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Assessing the propagation of uncertainties in multi-objective optimization for agro-ecosystem adaptation to climate change

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ABSTRACT

It is widely acknowledged that uncertainty needs to be accounted for in climate impact studies, be it in scenario analyses or optimization applications. In this study we investigate how climate and crop model uncertainties affect multi-objective optimization outputs aiming to identify optimum agricultural management adaptations for Western Switzerland. Results are visualized by ternary plots that map optimum management measures, crop yield, erosion and leaching with associated uncertainties for navigating through the optimum adaptation space. We find that the relevance of climate model vs. parameter uncertainty can differ substantially depending on the prioritization of objectives and local conditions. The optimum choice of irrigation level was found to be the decision variable subject to greatest uncertainty particularly on coarser soil. This finding suggests that for the long-term planning of irrigation infrastructure and management, a robust adaptation approach is required for approaching unavoidable uncertainty from a risk management perspective.

1. Introduction

With climate change, shifts in the conditions for agricultural production are expected (Olesen and Bindi, 2002; Ewert et al., 2005; Jaggard et al., 2010; Gornall et al., 2010). Adaptation measures are required to prevent negative impacts and to exploit emerging new potentials (Salinger et al., 2000; Falloon and Betts, 2010; Jarvis et al., 2011; Olesen et al., 2011). For the planning of such measures, possible impacts of uncertain future climate conditions must be anticipated. The scope for adaptation has mostly been investigated in model-based scenario analyses by testing impacts of climate change with or without different adaptation possibilities (e.g. Cho et al., 2012; Osborne et al., 2013). Alternative approaches such as the one by Klein et al. (2013) and Lehmann and Finger (2014) use optimization in combination with biophysical simulation models to identify most effective combinations of adaptation measures. These approaches have shown potential to inform the planning of agricultural adaptation strategies since they provide the advantage of systematically searching through a large space of possible combinations of adaptation options.

It is widely acknowledged that uncertainty (e.g. in model inputs, parameters and model structure of climate and impact models) needs to be accounted for in impact studies for decision support (Uusitalo et al., 2015). This is usually done by using model ensembles including multiple climate scenarios (i.e. projections from different models and for different emission scenarios), crop models, or crop model parameter sets (e.g. Challinor and Wheeler, 2008; Ruiz-Ramos and Minguez, 2010; Ceglar and Kajfez-Bogataj, 2012; Gouache et al., 2013; Hoffmann and Rath, 2013). For studies that aim to identify optimum adaptation strategies, the consideration of uncertainty is as important, but evermore challenging given the increased computational effort involved in optimization as opposed to scenario-based studies. Jakoby et al. (2014) applied a multi-objective optimization to identify robust optimum rangeland management strategies with respect to a series of synthetic climate scenarios. Klein et al. (2013) accounted for uncertainty in climate projections in a multi-criteria optimization approach and identified robust optimum management adaptations with regard to a worst case climate projection. Similar approaches of robust optimization have been applied in other contexts such as the evaluation of agricultural innovation (Doole, 2012), irrigation planning (Crespo et al., 2010; Dai and Li, 2013; Sabouni and Mardani, 2013), for scheduling grape harvesting (Bohle et al., 2010) or for water supply management (Chung et al., 2009; Kasprzky et al., 2013).

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However, to our knowledge the propagation of different sources of uncertainty from model simulations to optimization results has not been investigated so far. Simulation model uncertainty affects the multi-objective optimization results in terms of (i) estimates of the multiple objective values in the objective space and (ii) the set of decision variables that are selected as optimum from the decision space. The objective space is defined here as the space of possible objective values given different prioritizations of the objectives included in the goal function, while the decision space is the corresponding space of possible decision variables. In multi-objective decision problems – which are common in the context of environmental management – different sources of uncertainty may have different effects on optimization results (objective and decision variables) depending on the location within the Pareto-frontier. A Pareto-frontier consists of a set of optimum solutions to a multi-objective optimization problem, where the performance with regard to one objective cannot be improved without reducing the performance of another objective. In a regional context, the effects of uncertainties on impact estimates can differ further depending on local conditions and on the choice of management.

For the planning of adaptation measures, it is not only important to quantify uncertainty in impact estimates, but it can be of even greater value to identify the conditions under which uncertainty has the largest impacts on the selection of decision options for optimum adaptation, since these are the conditions under which the identification of robust measures and maintenance of adaptive capacity is most relevant (Ascough et al., 2008).

We therefore investigate the following question in a case study application: *How does uncertainty in model simulations propagate to uncertainty in the Pareto-optimal objective and decision spaces of multi-objective optimization results?*

2. Study area & data

The question is investigated in a region in Western Switzerland around the city of Payerne, where arable farming plays an important role with the major crops being winter wheat (~30%), silage/grain maize (~15%), winter barley (~9%), sugar beet (~7%), winter rapeseed (~5%), and potato (~5%) (FOAG, 2011). Irrigation is common practice for potato, sugar beet and maize and the demand for irrigation is expected to increase with climate change (Klein et al., 2013). At the same time water availability from the Broye river – the major source of irrigation water in the region – is expected to decrease (Fuhrer and Jasper, 2012). Trade-offs between agricultural functions (i.e. productivity, soil protection and groundwater protection) have been identified in this region and are likely to aggravate with climate change (Klein et al., 2013). Legal restrictions may be applied to avoid the overuse of water in the future, for example by introducing water quotas (Lehmann and Finger, 2014).

