View metadata, citation and similar papers at core.ac.uk

brought to you by CORE

provided by Elsevier - Publisher Connector

Climate Risk Management 13 (2016) 19–30

Contents lists available at ScienceDirect

Climate Risk Management

journal homepage: www.elsevier.com/locate/crm

Income and irrigation water use efficiency under climate change: An application of spatial stochastic crop and water allocation model to Western Uzbekistan

Ihtiyor Bobojonov [a,*], Ernst Berg [b], Jennifer Franz-Vasdeki [c], Christopher Martius [d], John P.A. Lamers [e]

[a] *Leibniz Institute of Agricultural Development in Transition Economies (IAMO). Theodor-Lieser-Str. 2, 06120 Halle (Saale), Germany*
[b] *Institute for Food and Resource Economics, University of Bonn, Germany*
[c] *Independent Researcher, Seattle, WA, USA*
[d] *Center for International Forestry Research (CIFOR), Indonesia*
[e] *Center for Development Research (ZEF), Bonn, Germany*

ARTICLE INFO

Article history:
Received 3 October 2015
Revised 20 April 2016
Accepted 3 May 2016
Available online 4 June 2016

Keywords:
Central Asia
Integrated modeling
Climate change
Risk management
Irrigation efficiency

ABSTRACT

A decline in water availability due to rising temperatures and growing water demand presents significant and unique challenges to agricultural producers in Uzbekistan. This study investigates the impact of climate change on farm revenues and water use efficiencies in Western Uzbekistan. A spatially explicit stochastic optimization model is used to analyze crop and water allocation decisions under conditions of uncertainty for irrigation water availability in the area for the first time.

Results show farmers' income could fall by as much as 25% with a 3.2 °C temperature increase and a 15% decline in irrigation. Farmers located in the tail end of the irrigation system could lose an even greater share of their revenues. A more conservative increase in temperature could increase farmer income by as much as 46% with a 2.2° temperature increase and only 8% decline in irrigation water since some crops benefit from extended vegetation periods. Under both pessimistic and optimistic scenarios, environmental challenges due to shallow groundwater tables may improve associated with enhanced water use efficiency.

© 2016 The Authors. Published by Elsevier B.V. This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/).

1. Introduction

The gradual disappearance of the Aral Sea in Central Asia has been caused by unabated irrigation of water intensive crops. While this trend began during the Soviet Union, it has continued largely unchanged since the collapse of the USSR. The extent of the crisis has gained international attention. A wide range of studies have investigated how water management policies and practices impact the environment, the economy and the health and livelihoods of those in the region (Micklin, 1988; Glantz, 2005; Bucknall et al., 2003; Bekchanov et al., 2010). The many, multi-dimensional problems surrounding the agricultural sector are increasing during the recent years. Coping mechanisms related to market production and risk have been further complicated by unpredictable and sudden changes in the climate (Bobojonov and Aw-Hassan, 2014; Bobojonov and Lamers, 2008).

* Corresponding author.
E-mail address: Bobojonov@iamo.de (I. Bobojonov).

http://dx.doi.org/10.1016/j.crm.2016.05.004
2212-0963/© 2016 The Authors. Published by Elsevier B.V.
This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/).

In Uzbekistan, farmers do not own the land, instead it is leased from the government (Djanibekov et al., 2012). Decision-making regarding land allocation and water use is heavily influenced by government directive (Veldwisch and Spoor, 2008). For example, 60–70% of agricultural land must be allocated to the two main state crops: cotton and wheat. Farmers are responsible for ensuring quotas on state crops are met; therefore, they must make decisions around the timing of planting according to field location within the irrigation system.

In flood and furrow irrigated systems, such as those in Uzbekistan, unpredictable weather patterns increase farmers' risk depending on where they are located within the irrigation system. Assessing the risk level is complex as it depends not only on the location within the irrigation system, but also on farm specialization, levels of market risks, temperature fluctuations, soil parameters (e.g. texture, fertility) and other weather uncertainties. Consideration of these multiple aspects requires the use of a spatial crop and water allocation model. A number of spatial bio-economic models exist which analyze the impacts of climate change on agricultural production worldwide (e.g. Busch, 2006; van Meijl et al., 2006). Some spatial models that consider biological and economic fluctuations on irrigated agriculture were particularly developed in northwest Uzbekistan (e.g. Sommer et al., 2011; Djanibekov et al., 2013), but these models do not incorporate risk into the decision analysis. The inclusion of risk in spatially explicit models greatly improves the analysis of farmers' decision-making, especially under climate change scenarios.

Studies over the last two decades prioritized the investigation of water productivity and increased efficiency (e.g. Abdullaev et al., 2007; Bekchanov et al., 2010). These studies were largely motivated by environmental problems. However, in recent years, studies concentrate on the importance of finding options to cope with the negative consequences of climate change (e.g. Mirzabaev, 2013; Bobojonov and Aw-Hassan, 2014). Therefore, increasing water use efficiency as well as identifying risk management options to cope with climate risks is becoming an important issue in the region. Yet, there are no studies available which analyze the impacts of climate change on income and water use efficiency. Therefore, this study attempts to analyze changes in income and water use efficiency under climate change for the first time. The integration of bio-physical and socio-economic aspects in the modeling framework provides for an in-depth analysis of complex problems in the irrigated farming systems of Uzbekistan. Although the integration of geographical and economic data in the spatial optimization model is becoming important in many land allocation models used worldwide (e.g. Briner et al., 2012; Meiyappan et al., 2014; Chen et al, 2015), risk management aspects in crop and irrigation water allocation at farm level is rarely discussed.

The contribution of this study to the existing literature is twofold. First, we discuss the possibilities and challenges of incorporating stochastic production functions into a crop and water allocation model under conditions of data scarcity at the farm level. Secondly, the developed model is used to test fluctuations in farm income under varying climate change scenarios; this is done while considering the adaptive capacity of the decision makers and the impact of their activities on the environment of the irrigated system. Thus, the scenario simulations contribute to the discussions about climate change impacts on income and water use efficiency at regional level.

