Assessment of the agricultural production with satellite earth observation – A case study in Fergana Valley, Uzbekistan

Draft v 1.0

Manuscript in preparation and not for distribution yet.

INTRODUCTION

Global cereal demand for food and animal feed is expected to total 2.8 billion tons per year by 2030, or 50% higher than in 2000 (Bruinsma, 2003). Hence, sustainable increase of crop production belongs to the major challenges for feeding the world's growing population (FAO). Because grain supply is the product of crop area and crop yields (production per hectare), meeting this higher demand will require an increase in one or both of these factors (c.f. Lobell et al., 2009). Given the limited potential to expand suitable cropland, intensification of crop production is the preferred means to enhance food supply (Foley et al., 2011; Wichelns and Oster, 2006). The reasons for this goal not only include improving food security, but also preservation of natural habitats and biodiversity, and protecting the climate system (Cassman, 1999; Cassman et al., 2003).

However, unsustainable practice in land and water management at different scales, from the farmer's decision (furrow irrigation, application of fertilizer) to governmental rules (state order, mono-cultivation) jeopardize the productive potential in the future. Usually, higher cropping intensities can be found in irrigated systems, where double or even triple cropping, and higher average yields account for this level of productivity. But at times, irrigation-related problems are often the result of a distorted macro economy, which despite providing operating subsidies, renders farming unprofitable and results in repeated underinvestment on farms over long periods. Especially irrigated agriculture is highly sensitive for unsustainable practices that can lead to soil degradation, reduced soil fertility, water scarcity, and diseases that in turn trigger productivity decline.

For these reasons, many irrigation systems are performing below their actual potential, so that there is considerable scope for improving the agricultural productivity (FAO, 2013). In such cases, losses in economic revenues, income, and agro-ecosystem services can occur. The United Nations Environment Programme (UNEP) has estimated that unsustainable land use practices result in global net losses of cropland productivity averaging 0.2 percent a year (Nellemann et al., 2009). In (semi-) arid environments, disentangling the reasons and support spatially targeted improvements for production patterns can be seen of paramount importance as irrigated agriculture accounts with 16% of the arable area for 44% of total crop production (Alexandratos and Bruinsma, 2012).

Yield estimates that are able to resolve individual fields within an agricultural landscape are particularly useful for understanding how crop productivity responds to various management and environmental factors (Lobell, 2013), as well as for management decisions that require information about mean and variability of yields at the field scale. Looking to an agricultural region, the picture of crop production, which can be observed, is a result of a complex constellation of individual decisions in different ecological and infrastructural settings, variable climate, and within a legal framework from local to governmental rules. Remote sensing can draw this picture of land use and crop production over large areas. It has repeatedly been shown to provide information that, by itself or in combination with other data and models, can accurately estimate crop production, i.e. crop acreage and crop yield (Justice and Becker-Reshef, 2007), at the field scale and over large geographic extents (Conrad et al., 2014; Lobell, 2013). In combination with Geographical Information Systems (GIS) it has shown the potential for improving data situations in irrigation management (Bastiaanssen and Bos, 1999; Biradar et al., 2009; D'Urso et al., 2010). Through classification of satellite images, archives of crop maps allow for back-tracing and monitoring the diversity and cropping intensity (Conrad et al. 2015, JAE) (Martinez-Casasnovas et al., 2005). Such statistical results can support analysts and decision makers in identifying site-specific reasons for unfavourable cultivation practices or controlling the compliance with official cropping standards (Conrad et al. 2015, JAE), thus guiding sustainable crop production intensification (FAO). Monitoring crop yield variability over several years was shown to be an accurate means to detect yield gaps (Lobel) and contribute to marginal land detection (Fritsch et al., 2015). Methods to derive crop yields range from empirical relationships between satellite derived vegetation indices (VI) and ground based yield measurements or official statistics (Bolton and Friedl, 2013), to more sophisticated crop simulation models with high input data requirements (Doraiswamy et al., 2004, 2005). Beside these, models based on the light use efficiency (LUE) approach (Monteith and Moss, 1977) gained wide attention and were shown to provide reliable yield estimations (Lobell, 2013; Lobell et al., 2003).

Although variability in crop yields between fields is a ubiquitous feature of agricultural landscapes, there is often a gap between average yields and those achieved on the highest-yielding lands (Lobell et al., 2005). Narrowing this yield gap could play a critical role in raising food production in step with continued growth in demand. Improved understanding of which factors most limit or determined spatial variation of yields in farmers' fields is a precondition to reduce environmental impacts of agriculture, such as those resulting from over application of fertilizers, and to identify opportunities for improving productivity and farmer income. However, in fact the causes of differences in production patterns or potential yield gaps in many regions are often not well-investigated, sometime due to a lack of information on spatial variation of production (crop yield) and yield-controlling factors (soil condition, application of fertilizers, irrigation infrastructure) (c.f. Lobell et al., 2005).

The irrigation systems of Central Asia are one prominent example for arid production systems highly exposed to production losses caused by inefficient land and water use (e.g, Orlovsky et al. 2001, Glantz 2005, Saigal 2003). Hence, the Fergana Valley in Uzbekistan was selected as study region. It 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 (SIC-ICWC, 2011). Around 70% of the 11 Million 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).

Whilst crop diversification and intensification are important parameters for a sustainable agriculture, this study focusses on assessing and explaining pattern of production. Specifically, the aim is to quantify and assess crop yield using satellite remote sensing and to investigate yield variations across the Fergana Valley for the period 2010–2014. Annual crop yield maps will be created based on the LUE approach. At issue in this study is the relative importance of different potential yield constraints and to assess the driving factors of the observed yield variability and pattern. The results are then discussed in the context of potentials for improving agriculture in Fergana Valley.

STUDY AREA

The Fergana Valley is located in the southeast of Central Asia and the eastern part of the Aral Sea Basin, amid the Alatau Range in the north, the Tian Shan Mountains in the east and the Alay Mountains in the south (Figure 1). The larger central part of the valley falls within the Republic of Uzbekistan, while the northern and eastern fringes are located in the Kyrgyz Republic and a small area in the valley’s west and southwest belongs to the Republic of Tajikistan. The climate is continental dry with 100–200 mm average annual precipitation and a potential annual evapotranspiration of up to 1,300 mm (Umarov et al., 2010). The average temperature ranges from −3.9 °C to 3.9 °C in January to 20.2 °C to 34.7 °C in July (Munoz and Grieser, 2006).

The Fergana Valley is located at the upper to mid-reach of the Syrdarya River catchment. The Naryn and Karadarya Rivers,flow together within the valley and create the Syr Darya. The two major head flows generate almost 70% of the valleys surface water (SIC-ICWC, CAWATER). The river's nourishment is classified as mixed snow-glacial and is formed in the surrounding mountains (Savoskul et al., 2003).

Fergana Valley is one of the oldest and most intensely used irrigation systems in CA, dominated by cotton and wheat cultivation. Despite its upstream location between the foothills of the Tian Shan Mountain, irrigated agriculture in the Fergana Valley suffers from low field application efficiencies, groundwater salinization (Reddy et al., 2013, Pereira et al., 2009) and high river water salinities (Qadir et al., 2009). Even within Fergana Valley, upstream-downstream disparities of water availability were reported (Abdullaev 2009). It is the most densely populated region in entire CA with more than 11 million inhabitants and population densities up to 500 inhabitants per km^2 (Filcak, 2008). The region’s population is even likely to grow by about twenty million over the next 40 years (UN World population 2010 revision, 2011), which will increase the demand for food and water resources. Due to population growth, availability of water in Uzbekistan already decreased from 2,457 (1990) to 1,837 m^3/yr per capita (2010) (FAO stat yearbook 2013). Future temperature increases are expected to be 1.5–2.5 °C (Lioubimtseva and Henebry, 2009) runoff peaks could shift from spring towards the late winter season in the Syrdarya catchment (Siegfried et al., 2012).

From 1960s onwards the main crop has been cotton, but it was successively supplemented by winter wheat, which was included to the Uzbek state-order system after independence in 1991 (Abdullaev et al., 2009b). Whilst wheat yields stabilized around 5 t/ha between 1980 and 2000, productivity in of cotton yield in Fergana Valley decreased from 4.6 t/ha (1980) to 2.9 t/ha (CAREWEB) and there is a significant non-productive depletion of irrigation water (Karimov et al., 2012).

