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Research article

The economic value of stochastic climate information for agricultural adaptation in a semi-arid region in Austria

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ABSTRACT

Identifying efficient adaptation measures in land and water use requires integrated approaches and a spatially and temporally explicit representation of water demand and supply. Stochastic climate information may further improve adaptation assessments to reduce the risk of misinterpretation of climate signals. We aim at developing an integrated modeling framework (IMF) that meets these requirements for assessing impacts of three stochastic climate scenarios (DRY, SIMILAR, WET), and regional irrigation water restrictions on land and water use. Furthermore, impacts on regional net benefits and the economic value of stochastic climate information (VOI) are assessed. The VOI is defined as the difference between regional net benefits with and without efficient adaptation of land and water use to a specific climate scenario. The IMF has been applied to the semi-arid Seewinkel region in Austria. Considering efficient adaptation, regional net benefits amount to 8 M€ and irrigation water use to 8.4 Mm^3 in a DRY climate scenario. In a WET climate scenario and a scenario with SIMILAR conditions compared to the past, regional net benefits amount to 38 and 20 M€ and irrigation water use to 41 and 21 Mm^3, respectively. High regional net benefits are obtained through an expansion of vineyards, irrigation, and fertilization. On average, the VOI is highest if land and water use is efficiently adapted to DRY but a WET scenario is realized (506 €/ha/a) and lowest with efficient adaptation to WET but the realization of a SIMILAR scenario (58 €/ha/a).

1. Introduction

Agricultural systems in semi-arid regions depend on irrigation and face increasing challenges due to climate change. Climate change affects plant water demand and growth, water supply by surface and groundwater as well as their interactions (Barthel et al., 2012). For instance, an increase in mean temperature rises plant water demand due to higher evapotranspiration (Iglesias and Garrote, 2015; Rowan et al., 2011). A higher concentration in atmospheric CO_2 may enhance plant growth through a range of effects including an improved water use efficiency (Drake et al., 1997). Precipitation volumes determine, among other factors, soil moisture and water storage in the unsaturated zone and water uptake of plants through roots (i.e. green water supply). Moreover, precipitation volume, intensity and seasonality influence water bodies through surface water discharge and groundwater recharge (Vassolo, 2007) affecting water supply, e.g. for irrigation in agriculture (i.e. blue water supply). In Austria, the north-eastern parts are influenced by semi-arid climate conditions where important agricultural production regions are located, and major crops such as field vegetables, maize, sugar beet, and potatoes as well as vineyards are irrigated (Statistics Austria, 2013).

Globally, agriculture is the main water use sector (Döll et al., 2009) and 42% of irrigation water withdrawals are from groundwater (Döll et al., 2012). The absolute and relative importance of groundwater use for irrigation has increased over the last decades, which has resulted in falling groundwater tables in major agricultural production regions (Siebert et al., 2010). In Austria, the main source of irrigation water is groundwater, whereas surface water from rivers, lakes, ponds or reservoirs is of marginal importance (Siebert et al., 2010; Statistics Austria, 2013). Under climate change, the relevance of groundwater for irrigation is likely to grow further. This is because extreme events such as droughts and floods – which are likely to increase in severity and duration due to climate change (IPCC, 2012) – may lead to higher variability in precipitation, soil moisture, and surface water (Taylor et al., 2013). Thus, efficient land and water use is key in climate change adaptation in agriculture in order to cope with the growing pressure on water resources (Iglesias et al., 2007).

Adaptation measures for agricultural land and water use include improved drainage systems, small-scale water reservoirs on farmland, changes in land use, crops and varieties, improved irrigation

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technology, coordinated use of surface and groundwater, reduced tillage, formal education programs, and creation and dissemination of climate information (Iglesias and Garrote, 2015; McCarl et al., 2016; Winter et al., 2017). For Austria, selected adaptation measures such as changes in crop rotations, soil conservation, and irrigation have been identified effective for reducing crop yield losses or negative environmental outcomes under climate change scenarios (Mitter et al., 2015a,b; Schönhart et al., 2014, 2016). Furthermore, climate information has been shown to be particularly relevant for adaptation measures with long decision lifetimes or high costs including, for instance, changes in land use, the investment in irrigation equipment, and the establishment of regional authorities that govern water use (Mitter et al., 2018, 2019).

Assessing the effectiveness of climate change adaptation measures for agricultural land and water use a priori requires integrated approaches (Falloon and Betts, 2010) and an explicit representation of water demand and supply, including green and blue water (Rockström et al., 2009). This is because changes in climate, agricultural production, and the water balance are interlinked and depend on interactions between atmosphere, biosphere, and hydrosphere (Harrison et al., 2015, 2016; Kebede et al., 2015; Rowan et al., 2011). Integrated approaches are characterized by combining theories, empirical datasets, and mathematical models from different disciplines to better understand complex phenomena (Rotmans and Van Asselt, 1996). They may contribute to overcome some limitations of disciplinary models in climate change adaptation research (Giuliani et al., 2016). For instance, hydrological models typically lack the capacity to economically allocate water and economic models mostly omit a hydrological component (Howitt et al., 2012), whereas integrated approaches may help to describe, explain, and explore relationships between bio-physical and socio-economic systems.

The number of studies, which use an integrated approach for assessing adaptation measures for land and water use, has risen lately. Approaches vary from crop models, which are coupled with hydrological (e.g. Elliott et al., 2014), economic and nutrient emission models (e.g. Zessner et al., 2017), economic agricultural optimization models, where agricultural production is extended by water allocation optimization (e.g. Howitt et al., 2012; Rowan et al., 2011; Zhang and Guo, 2016), economic models which are integrated with hydrological models (e.g. Khan et al., 2008; Schaldach et al., 2012), groundwater balance models, which are integrated with an agricultural sector optimization model (e.g. Balali et al., 2011) to soil water balance simulation models, which are linked with agricultural production models (Dono et al., 2013; Kreins et al., 2015; Qureshi et al., 2013).

In a recent review, Graveline (2016) specifies two major elements that need to be considered in an integrated approach for successfully analyzing interactions between hydrological processes, the groundwater status, land and water use. These elements refer to the ability of the mathematical models to represent varying land allocation patterns between plants and alternative activities, and varying levels of water application per plant including the substitution between inputs. Graveline (2016) also highlights the need for accounting for stochastic variables related to climate change and water demand and supply in models. Similarly, other authors stress the importance of considering stochastic climate information in adaptation assessments in order to reduce the risk of misinterpreting climate signals (Kassie et al., 2013; Rao et al., 2011; Simelton et al., 2013). Furthermore, providing stochastic climate information to improve adaptation decision making and calculating the value of potential improvements, i.e. the economic value of stochastic climate information (VOI), is of interest. The VOI represents an upper bound to rational actors of being willing to spend on climate information for improved adaptation.