2. Theoretical framework and methodology

The approach used in this study has two main characteristics: first, it explicitly considers the risk associated with decisions on crop allocation and irrigation. Since the risk level depends on the actually implemented cropping pattern and irrigation strategy, the choice of optimal actions requires that the decision makers' attitudes towards risk are considered as well. To accomplish this, a risk programming framework is used. Second, this study integrates bio-physical and socio-economic relationships into a spatially explicit model. Both characteristics are described in the following sections.

2.1. Risk programming framework

The most common and still widely accepted approach for assessing the impacts of risky choices on a decision maker's wellbeing is by means of expected utility (Hardaker and Lien, 2005). This requires that all possible outcomes of the risky prospect be translated into utility measures to compute the expected utility. Faced with a choice amongst a set of risky prospects, the expected utility hypothesis states that the prospect with the highest utility is preferred. The expected utility (EU) can be retranslated into a monetary measure, i.e. the certainty equivalent (CE), through the inverse of the utility function. The CE represents the amount of money a decision maker with a given utility function would rate as equivalent to the uncertain outcome of the risky prospect (cf. Robison and Barry 1987, p. 23ff). Ranking prospects by CE is equivalent to ranking them by EU.

By definition the CE equals the expected return E(y) minus the risk premium π, i.e. CE = E(y)–π. For the latter, Pratt has derived the approximate relationship $\pi = 1/2R[E(y)]\,V(y)$, where R[E(y)] indicates the decision maker's absolute risk aversion measured at the expected value E(y) and V(y) denotes the variance (cf. Robison and Barry 1987, p. 34). The CE is expressed in Eq. (1):

$$CE = \mathrm{E}(y) - \frac{1}{2}\mathrm{R}[\mathrm{E}(y)]\,\mathrm{V}(y) \qquad (1)$$

Eq. (1) is well-known as the value-variance (EV) approach. The conditions under which the EV approach yields results consistent with the more general EU model have been worked out by several authors (cf. Meyer, 1987; Robison and

Barry, 1987). While Arrow (1971) originally argued that this was only the case under the premise of either quadratic utility or normally distributed income, Meyer (1987) has shown that EV orderings are consistent with the EU model for all distributions fully distinguished by location and scale, i.e. virtually all two-parameter distributions including log-normal, beta and gamma distributions.

The EV approach naturally leads to quadratic risk programming (Hardaker et al., 2004, p. 193ff) which aims at selecting a portfolio of activities that maximize the CE according to the definition given in Eq. (1). The EV approach allows one to capture uncertainties which directly affect the objective function through the covariance matrix. For this reason, the approach leads to a compact model formulation that avoids "the curse of dimensionality" (Hardaker et al., 2004, p. 203) often associated with approaches that explicitly consider different states of nature and their associated outcomes. Therefore, the EV approach is chosen as the basic modeling framework; we have combined it with the chance constraint programming concept originally developed by Charnes and Coope (1959). The latter allows one to incorporate uncertainty that occurs within the constraints of the model. Thus, our combined approach provides for the consideration of multiple sources of risk in irrigated farming systems. Market and weather risks, which directly affect the farming outcome, are also considered in the objective function. Uncertainty associated with water availability is considered in the constraints of the model. More details on the risk programming approach are provided for download in the supplementary material.

2.2. Integrated modeling

The model simulations were carried out at the level of an entire Water Users' Association (WUA) to investigate spatial crop allocation and water use patterns under different policy scenarios. More explicit information about the integration of agro-ecological and socio-economic information included in the model is shown in Fig. 1.

The model consists of four main components, as denoted with A, B, C and D in Fig. 1. Part A of Fig. 1 represents the modeling environment, the variables of which are exogenous inputs of the model. The spatial data and agro-ecological properties of the fields (water distribution canals, distances, soil fertility, soil texture), the state regulations on crop allocation, and the available farm resources are processed in the model environment component, and are passed to the mathematical programming model. The information obtained from part A is processed according to bio-physical relations and used in part B along with socio-economic data to carry out stochastic simulations based on a production function approach (for details refer to the supplementary material). The stochastic simulations yield joint distributions of crop revenues as random samples. These joint distributions are then used in the optimization process in Part C. Furthermore, agro-ecological and socio-economic constraints are also incorporated into in the optimization process. Thus optimization process captures the adaptation behavior of farmers to climate related uncertainties. Part D finally visualizes the results of the optimization process and exports the model results into GIS maps. The estimation of irrigation efficiencies on the WUA and at field level are also estimated after the optimization process in Part D.

2.2.1. Modeling environment and assumptions

The analyses were carried out for 300 fields located on 99 farms (Fig. 2) in the Shamahulum WUA, located in the Khorezm region of western Uzbekistan. Cotton, winter wheat, rice, maize for grain, fodder crops, potatoes, vegetables and melons are the main crops considered in the model. Winter wheat is planted in October, while the other crops are planted in April and May—the period when the availability of irrigation water is uncertain. Secondary crops like rice or vegetables, which are planted on about 20% of the area after winter wheat harvesting in June, are excluded from the model as the water availability is less uncertain at this time of the year.

The size of the fields, their distance from the main water intake point, canal conveyance losses, available technology, input-output prices and state regulations are all considered as inputs for the model simulation of the model component A.

Water allocation is one of the main spatial parameters in the model. Irrigation water in the WUA is distributed to the agricultural fields through an irrigation network consisting of several canals. The canals have one main water inlet to the WUA, and water is delivered to the fields by on-farm and on-field level canals from this inlet point (Fig. 2).

The majority of farms in the study are between 5 and 10 ha in size (data for 2005). Except for the horticultural farms and households,[1] all other farmers were obliged to produce wheat and cotton, which cover about 70% of the total area.

The crop yields in the region from 1996 to 2005, input prices for 2005, and output prices from 2001 to 2006 were obtained from regional statistical departments (OblStat) and field experiments conducted in the region. Because of the emergence of newly privatized farms from former state farms, no reliable data at the farm level are available prior to 1996. Due to the limited number of observations, it is assumed that yields and prices are approximately normally distributed. Descriptive statistics show that negative yields and prices are negligible in the simulations as they are located more than three standard deviations below their respective means. Finally, data on yield potential based on soil fertility and bio-physical conditions were available from other studies in the region (Ramazanov and Yusupbekov, 2003) and used to derive the model parameters and assumptions.

