The economic value of climate information for water stress management in crop production: an Austrian case study

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Abstract:

Climate information appears to be underutilized in water stress management in agriculture. A systematic analysis of potential impacts related to multi-seasonal dry spells, effective adaptation measures, and the economic value of climate information may inform decision making and facilitate the uptake and use of climate information. Hence, we have developed an integrated modeling framework consisting of a statistical climate model, a crop rotation model, a bio-physical process model, a portfolio optimization model, the computation of the economic value of climate information, and a spatial hot spot analysis and applied it to the context of water stress management in crop production in Austria. Results from the integrated modeling framework show that the average economic value of climate information ranges between 13 and 99 €/ha for Austrian cropland, depending on the scenario of multi-seasonal dry spells and the farmers' risk aversion level. On average, the value of climate information is highest on flat and productive soils, for root and oil crops, under more extreme dry spells, and if farmers are highly risk averse. Quantifying the value of climate information may guide data provision efforts and highlight agricultural production regions, which would particularly benefit from such information to improve water stress management.

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Abstract

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1 Introduction

Dry spells and droughts can severely affect crop production systems across the world (Thornton et al., 2014). Water deficits can limit crop growth, development and yield through lower photosynthesis and may thus lead to global food insecurity and substantial agro-economic losses if adequate water stress management is absent. In Europe, recent dry spell and drought events affected large parts of the continent and had considerable impacts on crop production with substantial economic losses. The drought and heat wave in 2003, for instance, hit a third of the EU territory and caused an economic damage of almost € 9 billion (European Commission, 2007). The droughts in 2013 and 2015 also affected much of the European continent and severe negative impacts on late harvested crops were reported. In Austria, grain maize and soybean yields were about 30% below the long-term averages (Mitter et al., 2015b) and total damages in agriculture were estimated to about € 400 million in 2013, as recorded in the European Drought Impact Inventory (see Stahl et al., 2016).

Dry spells and droughts could increase in duration and severity in major agricultural production regions over the next decades as a result of climate change which may lead to even more severe impacts on agricultural production (IPCC, 2012). The likely increase in frequency and severity of dry spells and droughts has stimulated the development of information systems for water stress management. Currently, such systems are available to the public at different scales (e.g. global, continental, national) and with varying spatial and temporal resolutions (e.g. Deng et al., 2013; Horion et al., 2012). For Austria, a crop specific monitoring system has recently been launched and provides a 10-day forecast on plant available water, drought intensity, and drought and heat stress (Eitzinger, 2016). Substantial advances in near-term and seasonal weather and climate forecasts during the past decades have improved the decision-making basis for anticipatory water stress management and thus farmers' interest and acceptance (Zebiak et al., 2015). Additionally, efforts are devoted to projections of dry spells and droughts on inter-annual to decadal time scales (e.g. Ionita et al., 2017; Schubert et al., 2007; Strauss et al., 2013) which should inform adaptation processes. However, uncertainties in projections increase with greater lead times and should thus be considered in impact and adaptation assessments (Kusunose and Mahmood, 2016).

Quantifying the economic value of climate information (VoI) for water stress management is crucial in order to guide information collection and processing to reduce uncertainty in agricultural decision-making. Information on dry spells and droughts can be of economic value if its use improves adaptation, farm income, resource-use efficiency, environmental quality, or efficiency of public expenditure (Schubert et al., 2007; Vaughan and Dessai, 2014). In decision theory, the value of information is defined as the amount a rational actor would be willing to pay to gain this information (Raiffa and Schlaifer, 1961). Thus, it represents the difference between the expected outcome of crop management choices based on prior beliefs, i.e. the initial state of knowledge, and when additional information is obtained. The level of the VoI depends on the initial state of knowledge, the quality of the additional information, the expected outcome of available adaptation measures, and the individuals' risk attitude (Canessa et al., 2015).

Previous research on the VoI has focused on seasonal forecasts (Choi et al., 2015; Crean et al., 2015; Mushtaq et al., 2012; Solís and Letson, 2013) and much of this work was initiated as a response to the El Niño Southern Oscillation (ENSO)-phenomenon (Letson et al., 2009; Meza et al., 2003). Different methodological approaches have been used to study the economic value of climate information. For instance, Solís and Letson (2013) employ a multi-output/input stochastic distance frontier model to analyze the value of climate information for the agricultural sector in the Southern U.S. and find positive effects of seasonal forecasts on agricultural production. Crean et al. (2015) apply a state-contingent approach and reveal that the value of seasonal climate forecasts is relatively low for an agricultural production region in Australia mainly because of low forecast skill during sensitive phases of decision-making. Mushtaq et al. (2012) use a non-linear programming model to estimate the economic value of water allocation forecasts in southeastern Australia showing high benefits from forecasts under water-scarcity. Choi et al. (2015) establish an integrated modeling framework and show that seasonal climate forecasts may be beneficial to society by enhancing agricultural and resource use efficiency. Quiroga et al. (2011a, 2011b) use the certainty equivalence approach and show that both, the availability of drought information and risk attitude affect farmers' decisions and thus maize and rice production in Spain.