Studies following a VOI approach differ with respect to the period that climate information addresses (seasonal vs. long-term) and applied methodology, whereby seasonal climate information evaluated under the expected utility framework plays an important role (Meza et al., 2008). Recent studies have assessed the value of decadal or long-term climate information, i.e. for different climate scenarios, implementing VOI calculation into a stochastic programming model (Fernandez et al., 2016), a structural dynamic decision model (Guo and Costello, 2013), an integrated modeling framework (Mitter and Schmid, 2019) or an expected utility and certainty equivalence approach (Quiroga et al., 2011).

These efforts form a solid basis but a number of challenges remain. For instance, most assessments of agricultural adaptation measures consider some aspects of water demand or supply, but rarely both green and blue water are explicitly addressed. This is also true for VOI studies disregarding either blue (e.g.Adams et al., 1995, 2003; Choi et al., 2015; Crean et al., 2015; Fernandez et al., 2016) or green water supply (e.g. Mushtaq et al., 2012). Furthermore, improvements in decision making due to the availability and use of stochastic climate information is often neglected in adaptation studies (except for Dono et al., 2013), even though its importance has been stressed for private and public adaptation decisions (e.g. Adamson and Loch, 2014). Qureshi et al. (2013) recommend to focus on the integration of bio-physical and socio-economic models, because it allows to consider stochastic key variables such as precipitation volumes and groundwater dynamics, and may help to increase model accuracy of water allocation. In this context, Graveline (2016) suggests to explore the trade-off between constraining a socio-economic model to represent observations and allowing for sufficient model flexibility to acknowledge behavioral changes such as the adoption of new adaptation measures and technologies affecting water demand and supply.

In this article, we aim to contribute to the climate change adaptation and the VOI literature by considering variability of both plant water demand and water supply, including green and blue water. We assess efficient adaptation measures in land and water use and quantify the economic value of stochastic climate information (VOI). Therefore, we have developed an integrated modeling framework, which is applied to the semi-arid agricultural production region Seewinkel in eastern Austria.

The article is structured as follows. In the next section, the integrated modeling framework and the computation of the VOI are described. In section 3, the results on efficient adaptation in land and water use as well as the VOI are presented for the Austrian case study region Seewinkel. Key results are discussed in section 5 and conclusions are drawn in the last section.

2. The integrated modeling framework (IMF)

An integrated modeling framework (IMF) has been developed and applied in the Austrian case study region, the Seewinkel, to identify efficient adaptation measures in land and water use and to quantify the VOI for adaptation decision making. The IMF consists of a statistical climate model for Austria (Strauss et al., 2013), a crop rotation model (CropRota; Schönhart et al., 2011), a bio-physical process model (EPIC; Williams, 1995), a bottom-up economic land and water use optimization model (BiomAT; Feusthuber et al., 2017; Mitter et al., 2015b; Stürmer et al., 2013), and the computation of the economic value of stochastic climate information (see Fig. 1). The IMF is applied at 500 m grid resolution for the Seewinkel region and a future period of 31 years (2010–2040). In total, the case study region consists of 1804 grids of 25 ha each. The entire land is assigned to five different land use classes, i.e. cropland, intensive and extensive permanent grasslands, vineyards, and other land. The case study region and each model of the integrated modeling framework are described briefly in the following sub-sections and in more detail in the supporting information/appendix A.

2.1. Description of the Seewinkel case study region

The Seewinkel is a semi-arid region of about 45,100 ha in the East of Austria with mean annual precipitation below 600 mm and an average

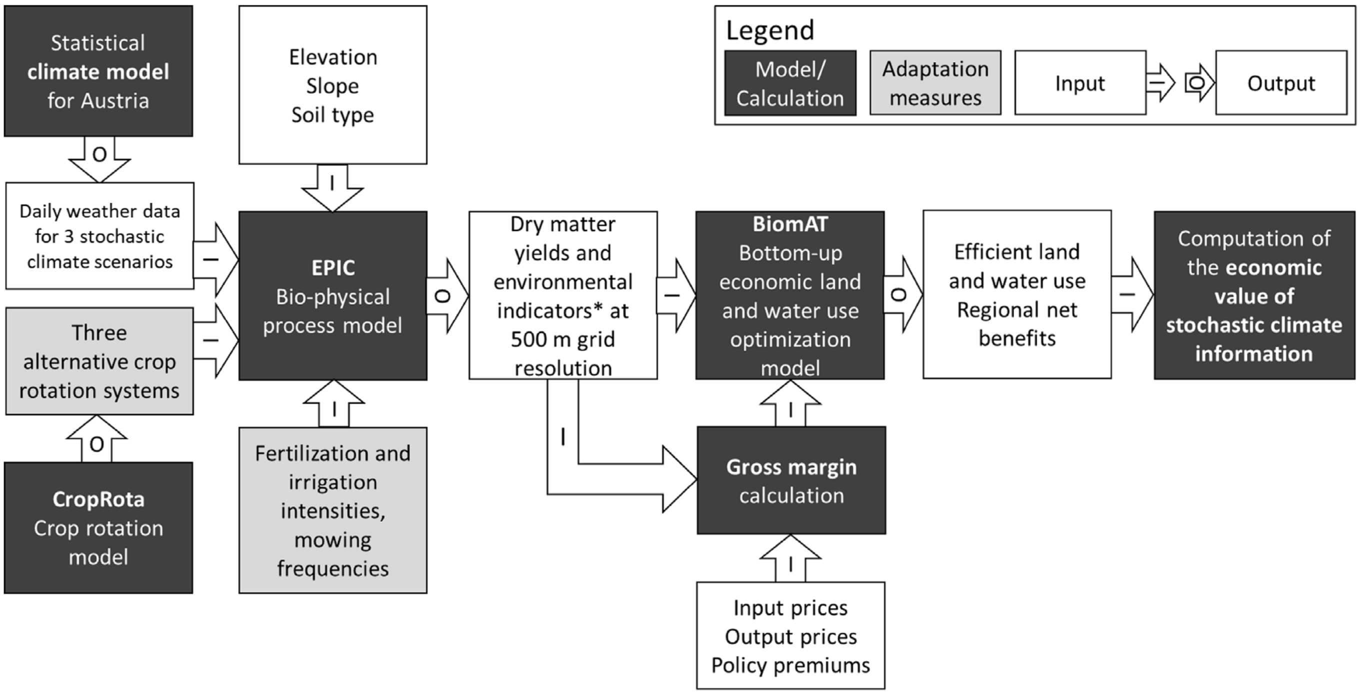

Fig. 1. Schematic overview on the integrated modeling framework (IMF)
*e.g. irrigation water use, percolation.

annual temperature around 10 °C (Blaschke and Gschöpf, 2011). In the Seewinkel, the majority of the land is used for agricultural production, i.e. 56% for cropland, 6% for grassland, and 10% for vineyards. The agricultural sector is also the main user of groundwater in the region (Reisner, 2014), whereby cropland and vineyards are mostly irrigated. The Seewinkel region has been identified as an individual groundwater body, which is influenced by low natural runoff (Blaschke et al., 2011). Climate change induced dry spells and droughts might impede the renewal of the groundwater body (Reisner, 2014). However, changes in annual precipitation volumes and shifts in seasonal patterns due to climate change are highly uncertain in this region (Chimani et al., 2016; Gobiet et al., 2014). Parts of the Seewinkel region have a high ecological value due to the existing saltine lakes, which form unique biotopes. A high groundwater table is required for stabilizing the salt content and ensuring the capillary uptake of salt from the soil (Blaschke et al., 2011). The national park 'Neusiedler See-Seewinkel' is located in the western part of the region, where the largest endorheic lake of Central Europe is situated.