In the scope of this study, other risk sources such as political (e.g. changing state policies), single farm related risks due to unreliable farm machinery (e.g. broken tractors), and other sources (e.g. lack of electricity during the irrigation period) are

[1] Households in the rural areas have 0.23 ha of land on their disposal which is mainly used for vegetable of fodder production for own use in the region.

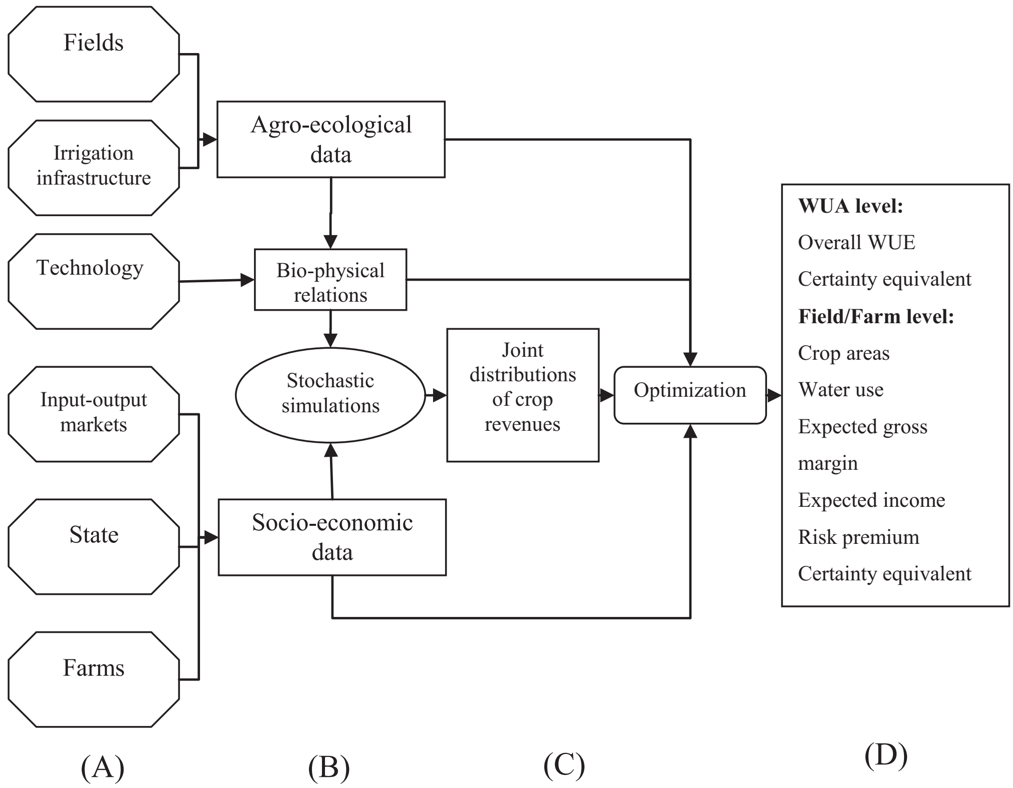


Fig. 1. Main model components.

not considered. However, through the modeling of crop allocation at the sub-system level, price, yield and water availability uncertainties, the dominant risk sources faced by all farmers in the irrigation system are captured.

2.2.2. The production function and optimization

Water is one of the most important and often the limiting growth factors for crop production in arid zones. Modeling the impact of water availability requires assessing the yield response to precipitation and/or irrigation water via a production function. Stochastic simulations are carried out in order to establish yield functions which depend on water application. The production function is estimated for each of these 300 fields depending on differences in maximum yield and soil properties. More detailed information about the production function elicitation is provided in the supplementary material.

Modeling crop and water allocation at the level of the WUA requires that the institutional arrangements are adequately captured, i.e. the model has to represent farm level decision making, which in Uzbekistan is still carried out under the guidance of government organizations (Veldwisch and Spoor, 2008), but must also embody regional constraints given by the availability of irrigation water. Furthermore, uncertainty and the decision makers' attitudes towards risk shall be considered in the model. To achieve these goals a constraint optimization model was formulated that maximizes the total CE according to Eq. (1).

The decision variables of the model are hectare allocation of crops and amount of irrigation water use for each crop. Crop and water allocation decisions are subject to several sets of constraints. Besides the non-negativity condition for crop allocation and water use, the resource availability at the field, farm and regional level, i.e. the WUA, are also considered in the model. At field level, land constraints assure that the total area allocated to the different crops on each of the fields does not exceed the size of the respective field as estimated from GIS data. Constraints used at the farm level assure the resource requirements of the activities are within the limits posed by the fixed resources, e.g. land and labor but also the state orders for cotton and winter wheat. An important constraint at the level of the WUA is the uncertain availability of irrigation water. The risk associated with water availability differs from price and yield risks as it enters the model through the constraints rather than through the objective function. We use common methodology to handle the risk associated with resource availability; this method is called the *chance constraint programming approach* and was originally introduced by Charnes and Coope (1959). Further information about the model objective function and constraints is provided in the supplementary materials.

a) Spatial distribution of rice in the WUA.

b) Spatial distribution of expected GM

Fig. 2. Model results for baseline scenario.

