Modelling impacts of drought and adaptation scenarios on crop production in Austria

Modellierung von Auswirkungen verschiedener Dürre- und Anpassungsszenarien auf die agrarische Pflanzenproduktion in Österreich

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Summary

We use a spatially explicit, integrated drought assessment framework to (i) assess drought scenario impacts on Austrian crop production, (ii) identify optimal crop production portfolios to effectively adapt to drought scenarios, and (iii) quantify the value of drought prediction for adaptation. The assessment framework consists of a statistical climate model, the bio-physical process model EPIC, and a portfolio optimization model. Model results at national level indicate that, under drought scenarios, rain-fed cropping may lead to average crop yield losses between 1.7% and 6.9%, compared to the baseline climate scenario with similar precipitation sums than in the past. Optimal crop production portfolios including irrigation intensities are effective for adapting to droughts leading to almost stable average annual crop yields. The average annual value of drought prediction is highest in the semi-arid regions in eastern Austria and amounts to 200 €/ha or more.
Keywords: value of drought prediction, climate change, adaptation, integrated assessment, portfolio optimization

Zusammenfassung

Wir verwenden ein räumlich explizites, integriertes Dürre-Assessment-Framework, um (i) die Wirkung von Dürreszenarien auf die österreichische Pflanzenproduktion zu untersuchen, (ii) optimale Bewirtschaftungsportfolios zur Anpassung an Dürreszenarien zu ermitteln und (iii) den Dürre-Informationswert für effektive Anpassung zu quantifizieren. Das Assessment-Framework besteht aus einem statistischen Klimamodell, dem bio-physikalischen Prozess-

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modell EPIC und einem Portfoliooptimierungsmodell. Im Vergleich zum Basis-Klimaszenario mit ähnlichen Niederschlagssummen wie in der Vergangenheit zeigen die Modellergebnisse auf nationaler Ebene, dass ohne Bewässerung mit durchschnittlichen Ertragsverlusten zwischen 1,7% und 6,9% (je nach Dürreszenario) zu rechnen ist. Optimale Bewirtschaftungsportfolios mit Bewässerungsintensitäten führen zu beinahe stabilen mittleren jährlichen Pflanzenerträgen und eignen sich daher als Anpassungsmaßnahme. Der mittlere jährliche Dürre-Informationswert ist im semi-ariden Osten Österreichs am höchsten und beträgt dort in etwa 200 €/ha oder mehr.
Schlagworte: Dürre-Informationswert, Klimawandel, Adaptation, integratives Assessment, Portfoliooptimierung

1. Introduction

Climatic droughts may amplify global food insecurity and inter-annual yield variability. The latest Central European drought and heat wave in 2013 had a significant impact, especially on late harvested crops. For instance, Austrian corn yields were 18% below the ten years average as reported by Statistics Austria. Drought events could increase in frequency, magnitude, and duration due to climate change, thereby affecting agricultural production (DAI, 2013). Drought information systems have been developed at various scales with different spatial and temporal resolutions in order to overcome such challenges. The Global Agricultural Drought Monitoring and Forecasting System (GADMFS), for instance, provides world-wide datasets on drought conditions and forecasts at ~1 km spatial and daily temporal resolutions (DENG et al., 2013). The European Drought Observatory (EDO) provides maps for drought-relevant indicators such as daily soil moisture, standard precipitation index, vegetation productivity, and vegetation water content. Some selected results feed into the GADMFS (HORION et al., 2012). In Austria, a crop specific drought monitoring and forecasting system is currently being developed (see EITZINGER, 2014). Our analysis extends this on-going research by introducing a bio-physical and economic analysis of drought scenarios focusing on three aspects. First, we investigate potential impacts of regional drought scenarios on both rain-fed and irrigated agriculture in Austria, expressed as expected changes in crop production. Second, we identify

optimal crop production portfolios for different levels of farmers' risk aversion to effectively adapt to drought scenarios by accounting for regional heterogeneities and opportunity costs. Third, we calculate the economic value of drought prediction for adaptation at 1 km pixel resolution and assess the effect of risk aversion on its magnitude.
Therefore, we have developed a spatially explicit, integrated drought assessment framework which is described in section 2. In section 3, we present selected results which are discussed in section 4.

