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Satellite based calculation of spatially distributed crop water requirements for cotton and wheat cultivation in Fergana Valley, Uzbekistan

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ABSTRACT

This study focuses on the generation of reliable data for improving land and water use in Central Asia. An object-based remote sensing classification is applied and combined with the CropWat model developed by the Food and Agriculture Organization (FAO) to determine crop distribution and water requirements for irrigation of cotton and winter-wheat in Fergana Valley, Uzbekistan. The crop classification is conducted on RapidEye and Landsat data acquired before the onset of the main summer irrigation phases in July using a random forest algorithm. The ClimWat database of FAO is utilized for calculating crop water requirements (CWR) and crop irrigation requirements (CIR).

Classification reveals an overall accuracy of 86.2% and exceeds a producer's (user's) accuracy of 95% (89%) for both, cotton and wheat. In 2010, cotton and winter-wheat are planted on 66.7% of the agricultural area under investigation, whereas orchard areas amount to 15.5%. The CWR modelled for winter-wheat and cotton cultivation revealed 5443 m^3 ha^{-1} and 9278 m^3 ha^{-1}, respectively. Subtracting effective precipitation leads to CIR of 4133 m^3 ha^{-1} and 8813 m^3 ha^{-1}. Comparisons of CWR and CIR for the area dominating crops with the total of water officially allocated for irrigation underline the pressure on the water resources in the entire Syr Darya catchment and suggest modifications of the cropping system towards more winter crops. The early season crop maps can be used for water saving as they enable modifications of water allocation plans within the different irrigation subsystems of the valley. The method for mapping spatially distributed CWR and CIR can be transferred to other irrigated areas in Central Asia and beyond.

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1. Introduction

Initiated by the Soviet expansion and intensification of crop production starting in 1960 (Létolle, 1993), irrigation of crops on around 8 million ha of land utilizes more than 90% of the annually available 120 km^3 of freshwater in the Aral Sea Basin (ASB) today (Roll et al., 2005). But the peak of productivity along the Amudarya and Syrdarya Rivers achieved by high inputs of water, fertilizers, and pesticides to soils of low natural fertility ended already in the mid1980s (Giese et al., 1998). The permanent overexploitation has resulted in the degradation of croplands due to salinity which caused yields to decline by about 30% already before the break-down of the Soviet Union in 1991 (Létolle, 1993). In the five Central Asian (CA) successor states, Uzbekistan, Kyrgyzstan, Tajikistan, Kazakhstan, and Turkmenistan, approximately 50% of the irrigated land is affected by salinization (Reddy et al., 2013). Moreover, the agricultural sector of these countries is economically incapable to maintain the irrigation and drainage system or to introduce water saving irrigation methods. As a result, land productivity and especially water use efficiency are reported to be low throughout the ASB (e.g. Granit et al., 2010; Tischbein et al., 2013).

The Fergana Valley is a rather typical and maybe the most prominent example of large-scale irrigation systems in Central Asia. Very low field application efficiencies of 49% (Reddy et al., 2013) and contributions of shallow groundwater to irrigation amounting to 23% have been observed in field experiments (Pereira et al., 2009). Despite its upstream location of the major irrigation systems along the Syrdarya River, upstream–downstream disparities of water availability and access to water have been reported within the irrigation system of Fergana Valley (Abdullaev et al., 2009a). These characteristics are similar to other irrigation systems in the ASB (e.g. Dukhovny et al., 2004; El-Magd and Tanton, 2005; Tischbein et al., 2013; Conrad et al., 2013). But the

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irrigation complex is trans-boundary and shared by three countries, Kyrgyzstan, Tajikistan and Uzbekistan. Moreover, the Fergana Valley is the most densely populated region in entire Central Asia with more than 11 million inhabitants and exceeding 500 inhabitants per km^2 in some of its parts (Filcak, 2008). The annual population growth rate in the three Central Asian countries 1998–2015 varies between 1.1% and 1.5% (World Bank, 2013).

Improvements of the water use within Fergana Valley are urgently needed especially in face of still increasing pressure on the water resources, e.g. by impacts of temperature increases expected to be around 1.5–2.5 °C (Lioubimtseva and Henebry, 2009) on snow cover parameters and glacier melting. Diverging prognoses of precipitation patterns show high uncertainties of climate models when predicting future water availability in the upstream catchments (Mannig et al., 2013). However, scenarios of a coupled climate, land-ice and rainfall-runoff model indicated runoff peaks shifting from spring towards the late winter season in the Syrdarya catchment (Siegfried et al., 2012). Another source for increasing pressure is the energy demand of Kyrgyzstan and Tajikistan, which want to make use of the high hydropower potential stored in numerous reservoirs. Most of them were constructed on the territory of today's upstream countries in Soviet times (Rakhmatullaev et al., 2010). Water releases especially during the winter period can reduce water availability at the irrigation system boundaries during the vegetation period (Karimov et al., 2010). For this reason conflicts rose between the states as previously described by Sehring (2008) and an update of the former Soviet inter-provincial distribution schemes is still a matter of dispute 20 years after independence in 1991.

Among others one starting point for improvement could be a better matching of water demands to the availability within the irrigation system irrespectively of external pressure on water resources. Reddy et al. (2013) assigned low field application efficiencies to high application rates accompanied with runoff losses up to 64%. Suggestions are made, even for increasing irrigation efficiencies by introducing suitable water application strategies (Horst et al., 2005; Webber et al., 2006) or improving irrigation scheduling (Pereira et al., 2009). However, the extrapolation of this findings and potential water saving options from field to system level would require area wide information in a spatially explicit way. For some of the parameters (e.g. soil moisture) exhaustive field surveys would be necessary, but with known land use patterns, at least area wide crop water requirements (CWR) and, utilizing meteorological measurements, crop irrigation requirements (CIR) could be calculated at the field level. Aggregated to sub-system level allocation plans and water distribution in the channel system can be optimized (El Nahry et al., 2011). But due to missing and unreliable data in the land and water sector in entire Central Asia (Giese and Mossig, 2004; Oberkircher, 2010), area-wide CWR/CIR calculations would most likely comprise uncertainties: In addition, the sparse information is mostly available in a tabular way. The latter hinders the location based analyses and the implementation of solutions at different scales.

Remote sensing in combination with Geographical Information Systems (GIS) has shown the potential for improving data situations in irrigation management (Bastiaanssen and Bos, 1999; D'Urso et al., 2010). Satellite remote sensing is for instance an accurate, time and cost-efficient tool for mapping crop distribution at different scales (e.g. GEOSS, 2009; Wardlow et al., 2010; Conrad et al., 2011). The accuracy for instance relies on the spatial resolution of the available satellite data which needs to match the heterogeneity of the agricultural landscape (Wardlow and Egbert, 2008; Conrad et al., 2010). Multi-temporal approaches can return high mapping accuracies (Barrett and Curtis, 1992), however, studies by Murakami et al. (2001) and VanNiel and McVicar (2004) outline the suitability of selecting a few but optimal temporal windows for accurately distinguishing between different crops. For water saving within a vegetation period, initial crop classifications would be helpful to adjust water allocation plans and refine water distribution schedules in the early irrigation season (Oberkircher, 2010).