2.3. Model outputs

The primary model outputs such as water application, cropping areas, and the CE were determined during the optimization process, while irrigation efficiency was computed post optimization. Environmental problems are often caused by low irrigation efficiencies in the region (Ibrakhimov et al., 2007; Awan et al., 2011). Therefore, irrigation efficiency is considered as an indicator for the environmental friendliness of the crop and water allocation decisions. Irrigation efficiency (E_i) is calculated via dividing the total useful water uptake of the crops (V_{et}) by the total water inflow into the WUA (V_d), and expressed as a percentage (Stewart and Nielsen, 1990):

$$E_i = \frac{V_{et}}{V_d} 100 \quad (2)$$

Useful water uptake is equal to crop evapotranspiration. The V_{et} in Eq. (2) is estimated as the sum of crop evapotranspiration from each field in the WUA. Evapotranspiration for crops considered in the model is estimated according to Food and Agricultural Organization (FAO) guidelines (Allen et al., 1998). Water use efficiency captures how much water obtained by the farmers in the WUA was consumed by the crops; when it is equal to 100%, all water obtained by farmers is used to fulfill crop water demand and no water loss occurs. In reality, however, there are losses associated with transportation inefficiencies as well as losses due to inefficiencies of the employed irrigation techniques (Awan et al., 2011). Application and conveyance losses associated with different cropping activities in order to investigate the environmental impacts of specific activities are also analyzed. Conveyance losses mainly depend on the location within the irrigation system and the conveyance efficiency of the irrigation systems.

3. Results

The model output reports the CE, risk premium, expected income, crop mix, overall water use, and irrigation efficiency. Crop acreages, water use and expected gross margins are computed for each of the 300 fields in the WUA. Expected income, risk premium, and CE are computed at the farm level (99 farms); irrigation efficiency is estimated for the whole WUA. After calibration of the model to actual crop allocation in the WUA, validation of the model outputs with the observed situation was implemented before scenario simulations were conducted. Validation results are reported in the supplementary materials.

3.1. Certainty equivalent (CE)

The CE was calculated for each farm as expected income minus risk premium. The obtained aggregated (WUA total) CE is equal to 203.6 thousand USD,[2] while the expected income amounts to 226.4 thousand USD. The risk premium is equal to 22.7 thousand USD. Similar studies on risk analysis are not available for the region; therefore, a direct comparison of these results was not possible. However, the comparison of other model results with existing studies is given in the fallowing sections.

3.2. Crop selection and spatial distribution

The largest acreage among the 99 farms is allocated to cotton; this is captured by minimum level constraint included in the model to reflect the actual situation in the WUA (Bobojonov et al., 2013).

Analyzing the spatial distribution of crops is also critical to understand the importance of the farm location within the irrigation system. The model results show that the crops are almost equally distributed over all locations in the WUA. Only in the case of rice, a clear spatial dependence is observed. Due to the high water demands of the crop, farmers located nearer to the main water inlet point plant more rice than farmers located further away from the water source (cf. Fig. 2a).

3.3. Expected income

The expected GM from cotton is very low for the aggregated sample, with clear differences between farms. The maximum GM amounts to 252 USD ha^{-1} while the minimum reveals a net loss of 170 USD ha^{-1}. Our results are in line with previous estimations of Djanibekov et al. (2013), although calibration years in the studies differ. This could be due to fewer variations in cotton prices from year to year due to the state procurement mechanism.

The expected GM from growing winter wheat is similarly low at approximately 189.7 USD ha^{-1}, however, this crop exhibits the smallest standard deviation of all crops in the model. While rice, potatoes and vegetables have the highest expected income per hectare, water demand for these crops was also very high and thus income from these crops may vary according to the water availability in any given year. Therefore, due to risk aversion, the largest share of the area is allocated to fodder crops and maize for grain, despite the fact that these crops lead to a lower expected income compared to rice, potatoes and vegetables (Table 1).

Although it was hypothesized that the expected income would depend on the distance from the water source, no clear relationship between this distance and the expected income can be observed from the model results (Fig. 2b). Expected income in the first distance class (<5 km), is equal to 183.6 USD ha^{-1}, in the second distance class (5–10 km) it amounts to 206.7 USD ha^{-1}, and in the third distance class 145 USD ha^{-1}. These results are primarily determined by the existence

[2] All estimations were done in the local currency and converted to USD, approximate exchange rate was 1 USD = 1250 Uzbek Soums (UZS) in 2005.

Table 1
Main model results, aggregated at the WUA level.

	Cotton	Winter wheat	Rice	Maize	Fodder crops	Potato	Melons	Vegetables
Total planted area, ha	687.1	233.1	26.1	45.2	140.0	85.9	3.9	5.6
Expected GM, USD ha^{-1}	100.48	189.68	1276.4	852.48	942.4	1164.64	858.32	1033.84
Variance, USD	7120	3680	18,240	9040	20,400	30,960	45,600	15,760

of the state order mechanism in the region. Relaxation of this government policy may lead to quite different expected incomes for these distance classes (Djanibekov et al., 2013). Similarly, relaxation of the state order would also yield higher risk level than the current levels since crops with higher income, yield and price volatility may enter into the crop portfolio (Bobojonov et al., 2010).

The expected income in the second distance class is higher than the first; this is due primarily to variation in soil type and fertility. Consequently, there is a clear trend in earnings depending on the soil fertility of the farm. The average income of farms with low, average and good soil fertility,[3] is equal to 94.4 USD ha^{-1}, 227.2 USD ha^{-1}, 353.6 USD ha^{-1}, respectively. Farms with low soil fertility obtain only 27% of the income obtained by farms with highly fertile soils. The important role of soil quality was also derived from a deterministic bio-economic model for the region (Sommer et al., 2011).

Farms were grouped into three sizes to better visualize the model results: small-scale (<5 ha), medium-scale (5–15 ha) and large-scale (>15 ha). The expected income varies significantly among the three size categories: small-scale farms achieve returns equal to 261.6 USD ha^{-1}, this is compared to 181.2 USD ha^{-1} for medium-scale farms and and 184.8 USD ha^{-1} in large-scale operations. In the case of small farms in the study WUA, this may be explained by the allocation of good soils closer to the water source.

3.4. Water allocation

Total water use and losses among crops is highest for rice and lowest for melons and fodder crops (Fig. 3). More than 2500 mm (=25,000 m^2 ha^{-1}) water drains to the groundwater when planting rice, which demonstrates the heavy environmental burden associated with this crop and due to the deteriorated drainage systems in the region (Bucknall et al., 2003). A water fee is paid depending on crop type since volumetric charging is not yet practiced in the region. The fee is equal to 0.4 USD per thousand m^3 on average. A significantly higher shadow price for water was identified from the model results, revolving around 7 USD per thousand m^3. This result indicates that the price of water must be several times higher to create an economic incentive to save irrigation water.