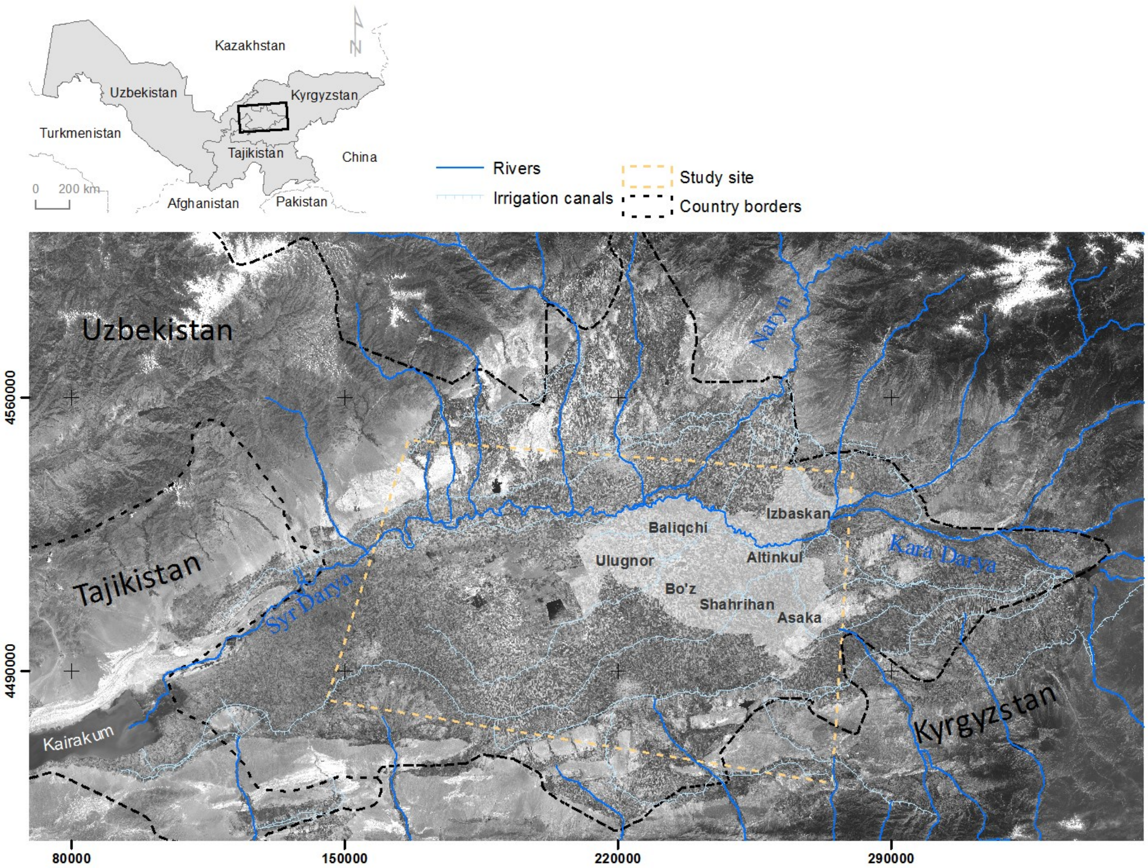

Figure 1: Study area (orange rectangle) in the Fergana Valley. Image backdrop is a Landsat image from May 2014, displaying the near infrared channel. For the districts in the eastern and south-eastern part (grey polygons) official crop yield statistics are available.

DATASETS AND PREPROCESSING

Satellite data for classification and yield modelling

The analysis was based on multispectral RapidEye and Landsat data (Table 1). Each growing season, several images were chosen, ideally with acquisition dates at intervals of 1 month and with at least one image taken near the peak of the season (mid-August to early September), though unavailability of certain images and extensive cloud cover on others limited ultimate image selection. 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), with a pixel size of 6.5 m (Tyc et al., 2005). Landsat-5 TM comprises several channels including visible (blue, green, red), near infrared (NIR), and shortwave infrared (SWIR-1, SWIR-2) spectra, with a pixel size of 30 m. Thermal and pan-chromatic bands were not used.

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 neighbour resampling technique were applied for geometric correction using GPS data collected in the research area. Sub-pixel accuracies for all scenes were achieved. To correct for different atmospheric conditions in each image, an atmospheric correction was conducted using the Atmospheric and Topographic Correction (ATCOR) tool, version 7.1, which is based on the MODTRAN model (Richter, 2011). As a result, top-of-canopy (TOC) reflectances were available for each image (Landsat and RapidEye).

In order to have comparable input data for the estimation of fPAR (see section xx), the RapidEye images were downscaled to the spatial resolution of Landsat (30 m), using a convolution model that estimates the point spread function of the TM sensor (Schowengerdt, 2007).

Table 1: Overview on the available satellite images. RE = RapidEye, LS = Landsat. RapidEye data often consist of several images per time step, hence the date range is partly given instead of the exact acquisition dates.

Time step	2010	2011	2012	2014
1	14./19. May (RE)	2. May (LS)	3./4. April (RE)	3.-14. April (RE)
2	13./15. June (RE)	13./20. May (RE)	21./23. May (RE)	1.-08. May (RE)
3	2. July (LS)	3. June (LS)	30. May/1. June (RE)	3.-11. June (RE)
4	4. September (LS)	23.-31. July (RE)	17./29. June (RE)	3.-8. July (RE)
5	6. October (LS)	7. August (RE)	2./5. July (RE)	18.-23. August (RE)
6		22. August (LS)	1./3. August (RE)	10. October (LS)
7		7. September (LS)		

Field mask

Since a digital field cadastre database was unavailable for this study, RapidEye data in 2010 were segmented using a multi-resolution algorithm included in the software eCognition Developer 8.64 (Trimble Germany GmbH, 2011) and described in (Conrad et al., 2013). In the beginning of the summer season vegetation cover within the field is low and the spectral contrast between the field and the tree-covered surrounding canals is high, hence the images from May 2010 were segmented. The optimal segmentation parameter settings were assessed based on reference polygons. Afterwards, all objects were assigned to the classes "field" and "no field" via supervised image classification, resulting in classification accuracy of 93% (field vs. non-field). The resulting number of field objects was 67,453 covering an area of 440,445 ha.

Crop yield validation data

Official agricultural statistics from seven districts in Fergana valley (cf. Figure 1) on crop yield (t/ha for wheat, rice, and cotton) and acreage were available (SIC-ICWC). This information could be used to validate the results from the yield model in the years 2010–2012. For 2014, no such reference data was available.

Auxiliary data sets for regression

In order to analyse potential sources of spatial variations in crop yield, several variables related to the topography or irrigation infrastructure were obtained. Unfortunately, numerous desirable data sets such as groundwater information, drainage, irrigation infrastructure such as pumps, canal properties, population information, labour structure, or degree of mechanization or application of fertilisers were unavailable. The available variables were divided into four groups (a-d), and their assumed impact on crop yield is summarized in Table 2:

a) Site-specific characteristics include natural and artificial characteristics of the study site like the density of irrigation canal networks (based on Open Street Map (OSM), ©OpenStreetMap contributors) and www.cawater-info.net, last accessed 27th June 2015) and roads (based on Open Street Map (OSM), ©OpenStreetMap contributors). Elevation and terrain slope was computed in percentage based in a digital elevation model from the ASTER satellite (30 m pixel size, http://asterweb.jpl.nasa.gov/gdem.asp, last accessed 03. June 2015). Soil salinity was provided by the FAO/IIASA/ISRIC/ISS-CAS/JRC (2012). Soil types for Fergana Valley were made available from digitized soil maps Genusov et al. (2012). A settlement layer was based on On-screen digitization using RapidEye data and Google Earth from 2014.
b) Proximity characteristics include distance to canals, intake points, or settlements. A settlement layer was derived by on-screen digitization of GoogleEarth images from

2014. Layers for canals and roads were downloaded from OSM. Factor maps depicting distances were derived based on cost-weighted Euclidean distances, calculated in ArcGIS. For the settlements, different types of roads (asphalted main roads, secondary roads, and smaller trails) were assigned different costs, with the lowest cost assigned to the major asphalted roads. For the intake points, lowest costs were assigned to the canals whilst highest costs were assigned to the surrounding area. It must be noted that detailed spatial information about the irrigation network, including different hierarchies of drainage and irrigation canals, was not available for this study and could not be digitized on-screen because these differences were not recognizable. For the roads and canals, the Euclidian distances were calculated.

c) <u>Field characteristics:</u> For assessing the influence of the field, configuration on crop yield, area and perimeter was computed for each object in the landscape.
d) <u>Cropping pattern characteristics:</u> The Simpson Index of Diversity (SID, Simpson 1949, Magurran (2004)) was used for quantifying the spatial crop pattern, based on the pre-existing crop maps (Conrad) and the maps of 2014. First, SID was calculated for the four annual crop maps and statistics of the period 2010-2014 were aggregated at the field-level. Then the temporal dimension was included by calculating SID for the crop rotations, i.e. the four crop maps were overlaid.

Table 2: Explanatory variables used in the random forest (RF) regression analysis.