Calculations of CWR and CIR are usually based on the crop specific reference evapotranspiration (ET_c, Allen et al., 1998). It can be obtained at different levels of detail via crop coefficients based on agro-meteorological data, soil and plant information e.g. as implemented in the CropWat model designed by the FAO (Smith et al., 1996). For mapping extensive areas, this approach has been frequently linked with remotely sensed crop maps. Rao et al. (2001) analyzed the CIR of different crops using Landsat-TM 5 satellite images with a spatial resolution of 30 m for crop mapping and the CropWat model for CWR assessments. Casa et al. (2009) utilized a similar approach for mapping CWR in central Italy based on a crop map from four Landsat ETM + images. Also the field based approach has been supplemented with remote sensing information. Er-Raki et al. (2010) derived multi-temporal vegetation indices using a handheld spectrometer for simulating spatially distributed ET_c on experimental sites in Morocco. Extrapolations to multi-temporal Landsat TM spectral data were investigated by D'Urso and Menenti (1995). Thermal Landsat observations were included into CWR estimations e.g. by El-Magd and Tanton (2005) in the Kyzyl-Orda region of Kazakhstan. Thermal information also enables the calculation of ET_c solely based on remote sensing data (Tasumi and Allen, 2007; Ahmed et al., 2010; El Nahry et al., 2011). However, the fact that multi-temporal thermal data covering a complete vegetation period with spatial resolution suitable to match the field sizes are rare limits the derivation of ET_c in the different growth phases (Casa et al., 2009).

This study aims at quantifying and assessing irrigation water use for cotton and wheat in the Fergana Valley by combining crop classifications with calculations of CWR and CIR. Methodological focus is set on early season mapping of the major crops, as accurate maps already before main irrigation phases are seen as one option to save water as they allow for within-season adjustments of water allocation plans. Thus, bi-temporal 6.5 m RapidEye data acquired in May and June 2010 and one Landsat TM5 scene recorded in early July 2010 were utilized. Due to the unavailability of digital cadaster maps, field boundaries were derived via segmentation of RapidEye data. The widely used 'random forest' algorithm is selected for classifying crop distribution. CWR and CIR assessments are conducted with CropWat based on meteorological data from ClimWat data base and local knowledge. The results are discussed in the light of water saving options and potentials for increasing water use efficiency in the Fergana Valley.

2. Study area

The Fergana Valley, situated in the south-eastern part of Uzbekistan (Fig. 1) is bordered by two mountains, the Tien Shan in the north and the Alai in the south (Filcak, 2008). The climate can be classified as continental with 100–200 mm average annual precipitation and a potential evapotranspiration of up to 1300 mm (Umarov et al., 2010). The average temperature in the valley ranges from −3.9 °C to 3.9 °C in January to 20.2 °C to 34.7 °C in July (Table 4).

The Fergana Valley forms the upper to mid-reach of the Syrdarya basin. It generates almost 70% of the valleys surface water and his tributaries Naryn and Karadarya. The river's nourishment is classified as mixed snow-glacial and is formed in the surrounding mountains (Savoskul et al., 2003).

The Fergana Valley is one of the most important areas for agriculture in Central Asia (Abdullaev et al., 2009a). It represents one large-scale cotton production system of the former Soviet Union, with 1.653 million ha irrigated land (including homesteads: 193 ha, SIC-ICWC, 2011). Around 70% of the 11,342,000 inhabitants (Reddy et al., 2012) still depend on income from the agricultural sector and agriculture contributes approximately 24% to the country's gross domestic product (Bichsel, 2009).

The Uzbek part of the Valley consists of three provinces (Oblasts): Fergana, Namangan and Andijan, of which about 1 million ha is under

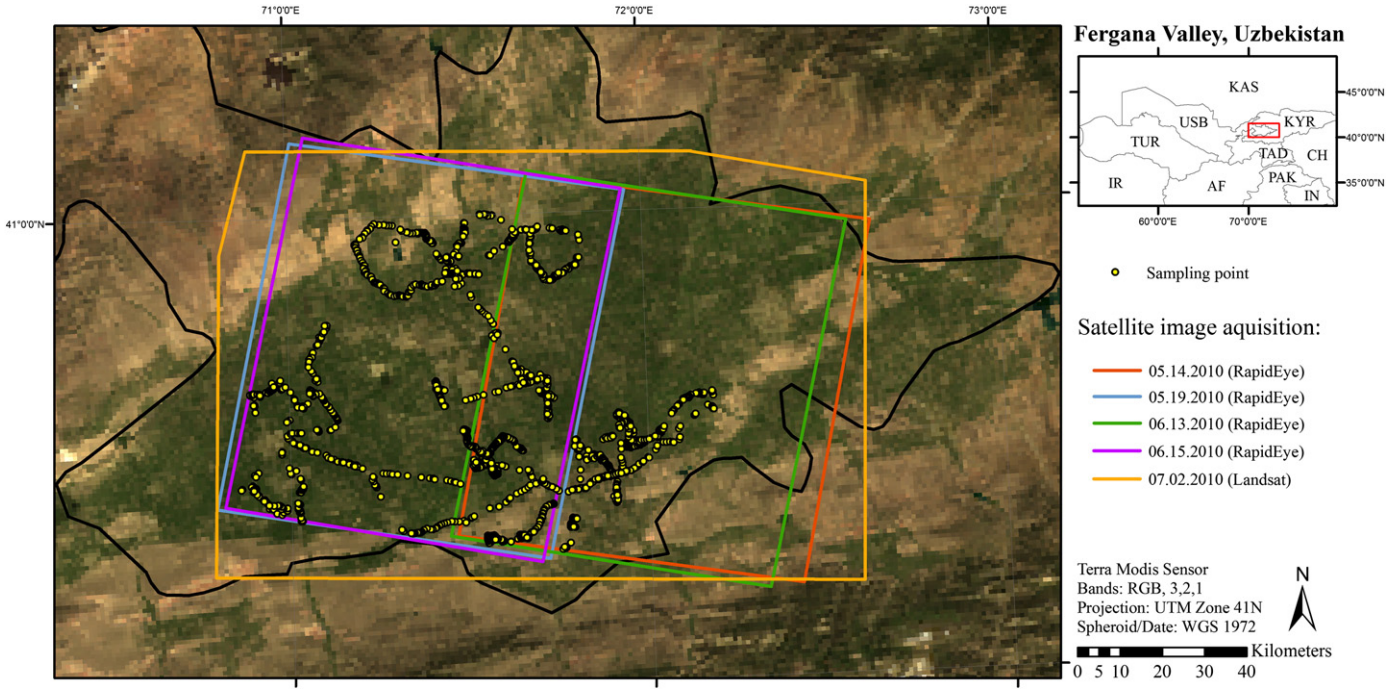

Fig. 1. Spatial and temporal distribution of the RapidEye satellite scenes and sampling points.

irrigation. From 1960s onwards the main crop has been cotton, but it was supplemented by winter-wheat included to the Uzbek state-order system after independence in 1991 (Abdullaev et al., 2009b). Fig. 2 (first row) shows the cropland development in the Uzbek part of the Fergana Valley between 1980 and 2000. The blue line shows the total area (ha) and the percentage of cotton, grain crops and orchard areas is presented in bright green, orange, and dark green columns, respectively. The change situation after the break-up of the Soviet Union led to a decline of cotton area at the expense of grain crops, and orchards. Forage crops (e.g. alfalfa) were also reduced.