Despite interest in climate services has increased in the agricultural sector (Zebiak et al., 2015), information on multi-seasonal dry spells and droughts is not yet commonly used for adaptation decision-making. Climate and drought information appears to be underutilized, mainly because farmers doubt their relevance and accuracy (Kusunose and Mahmood, 2016). A systematic assessment of potential impacts related to multi-seasonal dry spells, effective water stress management for adaptation, and the VoI may inform decision-making and may thus facilitate the uptake and use of information on multi-seasonal dry spells and droughts.

Therefore, we aim at developing a spatially explicit, integrated modeling framework and apply it to the context of water stress management in Austrian crop production. Hence, we (i) investigate impacts of multi-seasonal dry spells on gross margins and irrigation water inputs of optimal crop production portfolios, (ii) quantify the VoI, and (iii) assess the effect of farmers' risk aversion on the VoI. The economic value of information has been discussed in the literature. Despite its potential, there are only few applications in agri-environmental and climate change adaptation decision-making (Canessa et al., 2015) and its level and variability have rarely been examined in an integrated modeling framework. The major advantages of our integrated, spatially explicit approach are to (i) consider a set of potential adaptation measures, (ii) analyze irrigation water input in addition to crop yields and gross margins, and (iii) explicitly address uncertainties in projections of multi-seasonal dry spells.

The article is structured as follows. In section 2, we describe the integrated modeling framework which is applied for Austrian cropland. In section 3, we present results on impacts from multi-seasonal dry spells and the computation of the VoI. We discuss obtained results with respect to the applied integrated modeling framework in section 4 and draw conclusions in section 5.

2 Integrated modeling framework

We combine a statistical climate model for Austria (Strauss et al., 2013), the crop rotation model CropRota (Schönhart et al., 2011), the bio-physical process model EPIC (Williams, 1995), crop gross margin calculations, and a portfolio optimization model (Mitter et al., 2015a) to calculate the VoI for three scenarios on multi-seasonal dry spells on Austrian cropland. The integrated modeling framework is illustrated in Figure 1 and explained in the following sub-sections.

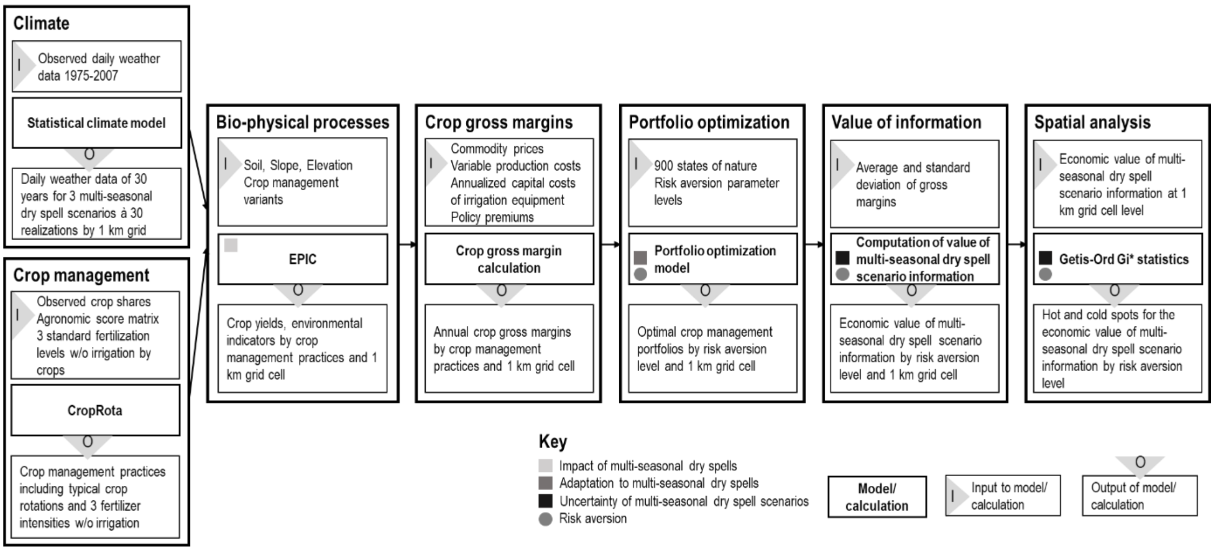

Figure 1. Integrated modeling framework
Note: fert = fertilization, mana = management

2.1 *Statistical climate model for Austria*

Three spatially explicit scenarios on multi-seasonal dry spells are provided by a statistical climate model for Austria considering a period of 30 years (Strauss et al., 2013). The scenarios have been specified based on a dry day index which is combined with block bootstrapping from historically observed daily weather data for the period 1975-2007 (Strauss et al., 2012). The dry day index represents the proportion of the Austrian territory, which is dry on a random day. It ranges between zero, if it is raining or snowing in the entire country, and one if it is completely dry. In the block bootstrapping procedure, each month is divided in four blocks of eight (seven) days. The dry day index is calculated for each historical eight (seven) day block which is the proportion of total area dry during those days. This calculation allows to identify 'dry' and 'wet' blocks. For a scenario period of 30 years, daily weather data are derived by drawing samples from the historical eight (seven) day blocks of a specific month. The block bootstrapping procedure is repeated 30 times in order to consider uncertainties. Hence, a distribution of daily weather data is available at 1 km grid resolution and a period of 30 years, i.e. 30 bootstrapped realizations for each scenario on multi-seasonal dry spells with a spatial-temporal resolution of 1 km and 1 day. The dataset for each realization includes daily weather data for maximum and minimum temperature, precipitation, solar radiation, relative humidity and wind speed for a period of 30 years and thus represents daily and inter-annual weather variabilities (Strauss et al., 2013).