2.2. Statistical climate model for Austria

The statistical climate model for Austria is based on observed daily weather data for the period 1975–2007 and combines a dry day index with a block bootstrapping procedure to stochastically project daily minimum and maximum temperatures, wind speed, relative humidity, solar radiation, and precipitation at 1 km grid resolution for the future period 2010–2040 (Strauss et al., 2013). Three different climate scenarios have been computed by block bootstrapping and through varying the distribution of the dry day index: (i) SIMILAR, where the distribution of the dry day index is similar to the past period, (ii) DRY, with a higher proportion of dry days compared to the past period which is derived by sampling more frequently from the drier blocks, and (iii) WET, with a higher proportion of wet days compared to the past period which is derived by sampling more frequently from wetter blocks. For each of the three climate scenarios, 30 realizations have been computed by repeated bootstrapping. Therefore, we refer to the three climate scenarios and 30 realizations as stochastic climate scenarios. The daily weather data for the future period 2010–2040 are input into the bio-physical process model EPIC.

2.3. Crop rotation model CropRota

CropRota is based on observed land use, an agronomic score matrix valuing pre-crop-main crop sequences, and agronomic constraints to crop rotations (Schönhart et al., 2011). In total, 24 arable crops are considered in the model. For the Seewinkel region, typical crop rotations and their relative weights are modelled with CropRota at municipality level and then assigned to cropland at 500°m grid resolution. In total, three different crop rotations are modelled and used as an input to the bio-physical process model EPIC.

2.4. Bio-physical process model EPIC

The bio-physical process model EPIC (Environmental Policy Integrated Climate; Williams, 1995) is used to simulate annual dry matter yields for crops, intensive and extensive permanent grasslands, as well as vineyards at 500 m grid resolution. The land use class 'other land' is considered as rangeland without harvesting in EPIC. Simulations are conducted for a future period of 31 years for the three stochastic climate scenarios, i.e. for each land use class a 31-year period is simulated with the 30 realizations of each of the three climate scenarios. The validated EPIC for Austria (see e.g. Heumesser et al., 2012; Mitter et al., 2015a; Schmid, 2006; Schönhart et al., 2014; Strauss et al., 2012; Stürmer et al., 2013) provides outputs – inter alia – on annual dry matter yields and the water balance (e.g. irrigation water use, percolation) at grid level by considering site specific bio-physical data (e.g. elevation, slope, soil characteristics), daily weather data (from the statistical climate model), and adaptation measures for land and water use.

Adaptation measures considered in EPIC include crop rotations on cropland, mowing frequencies on grassland, and several fertilization intensities on rain-fed and irrigated agricultural land (i.e. cropland, permanent grassland, and vineyards). Irrigation water is assumed to be only withdrawn from groundwater, which reflects the current practice in Austria (Statistics Austria, 2013). Sprinkler irrigation is simulated with four intensities for cropland because it is the preferred technology by Austrian crop farmers (BMLFUW, 2013). We consider only one irrigation intensity for intensive grassland because irrigation on grassland is currently of minor relevance in the Seewinkel region (Statistics Austria, 2013). Extensive grassland and other land are assumed to be rain-fed because they are typically classified as 'not worthy of being irrigated' (wpa Beratende Ingenieure, 2011).

For vineyards drip irrigation is simulated with two different intensities because it is the dominant irrigation technology for wine growing in the Seewinkel region (Reisner, 2014). The assumptions for maximum annual irrigation volumes build on information from regional water cooperatives (Reisner, 2014). For each land use class several adaptation measures are simulated, which result from combinations of rain-fed farming, irrigation, and fertilization intensities.

2.5. Gross margin calculation

Annual gross margins for arable crops, permanent grass, and wine are calculated by using the simulated yields from EPIC and respective commodity prices, variable production costs, and policy premiums. The latter are kept constant in the future for the three stochastic climate scenarios in order to isolate climate change impacts.

2.6. Bottom-up economic land and water use optimization model BiomAT

A PMP (Positive Mathematical Programming) version of the bottom-up economic land and water use optimization model BiomAT (Mitter et al., 2015b; Stürmer et al., 2013) has been developed, following the suggestions by Mérel and Howitt (2014) and Solazzo et al. (2016). It allows calibration of land use to reported data from the past (i.e. year 2014), and is able to assess efficient adaptation measures in land and water use for the stochastic climate scenarios at 500 m grid resolution. The PMP version of BiomAT developed by Feusthuber et al. (2017) and Karner et al. (2018) has been extended by a regional water balance using monthly outputs from EPIC on water supply (i.e. percolation) and demand (i.e. irrigation water use). This model extension allows us to identify efficient adaptation in land and water use at grid level considering hydrological restrictions, i.e. regional irrigation water use cannot exceed groundwater recharge through percolation. Furthermore, the rather restrictive assumption that land use change is limited to historical observations in the respective grid (see Karner et al., 2018) has been relaxed such that each land use class can be chosen in each grid.

The PMP version of BiomAT maximizes regional net benefits using a non-linear objective function consisting of the gross margins and the marginal dual values of water (λ) and land (η) use (see equation (1)). We consider constraints regarding total land endowment per grid (2–3) as well as the regional water balance (4). Constraints (5) and (6) are only used in the linear model to derive the marginal dual values of water and land use (λ, η). BiomAT is solved for the 30 realizations of each of the three climate scenarios. The model is extended by this stochastic component, which allows us to include climate variability and hence represents the inherent uncertainties of future climate change.