Variable		Description	Meaning
I Dependent:	y	Crop yield [t/ha]	
II Independent:			
(a) Site specific			
Canal density	x_1	Density of irrigation canals [km/km²]	Water access, irrigation water supply
Road density	x_2	Density of roads and streets [km/km²]	Field access for farmers (neighbourhood indicates accessibility, improved machinery access most likely influencing the fertilizer application
Soil salinity	x_3	Harmonized World Soil Database (version 1.2), layer "Soil salinity", 1km raster data, ranked between 0 and 100	Land degradation, direct indicator for low productivity (often related to high groundwater levels)
Slope	x_4	Slope [%]	Indicates irrigation efforts, higher slopes require more likely electricity for pumping, higher water supply
Elevation	x_5	[m a.s.l.]	
Soil type	x_{6-14}	Categorical information about the soil distribution in Uzbekistan of 1960. Soil categories: Sandy cambic solonchak (1), takyric soils and takyrs (takyric salic solonetz (2), sandy desert soils (3), meadow soil on alluvial (4), meadow march soil on alluvial (5), solonchak on alluvial deposits (6), light sierozem zone (7), typical sierozem (8), meadow saz soil of sierozem zone (9)	Suitability for irrigated agriculture, e.g. zones of varying irrigation application efficiency, and different management demands.
(b) Proximity characteristics			
Distance to canals	x_{15}	Distance to canals [m]	Water access, irrigation water supply

Distance to roads	x_{16}	Distance to roads [m]	Field access for farmers
Distance to settlements	x_{17}	Distance to settlements [m]	Field access for farmers, market access
Distance to intake point	x_{18}	Distance to water intake points [m]	Water access, irrigation water supply
(c) Object characteristics			
Object perimeter	x_{19}	Object perimeter [m]	Small and compact fields may be easier to manage, large fields may be more suitable for machinery
Object area	x_{20}	Shape area [m²]	
(d) Cropping pattern statistics			
Land use intensity in the neighbourhood (PERC)	x_{21}	The location of the field in the irrigation system, low and high values indicate its location in the distal and central parts, respectively.	Areas with low agricultural activity might be at the marginal or remote parts of the agricultural system
Cropping diversity (AV)	x_{22}	Average Simpson Index of diversity of crop types (2010-2012, 2014)	Higher crop diversity indicates presences of multi-annual cropping rotations
Rotation diversity (SID)	x_{23}	Simpson Index of diversity of crop types for a four-year observation period (2010-2012, 2014)	

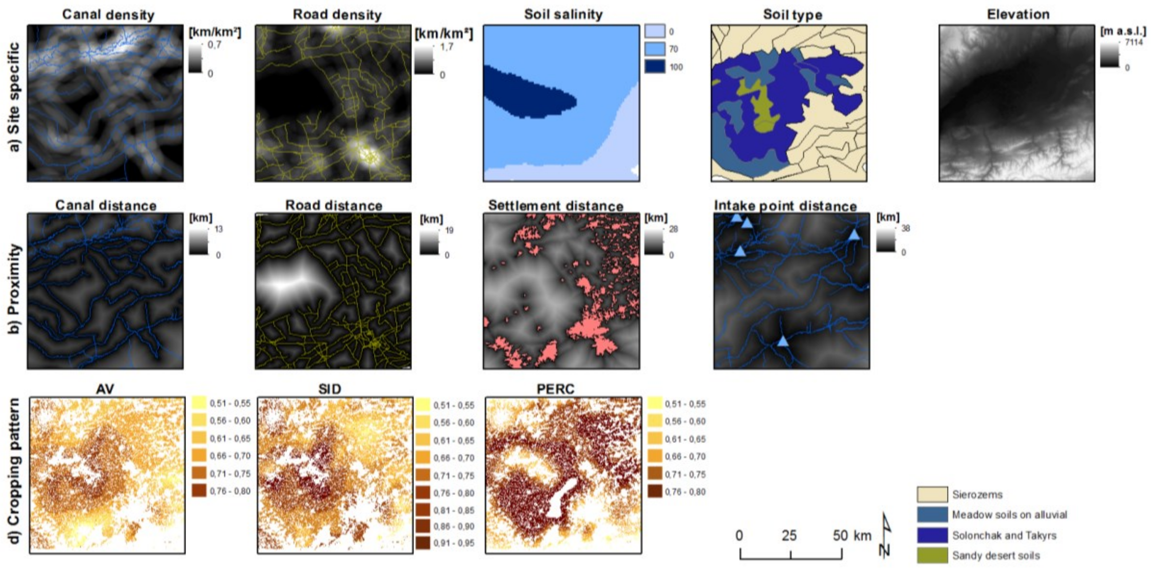

Figure 2: Factor maps of the independent variables from categories a), b), and d), used for the RF regression modelling. Soil properties are listed in Table 2.

METHODS

Crop classification

The map in 2014 was created accordingly for this study. In 2013, no reference data was available. Predictor variables for the classification were extracted from the satellite data. It included mean and standard deviation values for each image object (i.e. agricultural field) from the spectral bands (RapidEye: 1–5, Landsat: 1–5, and 7) and a huge set of vegetation indices including NDVI (Rouse et al., 1974) and EVI (Huete et al., 2002), which are further described in Löw et al. (2013). This resulted in 29 predictor variables (19 for Landsat) for each acquisition date as classification input for RF. The following seven classes were included in the class legend in each observation year: cotton, fallow / unused, orchards / vineyards, rice, and winter-wheat, and water / fishponds.

Crop yield modelling

Crop yields were estimated using the general LUE approach in combination with the concept of a stress-induced reduction in daily RUE. A similar approach was previously implemented to simulate cotton yields for the Khorezm region based on MODIS data (Shi et al. 2007) and also successfully implemented for yield estimation in northwest Mexico (Lobell et al., 2003). The NDVI values from the satellite images were used to estimate fPAR for each field, based on regression equations between NDVI and measurements of fPAR from test fields during the growing period in Fergana Valley (Lex et al., 2015). In that study, NDVI was shown to be superior in estimating fPAR over other potential VIs like simple ratio (SR), which is frequently being used in other studies (Goward and Huemmrich, 1992, Lobell et al. 2003). In order to estimate daily fPAR values throughout the growing season, fPAR values were interpolated linearly between the existing observations (see Table 1). The growing period was defined according to Stulina (2010) (Table 3). The NDVI values were then used to estimate fPAR, following a well-established method that scales values linearly so that the 2nd and 98th percentile of fPAR across all images are 0.1% and 95%, respectively (Sellers 1994, 1996; Lex et al., 2015).

Table 3: Growing seasons of cotton, rice, and winter wheat in Fergana Valley, according to Stulina (2010).

Crop	Growing season
Cotton	Apr–Sep
Rice	Apr–Sep
Winter wheat	Oct–Jun

Finally, crop yield (t/ha per field) was calculated as

$$\boldsymbol{Crop\ yield} = \left(\sum_{SOS}^{EOS}(\boldsymbol{FPAR} \times \boldsymbol{\varepsilon} \times \boldsymbol{PAR})\right) \times \boldsymbol{H_i} \qquad \text{Eq. 1}$$

where $\mathrm{fPAR_t}$ is the fraction of PAR absorbed by the crop canopy at time t,n the total number of observations during the growing period, ε is plant RUE, and HI is the harvest index, or the ratio of yield to total biomass. HI was set as follows: 0.36 (cotton), 0.44 (rice), 0.40 (wheat). ε was set to 2.0 (cotton), 2.2 (rice), 2.0 (wheat). Though yield assessments can be sensitive to estimates of HI or ε, results of the Monte Carlo analysis revealed that yield assessments were primarily sensitive to the method used to compute fPAR (Lobell et al., 2003). Further, values for HI and ε adjusted by Fritsch (2013) through sensitivity analysis.

Analysis of crop yield in relation to other factors

One important factor for understanding yield constraints is the type of model used to analyse possible factors. Multiple linear regressions modelling, for example, is a commonly used approach but can lead to inaccurate and unstable solutions (cf. Lobell et al. (2005) when applied to data sets with certain characteristics, such as a large number of insignificant predictor variables or the presence of strong interactions between variables (Hastie et al., 2001). Non-parametric approaches like regression trees of RF was can easier accommodate non-linear interactions between variables than linear regression modelling (Hastie et al., 2009). Moreover, these algorithms do not require that assumptions such as normality and homogeneity of variance are met, unlike methods based on linear regression (Manly, 2004). The RF method developed by Breiman (2001) was selected here. This method has been shown to result in very accurate regression accuracies (Breiman, 1996; Gessner et al., 2013) and was shown to be more accurate than, for example, linear regression, DT, or bagging in predicting spatial phenomena via regression (Löw et al., 2015; Prasad et al., 2006). Actually, RF is an ensemble of several decision trees (DT) that are independently trained on random subsets of the input data (predictor variables. DTs predict class memberships by recursively partitioning the given data set into more homogenous subsets (Hansen et al., 2000). Finally, the results of each DT are fused by a simple majority vote. The high prediction and regression accuracy of RF compared to other algorithms, based on diverse remote sensing data sets was demonstrated in numerous studies (Prasad et al., 2006; Waske and Braun, 2009).

The RF method provides an original variable's importance score for classification and regression. First, the individual regression trees were constructed. During this construction process, binary recursive partitioning is applied with the aim to estimate a dependent variable by means of multiple independent variables (here: explanatory variable defined in Table 2). The regression trees are constructed on the basis of a set of so called learning samples, which are comparable to the training data of traditional supervised classification approaches. Starting at the root of a regression tree (root node) and in a hierarchical sequence of binary splits, the dataset is divided into subspaces (nodes), which are as homogeneous as possible. As splitting criterion, a threshold value s is chosen such that the following term is minimized.

$$\sum_{i:x_j \leq s}(y_i - \mu_1)^2 + \sum_{i:x_j > s}(y_i - \mu_2)^2 \qquad \text{Eq. 2}$$

Here, y denotes the dependent and x_j the independent variables. $\bar{y}$ represents the mean of all elements y_i within the regarded subnode (two values, one for the left sum, another for the right sum), and the threshold value s can take any value of the independent variables X_j. The final nodes of a tree are called leaves. The mean value of the dependent variable of all leaf elements is assigned to each of these leaves.