The three scenarios on multi-seasonal dry spells differ in the projected proportion of dry days and its spatial extents. In the reference scenario (SDRY1), the distribution of the dry day index nearly resembles historically observed values. Daily weather data for a particular month are randomly sampled from the pool of all historical blocks for the respective month, i.e. each eight (seven) day block has an equal probability of being sampled. SDRY1 can be interpreted as a projection of historically reported dry spells and droughts. Historically experienced dry spells and droughts are typically argued to be a major information source for water stress management and agricultural adaptation decisions and can be interpreted as the initial state of farmers' knowledge. In the scenarios on moderate (SDRY2) and severe multi-seasonal dry spells (SDRY3), 'dry blocks' are chosen more frequently such that the situation where nearly the whole country is dry in an eight (seven) day block occurs more often than in SDRY1. Largest reductions in precipitation sums are modelled in SDRY3 with about 40% prevailing in the autumn and winter seasons (Strauss et al., 2013).

2.2 Crop rotation model CropRota

CropRota is applied to derive crop rotations typical to each Austrian municipality and their relative shares on cropland. Input data to CropRota comprise of historically observed crop mixes extracted from the IACS (Integrated Administration and Control System) database and an agronomic score matrix that values pre-crop/main-crop combinations of 22 crops according to their agronomic suitability. CropRota maximizes the total value of agronomic suitability over all crop rotations at municipality level in order to generate typical crop rotations and relative shares (Schönhart et al., 2011). Up to 22 different crop rotations are derived per municipality. They consist of one (monoculture) to six crops in a sequence and are proportionally assigned to the observed cropland shares at 1 km grid level such that spatially explicit crop rotations are available for Austrian cropland. Considering crop rotations acknowledges that crops and crop rotations differ in their effects on soil hydraulic properties and thus water movement. .

2.3 Bio-physical process model EPIC

The Environmental Policy Integrated Climate model (EPIC) is applied to simulate annual dry matter crop yields and hydrology at 1 km grid resolution for different crop management practices and the 30 bootstrapped realizations for each of the three scenarios SDRY1-3 covering a period of 30 years. EPIC builds on theoretically established and empirically verified knowledge on bio-physical processes in the soil-crop-atmosphere system and has been validated extensively, both at global and regional scales (see e.g. Eitzinger et al., 2013). Major bio-physical processes simulated in EPIC at daily time steps are, among others, crop growth, evapotranspiration, runoff, percolation, mineralization and nitrification as well as water and wind erosion (Williams, 1995). EPIC simulates crop biomass accumulation by converting intercepted photo-synthetically active radiation through a synthetic coefficient known as radiation use efficiency. Crop yields are calculated using crop-specific harvest indices. They define crop yields as a fraction of above-ground biomass and are adjusted as water stress occurs. Other crop growth constraints considered in EPIC are temperature, nutrient, aluminum toxicity and aeration stresses. Major model outputs include dry matter crop yields, evapotranspiration, surface and sub-surface runoff, percolation, and the number of stress days.

Typical model inputs are data on soil properties, topography and geometry, daily weather parameters, and crop characteristics and management (Williams, 1995). Soil data comprise information on soil texture, pH, organic carbon, coarse fragment, calcium carbonate contents, and bulk density with up to 7 soil layers, which have been extracted from the Austrian Soil Map. Elevation and slope data have been derived from the global shuttle radar topography mission (SRTM) digital elevation model. The statistical climate model for Austria as described in 2.1 provides daily weather data for six parameters, i.e. maximum and minimum temperature, precipitation, solar radiation, relative humidity and wind speed, for each of the 30 bootstrapped realizations of the three scenarios SDRY1-3. Potential evapotranspiration is estimated with the Penman-Monteith method (Monteith, 1965; Stockle et al., 1992).

Crop management practices for adaptation include changes in timing of cultivation (i.e. sowing, fertilizer application, and harvesting dates), crop rotations (section 2.2), and three (two) fertilizer application levels under rain-fed (irrigated) conditions. Timing of cultivation is automatically adjusted in EPIC to account for inter-annual variabilities and changes in seasonal growing conditions. It is specified by using fractions of total heat units a crop requires to reach maturity. It differs between the three scenarios on multi-seasonal dry spells because temperature increases are higher in more severe scenarios. Crop rotations are modelled over a period of 30 years and are combined with three fertilizer application levels under rain-fed conditions, i.e. “high”, “moderate”, and “low”, and two fertilizer application levels (i.e. “high” and “moderate”) with sprinkler irrigation, i.e. “airr” and “rirr”. Fertilizer application levels are crop specific and kept constant among the scenarios. They refer to legal standards and policy guidelines. Sprinkler irrigation is chosen because it is the technology preferred by Austrian farmers. Application of irrigation water is automatically triggered in EPIC such that 90% of the crop growth period is water-stress free until a total limit of 500 mm per annum is reached. A single irrigation activity is limited between 20 and 50 mm. In Austria, irrigation water is mostly withdrawn form groundwater, whereas surface water from lakes, rivers or reservoirs is of minor relevance. We assume sufficient irrigation water availability across Austria because data on groundwater levels and flows and surface water regime are not available for this analysis.