3.5. Irrigation efficiency

Irrigation efficiency at the WUA level was estimated according to the Eq. (2) and amounts to 65.2%. This indicates that approximately 35% of the total water received was lost during conveyance and application. Irrigation efficiency is higher than presented previously by Conrad (2006) and amounts to 48% if the entire vegetation period is considered. The discrepancy between the present and previous findings is likely due to the difference in the spatial and temporal resolution used in the different studies. Once farms have satisfied the state order (i.e. in the second half of the planting period), the water demand for crops such as rice and vegetables in most areas increases (Veldwisch, 2008). Therefore, irrigation efficiency is lower if second half of the vegetation period is considered.

4. Simulating the impact of yield and water availability changes under climate change

After checking the validity of the model results under the baseline scenario, two scenarios are tested in order to demonstrate the application of the model for analyzing the impact of future climate change. Crop yields and variances of yields as well as availability of irrigation water are the main variables expected to change depending on the climate change scenario in the model simulations. These parameters are taken from the simulations of agronomic and hydrological studies previously conducted in the region.

The IPCC (2007) provides six emission scenarios (A1F1, A1T, A1b, A2, B1 and B2) according to expectations of changes in demographic development, socio-economic development and technological progress. Furthermore, there are 23 global circulation models (GCM) used in order to analyze the temperature and precipitation changes under each of these six emission scenarios in the future. Spectorman and Petrova (2008) analyzed the suitability of GCMs to capture agro-climatic particularities in Uzbekistan and found six of these models closely predict climate patterns in this region. Chub (2007) analyzed irrigation water availability and crop yields in the future using the average of these six GCMs under the

[3] For visualization purposes only; soil fertility is classified into three classes based on expert knowledge.

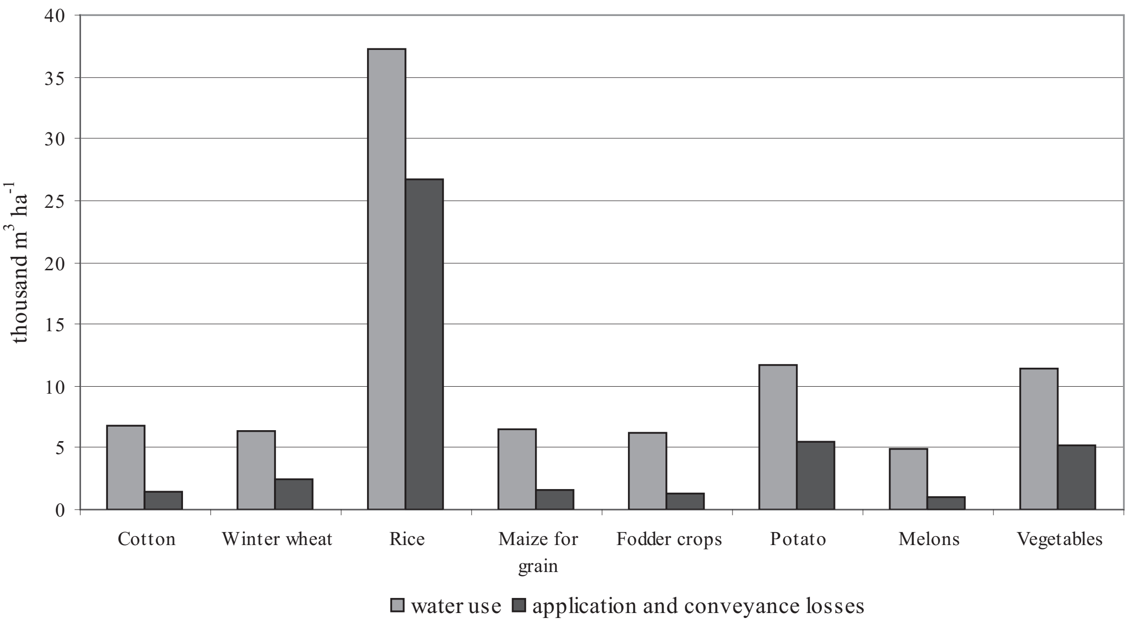


Fig. 3. Water application and beneficial water use of different crops.

respective emission scenarios. Changes in water availability and crop yields were reported only for A2 and B2 scenarios due to the similarity of the GCM projections under other emission scenarios.[4] Sommer et al. (2013) analyzed wheat yield changes under A1b and A2 scenarios; they used average temperature and precipitation changes from 7 GCM models. Sutton et al. (2013) also analyzed water availability and yield changes under optimistic, average and pessimistic climate change projections.[5]

Most of the available studies present changes in water availability and crops yields under climate change scenarios for three different time horizons (e.g. 2030, 2050 and 2080). However, only the year 2050 is considered since temperature and precipitation projection in 2030 is very similar to the observed situation and there is a high uncertainty about the development of agricultural technology and crop varieties in the distant future (e.g. 2080). The studies demonstrate very sudden changes in weather even in shorter time intervals (e.g. Wang et al., 2013) and therefore make the results of ex-ante impact assessments for the distant future less reliable. For these reasons, the year 2050 was selected for this study.

Available studies vary significantly both in differences in crop yields, as well as between climate change scenarios used. As expected, the results from these varying studies also show considerable variation. For example, wheat may benefit from increasing temperature and precipitation during winter periods (Sommer et al., 2013), while cotton may have reduced yields due to increased temperature and less precipitation during the summer months (Sutton et al., 2013). Table 2 shows the changes of model parameters in order to consider the impact of climate projections under two emission scenarios. The abovementioned bio-physical estimations often provide yield and water availability changes while using different emission scenarios and GCM models. Therefore, the climate change scenarios are conditionally divided into optimistic (favorable) and pessimistic (unfavorable) according to the impact of the projections on crop yield and water availability. Two of the most widely used scenarios of IPCC (2007)[6] are considered in the scope of this study where Scenario A2 analyzes changes in crop allocation and income volatility under pessimistic projections (e.g. A2 emission scenario), and Scenario B2 considers the impact of changes under optimistic (the B2 emission scenario) climate change projections.[7] The average annual temperature (average of all considered GCMs) is expected to increase by about 3.2° under an optimistic scenario (Scenario A2), and about 2.2° under Scenario B2. Changes in precipitation differ from month to month but are expected to increase by about 10–20% on average under both scenarios until 2050.