A measure that indicates the importance of each of the independent variables is the increase in mean squared error ("%IncMSE"). The performance of each tree is computed over the corresponding OOB sample. %IncMSE is calculated by constructing each tree of an ensemble with and without the specific variable. The observations of each variable in the OOB sample are randomly permuted, and the trees' performance is computed over the permuted OOB samples. For all trees, the differences in error of these two variants are recorded, averaged and normalized by their standard deviation.

RESULTS

Crop classification

Crop maps were created for each survey year. Based on confusion matrices, the classification accuracy of these maps ranged from 0.78–0.85 (Table 4). Cotton, winter wheat and rice could clearly be distinguished from other crops as indicated by their high class-wise accuracies. Yet, classification accuracies were generally lower in 2014, most obvious because fewer reference samples were available for the classifier training (230 in 2014, compared to 602–1,425 (Conrad et al. submitted). Crop acreages are given in Table 5 and the spatial distribution of the three main crops is shown in (Figure 4). It shows that the dominant crop in the study site was cotton (39 % – 43 % of all fields from 2010–2014), followed by winter wheat (26 % – 36 % of all fields). Both crops were cultivated all over the landscape, albeit cotton tended to be more concentrated in the central parts of the study area. Rice fields only covered minor parts of the landscape (2 % – 6 % of all fields) and were almost exclusively cultivated in the central part.

Table 4: Overall and class-wise accuracies for the crop maps. Note that for fishponds no reference data was available in 2014, hence the class water/fishponds, which cover less then 0.5% of all fields, was assigned via visual interpretation of GoogleEarth images from 2014.

	2010	2011	2012	2014
Class	**Class wise accuracy**	**Class wise accuracy**	**Class wise accuracy**	**Class wise accuracy**
Cotton	0.92	0.92	0.95	0.76
Rice	0.85	0.82	0.71	0.50
Winter wheat	0.94	0.85	0.84	0.67
Orchard	0.78	0.60	0.62	0.96
Other	0.47	0.38	0.31	0.22

Fallow	0.77	0.86	0.88	0.90
Water/fishponds	0.86	0.77	0.75	-
Overall accuracy	**0.85**	**0.81**	**0.84**	**0.78**

Crop yield

The potential accuracy of the yield estimations was assessed. Remotely sensed estimates of area and yield in Fergana Valley were compared with statistics provided by SIC-ICWC (Figure 3). The estimates were both in agreement with statistics reported yet provide much finer spatial resolution (field scale) than the finest scale of available statistics (district averages). The assessment of yield using the proposed RUE model under- and overestimated reported yields, respectively, in all survey years of data by ~10% on average (over all districts). Coefficients of determination (R^2) were 0.846 (crop yield) and 0.866 (crop acreage).

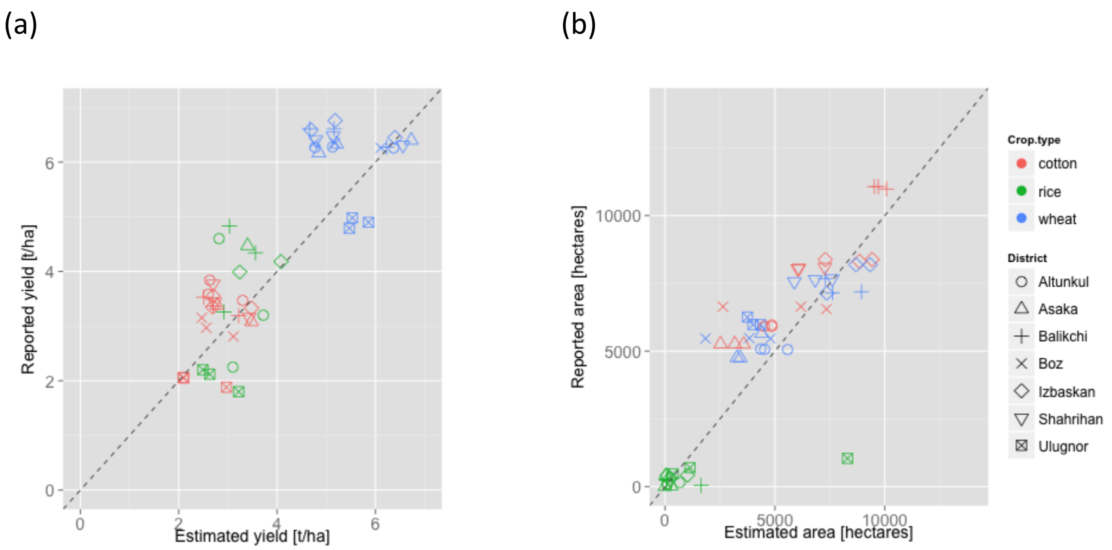

Figure 3: (a) Estimated crop yield by district and year plotted against reported crop yield for 2010–2012. (b) Same as (a) but for estimated crop area. Coefficients of determination R^2 were 0.846 (crop yield) and 0.866 (crop acreage).

Of particular interest for the current study were the temporal and spatial variations in crop yield. To assess these visually, the deviation o crop yield from the crops regional average yield was computed for each field (Figure 4).Two patterns are immediately evident in Figure 4. First, crop yields exhibit a high degree of spatial heterogeneity, with more than two-fold variation in yields, even across short distances. Second, lower crop yield tend to occur in the central parts of the study area, where crop yields deviate from the average by 10% to 40%. In 2011 and specifically in 2014, crop yields tended to be generally lower, as indicated by the higher amount of fields with negative yield deviations from the regional average (Figure 4), and these were also the years with the lowest share of rice fields (Table 5).

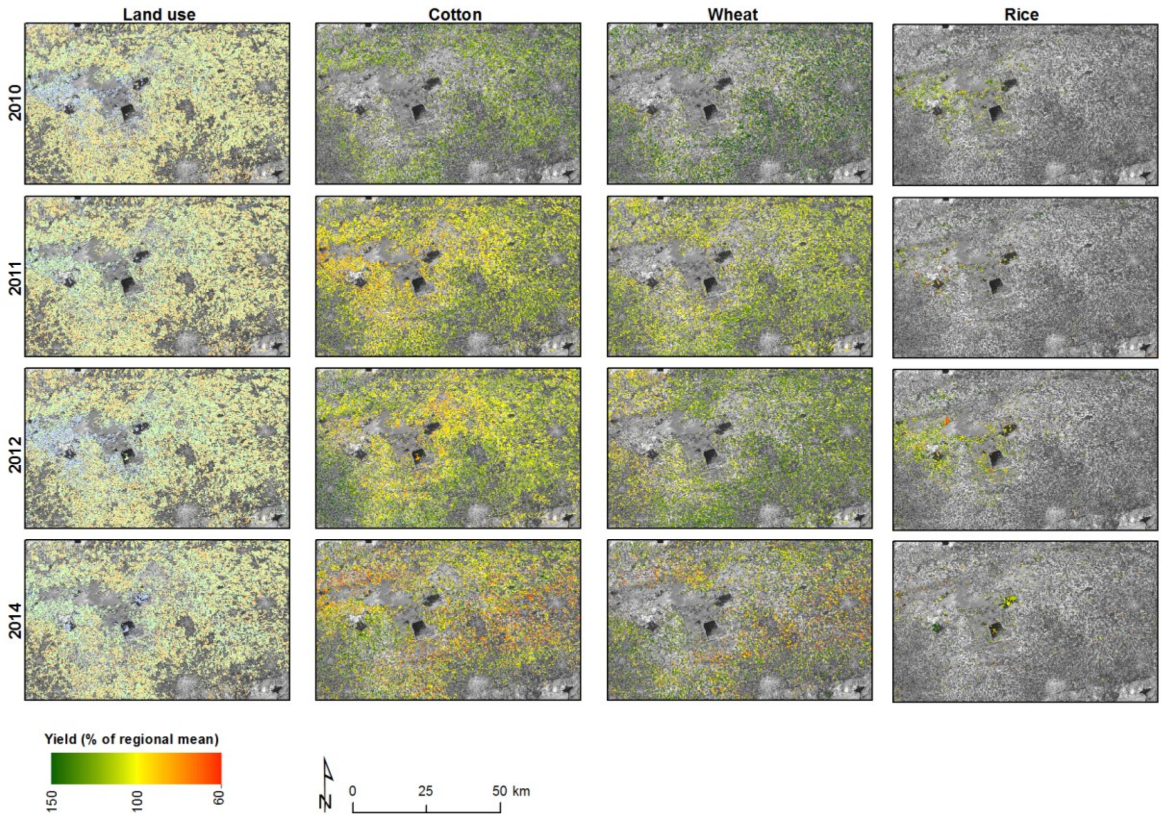

Figure 4: Spatial distribution of major crops and crop yields in Fergana Valley as percentage of the regional mean in the corresponding survey year.