2.4 Crop gross margin calculation

Annual crop gross margins per hectare are calculated by crop management practice and bootstrapped realization of the three scenarios on multi-seasonal dry spells. Crop gross margins are defined as revenues minus variable production costs. Revenues are calculated by multiplying annual dry matter crop yields simulated with EPIC by the respective commodity prices from Statistics Austria averaged over a period of three years (2010-2012) and by adding agricultural policy premiums. The latter comprise of a uniform decoupled payment of 290 €/ha and agri-environmental payments for moderate (50 €/ha) and low fertilizer application levels (115 €/ha; BMLFUW, 2009). Variable production costs for standard crop management in Austria are based on reported levels from the past (e.g. AWI, 2016). They apply for rain-fed and irrigated conditions and include costs for seeds, fertilizers, pesticides, irrigation water, fuel, electricity, repair, insurance and labor. Fertilizer and irrigation water costs are derived by multiplying the input levels per hectare simulated with EPIC by constant nitrogen (1.1 €/kg), phosphorus (1.6 €/kg) and irrigation water pumping costs including annualized capital, labor and electricity costs (Heumesser et al., 2012). It is noted that groundwater and surface water are currently free of charge for agricultural use in Austria if officially imposed limits are not exceeded. Labor hours are valued with 10 €/ha. Commodity prices, variable production costs, annualized capital costs for sprinkler irrigation equipment and policy payments are kept constant in the 30 years period, because it allows us to separate effects of multi-seasonal dry spells from potential future price dynamics and agricultural policy developments.

2.5 Portfolio optimization model

A non-linear mean-standard deviation model (similar to mean-variance model; Markowitz, 1952, 1987) is applied to identify optimal crop production portfolios for adaptation, i.e. combinations of crop management practices that reduce adverse or take advantage of emerging opportunities due to changes in multi-seasonal dry spell conditions. The portfolio optimization model maximizes the weighted sum of expected crop gross margins per cropland grid cell minus the product of the risk aversion parameter θ and the standard deviation of crop gross margins (Freund, 1956; Mitter et al., 2015a). The risk aversion parameter θ represents different levels of farmers’ risk aversion in the context of crop management choices. We increase its level in four steps from $\theta = 0.0 \; to$ 2.5, whereby 0.0 may be interpreted that a farmer is risk neutral, 1.0 may be interpreted as low, 2.0 as moderate, and 2.5 as high risk aversion. The mean-standard deviation model is given in Equations 1-2. It derives crop production portfolios for the three scenarios SDRY1-3 independently for each 1 km cropland grid cell i and risk aversion parameter level θ. By applying a mean-standard deviation model, we implicitly assume constant absolute risk aversion as well as a normal distribution of crop gross margins in order to be consistent with the expected utility framework (Chavas, 2004).

$$\max_{x} Z_i = \sum_{m,s} x_{i,m} E(\pi_{i,m,s}) - \theta * [\frac{1}{S} \sum_{m,s} (\pi_{i,m,s} - E(\pi_{i,m,s}))^2]^{\frac{1}{2}} \qquad \forall i \qquad (1)$$

$$s.t. \sum_{m} (x_{i,m}) = b_i \qquad \forall i \qquad (2)$$

Z is the objective function value which is to be maximized, x represents the hectare shares that each crop management practice m (M=5) realizes in the portfolio of each cropland grid cell i (I=40,244) i. π are average annual crop gross margins, stratified by i, m, *and* s. The index s (S=900) denotes states of nature consisting of the 30 bootstrapped realizations with periods of 30 years for each scenario SDRY1-3. E is the expected value of the average annual crop gross margins and θ refers to the risk aversion parameter. The equality constraint controls that the hectare shares of crop management practices in the portfolio have to sum up to the cropland endowment b in cropland grid cell i.