2. Integrated drought assessment framework

Figure 1 shows an overview on the integrated drought assessment framework applied on the Austrian cropland at 1 km pixel resolution. More details are given in the following sub-sections.

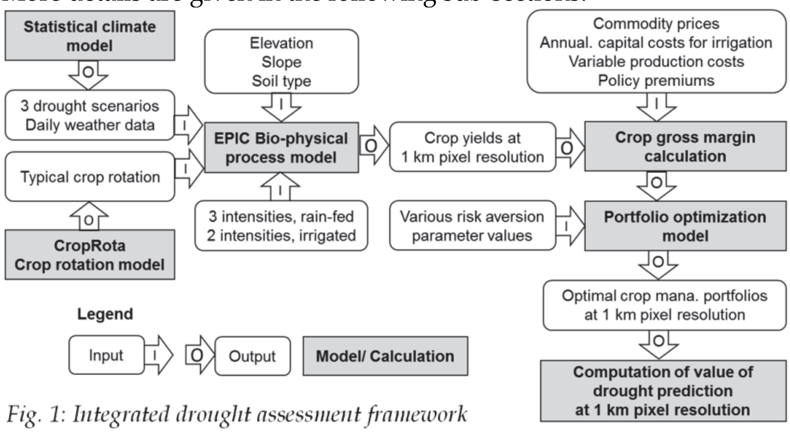

Fig. 1: Integrated drought assessment framework
Source: OWN ILLUSTRATION

2.1 Statistical climate model for Austria

Three climatic drought scenarios for the 31 years period 2010-2040 are provided by a statistical climate model for Austria. The climate model is based on daily weather station data from 1975–2007. It combines a dry day index for Austria with block-bootstrapping from the observed daily weather data to derive a set of climate data with spatial and temporal resolutions of 1 km and 1 day. In the baseline climate scenario (S1), the distribution of dry days nearly resembles past observations. The other two climate scenarios (S2, S3) are characterized by increasing severity of drought events in the future, i.e. lower seasonal and annual precipitation sums and a larger temperature increase compared to the past. For instance, the probability that more than 40% of the Austrian territory faces no precipitation events on a random day increases form 0.79 in S1 to 0.88 in S2 and 0.93 in S3 (STRAUSS et al., 2013).

2.2 Bio-physical process model EPIC

We apply the bio-physical process model EPIC (Environmental Policy Integrated Climate; WILLIAMS, 1995) to simulate average annual dry matter (DM) crop yields for the period 2010-2040 by considering – inter alia – the hydrological balance at field scale, i.e. precipitation, evapotranspiration, percolation, surface and sub-surface runoff, as well as the CO_2 fertilization effect. The simulations are repeated for the climate scenarios S1-S3, and for major field crops under alternative crop management practices including crop rotations, fertilization and irrigation intensities. Spatially explicit crop rotations are provided by the model CropRota which considers 22 major crops (e.g. maize, wheat; SCHÖNHART et al., 2011). The three levels of fertilization intensity (high, moderate, low) depict legal standards and policy guidelines and vary by crop. Irrigation intensities are combined with high and moderate fertilization intensities. We assume sufficient irrigation water supply across Austria. Farm-level autonomous adaptation is considered by adjusting sowing, tillage, fertilizer input, and harvesting dates to projected annual changes in the growing season.

2.3 Crop gross margin calculation

Average annual crop gross margins are computed by cropland pixel, climate scenario and crop management practice. We use the simulated average annual DM crop yields and respective commodity prices from Statistics Austria averaged over the period 2010-2012. Variable production costs (including costs of seeds, fertilizers, fuel, pesticides, electricity, repair, insurances, and labour) are based on reported levels from the past. Additionally, we consider annualized capital costs for irrigation equipment (see HEUMESSER et al., 2012), and agricultural policies such as a uniform decoupled payment of 290 €/ha and agri-environmental payments for reduced fertilizer input (i.e. 'moderate' intensity in EPIC; 50 €/ha) and the abandonment of mineral nitrogen fertilizer (i.e. 'low' intensity in EPIC; 115 €/ha). Commodity prices, variable production costs, annual capital costs of irrigation equipment, and policy payments are kept constant for all climate scenarios in order to disentangle drought impacts from price, market, and policy effects.