At issue here is the average yield pattern and the relative importance of different yield constraints. Figure 5 shows the crop productivity as percentage of average regional mean crop yield. Clearly, fields the central parts of the study area tended to have below average crop yields (up to 40% deviation from mean), reflecting the observed annual crop yield pattern. Even at close distances, there were huge variations in average yields between fields (see small image subset in Figure 5).

As proposed by Lobell et al. (2009), a useful initial analysis is to determine the level of persistency in observed yield patterns. That is, do fields with higher yields (relative to neighbouring fields) in one year tend also to have higher yields in the next, irrespective of the crop that was cultivated? Figure 6 illustrates one such measure of persistency, which is the effect of first averaging yields across multiple years before computing the spatial yield gap, defined here as the difference between the 95th percentile of yields and average yields (Bastiaanssen and Ali, 2003; Lobell, 2013). This approach assumes that some farmers achieve maximum possible yield in a given year, which could then be used to assess the yield gap. As this could not be validated with official data, this approach gives a proxy of maximum possible yield.

Table 5: Remotely sensed estimates of crop acreage [ha] and average yield [t/ha] for cotton, rice, and winter-wheat in the Fergana Valley.

	2010		2011		2012		2014	
Class	**Area**	**Yield**	**Area**	**Yield**	**Area**	**Yield**	**Area**	**Yield**
Cotton	181,240	3.15	182,469	2.41	191,710	2.69	172,614	2.44
Rice	22,289	3.25	6,891	2.85	26,170	2.91	12,141	2.89
Winter wheat	159,615	4.88	159,489	4.77	141,069	4.91	116,787	4.73

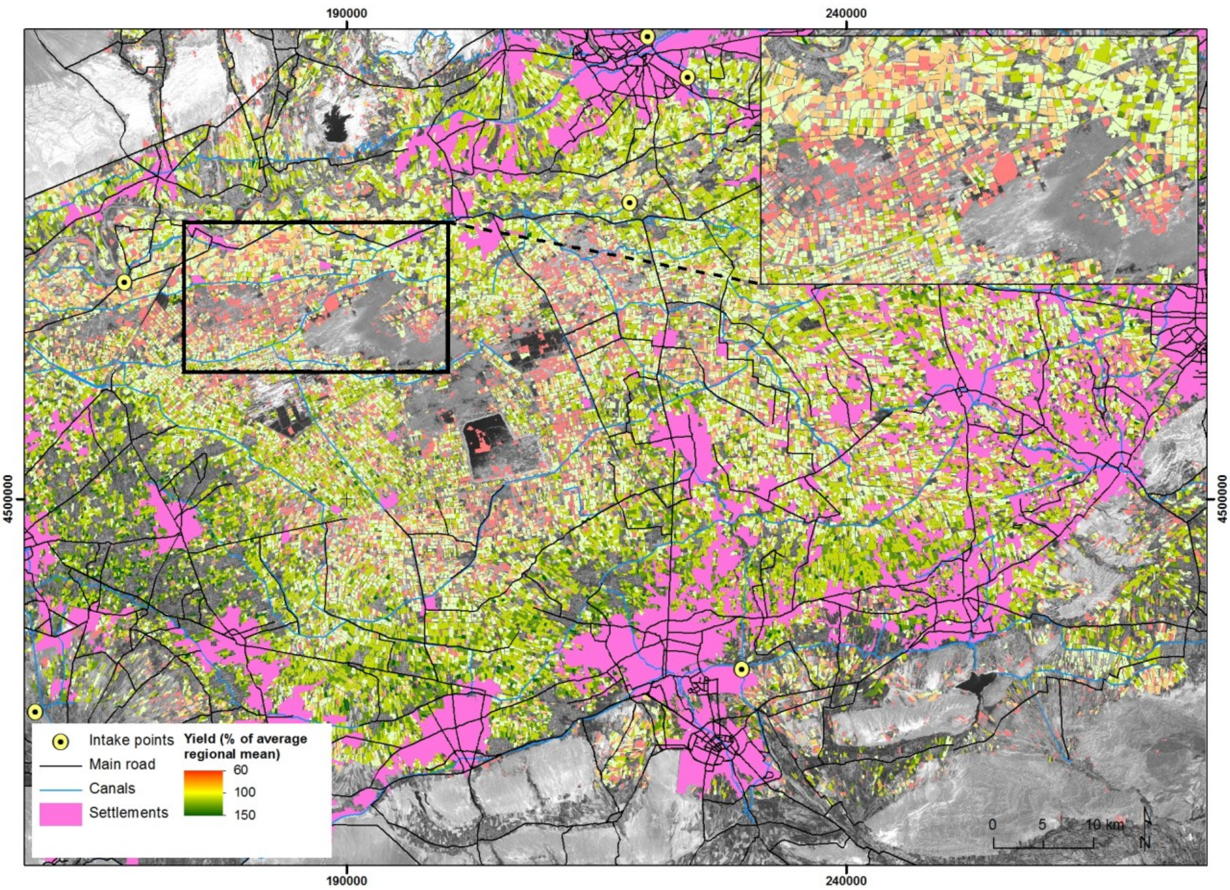

Figure 5: Spatial distribution of crop productivity in Fergana Valley. Crop productivity is given as percentage of average regional mean crop yield.

If yields were perfectly persistent, with the same fields always performing better, than time averaging should have no effect on the computed yield gap (Lobell et al., 2010). The results in Figure 6 indicate that yields are neither perfectly persistent nor perfectly random (cf. Lobell et al. (2010). Average yields for a given season tended to be roughly 1.6 t/ha below those achieved on the top 5% of fields, indicating a large spread between the best and average fields. The yield gap increased as yields are averaged over more years. This indicates that factors contributing to maximum yields had to a certain degree consistent effects across years. In contrast, if yields were perfectly random in space, and if there were only very there are very few persistent factors explaining factors the observed yield gap in Fergana Valley, then time averaging should tend to reduce the yield gap towards zero, which is indicated in Figure 6 (grey line).

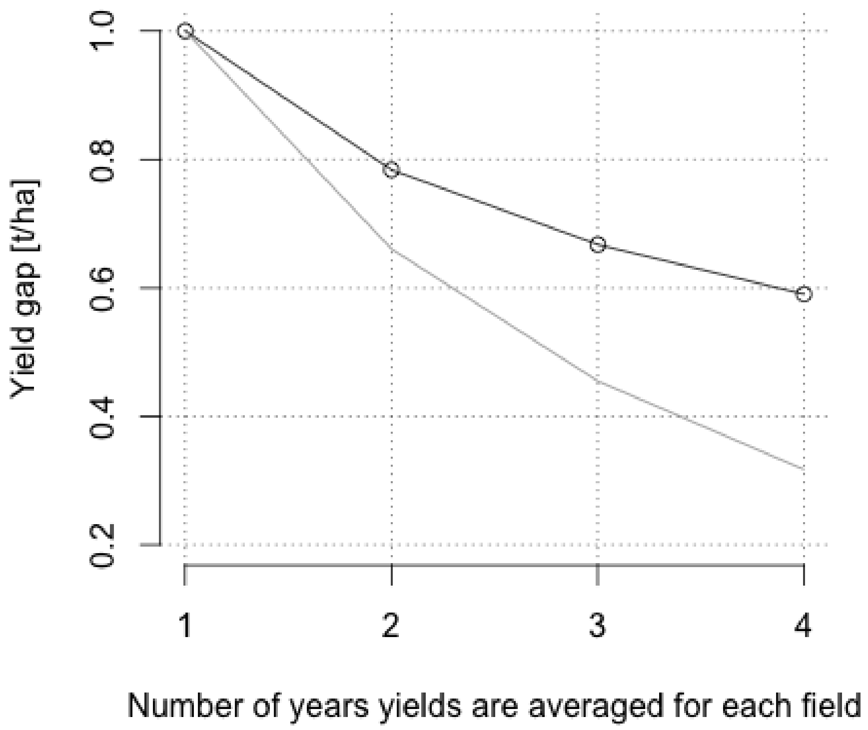

Figure 6: Yield gap curves for Fergana valley, displaying the difference between the 95th percentile and mean yield where yields are averaged over different numbers of years. A single year corresponds to the typical definition of yield gaps. For each average, all possible combinations of images were used. The gap shrinks as yields are averaged over more years, indicating that factors contributing to maximum yields do not have persistent effects across years. The grey line represents the expected change in yield gap with increasing years if yield patterns were entirely random in space (computed by randomly re-ordering the spatial distribution of yields in each year).

In order to assess which factors explain association of high (or low) yields the most, the RF regression was applied in each year for each crop separately (Table 6-Table 8

Table 6) and a %IncMSE-based ranking of each factor was calculated. The RF could explain the spatial variation of crop yields quite well, with R^2 values ranging from 0.60 to 0.80. In general, R^2 values were higher for cotton (0.71-0.80) than for the reminder crops (0.60-0.71).