2.6 Computing the economic value of climate information for water stress management (VoI)

We define the VoI as the net-benefit of adapting crop production portfolios to multi-seasonal dry spells conditions. Based on the results from the portfolio optimization model, it is quantified in two steps. First, we derive optimal crop production portfolios in SDRY1, SDRY2 and SDRY3. Second, differences in expected values of gross margins and corresponding standard deviations are calculated between optimal crop production portfolios realized in SDRY2(3) and optimal crop production portfolios realized in SDRY1 evaluated in SDRY2(3), respectively. The underlying assumption is that optimal crop management choices in SDRY2(3) would be based on the reference scenario SDRY1 if additional information on multi-seasonal dry spells was not available. The average annual *VoI* (in €/ha) is finally computed as described in Equation 3 and is always positive or zero.

$$VoI_i^{SDRY2(3)} = Z_i \left| {}^{SDRY2(3)}_{\sum_m x_{i,m}^{*[SDRY2(3)]}} \right. - Z_i \left| {}^{SDRY2(3)}_{\sum_m x_{i,m}^{*[SDRY1]}} \right. \qquad \forall i \qquad (3)$$

2.7 Spatial analysis

Spatial variability of the VoI, i.e. its distribution across agricultural production regions, indicates where information on multi-seasonal dry spells would be most relevant to inform adaptation. We use the Getis-Ord Gi* statistics (Getis and Ord, 1992; Ord and Getis, 1995) to identify significant clusters of high and low VoI by multi-seasonal dry spell scenario and risk aversion parameter level. Regions of particular interest, i.e. hot spots, are determined based on the calculations of the VoI at cropland grid cell level. We choose a fixed Euclidean distance band of 15 km for modeling spatial relationships. The fixed distance band is chosen such that each cropland grid cell has at least one neighbor and to show medium-scale patterns where high / low VoI concentrate. A False Discovery Rate (FDR) Correction is applied in order to account for multiple testing and spatial dependency (Benjamini and Hochberg, 1995; Caldas de Castro and Singer, 2006). Hot and cold spots of the VoI are identified at a significance level of 0.01.

3 Results

3.1 Gross margins and irrigation water inputs for efficient crop production portfolios

Results from the portfolio optimization model show how gross margins and irrigation water inputs are affected in the reference scenario (SDRY1), and the scenarios on moderate (SDRY2) and severe (SDRY3) multi-seasonal dry spells if scenario information and risk aversion parameter levels are considered in optimal crop management choices for adaptation.

At national level, we find that area-weighted average annual gross margins are between 422 €/ha (SDRY3 under high risk aversion) and 515 €/ha (SDRY1 under risk neutrality) and decrease under more extreme multi-seasonal dry spell conditions. Compared to SDRY1, average gross margins are about 6% lower in SDRY2 and about 12% lower in SDRY3, which reveals potential impacts related to multi-seasonal dry spells even though information is used for adapting crop production portfolios (see Table 1). However, model results show high spatial disparities. Model results show that gross margins increase in SDRY2 (SDRY3) on about 42% (30%) of the total cropland, compared to SDRY1. Highest increases are found in the western parts of the country with alpine climate where water is not limiting during the growing season. Highest decreases appear in the semi-arid eastern parts of Austria due to irrigation costs. Compared to risk neutrality, low (moderate/high) risk aversion decrease average gross margins between 1.4 and 2.1% (5.2 and 6.1% / 6.6 and 7.4%), depending on the scenario on multi-seasonal dry spells.

Table 1. Average annual gross margins in €/ha by risk aversion parameter levels (RAP, θ) and three scenarios on multi-seasonal dry spells (SDRY1-3) for Austrian cropland.

Scenario on multi-seasonal dry spells	RAP *(θ)* 0.0	1.0	2.0	2.5
SDRY1	515	507	489	480
SDRY2	486	477	460	453
SDRY3	452	443	429	422

Model results on impacts of multi-seasonal dry spell scenarios on irrigation water inputs show that average annual irrigation water input for all crops increases substantially in the moderate (SDRY2) and severe (SDRY3) multi-seasonal dry spell scenarios. Compared to the reference scenario SDRY1, irrigation water input is between 2.1 and 3.1 (3.4 and 6.1) times higher in SDRY2 (SDRY3). Model results also reveal that average annual irrigation water input rises with risk aversion. Compared to risk neutrality, irrigation water input is between 1.1 and 2.0 times higher with high risk aversion, whereby increases are highest under SDRY1 (see Table 2).

Table 2. Average annual irrigation water input for all crops in mm by risk aversion parameter levels (RAP, θ) and three scenarios on multi-seasonal dry spells (SDRY1-3) for Austrian cropland.

	Average annual irrigation water input in mm			
RAP *(θ)* Scenario on multi-seasonal dry spells	0.0 risk neutral	1.0 low risk aversion	2.0 mod risk aversion	2.5 high risk aversion
SDRY1	13	19	24	26
SDRY2	39	50	54	54
SDRY3	76	85	86	86

3.2 Economic value of climate information for water stress management (VoI)

3.2.1 National cropland level

Information on multi-seasonal dry spells needs to be available for efficient crop management adaptation. If information is lacking, we assume that the choice of crop production portfolios would be based on the reference scenario (SDRY1) even under more extreme multi-seasonal dry spell conditions (SDRY2-3). For Austria, we find that the average VoI is higher if multi-seasonal dry spells are expected to increase in severity and if farmers are more risk averse. Depending on the risk aversion parameter level θ, the VoI is between 13 and 33 €/ha in scenario SDRY2, and between 57 and 99 €/ha in scenario SDRY3 (Table 3).

Table 3. Average annual VoI in €/ha by risk aversion parameter levels (RAP, θ) and two scenarios on multi-seasonal dry spells (SDRY2-3) for Austrian cropland.