Congruently the yields of cotton and grain crops developed during the two decades (Fig. 2, middle row). Interestingly, orchard yields remained stable despite the significant increase of area. Cotton yields show the typical patterns for Central Asia which are usually explained by land degradation, mostly salinization (Létolle, 1993). After the peak time in the mid-1980s with productivities achieving 5 t/ha, a rapid drop below 3 t/ha can be found at the end of the same decade (Fig. 2, lower row). The productivity information discloses major problems of the official data. The productivity of grain crops increases which might be owed to improved management. But comparatively high values above 5 t/ha can hardly be explained similar to the productivity decline of orchards. There might be a change of tree types. Assumptions on changes in the crop class definitions are similar speculative. Overall, the transformation processes towards trees (orchards) and grain crops remain visible.

According to the cropping calendar, cotton is planted in mid-April, matures by August and is harvested by the end of October. Winter-wheat is sown in autumn, lies dormant during winter and reaches maturity in June to July (personal communication from Kenjabaev, 2010).

During the Soviet era a dense and complex irrigation and drainage network was constructed to balance river flows with irrigation requirements (Lètolle, 1993). But the infrastructure has been declining and even though references are unavailable, percolation losses in the mostly unlined channel system are very likely. At field level, inefficient irrigation methods, such as open basin or furrow irrigation, with high transpiration and infiltration losses, are still a common practice (Horst et al., 2005). Also direct losses caused by high surface runoff during irrigation events have been reported (Reddy et al., 2013).

Water releases of 4000–10,000 m^3 per ha land can be derived by combining the cropping area of the seven administrative districts (Uzbekistan: Andijan, Fergana, Namangan, Tajikistan: Sokh, Kyrgyzstan: Batken, Jalalabad, Osh) and fact water amounts distributed upstream the Kayrakum reservoir in the west of the valley. The variations of water available per ha are caused by annual fluctuation of water withdrawals presented in Fig. 3 for the period 1991–2010. An increase of water intake to the irrigation system in the non-vegetation period (October–March) documents increased water demand for the grain crop winter-wheat and leaching of saline soils. Moreover, especially between 2000 and 2004, the water extraction is far above the limits (SIC-ICWC, 2011) which indicates compensation of the aforementioned upstream releases for energy production in winter time. Field observations showed that water releases to the channel system can become necessary for regulating river runoffs exceeding capacities.

3. Materials and methods

The methodological focus of the analysis is the crop classification based on early season RapidEye data. The image acquisition dates were selected according to the crop calendar and should theoretically enable for distinguishing the most common crops, cotton and winter-wheat. It has to be noted, that crops planted after the harvest of winter-wheat remained excluded from the analysis.

The classification consisted of two steps, the separation of agricultural fields from other land cover and the crop discrimination within the field boundaries. The first step became necessary, as digital cadaster information was unavailable. Field boundaries were derived from satellite scenes by segmentation and agricultural fields were separated from other land use classes through a semi-automatic process. The different crops were discriminated through an object-based classification method. In the last step CWR and CIR of cotton and winter-wheat were estimated using the CropWat model. A detailed description of the input data and each step is provided in the following sections.

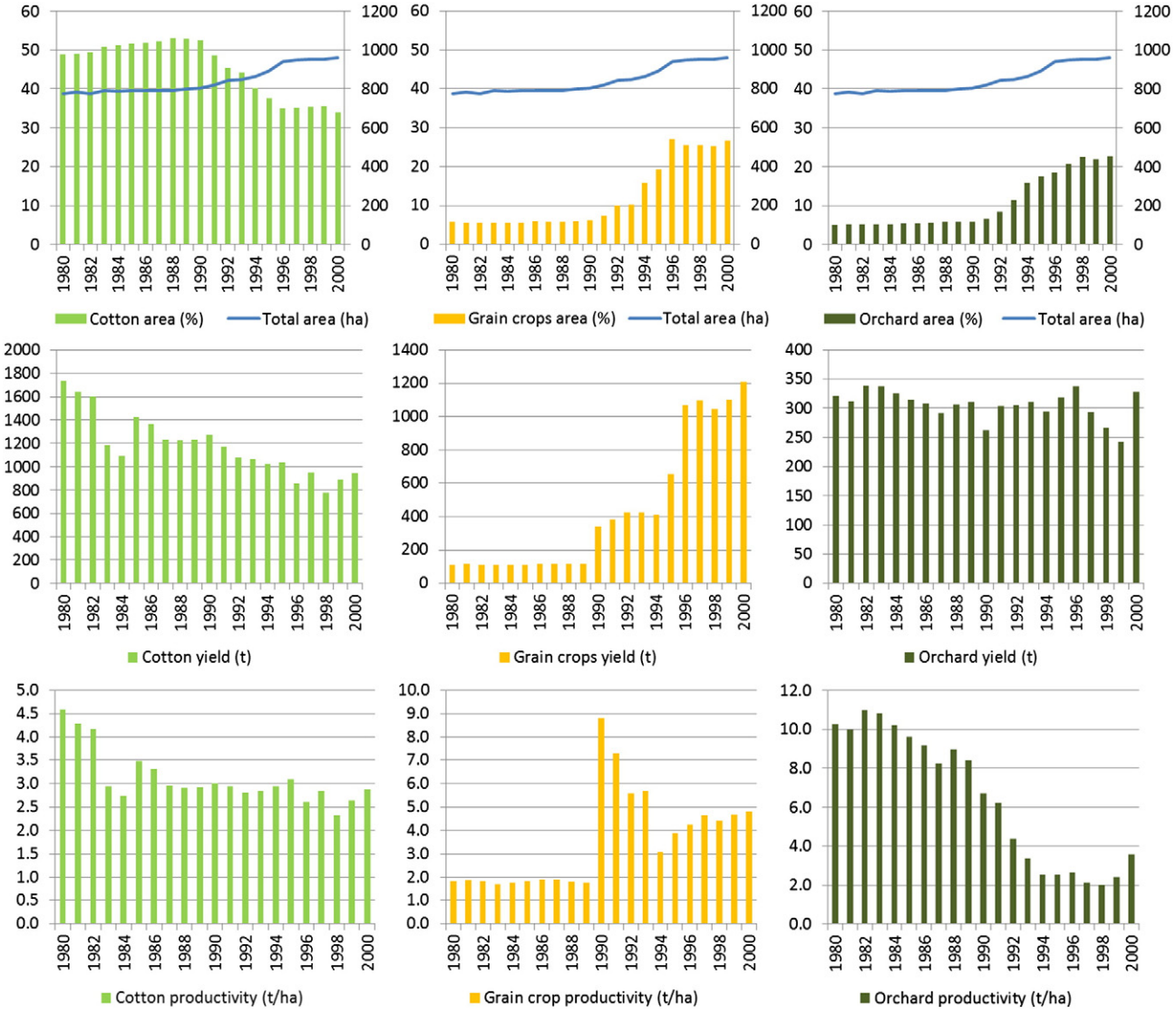

Fig. 2. Cropland information of the three Uzbek districts (Oblasts: Fergana, Namangan and Andijan) in Fergana Valley available via the CAREWIB database: Area percentage, yield and productivity (t/ha) of cotton, wheat, and orchard production between 1980 and 2000.

