



# ASSESSMENT OF IRRIGATION WATER USE EFFICIENCY USING REMOTE SENSING APPROACHES IN THE ARAL SEA BASIN, IN CENTRAL ASIA

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## ABSTRACT

Retrieving crops and their location, as well as their spatial extent, are useful information for agricultural planning and better management of irrigation water resources as well as for crop health monitoring, towards an increased food production and reduced water use. Multispectral remote sensing images with a spatial resolution of 30 m or greater are often used for mapping crops in extensive agricultural systems at global and regional scale. Analysis of multi-spectral images obtained from satellites on the basis of remote sensing technologies and identification of irrigated crop areas on the basis of GIS technologies, observation of crop types, assessment of productivity and regional distribution of surface water resources and calculation of water consumption possible. This is because, sustainable water use is one of the priorities in arid agriculture. Improvements in satellite imagery technology in recent decades have helped to track the development of agricultural crops. In this article, images from the Landsat 8 OLI satellite identified crop types in irrigated crop areas in terms of spectral, geometric, and periodicity. The training data were prepared from 450 areas of the most common crops in the area: cotton, rice, wheat-rice, wheat and secondary crops and fodder crops. The calculation of the level of accuracy of reading data was tested on the basis of special kits of the Rstudio program, developed in collaboration with scientists from the University of Wuerburg (Germany). The results obtained are analytical methods with landsat images and Rstudio software that are convenient for identifying and monitoring crop types. Based on the maps created, we can achieve water savings for crops by considering several factors.

**KEYWORDS.** CAWa, Landsat, GPS, Irrigated Lands, Crop Types, Classification

## INTRODUCTION

Water scarcity is a growing issue across the globe and because agriculture is the main consumer of water (Merks, 2018). In particular, the water level in the Aral Sea, the world's fourth largest lake, has fallen sharply since the 1960s from the Amudarya and Syrdarya rivers in Central Asia for agricultural use. It became an "island desert" (Savoskul et al., 2003). This process is leading to deterioration of environmental conditions, salinization of lands and, consequently, a decrease in crop yields (World Bank, 2013). The Amudarya annually receives 57  $km^3$  of water in Uzbekistan. More than four million hectares of land in the Syrdarya basin are used for irrigation. Today, agriculture is a

major part of the economy and a large amount of water resources is used for agricultural irrigation (Awan et al., 2011). Indeed, after the independence of Uzbekistan, the agro-policy pursued in the country, bringing agriculture to the level of developed countries, is aimed at meeting the needs of the population in food and other agricultural products (Vazirligi, 2014). As noted by the first President of the Republic of Uzbekistan IA Karimov, In the second stage of the reforms, the resource potential of production in general in the agricultural sector, Achieving truly progressive shifts, including by optimizing the composition of arable land, taking into account the specifics of each region, is one of the most important priorities of



structural change policy (Nomidagi et al., 2012). It was noted that the total area of the country is 447.4 thousand  $km^2$  and the area of agricultural land is 22614 thousand hectares. The area of irrigated land has increased 2.36 times over the last century: from 1,809.5 thousand hectares (1914) to 4276.1 thousand hectares.

Uzbekistan's water industry has a complex character. At present, the total demand for water in the country is 56-60 billion  $m^3$  per year. Of this, 92% is spent on agriculture, 5.5% on household needs and 1.5% on industry, 0.8% on fisheries and 0.2% on energy (Maxsus et al., 2007). At the same time, in addition to saving irrigation water for agriculture, one of the constant needs is to grow enough food for the growing population. According to Weiss, the world's population is expected to increase by about 10 billion by 2050, which is almost 50% more than in 2013 in terms of economic growth (Weiss et al., 2020). Sustainable growth in crop yields (productivity) is one of the main challenges due to the high demand to meet the needs of the rapidly growing world population. In particular, sustainable intensification of crop growth is almost the only way to increase food security (L w et al., 2017). However, the optimal step in improving the efficiency of water use in the agricultural management scheme is to ensure that the water meets the specific needs and the need for water for irrigation, ie the need to properly assess the rate of irrigation. will provide. The norm of irrigation of agricultural crops is the amount of water given for one irrigation per 1 hectare, determined in  $m^3$  / ha or mm. The norm of irrigation is the water-physical properties of the soil, the area will vary depending on factors such as relief, type of crop, irrigation methods and their transfer technology (Maxsus et al., 2007). In particular, continuous monitoring of groundwater levels to improve yields and crop quality, reduce the risk of salinity, and increase sustainability is one of the most important events in agriculture. Assessing and applying the water needed for good plant growth is associated with many challenges: agronomic, economic, and environmental (Alvino & Marino, 2017). In particular, the main purpose of implementing strategies such as maximizing productivity, saving water, improving the reclamation condition of the soil, limiting saline leaching is inefficient water resources management, lack of reliable hydrological data, lack of training of farmers and of course, the construction of the Aral Sea, which is important for Central Asia. The goal of this program is to modernize irrigated lands for efficient use of water as a result of the drying up of the Aral Sea. Climate change and sandstorms are having a negative impact on