Scenario on multi-seasonal dry spells	RAP *(θ)*			
	0.0	1.0	2.0	2.5
SDRY2	13	23	30	33
SDRY3	57	78	93	99

Average annual gross margins are up to 3% (SDRY2) and between 5 and 14% (SDRY3) higher if information on multi-seasonal dry spells is accessed for crop management choices, compared to the situation where this information is not available. Irrigation water inputs are also affected if additional information on multi-seasonal dry spells is used for crop management choices. It is between 1.6 and 2.4 (2.1 and 4.1) times higher in SDRY2 (SDRY3) if crop management choices are based on multi-seasonal dry spell scenario information. The model results show that this is mainly because crop management choices change from rain-fed to irrigation in particularly dry regions if more severe dry spells are expected.

3.2.2 Regional cropland level

Spatial disparities in the annual VoI reflect where information on multi-seasonal dry spells is more or less beneficial to inform adaptation. Results from the spatial analysis reveal that the VoI follows climate, topographic and soil gradients (Figure 2). Hot spots with values above 150 €/ha are concentrated in the semi-arid eastern parts of Austria which are characterized by flat and fertile soils. Such high values are also found in some inner alpine valleys, particularly under risk neutrality (θ = 0.0). Cold spots with values of 50 €/ha or less are found in the hilly and mountainous western parts of the country with alpine climate, regardless of the risk aversion parameter level. However, the values show a rising trend in western Austria under more severe multi-seasonal dry spell conditions indicating that scenario information gains in importance across the country. If the VoI equals zero, crop management choices are deemed to be robust to a range of plausible scenarios on multi-seasonal dry spells. A VoI of 0 €/ha is found in the hilly and mountainous western parts of Austria, mainly under risk neutrality. In these regions, crop production portfolios do not change with additional information on multi-seasonal dry spells.

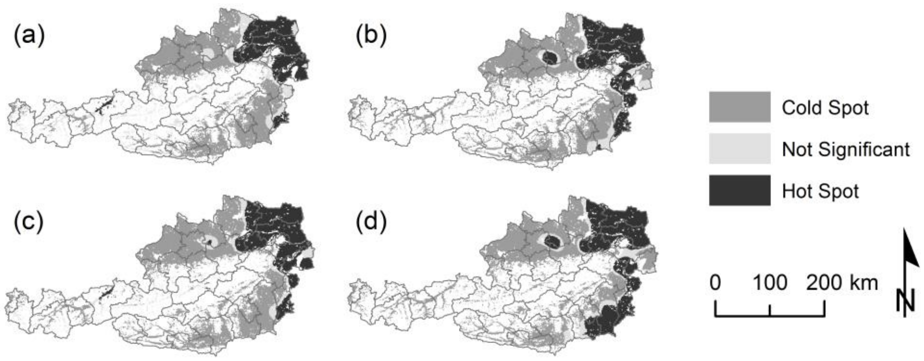

Figure 2. Hot and cold cropland spots of the average annual VoI for (a) SDRY2, θ = 0.0 (risk neutral), (b) SDRY2, θ = 2.5 (high risk aversion), (c) SDRY3, θ = 0.0 (risk neutral), and (d) SDRY3, θ = 2.5 (high risk aversion).

Average annual VoI has been calculated by soil type, altitude, slope, and crop group in order to show how site conditions and crops affect its level. Brown earth (i.e. cambisol and luvisol), black soil (i.e. chernozem and phaeozem), and pseudogley (i.e. stagnosol) are the three major soil types and represent about 75% of Austrian cropland. Average annual VoI is highest on black soils which are typically rich in humus and offer good growing conditions for crops, i.e. between 29 and 145 €/ha, depending on the multi-seasonal dry spell scenario and the risk aversion parameter level. The productivity of pseudogley and brown earth for crop production is generally lower than for black soils. Average VoI for pseudogley is similar to the national averages (between 6 and 107 €/ha). Those for brown earth are between 5 and 64 €/ha in SDRY3.

With respect to topography, we find that average annual VoI is highest in flat regions and at low altitudes where cropland is preferably located. Almost three quarters of the Austrian cropland is found on plains with slopes below 5%. Average VoI for plains are above the national averages and range between 17 and 116 €/ha, depending on the scenario on multi-seasonal dry spells and the risk aversion parameter level. The VoI decreases with increasing steepness. For instance, average values for slopes between 5 and < 10% are between 32 and 57% of those for plains. However, VoI exceeds 50 €/ha on slopes between 10 and < 15% under severe multi-seasonal dry spells (SDRY3) and high risk aversion. In lowland (altitude below 300 m), where about 46% of the cropland is located, average annual VoI is between 26 and 163 €/ha, depending on the scenario on multi-seasonal dry spells and the risk aversion parameter level. The average values for cropland decrease with higher altitudes. For altitudes between 300 and < 600 m (600 and < 1,100 m), they are between 11 and 33% (4 and 7%) of the values for lowland.

