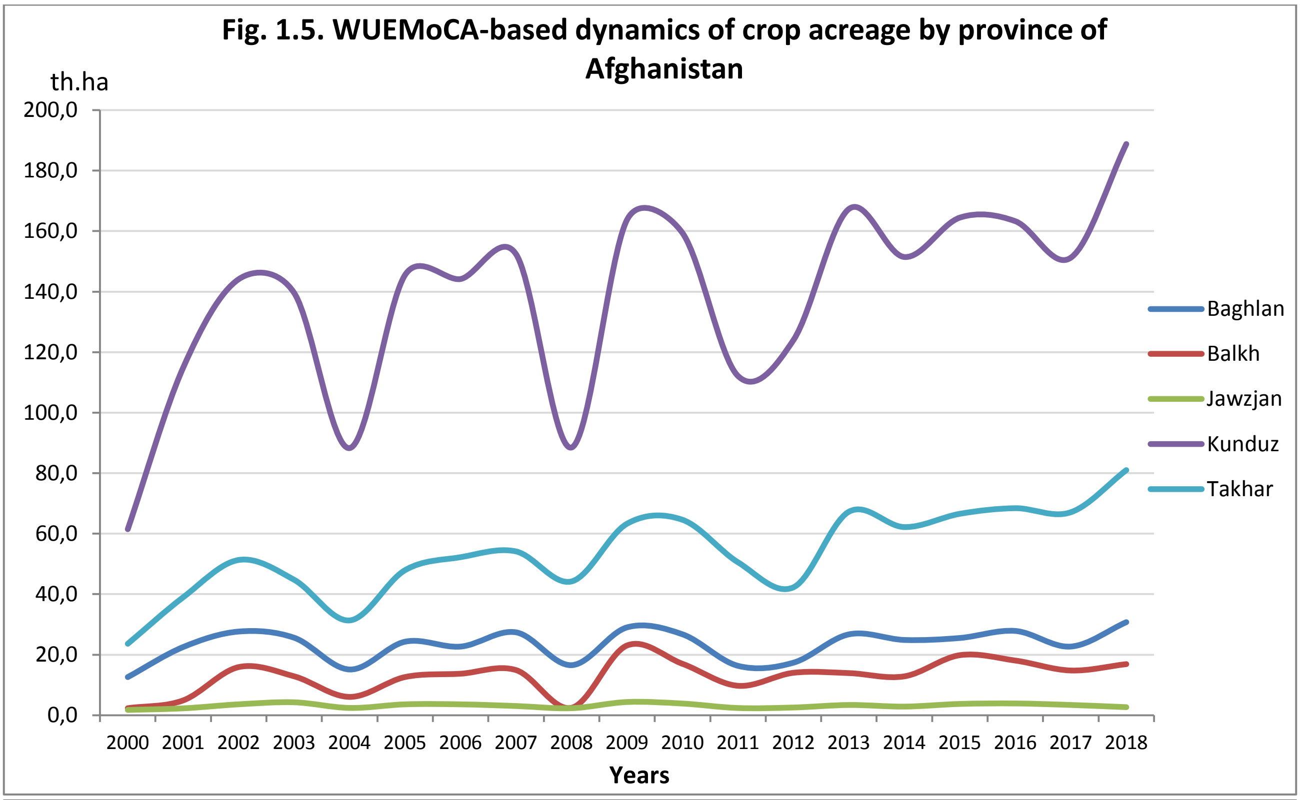


Fig. 1.5. WUEMoCA-based dynamics of crop acreage by province of Afghanistan
th.ha
200,0
180,0
160,0
140,0
120,0
100,0
80,0
60,0
40,0
20,0
0,0
2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017 2018
Years
Baghlan
Balkh
Jawzjan
Kunduz
Takhar

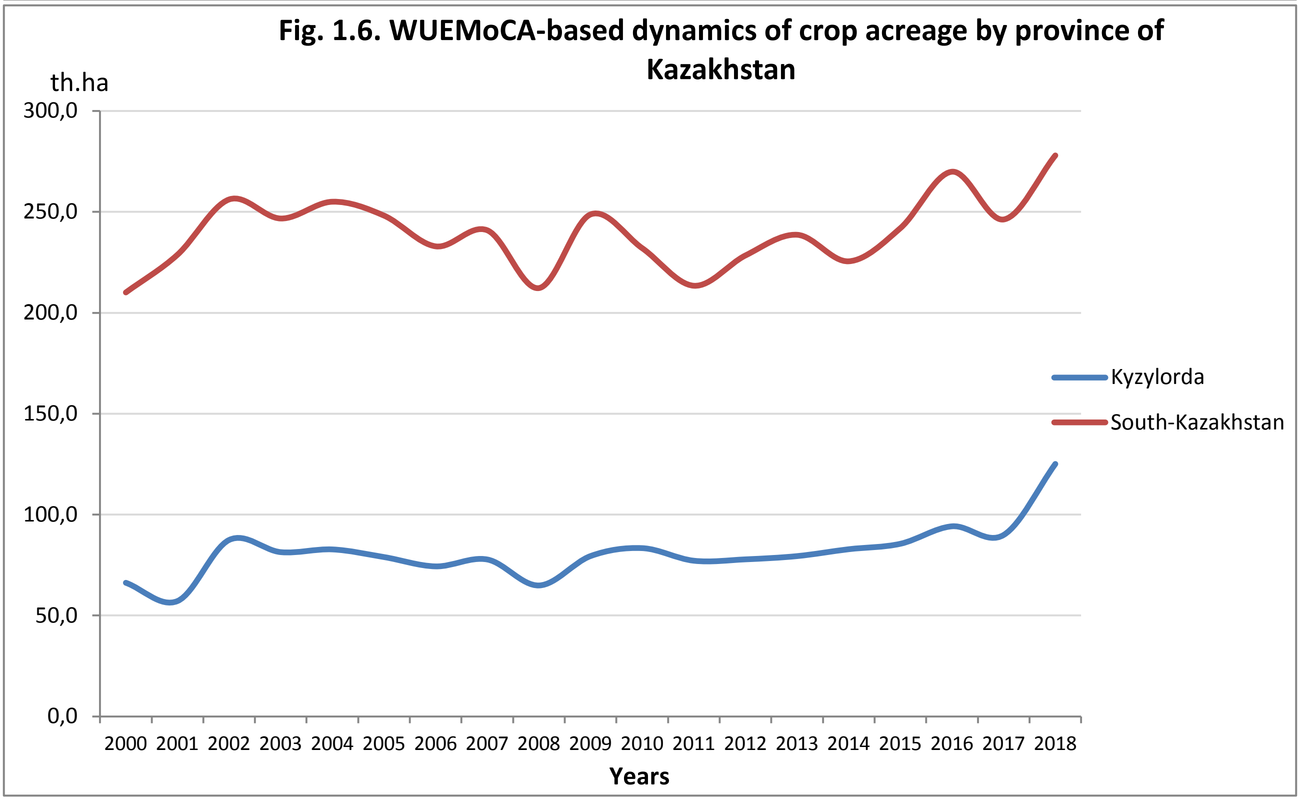


Fig. 1.6. WUEMoCA-based dynamics of crop acreage by province of Kazakhstan
th.ha
300,0
250,0
200,0
150,0
100,0
50,0
0,0
2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017 2018
Years
Kyzylorda
South-Kazakhstan

Fig.1.7 WUEMoCA-based dynamics of crop acreage by province of Kyrgyzstan

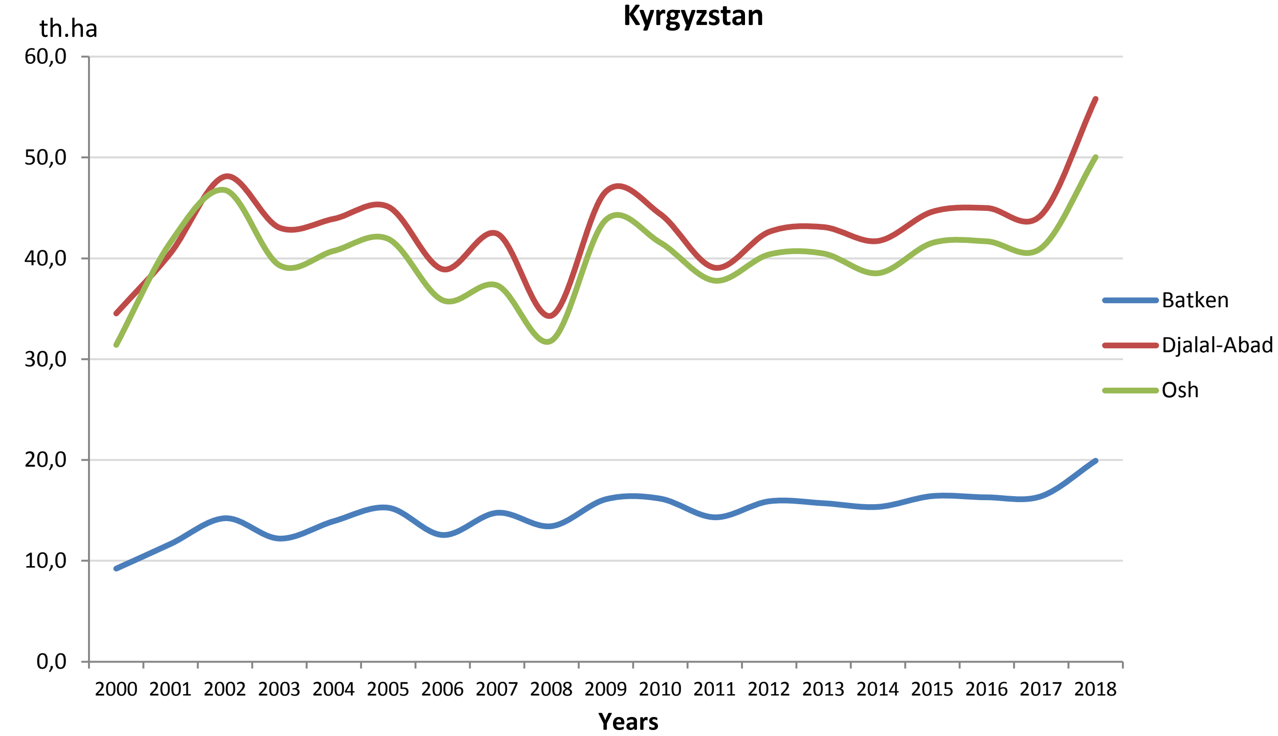


Fig. 1.8. WUEMoCA-based dynamics of crop acreage by province of Tajikistan

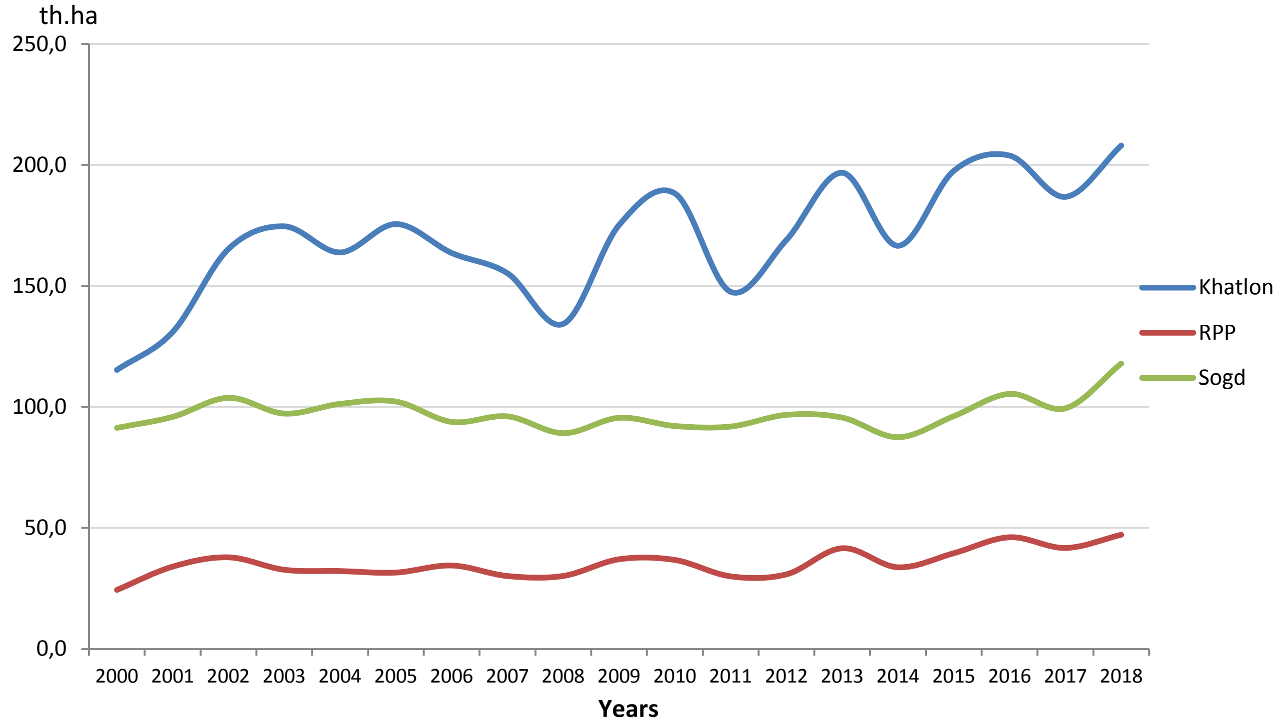


Fig. 1.9. WUEMoCA-based dynamics of crop acreage by province of Uzbekistan

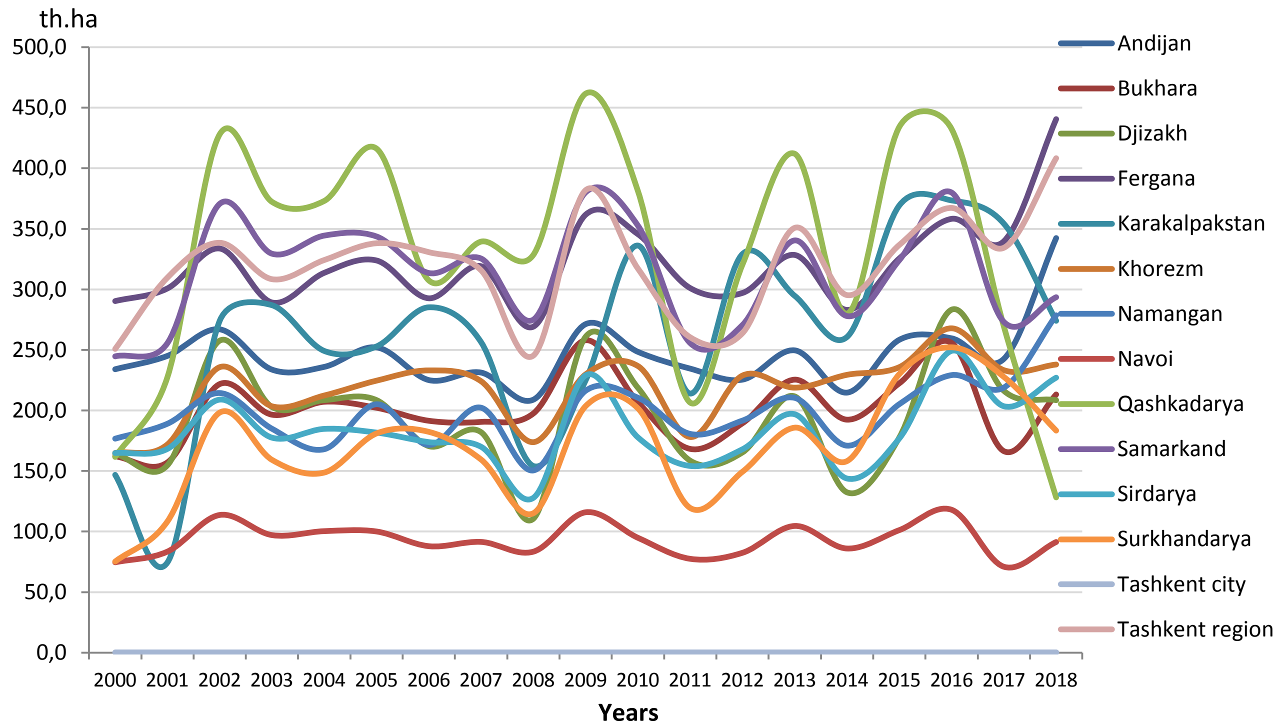
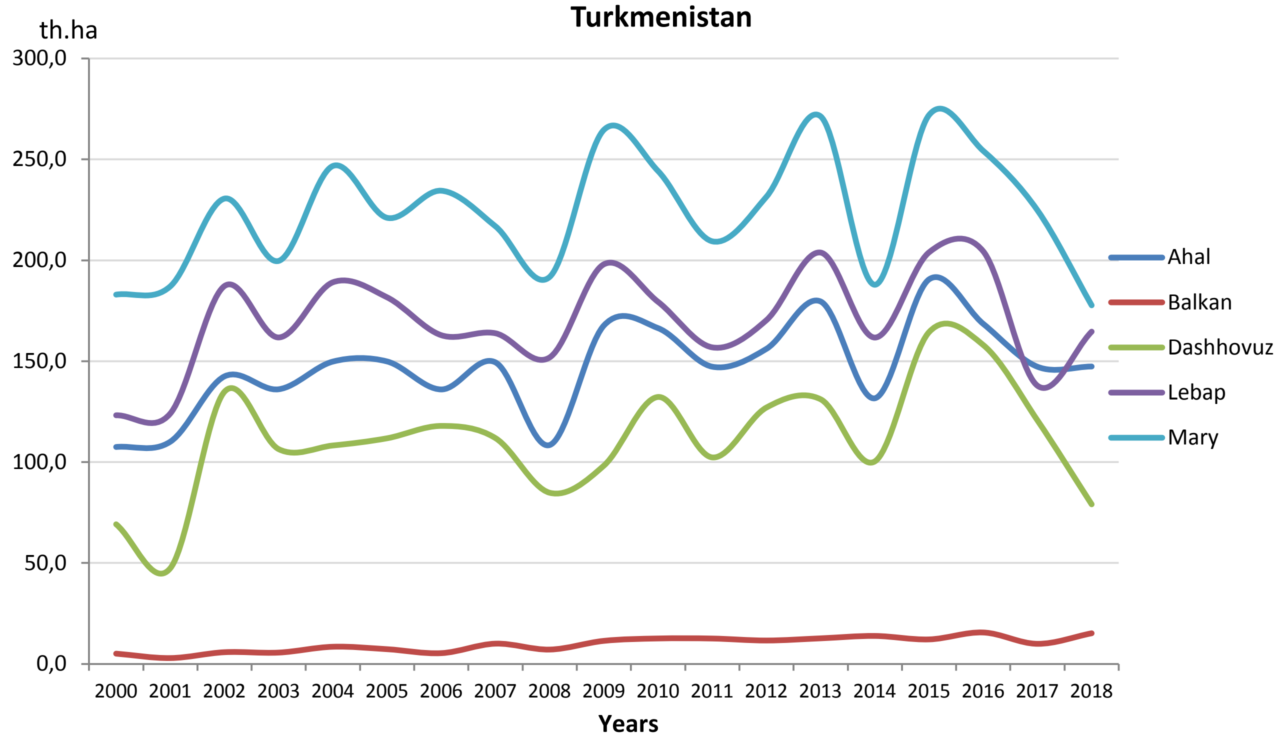