Soil information for the study region was derived from the Soil Suitability Map of Switzerland (1:200.000; BFS, 2012) and adjusted according to soil profile information from the Swiss Soil Monitoring Network (BUWAL, 2003). We consider sandy loam (65% sand, 25% silt, 10% clay) and loam (40% sand, 40% silt, 20% clay), which are two most common soil types in this region according to these data sources.

To represent climate model uncertainty, climate change signals were extracted for climate projections from two different GCM-RCM model chains (HadCM3Q0-CLM, HadCM3Q3-RCA assuming emission scenario A1B) applied within the ENSEMBLES project (Hewitt, 2005) for the time horizon 2036–2065. The stochastic weather generator LARS-WG (Semenov and Barrow, 1997) was applied to downscale these climate change signals to the location of the meteorological station Payerne. LARS-WG was first trained based on observed daily data for the period 1981–2010 (MeteoSwiss). In a second step the statistical properties derived from observed data were modified according to the extracted climate change signals to generate 20 individual years of synthetic daily weather data for each of the two climate projections. According to the two institutions operating the climate model chains, our two projections are named ETHZ (HadCM3Q0-CLM) and SMH (HadCM3Q3-RCA) hereafter. They cover approximately the upper and lower limits of temperature and precipitation changes projected for the study region in CH 2011 (2011) for the time horizon 2045–2075 under the A1B scenario.

3. Methods

3.1. Approach

In a first step, the crop model CropSyst (Stöckle et al., 2003) is applied to simulate climate impacts on yields, soil loss and nutrient leaching based on ten parameter sets representing crop model parameter uncertainty (Fig. 1). This simulation experiment follows a balanced factorial design, where impacts are simulated for all combinations of parameter sets, climate projections, management options and site conditions (i.e. soil types). Variance partitioning of simulated results is applied to identify contributions of climate model and impact model parameter uncertainty in relation to effects of management and soil conditions. This first step allows to identify effects of uncertainty in climate projections and crop model parameters on impact estimates in relation to management and site effects.

Based on the simulation results, in the second step, a multi-objective optimization is applied to identify optimum combinations of management decisions for each climate projection, parameter set and soil type. The full space of possible optimization solutions is estimated by applying systematically varying combinations of weights to the three objectives (productivity maximization, erosion minimization and leaching minimization) given a constraint on water consumption for irrigation. Since the model system is strongly nonlinear, it can be expected that effects of model uncertainty on optimization outputs differ depending on the prioritization of different optimization objectives. Standard deviations estimated over the 20 optimization runs (2 climate projections × 10 parameter sets) represent uncertainty in optimization outputs. Variance partitioning of optimization outcomes for all considered weight combinations reveals how robust the optimization results are with respect to climate model and impact model parameter uncertainty, depending on the choice of weights and site conditions (= uncertainty partitioning).

3.2. Impact model setup

We apply the generic crop model CropSyst (Stöckle et al., 2003) to simulate effects of climate, agricultural management and site conditions on yields, soil loss and nutrient leaching. Ten model parameter sets are generated based on different realizations of the automated stochastic calibration procedure for the main arable crops winter wheat, winter barley, winter rapeseed, sugar beet, grain maize and potato (Klein et al., 2012). In a first step of this procedure, a parameter screening identifies most sensitive crop parameters and in a second step these parameters are automatically adjusted within a predefined range of realistic values until simulation model performance converges (performance measures achieved with the calibrations are shown in Table 1). Willmott index of agreement (Willmott, 1981) is used as the performance measure for the automated calibration since it accounts for differences in modeled and observed means and variances and also considers the model's ability to preserve the data pattern within yield time series, which is a particularly relevant feature for crop models (Bennett et al., 2013). Visual inspection of simulated and observed yield time series and additional performance measures were used to check calibration results for over-/underestimation (bias) and mean deviation (Root Mean Square Error, RMSE). Since the calibration procedure is stochastic, it generates different parameter sets with similar performances with each repeated application. The 10 parameter sets, thus, represent crop model parameter uncertainty originating from model equifinality.

Eight different 5-year crop rotations were defined, which are set up by six crops to capture the effects of crop rotation choice on the variability of yields, erosion and leaching. The order of crops in the rotations was sampled randomly and only accepted if the rotation was feasible in terms of recommended maximum crop shares and pre-crop suitability described in Vullioud (2005). A cover crop was added to a crop rotation if harvest occurred before August, 31st and the following crop was not a winter crop. For each rotation different management possibilities were applicable as summarized in Table 2.

3.3. Model simulations and variance partitioning

Given the two different climate projections, 8 rotations with 10 parameter sets, two irrigation options, three fertilization options, and two tillage options on two soil types (sandy loam, loam), 3840 combinations are possible ($2*8*10*2*3*2*2 = 3840$). CropSyst was set up as described in Klein et al. (2014) and run for all these combinations of model inputs over 20 years and outputs on annual yields, soil loss, erosion and water consumption for irrigation were stored. All simulated outputs