agricultural crops, while over-irrigation is also reducing yields. In particular, due to the lack of moisture in the fertile soils of arid regions, the difficulty of creating favorable conditions for plant life, the productivity of plants there is low (Respublikasi et al., 2008). Satellite imaging is widely used in the control and management of water used for agricultural crops. Currently, new capabilities for mapping and monitoring crop yields are provided by high-precision satellite sensors (Alvino & Marino, 2017). Remote sensing sensors play an important role in crop classification, growth monitoring, and detection of affected crops and crop types. Remote sensing, in turn, has a number of advantages for agronomic research purposes. In particular, the method of remote sensing in the assessment of agricultural crops provides valuable information to agronomists (Shanmugapriya et al. 2019). Timely monitoring ensures productivity and economic growth. Over the last 30 years, remote sensing data has been used successfully to obtain accurate data for irrigation planning and management. The main approaches focus on the parameters that are directly related to the process of crop growth (photosynthesis, metabolism, leaf expansion, phenological stage) (Moran et al., n.d.). Today, remote sensing satellite imagery is used for a variety of purposes in almost every field. Digital satellite imagery consists of pixels, each of which has its own spectral and spatial characteristics (Alvino & Marino, 2017). Remote sensing is based on the assessment of plant spectral parameters, biomass, water and crops (Sanli et al., 2014). Depending on the type and method of use, we can select the appropriate satellite imagery for remote sensing. MODIS, Landsat, Sentinel-2, Landsat 8, Landsat 7 (ETM+) The use of satellite imagery is free, plus high definition AVHRR, CARTOSAT, Aqua, Cloudsat, GPM, Pleiades-1A, QuickBird, Rapideye, SMAP, SMOS, Spot-6 and 7, IKONOS, Worldwide-1, Worldwide-2, ASTER, Geoeye-1 widely used in satellite imagery such as, irrigation systems based on these sensors have been studied by many researchers (Stone 1985; Jacobson 1989; Zazueta and Smajstrla; Meron 1995; Testezlaf 1997; Stone 1985 and others) (Kim & Evans, 2009). In particular, in the remote study of agriculture in Khorezm region, MODIS satellite data were used to classify the use of 7 types of crops over the past 10 years: cotton, rice, wheat- rice, wheat-fallow, orchard, vegetables, alfalfa and empty fields. Classification is done to differentiate classes based on the year-round development of plants. We tried to take samples from all the fields of Khorezm region and identify different types of crops. In this process, we identified 8 different types of crops. Our goal is to



classify and map the growth and development of crops throughout the year so that we can identify plant drinking water and use water resources with reliable statistics.

## MATERIALS AND METHODS

The total study area covers the entire territory of Khorezm region. Khorezm region is located in the north of the Republic of Uzbekistan, in the lower Amudarya region, occupying an area of 6.1 thousand  $km^2$ . The region can be divided into two parts in terms of land structure: the large northern part, located at an altitude of 100-110 m above sea level, and the southern part, located at an altitude of 120-150 m above sea level (Nomidagi et al., 2012). The Amudarya River flows through the right side of the region. Agricultural fields in the study area are irrigated by the Amudarya River. The focus for this study is to identify different crop types using satellite imagery to accurately distribute water used in agriculture, one of the main tasks to be performed in the next stage of this process is to determine the water demand of each type of crop by

studying the types of crops and to calculate the water consumption for agriculture, by summarizing the results of scientific research, such as determining soil salinity, studying the reclamation of the soil, it is possible to rationally use limited water resources, along with good yields as a result of adequate irrigation of each crop field contour. Subsequent modeling allows you to classify the yield by crop type for each pixel. Satellite data can be reliable information for water users. This process is done using Landsat images. A total of 10 multi-spectral images of the Landsat satellite were used from April 30 to August 4 (Table 1).