2.4 Portfolio optimization model

The simulated DM crop yields and the calculated crop gross margins serve as input into a non-linear mean-standard deviation model (similar to mean-variance model; MARKOWITZ, 1952). The model seeks to find optimal crop production portfolios for the 31 years period 2010-2040 for each cropland pixel, climate scenario, and farmers' level of risk aversion. It maximizes the weighted sum of expected crop gross margins discounted by the standard deviation using a risk aversion parameter value (θ). We successively raise θ in the objective function to show the effect of risk neutrality (θ=0.0) and increasing levels of risk aversion – from low (θ=1.0) to moderate (θ=2.0) and high risk aversion (θ=2.5) – on crop production portfolios (see MITTER et al., 2015).

2.5 Computing the value of drought prediction for adaptation

The value of drought prediction is calculated as the net-benefit of adapting crop production portfolios to dry climates. It is calculated in three steps. First, we compute the optimal crop production portfolios in S1–S3 for each level of risk aversion. Second, we use the optimal crop production portfolios realized in the baseline climate scenario S1 to quantify average annual DM crop yields and gross margins that could be achieved in the climates of S2 and S3 assuming that drought prediction is not available. Third, we compute the differences in mean gross margins *(ΔMeanGM)* and corresponding standard deviations *(ΔStdGM)* between optimal crop production portfolios in S2/S3 and optimal crop production portfolios in S1 evaluated in S2/S3. Therefore, the value of drought prediction is calculated according to Equation 1:

$$VoI_{i,s} = \Delta MeanGM_{i,s} - \theta * \Delta StdGM_{i,s} \qquad \forall\, i,s \qquad (1)$$

where *VoI* is the average annual value of drought prediction in €/ha, *ΔMeanGM* and *ΔStdGM* are the differences in mean annual gross margins and standard deviations between optimal crop production portfolios in S2/S3 and optimal crop production portfolios in S1 evaluated in S2/S3, and θ is the risk aversion parameter. The index i

represents cropland pixels in Austria (I = 40,244), and *s* the climate scenarios S2 and S3. According to Equation 1, the value of drought prediction takes on values ≥ 0.

3. Results

3.1 Impact of climate scenarios on crop production

The impact of climatic droughts on crop production is shown in Table 1. Simulated average annual DM crop yields at 1 km pixel level are aggregated to the Austrian cropland and averaged over crops and the period 2010-2040. At national level, average annual DM crop yields change moderately in S2 (between -2.8% and +3.5%) and S3 (-6.9% and +6.9%), compared to S1. Highest average declines in crop production are simulated for high fertilization intensity on rain-fed agriculture. Average increases are achievable if irrigation is considered – either in combination with high or moderate fertilization intensity – indicating that crop yields respond to higher temperatures and elevated atmospheric CO_2 concentrations if water is not a limiting factor.

Changes in average crop yields vary between crops and regions due to differences in agronomic, topographic, and drought conditions. For instance, rain-fed cropping in S3 can lead to crop yield losses of 30% or more in the semi-arid eastern parts of Austria and gains of 10% or more in the mountainous western parts of the country, compared to S1. The Pearson correlation coefficient of -0.8 indicates a strong negative relationship between water stress days and crop yield changes.

Tab. 1: Average annual dry matter crop yields in t/ha and standard deviations (in brackets) by climate scenarios and crop management practices at national level

	rain-fed			irrigated	
Scenario	**high**	**moderate**	**low**	**high**	**moderate**
S1	8.1 (3.3)	7.4 (2.9)	6.1 (2.6)	8.5 (3.2)	7.8 (2.9)
S2	7.9 (3.6)	7.3 (3.2)	6.0 (2.8)	8.7 (3.3)	8.0 (3.1)
S3	7.6 (3.7)	7.0 (3.3)	5.9 (2.9)	9.0 (3.4)	8.3 (3.3)

Note: Calculations are based on EPIC outputs for rain-fed and irrigated cropland and high, moderate, and low intensities (fertilization *and* irrigation, respectively). Results are rounded to one decimal figure.