Cropping acreages of cotton and wheat remain unchanged due to limitations associated with the state order (as discussed previously). It can be seen from Table 3 that the overall CE declines by 25% under Scenario A2. This level of drop may not seem too drastic under such unfavorable conditions; this can be explained by the adaptation of farmers via changing

[4] A2 are considered as a representative for A1F1, A1T, A1b and B2 is found similar to B1.
[5] SRES and GCM names are not explicitly mentioned in both studies.
[6] Although new scenarios are available in in IPCC (2014), no yield estimations were available for the new scenarios during the model calibration period.
[7] Average of 6 GCMs are considered under both emission scenarios.

Table 2
Adjustment of model parameters under climate change scenarios. Source: Summarized from Chub (2007), Sommer et al. (2013), Sutton et al. (2013).

	Scenario A2 (pessimistic)	Scenario B2 (optimistic)
Description	More arid climate, less favorable weather conditions for crop production, higher risk	More humid climate, more favorable production environment for crops
Adjustment of model inputs parameters, in percentage to the baseline scenarios		
Expected change in mean yields	Wheat (+22) Cotton (−10) Other (−4)	Wheat (+23) Grain (+15) Other (+10)
Crop water demand change	+6	+6
Change in mean irrigation water availability	−15	−8

The results of the scenario simulations are presented at the WUA level (Table 3), and show that even a slight change in water distribution and yields would lead to considerable changes in crop allocation, income, and irrigation efficiency.

Table 3
Crop allocation, expected income and CE, Baseline vs. Scenario simulations.

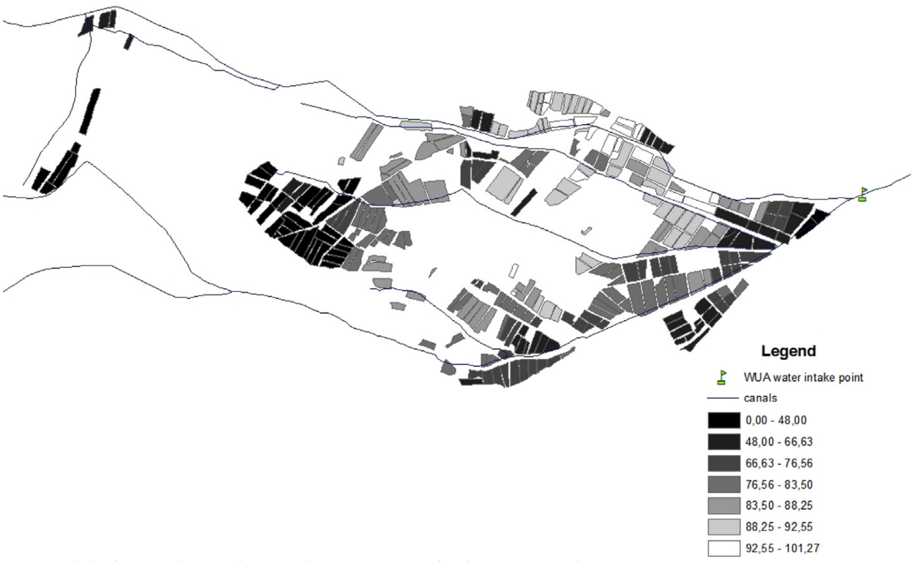
	Scenario No.	Baseline	Scenario A2 (pessimistic)	Scenario B2 (optimistic)
Crop allocation (ha)	Cotton	687.1	687.06	687.06
	Winter wheat	233.1	233.2	233.2
	Rice	26.1	–	–
	Maize	45.2	42.3	213.2
	Fodder	140	231.5	62.5
	Potato	85.9	1.1	21.9
	Melons	3.9	31.7	9.3
	Vegetables	5.6	–	–
Expected income (thousand USD)		226.4	176.8	316.5
CE (thousand USD)		203.6	153.8	297.9
Risk premium (thousand USD)		22.4	24.2	20.9
Overall WUE		65.2	75.8	73.9

cropping patters and irrigation water use intensity. In contrast, a 46% increase in the CE is obtained under more favorable Scenario B2. This shows that some level of increase may provide benefits due to increasing vegetation periods when enough irrigation water is available. However, too much increase, as considered in Scenario A2, may harm farmers due to a reduction in yields associated with heat and water stress. There are also very large changes in the spatial distribution of farm level utilities; these changes are observed under both scenarios (Fig. 4a and b). Where farmers are located furthers from the water source, income losses are greater under an unfavorable climate change scenario. Farmers in all locations will benefit under a more optimistic scenario, as is shown in Fig. 4b.

Cropping areas, expected incomes, and risk premiums all vary between the different scenarios, thereby making it difficult to draw general conclusions about the impact of climate change in the region. However, under both scenarios, rice disappears from the crop portfolio due to its high demand for water, while drought tolerant crops become more favorable. Similarly, irrigation efficiency increases in both scenarios due to allocation of limited amount of water to less water demanding crops such as maize and fodder crops instead of high water demanding crop rice under rising temperatures and a decline in irrigation water supply. Those crops have less infiltration losses to the groundwater. This could result in improved ecological conditions in the region due to a reduction in water loss during water transportation along the irrigation system.

Modifications of the existing state procurement policies for cotton and wheat would lead to changes in land and water use decisions, as would changes in technological advances (i.e. improved irrigation methods) in the region (cf. Bobojonov et al., 2010). The model results, therefore, under increased climate variability are valid only under existing agricultural policies and the presently available technology and crop varieties. There are also very large variations in the climate scenarios in the existing studies and more accurate information about future climate and bio-physical impact on irrigation water availability and yields is required.