The number of cloud images is also high, which reduces the accuracy of the data, but in the CAWa Rstudio model, this problem is solved using the necessary code. In the CAWa model, several steps are taken to create a reliable map. These include downloading and processing landsat images, and training data from the field. Field training data will be validated using GIS technology and the CAWa model. The CAWaR model automatically corrects detected errors.

**Table. 1**

No	159	160
1.		30 April
2.	9 May	
3.		16 May
4.	25 May	
5.		10 June
6.	26 June	
7.		3 July
8.	28 July	
9.		4 August

### Dates of landsat multispectral images

In Khorezm region, 220,000 hectares out of 300,000 hectares will be irrigated. We can also use satellite imagery to get information about irrigated fields, but this information may not be accurate. Field remon sensing training information from the field will help us draw the fields. More than a thousand training data were collected in the field and more than 12 crop types were identified. Of these, 50 training data were collected for the minimum crop type and 250 for the maximum crop type. Two GPSs, Magellan and Etrex, were used to collect data from the field. Before taking a sample from a field by Magellan, we need to upload a road map so that we can determine how far the crop fields are from the roads. Magellan has the advantage of displaying files in ARCPAD. Before going out into

the field, the magellan is loaded with Field Remon Sensing data, which also serves as a map of the studied area, dividing the same crop species into fields by color, but not showing the crop type and name. We take into account criteria such as crop diversity and yield when allocating landfills. We take into account criteria such as crop diversity and yield when placing fields. Once we have identified the area identified in the GPS, an attribute table is created, and we type the crop type and click the save button, the received data is stored in GPS memory. In addition to Magellan, we also used a second GPS etrex. In Magellan, not all areas can be identified, in which case etrex is used. In Magellan, not all areas can be identified, in which case etrex is used. In Etrex, the coordinates are taken from the field, an automatic number is written to the obtained



coordinates, and the outline of the field is drawn there and numbered according to the GPS number.

After completing the fieldwork, separate drawings will be made for the two GPSs. The coordinates of the fields obtained in Etrex are loaded into GIS Google Earth is used in the GIS toolbar to draw the fields. The next step is to create a shp file and put a few columns in the attribute table: sampler - the name of the person responsible for sampling, yyyy-mm-dd - the date of sampling, label - the class of the sample from which the characters are taken. After adding the columns, we can start drawing the fields. The number of fields obtained by Etrex is 657.

Identified crop types: alfalfa, wheat-maize, wheat-fallow, orchard, cotton, rice, sunflower, wheat-rice, wheat-mung bean, maize, wheat-vegetables, grapes. In addition to Google Earth, an NDVI (Normalized Difference Vegetation Index) image is also used to check the accuracy of the fields during the drawing process. NDVI uses the NIR and Red bands of the Normalized Differentiation Vegetation Index of the electromagnetic spectrum. In agriculture, plant parameters show several indices. The following table describes several plant indices, detection formulas, and variability