Fig. 1.10. WUEMoCA-based dynamics of crop acreage by province of Turkmenistan



The average deviations on crop acreage are given in Table 1.3.

Table 1.3. Comparison of statistics with RS results

Province	Q-ty of districts	Statistics	WUEMoCA calculation results	Deviation from statistics, %	Statistics	WUEMoCA calculation results	Deviation from statistics, %
		Irrigated area, thousand ha			Crop acreage, thousand ha		
Andijan	14	217.2	213.3	-1.8	239.1	242.6	1.5
Djizakh	12	230.1	199.7	-13.2	269.2	216.2	-19.7
Namangan	11	**200.7**	187.9	-6.4	221.3	218.9	-1.1
Syrdarya	8	214	**186.9**	-12.7	**208.6**	**203.5**	-2.4
Tashkent	14	280.5	271.2	-3.3	**300.6**	334.4	11.2
Fergana	16	**307.7**	**295.7**	-3.9	295	**339.8**	15.2
Min		**200.7**	**186.9**	**-13.2**	**208.6**	**203.5**	**-19.7**
Max		**307.7**	**295.7**	**-1.8**	**300.6**	**339.8**	**15.2**
Avr		**241.7**	**225.8**	**-6.9**	**255.6**	**259.2**	**0.8**
Sum	75	**1450.2**	**1354.7**	**-6.6**	**1533.8**	**1555.4**	**1.4**

The main causes of such large deviations of crop acreage values are as follows:

- Incorrect boundaries of districts and provinces;
- Misinterpretation of MODIS images of 250 m, with 6.25 ha per pixel. From the very beginning we insisted on transferring to Landsat.

This is proven by research of Sh. Zaitov and Sh. Kenjabayev on validation of polygon areas for Fergana province and Kashkadarya province, where all available indices were identified and provided quite high accuracy of crop identification. Oktepa Zilol Chashmasi WUA in Akhunbabaev district, Fergana province (Figure 1.11) was chosen as a study area. As part of Package 1, satellite images were to be analyzed to determine phenology of wheat and cotton.

Figure 1.11 Sentinel 2 images

After downloading of satellite images, we firstly cut raster image for the study area. We used a shape file of WUA's boundaries in ArcGIS 10.3.

The comparison was made for 20 fields of cotton and wheat and resulted in a small difference between areas derived from two images.

Crop	**Cadastre**	Landsat 8 OLI	Sentinel 2
Cotton	160	173.8	171.8
Wheat	149	193.1	193.0

Images for August 2018 to October 2019 allow tracking wheat and cotton from sowing till harvesting. For given task, boundaries of each pilot plot were used. Before extraction of NDVI, boundaries were checked by overlaying these boundaries in Google Earth, Landsat 8 and Sentinel 2. After checking, the boundaries were overlaid on Landsat NDVI to have phenology of cotton and wheat. When comparing satellite images with cadaster data, wheat boundaries were extracted for two sites. Two images were downloaded: Landsat 8 OLI and Sentinel 2 for the Fergana Valley (Landsat 8 OLI - 152/32 and 153/32, Sentinel 2 - 42 TYK) and Kashkadarya province (Landsat 8 OLI – 155/33 and 156/33 for 2019). This allowed working with several indices, including NDVI.

picdat	blockid	fieldid	cropid	ndwi	ndvi	savi	vari	arvi	eta	yearday	eto
10/1/2018	14	59	37	14.7059	0.52693	0.790298	0.748781	0.632763	1.98899	275	2.69172
10/4/2018	14	59	37	15.4785	0.490843	0.736172	5.64935	0.563056	1.99696	278	2.92516
10/11/2018	14	59	37	15.4416	0.343609	0.51535	6.6125	0.436654	0.592691	285	0.989403
10/21/2018	14	59	37	16.9634	0.272077	0.408063	37.2579	0.265601	0.483858	295	1.21485
11/10/2018	14	59	37	20.6384	0.10508	0.157595	46.172	0.165198	0.144866	315	0.732081
12/3/2018	14	59	37	22.2325	0.195423	0.293082	51.4207	0.100098	0.229636	338	0.490324
1/19/2019	14	59	37	69.9015	0.255148	0.382571	107.783	36.5223	0.15094	19	0.498931
3/10/2019	14	59	37	40.407	0.238243	0.357274	58.8198	23.4667	0.37485	70	1.56569
3/13/2019	14	59	37	30.7901	0.157221	0.235781	52.1798	22.2106	0.475227	73	2.19779
4/2/2019	14	59	37	14.8875	0.099836	0.149737	26.3915	11.3279	0.274299	93	2.49258
4/12/2019	14	59	37	17.3361	0.066877	0.100303	28.536	12.8848	0.14928	103	2.24333
4/19/2019	14	59	37	13.2417	0.091264	0.136882	22.8247	9.88852	0.389187	110	4.04733
4/29/2019	14	59	37	14.7448	0.171025	0.256509	28.7732	0.087721	0.601613	120	3.9706
5/2/2019	14	59	37	15.326	0.067992	0.101977	25.9773	11.8266	0.288909	123	4.18469
5/9/2019	14	59	37	13.1192	0.083173	0.124748	22.984	9.89576	0.464564	130	5.36752
5/12/2019	14	59	37	15.1354	0.066649	0.099962	25.5907	11.4829	0.364719	133	5.35978
6/8/2019	14	59	37	15.2904	0.148186	0.222254	29.4648	4.70699	0.937195	160	5.51664

Figure 1.12. Indices derived from Sentinel 2

Chapter 2. Assessment of water availability and efficiency of irrigated agriculture

2.1. Indicators

In water economy, the irrigation water use efficiency is understood frequently as a ratio of the produced output cost and the production inputs. In a broader sense, efficiency can be represented as a ratio between the achieved result and the resources used.

If one of the tasks of irrigation system is meant to deliver irrigation water from the source to plant while avoiding water losses as much as possible, then the irrigation water use efficiency can be expressed as a ratio of the amount of water used by plants ($ETa * F$, m^3) to the amount of water delivered to the irrigation system, district or province (W, m^3) plus rainfall ($O * F$, m^3) and groundwater contribution (G, m^3):

$ETa * F / (W + G + O * F)$ … (1)

where: ETa is actual evapotranspiration (m), O is rainfall (m), G is groundwater contribution by Khardtchenko-Laktaev's formula (m^3), and F is irrigated area (m^2).

Indicator (1) can be translated to form (2), which characterizes water losses in given boundary (big irrigation system, district, and province) in percent (%) of water intake:

$[1 - ETa * F / (W + G + O * F)] * 100$ … (2)

Independent satellite remote sensing (RS) information (data) supported by ground-based calibration is critical for sound analysis on indicators (1, 2). The energy-balance models using RS data allow determining ETa as a remainder term of the energy balance equation.
Dynamics of ETa at district or province level in CA can be traced with the help of the online RS-based platform WUEMoCA based on free satellite imagery MODIS 250 m and open global climate data. WUEMoCA beta-version is available on SIC ICWC server in Tashkent on http://wuemoca.net/.
Another indicator of irrigation water use efficiency can be the ratio of the actual amount of water used for growing harvest (ETa, m) to the amount of water needed for plant (ETc, m):

ETa / ETc … (3)

The ratio ETa/ETc characterizes water availability for plants in given boundary of irrigated land and also mirrors probable effects of other stress factors; if other factors but water are neglected, this indicator may indicate to: deficit ($ETa/ETc < 1$) or excess of water, i.e. unreasonable losses ($ETa/ETc > 1$), when more water is applied to plant than needed. Evapotranspiration, which reflects crop water requirements, is derived from linear relationship:

$ETc = Kc * ETo$ … (4)

where: Kc is crop coefficient,
ETo (m) - the evaporating power of the atmosphere expressed as reference evapotranspiration is a climatic parameter (i.e. depends on climate data) and is calculated according to FAO methodology (Penman-Monteith equation),
ETc is crop evapotranspiration under standard conditions – the average weighted over F area ($ETc = \sum ETci * Fi \ / \sum Fi$) (m)

Indicator (3) can be translated to form (5) which characterizes deficit (minus "-") or excess (plus "+") of water used by plant, in per cent (%) of calculated requirements (norm):

$[ETa / ETc - 1] * 100$ … (5)

2.2. Assessment

Assessment of irrigation water use efficiency is demonstrated below for provinces and districts in the Central Asian countries. The assessment was done for growing seasons on the base of the RS-based WUEMoCA tool and the ground data over 2012-2017.

Table 2.1 shows the indicators of water availability (3) and irrigation water use efficiency (1) for the growing season on average by country.

Table 2.1. Dynamics of water availability and irrigation water use efficiency for growing seasons 2012-2017 in CA countries

Country	2012	2013	2014	2015	2016	2017	Average
Water availability ETa / ETc							
Kazakhstan	0.86	0.8	0.87	0.81	0.89	0.93	0.86
Kyrgyzstan	0.76	0.71	0.88	0.87	0.87	0.86	0.83
Tajikistan	0.84	0.82	0.86	0.85	0.89	0.88	0.86
Uzbekistan	1.01	0.95	0.9	0.89	0.94	0.89	0.93
Average by country	0.87	0.82	0.88	0.86	0.9	0.89	0.87
Irrigation water use efficiency ETa * F / (W + G + O * F)							
Kazakhstan	0.67	0.63	0.64	0.64	0.67	0.69	0.66
Kyrgyzstan	0.62	0.59	0.65	0.66	0.64	0.59	0.63
Tajikistan	0.54	0.52	0.5	0.47	0.52	0.45	0.5
Uzbekistan	0.56	0.56	0.56	0.53	0.57	0.56	0.55
Average by country	0.6	0.58	0.59	0.57	0.6	0.54	0.58

Kazakhstan

The indicators on Kazakhstan are the average for Kyzylorda and Turkestan (former South-Kazakhstan until 2018) provinces.
On average, the water availability indicator changed from 0.8 to 0.93 in Kazakhstan over 2012-2017. This indicates to 1.2 – 0.4 km^3 shortage of water for crops during the growing season. The indicator varied from 0.75 to 0.94 at province level and within 0.65 – 1.02 by district.
The irrigation water use efficiency indicator varied on average from 0.63 to 0.69 over 2012-2017. This shows to water losses of 1.9 – 2.2 km^3 in irrigation systems during the growing season. The indicator even decreased to 0.37 (63% of losses in irrigation systems) in some districts.

Kyrgyzstan

The indicators on Kyrgyzstan are the average for Djalal-Abad, Batken and Osh provinces. No estimation was made for Naryn province, as well as for provinces that are situated outside the Aral Sea basin (such as Issyk-Kul, Talass, and Chu provinces).
The water availability indicator varied on average from 0.71 to 0.88 in Kyrgyzstan over 2012-2017 and indicated to 0.8 – 0.3 km^3 shortage of water during the growing season. The value of this indicator is 0.61 – 0.89 by province and 0.4 – 1.0 by district.
The efficiency indicator averaged 0.59 to 0.65 in the republic. This means that water losses in irrigation systems amounted to 0.9 – 1.1 km^3 during the growing season over 2012-2017. The indicator dropped to 0.57 in provinces in some years. In some of certain districts water losses amounted to 64% (efficiency indicator 0.36).

Tajikistan

The indicators on Tajikistan are the average for Khatlon and Sogd provinces and for Districts of Republican Subordination (RPP). The estimation was not made for the Gorno-Badakhshan Autonomous Region (GBAR).

The water availability indicator ETa/ETc varied within 0.82 – 0.89 (1.26 – 0.78 km^3 shortage of water) on average in Tajikistan over 2012-2017 and within 0.76 to 0.94 by province. Individual cases were found in districts of Sogd province and RPP, where this indicator was 10-20% more than one, i.e. excessive amount of water was applied to crops during the growing season.

The efficiency indicator ETa * F / (W + G + O * F) changed from 0.45 to 0.54 on average over the republic in 2012-2017, i.e. 4.2 – 3.4 km^3 of water were lost in irrigation system during the growing season. This indicator varied within 0.43 – 0.67 by provinces in Tajikistan over the same period of time. The value of 0.67 derived from the data on RPP (indicating to 37% losses in irrigation system) raises questions. It seems that this indicator is somewhat high because of inaccurate (under-reported) data on water use.

Uzbekistan

The water availability (3) and irrigation water use efficiency (1) by water-management districts of Uzbekistan are shown in Table 2.2 over the period 2012-2017. Indicators on the Fergana Valley are the average of Namangan, Andijan and Fergana provinces, while those on the Syr Darya middle reaches are the average of Tashkent, Syrdarya, and Djizakh provinces. The Amu Darya upper reaches provisionally include Surkhandarya and Qashkadarya provinces. Then, Samarkand, Bukhara, and Navoi provinces were considered as those referred to the Amu Darya middle reaches. Indicators on the Amu Darya lower reaches are the average of the Khorezm province and the Republic of Karakalpakstan. The assessment was made for growing seasons.

Table 2.2. Dynamics of water availability and irrigation water use efficiency over 2012-2017 by water-management district of Uzbekistan

Water-management district	2012	2013	2014	2015	2016	2017	Average
Water availability ETa / ETc							
Syr Darya basin	1.14	1.04	1.01	0.94	0.98	1.01	1.02
of which:							
Fergana Valley	1.27	1.15	1.11	1.01	1.03	1.14	1.12
Middle reaches	1.01	0.93	0.92	0.87	0.94	0.88	0.93
Amu Darya basin	0.91	0.88	0.81	0.85	0.91	0.79	0.86
of which:							
Upper reaches	0.95	0.86	0.84	0.82	0.88	0.88	0.87
Middle reaches	1.00	0.91	0.88	0.91	1.00	0.87	0.93
Lower reaches	0.77	0.87	0.72	0.83	0.85	0.61	0.78
Irrigation water use efficiency ETa * F / (W + G + O * F)							
Syr Darya basin	0.53	0.53	0.55	0.5	0.53	0.5	0.52
of which:							
Fergana Valley	0.57	0.56	0.57	0.51	0.54	0.55	0.55
Middle reaches	0.48	0.5	0.53	0.49	0.52	0.46	0.49
Amu Darya basin	0.58	0.59	0.57	0.55	0.6	0.55	0.57
of which:							
Upper reaches	0.65	0.64	0.65	0.62	0.69	0.61	0.64

Middle reaches	0.61	0.57	0.6	0.54	0.59	0.59	0.58
Lower reaches	0.45	0.54	0.47	0.49	0.50	0.44	0.48

As Table 2.1 shows, the average water availability over 2012-2017 was estimated at 0.93; this means that crops lack 7% of delivered water as compared to FAO recommendations or 2.8 km^3 of flow during the growing season. There is small trend towards an increase in water deficit – from excess water in 2012 (0.4 km^3) to maximal deficit in 2017 (4.5 km^3).