$$Max\ NB = \sum_{i,j,k} GM_{i,j,k}x_{i,j,k} - \sum_{i,m} gwex_{i,m}\lambda - \begin{cases} \sum_{i,j} \frac{\eta_{i,j}\,\tilde{x}_{i,j}^{\alpha}}{\alpha\,(x_{i,j}^{0})^{(\alpha-1)}} & x_{i,j}^{0} > 0 \\ \sum_{i,h} \eta_{i,j}\,\tilde{x}_{i,j} & x_{i,j}^{0} = 0 \end{cases} \tag{1}$$

$$\sum_{j} \tilde{x}_{i,j} = 25 \qquad \forall\ i \tag{2}$$

$$\tilde{x}_{i,j} = \sum_{k} x_{i,j,k} \qquad \forall\ i,\ j \tag{3}$$

$$- \sum_{j,k} PRK_{i,j,k,m}x_{i,j,k} - \sum_{\tilde{i}} inf_{i,\tilde{i},m} - gwex_{i,m} - wl_{i,m-1} + \sum_{j,k} IRGA_{i,j,k,m}x_{i,j,k} + \sum_{\tilde{i}} outf_{\tilde{i},i,m} + wl_{i,m} \le 0 \quad \forall\ i,\ m \tag{4}$$

$$\sum_{k} x_{i,j,k} = x_{i,j}^{0} \qquad \forall\ i,\ j \tag{5}$$

$$\sum_{i,m} gwex_{i,m} = 0 \tag{6}$$

Equation (1) represents the objective function of the PMP version of BiomAT. The first term of (1) sums the product of gross margins (in €/ha) and land use x (in ha) for each grid i (I = 1,804), land use class j (J = 5), and adaptation measure k (including crop rotations, fertilization and irrigation intensities, and mowing frequencies). The second term represents the costs of groundwater extraction (in €), where λ is the marginal dual value (in €/m^3) and *gwex* the volume of groundwater extraction (in m^3) in each grid i and month m (M = 12). *gwex* is calibrated to zero in all scenarios, which is represented by the marginal dual value of water λ. The third term represents the PMP cost function, where the product of marginal dual values (η) of land use j in grid i (in €/ha by land use j) and land use $\tilde{x}$to the power of the PMP coefficient α (in ha by land use class j and grid i) is divided by observed land use x^0 (in ha per land use class j and grid i). The non-linear part of the function is used if observed land use is greater than zero, otherwise the linear part is used in the model. α represents the PMP coefficient, which we assume to be 2 representing a quadratic cost function. The marginal dual values of land and water use (η, λ) are derived in a linear model with maximizing regional net benefits $\left(\sum_{i,j,k} GM_{i,j,k}\, x_{i,j,k}\right)$ subject to constraints (Eq. (5)) and (Eq. (6)) where modelled land use is forced to observed land use $x^{0.}$ in the past and groundwater extraction is calibrated to zero. The marginal dual values from the past period are used to quantify climate change impacts for the scenarios SIMILAR, WET, and DRY. The PMP model (with equations (1)–(4)) ensures that in each grid i the sum of land x under land use j (in ha) amounts to the 25 ha of each grid. Equation (4) represents the monthly water balance equation, which ensures that regional irrigation water use does not exceed percolation. It balances monthly percolation (*PRK*) in grid *i,* land use j and management *k,* monthly inflow (*inf*) from neighboring grids $\tilde{i}$ to grid i and monthly groundwater extraction (*gwex*) in grid i with monthly irrigation (*IRGA*) in grid *i,* land use *j,* management k as well as monthly water outflow (*outf*) from grid i to neighboring grids $\tilde{i}$ (all in m^3). The water balance equation also allows water storage from the previous month ($wl_{i,m-1}$) and the current month ($wl_{i,m}$) in each grid *i.*

2.7. Computation of the economic value of stochastic climate information (VOI)

The VOI represents the value of periodic climate information. It is calculated as the difference between regional net benefits with and without efficient adaptation of land and water use to a particular climate scenario. Each of the 30 realizations of one climate scenario is evaluated in each of the 30 realizations of the other two climate scenarios (see equation (7)).

$$VOI|^{Scenario_r} = NB|^{Scenario_r}_{X^*_{Scenario_r}} - NB|^{Scenario_r}_{X^*_{Scenario-other_r}} \tag{7}$$

Scenario represents any of the three climate scenarios (SIMILAR, DRY, or WET), r represents the realizations of each climate scenario (R = 30), and *Scenario-other* represents one climate scenario different from the chosen *Scenario*. This procedure results in 900 possible combinations for computing the VOI of a particular *Scenario* and *Scenario-other* combination.

The VOI is calculated in three steps. First, we compute the efficient adaptation of land and water use $x^*$and regional net benefits (NB) for each realization r and climate scenario using the calibrated BiomAT model. Hence, we receive the first part in equation (7), e.g. $NB|_{X^*_{DRY_r}}^{DRY_r}$. Second, we use the efficient adaptation of land and water use x^* of a particular realization in $Scenario\text{-}other_r$ and evaluate these with impacts of a particular realization in $Scenario_r$ to compute regional net benefits. Hence, we receive the second part in equation (7), e.g. $NB|_{X^*_{WET_r}}^{DRY_r}$. Third, we calculate the differences in regional net benefits between efficient and inefficient adaptation for each realization r and *Scenario* and *Scenario-other* combination. Hence, we receive our VOI e.g. $VOI|^{DRY_r}$.

3. Results

Results from the BiomAT model and the VOI computation are presented for the case study region Seewinkel and the three stochastic climate scenarios. They include efficient land use choices, irrigation water use, regional net benefits, and the economic value of stochastic climate information.

3.1. Land use and stochastic climate scenarios

BiomAT model results for the Seewinkel region are summarized in Table 1 for the three stochastic climate scenarios DRY, SIMILAR, and WET. The table contains averages of the 30 realizations for regional net benefits, irrigation water use, and areas of land use classes. Efficient land use for adaptation differs considerably between climate scenarios, especially for vineyards and other land. Compared to SIMILAR, the model results suggest that, on average, the share of vineyards and intensive grassland is higher by 159% and 29% in WET. By contrast, the share of other land, extensive grassland, and cropland is lower by 71%, 52%, and 20%, respectively. In DRY, the shares of other land and extensive grassland are, on average, 89% and 53% higher than in SIMILAR, whereas vineyards, intensive grassland, and cropland are about 64%, 57%, and 11% lower, respectively. These model results indicate that expanding vineyards is the major land use adaptation strategy under a WET climate scenario, whereas extensification in land use is the major adaptation strategy under a DRY climate scenario.

The boxplots in Fig. 2 illustrate differences in land use choices among the 30 realizations by climate scenarios. For cropland and grassland, the realizations of the alternative climate scenarios partly overlap, which is not the case for vineyards and other land. Further details on the spatial distribution of land use in the three stochastic climate scenarios are summarized in Fig. B1 in the supporting information/appendix B.

3.2. Irrigation water use and stochastic climate scenarios

Irrigation water use differs by climate scenario and land use. Boxplots of the 30 realizations on annual irrigation water use (in Mm^3) are shown in Fig. 3a by climate scenarios. According to the model result, it is highest in WET (41.1 Mm^3 on average) and lowest in DRY (8.4 Mm^3 on average). It may seem counter-intuitive that irrigation water use is lower in DRY than in WET. However, it is the effect of the assumption in the regional water balance to limit regional water demand for irrigation to water supply from percolation.

Model results show that the irrigated agricultural land is largest in WET (19,225 ha), followed by SIMILAR (8228 ha) and DRY (3134 ha). Irrigation is predominantly applied in vineyards and of lower importance on cropland, regardless of the climate scenario (Fig. 3b). Intensive grassland is not irrigated in any climate scenario, according to the model results. Extensive grassland and other land are assumed to be rain-fed. The model results also show differences in fertilizer inputs by climate scenario. While moderate fertilizer input is chosen most often in WET, low fertilizer input is dominant in SIMILAR and DRY. Fertilizer input is crop specific, but average annual values for a moderate (low) intensity are 111 (76 kg/ha) of nitrogen and 30 (24 kg/ha) of phosphorus fertilizers.