**Table. 2**

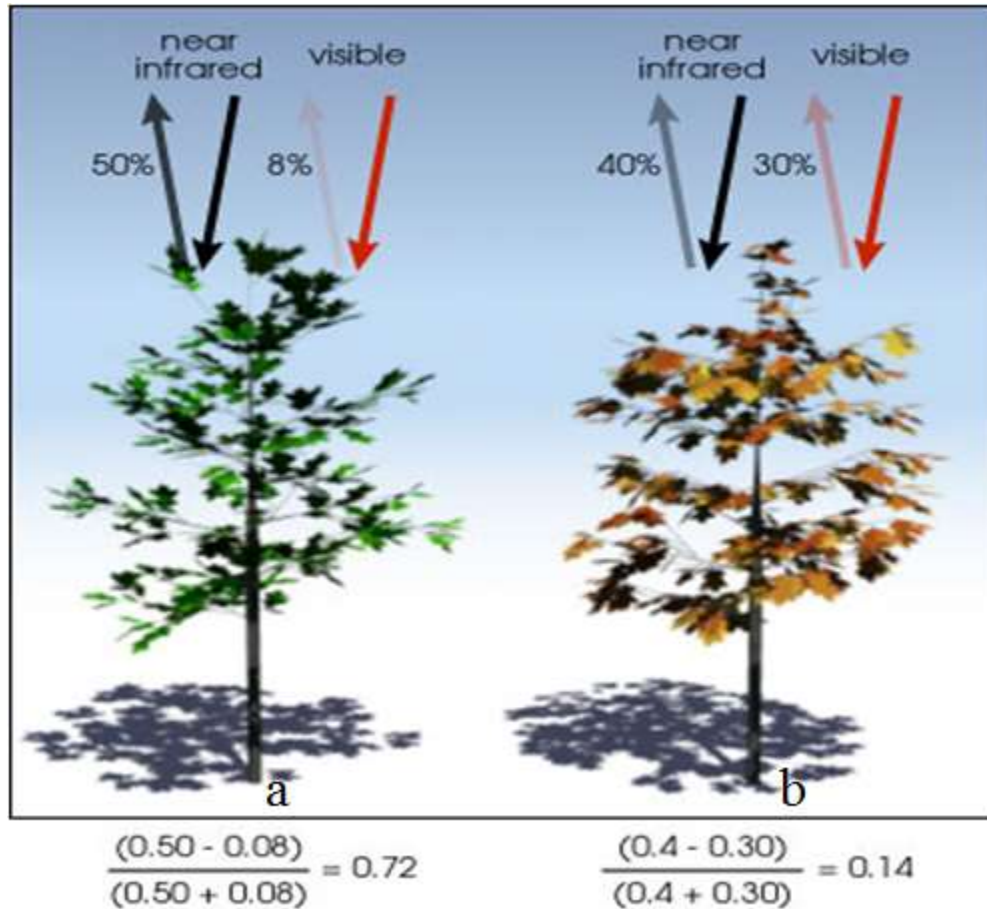
No	Name	Formula	Variables
1	Crop water stress Index	$\frac{C - A}{B - A}$	
2	Green leaf Index	$\frac{2GREEN - RED - BLUE}{2GREEN + RED + BLUE}$	
3	Normalized Difference Vegetation Index	$\frac{NIR - RED}{NIR + RED}$	RED=[670;50;30],NIR=[800;10;10]
4	Soil Adjusted Vegetation Index	$\frac{800nm - 670nm}{800nm + 670nm + L}$	L=0,5

### Vegetation (spectral) index

NDVI has been used for plant identification and various research purposes since its introduction in the 1970s (Yeom et al., 2019). Basically, NDVI is widely used in agricultural monitoring to determine the

vegetation period of a plant, and NDVI is calculated as follows.

$$NDVI = \frac{NIR - Red}{NIR + Red}$$



**Figure. 1 Normalized Difference Vegetation Index (NDVI) indicator**

Here, it measures the difference between NIR (which the plant strongly reflects) and Red (which plant wins) and determines the amount of plant. The ratio of near-infrared rays is calculated from minus (-1) to (+1). The result of this calculation is called the normalized differentiation vegetation index or NDVI. A zero value of NDVI means no green vegetation and a high density of green leaves of about 1 (0.8 - 0.9) (Figure. 1). In the figure below, a) NIR = 0.50 for the plant and Red = 0.08 as a result of the plant absorbing and returning light NDVI = 0.72, the plant is healthy, and b) the NDVI value of the plant is 0.14 resulted in the process of plant construction. After completing the mapping of the fields using the NDVI image using Etrex data, the mapping of the fields based on the data collected from the Magellan GPS is also performed according to the order of the work performed in the etrex. When the drawings are completed, the attribute tables of Magellan and etrex are combined, the overlapping areas and some of the shortcomings are corrected. In the next step, we will start by entering the generalized

GPS data into the CAWaRStudio project. The CAWa (Central Asian Water) project plans to contribute to a reliable scientific and regional database to develop a strategy for sustainable water management in Central Asia. The sample data obtained in the field are closely related to the CAWaR project.