In the Republic of Uzbekistan, variations of water availability indicator over the territory and by year were within 25-40%: from the indicator values of more than one (i.e. water applied in excess of crop requirements) to less than one (water deficit). The reasons could be inaccuracies in estimation of water requirements and non-uniform distribution of water over the territory.

Over 2012 – 2017, the water availability indicator varied from 0.94 to 1.14 in the Syr Darya basin and from 0.79 to 0.91 in the Amu Darya basin. On average, this indicator is estimated at 1.02 for the Syr Darya basin and 0.86 for the Amu Darya basin. Thus, excessive application of water to crops (2%), was observed in the Syr Darya basin, while the Amu Darya basin experienced 14% of water deficit.

Highest values of water availability ETa/ETc were observed in Namangan (1.2), Andijan (1.11), and Fergana (1.06) provinces, while the lowest values were in Khorezm (0.81) and Navoi (0.79) provinces and in Karakalpakstan (0.76). Thus, more water than required is applied to crops in some of provinces, while others suffer from water deficit. Such inequality contributes to lower productivity of irrigation water. Variations of ETa/ETc in district dimension are even wider. District-level water availability differs from the average province-level one from + 48% to -28% in the Fergana Valley.

Water deficit for plants can be avoided by reducing water losses in irrigation systems and on fields. These losses are estimated on average at 45% or 17.8 km^3 during the growing season (efficiency indicator 0.55). Over 2012-2017, water losses varied from 16.2 km^3 to 18.9 km^3 of water delivered during the growing season.

Dynamics of water availability indicators by province in Uzbekistan over 2012-2017 is shown in Fig. 2.1.

The efficiency indicator is estimated at 0.5 – 0.55 in the Syr Darya basin and 0.55 – 0.6 in the Amu Darya basin (see Table 2.2). Thus, on average over 2012-2017 water losses in irrigation system are estimated at 48% in the Syr Darya basin during the growing season, whereas in the Amu Darya basin those are 5% lower than in the Syr Darya and reach 43%. Moreover, losses in rivers and reservoirs in the Amu Darya basin (in the Uzbek territory) well exceed open channel losses in the Syr Darya.

The highest values of efficiency ETa * F / (W + G + O * F) are observed in Djizakh (0.7), Kashkadarya (0.69) and Samarkand (0.64) provinces, while the lowest ones (indicating to substantial water losses) – in Karakalpakstan (0.49), Khorezm (0.47) and Tashkent (0.4) provinces.

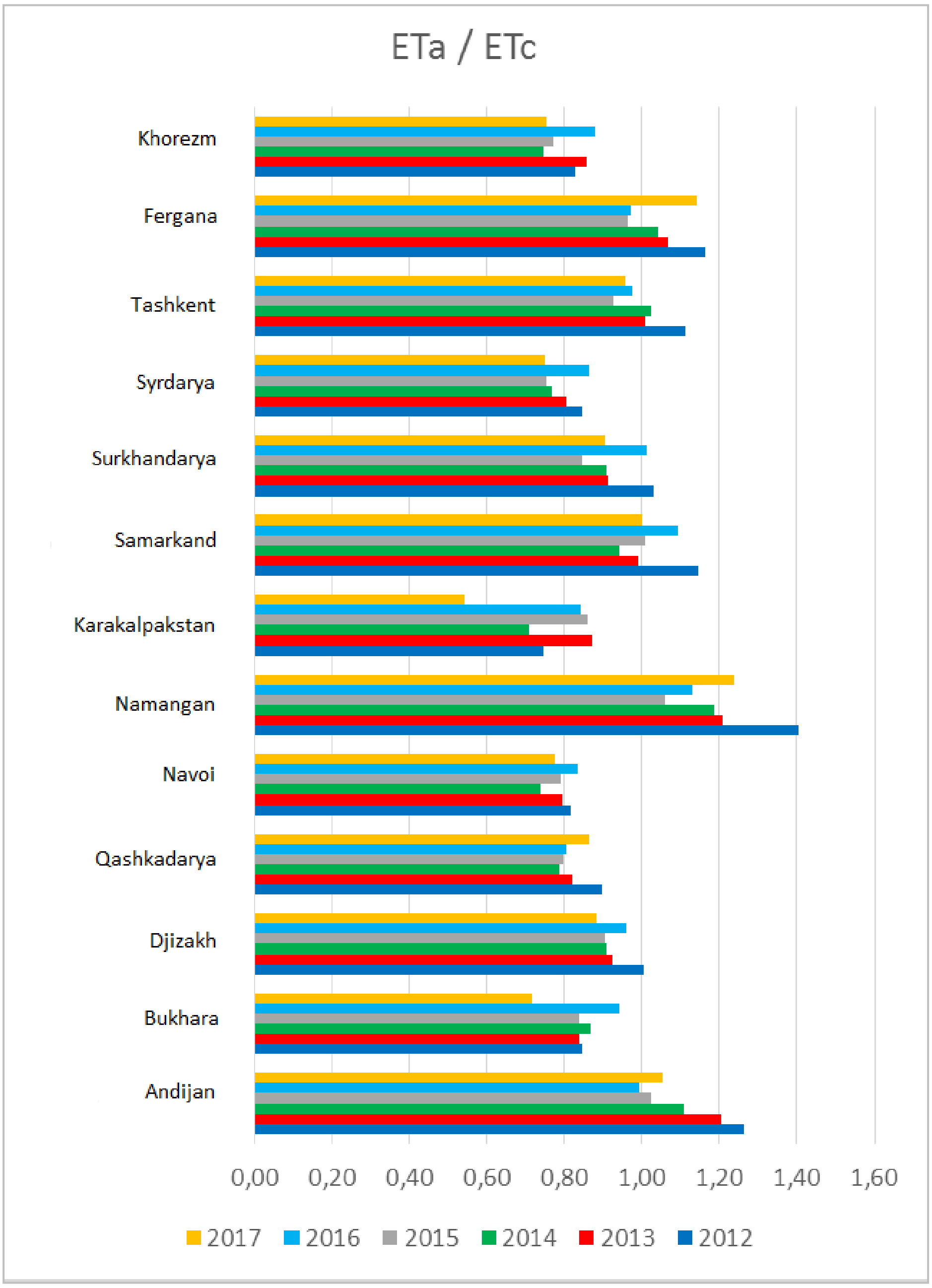


Figure 2.1. Dynamics of water availability by province in Uzbekistan

According to the data of the Uzbek Ministry of Agriculture and Water Resources over 2017, the irrigation system efficiency in provincial dimension varies from 0.56 (Karakalpakstan) to 0.77 (Djizakh province). The whole system efficiency (including on- and inter-farm network) in Uzbekistan is estimated on average at 0.64, and, if consider field losses, at 0.5. Thus, WUEMoCA-based estimations of the efficiency indicator for the growing season show values that are 5% lower than those based on the Ministry's data for the whole year.

Dynamics of water use efficiency indicator in provincial dimension over 2012-2017 is shown in Figure 2.2.

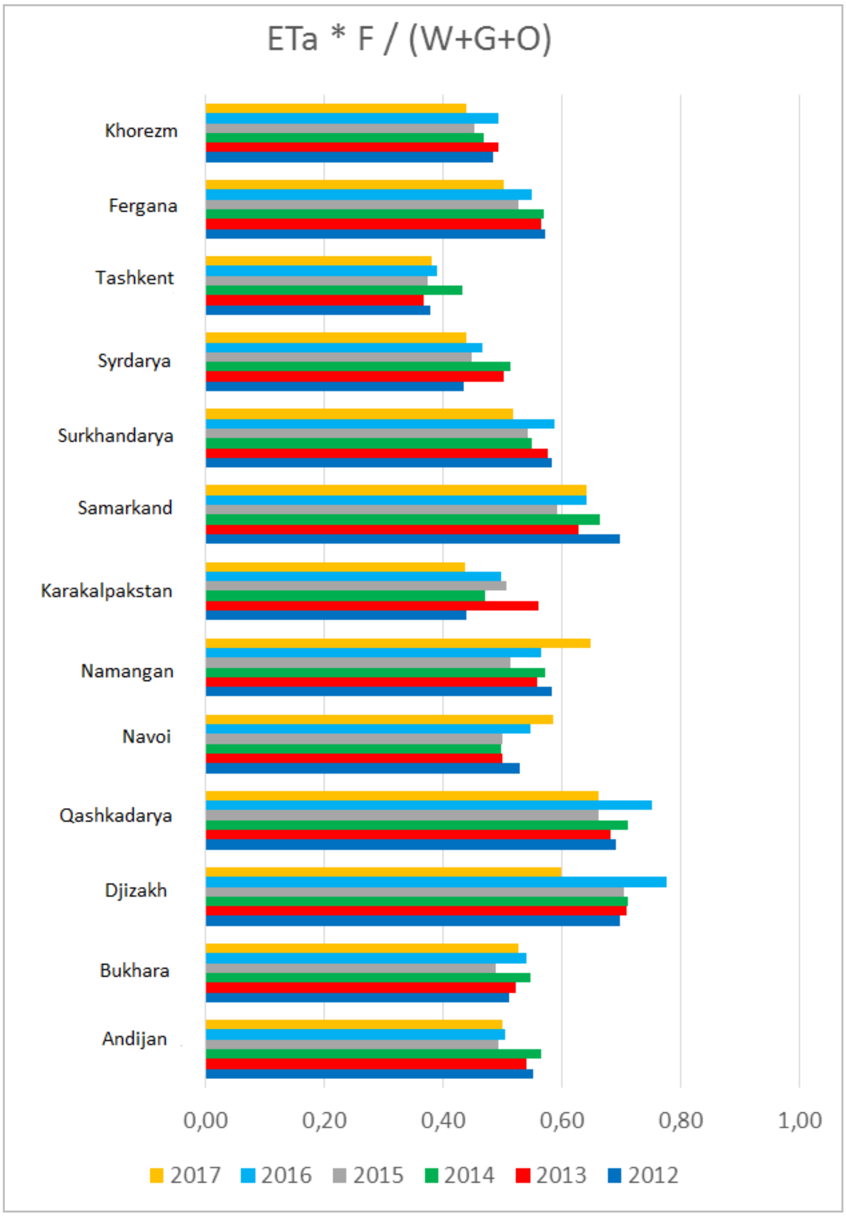


Figure 2.2. Dynamics of efficiency indicator by province in Uzbekistan

The indicators of efficiency and water availability at province level in Tajikistan, Kyrgyzstan and Kazakhstan are shown in Figures 2.3 and 2.4.

For interpretation of WUEMoCA indicators on maps, an online tool (*http://cawater-info.net/data*) was used. This tool visualizes efficiency indicators in map format by color zones, depending on available data range (developed by D. Sorokin). The information is displayed within administrative district boundaries on a map (see Fig. 2.5).

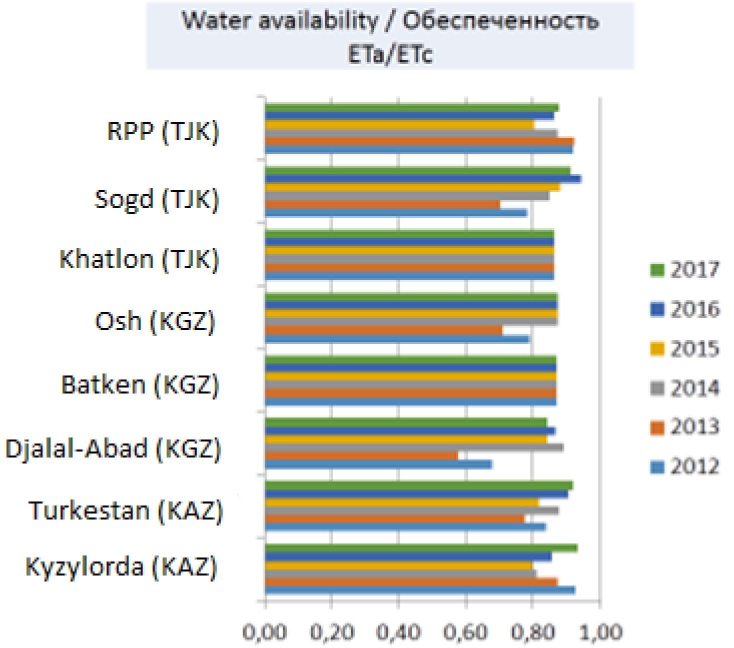


Figure 2.3. Dynamics of water availability by province in Tajikistan, Kyrgyzstan and Kazakhstan

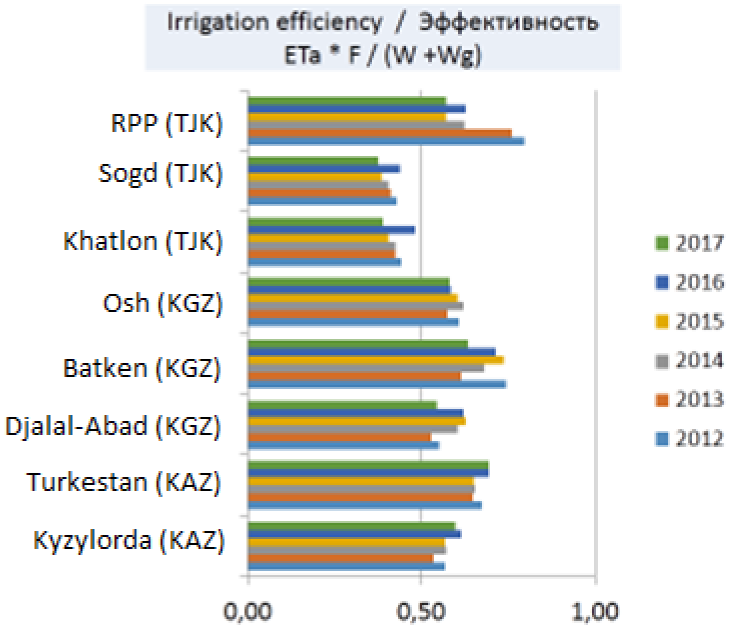


Figure 2.4. Dynamics of irrigation efficiency by province in Tajikistan, Kyrgyzstan and Kazakhstan

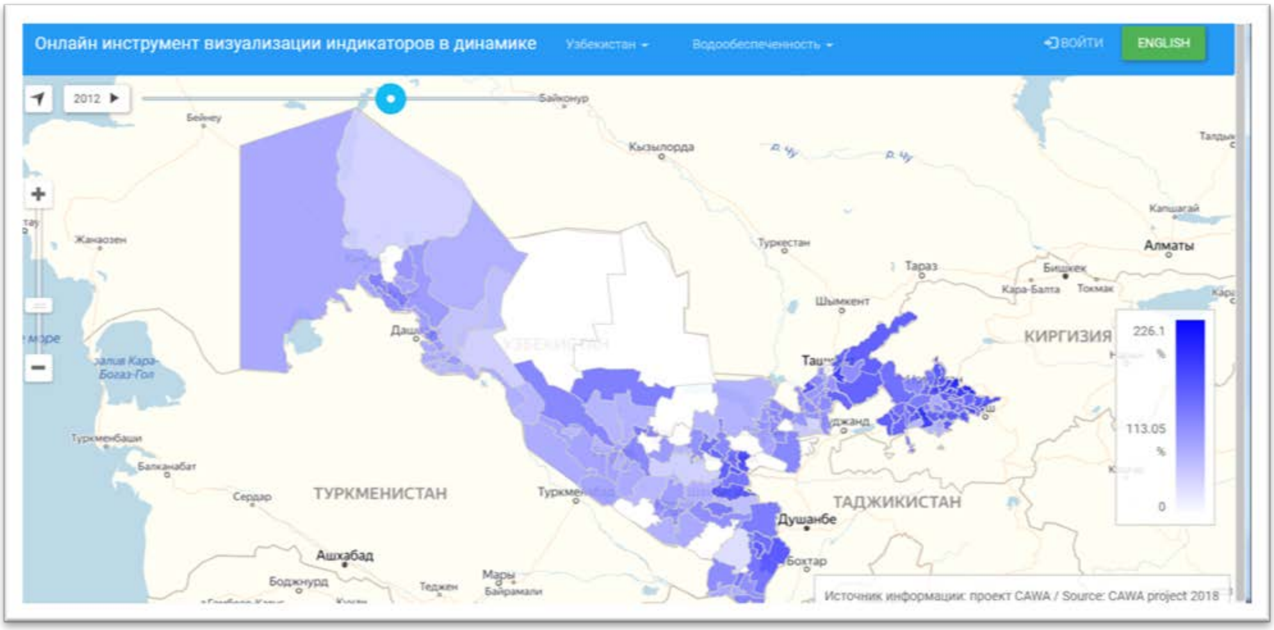


Figure 2.5. Visualization of ETa/ETc by district of the Republic of Uzbekistan over time from 2012 to 2017

CONCLUSIONS on Chapter 2

1. At present, WUEMoCA is as close to user needs as possible and represents an effective system for collection, analysis and dissemination of data for assessment of water management at province, district and large irrigation system levels in CA countries (within the Aral Sea basin) based on the combination of remote sensing data and ground-based observations (from operation services and statistics).
2. The analysis shows that the results of assessment of water availability and irrigation water use efficiency in districts and provinces of CA countries on the base of WUEMoCA can be considered preliminary and require further clarification through checking of statistics for completeness and reliability and improvement of satellite imagery processing algorithm.
3. The proposed methodology for assessment of irrigation water use efficiency on the base of WUEMoCA data and ground-based observations allows finding potential for improvement of water and land use efficiency as early as at the current stage of development (end of 2019): it is possible to save water and reduce deficit through better management of water supply (reduction of losses in irrigation systems, even spread of water deficit by improving water planning and accounting) and demand (more accurate definition of crop water requirements).