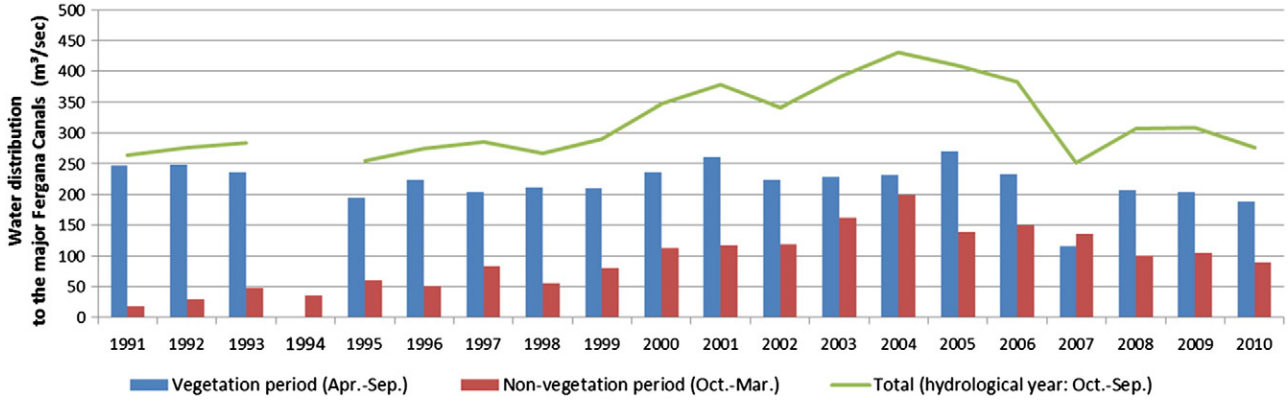

Fig. 3. Discharge to the major Fergana irrigation channels till Uchkurgan headwork (total of: SFC — South Fergana Channel, BFC — Big Fergana Channel, LNC — Channel situated on the left bank of the Namangan channel, NBC: Big Namangan Channel) between 1991 and 2010.
Source: SIC-ICWC, 2011.

3.1. Satellite data and pre-processing

The land use classification is based on four multispectral RapidEye data sets and one Landsat5 TM image, which were acquired at three time steps in May, June, and July 2010. The RapidEye images spatially covered approximately 66% (12,237 km^2) of the Fergana Valley (Fig. 1).

The RapidEye system is a constellation of five identical satellites with a spectral range covering five channels (blue, green, red, red edge and near infrared, Tyc et al., 2005). Its spatial resolution of 6.5 m was assumed to be suitable for the delineation of agricultural fields (Section 3.2), which have an average size of 7 ha in the study area. Landsat5 TM comprises six channels including visible (blue, green, red), near infrared (NIR), and short wave infrared (SWIR-1, SWIR-2) spectra.

Two pre-processing steps (geometric and atmospheric correction) were subsequently conducted to ensure that the images were geographically adjusted and free of atmospheric noise. A second-degree polynomial model and a nearest neighbor resampling technique were applied for geometric correction using differential GPS data collected in the research area. Sub-pixel accuracies for all scenes could be achieved. The atmospheric correction was conducted using ATCOR Version 7.1 (Atmospheric and Topographic Correction) and clouds and shadows were masked to remove contaminated pixels (Richter, 2010).

Similar to Conrad et al. (2010) a field-based classification approach was selected. Besides spectral information the Normalized Difference Vegetation Index (NDVI) was included into the feature space for classification. This factor for greenness and density of vegetation (Chen and Brutsaert, 1998) has been successfully used for crop mapping in many studies (e.g. Wardlow et al., 2010; Conrad et al., 2011). To compensate its sensitivity to perturbing factors such as soil or atmosphere, the Soil Adjusted Vegetation Index (SAVI) and the Enhanced Vegetation Index (EVI) were also calculated (Huete et al., 2002).

3.2. Field sampling

Sampling points are essential for training and validation of classifiers (Congalton and Green, 2009). Sampling points of crop types were collected during field-work conducted in June and July in the Fergana Valley. At this time, both dominating crops winter-wheat and cotton could be identified. Sampling points were chosen randomly and equally distributed over the entire study area (Fig. 1). For each sampling point the GPS-position was recorded and the class was denoted. Besides cotton (501) and winter-wheat (456), sorghum/maize (17), rice (57), orchards (223), vineyards (8), alfalfa (10), sunflower (13), watermelon (25), other fruits and vegetables including mungbean and tobacco (22), fallow land (50), and fishponds (7) were sampled for classification. Photos were taken of each sampled field for *ex post* verification of the class assignment. In total, 1425sampling points were acquired.

3.3. Obtaining field parcels by image segmentation

In contrast to pixel-based approaches field-based crop-classification methods can avoid the problem of misclassification caused by spectral within-field heterogeneity (de Wit and Clevers, 2004; Blaschke et al., 2008). As digital field parcel boundaries were unavailable, the two RapidEye scenes acquired in May 2010 were segmented and a pre-classification was conducted to distinguish fields from other land cover. Two field parcels are usually divided by irrigation or drainage channels covered by trees. In the beginning of the summer season vegetation cover within the field is low. The spectral contrast between the field and the tree-covered surrounding canals is high. Thus early season images were selected for the identification of field boundaries, similar to another approach conducted in the lower Amudarya catchment (Conrad et al., 2010).

Multi-pixel objects were generated using a multi-resolution algorithm included in the software eCognition Developer 8.64 (Definiens, 2010). The segmentation process was performed by equally weighting of all five bands in the blue, green, red, red edge and near infrared wavelength. A segmentation scheme with 27 different user-defined parameter combinations of the eCognition inherent thresholds for scale, shape and compactness was tested.

The accuracy of the field boundary delineation was assessed by a visual interpretation and the comparison of the area and shape of the segmentation results with ten randomly chosen and manually digitized reference fields. Main problems, which have to be avoided, were over- and under-segmentation, which stand for generating too many or too few objects, respectively (Delves et al., 1992).

Afterwards, all objects were assigned to the classes 'field' and 'no field' through a semi-automatic process. The accuracy was determined by calculating the user's, producer's, and overall accuracy according to Congalton and Green (2009). A confusion matrix for 281 randomly selected polygons was generated. The confusion matrix visualizes the number of correct and incorrect predictions made by the classification algorithm. The rows present the number of actual classifications in the test data and the columns present the number of predicted classifications. The overall accuracy is the ratio of correctly classified objects to all regarded objects. The producer's accuracy refers to the errors of omission and indicates the probability that a field on the ground is classified as such on the map, while the user's accuracy refers to the errors of commission and indicates the probability that an object labeled as a field in the map is really the same class (field) on the ground. For the subsequent crop classification process the field-polygons were exported in vector format.

3.4. Crop classification

A 'random forest' algorithm according to Breiman (2001) was used for the field-based crop classification. This algorithm belongs to the class of ensemble classifiers, which combine several automatically generated classification trees calculated for random data subsets. Classification trees predict class memberships by recursively partitioning the given data set into more homogenous subsets (Hansen et al., 2000). With 'random forest' a pre-defined number of such classification trees can be grown, each one from a random subset of samples and predictors. Every tree in the forest casts a unit vote for the most popular class and the classified output is determined by a majority vote. 'Random forest' classifiers have been found advantageous to single classification trees as they lack sensitivity to noise and avoid overfitting (Watts and Lawrence, 2008).