3.3. Regional net benefits and stochastic climate scenarios

Changes in land use (section 3.1.), irrigation water use and fertilizer inputs (section 3.2.) also affect regional net benefits, which are shown in Fig. 4 for the Seewinkel. Regional net benefits amount to 7.95 M€ in DRY, 20.2 M€ in SIMILAR, and 38.1 M€ in WET, on average (Table 1). They are, on average, 61% lower in DRY and 89% higher in WET, compared to SIMILAR. Variability between the 30 realizations is highest in WET followed by SIMILAR and DRY. Lower average regional net benefits in DRY are mainly because of reduced percolation, an increase in plant water stress, limited availability of irrigation water and thus extensification in land use. High regional net benefits in WET mainly result from an increase in average yields, the expansion of irrigated vineyards and the conversion of non-agricultural (other) land to agricultural land.

3.4. Economic value of stochastic climate information (VOI)

Boxplots on the VOI for the Seewinkel region are shown in Fig. 5 for any particular *Scenario* and *Scenario-other* combination. On average, the VOI is highest if efficient adaptation to a realization of a DRY or WET *Scenario-other* is evaluated in a realization of a WET or DRY *Scenario*, respectively. The average VOI for the Seewinkel region amounts to 22.8 M€ (14.1 M€) if efficient adaptation to a DRY (WET) *Scenario-other* is evaluated in a WET (DRY) *Scenario*, i.e. WET_DRY (DRY_WET) in Fig. 5. This is 66% (178%) of average regional net benefits of efficient adaptation to WET (DRY).

The VOI amounts to 7.6 M€, on average, if land and water use are efficiently adapted to a DRY *Scenario-other* and evaluated in a SIMILAR *Scenario*. This is about 37% of average regional net benefits of efficient adaptation to SIMILAR. With efficient adaptation to a SIMILAR *Scenario-other* evaluated in a DRY *Scenario*, the VOI amounts to 3.9 M€ on average, or 48% of average regional net benefits of efficient adaptation to DRY. The VOI is, on average, lowest if efficient adaptation to a WET *Scenario-other* is evaluated in a SIMILAR *Scenario*, i.e. SIMILAR_WET in Fig. 5. It amounts to 2.6 M€ which is about 13% of average regional net benefits of efficient adaptation to SIMILAR.

The spatial distribution of the average annual VOI (in €/ha) is shown in Fig. 6, considering all 900 possible combinations of each climate scenario pair. The highest average annual VOI with 506 €/ha is realized when land and water use are efficiently adapted to a DRY *Scenario-other* and evaluated in a WET *Scenario* (Fig. 6f). High average annual VOIs are also achieved with efficient adaptation to a WET *Scenario-other* which is evaluated in a DRY *Scenario* (313 €/ha, Fig. 6d),

Table 1
Average regional net benefits (in M€), irrigation water use (in Mm^3), and areas of land use classes (in ha) for the Seewinkel region by climate scenarios.

Climate scenario	Regional net benefit in M€	Irrigation water use in Mm^3	Cropland in ha	Intensive grassland in ha	Extensive grassland in ha	Vineyards in ha	Other land in ha
DRY	7.95	8.35	22,944	788	3,387	2,613	15,369
SIMILAR	20.20	20.78	25,660	1,813	2,209	7,294	8,123
WET	38.10	41.10	20,459	2,341	1,061	18,887	2,353

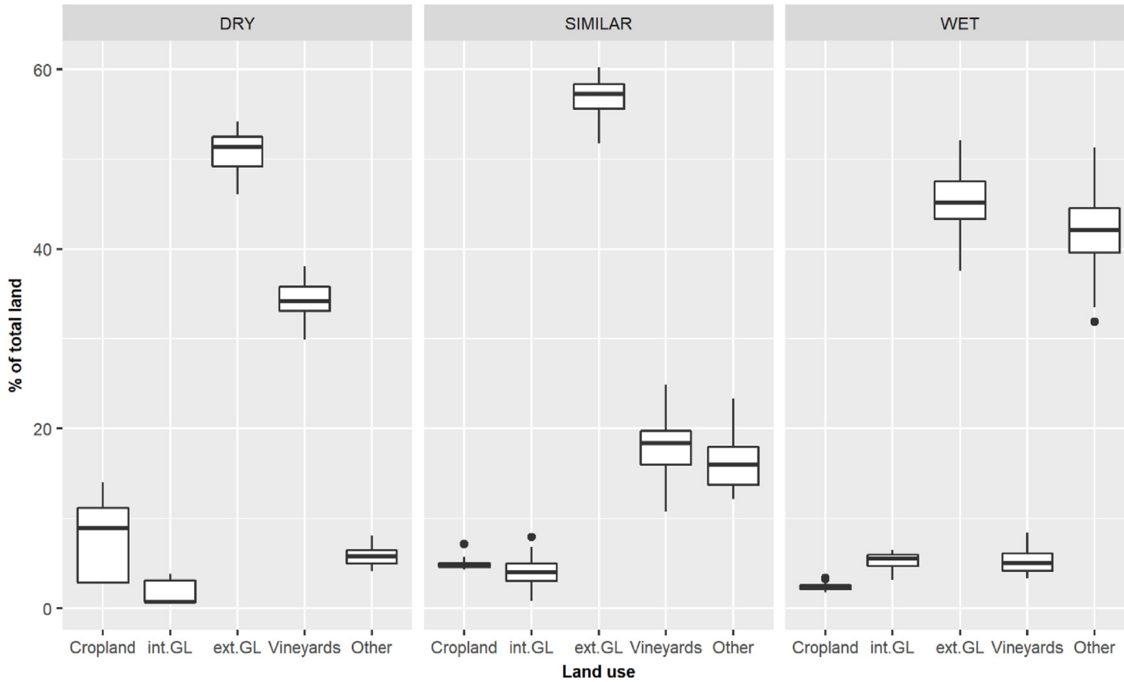

Fig. 2. Boxplots with 30 realizations of shares of cropland, intensive and extensive grassland (int. GL, ext. GL), vineyards, and other land (Other, in % of the total land) for the Seewinkel region by stochastic climate scenarios.

and with efficient adaptation to a SIMILAR *Scenario-other* which is evaluated in a WET *Scenario* (310 €/ha, Fig. 6e).