Chapter 3. Field research for RS-data validation

The objective of given chapter is to search approaches to further development of existing and potential RS-based tools for agricultural field monitoring to ensure effective routine management of crop growing.

The earlier work on yield programming [1] allowed assessing a contribution of every factor to crop production. Basic soil fertility and climatic conditions form potential field productivity. However, as was show in that work, different yields are achieved under similar basic conditions. This is caused by quality of agronomic process management. The yield programming method identifies controllable agronomic factors of agricultural production and estimates yield losses by the end of growing season. Many issues of crop management can be solved as early as during growing by keeping observation over plant conditions with the help of RS.

However, one of important issues is the provision of crop with irrigation water.

As a result of given work, the developed tool that provides current information on each field during growing season with the use of MODIS images (resolution 250x250 m), LANDSAT images (resolution 30x30 m), Sentinel 2 images (resolution 10x10 m) and WUEMoCA database will be tested. Water availability is estimated from the ratio of ETa (actual evapotranspiration from RS data analysis) to the estimated evapotranspiration.

The proposed method was checked on the fields of Oktepa Zilol WUA in Kushtepa district, Fergana province, Uzbekistan. Ground-based observations of agronomic operations, including actual water delivery, were made to estimate fitting of calculation results to the actual data. In the past few years, Oktepa Zilol WUA was selected as pilot one to study the possibility of using RS-based data in operational crop management. In 2019, the total area of WUA was 1,010.4 ha, of which 910.8 ha were irrigated. 13 farms, with the total crop acreage of 132.9 ha, were selected for observations.

Generally recognized and recommended crop cultivation technology was practiced in the fields. Autumn operations for cotton included plowing and land leveling. In 2019, cotton was sown earlier than in 2017 and 2018. The sowing season started in the end of March – from 23 March to 14 April. In 2018, only Namangan-77 cotton variety was sown, at the norm of 50-60 kg/ha, whereas C-65-24 variety, 25-40 kg/ha, was mainly sown in 2019. Just after sowing, fertilizers were applied: carbamide, agro, superphosphate, and potassium. During vegetation, 3-4 cultivations were made, including application of fertilizers, such as ammonium nitrate, hoeing after watering, hand weeding, and manual harvesting.

The norm of fertilizer application is set by Agroservice for all farmers. As a rule, 300 kg/ha of superphosphate, up to 500 kg/ha of ammonium nitrate, 60-100 kg/ha of Agro, 100kg/ha of carbamide, and 50 kg/ha of potassium were applied. After organization of clusters, specialists strictly control norms and dates of fertilizer application. Recharge irrigation was practiced at a norm of up to 3,500 m^3/ha, and 4 applications of water were made during vegetation at a norm of 900-1,000 m^3/ha; in general, the irrigation norm was 3,850-7,150 m^3/ha in the fields. In 2019, maize for silage was grown as a double-season crop in one pilot field only; carrot and other vegetables were mainly grown as double-season crops.

Phenological observations were made during the whole growing season, from sowing to harvesting. In the pilot fields, conditions of plants were monitored every 1st and 15th day of each month during several days. In parallel, a comparison was made with images taken from October 2018 to August 2019, which allowed tracking the growing season of wheat and cotton from sowing to harvesting. For given task, ground points were selected in each pilot plot. After that, accuracy was checked by overlaying ground points (GPS points) on Google Earth. Then, ground points were overlaid on Sentinel 2 NDVI images to detect crop phenology. After extraction of wheat, tables were compiled (Tables 3.1 and 3.2), and graphs were plotted with phenology of wheat (Figure 3.1) and cotton (Figure 3.2) based on these tables.

Table 3.1. Value of NDVI for winter wheat fields, OktepaZilol WUA, 2019

№	4 Oct	21 Oct	10 Nov	3 Dec	19 Jan	10 Mar	13 Mar	2 Apr	19 Apr	29 Apr	2 May	9 May	12 May	8 Jun	21 Jun	28 Jun	1 Jul
10	0.28	0.26	0.13	0.14	0.28	0.24	0.18	0.21	0.34	0.37	0.37	0.40	0.41	0.47	0.45	0.47	0.45
13	0.27	0.17	0.11	0.12	0.47	0.51	0.40	0.57	0.82	0.77	0.86	0.82	0.83	0.29	0.19	0.19	0.20
15	0.36	0.18	0.12	0.12	0.44	0.51	0.39	0.57	0.77	0.64	0.79	0.78	0.80	0.41	0.38	0.33	0.33
26	0.26	0.09	0.08	0.14	0.49	0.50	0.42	0.62	0.83	0.76	0.83	0.79	0.79	0.24	0.20	0.20	0.20
31	0.32	0.19	0.08	0.07	0.44	0.39	0.30	0.50	0.76	0.65	0.81	0.80	0.81	0.34	0.33	0.27	0.25
59	0.32	0.19	0.08	0.07	0.44	0.39	0.30	0.50	0.76	0.65	0.81	0.80	0.81	0.34	0.33	0.27	0.25
107	0.32	0.18	0.10	0.09	0.41	0.55	0.41	0.63	0.80	0.69	0.86	0.81	0.85	0.37	0.41	0.43	0.44
134	0.29	0.18	0.11	0.10	0.43	0.60	0.44	0.72	0.84	0.71	0.86	0.84	0.84	0.37	0.35	0.34	0.31
168	0.42	0.24	0.11	0.07	0.32	0.44	0.30	0.49	0.72	0.58	0.78	0.74	0.74	0.36	0.45	0.35	0.32
284	0.40	0.26	0.10	0.05	0.29	0.46	0.36	0.63	0.81	0.59	0.85	0.81	0.83	0.36	0.35	0.30	0.30
399	0.33	0.19	0.07	0.05	0.30	0.38	0.28	0.41	0.68	0.55	0.77	0.71	0.71	0.36	0.35	0.26	0.26
484	0.34	0.22	0.07	0.06	0.32	0.45	0.36	0.63	0.84	0.58	0.86	0.84	0.86	0.38	0.33	0.31	0.26
606	0.29	0.19	0.08	0.07	0.30	0.43	0.36	0.64	0.78	0.61	0.83	0.79	0.82	0.37	0.27	0.31	0.08

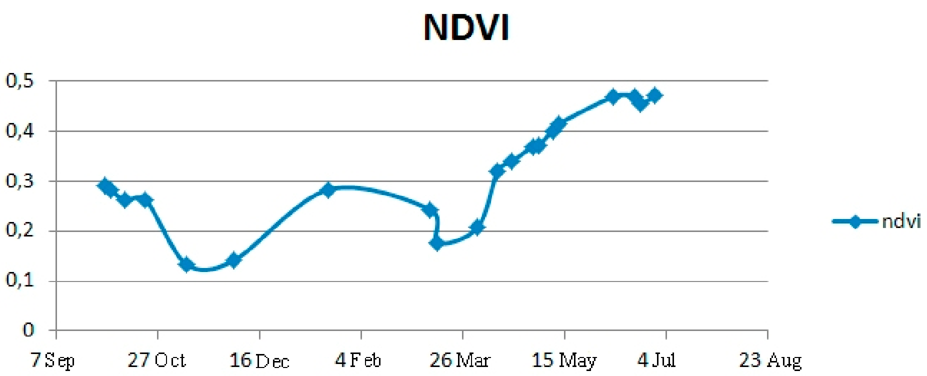


Figure 3.1. Wheat phenology, NDVI

Table 3.2. Value of NDVI for cotton fields, Oktepa Zilol WUA, 2019

№	2 Apr	19 Apr	29 Apr	2 May	12 May	8 Jun	21 Jun	1 Jul	18 Jul	28 Jul	31 Jul	7 Aug	10 Aug	17 Aug	20 Aug	27 Aug	30 Aug
14	0.10	0.09	0.17	0.07	0.07	0.15	0.23	0.36	0.64	0.69	0.72	0.73	0.68	0.66	0.72	0.67	0.67
15	0.09	0.09	0.13	0.09	0.07	0.25	0.35	0.36	0.63	0.71	0.71	0.75	0.73	0.72	0.77	0.71	0.71
18	0.11	0.08	0.12	0.08	0.06	0.17	0.27	0.36	0.55	0.61	0.62	0.67	0.65	0.62	0.66	0.64	0.65
20	0.11	0.08	0.16	0.09	0.08	0.17	0.27	0.35	0.59	0.62	0.63	0.73	0.70	0.68	0.72	0.67	0.70
24	0.09	0.10	0.15	0.11	0.13	0.27	0.39	0.54	0.79	0.82	0.81	0.84	0.79	0.76	0.80	0.72	0.70
63	0.20	0.24	0.27	0.19	0.21	0.25	0.33	0.42	0.61	0.66	0.66	0.67	0.68	0.68	0.73	0.68	0.69
137	0.15	0.15	0.22	0.14	0.13	0.22	0.30	0.49	0.70	0.69	0.69	0.70	0.63	0.53	0.58	0.55	0.55
377	0.12	0.15	0.24	0.13	0.11	0.21	0.32	0.54	0.67	0.73	0.73	0.74	0.72	0.70	0.75	0.73	0.70
394	0.13	0.15	0.24	0.13	0.13	0.26	0.40	0.58	0.69	0.71	0.71	0.69	0.63	0.63	0.69	0.62	0.67
411	0.09	0.11	0.22	0.10	0.09	0.15	0.21	0.31	0.57	0.61	0.67	0.73	0.71	0.68	0.73	0.68	0.72
480	0.13	0.19	0.24	0.13	0.14	0.21	0.32	0.44	0.64	0.75	0.76	0.74	0.73	0.70	0.76	0.73	0.72
538	0.10	0.13	0.22	0.11	0.10	0.22	0.25	0.33	0.68	0.74	0.73	0.72	0.72	0.68	0.73	0.66	0.69

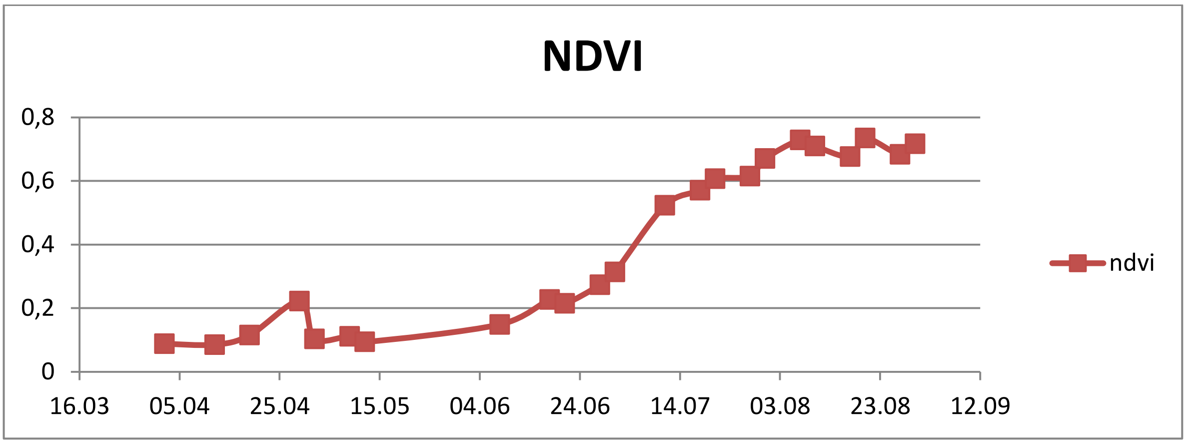


Figure 3.2. Cotton phenology, NDVI

Changes in cotton biomass in the pilot fields are shown in Figures 3.3 - 3.6.

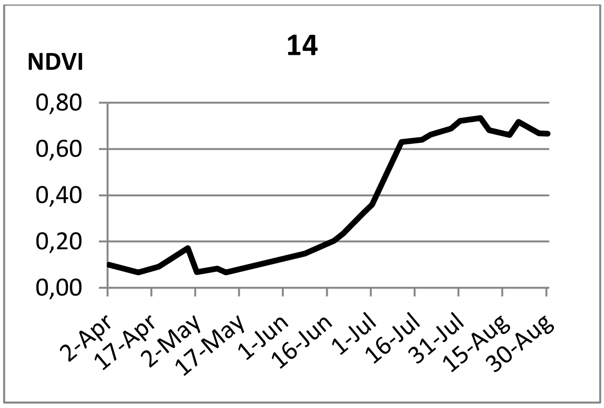


Figure. 3.3. Change in cotton biomass, area 14

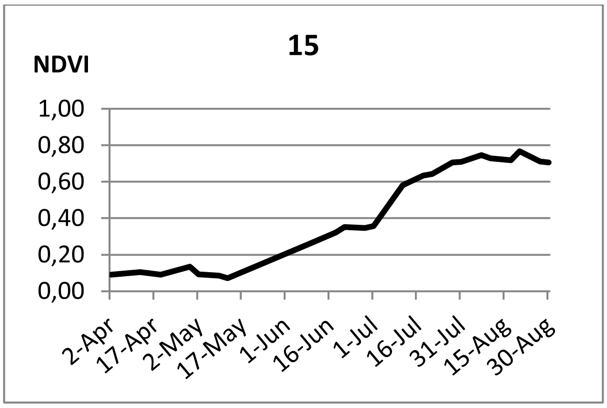


Figure. 3.4. Change in cotton biomass, area 15

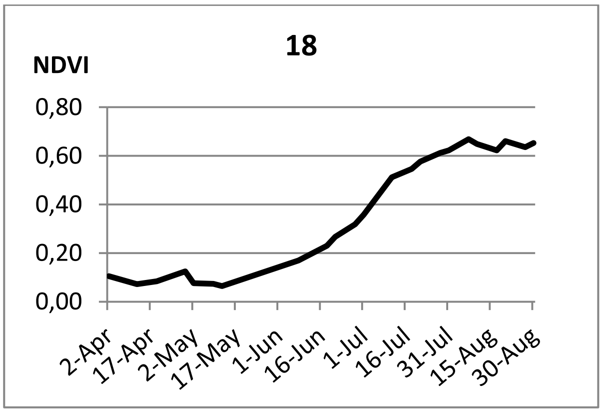


Figure 3.5. Change in cotton biomass, area 18

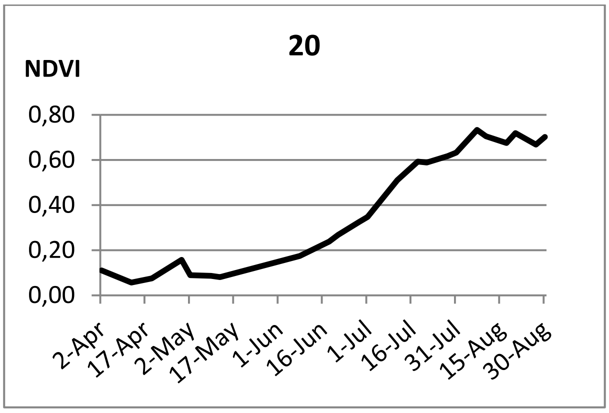


Figure 3.6. Change in cotton biomass, area 20

The analysis of images allowed fixing, processing, and analyzing NDVI from April till the end of vegetation. NDVI values vary from 0.09-0.20 in April to 0.52-0.71 in August, given that sowing time affected biomass formation in spring. The earliest sowing period, 24.03-31.03.2019, was observed in areas 63, 377, and 15, and the latest, 14.04. 2019 – in area 14. Biomass formation from the date of sowing is reflected on the dynamics of NDVI changes (Figure 3.3 - Figure 3.6).

The NDVI value was the highest on 29 April for field area 63 and equaled 0.27. This is clearly shown in the Graph (Figure 3.7).

NDVI value for cotton fields decreases in August, as the growing season comes to an end. Massive harvesting took place from mid to late September. In this period of time, NDVI decreased even more. According to the results of the last year, it decreased twice from maximum of 0.52-0.71 before harvesting to 0.17-0.31 after harvesting in late September. This year, the analysis was based on NDVI data acquired till September.