In this study, the randomForest package as implemented in the statistic software R was used (R Development Core Team, 2009). The Gini-index of node impurity was applied for determining splits in the predictor variables that result in the greatest classification accuracy. The sampling points of the crop classes were selected for training (Section 3.2), whereas alfalfa, vineyards, sunflowers, vegetables, and watermelons were grouped to one class other (78 samples). The 50 features extracted from the satellite data used as predictors included the mean and standard deviation values from the spectral bands (RapidEye: 1–5, Landsat: 1–6) and the vegetation indices (NDVI, EVI, SAVI).

Ten random forests were generated based on the training samples. Each 100 samplings of the cotton, wheat, and orchard samples were randomly selected for every classification run to counterbalance the uneven distribution of training samples (Section 3.2). A majority vote was applied for final class assignment. Each random forest was built using 500 generated classification trees. Class accuracies were determined through Out-Of-Bag (OOB) samples, i.e. validation based on the training data that was not included in the generation of a particular tree (Watts and Lawrence, 2008).

3.5. Calculation of CWR and CIR

The conceptual framework suggested by the FAO (Smith et al., 1996) and successfully applied for several regional assessments (e.g. Casa

et al., 2009) was applied for estimating the crop water requirements (CWR) and crop irrigation requirements (CIR) in the study area. CIR represent the difference between CWR and effective precipitation (P_{eff}, Allen et al., 1998). The CropWat model, version 8.0 was used for calculating CWR and CIR of cotton and winter-wheat. Table 1 shows the input parameters needed for the calculation of the CWR.

CropWat aims at obtaining ET_c by multiplying reference crop evapotranspiration (ET_0) with a specific crop coefficient (K_c, Allan, 1998):

$$ET_c = ET_0 {}^{*} K_c.$$

ET_0 is defined as the evapotranspiration of a standardized "reference" crop such as clipped grass or alfalfa. CropWat uses the Penman–Monteith equation to model ET_0 and to determine the specific CWR (Smith et al., 1996).

K_c is a coefficient related to the crop type and to its vegetative stage. According to the FAO manual two types of implementations are possible: the single and the dual K_c. Due to the lack of area-wide meteorological data and exact management dates and as regional scale was addressed rather than site specific information for single fields, the single K_c coefficient was selected. The single K_c values refer to the changing ground cover, crop height and the leaf area during the growing period of the crop. This period can be divided into four distinct growth stages: the initial stage which runs from planting date to approximately 10% ground cover, the crop development stage runs from 10% ground cover to effective full cover, which is for many crops at the initiation of flowering, the mid-season stage runs from effective full cover to the start of maturity and the late-season stage which runs from the start of maturity to harvest or full senescence (Allen et al., 1998). The K_c values for each growth stage and the duration of the stages including data on planting and harvest dates for cotton and winter-wheat are presented in Tables 2 and 3. They were provided from the database available at the Scientific Information Centre of Interstate Commission on Water Coordination in Central Asia (SIC-ICWC, Stulina, 2010).

The meteorological data available for the study area were provided by the ClimWat database of the FAO and consisted of monthly long-term averages of rainfall and temperature of the meteorological station in Fergana (40.36°N and 71.75°E, Munoz and Grieser, 2006, Table 4). P_{eff} was calculated using the USDA, 1993 Soil Conservation Service method, implemented in the CropWat model (Allen et al., 1998).

The results of the CWR and CIR calculations per hectare of cotton and winter-wheat were combined with the acreage information of the classification process. This is particularly of interest in Uzbekistan as both crops are cultivated according to a state quota system and have to be supplied directly after private gardening (Abdullaev et al., 2009a).

4. Results and discussion

4.1. Generation of the 'field-mask'

The optimal parameter settings which performed the best segmentation were found to be 100, 0.9 and 0.5 for scale, shape and compactness, respectively. Most fields could be accurately separated from each other (Fig. 4). Minor over-segmentation could be observed on fields which were partly under irrigation or irregularly covered by vegetation at the time of image acquisition. On the contrary, under-segmentation was mostly caused by low brightness contrasts between neighboring fields due to the lack of suitable boundary objects such as channels, pathways or trees. Best segmentation results could be achieved on non-vegetated and dry fields, which confirm the results received in irrigation systems of Khorezm in Uzbekistan based on 2.5 m SPOT data (Conrad et al., 2010).

Several parameters were tested for classifying the segmented polygons into the two classes 'field' and 'no field' (semi-automated approach). The parameter 'compactness' returned very good results as it optimally reflects the dominant rectangular form of the agricultural fields. The confusion among the two classes was low with an overall accuracy of 93.24% (Table 5).

Manual corrections were applied in areas with the steeper relief at the transition zone from the valley floor to the mountainous regions. Due to the relief, some fields were distorted and hardly recognized using the parameter 'compactness'. Also some urban areas showed compactness and texture values similar to those of agricultural fields.

4.2. Per-field crop classification

The overall accuracy of the classification was 86.2%. The kappa-coefficient which reflects the difference between the actual agreement and an agreement expected by chance shows with 0.79 a very good agreement (Table 6). The accuracy level agrees with other crop classifications conducted in other Central Asian irrigation systems, e.g. in the Kazakh Kyzyl Orda System (El-Magd and Tanton, 2003) or the Uzbek Khorezm Region (Conrad et al., 2010, 2011).

Class-wise statistics (Table 6) show highest producer's accuracy and user's accuracy for cotton, wheat, and orchard, but also for rice. Due to the optical properties of water, fishponds could be identified very well. The results show that area dominant crops cotton and wheat can be detected in early stages of the growing season.

Obviously spectral confusion occurred between minor crops like maize, fallow land, and the composite class of all other crops. One major error source can be found in the image acquisition dates. Many crops (vegetables, maize) are still in an early growing stage when the last image is recorded (2nd of July). These classes were poorly represented in the study region in May and June, because e.g. most maize or rice fields follow after winter wheat harvest. The inclusion of remote sensing data acquired at later stages of the cropping season could be beneficial for a more exact classification of underrepresented crops and rotations with

Table 1
Input-parameters for the CropWat model of the FAO (source: modified from Clarke, 1998).

Climate	Precipitation	Cultivation	Field crop
Min./max. temperature	Total	Cultivation area	Growing period
Rel. moisture	Effective	Seeding date	K_c-value
Sunshine duration			Rooting depth
Wind speed			Critical depletion
			Water-stress factor

Table 2
K_c values for cotton at the four different growth stages (according to Stulina, 2010).

Parameters	Planting: 04/06			Harvest: 10/11
	Initial	Development phase	Mid-season	Late-season
Growth stages, days	30	50	55	45
Crop coefficient, K_c	0.55		0.95–1.15	0.65
Critical depletion, p	0.6		0.6	0.9
Yield response factor, K_y	0.4	0.4	0.5	0.4
Rooting depth [m]	0.3		0.6	

Table 3
K_c values for winter wheat at the four different growth stages (according to Stulina, 2010).

Parameters	Planting: 10/12			Harvest: 06/09
	Initial	Development phase	Mid-season	Late-season
Growth stages, days	30	140	40	30
Crop coefficient, K_c	0.65		1.15	0.65
Critical depletion, p	0.6		0.6	0.9
Yield response factor, K_y	0.2	0.6	0.5	0.4
Rooting depth [m]	0.3		0.6	

Table 4
Long-term average meteorological data provided by the ClimWat database of FAO.