We define dominant crop groups if crops in the rotation belonging to a specific crop group are grown in at least 16 (out of 30) years on a particular cropland grid cell. Average annual VoI is highest for root and oil crops, which indicates that scenario information on multi-seasonal dry spells is of particular importance if the share of root and oil crops in the rotation should be increased. Their major production regions are in eastern Austria where a regional hot spot of the VoI has been identified (Figure 2). Average VoI for root and oil crops is clearly above the national average, i.e. between 16 and 301 €/ha, depending on the scenario on multi-seasonal dry spells and the risk aversion parameter level. Average values for maize are around the national averages and above those for cereals, protein crops and perennial grassland which reflects that maize is more sensitive to water reductions. Lowest values (between 2 and 17 €/ha) are found for perennial grass (Table 4).

Table 4. Average annual VoI in €/ha by risk aversion parameter levels (RAP, θ) and two scenarios on multi-seasonal dry spells (SDRY2-3).

Scenario on multi-seasonal dry spells	Crop group	RAP *(θ)*			
		0.0	1.0	2.0	2.5
SDRY2	Cereal	9	20	27	29
	Maize	16	22	29	33
	Perennial grass	3	4	4	4
	Oil crops	16	43	60	58
	Protein crops	4	7	21	29
	Root crops	49	84	99	115
SDRY3	Cereal	45	72	85	88
	Maize	63	84	116	133
	Perennial grass	13	14	16	17
	Oil crops	75	150	184	180
	Protein crops	27	55	89	107
	Root crops	205	257	275	301

Note: Dominant crop group in crop rotation in the respective cropland grid cell.

4 Discussion

4.1 Discussion of the economic value of climate information for water stress management (VoI)

Our analysis shows that the average VoI is highest on flat and productive soils, for root and oil crops, under more extreme multi-seasonal dry spell conditions, and if farmers are highly risk averse. Average annual values for Austrian cropland range between 13 and 99 €/ha, depending on the scenario on multi-seasonal dry spells and the risk aversion parameter level. The level seems to be reasonable, compared to other studies on the economic value of information using different methodological approaches. For instance, Meza and Wilks (2003) estimate the economic value of perfect forecast for seasonal sea surface temperature to range between 13(11) and 243 $/ha(202 €/ha), depending on cultivated crops and soil conditions. Mushtaq et al. (2012) find that the value of improved seasonal water allocation forecasts is between 1 and 6 €/ha for different levels of risk aversion. At farm level, Cabrera et al. (2007) show that the average value of ENSO-based climate information is between 3(2.5) and 25 $/ha(21 €/ha) for different levels of risk aversion.

The hot and cold cropland spots of the VoI are clearly influenced by a combination of soil, topographic and climate conditions affecting crop and management choices. Hot spots, for instance, are concentrated in the semi-arid eastern parts of Austria where fertile, black soils are dominating and root crops, which typically materialize high gross margins, are important in the crop rotation. Similar to our findings on the VoI, which is higher in semi-arid regions and under more extreme multi-seasonal dry spell conditions, Mushtaq et al. (2012) show higher benefits from additional information under water scarcity. By contrast, Choi et al. (2015) reveal that the value of climate information is lower under extreme drought conditions, compared to favorable climate conditions. This is mainly because of production and welfare transfers outside the country, which have not been considered in our analysis. Choi et al. (2015) also show that irrigation water input decreases if climate information is available and farmers adjust crop mixes. However, our analysis shows a significant increase in irrigation water input if drought information is available which results from changes from rain-fed (under reference climate conditions) to irrigated agriculture (under moderate and extreme multi-seasonal dry spell conditions) in large parts of the country.

Root and oil crops show highest average values of climate information in our analysis, followed by maize, cereals, protein crops, and perennial grassland. This finding is in line with previous studies indicating that the value of perfect information is on average lower for cereals such as wheat and oat than for root crops such as potato and sugar beet (Meza et al., 2003; Meza and Wilks, 2003). Maize typically experiences higher yield reductions than cereals if water is limiting (Daryanto et al., 2016) which may explain its higher average VoI. Exceptions are, however, found for specific soil characteristics (Meza et al., 2003) indicating the importance to consider spatial heterogeneities in such analyses.

Risk aversion leads to a higher average VoI in our analysis, which is also confirmed by other studies. For instance, Letson et al. (2009) and Cabrera et al. (2007) find that risk aversion increases the value of information on the ENSO-phenomenon and show that its effect is higher for land owners than for tenants. Similarly, Quiroga et al. (2011a) show that accurate information about drought probability is of higher value for risk averse actors. However, in many cases the effect of scenarios on multi-seasonal dry spells is determinant of the VoI-level.