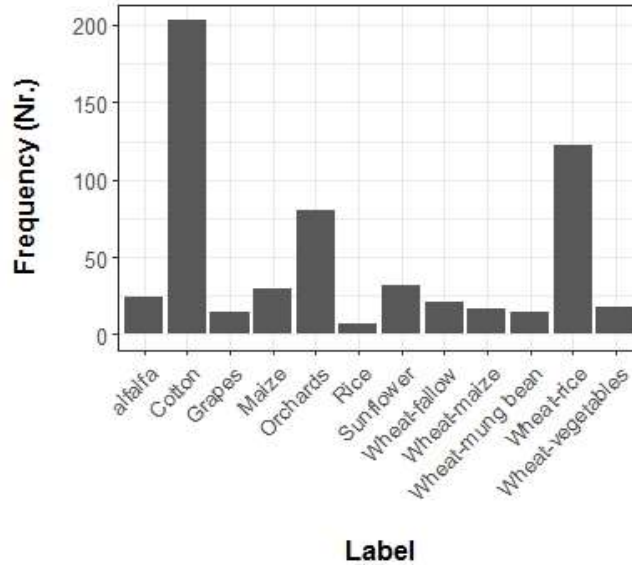
## RESULTS

CAWaR.R data geCheck()-detects geometric errors and speeds up the workflow. CheckSamples()-also checks the accuracy of the data, the relevant fields, and their formats and checkLabels()- checks for errors in the name of the crop types in the sample and automatically corrects them. SampleCorrect<-labelCheck (fieldData\$label) – training creates a graph of crop types based on data, in this case for analysis maize, sunflower, grapes, wheat-maize, wheat- mung bean, wheat-vegetables classes must be renamed.

checklable<-labelCheck(fieldData\$label)- to rename classes with a label that corresponds to the set of labels above. We can see it by the number of

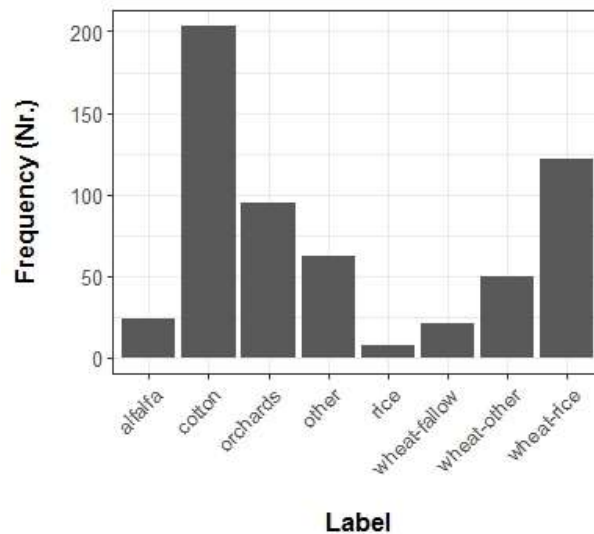


fieldData@data\$label2<-checklable\$labels- fully "labelCheck.RData")- saves the corrected label graph.  
corrected labels. Save(checklable, file =



**Figure.2 Graph of crop types in CAWaR model**

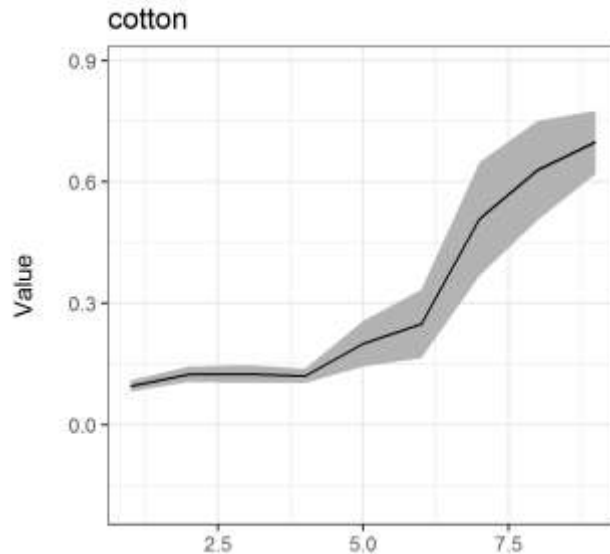
Figure. 3 shows a new view of the renamed crop types, such as alfalfa, cotton, orchards, rice wheat-fallow, wheat-rice. In this case, the types of crops belonging to the same category as wheat-mung bean, wheat-maize, wheat-vegetables, wheat-other as grapes and maize other are generalized and renamed.



**Figure.3 Graph of renamed crop species**

CheckTS1<analysTS(as.data.frame(fieldDataTS\$weighted.mean)fieldData\$label2)- creates a profile for each sample view. The profile indicates which crop type it is suitable for, whether the named label is true or false (Figure. 4). It is also possible to check the growth profile of each crop type on the dates of satellite

imagery. The planting time of cotton corresponds to the time taken from the satellite image in May. The growth schedule of the harvest coincides with the growing season of cotton in August, and we can determine the accuracy of the following growth profile of cotton as a result of inspections.