NDVI dynamics by date depends on growth and development of plants in some of areas, initial soil fertility and quality of agronomic operations (Figure 3.7.)

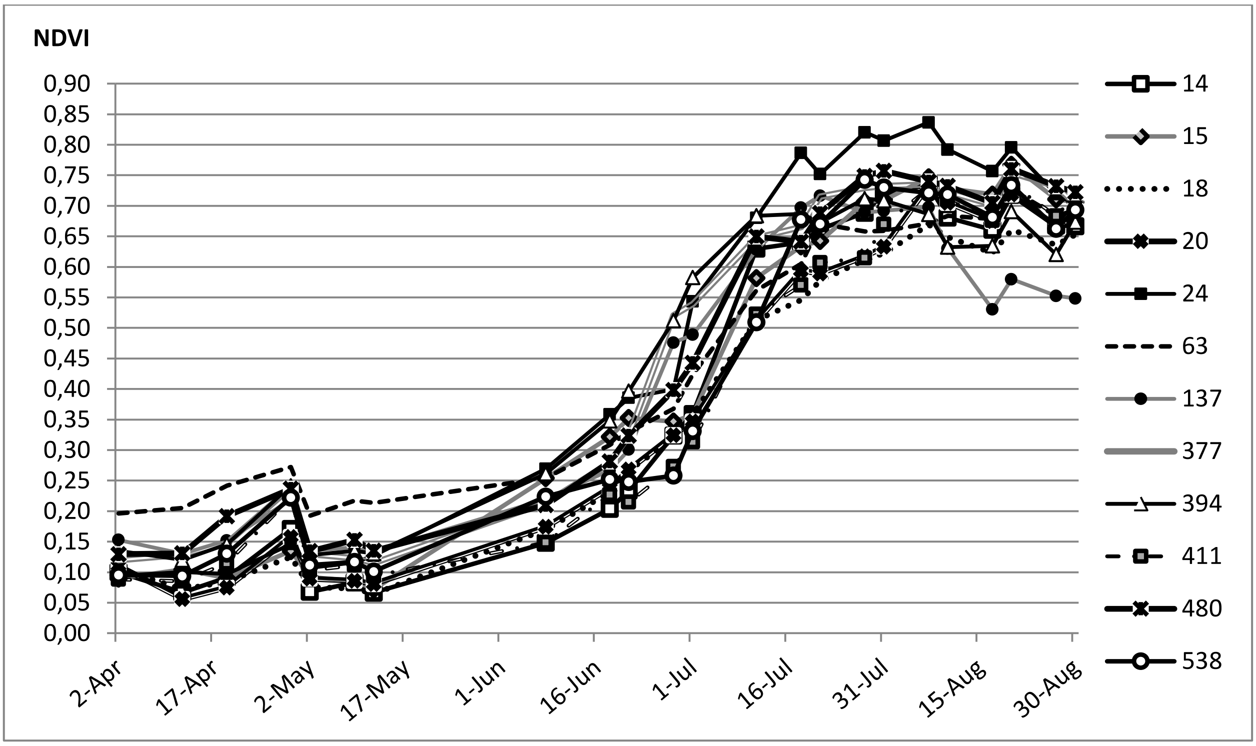


Figure 3.7. Change in cotton biomass in all areas

In given region, the maximum NDVI value was observed on 5 August, and the earliest cotton harvesting took place on 14-19 September.

Relationships between NDVI and cotton yields, especially between maximum yields and maximum NDVI value (Figures 3.8-3.9.), show the following: given the yield of up to 3 t/ha, cotton biomass should be from 0.65 to 0.75 and higher.

Given the yields of 3-4 t/ha, NDVI values vary slightly within 0.7-0.75. In this context, NDVI loses its sensitivity as an index, when biomass is formed higher of certain value.

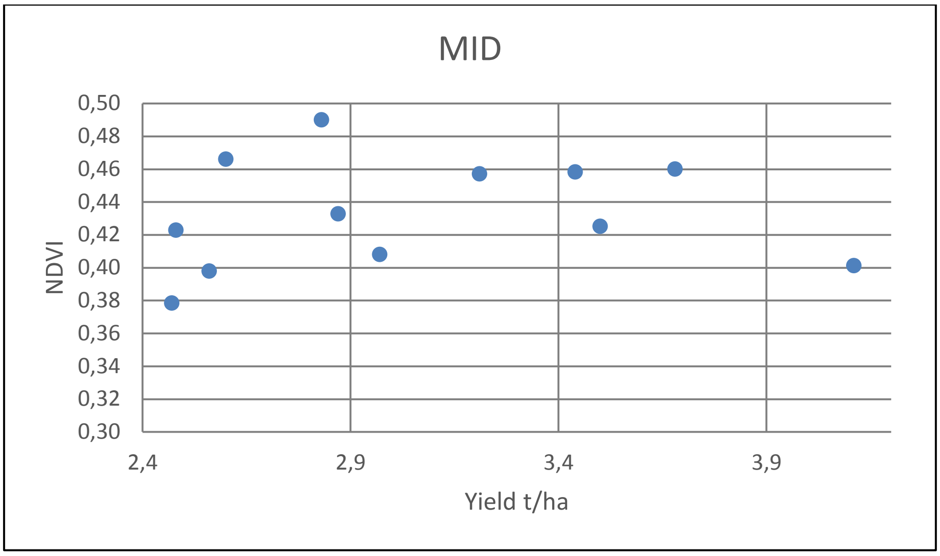


Figure 3.8. Relationship between cotton yield and average NDVI value

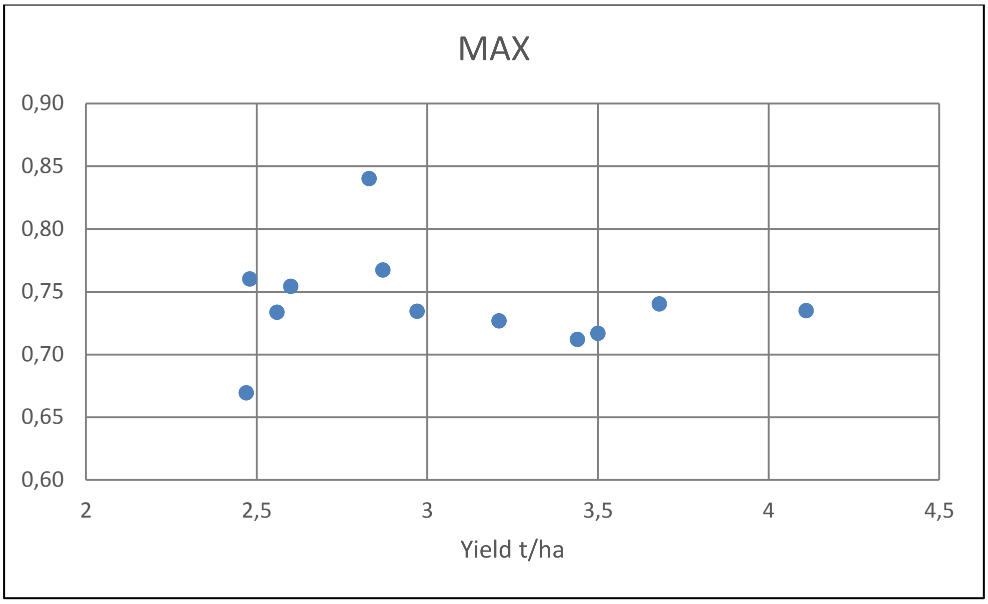


Figure 3.9. Relationship between cotton yield and maximum NDVI value

Yield depends on many factors. For instance, the height of plants, which is closely related to NDVI value as shown in the Figures, is not always the guarantee of good harvest. This can be seen in the field in area 411. The highest cotton plant was observed here during phenological observations. However, there was no maximum yield here.

Winter wheat

Winter wheat is sown under cotton at the beginning-end of November. The report shows NDVI change curves for wheat during vegetation since 1 October 2018 till harvest in June 2019. However, it is inappropriate to analyze NDVI changes in autumn and winter, when biomass on satellite images is almost the same as biomass of guzapoya (dry cotton stem). Guzapoya is completely removed from fields by spring.

Winter wheat starts developing in March-April; biomass is completely formed by the beginning of May (Figures 3.10 – 3. 13).

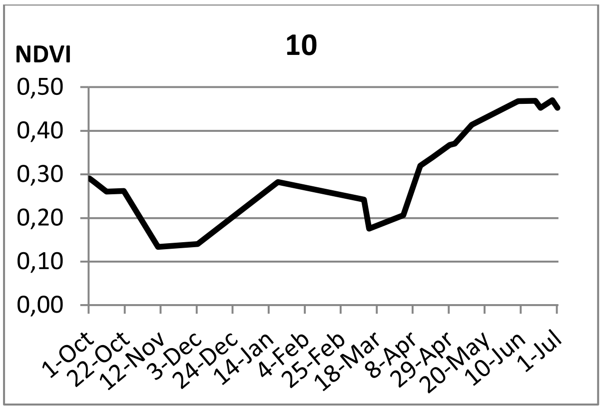


Figure 3.10. Change in wheat biomass, area 10

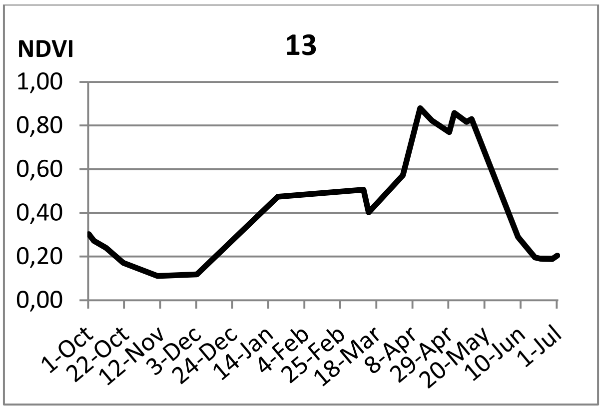


Figure 3.11. Change in wheat biomass, area 13

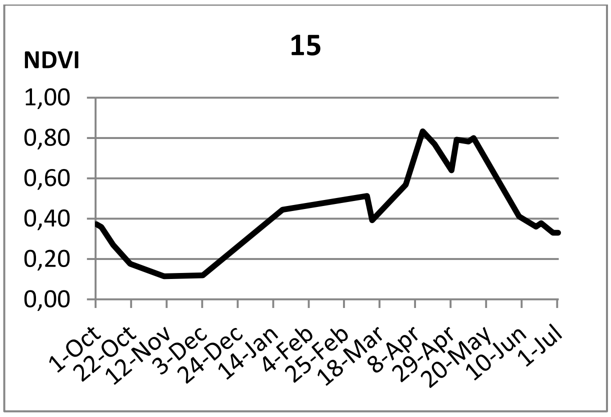


Figure 3.12. Change in wheat biomass, area 15

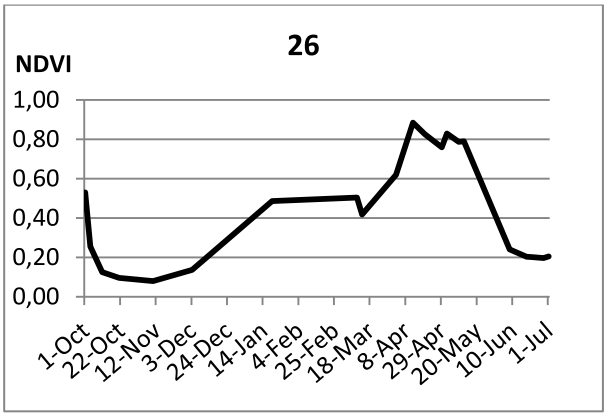


Figure 3.13. Change in wheat biomass

Wheat ripening was uniform in June. NDVI value decreases in May, apparently due to wheat yellowing. In pilot fields, harvesting time varied between 16 June (early harvesting) and 2 July (late harvesting). The highest NDVI value for wheat and its sharp decline are associated with wheat yellowing already from the end of May and harvesting in June (Figure 3.14).

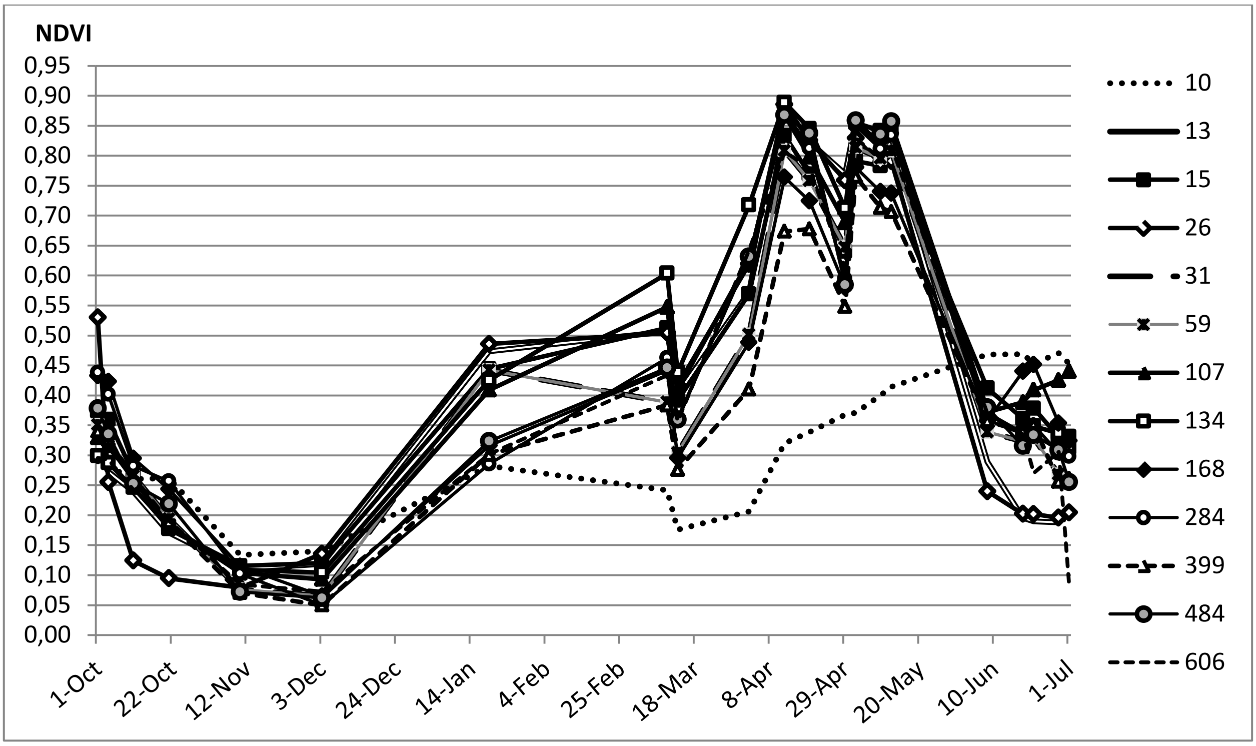


Figure 3.14. Change in wheat biomass in all areas

The derived relationship between wheat yield and average NDVI indicates to large scatter of data, without normal statistical distribution (Figure 3.15, Figure 3.16).