Month	Min. temp (°C)	Max. temp (°C)	Humidity (%)	Wind (km/day)	Sunshine hours	Radiation (MJ/m^3/day)	ETo (mm/day)	Precipitation (mm)	P_{eff} (mm)
Jan.	−3.9	3.8	81	277	3.1	6.2	0.67	17.3	13.8
Feb.	−2.6	6.2	78	294	3.9	8.8	0.96	26.5	21.2
March	4.0	13.5	69	302	4.7	12.3	1.94	24.6	19.7
April	10.6	22.4	59	294	6.9	17.7	3.74	21.4	17.1
May	14.5	27.6	54	302	8.6	21.9	5.25	20.1	16.1
June	18.3	32.9	46	337	11.0	25.9	7.19	8.1	6.5
July	20.2	34.7	47	380	11.4	26.0	7.84	3.9	3.1
Aug.	18.1	33.0	51	320	10.8	23.5	6.52	2.2	1.8
Sept.	13.3	28.4	55	259	9,5	18.9	4.56	5.8	4.6
Oct.	7.7	20.9	65	251	7.2	12.8	2.59	18.0	14.4
Nov.	2.7	13.0	74	251	4.6	7.8	1.34	17.3	13.8
Dec.	−1.4	6.3	81	251	2.8	5.4	0.75	17.4	13.9

wheat. However, for assessing early season CWR/CIR one relevant feature is the use of satellite images before the main irrigation phases.

Cotton and winter-wheat are cultivated on large, homogenously vegetated fields. This allowed the generation of better statistical values for classification, which could be concluded as another aspect for the comparatively good discrimination of cotton and wheat. The observation is contrary to the results from the Khorezm region in Uzbekistan, where problems of cotton and wheat-classification mainly occurred due to the high variability of vegetation cover within one field (Conrad et al., 2010, 2011).

Fig. 5 shows the spatial distribution of crop types in the study area between May and early July 2010. Cotton and winter-wheat are grown area-wide covering about 191,023 ha (34.7%) and winter-wheat on 175,916 ha (32.0%) of the study area with ~550,350 ha. Orchards particularly occurred in the transition zones to the mountains at the northern, eastern, and southern parts of the valley (15.5%). Rice is planted mainly on the sandy soils in the center of the valley and along the riverbed of the Syrdarya (5.3%). Maize-fields (~1%) are scattered throughout the study area. The summary class other was observed on 6.7% of the study area. It must be noted, that fallow land (4.7%) could still be cultivated with crops between July and October, which was not covered in this study.

Cotton and wheat area exceed official statistics for the inner Fergana Valley from 2000 (Fig. 2), but only by a few percent. The contrary tendency was observed for orchards. This might be attributed to minor changes in the past decade. However, as the study area covers more central parts of the valley, the distribution can be slightly shifted to a higher percentage of orchard area at the fringes which are not observed in this study. The contrast between official statistics and actual rice cropping area is a typical phenomenon for Uzbek study areas. Due to the high water demands for rice, its cultivation is frequently informal and thus blurring official statistics (Oberkircher, 2010). Other comparisons, e.g. with forage crop areas or other cultivars, are limited due to multiple use options of many crops (maize/sorghum, alfalfa), and the double use of many orchards. Moreover, during the field campaign, nearly all crops (sunflower, alfalfa, vegetables, etc.) occurred as second land use in many orchards. But sub-tree coverage of crops could not be assessed by the presented means.

4.3. CWR and CIR of cotton and wheat

Fig. 6 depicts the course of CWR (blue line) and its division in CIR (red part of the bar) and P_{eff} (blue part) given in mm/decade (10 day period calculated for average data received from ClimWat). Fig. 6a) and b) shows the results for cotton and winter-wheat modeled for Fergana Valley.

The CWR of cotton is increasing with the passage of time, whereas maximum amounts of water are required at the crop development during mid-season stage from June to August. The CWR varies from less than 10 mm/decade to over 80 mm/decade. Maximum CWR was observed in July and August during the flowering of the plant. In comparison, minimum CWR was observed at the early vegetative period in April and at the end of season in September before harvest. The total amount of CWR during the vegetation period of cotton is 927.8 mm or 9278 m^3 ha^{-1}.

During the vegetation period of cotton P_{eff} is very low, because cotton grows during the dry summer months. It varies from almost 6 mm/decade at the beginning of the vegetation period to less than 1 mm/decade when cotton matures in July and August. Therefore, CIR is nearly equivalent to the CWR and varies from less than 10 mm/decade to over 80 mm/decade at the end of July. The total CIR during the vegetation period of cotton amounts to 881.3 mm or 8813 m^3 ha^{-1}.

CWR of winter-wheat is also increasing with time. Maximum water amounts are required at the crop development and mid-season stage from April to May. The CWR varies from 6 mm/decade to almost 60 mm/decade with a maximum at the end of May. The minimum

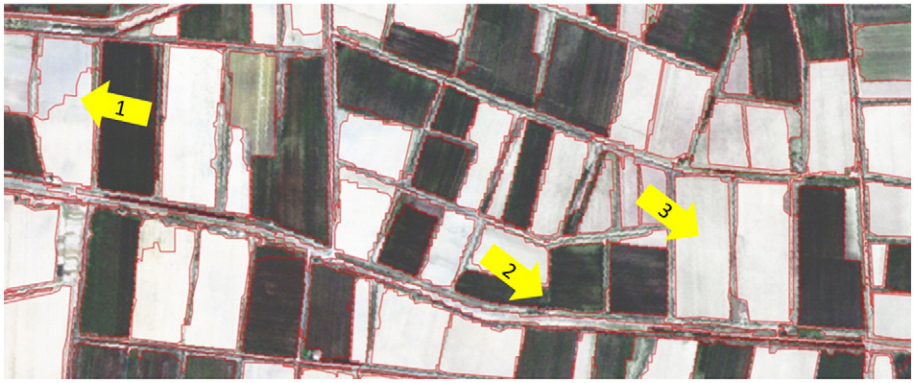

Fig. 4. Results of the RapidEye segmentation. 1 = over-segmentation of an irrigated field, 2 = under-segmentation of vegetated areas, 3 = optimal segmentation result of a non-irrigated and non-vegetated homogeny area.
Data source: RapidEye sensor, bands: RGB,3,2,1.

Table 5
Confusion-matrix of the classification process of the segments into 'fields' and 'no fields'.

	'Fields'	'No fields'	∑
'Fields'	138	12	150
'No fields'	7	124	131
∑	145	136	281
	User's acc.	Producer's acc.	Overall acc.
	92.0	95.17	93.24

CWR was observed during dormancy of winter-wheat from November till February. The total amount of CWR during the vegetation period of winter-wheat is 544.3 mm or 5443 m^3 ha^{-1}.

In contrast to cotton, winter-wheat profits from comparatively high precipitation values (P_{eff}) between October and May. The potential evapotranspiration remains also at a low level until wheat harvest. The amount of rainfall ranges from over 4 mm/decade at the beginning of the vegetation period to more than 7 mm/decade in February. Accordingly, CIR of winter-wheat varies between 1 mm/decade to over 50 mm/decade before winter-wheat is harvested in May. The total CIR of winter-wheat during the vegetation period amounts to 413.3 mm or 4133 m^3 ha^{-1}.