Among the factors that could explain association of high (or low) yields with particular locations the most, i.e. with highest %IncMSE-rank, ranged infrastructure density, distances to settlements and intake points. However, the indices describing cropping pattern and diversity, SID, AV, and PERC, plus elevation were the most important factors. From these factors, road density, elevation, SID, AV and PERC were among the five most important in four years. For rice, the distance to the intake points tended to be more important than for the other crops. Most factors tended to have a similar rank across years, i.e. the important (unimportant) factors tended to remain important (unimportant) across years. An exemption from this the distance to intake points, canal density, and road density, which either tended to become more important from 2010-2014 or were the most important in 2014.

This indicates the relative importance of factors related with the agricultural management and irrigation infrastructure (e.g. access to the fields, distance to markets, distance to intake points and canal density). The importance of infrastructure is also visually evident on the average yield map overlaid with canals, intake points, roads, and settlements (Figure 5), showing that most high yielding areas are near settlements and in areas with higher road density. Yet, even more important appeared the spatial and temporal diversity of crops, i.e. areas with higher cropping diversity (or fields were different crops were cultivated across years) tended to have persistently higher yields.

Table 6: Variable importance predicted by RF for cotton yields, averaged over the period 2010-2014.

		Cotton					
Variable		**2010**	**2011**	**2012**	**2014**	**Range**	**N top-5**
(a) Site specific							
Canal density	x_1	8	6	9	6	6-9	
Road density	x_2	**5**	**4**	**5**	**1**	1-5	4
Soil salinity	x_3	21	23	21	19	19-23	
Slope	x_4	15	11	12	15	11-15	
Elevation	x_5	**2**	**1**	**2**	**2**	1-2	4
Soil type 1	x_6	20	20	22	20	20-22	
Soil type 2	x_7	22	21	20	23	20-23	
Soil type 3	x_8	18	18	18	17	17-18	
Soil type 4	x_9	11	17	6	11	6-17	
Soil type 5	x_{10}	23	22	23	21	21-23	
Soil type 6	x_{11}	12	16	15	14	12-16	
Soil type 7	x_{12}	14	13	16	16	13-16	

Soil type 8	x_{13}	19	19	19	22	19-22	
Soil type 9	x_{14}	13	12	17	18	12-18	
(b) Proximity characteristics							
Distance to canals	x_{15}	10	10	11	9	9-11	
Distance to roads	x_{16}	9	9	10	10	9-10	
Distance to settlements	x_{17}	**3**	**5**	7	8	3-8	2
Distance to intake point	x_{18}	7	8	8	**3**	3-8	1
(c) Object characteristics							
Object perimeter	x_{19}	16	14	14	13	13-16	
Object area	x_{20}	17	15	15	12	12-17	
(d) Cropping pattern characteristics							
Land use intensity in the neighbourhood	x_{21}	**4**	7	**3**	7	3-7	2
Cropping diversity AV	x_{22}	6	**3**	**4**	**4**	3-6	4
Cropping diversity SID	x_{23}	**1**	**2**	**1**	**5**	1-5	4
R^2		0.80	0.71	0.78	0.75	3.6	

Table 7: Variable importance predicted by RF for wheat yields, averaged over the period 2010-2014.

		Wheat					
Variable		**2010**	**2011**	**2012**	**2014**	**Average**	**N top-5**
(a) Site specific							
Canal density	x_1	7	7	7	7	7-7	
Road density	x_2	**5**	6	8	**1**	1-8	2
Soil salinity	x_3	21	21	21	19	19-21	
Slope	x_4	12	14	11	12	11-14	
Elevation	x_5	**1**	**1**	**2**	**2**	1-2	4
Soil type 1	x_6	20	18	18	20	18-20	
Soil type 2	x_7	22	22	23	23	22-23	
Soil type 3	x_8	18	19	20	18	18-20	
Soil type 4	x_9	17	8	9	10	8-17	
Soil type 5	x_{10}	23	23	22	22	22-23	
Soil type 6	x_{11}	13	17	14	15	13-17	
Soil type 7	x_{12}	14	10	15	16	10-16	
Soil type 8	x_{13}	19	20	19	21	19-21	
Soil type 9	x_{14}	11	16	10	17	10-17	
(b) Proximity characteristics							
Distance to canals	x_{15}	9	11	12	9	9-12	
Distance to roads	x_{16}	10	12	13	11	10-13	
Distance to settlements	x_{17}	8	9	**5**	8	5-9	1

Distance to intake point	x_{18}	**3**	**5**	6	**4**	3-6	3
(c) Object characteristics							
Object perimeter	x_{19}	15	13	16	13	13-16	
Object area	x_{20}	16	15	17	14	14-17	
(d) Cropping pattern characteristics							
Land use intensity in the neighbourhood	x_{21}	**4**	**2**	**3**	**3**	2-4	4
Cropping diversity AV	x_{22}	6	**4**	**4**	**5**	4-6	3
Cropping diversity SID	x_{23}	**2**	**3**	**1**	6	1-6	3
R^2		0.68	0.63	0.71	0.63	3.2	

Table 8: Variable importance predicted by RF for rice yields, averaged over the period 2010-2014.

		Rice					
Variable		**2010**	**2011**	**2012**	**2014**	**Average**	**N top-5**
(a) Site specific							
Canal density	x_1	6	7	11	**5**	5-11	1
Road density	x_2	**4**	6	**5**	**3**	3-6	3
Soil salinity	x_3	23	23	23	20	20-23	
Slope	x_4	12	13	14	13	12-14	
Elevation	x_5	10	8	7	**1**	1-10	1
Soil type 1	x_6	22	20	21	21	20-22	
Soil type 2	x_7	21	22	20	22	20-22	
Soil type 3	x_8	11	16	16	17	11-17	
Soil type 4	x_9	16	17	9	14	9-17	
Soil type 5	x_{10}	19	21	22	23	19-23	
Soil type 6	x_{11}	15	15	15	15	15-15	
Soil type 7	x_{12}	17	14	16	16	14-17	
Soil type 8	x_{13}	20	19	19	19	19-20	
Soil type 9	x_{14}	18	18	17	18	17-18	
(b) Proximity characteristics							
Distance to canals	x_{15}	9	9	13	10	9-13	
Distance to roads	x_{16}	**1**	11	8	8	1-11	1
Distance to settlements	x_{17}	**3**	**2**	**2**	6	2-6	3
Distance to intake point	x_{18}	7	**4**	**3**	**2**	2-7	3
(c) Object characteristics							
Object perimeter	x_{19}	14	12	12	11	11-14	
Object area	x_{20}	15	10	10	12	10-15	
(d) Cropping pattern characteristics							

Land use intensity in the neighbourhood	x_{21}	**5**	**5**	**5**	**4**	4-5	4
Cropping diversity AV	x_{22}	8	**3**	**4**	9	3-9	2
Cropping diversity SID	x_{23}	**2**	**1**	**1**	**5**	1-5	4
R^2		0.69	0.69	0.61	0.60	4.0	

The RF variable importance only gives insight into which factor are important but without quantifying these impacts. Hence, plots of average crop yield versus distance to intake points, settlements, and roads (Figure 7) were created. They support the results from RF regression analysis and present evidence for a rather strong influence of infrastructure and accessibility of fields on crop yields. In particular, fields that are 5–6 km apart from settlements tended to have 5% (cotton and wheat) or 10% (rice) lower crop yields than fields adjacent to settlements, with the strongest impact of distance on rice yield. Whilst cotton yields were almost unaffected by the distance to the next intake point, rice fields were the most impacted, with fluctuations up to 10% but with no clear trend as a function of the distance. It must be noted that ∼80% of all rice fields were more than 6 km from the nearest intake point and concentrated in the central parts of the study region. On the other site, only ∼20% of all cotton and wheat fields, respectively are more than 5-6 km from the next settlement, hence the overall effect of this remoteness on crop yields is less severe. For example, cotton yields within 1 km distance of settlements average 2.69 t/ha or less than 1% higher than the regional average (2.65 t/ha). For wheat, yields within 1 km distance of settlements average 5.02 t/ha or 4% higher than the regional average (4.83 t/ha). In general, fields remote from infrastructure tended to be stronger affected in dryer years (Table 9).