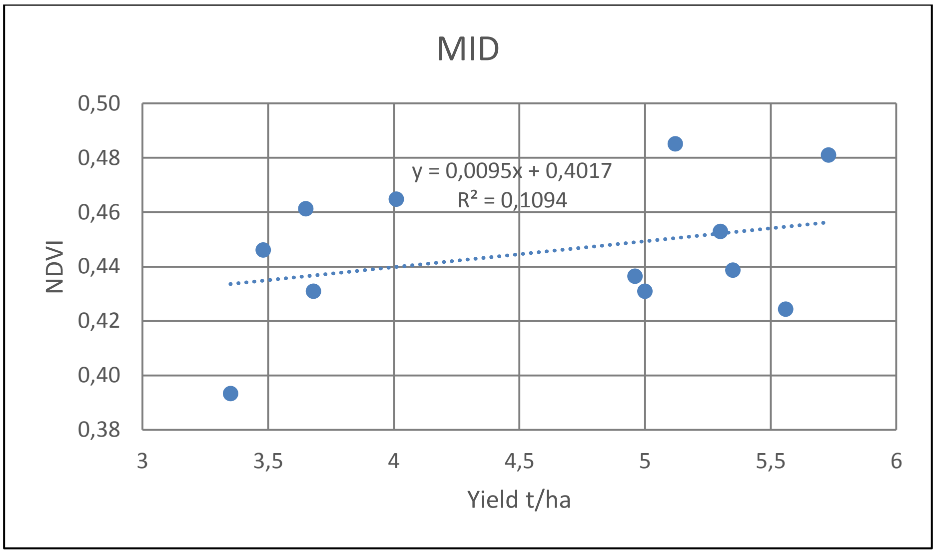


Figure 3.15. Relationship between wheat yield and average NDVI values, pilot fields of Oktepa Zilol WUA

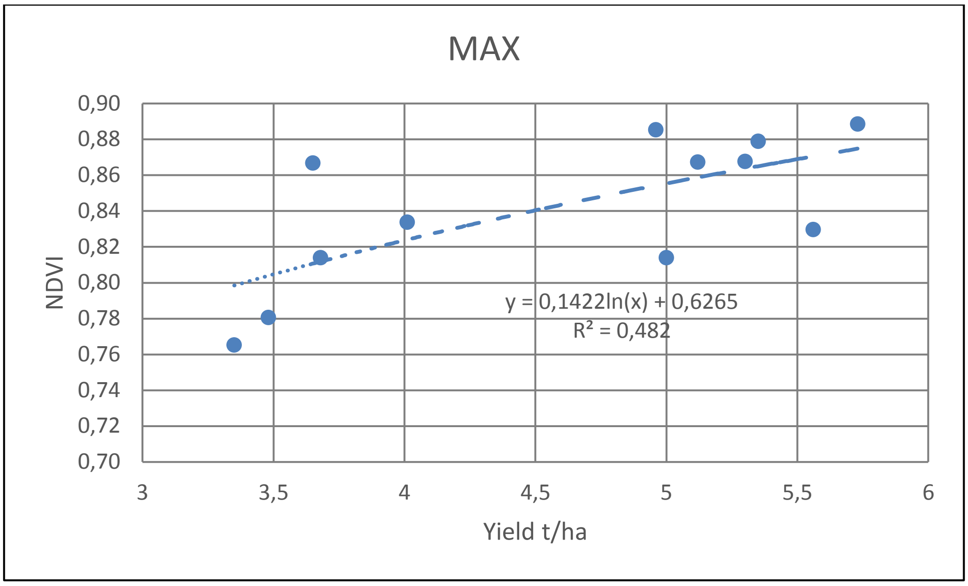


Figure 3.16. Relationship between wheat yield and maximum NDVI values, pilot fields of Oktepa Zilol WUA

In this case, the correlation relationship is weak, and correlation coefficients of relationships between wheat yield and average NDVI values are $R^2 = 0.1094$. At the same time, the correlation coefficients of relationships between wheat yield and maximum NDVI values are $R^2 = 0.482$.

Description of task for identification of damaged fields

Calculation of ETa

ETa was calculated on the base of the methodology described in "**Water Consumption of Agriculture and Natural Ecosystems along the Ili River in China and Kazakhstan".**

https://doi.org/10.3390/w9030207

The formula for calculation of ETa is shown below

$$ET_a = ET_f * ET_{pot} \qquad (4)$$

where

ET_a – actual evapotranspiration.
ET_{pot} – potential evapotranspiration
ET_f – coefficient to account for plant density or decree of soil canopy cover.

$$ET_f = (T_h - T_x) / (T_h - T_c) \qquad (5)$$

where

LST – land surface temperature
T_h - LST at hot pixels
T_c - LST at cold pixels
T_x - LST at the pixel, for which ET_f is calculated.

Hot pixels are areas without vegetation coverage or with rare vegetation. NDVI is lowest in those areas. Cold pixels are areas densely covered with vegetation with intensive evaporation. NDVI is highest in such areas.

“In the S-SEBI approach, a linear relationship between the land surface temperature (LST) and

ET_f is assumed.” In turn, we assume that ET_f and NDVI are also linearly related. Therefore, ET_f can be calculated from NDVI:

$$ET_f = (NDVI_x - NDVI_{min}) / (NDVI_{max} - NDVI_{min}) \qquad (6)$$

ET_{pot} is calculated by Penman-Monteith formular for centroid of WUA. This value will be used for all fields in WUA.

Then, by using the earlier estimated NDVI, we calculate ET_f and ETa. The calculated ETa is processed then as a vegetation index, i.e. saved as *.tif-file and the average weighted value is calculated for each field.

Doubts remain about the correctness of formula (4). ET_f calculated by formulas (5) or (6) is a decreasing coefficient only for ET_{pot}. Probably, this is related to density of canopy coverage. It is worth remembering the definition of potential evapotranspiration as evaporation from a hypothetical grass free from water stress, which **densely covers** the soil cover.

Implicitly these doubts are supported by the fact that expressions (5) and (6) cannot be more than 1.0. This means that ETa will be equal to ET_{pot} at the best. However, a number of crop coefficients can be higher than 1.0 (1.15, 1.2). In our case, when we know which crop is grown in every field of WUA, appropriate crop coefficient could be found for every field and multiplied by ETa of pixels falling in given field.

Despite an obvious assumption, the use of NDVI for calculation of ETa (idea suggested by Gunther from “green spin GmbH”) should be checked for its robustness by comparing ETa derived via LST and NDVI. This work is planned after completion of an expedition to the Aral Sea. It is expected to calculate ETa by SEBAL program and use this calculation result as a reference. Similarly, ETa will be calculated on the base of LST and NDVI. The calculation results will be compared with the reference value, and the robustness of our approach will be judged accordingly.

In my opinion, hot and cold pixels can be determined without estimation of temperature. To this end, available infrared channels can be used.

CALCULATION OF FIELD-AVERAGED VEGETATION INDICES AND ETa

To determine the average weighted values of vegetation indices and ETa, the earlier mentioned pixel grid is used. Polygons of fields are selected successively and a rectangle delimiting the field polygon is shaped. Within the boundaries of this rectangle the pixel polygons of the grid are overlaid on the field polygon. If they intersect, the area of intersection is estimated – if the area is more than 50%, then the value of respective pixel is multiplied with area and summed up to get the average weighted value.

After calculation of all indices is completed, they are saved in PostgreSQL DB. The results are stored in DB on all images. The results also can be provided in EXCEL format.

Analysis of ETa

Cotton

The total ETa varies from 10 mm to 42 mm (Fig. 3.17). Lower values refer to fields 411, 538 and 20.

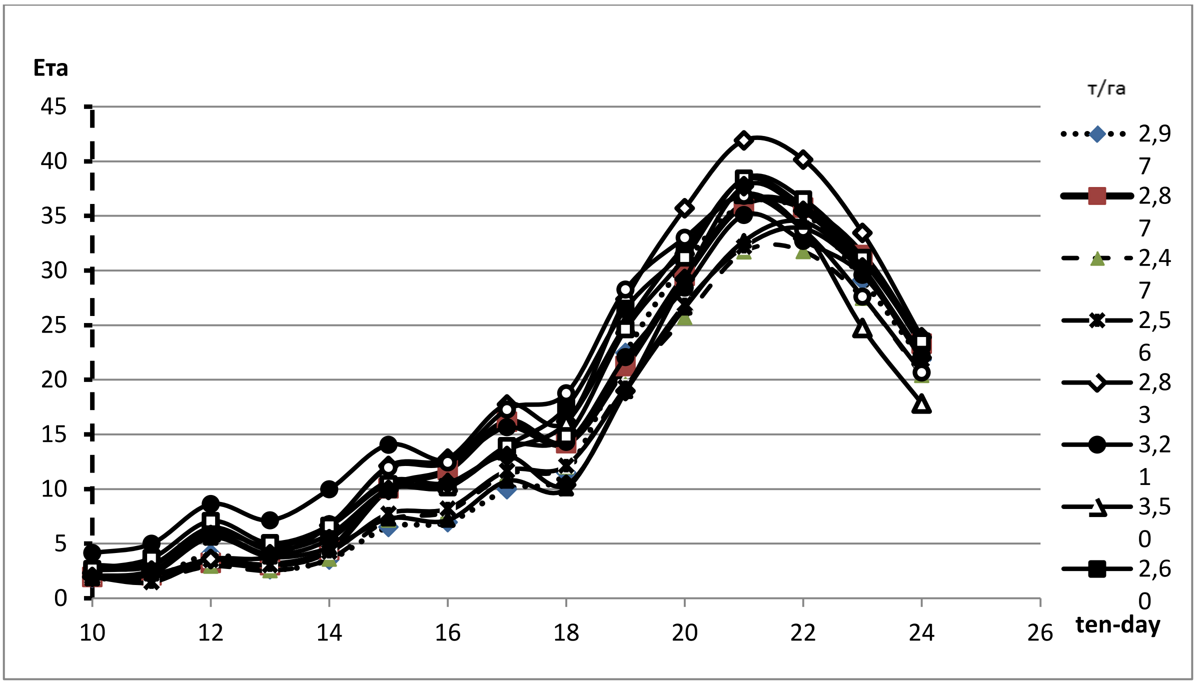


Figure 3.17. Changes during vegetation, ETa, cotton

Breach of agronomic operations, even in case of sufficient irrigation rate, leads to lower yields (Figure 3.17, Figure 3.18). Given the irrigation rate of 70 mm, low yield of 2.48 t/ha was observed in area 538; low yield of 2.47 t/ha was observed also in area 18, even when the irrigation rate was 38.5 mm.

Good correlation between the total ETa and irrigation rate should be underlined (Figure 3.18). Taking into account that ETa value correlates with total water application, this value may indicate to sufficient water delivery alongside with or instead of irrigation rate.

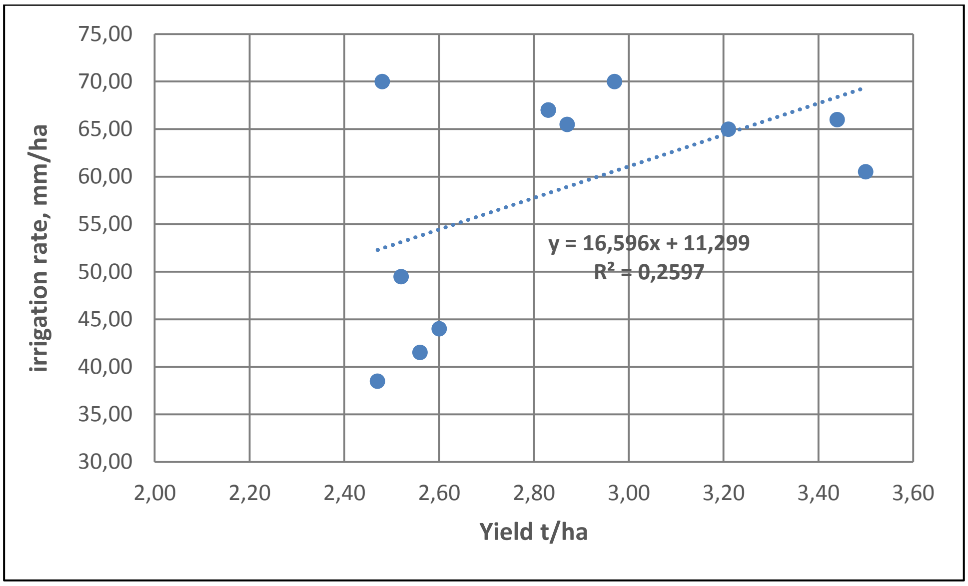


Figure 3.18. Relationship between water delivery and cotton yields

Determination of field available water supply

Given semi-automorphic and gray-meadow soil and the groundwater table of 2-2.5 m in Oktepa Zilol WUA, the irrigation rate of 60-65 mm is sufficient to produce cotton yields of 3.44 t/ha in area 394 and 3.50 in area 137, when the recommended technology is observed.

The comparison of water delivery and total active evapotranspiration (Figure 3.19) showed the correlation coefficient $R^2 = 0.2593$.

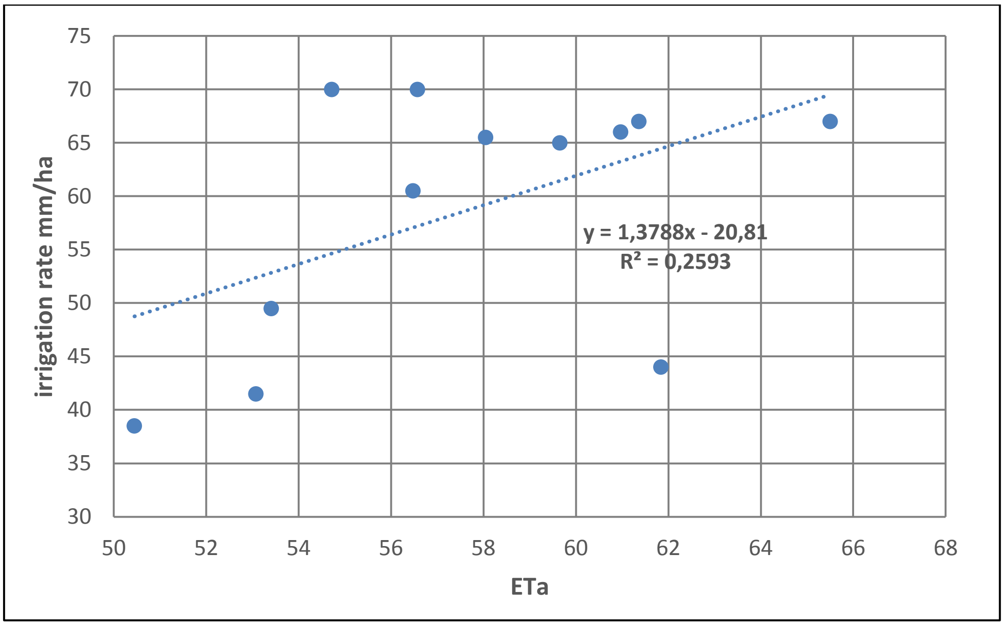


Figure 3.19. Relationship between ETa and water delivery for cotton

Winter wheat

Figure 3.20 shows the change in ETa values in control wheat fields during vegetation.

ETa, an indicator corresponding to field evapotranspiration, should correlate with the amount of irrigation water delivered to the field (Figure 3.21).

Although the results of approximation of the relationship are not illogical, and huge irrigation rates correspond to higher value of evapotranspiration, the relationship between ETa and water delivery is not close and R^2 = 0.0977.

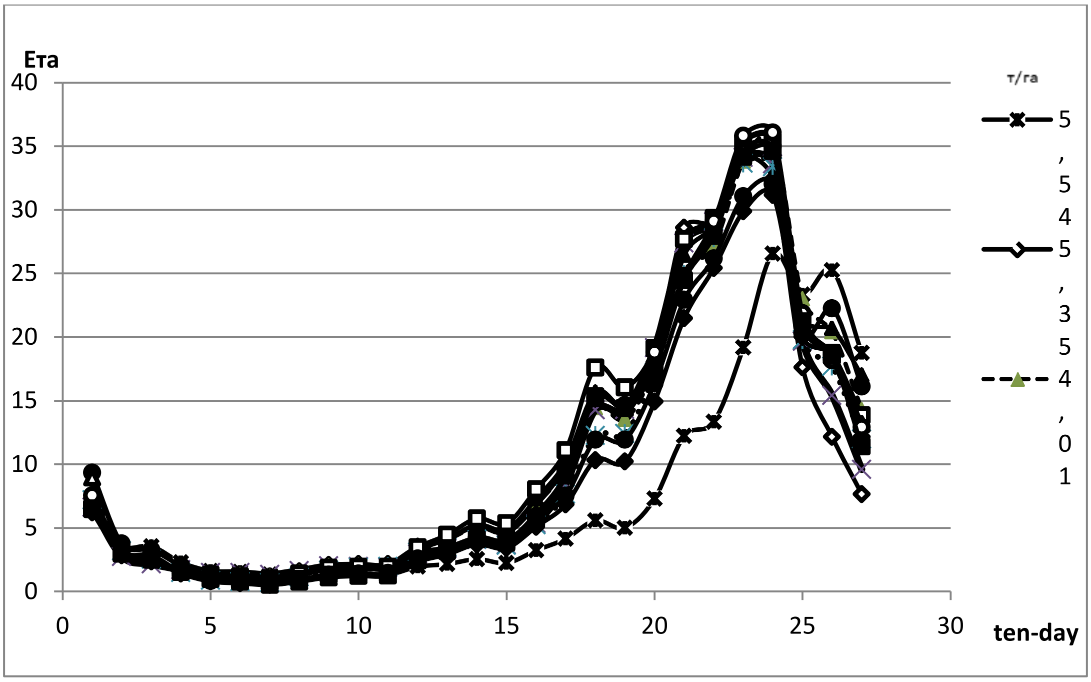


Figure 3.20. Changes during vegetation, ETa

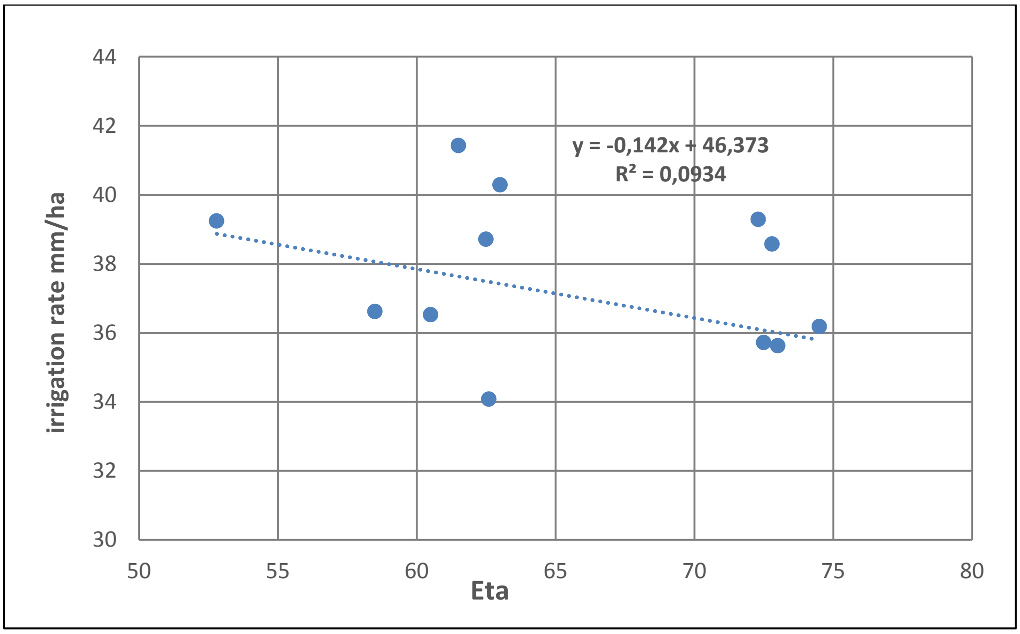


Figure 3.21. Relationship between irrigation rate for wheat and ETa

The relationship between water delivery and yield should be similar to that between ETa (Figure 3.22, Figure 3.23) and yield. The resulting relationships are inverse, namely, the more water is delivered and the higher evapotranspiration is, the lesser yield is achieved. Hence, it can be concluded that evapotranspiration or active consumptive use are not the only indicators of crop productivity.