The average annual VOI amounts to 168 €/ha with efficient adaptation to a DRY *Scenario-other* evaluated in a SIMILAR *Scenario* (Figs. 6a), 59 €/ha with efficient adaptation to a SIMILAR *Scenario-other* evaluated in a DRY *Scenario* (Figs. 6c), and 58 €/ha with efficient adaptation to a WET *Scenario-other* evaluated in a SIMILAR *Scenario* (Fig. 6b) and the average annual VOI is negative in several grids (Fig. 6b). These are either grids where wine would be grown in a WET but not in a SIMILAR scenario (see Fig. B1 in the supporting information/appendix B) or where additional groundwater extraction is required on cropland (see Fig. B2 in the supporting information/appendix B). Both factors lead to higher yields than with efficient adaptation to a SIMILAR climate and related economic benefits may be higher than the costs for groundwater extraction. Moreover, optimization follows a regional approach, i.e. net benefits are optimized for the entire Seewinkel region, which may lead to a lower VOI for certain grids in some scenarios, compared to others. Nevertheless, regional VOI (in €) as well as the area VOI (in €/ha) are positive with efficient adaptation to a WET *Scenario-other* evaluated in a SIMILAR *Scenario*.

3.5. Groundwater extraction externalities

Some *Scenario* and *Scenario-other* combinations require groundwater extraction in order to assure feasibility in computing the VOI. Fig. 7 shows all *Scenario* and *Scenario-other* combinations with or without groundwater extractions. The amount of groundwater extraction is valued by the marginal dual value of water λ. For instance, groundwater extraction exceeds natural recharge by 46.5 Mm^3 (14 Mm^3), on average, if land and water use are effectively adapted to a WET (SIMILAR) *Scenario-other* but evaluated in a DRY *Scenario*. Compared to efficient adaptation to DRY, this is about 556% (167%) of average

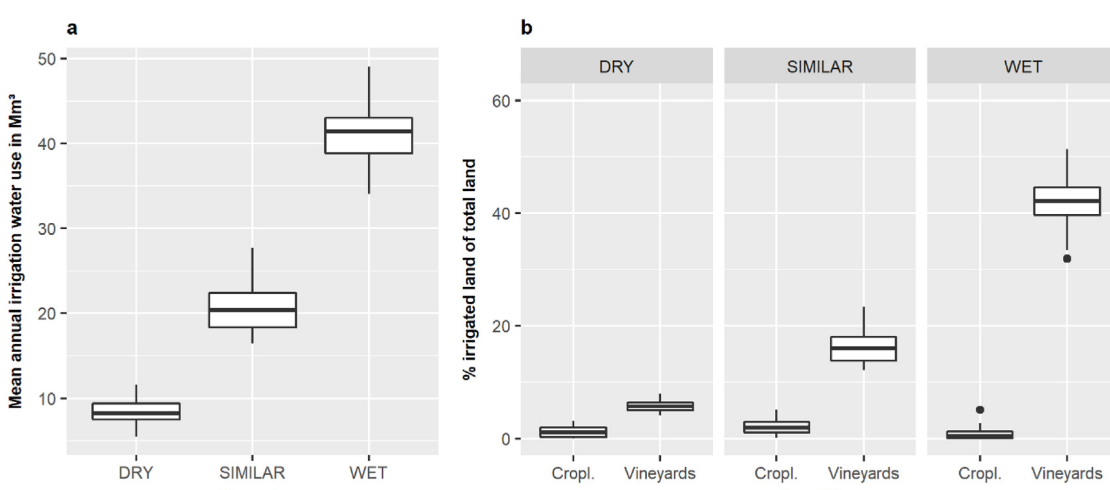

Fig. 3. Boxplots with 30 realizations of (a) annual irrigation water use (in Mm^3) and (b) the share of irrigated land (in % of the total land) for the Seewinkel region by stochastic climate scenarios.

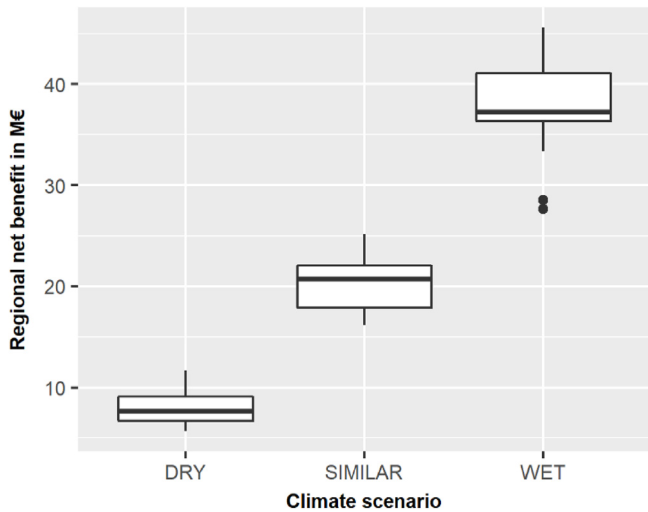

Fig. 4. Boxplots with 30 realizations of regional net benefits (in M€) for the Seewinkel region by stochastic climate scenarios.

irrigation water use.

Groundwater extraction is also required with efficient adaptation to a WET *Scenario-other* which is evaluated in a SIMILAR *Scenario*. On average, it amounts to 30.7 Mm^3. This is about 148% of average irrigation water use when adapted efficiently to a SIMILAR *Scenario*. Groundwater extraction is not taking place in the other *Scenario* and *Scenario-other* combinations, i.e. SIMILAR_DRY, WET_DRY and WET_SIMILAR. Fig. B2 in the supporting information/appendix B shows where water extraction would occur in the Seewinkel region.

4. Discussion

An integrated modeling framework (IMF) has been developed and applied to the semi-arid Seewinkel region to assess impacts of three stochastic climate scenarios (i.e. DRY, SIMILAR, and WET) and regional irrigation water restrictions on land and water use as well as on the economic value of stochastic climate information.

In the DRY stochastic climate scenario, plant water demand is higher, while water supply through percolation is lower, compared to the other stochastic climate scenarios. Plant water stress and lower average yields lead to an extensification in land use, which is indicated by a high average share of non-agricultural land (34%) and extensive grassland (8% of the total land), and low regional net benefits. Although irrigation could be an effective adaptation measure to increase crop, grass, and wine yields and thus regional net benefits, groundwater recharge by percolation is not sufficient for a wide application of irrigation in this scenario. Other modeling studies have come to a similar conclusion suggesting that irrigation could be an effective adaptation measure in semi-arid regions but its successful implementation largely depends on the availability of groundwater water resources (Eitzinger et al., 2013). In our IMF, limited irrigation results from the assumption in the regional water balance, which restricts irrigation water use to groundwater recharge. This assumption reflects water policies and regulations which are typically implemented in order to stabilize groundwater tables and facilitate efficient water allocation to various users. As such, it illustrates the effect of both regional water supply as well as water policies and regulations on land and water use in agriculture and related groundwater externalities.