Source: OWN CALCULATIONS

3.2 Optimal crop production portfolios for climate scenarios

Optimal crop production portfolios are determined in order to reveal management strategies to effectively cope with and adapt to climatic droughts. Such portfolios are identified for each climate scenario and four levels of risk aversion. Under risk neutrality, we find that moderate (50% in S1 and 46% in S2) and high fertilization intensity on rain-fed cropland (31% in S1 and 24% in S2) are most frequently chosen in crop management portfolios in S1 and S2. Moderate fertilization intensity on irrigated cropland is gaining in importance under dry conditions and reaches a share of 18% in S3. With increasing risk aversion, we find an increase in portfolios including low fertilization intensity (rain-fed) or irrigation (in combination with high or moderate fertilization intensity) either as single management strategy or in combination with others. However, it appears that changes in drought conditions rather than risk aversion will influence the adoption of irrigation in the next decades. Portfolio diversification seems to reduce drought risks in crop production. As expected, diversification increases with risk aversion and in the more extreme climatic droughts, i.e. S3.
Figure 2 shows average annual DM crop yields and gross margins that can be obtained with optimal crop production choices. Crop yields remain almost stable regardless of the risk aversion level and the climate scenario indicating the effectiveness of diversification and

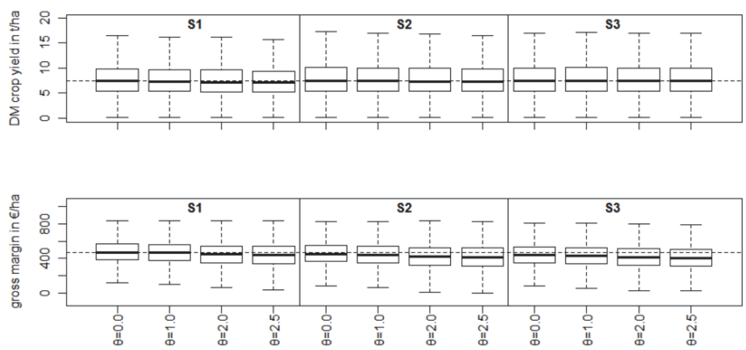

Fig. 2: Average annual dry matter crop yields in t/ha and gross margins in €/ha by climate scenarios and levels of risk aversion at national level

Note: Boxplots are based on portfolio model outputs. Outliers are not presented.

Source: OWN ILLUSTRATION

irrigation as drought adaptation measures. However, average annual gross margins decrease under more extreme drought conditions. This is mainly because of higher costs for irrigation (i.e. irrigation equipment) which is chosen more often in S2 and S3, compared to S1.

3.3 Value of drought prediction in crop management adaptation

Average annual values of drought prediction are presented in *table 2* for four levels of risk aversion and climate scenarios S2 and S3. The results indicate that higher risk aversion and more extreme climatic droughts increase the value of drought prediction. Again, the results differ by cropland regions. The highest values of drought prediction are found in the semi-arid eastern parts of Austria (200 €/ha and more) whereas values of 50 €/ha or less are clustered in the mountainous western parts. Cropland pixels with a value of drought prediction of 0 €/ha are typically found in the west, mainly under risk neutrality and low risk aversion. In such pixels, crop production portfolios are identified to be robust, i.e. they stay the same with or without drought.

Tab. 2: Average annual value of drought prediction in €/ha by climate scenarios and levels of risk aversion (RA) at national level

Scenario	θ=0.0 risk neutral	θ=1.0 low RA	θ=2.0 moderate RA	θ=2.5 high RA
S2	20	35	49	55
S3	60	76	93	102

Note: θ = RAP = risk aversion parameter value
Source: OWN CALCULATIONS

4. Discussion and conclusions

Climatic droughts may increase production risks for farmers in Austria and beyond. Information exchange on the likely impact of droughts on crop production and effective adaptation measures may facilitate decision making and enhance adaptation efforts. The economic value of such information reflects the opportunity costs of not having this information available to adapt crop production choices. Our spatially explicit, integrated drought assessment framework reveals regional vulnerabilities in crop production, identifies optimal crop production portfolios for adaptation, and quantifies the value of drought prediction. The effect of risk aversion on the composition of crop production portfolios is taken into account as well.