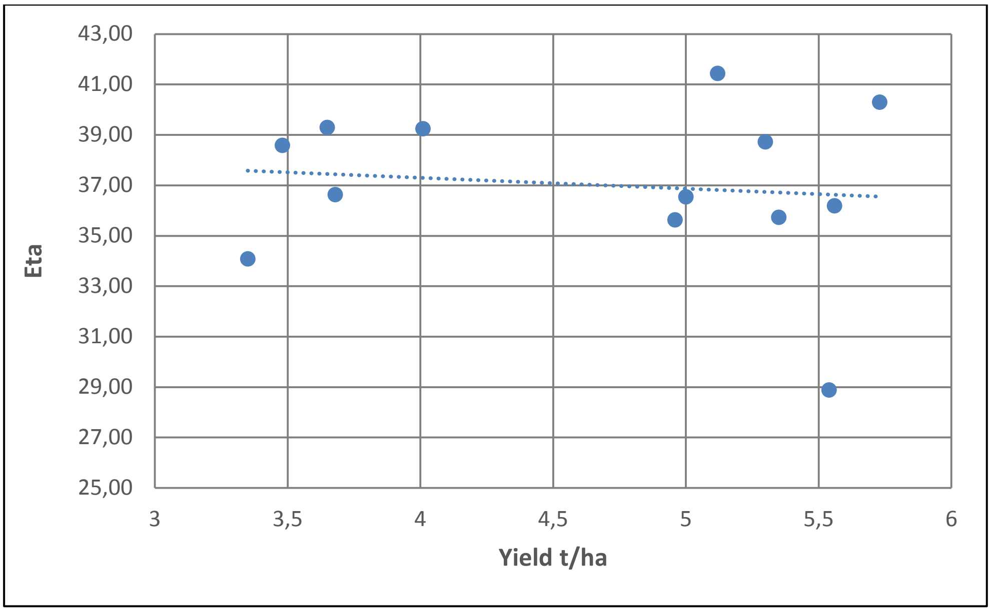


Figure 3.22. Relationship between ETa and wheat yield

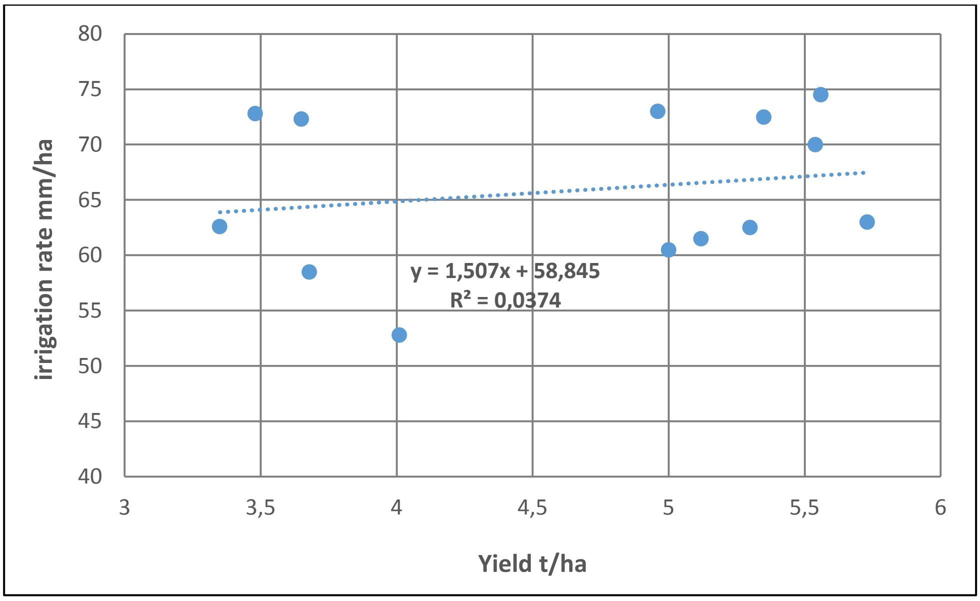


Figure 3.23. Relationship between irrigation rate and wheat yield

Analysis of the results showed that harvest depends on many factors, and the two-dimensional correlation does not allow identifying contribution of each of these factors

Other conclusions were made from the analysis of miltivariable correlation by the R program, which allows taking into account mutual influence of factors in yield production, considering the weight of each of the factors.

Chapter 4. Results of the R software to predict crop yield

We used R software in order to find factors affecting crop yield of main crops – cotton and wheat with overall aim to explain land productivity and yield loss that highlight pixel-by-pixel and farm-by-farm variability in biophysical quantities and yield considering a wide range of environmental conditions (strata). In order to model crop yield as a function of field measured irrigation depth, applied NPK, as well as RS-based vegetation index, well-understood spectro-biophysical relationships are necessary. Therefore relationships between seasonal (crop growth period) normalized differential vegetation index (NDVI) and biophysical quantities, both linear and non-linear models have been developed based on the best-fit R^2 values (Thenkabail, 2003). Pearson's correlation coefficient (R^2) for all possible pairs of spectro-biophysicalparameters is calculated using the R software.

4.1 Used data

In order to develop spectro-biophysical and yield relationships, vegetation index (such as normalized differential vegetation index, NDVI) values are needed to be extracted from Landsat-8 OLI data based on one plot located pixel within each field. Anderson et al (1993) suggested that it is more desirable when sample point data is compared with vegetation index value obtained for a single pixel (900 m^2). Hence, the main goal of this section is to combine point based NDVI per field into a master table that include crop biophysical parameters. For this purpose time series of NDVI for the growing period of cotton and wheat were extracted depending on availability, e.g., minimal percentage of cloud cover (up to 10%). For analysis of NDVI data, the date of acquisition was given as day of year (DoY), e.g., August 22, 2018 => 234. Time series of NDVI were averaged in order to get mean value (*ndvi_avg*). Field measured (farmer reported) crop yield (*cryd*) was also averaged per crop field (*crnm*). In addition, total volumes of irrigation as well as nitrogen were summed up in order to get seasonal norm of applied irrigation (*irri*) and nitrogen (*nitr*). Used data for cotton and wheat is given in Tables 3.3 and 3.4, respectively.

Table 3.3. Spectro-biophysical parameters of cotton used in R

crnm	cryd	nitr	phos	pota	irri	ndvi125	ndvi141	ndvi157	ndvi173	ndvi189	ndvi205	ndvi221	ndvi241	ndvi253	ndvi269	ndvi285	ndvi_avg
cot_15	1.51	146	87	30	5450	0.12	0.13	0.09	0.12	0.19	0.47	0.45	0.51	0.52	0.27	0.42	0.30
cot_31	1.81	183	39	30	4600	0.08	0.11	0.08	0.13	0.23	0.42	0.51	0.53	0.54	0.24	0.42	0.30
cot_59	1.49	200	75	30	3250	0.10	0.13	0.09	0.13	0.20	0.37	0.50	0.66	0.64	0.29	0.38	0.32
cot_107	1.69	213	45	30	850	0.11	0.15	0.13	0.19	0.27	0.54	0.65	0.69	0.66	0.26	0.42	0.37
cot_134	2.45	230	63	30	4850	0.10	0.14	0.12	0.17	0.26	0.58	0.71	0.70	0.61	0.25	0.37	0.36
cot_168	1.93	252	15	90	850	0.13	0.18	0.13	0.16	0.18	0.46	0.53	0.53	0.49	0.24	0.40	0.31
cot_284	2.53	267	42	30	3800	0.11	0.14	0.13	0.24	0.29	0.57	0.57	0.67	0.69	0.31	0.48	0.38
cot_399	2.25	192	30	30	2300	0.12	0.15	0.12	0.22	0.27	0.57	0.67	0.72	0.68	0.21	0.35	0.37
cot_484	2.13	222	36	45	4280	0.10	0.14	0.12	0.16	0.25	0.57	0.66	0.63	0.64	0.26	0.40	0.36
cot_606	1.72	118	54	30	2300	0.10	0.13	0.10	0.19	0.22	0.52	0.60	0.61	0.58	0.17	0.32	0.32

Table 3.4. Spectro-biophysical parameters of winter wheat used in R

nm	cryd	nitr	irri	ndvi234	ndvi250	ndvi266	ndvi282	ndvi298	ndvi314	ndvi362	ndvi021	ndvi125	ndvi141	ndvi157	ndvi173	ndvi189	ndvi_avg
wht_14	3.63	267	5380	0.49	0.45	0.24	0.18	0.09	0.07	0.07	0.08	0.36	0.27	0.20	0.22	0.16	0.22
wht_15	4.87	226	5450	0.48	0.49	0.37	0.22	0.10	0.04	0.03	0.05	0.12	0.13	0.09	0.13	0.20	0.19
wht_18	5.4	258	5610	0.49	0.45	0.28	0.25	0.10	0.10	0.14	0.13	0.51	0.36	0.21	0.16	0.07	0.25
wht_20	2.53	261	6150	0.40	0.41	0.25	0.18	0.11	0.12	0.09	0.08	0.40	0.31	0.18	0.19	0.19	0.22
wht_24	4.5	259	5100	0.41	0.41	0.26	0.17	0.11	0.09	0.09	0.08	0.43	0.35	0.18	0.17	0.18	0.22
wht_26	5.44	246	5420	0.47	0.32	0.26	0.16	0.13	0.18	0.23	0.13	0.53	0.39	0.20	0.15	0.08	0.25
wht_63	5.62	236	6380	0.51	0.51	0.35	0.26	0.13	0.12	0.15	0.14	0.55	0.41	0.26	0.16	0.17	0.28
wht_137	5.36	246	5130	0.50	0.47	0.25	0.14	0.10	0.09	0.11	0.02	0.51	0.30	0.26	0.18	0.22	0.24
wht_377	3.5	335	6090	0.47	0.48	0.28	0.19	0.14	0.15	0.19	0.03	0.51	0.29	0.21	0.17	0.18	0.25
wht_394	5.15	265	5840	0.50	0.44	0.31	0.12	0.09	0.06	0.06	0.09	0.35	0.26	0.18	0.18	0.10	0.21
wht_411	4	276	5980	0.47	0.40	0.28	0.15	0.13	0.12	0.14	0.10	0.47	0.29	0.20	0.18	0.17	0.24
wht_433	3.03	278	6000	0.07	0.08	0.07	0.08	0.16	0.18	0.20	0.16	0.45	0.29	0.15	0.17	0.08	0.16
wht_473	3.92	264	6430	0.43	0.37	0.28	0.13	0.11	0.09	0.05	0.16	0.46	0.23	0.22	0.21	0.10	0.22
wht_480	3.68	247	6100	0.48	0.46	0.30	0.18	0.12	0.09	0.10	0.08	0.55	0.30	0.19	0.14	0.09	0.24
wht_538	4.17	265	6050	0.46	0.42	0.25	0.15	0.12	0.09	0.07	0.08	0.39	0.28	0.16	0.18	0.05	0.21

4.2 Correlation coefficients

Correlation coefficients (R^2) for all possible pairs of spectro-biophysical parameters of cotton and winter wheat are given in Tables 3.5 and 3.6. Among all spectro-biophysical parameters, application amount of nitrogen (*nitr*) and NDVI from June 6 to August 9, 2018 (*ndvi157-ndvi221*) were found to be the best predictor of cotton yield, explaining 60-70% variability (Table 3.7). However, negative R^2 (-0.4) was observed when *cryd* correlated with total amount of phosphorous application (*phos*). There is no explanation for this phenomenon.

Negative correlation was found between *cryd* with nitrogen application rate (*nitr*) as well as with irrigation amount (*irri*) in case for winter wheat (Table 3.6). This could be explained by the fact that higher amount of nitrogen application together with over-irrigation causes development of plants with weak stem and smaller ears. Therefore cryd was lower in the fields, where high amount of water and nitrogen were applied compared to those with lesser application rate (Table 3.6).

Table 3.5. Pearson correlation matrix (R^2) of the paired spectro-biophysical parameters of cotton

	cryd	nitr	phos	pota	irri	ndvi125	ndvi141	ndvi157	ndvi173	ndvi189	ndvi205	ndvi221	ndvi241	ndvi253	ndvi269	ndvi285	ndvi_avg
cryd	1.0	0.6	-0.4	0.0	0.1	0.0	0.3	0.6	0.7	0.7	0.7	0.6	0.5	0.4	0.1	0.2	0.7
nitr		1.0	-0.5	0.4	-0.2	0.2	0.5	0.7	0.3	0.4	0.3	0.3	0.3	0.3	0.6	0.6	0.5
phos			1.0	-0.6	0.6	-0.2	-0.6	-0.6	-0.5	-0.3	-0.3	-0.3	0.0	0.0	0.3	-0.1	-0.3
pota				1.0	-0.5	0.6	0.8	0.4	-0.1	-0.5	-0.1	-0.1	-0.4	-0.5	-0.1	0.1	-0.2
irri					1.0	-0.4	-0.7	-0.5	-0.4	0.0	-0.1	-0.2	-0.2	-0.1	0.3	0.2	-0.2
ndvi125						1.0	0.8	0.6	0.2	-0.2	0.2	-0.1	-0.1	-0.1	0.1	0.1	0.1
ndvi141							1.0	0.8	0.4	0.0	0.3	0.3	0.1	0.0	-0.1	0.0	0.3
ndvi157								1.0	0.7	0.5	0.7	0.6	0.5	0.4	0.1	0.2	0.8
ndvi173									1.0	0.8	0.8	0.6	0.6	0.6	-0.1	0.1	0.8
ndvi189										1.0	0.8	0.7	0.8	0.8	0.1	0.2	0.9
ndvi205											1.0	0.8	0.6	0.5	-0.2	0.0	0.8
ndvi221												1.0	0.8	0.6	-0.3	-0.3	0.8
ndvi241													1.0	0.9	0.1	-0.2	0.9
ndvi253														1.0	0.3	0.1	0.8
ndvi269															1.0	0.8	0.2
ndvi285																1.0	0.2
ndvi_avg																	1.0

Table 3.6. Pearson correlation matrix (R^2) of the paired spectro-biophysical parameters of winter wheat

	cryd	nitr	irri	ndvi234	ndvi250	ndvi266	ndvi282	ndvi298	ndvi314	ndvi362	ndvi021	ndvi125	ndvi141	ndvi157	ndvi173	ndvi189	ndvi_avg
cryd	1.0	-0.5	-0.4	0.5	0.4	0.5	0.4	-0.3	-0.2	0.0	0.0	0.1	0.3	0.3	-0.4	0.0	0.4
nitr		1.0	0.3	-0.2	-0.2	-0.4	-0.3	0.4	0.4	0.3	-0.2	0.2	0.0	0.1	0.4	0.0	0.0
irri			1.0	-0.2	-0.1	0.0	0.0	0.4	0.2	0.0	0.4	0.2	0.0	0.2	0.1	-0.3	0.1

ndvi234	1.0	0.9	0.9	0.6	-0.6	-0.5	-0.3	-0.4	0.0	0.0	0.3	-0.1	0.2	0.7
ndvi250		1.0	0.9	0.7	-0.6	-0.6	-0.5	-0.6	-0.1	-0.1	0.2	-0.1	0.4	0.6
ndvi266			1.0	0.7	-0.5	-0.6	-0.4	-0.3	-0.2	-0.1	0.1	-0.3	0.3	0.5
ndvi282				1.0	-0.3	-0.2	-0.1	-0.1	0.0	0.2	0.1	-0.4	0.3	0.6
ndvi298					1.0	0.8	0.7	0.3	0.4	0.3	0.0	-0.2	-0.1	-0.1
ndvi314						1.0	0.9	0.4	0.6	0.6	0.2	-0.1	-0.2	0.2
ndvi362							1.0	0.3	0.6	0.7	0.3	-0.2	-0.2	0.3
ndvi021								1.0	0.3	0.3	0.1	0.1	-0.6	-0.1
ndvi125									1.0	0.8	0.8	0.1	-0.2	0.7
ndvi141										1.0	0.6	0.0	-0.2	0.7
ndvi157											1.0	0.4	0.1	0.8
ndvi173												1.0	0.0	-0.1
ndvi189													1.0	0.2
ndvi_avg														1.0

4.3 Multivariate regression model to predict crop yield

A multivariate linear model predicts the value of a dependent continuous variable from more explanatory independent variables (Rencher&Schaalje, 2008). A general multivariate linear model is given in Equation 4.1:

$$y = \beta_0 + \sum_{i=1}^{n} \beta_i x_i + \varepsilon \qquad \text{[Eq. 4.1]}$$

where y is the response variable, x_i are the explanatory variables, β_i are coefficients to be estimated and εrepresents the residual, i.e. the deviation of the model from y which could not be explained by the x_i variables. It is a statistical term representing random fluctuations, measurement errors, or the effect of other uncontrollable factors. This model was fitted with the *lm* function in the statistical software package R (Fox & Weisberg, 2011).