In the WET climate scenario, water supply by percolation is higher than in SIMILAR and DRY. This allows an extension of irrigated vineyards to 42% of total land whereas non-agricultural land diminishes to 5%. In WET, efficient land and water use lead to the highest regional net benefits among all stochastic climate scenarios. However, some limitations of the IMF need to be considered when interpreting high regional net benefits in WET. For instance, qualitative changes are not considered in EPIC and commodity prices are kept constant across all climate scenarios. Yield quality is particularly important for winemaking and selling which potentially leads to an overestimation of regional net benefits in WET. Furthermore, van der Velde et al. (2012) have shown that EPIC satisfactorily reproduces yield responses to dry climate conditions but may underestimate negative impacts of excessively wet conditions. This may lead to an overestimation of yield quantities and thus regional net benefits in WET. Finally, the EU regulation 1308/2013 (European Parliament and the Council of the European Union, 2013) limits the annual extension of vineyards to 1% of the total area that is actually planted with vines in a Member State's territory. Thus, a maximum of about 6,100 ha of vineyards can be expected for the Seewinkel region in the 31-year period under consideration. Compared to the optimization results, this is only about a third, which may again contribute to an overestimation of the economic effects of a WET climate.

We have computed the VOI to quantify the value of periodic climate information for decision making in agricultural adaptation. It is defined as the difference between regional net benefits with and without efficient adaptation of land and water use to a specific climate scenario. According to our results, the VOI is highest if efficient adaptation to a

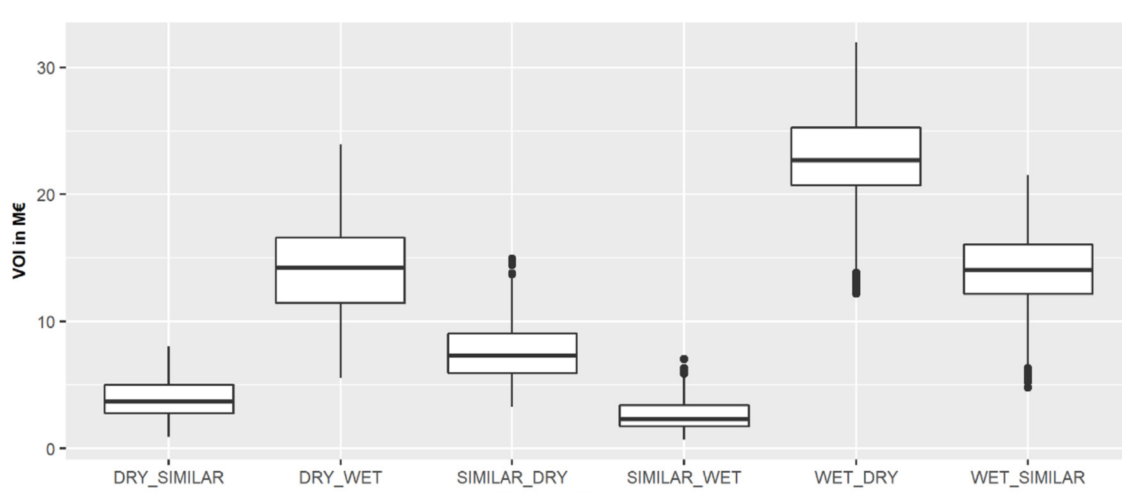

Fig. 5. Boxplots on the economic value of stochastic climate information (VOI, in M€) for the Seewinkel region for any particular *Scenario* and *Scenario-other* combination.

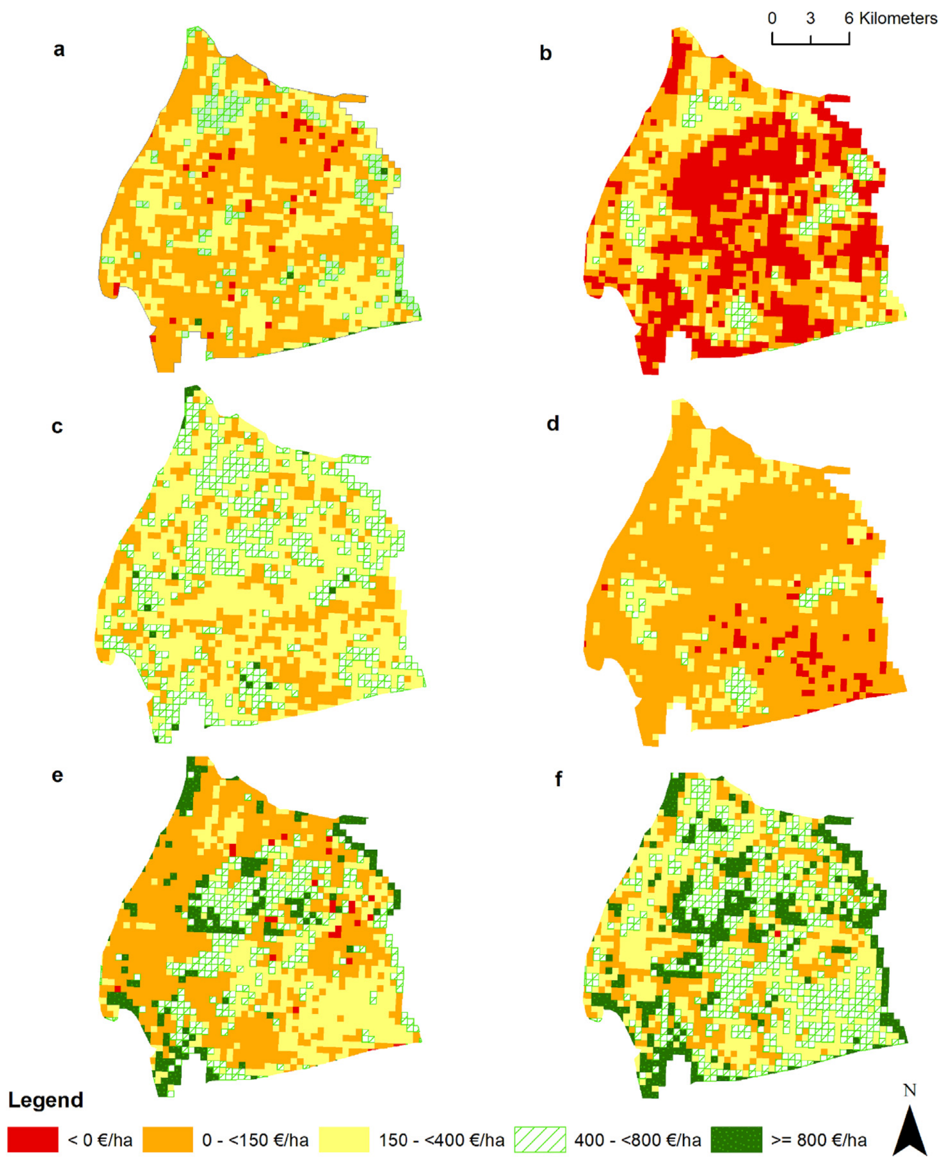

Fig. 6. Average annual economic value of stochastic climate information (VOI, in €/ha) for the Seewinkel region for *Scenario* and *Scenario-other* combination (a) SIMILAR_DRY, (b) SIMILAR_WET, (c) DRY_SIMILAR, (d) DRY_WET, (e) WET_SIMILAR, and (f) WET_DRY (print in black and white).