Diversification and irrigation appear as potentially useful to cope with droughts in the next decades though investment in irrigation equipment and water governance structures would be required. Extensification seems to be an effective adaptation strategy for risk-averse farmers. These insights are supported by other integrated modeling studies showing that nitrogen input may increase and irrigation may decrease crop yield variability (FINGER et al., 2011). However, high risk aversion generally results in lower average gross margins which conforms to portfolio theory and empirical findings (see e.g. BEZABIH and SARR, 2012). The average annual value of drought prediction is found to be highest in the semi-arid eastern parts of Austria where cropland is the dominating land cover. Furthermore, it increases with the level of risk aversion. Since some empirical studies evince that farmers' risk aversion rises under climate change (e.g. BEZABIH and SARR, 2012), the value of drought prediction might gain in importance in the next decades.

However, our analysis has limitations and some aspects are planned to be considered in the next step. This may include the integration of additional adaptation measures (e.g. crop rotations) which would allow for more flexibility in crop management choices in the portfolio optimization model. Furthermore, the investigation could benefit from identifying changes in irrigation water demand and introducing a water price or more water efficient irrigation systems such as drip irrigation. Comparing the water demand to available groundwater resources and recharge would enable us to identify regions where groundwater limitations could constrain irrigation activities and drinking water supply leading to higher values of drought prediction. Such spatially explicit results may be of interest for different stakeholder groups such as farmers, policy makers, and water management authorities.

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References

BEZABIH, M. and SARR, M. (2012): Risk Preferences and Environmental Uncertainty: Implications for Crop Diversification Decisions in Ethiopia. Environmental Resource Economics, 53, 483-505.

DAI, A. (2013): Increasing drought under global warming in observations and models. Nature Climate Change, 3, 52-58.

DENG, M., DI, L., HAN, W. et al. (2013): Web-service-based Monitoring and Analysis of Global Agricultural Drought. Photogrammetric Engineering & Remote Sensing, 79, 929–943.

EITZINGER, J. (2014): AgroDroughtAustria. Trockenheitsmonitoringssystem für die Landwirtschaft Österreichs. In: Klima- und Energiefonds (Ed.): Austrian Climate Research Programme in Essence. Wien, 12-17.

FINGER, R., HEDIGER, W. and SCHMID, S. (2011): Irrigation as adaptation strategy to climate change – a biophysical and economic appraisal for Swiss maize production. Climatic Change, 105, 509-528.

HEUMESSER, C., FUSS, S., SZOLGAYOVÁ, J. et al. (2012): Investment in Irrigation Systems under Precipitation Uncertainty. Water Resource Management, 26, 3113-3137.

HORION, S., CARRÃO, H., SINGLETON, A. et al. (2012): JRC experience on the development of Drought Information Systems. Europe, Africa and Latin America. Luxembourg: Publications Office of the European Union, JRC68769.

MARKOWITZ, H. (1952): Portfolio Selection*. The Journal of Finance, 7, 7791.

MITTER, H., HEUMESSER, C. and SCHMID, E. (2015): Spatial modeling of robust crop production portfolios to assess agricultural vulnerability and adaptation to climate change. Land Use Policy, 46, 75-90.

SCHÖNHART, M., SCHMID, E. and SCHNEIDER, U. A. (2011): CropRota – A crop rotation model to support integrated land use assessments. European Journal of Agronomy, 34, 263–277.

STRAUSS, F., MOLTCHANOVA, E. and SCHMID, E. (2013): Spatially Explicit Modeling of Long-Term Drought Impacts on Crop Production in Austria. American Journal of Climate Change, 2, 1-11.

WILLIAMS, J. R. (1995): The EPIC Model. In: Computer Models of Watershed Hydrology, Water Resources Publications. Singh V.P., 909-1000.

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