Furthermore, analyses are mainly based on objective probabilities governing the decision-making, which, however, may not adequately reflect the decision makers' perceptions of climate change impacts. A more accurate assessment of the impacts of climate change on income may require studies assessing the personal beliefs of farmers themselves regarding changes in water availability and temperature. Those beliefs may have a high impact on attitudes and behavior of the decision makers (Hardaker and Lien, 2010). In order to incorporate these aspects in the model, further interviews need to be conducted with farmers and regional agricultural land and water management organizations (which have a significant influence on farm-level decision making) on their perceptions of yield and water availability fluctuations.



a) Spatial change in CE in A2, in percent to the base scenario

b) Spatial change in CE in B2 scenario, in percent to the base scenario

Fig. 4. Scenario simulation results.

5. Summary and conclusions

This study investigated the impact of climate change on farm income, land and water use in Western Uzbekistan. We used an integrated model that incorporated crop and water allocation information under conditions of data scarcity at the farm level. This approach allows the consideration of multiple risk sources in a spatial crop and water allocation decision framework. This was achieved by combining a mathematical programming model with Geographical Information System (GIS) data; this approach allows for better elaboration of spatial agronomic aspects in the economic analysis. We also considered market and weather risks that directly affect the farming outcome, as well as uncertainty associated with water availability.

Our results demonstrate potential changes to expected income, crop allocation and water use in the irrigation subsystem under different climate change scenarios. Farmers' utility could drastically decline by 25% when considering a 3.2° temperature increase and a 15% decline in irrigation water. This could cause serious challenges for the farms located at the end of the irrigation systems. Utility could increase by as much as 46% with a 2.2° temperature increase and only 8% decline in irrigation water, when analyzing more optimistic climate conditions. This may seem surprising since climate change is often associated with negative impact on farm revenues. However, extended vegetation periods in the case study region may offer increased yields for several crops when enough irrigation water is available. However, too much increase still harm causing water and heat stress as considered in the previous scenario. This shows that even one degree difference between the projected temperatures would create considerable differences in revenues and other aspects of the irrigation system. This is mainly explained by the nonlinear effect of changing temperature and precipitation patterns on agricultural crops and the availability of irrigation water resources in the region.

The direction of change in utilities varies between two different scenarios, thereby making it difficult to draw general conclusions about the impact of climate change on revenues in the region. However, environmental problems caused by shallow groundwater tables may improve in the region under both pessimistic and optimistic scenarios. Therefore, future studies analyzing the irrigation water use problems in Central Asia need mainly investigate irrigation management options with the aim to reduce income volatilities rather than pure environmental effects.

Acknowledgements

The German Ministry for Education and Research (BMBF) supported this study. The first author acknowledges the financial support from CGIAR Program on Climate Change, Agriculture and Food Security (CCAFS) during the finalization of the study. The authors wish to thank Dr. Rolf Sommer and Dr. Aden Aw-Hassan for their very useful comments on an earlier version of this manuscript. We are also very grateful to the editor and two anonymous reviewers for their comments and suggestions. All remaining errors are ours.

Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.crm.2016.05.004.

References

Abdullaev, I., Hassan, M., Jumaboev, K., 2007. Water saving and economic impacts of land leveling: the case study of cotton production in Tajikistan. Irrigation Drainage Syst. 21, 251–263.
Allen, R.G., Pereira, L.S., Raes, D., and Smith, M., 1998. Crop evapotranspiration: guidelines for computing crop requirements. Irrigation and Drainage Paper No. 56, FAO, Rome, Italy.
Arrow, K., 1971. Essays in the Theory of Risk-Bearing. Markham Publishing Co., Chicago.
Awan, U.K., Ibrakhimov, M., Tischbein, B., Kamalov, P., Martius, C., Lamers, J.P.A., 2011. Improving irrigation water operation in the lower reaches of the Amu Darya River – current status and suggestions. Irrigation Drainage 60 (5), 600–612.
Bekchanov, M., Lamers, J.P.A., Martius, C., 2010. Pros and cons of adopting water-wise approaches in the lower reaches of the Amu Darya: a socio-economic view. Water 2 (2), 200–216 (Special Issue: Challenges and developments on water resources management in Central Asia).
Bobojonov, I., Aw-Hassan, A., 2014. Impacts of climate change on farm income security in Central Asia: an integrated modeling approach. Agric. Ecosyst. Environ. 188, 245–255.
Bobojonov, I., Lamers, J.P.A., 2008. Analysis of Agricultural Markets in Khorezm, Uzbekistan. In: Wehrheim, P., Schoeller-Schletter, A., Martius, C. (Eds.), Land and Water use Reforms in Rural Uzbekistan. Socio-economic and Legal Analyses for the Region Khorezm. IAMO, Halle/Saale, pp. 63–86.
Bobojonov, I., Franz, J., Berg, E., Lamers, J.P.A., Martius, C., 2010. Improved policy making for sustainable farming: a case study on irrigated dryland agriculture in Western Uzbekistan. J. Sustainable Agric. 34 (7), 800–817.
Bobojonov, I., Lamers, J.P.A., Bekchanov, M., Djanibekov, N., Franz-Vasdeki, J., Ruzimov, J., Martius, C., 2013. Options and constraints for crop diversification: a case study in sustainable agriculture in Uzbekistan. Agroecol. Sustainable Food Syst. 37 (7), 788–811.
Briner, S., Elkin, C., Huber, R., Grêt-Regamey, A., 2012. Assessing the impacts of economic and climate changes on land-use in mountain regions: a spatial dynamic modeling approach. Agric. Ecosyst. Environ. 149, 50–63.
Bucknall, L., Klytchnikova, I., Lampietti, J., Lundell, M., Scatasta, M., Thurman, M., 2003. Irrigation in Central Asia. Social, Economic and Environment Considerations. World Bank.
Busch, G., 2006. Future European agricultural landscapes – what can we learn from existing quantitative land use scenario studies? Agric. Ecosyst. Environ. 114, 121–140.
Charnes, A., Coope, W.W., 1959. Chance constraint programming. Manage. Sci. 6 (1), 73–79.
Chen, W., Carsjens, G.J., Zhao, L., Li, H., 2015. A spatial optimization model for sustainable land use at regional level in china: a case study for Poyang lake region. Sustainability 2015 (7), 35–55.
Chub, V.E., 2007. Climate Change and its Impact on Hydro-Metrological Process, Agro-Climatic and Water Resources of the Republic of Uzbekistan. Voris-Nashryot publishing house, Tashkent, Uzbekistan.
Conrad, C., 2006. Fernerkundungsbasierte Modellierung und hydrologische Messungen zur Analyse und Bewertung der landwirtschaftlichen Wassernutzung in der Region Khorezm (Usbekistan) Ph.D. thesis. Universität Würzburg.
Djanibekov, N., van Assche, K., Bobojonov, I., Lamers, J.P.A., 2012. Farm restructuring and land consolidation in Uzbekistan: new farms with old barriers. Eur. Asia Stud. 64, 1101–1126.
Djanibekov, N., Sommer, R., Djanibekov, U., 2013. Evaluation of effects of cotton policy changes on land and water use in Uzbekistan: application of a bio-economic farm model at the level of a water users association. Agric. Syst. 118, 1–13.
Glantz, M., 2005. Water, climate, and development issues in the Amu Darya Basin. Mitigation Adapt. Strategies Global Change 10, 23–50.
Hardaker, J.B., Lien, G., 2005. Towards Some Principles of Good Practice for Decision Analysis in Agriculture. Norwegian Agricultural Economics Research Institute, Oslo, Working paper 2005-1.
Hardaker, J.B., Lien, G., 2010. Probabilities for decision analysis in agriculture and rural resource economics: the need for a paradigm change. Agric. Syst. 103 (6), 345–350.
Hardaker, J.B., Huirne, R.B.M., Anderson, J.R., Lien, G., 2004. Coping with Risk in Agriculture, second ed. CAB International, UK.
Ibrakhimov, M., Khamzina, A., Forkutsa, I., Paluasheva, G., Lamers, J.P.A., Tischbein, B., Vlek, P.L.G., Martius, C., 2007. Groundwater table and salinity: spatial and temporal distribution and influence on soil salinization in Khorezm region (Uzbekistan, Aral Sea Basin). Irrigation Drainage Syst. 21 (3–4), 219–236.
IPCC, 2007. Regional Climate Projections. In: Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