**Figure.4 Crop type growth profile**

`cl<-compare`  
`(as.data.frame(fieldDataTS$weight.mean),`  
`reference.profiles, fieldData$label2, checkTS1$labels)-`  
 matching of samples to classify profiles or determines  
 incompatibility (Figure.5) Field training data collection  
 may result in certain errors, as a result of which the  
 CAWa R model uses the following image to determine  
 whether the samples are compatible with each other.

Label

Field training data gives TRUE if correct and FALSE if  
 incorrect. `fieldData$validation`  
`<-`  
`as.factor(cropVal$sample.validation)-` determines  
 whether the samples are classified correctly and  
 incorrectly. This result determines the distribution of  
 errors and, in some cases, helps to identify incorrect  
 samples that have been skipped during the initial tests.

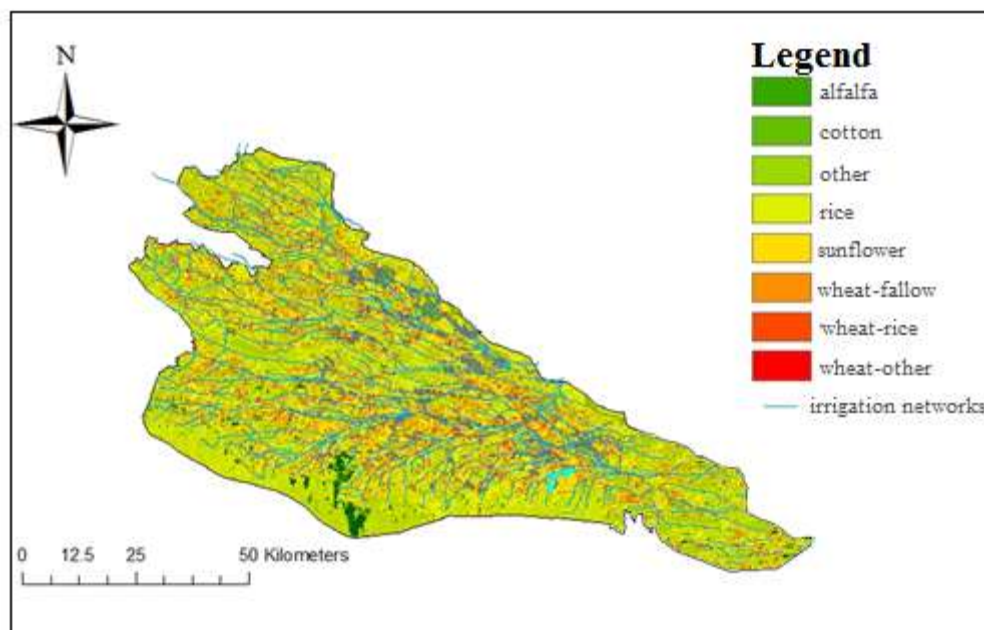
x.label	y.label	pearson	compare
cotton	cotton	0.91	TRUE
cotton	cotton	0.91	TRUE
wheat-other	wheat-other	0.93	TRUE
cotton	cotton	0.83	TRUE
cotton	cotton	0.89	TRUE
cotton	cotton	0.91	TRUE
cotton	cotton	0.89	TRUE
cotton	cotton	0.92	TRUE
cotton	cotton	0.94	TRUE

**Figure.5 Profiles Classification Indicator**



Crop mapping is a challenging task due to spectral similarity of various crops. In the map of the location of the following crops created by the CAWaRsudio model and GIS in Khorezm region, we can see that the main crop of this region is cotton, alfalfa and other (Fig.6). In order not to make it difficult to read on the

map, similar crops were named wheat-other and other using the CAWaRsudio model. The appropriate Landsat-8 OLI data set for the CAWaR model includes a normalized differential index (NDVI) and plant distribution data for May and August for each selected area.