4.2 Discussion of the integrated modeling framework

We present a spatially explicit integrated modeling framework for Austrian cropland that integrates bio-physical and socio-economic data and models to calculate the VoI for different scenarios on multi-seasonal dry spells and risk aversion parameter levels. A broad range of aspects is considered in our analysis including scenarios on multi-seasonal dry spells, soil and topographic conditions, adaptation measures to dry spells, and farmers' risk aversion levels. However, our approach has limitations because of underlying assumptions and aspects that have not been incorporated yet. An aspect yet to be explored are potential irrigation water constraints in the future, which could necessitate the reversion of irrigated to rain-fed management. Currently, we consider sprinkler irrigation as the preferred irrigation technology in Austria and assume that irrigation water supply is not limited. More efficient technologies could help to save water, decrease resource depletion and reduce detrimental impacts of multi-seasonal dry spells on agricultural productivity (Perea et al., 2017). However, their nationwide implementation may require long lead times because of high investment costs (Heumesser et al., 2012). Comparing irrigation water demand to available resources from rivers, lakes and groundwater aquifers would enable us to identify regions most vulnerable to water scarcity. In these regions we would expect a higher average VoI, similar to the findings of Mushtaq et al. (2012).

We assume that information on multi-seasonal dry spells is available, disseminated and fully taken up by farmers to inform their adaptation decisions. The magnitude of the calculated VoI can thus be interpreted as an upper bound. However, previous research suggests that climate and drought information is underutilized (Kusunose and Mahmood, 2016). Furthermore, the use of climate services in agriculture has been shown to depend on their saliency, robustness and reliability and may decline with higher uncertainties and low adaptive capacity (Hansen et al., 2011). The crucial role of knowledge brokers working as intermediaries between producers and users of climate and drought information has been emphasized in order to increase information uptake and knowledge transfer in agriculture (Kirchhoff et al., 2013; Zebiak et al., 2015). Our systematic analysis of potential impacts related to multi-seasonal dry spells, effective adaptation measures and the VoI may facilitate information brokering and uptake to realize the evident adaptation potential.

In any integrated modelling activity, uncertainty regarding data and models which accumulate steadily over each step of the modeling process has to be kept in mind (Walker et al., 2003; Wilby and Dessai, 2010). This may include uncertainties in model quantities such as input data and parameters (i.e. technical uncertainties), model form (i.e. methodological uncertainties), and model completeness (i.e. epistemological uncertainties). For instance, model inter-comparison studies at global scale have revealed considerable uncertainties as to how effects of temperature and precipitation extremes are represented in bio-physical process models (Rosenzweig et al., 2014). For EPIC, previous studies showed that it can satisfactorily reproduce crop yield responses to heat waves, dry spells and droughts (Easterling et al., 1996; van der Velde et al., 2012). Following the suggestion by Gabbert et al. (2009) we do not aim for an exhaustive uncertainty analysis but rather focus on the investigation of multi-seasonal dry spell scenario uncertainty on the VoI. However, additional research is needed in order to fully understand and trace uncertainties in integrated modeling frameworks.

5 Summary and conclusions

We have analyzed how scenarios on multi-seasonal dry spells affect gross margins and irrigation water input in Austria. Model results show that total gross margins are between 6 and 13% lower under more extreme scenarios on multi-seasonal dry spells, compared to the reference scenario. Reductions in total gross margins are due to higher costs, e.g. for irrigation water, and lower agricultural policy premiums, e.g. due to intensification. A switch from rain-fed to irrigated agriculture in major production regions under more extreme scenarios on multi-seasonal dry spells results in a 3 to 6fold increase in irrigation water inputs in SDRY2-3, compared to SDRY1.

Information on multi-seasonal dry spells is required to facilitate agricultural adaptation and water stress management. The economic value of information represents the net-benefit of adapting crop production portfolios to multi-seasonal dry spell conditions and reflects the opportunity costs of not having the information available for decision-making. Quantifying the VoI may help to direct climate data provision, guide regional water governance and drought policy efforts, and to highlight agricultural production regions which would particularly benefit from such information. Model results reveal that the average VoI increases under more extreme multi-seasonal dry spell conditions and with farmers' risk aversion. These results suggest that information on multi-seasonal dry spells gains in importance with the projected increase in frequency and severity of dry spells and droughts in the alpine region in the 21st century. The VoI is even higher, if farmers' risk aversion rises due to uncertainty in dry spell and drought conditions. Such an increase in risk aversion seems reasonable because of empirically based evidence for both, an increase in risk aversion with climate-induced risks as well as negative correlations between risk aversion and mean annual precipitation sums (see Alpizar et al., 2011; Di Falco, 2014). The VoI is also related to site conditions and crops. Our spatially explicit results suggest that the highly productive flat regions in the semi-arid eastern parts of Austria where cropland is the dominating land cover would benefit most of additional information on multi-seasonal dry spells. Crop-specific information on multi-seasonal dry spells would be most desirable for root and oil crops indicating that the relevance of information increases if root and oil crops should gain in importance in the crop rotation.

The spatially explicit, integrated modeling framework allows to systematically analyze impacts of multi-seasonal dry spells on gross margins and irrigation water input even if adaptation is considered, and to quantify the VoI while explicitly addressing uncertainty. The results may improve the provision, uptake and use of information on multi-seasonal dry spells for adaptation decision-making, facilitate the development of water management plans, and guide the design of structured monitoring and evaluation processes for adaptation to multi-seasonal dry spells and droughts. We suggest that scenario uncertainties are considered as a standard feature in integrated assessments, which could be extended by empirical research on the uptake and use of imperfect information on multi-seasonal dry spells by land and water users.

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