IPCC, 2014. Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part B: Regional Aspects. In: Barros, V.R., Field, C.B., Dokken, D.J., Mastrandrea, M.D., Mach, K.J., Bilir, T.E., Chatterjee, M., Ebi, K.L., Estrada, Y.O., Genova, R.C., Girma, B., Kissel, E.S., Levy, A.N., MacCracken, S., Mastrandrea, P.R., White, L.L. (Eds.), Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, p. 688.

Meiyappan, P., Dalton, M., O'Neill, B.C., Jain, A.K., 2014. Spatial modeling of agricultural land use change at global scale. Ecol. Model. 291, 152–174.

Meyer, J., 1987. Two-moment decision models and expected utility maximization. Am. Econ. Rev. 77, 421–430.

Micklin, P.P., 1988. Desiccation of the Aral Sea: a water management disaster in the Soviet Union. Science 241, 1170–1176.

Mirzabaev, A., 2013. Impact of weather variability and climate change on agricultural revenues in Central Asia. Q. J. Int. Agric. 3, 179–194.

Ramazanov, O., Yusupbekov, O., 2003. Tuproqshunoslik va dehqonchilik. Sharq nashiryoti, Tashkent.

Robison, L.J., Barry, P.J., 1987. The Competitive Firm's Response to Risk. Macmillan, New York.

Sommer, R., Djanibekov, N., Müller, M., Salayev, O., 2011. Economic-Ecological Optimization Model of Land and Resource Use at Farm-Aggregated Level. In: Martius, C., Rudenko, I., Lamers, J.P.A., Vlek, P.L.G. (Eds.), Cotton, Water, Salts and Soums: Economic and Ecological Restructuring in Khorezm, Uzbekistan. Springer, Dordrecht/Berlin/Heidelberg/New York.

Sommer, R., Glazirin, M., Yuldashev, T., Otarov, A., Ibraeva, M., Martynova, L., Bekenov, M., Kholov, B., Ibragimov, N., Kobilov, R., Karaev, S., Sultonov, M., Khasanova, F., Esanbekov, M., Mavlyanov, D., Isaev, S., Abdurahimov, S., Ikramov, R., Shezdyukova, L., de Pauw, E., 2013. Impact of climate change on wheat productivity in Central Asia. Agric. Ecosyst. Environ. 178, 78–99.

Spectorman, T.Y., Petrova, E.V., 2008. Climate SCENARIOS on the Territory of Uzbekistan. In: Climate Scenarios, Climate Change Impact Assessment. Bulletin, 6. NIGMI, Tashkent, pp. 14–21.

Stewart, B.A., Nielsen, D.R., 1990. Irrigation of Agricultural Crops. American Society of Agronomy, Inc., Madison, Wis., USA, p. 1218.

Sutton, W.R., Srivastava, J.P., Neumann, J.E., 2013. Looking Beyond the Horizon. In: How Climate Change Impacts and Adaptation Responses will Reshape Agriculture in Eastern Europe and Central Asia. The World Bank, Washington DC.

Van Meijl, H., van Rheenen, T., Tabeau, A., Eickhout, B., 2006. The impact of different policy environments on agricultural land use in Europe. Agric. Ecosyst. Environ. 114 (1), 21–38.

Veldwisch, G.J.A., 2008. Cotton, Rice & Water. The Transformation of Agrarian Relations, Irrigation Technology and Water Distribution in Khorezm, Uzbekistan Ph.D. Thesis. Bonn University, Center for Development Research.

Veldwisch, G.J., Spoor, M., 2008. Contesting rural resources: emerging 'Forms' of agrarian production in Uzbekistan. J. Peasant Stud. 35 (3), 424–451.

Wang, W., Bobojonov, I., Härdle, W.K., Odening, M., 2013. Testing for increasing weather risk. Stoch. Environ. Res. Risk Assess. 27, 1565–1574.