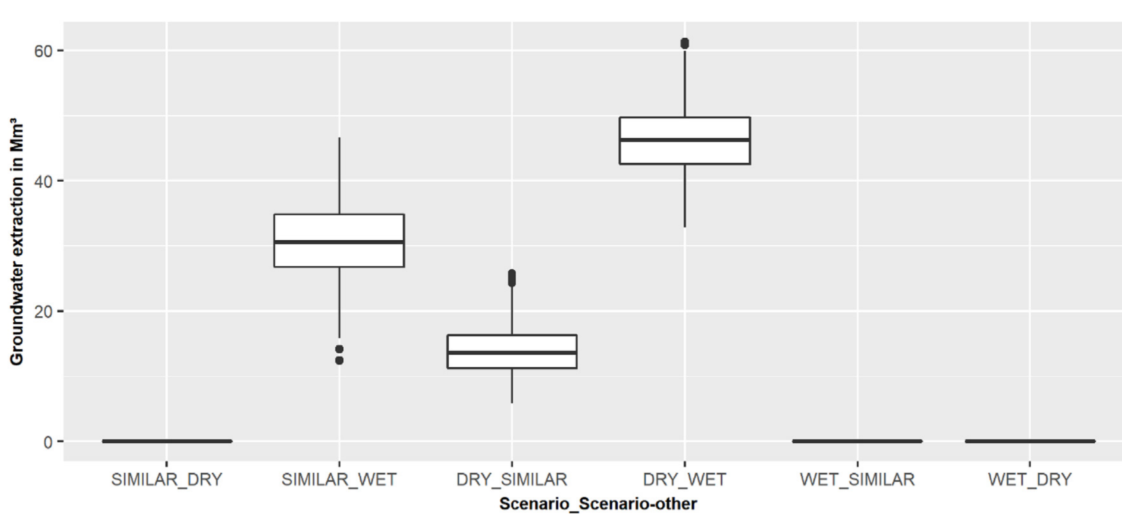

Fig. 7. Boxplots of groundwater extraction by *Scenario* and *Scenario-other* combination (in Mm^3) for the Seewinkel region.

DRY *Scenario-other* is evaluated in a WET *Scenario*. The underlying assumption is that climate information is not available and farmers adapt to a DRY *Scenario-other*. In this context, limited climate information would lead to foregone economic benefits due to lower yields and less area devoted to vineyards. Furthermore, the high VOI is closely linked to the water use restriction in BiomAT, which limits irrigation water use to groundwater recharge by percolation. Relaxing this assumption towards more flexible irrigation water use would lead to a decrease in VOI and higher groundwater externalities.

A high VOI is also computed if land and water use are efficiently adapted to a WET *Scenario-other* and evaluated in a DRY *Scenario*. In such a case, irrigation water demand exceeds water supply from percolation leading to groundwater extraction externalities. Specifically, groundwater extraction surpasses total irrigation volumes of efficient adaptation to DRY by 456%. The groundwater table would decline and threaten the saltine lakes and related biotopes in the Seewinkel region. Moreover, high water demand in the agricultural sector reduces water supply for other water users or future irrigation activities. In this *Scenario* and *Scenario-other* combination, limited information represents costs for the required groundwater extraction.

If a SIMILAR *Scenario* is realized, insufficient information is related to both, foregone economic benefits if adaptation occurs to a DRY *Scenario-other* and costs if adaptation occurs to a WET *Scenario-other* due to the additional groundwater extraction.

With respect to the computation of the VOI, we implicitly assume that lack of climate information or limited access to the information is the main risk for inefficient adaptation. However, there are other causes of inefficient adaptation as well, which we currently do not consider in our IMF including, for instance, human resource, social and cultural constraints, competing values that lead to other actions being preferred, and limited belief in the need for adaptation (McCarl et al., 2016).

5. Conclusions

The integrated modeling framework presented in this article has been developed with the aim to identify efficient adaptation measures in land and water use, and to quantify the economic value of stochastic climate information (VOI). The major novelty of the IMF is that stochastic climate scenarios as well as plant water demand and water supply are explicitly considered. Its applicability has been proven in the semi-arid Seewinkel region in Austria. The bio-physical process model EPIC has the advantage to provide information on percolation and irrigation water use, which can be introduced into the bottom-up economic land and water use optimization model BiomAT. The regional water balance equation in BiomAT limits regional irrigation water use to groundwater recharge by percolation. The PMP approach applied in BiomAT allows calibration of land use to reported data from the past. The computation of the VOI represents the value of periodic climate information, i.e. the difference between regional net benefits with and without efficient adaptation of land and water use to a specific stochastic climate scenario.

The results presented in this article suggest the usefulness of the IMF for (i) defining efficient adaptation measures, (ii) computing the VOI in water-constrained regions, and (iii) revealing whether unavailable climate information would be associated with groundwater externalities or foregone economic benefits. The IMF can be applied in other agricultural productions regions and additional adaptation measures can be considered if climate, soil, topographic, economic and management data are available. Results on regional net benefits, and efficient land and irrigation water use under climate change are of particular importance for agricultural extension experts and staff from regional water authorities to evaluate potential climate change impacts, improve water allocation practices and design climate change adaptation and water policies and regulations. Regional net benefits are mainly driven by water supply for irrigation and fertilizer application, which emphasizes the importance of considering stochastic climate scenarios and various adaptation measures in such analyses. High water supply allows an expansion of vineyards in the region leading to an increase in regional net benefits. However, efficient adaptation to a climate scenario would require high flexibility in terms of land and water use, or lead to severe groundwater externalities.

The VOI reveals the economic value of timely and accurate climate information for decision making in agricultural adaptation, which is of particular importance in a water-constrained environment. Considering stochastic climate scenarios in the analysis even increases the scientific and practical relevance of the work. When land and water use in the case study region is efficiently adapted to a climate similar to the past (which represents a situation where climate information is absent), falling groundwater tables or economic losses have to be expected in the long run if a dry or wet climate is realized. This is mainly due to excess irrigation water use. If farmers adapt to a dry climate or a climate similar to the past but wet conditions prevail, land and irrigation water use is inefficient and result in foregone economic benefits. From the VOI computation, we can conclude that absent climate information bears a high economic and environmental risk affecting not only farmers but also the public. VOI computations may thus inform the provision of climate data and impact studies.

While the described IMF has several components that improve and distinguish it from previous research, such as explicit inclusion of plant water demand, blue and green water supply, various irrigation technologies and intensities as well as stochastic climate scenarios, a number of opportunities for further research remain. We propose that future work could differentiate between farm and farming types and respective differences in adaptation decision making, assess water price and water policy scenarios, analyze plant water productivity, restrict land use change in areas with high ecological value, evaluate the accuracy of water allocation, and include additional adaptation measures, which might allow a more flexible groundwater use.

Conflict of interest statement

The authors declare that they have no conflict of interest.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jenvman.2019.109431.

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