The presented CWRs agree with several CropWat-based studies conducted in Central Asia even though deviations occur. Pereira et al. (2009) modeled an ET_c (CWR) between 8670 m^3 ha^{-1} and 8160 m^3 ha^{-1} for a farm close to the meteorological station Fergana (1970–2003), however – as mentioned above – on significantly lower K_c values for the initial and development stages (0.3, Pereira et al., 2009) than used in this study (0.55).

Chapagain et al. (2005) reported an Uzbekistan-wide CWR average for cotton of 9990 m^3 ha^{-1} (CIR: 9810 m^3 ha^{-1}). Beside varying crop coefficients applied for ET_c also the spatial variability of climate conditions are very likely responsible for the deviations. In Fergana Valley below average air temperatures and higher P_{eff} than in other Uzbek irrigation systems (19 mm according to Chapagain et al., 2005) occur. Similar reasons resulted in a CWR for cotton of 10,166 m^3 ha^{-1} in the Uzbek province Khorezm located in the lower Amudarya basin (Bobojonov et al., 2008). Remote sensing based modeling of actual ET (ET_{act}) averaged at 7680 m^3 ha^{-1} for the same region (Conrad et al., 2007). But ET_{act} usually underestimates ET_c, because it includes crop water stress situations, which obviously had occurred in that study. Comparable values of CWR for wheat production in Central Asia are rare.

5. Implications for water use in Fergana Valley

The relation of CIR to CWR approves that winter-wheat (CIR/CWR: 0.75) cultivation in Fergana Valley is less depending on external irrigation water input than cotton (CIR/CWR: 0.95). Comparing the absolute values, winter-wheat needs approximately half of the irrigation water cotton requires during the vegetation period. The introduction of other crops, i.e. crops being tolerant to low winter temperatures can be one option for water saving, especially winter cereals other than wheat (e.g. varieties of rye, barley, or triticale) or winter vegetables.

However, Abdullaev et al. (2009b) identified winter-wheat scattered throughout the landscape having negative impact on the maintenance on the irrigation infrastructure. Before the introduction of winter-wheat, the irrigation channels were cleaned and repaired during winter time. The same authors also point at the design of the channel and cropping system, which was adjusted to cotton monoculture during the Soviet era: They argue that having different crops on neighbored fields requires more frequently watering of the channels which in turn lowers the water use efficiency at system level. Spatially explicit crop maps in combination with geographical information systems (GIS) can support the identification of such management problems and planning of channel maintenance or water saving (Fig. 7).

For the entire area under investigation, the CWR of cotton amounts to 1.77 km^3 and a CIR of 1.68 km^3. Analogous, CWR and CIR of wheat were calculated to be 1.15 km^3 and 0.87 km^3, respectively. Wheat and cotton covered approximately 65% of the study area. The area under investigation comprised 553,219 ha of agricultural fields, which is 60% of the entire irrigated land in the Uzbek part of the Fergana Valley (907,000 ha; UNDP, 2007, see also Fig. 2). Assuming constant portions of cotton and wheat this results in a CIR of 4.01 km^3. For comparison, the average of water withdrawals for Fergana Valley between 1991 and 2010 (limit), which is in accordance with the principle of inter-republican water allocation, is approximately 10 km^3 per year (SIC-ICWC, 2011, upstream Kayrakum reservoir). CIR for cotton and wheat in the Uzbek part of the Fergana Valley amount to ~40% of the average water withdrawals permitted for the entire valley. In the drought year 2007, the limit water intake for Fergana Valley was 6.9 km^3.

Utilizing existing average values of field experiments with groundwater and soil moisture contributions of 16.4% and 8%, respectively (Pereira et al., 2009), and a field application efficiency of 49% (Reddy et al., 2013) but excluding channel losses leads to a total irrigation water demand of 6.13 km^3 only for the cultivation of cotton and wheat in 2010. Under the aforementioned assumptions, the total irrigation requirements for optimum cotton and wheat production in the Uzbek part of the Fergana Valley accounts already to ~22% of the average annual water amount in the entire catchment (37.9 km^3, SIC-ICWC, 2011).

In general, parameters such as field application efficiencies, soil water status before and after the vegetation period and groundwater levels are highly variable in space and time. The aforementioned studies showed this complexity also for Fergana Valley. But the parameters are hardly to measure area-wide. Thus Karimov et al. (2012) considered different groundwater level zones for recommendations of changing farm practices or utilizing groundwater resources for water saving. In GIS an overlay of the remotely sensed land use information with the groundwater level zones could help to make such recommendations more spatially explicit.

Under high water pressure conditions as found in Fergana Valley rice cultivation can be reflected critically. Rice copping is relevant for income generation in the region. But the norm of CWR for rice in the Fergana Valley established during the Soviet era amounts to 24,800 m^3 ha^{-1} (Raskin et al., 1992). In most cases rice is planted after winter-wheat. As this study addressed early water demand assessments for the area dominating wheat and cotton crops, CWR for rice were not included. The high percentage of orchard area in turn can be assessed as a diversification option with less water demands. But in many locations a second cultivar can be found below the trees. Frequently alfalfa, wheat, and also vegetables, maize, and sometimes cotton were observed below the tree cover during field sampling. The detection of sub-tree-cropping by means of remote sensing could be a valuable contribution but is a challenging task. It has to be noted, that homestead areas which are first served with irrigation water were also excluded from this study.

Table 6
Producer's, user's and overall accuracy, and kappa-coefficient of the crop classification.

Class	Producer's acc.	User's acc.
Cotton	95.96	89.20
Winter-wheat	95.17	93.09
Orchard	96.12	71.22
Rice	82.46	88.68
Other	53.85	73.68
Maize	13.46	89.66
Fallow	70.00	85.37
Fishponds (water bodies)	100.00	100.00
Overall acc.	86.2	
Kappa	0.79	