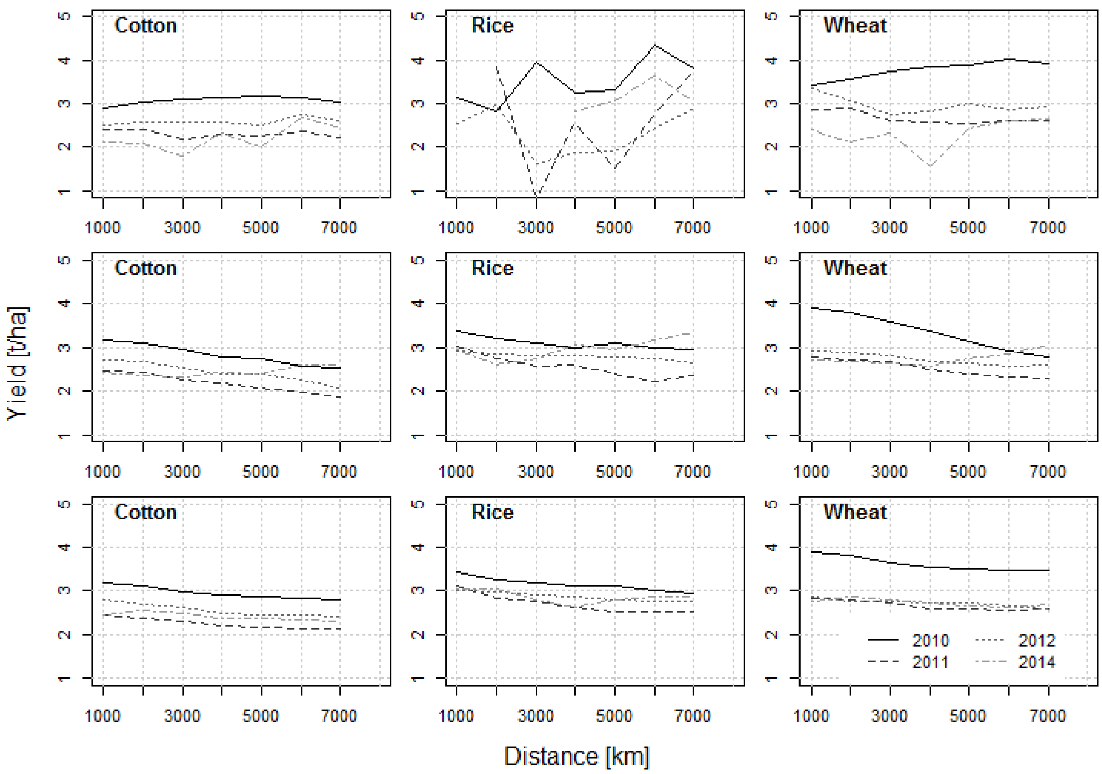

Figure 7: Average model estimates for crops yields as a function of distance from the nearest intake point (top row), roads (middle row) and settlements (bottom row). Yield averages represented are calculated at 1,000 m increments in t/ha and represent average crop yield of all fields at given distance from intake point, roads or settlements.

The impact of the cropping pattern, as quantified by x_{21-23}, shows that a higher share of crop rotations results in higher crop yield (Figure 8). The impact of AV (x_{22}) was more persistent on all crops than SID (x_{23}). For the latter, rice yields showed no such clear decreasing yields trend with higher values than for AV. Besides this, higher crop yields were found in areas with a higher share of agricultural area (PERC, x_{21}). An exemption from this is rice yields in 2011, as well as cotton and wheat in 2014, where lower yields were found in areas with highest PERC values.

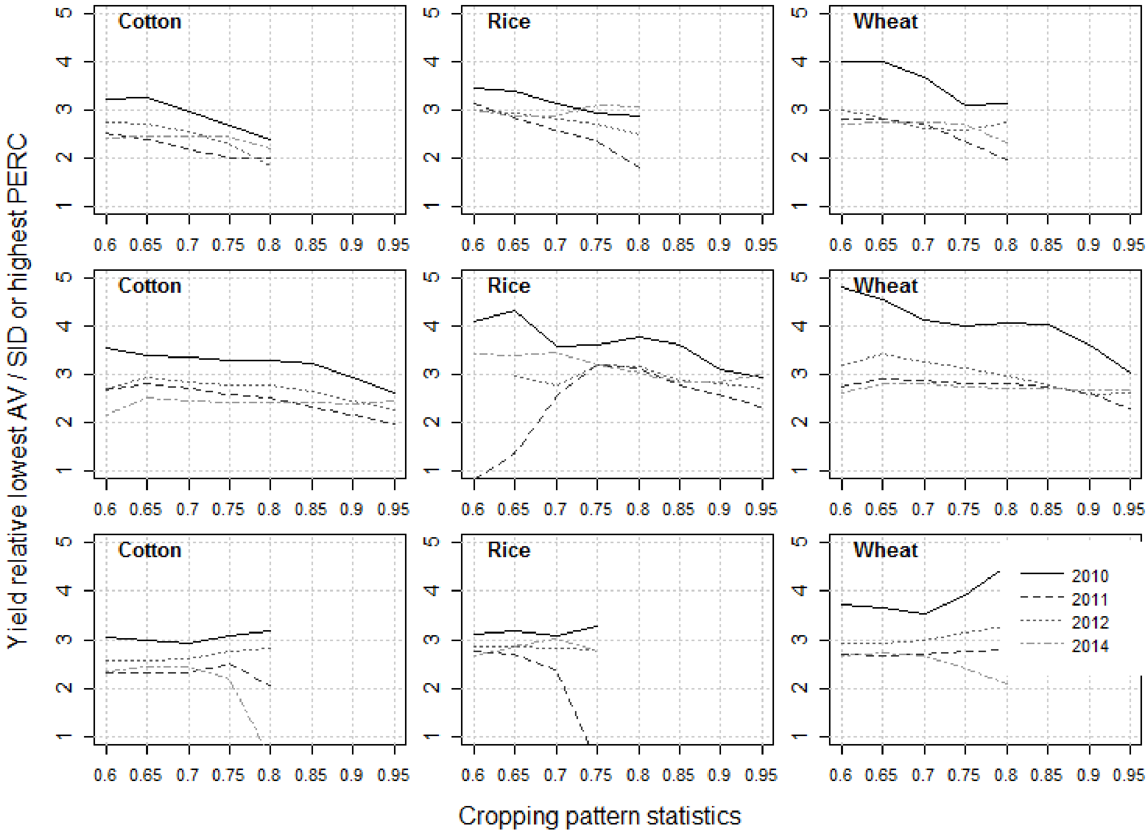

Figure 8: Average model estimates for crops yields as a function of AV (top row), SID (middle row) and PERC (bottom row), expressed as average crop yields in t/ha.

DISCUSSION

Crop rotation

The crop maps provide valuable information for land use and management efforts like crop water requirements assessments (Conrad et al., 2013). The overall high classification accuracy of the crop maps was comparable to other object-based crop classifications in Central Asia. For instance, Conrad et al. (2013, 2014) achieved overall accuracies of 86.2 in Fergana and 88.0% in Khorezm. Whilst errors in the maps could be reduced with more frequent observations, the low error rates of the three focused crops offer positive prospective for an operational monitoring and the maps provide useful input to the RUE based crop yield model. The area shares of cotton (41% on average) and wheat (32% on average) fit well with reference statistics (Figure 3).

Crop yield – uncertainty, official statistics, usability for operational monitoring

The agreement between estimated crop yields and acreages, based on remote sensing and official statistics were notable. It must be noted that the parameters for fPAR derivation were calibrated to the local data in Fergana valley (Lex et al., 2015), which is assumed by some authors to have a higher impact on the final model results than, for example, biases in the estimates of HI or ε resulting from inter-annual changes in in practices, cultivars or environmental conditions (Choudhury 2000, Lobel). The reported deviation between estimated and reported yields is comparable to the accuracies of yields in other studies. Reported deviations of estimated and reported governmental yield statistics with similar approaches were reported to be 11% for cotton yield in Khorezm, Uzbekistan based on MODIS data (Shi et al., 2007). Lobell et al. (2003) reported 3.3% over-estimation of wheat yields in Yaqui Valley, Mexico for a RUE model based on Landsat data. Fritsch (2013) reported 16.8% error on average for cotton yield in the period 2004-2009, and 9.0% for rice over the same period in Khorezm, Uzbekistan, based on MODIS data and at the district level. Reeves et al. (2005) found accuracies to within 5% for state level estimates of wheat yield in North Dakota and Montana. Crop yields reported by Doraiswamy et al. (2005), using a crop growth simulation model based on MODIS were within 10% official county yield statistics for corn and soybean. Although it is difficult to precisely measure the skill of the remote sensing data without an independent estimate of the reliability of reported district yields (which could not be obtained in this study), the observed agreement is statistically significant and suggests that the estimates provide useful information on spatial yield variability.

Overall, the accuracy and low uncertainty of yield and area estimates in this study strongly support the use the RUE model (Eq. 1) for regional studies on agricultural production in Fergana Valley, and specially for identifying potential yield gaps. This offers positive prospective towards an operational used of this approach, which has the advantage that relatively few parameters are required as input, compared to approaches that fully integrate crop simulation models with remote sensing data (e.g. Doraiswamy et al. (2004). It should be noted, however, that yields were not evaluated with field scale measurements in the current study and potential improvements like fine-tuning of the parameters HI and ε could be envisaged.

Explanation of the observed crop yield pattern

Despite a certain degree of random distribution of yields, which was evidenced by the analysis of yield gap persistence (Figure 6), there was a steady influence by some of the investigated factors.