Out of all spectro-biophysical parameters for cotton and winter wheat, applied amount of nitrogen (*nitr*) and irrigation (*irri*), as well as average NDVI for the period (*ndvi_avg*) were used as the explanatory variables in order to predict crop yield (*cyld*).

The resulting multivariate linear model to predict cotton and wheat yield is given in Eq. 4.2 and Eq. 4.3, respectively.

$cryd_{cotton}$ *=0.002943*nitr + 0.0000697*irri + 6.932*ndvi_avg – 1.223* [Eq. 4.2]

Statistics for Eq. 4.2 is given below:

```
Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept) -1.223e+00  9.399e-01  -1.301   0.2408
nitr         2.943e-03  2.144e-03   1.373   0.2189
irri         6.968e-05  5.182e-05   1.345   0.2274
ndvi_avg     6.932e+00  3.046e+00   2.276   0.0631 .
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.2484 on 6 degrees of freedom
Multiple R-squared:  0.7048,   Adjusted R-squared:  0.5572
F-statistic: 4.775 on 3 and 6 DF  p-value: 0.04961
```

$$cryd_{wheat} = -0.01633*nitr - 0.00071*irri + 15.4668*ndvi\_avg + 9.2001 \qquad \text{[Eq. 4.3]}$$

Statistics for Eq. 4.3 is given below:

```
Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  9.2001270  3.3077090   2.781   0.0179 *
nitr        -0.0163319  0.0082310  -1.984   0.0727 .
irri        -0.0007091  0.0004764  -1.489   0.1647
ndvi_avg    15.4668322  6.8091369   2.271   0.0442 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.7352 on 11 degrees of freedom
Multiple R-squared:  0.5401,   Adjusted R-squared:  0.4147
F-statistic: 4.306 on 3 and 11 DF,  p-value: 0.03074
```

Based on Eq. 4.2 and Eq. 4.3, crop yields (*cryd*) for each field were estimated by multiplying corresponding coefficients by explanatory variables (e.g., applied amount of nitrogen (*nitr*) and irrigation (*irri*), as well as average NDVI for the period (*ndvi_avg*)). Comparison of field observed crop yield (Y_O) vs. model predicted crop yield (Y_P) for cotton and winter wheat is given in Figure 3.24. The results show that multivariate regression (R^2=0.7 for cotton and R^2=0.5 for wheat) supplemented the univariate regressions (see Tables 3.5 and 3.6).

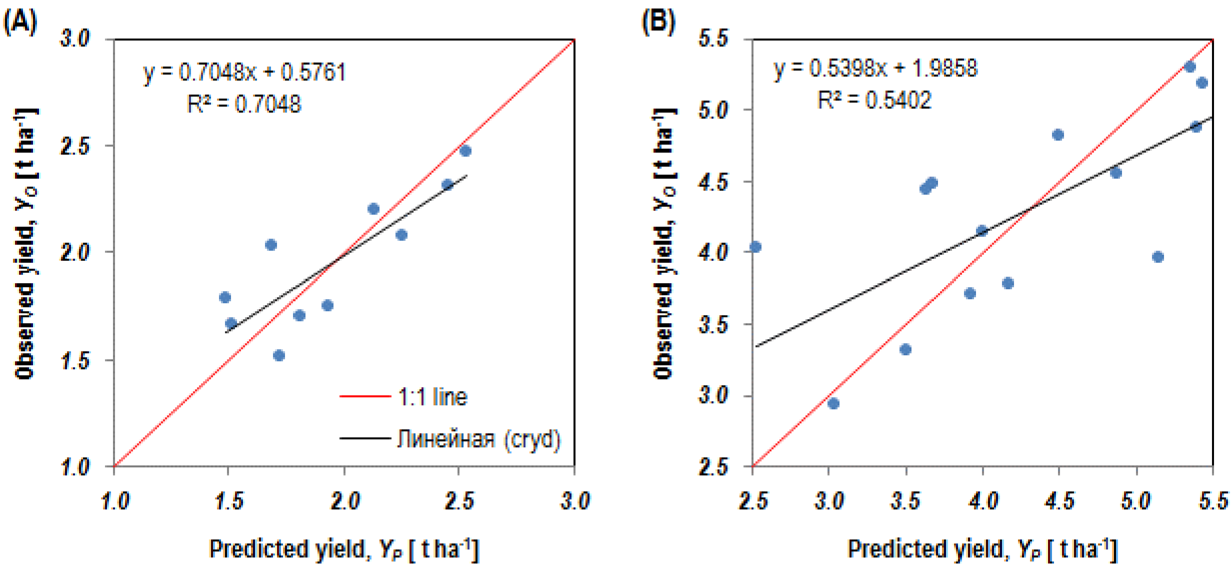


Figure 3.24.Comparison of field observed vs. predicted (using Equations 4.2-4.3) crop yield for cotton (A) and winter wheat (B)

The following conclusions can be drawn from the research results.

Paired regression analysis exhibited a remarkable explanatory power of the NDVI, the index to which so far much attention was paid to in crop biophysical monitoring. However, biophysical parameters cannot be mapped in general, using spectral indices. The paired regression approach worked out for *cryd* vs. *ndvi*, but especially for cotton at the mid growing stage or averaged NDVI for the whole season. While comparably low coefficients of determination were found in case for winter wheat. The application of remote sensing data or methods with accurate field measurements may be more promising.

The multivariate linear regression model exhibited a very high explanatory power to predict the *cryd*. The results suggest further investigation of multivariate assessments of biophysical parameters because of promising outputs in contrast to univariate assessments of *cryd* with limited data. Nevertheless, as the study was applied to data of 2017-2018 only (one crop season for cotton and wheat) with limited biophysical parameters (e.g., *nitr* & *irri*), more detailed investigations on transferability for other years and among different sites (including practices) is the outstanding task.

Our previous studies have shown that water availability can be measured by ETa/ETc. Such approach was tested in provinces and districts. However, for the field (contour) level, as well as for monitoring of field conditions during vegetation and for decision making, further research is needed, namely the algorithm needs to be improved to recalculate pixel-by-pixel ETa into farm-by-farm ETa, making use of **Sentinel-2** images from the European Space Agency's family of remote sensing satellites for monitoring of land use, vegetation, forest and water resources with a resolution of 10, 60 meters.

CONCLUSIONS on Chapter 4

Our previous studies have shown that water availability can be measured by ETa/ETc. Such approach was tested in provinces and districts. However, for the field (contour) level, as well as for monitoring of field conditions during vegetation and for decision making, further research is needed.

The analysis of the results of possible use of satellite images to determine the damage to fields' productivity showed the need for clarification and improvement:

1. Determination of ETa and improvement of the algorithm for recalculation of pixel-by-pixel ETa into farm-by-farm ETa.
2. More precise accounting of water actually delivered to fields.
3. Work done in 2019 on the use of Sentinel-2 images allowed getting more detailed data in time and space required for monitoring at the WUA and field level.
4. Usage of RS-based data or methods together precise field measurements can be promising.
5. The multivariate regression model showed a very high explanatory power to predict *cryd*.
6. The derived results suggest for further study of multivariate estimations of biophysical parameters proceeding from promising results by contrast with univariate estimations of cryd with limited data.

Chapter 5. Prospects for application of remote sensing for the improvement of yield programming methods to the benefit of farmer's extension services

By present, the national science and practices in the region's countries have accumulated significant stock of methods, techniques and technologies that, along with the improvement of irrigated agriculture infrastructure, allow building a system that guarantees sustainability of agricultural production and increases its resilience to climate change. This is proven by the fact that the acutely dry year 2008 was successfully managed on an area of more than 130,000 ha in Kyrgyzstan, Tajikistan and Uzbekistan within the IWRM-Fergana Project implemented by SIC ICWC together with representatives of three countries with the support of Swiss Development Cooperation.

Advantages of remote sensing (RS) based methods, which were tested in the CAWa project implemented by the University of Würzburg in cooperation with SIC ICWC and a number of other organizations, include the possibility to get most of the main water and irrigated agriculture characteristics on wider spatial scale, as well as to see dynamics of temporal estimations depending on the frequency of satellite data acquisition. Therefore, the developed methodology for the assessment of water availability of irrigated land and uniformity of irrigation water distribution, which cannot be analyzed by traditional methods on a large scale, becomes feasible with RS-derived ten-day information even for the whole of Central Asia.

As part of the above mentioned German-Central Asian project, it was attempted to re-start the earlier developed method of yield programming in combination with RS. Yield programming (YP) involves a set of agronomic and reclamation measures, efficient implementation of which in due time ensures production of design yield, while reclaiming soil fertility and improving environmental conditions. The yield programming technique proceeds from the premise that for each field a certain level of yield can be planned and achieved by considering all soil-climatic factors, differentiating agronomic and soil reclamation methods, and making optimal use of physical and human resources. RS is a tool, which helps to assess land productivity not only at the end of the growing season through harvest losses but also control productivity in the course of the growing season. The combination of yield programming with RS should make operations more target-oriented, enhance observance of technology, ensure more effective utilization of soil-climatic resources, water, chemicals, machines, and improve revenues of agricultural producers and economy as a whole. Practical implementation of the proposed YP-RS – yield programming on the basis of remote sensing – is a complex multidimensional task since it assumes consideration of multiple factors of continuously changing situation in agriculture, including poorly predictable weather conditions, complicated and largely uncertain plant response to external factors, and economic aspects. YP implies the development and implementation of the automated control system (ACS) in crop farming. Moreover, at the first stage, the technological process control system in general is very important as this system enables:

- development of a tool set for efficient organization and functioning of agricultural extension services;
- enough qualified team to have a program of actions in case of any deviations in natural, economic and institutional conditions from optimal ones, as well as the clear operations sequence, schedules and timelines in order to deal with all encountered difficulties with minimum productivity losses;
- a comprehensive collection of ‘know-how’ along with relevant recommendations, climatic and organizational ones, to be provided for each farmer. This is especially relevant in light of newly formed agricultural clusters.

Key elements

The proposed YP-RS is based on the fact that RS can reflect variety of ground-based natural conditions and that satellite imagery may detect and correlate with a wide set of vegetation cover indices. Presentations of Sh. Kenjabayev, A. Sorokin and D. Sorokin demonstrated the results of identification of water availability through NDVI. There are dozens of other indices that can mirror characteristics of vegetation cover and that need to be elaborated in practical work. RS is easily combinable with GIS. This allows using the data of other water-management, agronomic and soil-hydrogeological organizations (such as Hydrogy and Land Reclamation Field Offices, Geocadastre, Hydromet, BISA) in spatial format for analysis.

To this end, it seems advisable to come back to developments the 1970-90s of the so called yield programming.

Yield programming shows the process of achieving the maximum possible yield by controlling individual factors of yield formation. Such factors include soil conditions, agronomic operations, selection of crop varieties that are most suitable for farm conditions, market prices and demand, production inputs, etc.

RS can be applied as the indicator of conditions of land and crops. This is important both at initial (pre-seeding) stage of farming activity – estimation of future harvest under different starting conditions – and during growing – estimation of changes in crops as a result of agronomic measures.

At the initial stage, when the soil is bare (the period from melting of snow cover till sprouting), one will attempt to determine humus and NPK contents, PH, salinity, gypsum content and other soil characteristics. Further one, based on regular analysis of satellite passes, continuous monitoring of agronomic operations can be maintained.

YP-RS will be formed as a computer-controlled information complex in support of profitable agricultural production in a farm or a water user association (in this case, we add here development of water use plans and calculation of ten-day water inputs at off-takes of command irrigation system). The infrastructure of an economic entity to be served will be determinant in the development of this complex. This includes connections and status of irrigation system, access to fertilizer and irrigation water sources. The degree of economic independence of farm entities, access to markets (exchange), futures transaction opportunities, etc. are also of equal importance. The main objective of the extension service based on this complex is introducing to farming activities the cost-effective management practices. Additionally, more knowledge intensive technology will be introduced in the course of development of the complex. In parallel, training of farmers in application of well-adjusted farming methods is needed. This could be very useful for currently established network of clusters.

The information complex will be based on the database to store all information on served farms (survey and monitoring of farms, field passports) and, in case of WUAs, the information on irrigation system and offtakes of the command irrigation system, which serves WUA. The irrigation network of WUA/farms should be also inputted into DB. Geometries of irrigation system, WUA, farms and fields will be RS-based and inputted through GIS (MapInfo or ArcInfo).

It is assumed that the core element of the farmer's extension service will be a control center serving a district or group of districts, equipped with weather stations (one station per 20,000 ha) and connected with district irrigation divisions and land reclamation field offices, as well as with farms and WUA. To launch this project, it would be needed to:

- adapt scientific basis and methods of yield programming to application of RS tools, i.e. find for every factor of harvest formation (soil conditions and its treatment, fertilizers, water, heat, nutrients, etc.) such spectral analysis indices that will serve as indicators of technological excellence and sufficiency as does NDVI for water availability. It is clear that this part of work is the most diligent and important part of scientific justification of this method and must take at least three years of efforts in order to achieve reliable results of relationship between harvest factors and specific RS-indices. Ground-based identification of harvest formation factors should be made in parallel to enhance the database and the set of relationships that were established in this direction – yield programming – in USSR (AFI, SANIIRI, UkrNIIGIM and others). As part of this work, pilotless aerial vehicles can be used in parallel as an alternative to RS.
- Simultaneously with theoretical development of RS-based yield programming, a help desk will be established for farmers and WUAs. The functions of this help desk will include:

    - systematic (daily) taking of readings of the climatic network and data processing to produce (correct) ten-day weather forecasts;

- search for the analogue and building long-term forecasts of climatic events, including the forecast of crop water requirements and adjustment of irrigation schedules;
- acquisition of data from Land Reclamation field offices on drainage operation and water tables; account of these data in the forecast and calculation of crop water requirements, adjusted for groundwater contribution; use of collector water for irrigation in case of water shortage;
- acquisition of LANDSAT and SENTINEL satellite data once in ten-day and information of farmers in case of detection of risks related to breach of technology or moisture deficit;
- periodic control of ground-based agronomic and irrigation operations to accumulate experience and gain skills of work with stakeholders, also to make more precise definition of FAO methodology based crop coefficients.

- develop the order of interaction between all district elements of the proposed complex in order to establish an automated agronomic and irrigation management system and create the most favorable conditions to grow crops over the whole served area.
- set a system for data exchange and information of end users (farmers and WUAs) to help them to achieve higher crop yields.

References

1 *V.A. Dukhovniy, S.A. Nerozin, G.V. Stulina, G.F. Solodkiy.* Programming of Crop Yields (Systems approach as applied to soil reclamation). SIC ICWC, Tashkent, 2015.

2 Fox J., Weisberg S., 2011. Multivariate Linear Models in R. An Appendix to An R Companion to Applied Regression, Second Edition.

3 Rencher A., Schaalje B., 2008. Linear models in statistics, Second edition. John Wiley & Sons, Inc. Publication, p. 672.

4 *Dimo Dimov, Fabian Löw, Mirzahayot Ibrakhimov, Galina Stulina, Christopher Conrad.* Salt and Optical Time Series for Crop Classification. 2017.

5 Rencher A., Schaalje B., 2008. Linear models in statistics, Second edition. John Wiley & Sons, Inc. Publication, p. 672.

6 Fox J., Weisberg S., 2011. Multivariate Linear Models in R. An Appendix to An R Companion to Applied Regression, Second Edition.