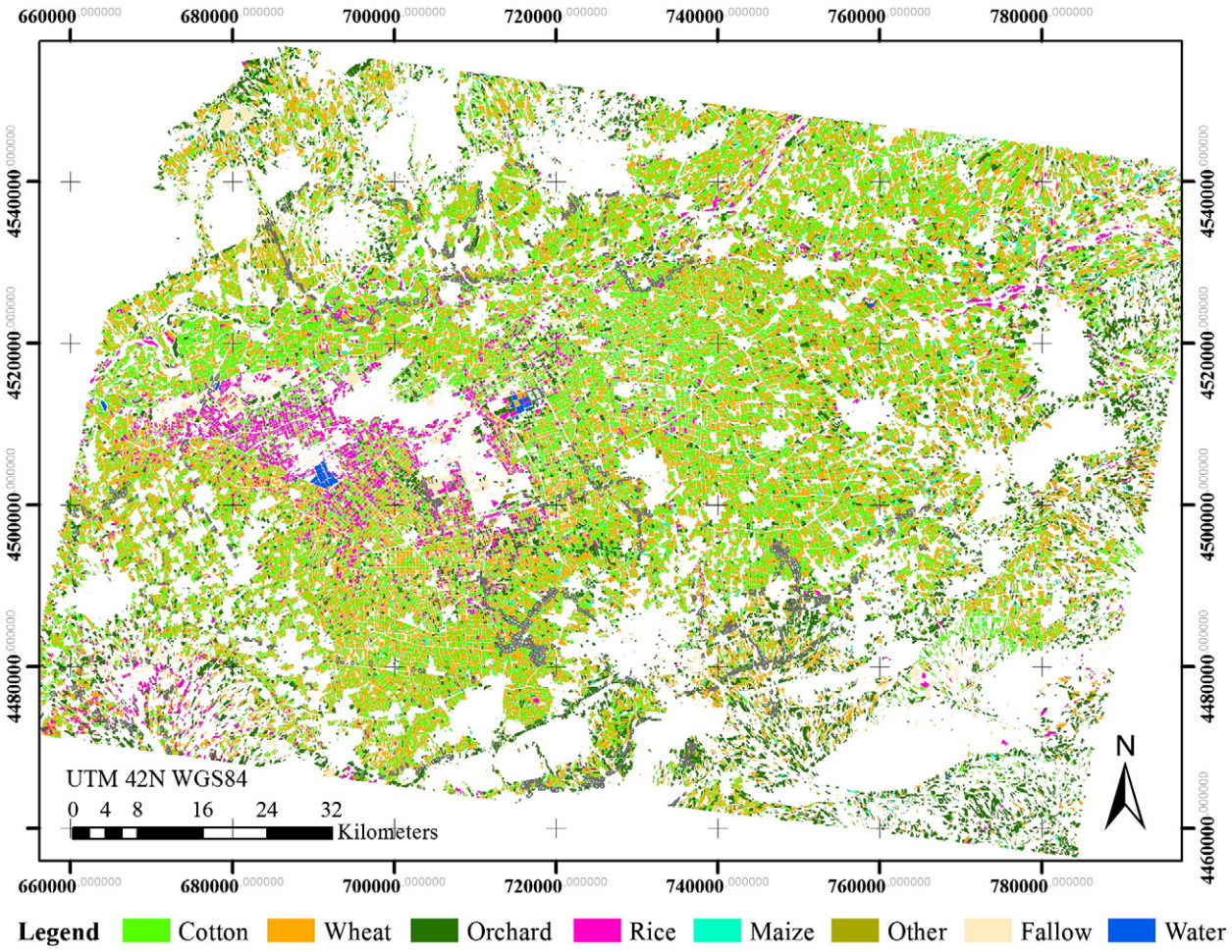

Fig. 5. Classification result, winter-wheat can be in rotation with other crops, e.g. rice, maize, sunflowers, mungbeans, or watermelon. The class other also comprises sunflower, vineyard, vegetable, and alfalfa. Water refers to the fishponds within the study region.

Homestead areas comprised ~200,000 ha all over Fergana Valley in 2000 (SIC-ICWC, 2011).

6. Summary and conclusion

An object-based remote sensing method was combined with the FAO CropWat model to determine crop distribution and water requirements for irrigation of cotton and winter-wheat in the Uzbek part of Fergana Valley. The crop classification was conducted on RapidEye and Landsat data acquired before the onset of the main summer irrigation phases using a random forest algorithm. It achieved an overall accuracy of 86.2% and showed a high performance for cotton and wheat by exceeding a producer's (user's) accuracy of 95% (89%). The CWR for winter-wheat (cotton) cultivation received from ClimWat data was 5443 m^3 ha^{-1} (9278 m^3 ha^{-1}). Subtracting effective precipitation led to 4133 m^3 ha^{-1} (8813 m^3 ha^{-1}) CIR.

In 2010, cotton and winter-wheat were planted on 66.7% of the agricultural area under investigation, whereas orchard areas amount to 15.5%. The early season crop maps enable for water saving as water allocation plans within the different irrigation subsystems of the valley

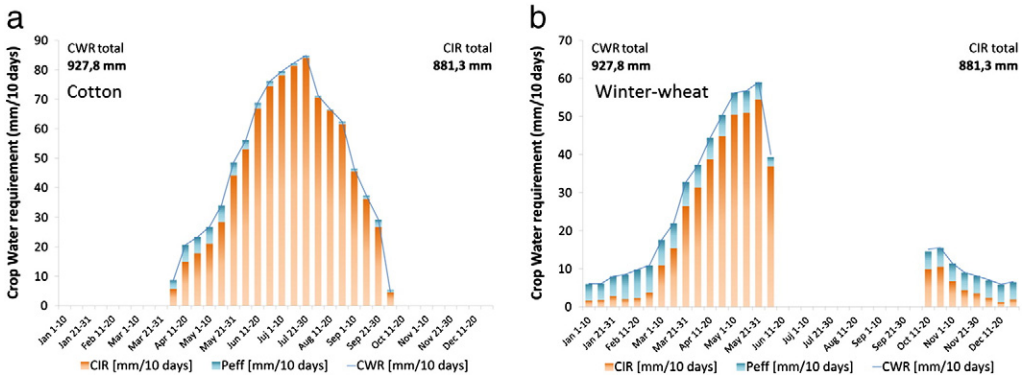

Fig. 6. a (left): CWR and CIR of cotton and P_{eff} during the vegetation period in the Fergana Valley, b (right): CWR and CIR of winter-wheat and P_{eff} during the vegetation period in the Fergana Valley.

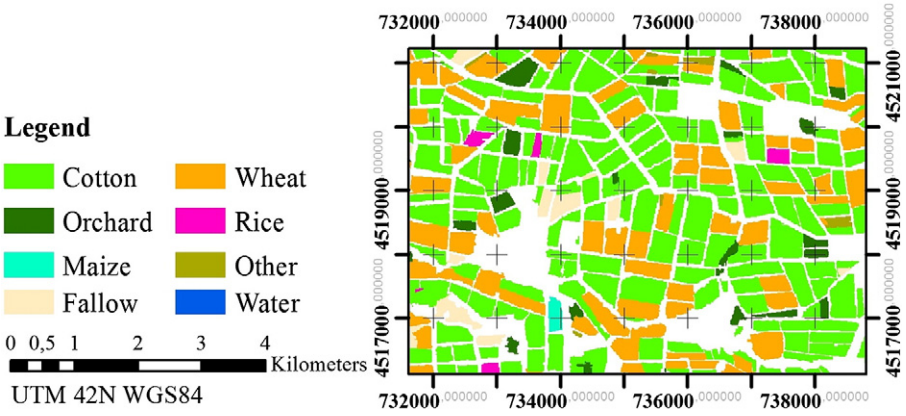

Fig. 7. Zoom to the inner Fergana Valley showing different levels of crop diversity.

can be modified. According to the current Uzbek state order system, water limits for the cultivation of other crops planted after winter wheat harvest can be adjusted in a spatially explicit manner.

Comparisons of CWR and CIR for the area dominating crops with the total of water officially allocated for irrigation underlined the pressure on the water resources in the region. The situation of changing climate leading at least for higher uncertainty of water availability, growing industrial sector, and increasing population showed the necessity for quantitative monitoring and exact localization of water demands in Fergana Valley and in the entire Syrdarya catchment.

The ratio of CIR/CWR indicates the suitability of winter crops for saving river water. However, the economic dependency on cotton production in Uzbekistan leaves little room for change at the moment. On the other hand, in increased area portion of winter-wheat for instance requires attention on the development of plans for cleaning and restoration of the channel system. Spatially distributed crop maps enable spatial planning of such maintenance measures. For complete crop maps the inclusion of mid and late season satellite acquisitions can solve confusions between minor crops and rotations with winter-wheat.

The combination of remote sensing based crop classifications with CropWat offers fast and low-cost information about the amount of water needed for agricultural production for large areas at different scales. The methods can be easily assigned to other irrigated areas worldwide by adapting regional meteorological and crop-specific parameters.

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