Diversity

Most notably, cropping diversity (x_{22}) and rotation diversity (x_{23}), had a pronounced impact across the observation years for all crops and ranging among the top-5 factors. Diverse spatiotemporal patterns of land use in agrarian landscapes can influence the agricultural production (Ekroos et al., 2014). For instance, cropping of various crops and multi-annual rotation of crops instead of monoculture use if land can contribute to preventing soil degradation, maintaining soil fertility, or reducing soil erosion (Black et al. 1981, Bullock 1992, Wright et al. 2005). These practices also help to avoid pest propagation and harvest damage (Matson et al. 1997, Bellinger 2010). The implementation of such practices is, among others, assessed valuable for maintaining soil health, which in turn ensures sustainable production (Dick 1992). Moreover, diverse cropping patterns can also contribute to biodiversity and positively affect the ecosystem functions within an agricultural landscape (Thrupp 2000, Chapin et al. 1997, Naeem et al. 1994). Favourable approaches for enhancing crop nutrition and improving resilience of agricultural ecosystems also include the cultivation of wide ranges of annual and perennial plant species such as fruit trees, shrubs, pastures, and crops (FAO 2011).

The unprecedented intensification of cotton production in the former Soviet Union replaced historical crop rotation patterns. Crop rotations are globally among the oldest-known cultural practices to prevent soil degradation, maintain soil fertility, or reduce soil erosion (Bullock 1992, Wright et al. 2005). They are also declared means to avoid pest propagation and harvest damage (Bellinger 2010). Cotton rotations with wheat, irrespectively if one or two years of cotton are followed by the grain crop, have been more economically profitable than other cotton rotating schemes (Hullugalle et al. 1998). However, attempting to reach economic sustainability by solely implementing rotations for maximizing the profits has been critically discussed. Hake et al. (1991) for instance emphasized that cotton mono-sequences can be supported by rotations in areas suffering from soil-borne diseases or weed problems, and where these cannot be managed otherwise. The same authors state, however, that cotton in rotation with other profitable crops can support economic stability. Cotton rotation systems are thus considered an important instrument for economically sustainable and soil conserving crop production.

On the other site, Abdullaev et al. (2009) 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 in the off-season period (October-March). They argue that having different crops on neighboured fields requires more frequently watering of the channels, which in turn lowers the water use efficiency at the system level. Further, Abdullaev et al. (xxxx) states that low cotton productivity Fergana is strongly influence by policy (quota system), i.e. the stagnation in cotton yield in the last years appears to be largely a response to government's quota system for the cotton area, which gives little, if any, incentive to increase productivity beyond the levels required to meet production quotas. The persistent impact of distances to settlement (x_{17}) and roads (x_{16}) and road density (x_2) are likely to reflect the unwillingness or inability (e.g. due to financial constraints) of the farmers to maintain the irrigation infrastructure especially in remote areas. Any citation for this, is my line of argumentation at least a little logical?

Elevation

Besides cropping diversity, elevation strongly influenced crop yields of wheat and cotton. Areas in elevated areas can be assumed those near the intake pints or source regions of water, as most water is distributed gravitational. Hence, elevated terrain can be assumed better supported with irrigation water, compared to downstream or down canal areas where some of the water has already been consummated. On contrast, rice yield was only strongly influenced in the year 2014. Although this seems at first counterintuitive, since rice needs more irrigation water than cotton (xxx), it can be explained by the fact that rice fields are mostly located in the central part of the study area, with no big differences in elevation, e.g. range of DEM in cotton is xxx meters, for rice only xxx m.

Intake points and canal density, and their changes over the year

Distances to intake points (x_{18}) and canal density (x_1) were important factors that relate to the water supply of fields. Locations close to the intake points tended to have a persistently higher yield, which likely reflects the importance of access to irrigation water. Likewise, in dryer years like 2014 (Table 9) their relative importance of these factors increased for cotton and rice, whilst there was no such clear trend for wheat (Table 7). Besides factors related to the water distribution system, the impact of read density was the most important in 2014 for all crops including wheat. The most obvious reason for this is that in years with only low water supply, areas near the intake points or main canals are usually better supplied than remote areas, which also tend to be characterized by a lower canal density. Some ideas what exactly the reasons for this are?

Table 9: Water inflow [Million m^3] from the three main tributaries of the Syrdarya: Naryn, Karadarya and Tschirtschik from 2007-2014 (source: SIC-ICWC 2014).

Year	Naryn	Karadarya	Tschirtschik	Total
2008	13,335	3,764	7,723	24,822
2009	19,166	7,628	9,301	36,095
2010	13,783	4,131	5,509	23,424
2011	12,401	3,625	6,825	22,851
2012	11,776	3,484	6,277	21,537
2013	10,079	2,591	6,734	19,404
2014	9,884	2,361	5,061	17,307

Road density, distance to settlements

Further, road density (x_2) and distance to settlements (x_{17}) tended to be the important variables. The reduction of funding for the operation and maintenance of the irrigation infrastructure in all Central Asian states after independence has led to a deterioration of the infrastructure and to a decrease of the management control (SIC ICWC, 1999). Infrastructure deterioration has widely been reported as one major factor limiting crop productivity (Abdullaev 2009; Cai et al. 2003). The results of this study suppose the assumption that the condition of the irrigation infrastructure near settlements or in areas with higher road densities could be better maintained, compared to remote areas which could explain the persistent, i.e. across all years, effect of the observed yield decline (Figure 7).

The results imply that providing widespread access to water at the level currently experienced near settlements could improve crop yields by roughly up to 5% in this region, corresponding to xxx t/ha (cotton), xxx t/ha (wheat), and xxx t/ha (rice). Compared with this, there seems to be less room for improvements when looking at the distances to the intake points, at least for cotton and wheat (Figure 7). However, it must be considered that there remain uncertainties in this estimate because

Also calculate this figure for different AV/SID/PERC levels, how much higher could it be?

It must be noted that the method to estimate the yield gap in, namely by comparing farmer´s yields with maximum farmer yields, could even underestimate the actual yield gap. As was discussed by Lobell (2009), estimates of maximum possible yields by crop growth models could be higher than what can be expected from the maximum of farmer´s yields. On top of this, there was a consistently decline in average crop yields in the study area. For example, wheat yield decreased from 5.18 t/ha (2010) to 4.48 t/ha (2014), and cotton yields decreased from 3.18 t/ha to 2.21 t/ha in 2014. It is likely that Fergana Valley experiences a serious decline in water inflow from the three main tributaries in the observation period of almost 26% (Table 9). Although this impact of overall water availability cannot be neglected, the infrastructure (roads and settlements) but especially the cropping diversity played an important role on top of this, as was demonstrated by a more persistent impact on yields, compared to distance to intake points or canal density.

Beyond the persistent factors of cropping diversity, infrastructure and proximity to intake points and canals, however, there appears to be little yield impact of persistent differences between field sizes, slope or soil conditions in different fields. Although (Giese and Sehring 2007?) reported that in Fergana valley up to 80% of the soils were affected by salinization, there was little evidence, for instance, that soil salinity is a major constraint to yields in this region, as this would reveal itself in a high fraction of consistently underperforming areas within the image. There is however, evidence that differences among farmers in persistent factors such as distance to roads has a significant yield effect. It must be noted that the overall quality of the RS regression in terms of R^2 might be improved by the provision of other factors like drainage infrastructure or groundwater table and salinity. Hence, whether these lessons hold true beyond the extent of this study will require future work in adjacent areas.

CONCLUSIONS

The application of the RUE based crop yield model, in combination with remote sensing and GIS has provided several insights into the agricultural system in Fergana Valley. Remote sensing allowed assessing agricultural production (yield) at the per-field level, which is a critical contribution to agricultural management in Fergana Valley. Results show that there is strong indication that there was heterogeneity in crop yields even within small distances. The most prominent factors affecting yield was the spatial and temporal diversity of the cropping pattern, i.e. locations with a higher diversity tended to have higher yields. Further, fields located in areas with a small share of agricultural tended to be less productive.

Further analysis to explain the observed yield pattern depend in data availability but could include to assess the impact of distances to location of wheat mills or cotton producing factories, and the inclusion of ground water data (depth and salinity).

The cropping pattern, i.e. the presence or absence of multi-annual crop rotations, and the spatial diversity of crops had the most persistent effects on crop yields across years. Areas with a lower diversity or abundance of crop rotation tended to have lower crop yields, with differences of partly more than one t/ha yield.

It was shown that factors related with the infrastructure, for example the distance of farms to the next settlement or the density of roads had a strong effect on crop yields over several years. Potential improvements of cotton and wheat yields were estimated 5%, compared to crop yields of farms directly adjacent to settlements or roads. The irrigation infrastructure had a less pronounced impact on crop yields, which were most likely stronger impacted by the decreasing overall water availability observed between 2010-2014, which lead to a region wide decline of all crop yields.

The study demonstrate the ease with which ten-thousands of fields in Fergana Valley can be monitored through time, and although there was some error in the satellite remote sensing based crop yield estimates, it was very useful to assess the spatial and temporal variations in crop yields and to assess the potential factors that explain the observed pattern. Given the growing demand for food and the environmental consequences associated with over-application of inputs, improved understanding of spatial variations in crop yields is greatly needed. Remotely sensed estimates of crop production provide a unique perspective that, when combined with field surveys, should enhance the ability to identify management priorities for improving regional production and/or reducing environmental impacts. The methods could be implemented in other irrigated areas worldwide by adapting regional meteorological and crop-specific parameters.