**Figure.6 Crop Type Map Obtained As A Result Cawarstudio Model and GIS**

## CONCLUSIONS

At present, not enough attention is paid to soil, water and plant conditions at the field level, although monitoring of soil moisture and crop species monitoring will meet the demand in terms of organic correlation, it satisfies professionally managed irrigation. The identification and mapping of irrigated crops are a very important step for agricultural management and food security control towards an increased food production and reduced water use. Undoubtedly, traditional mapping techniques and monitoring crops are laborious, time-consuming and costly. The aim of this study is to map the types of irrigated crops using remote sensing data. Following the collection of training data from the “crop mapping” field based on Landsat-8 OLI satellite imagery, the above steps were gradually performed on the CAWaR model. Some of the shortcomings encountered in the process of mapping crop types were attempted to address some of the shortcomings in the collection of cloud images and training data from satellite images, the article noted. The results show that measures based on satellite imagery in solving the Aral Sea-based water

problem for Central Asia are crucial for creating a comprehensive system for water use analysis. Collaborative reports based on satellite imagery maps and water supply survey data are based on the evaluation of irrigation efficiency indicators over a period of time and for individual crops. The results of this study will be used to develop an irrigation water use assessment system and a water use efficiency report. As a recommendation for future work, the use of new systems with spatial, spectral, and temporal resolution, such as MODIS, will improve the accuracy of the results. The use of these systems standalone or in synergy with radar systems such as Sentinel-1 will alleviate the confusion of unstable or short-cycle crops like alfalfa and ensures better phenological monitoring of crops during the cloudy days in arid and semi-arid regions.

## REFERENCES

1. Alvino, A., & Marino, S. (2017). *horticulturæ Remote Sensing for Irrigation of Horticultural Crops*. January. <https://doi.org/10.3390/horticulturæ3020040>





2. Awan, U. K., Tischbein, B., Conrad, C., Martius, C., & Hafeez, M. (2011). *Remote Sensing and Hydrological Measurements for Irrigation Performance Assessments in a Water User Association in the Lower Amu Darya River Basin*. *Water Resources Management*, 25(10), 2467–2485. <https://doi.org/10.1007/s11269-011-9821-2>
3. Kim, Y., & Evans, R. G. (2009). *Software design for wireless sensor-based site-specific irrigation*. 66, 159–165. <https://doi.org/10.1016/j.compag.2009.01.007>
4. Löw, F., Biradar, C., Fliemann, E., Lamers, J. P. A., & Conrad, C. (2017). *International Journal of Applied Earth Observation and Geoinformation Assessing gaps in irrigated agricultural productivity through satellite earth observations — A case study of the Fergana Valley , Central Asia*. *International Journal of Applied Earth Observations and Geoinformation*, 59, 118–134. <https://doi.org/10.1016/j.jag.2017.02.014>
5. Yeom, J., Jung, J., Chang, A., Ashapure, A., & Maeda, M. (2019). *Comparison of Vegetation Indices Derived from UAV Data for Differentiation of Tillage Effects in Agriculture*.
6. World Bank. (2013). *Strengthening Analysis for Integrated Water Resources Management in Central Asia : Strengthening Analysis for Integrated Water Resources A Road Map for Action (Issue September)*.
7. Moran, M. S., Maas, S. J., Vanderbilt, V. C., Barnes, E. M., Carolina, N., Miller, S. N., & Clarke, T. R. (n.d.). *Application of Image-Based Remote Sensing to Irrigated Agriculture (Vol. 4)*.
8. Sanli, F. B., Abdikan, S., & Esetili, M. T. (2014). *Crop Type Classification Using Vegetation Indices of RapidEye Imagery CROP TYPE CLASSIFICATION USING VEGETATION INDICES OF RAPIDEYE*. September. <https://doi.org/10.5194/isprsarchives-XL-7-195-2014>
9. Savoskul, O. S., Chevnina, E. V., Perziger, F. I., Baburin, V. L., Matyakubov, B., & Murakaev, R. R. (2003). *Water , Climate , Food , and Environment in the Syr Darya Basin. Contribution to the project ADAPT*. Change, July. <https://www.ijraset.com/files/serve.php?FID=12295>
10. Shanmugapriya, P., Rathika, S., Ramesh, T., & Janaki, P. (2019). *Applications of Remote Sensing in Agriculture - A Review*. 8(01), 2270–2283.
11. Weiss, M., Jacob, F., & Duveiller, G. (2020). *Remote Sensing of Environment Remote sensing for agricultural applications : A meta-review*. *Remote Sensing of Environment*, 236(December 2018), 111402. <https://doi.org/10.1016/j.rse.2019.111402>