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Assessing climate change and associated socio-economic scenarios for arable farming in the Netherlands: An application of benchmarking and bio-economic farm modelling

A. Kanellopoulos*, P. Reidsma, J. Wolf, M.K. van Ittersum

Plant Production Systems Group, Wageningen University, P.O. Box 430, 6700 AK Wageningen, The Netherlands

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ABSTRACT

Future farming systems are challenged to adapt to the changing socio-economic and bio-physical environment in order to remain competitive and to meet the increasing requirements for food and fibres. The scientific challenge is to evaluate the consequences of predefined scenarios, identify current "best" practices and explore future adaptation strategies at farm level. The objective of this article is to assess the impact of different climate change and socio-economic scenarios on arable farming systems in Flevoland (the Netherlands) and to explore possible adaptation strategies. Data Envelopment Analysis was used to identify these current "best" practices while bio-economic modelling was used to calculate a number of important economic and environmental indicators in scenarios for 2050. Relative differences between yields with and without climate change and technological change were simulated with a crop bio-physical model and used as a correction factors for the observed crop yields of current "best" practices. We demonstrated the capacity of the proposed methodology to explore multiple scenarios by analysing the importance of drivers of change, while accounting for variation between individual farms. It was found that farmers in Flevoland are in general technically efficient and a substantial share of the arable land is currently under profit maximization. We found that climate change increased productivity in all tested scenarios. However, the effects of different socio-economic scenarios (globalized and regionalized economies) on the economic and environmental performance of the farms were variable. Scenarios of a globalized economy where the prices of outputs were simulated to increase substantially might result in increased average gross margin and lower average (per ha) applications of crop protection and fertilizers. However, the effects might differ between different farm types. It was found that, the abolishment of sugar beet quota and changes of future prices of agricultural inputs and outputs in such socio-economic scenario (i.e. globalized economy) caused a decrease in gross margins of smaller (in terms of economic size) farms, while gross margin of larger farms increased. In scenarios where more regionalized economies and a moderate climate change are assumed, the future price ratios between inputs and outputs are shown to be the key factors for the viability of arable farms in our simulations.

1. Introduction

Interrelated changes of climate, market and agro-environmental policies affect agricultural production all over the world (O'Brien and Leichenko, 2000; Lobell et al., 2008; Van Ittersum et al., 2008; Giller et al., 2011; Schneider et al., 2011; Ray et al., 2013). Future farming systems are challenged to adapt to the changing socio-economic and bio-physical environment in order to remain competitive and to meet the increasing requirements for food and fibre. To deal with the uncertainty related to how climate, markets and technology will change, research focused on developing integrated scenarios to provide images of the world in the future (Westhoek et al., 2006; Abildtrup et al., 2006; Riedijk et al., 2007; Van Drunen and Berkhout, 2008). Issues such as rise of temperature, changes in precipitation patterns, rise of sea level, the state of international cooperation and the role of public and private sector in future economies have been taken into account. This enables the quantification of important economic and environmental indicators at macro-level and the definition of comprehensive story lines of future development in agriculture and food production (Audsley et al., 2006; Riedijk et al., 2007). The consequences of these global and regional scenarios on farm structure have been assessed based on historical analysis of driver-impact relationships (Mandryk et al., 2012b). However, detailed quantitative, analysis at farm level, which will improve understanding of farm level

* Corresponding author. Tel.: +31 317482141; fax: +31 621905219.
E-mail addresses: Argyris.Kanellopoulos@wur.nl, Argyris.Kanellopoulos@gmail.com (A. Kanellopoulos).

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adaptation, is still a challenge (Reidsma et al., 2010). With regard to climate change adaptation, the focus has mainly been on adapting crop management to increase or maintain yields at field level (Easterling et al., 2007). Nevertheless, at farm level, other options such as adjusting specialization (e.g. land use, livestock types) and changing level of diversification and scale of production might be better adaptation measures (Reidsma et al., 2009). To assess the effectiveness and adoption of such adaptations at farm level, integrated analysis of changes in the climate and the socio-economic context is required.

Bio-economic farm modelling (Janssen and van Ittersum, 2007), can be used to evaluate different adaptation options and to reveal the consequences of climatic, socio-economic, technological and institutional (policy) changes. The available set of production activities is identified and the relationship between agricultural inputs and outputs is quantified. Economic criteria are used to simulate the farmer's behaviour. In many cases, bio-economic studies assume that the relationship between agricultural inputs and outputs is linear and independent of the scale of production (Louhichi et al., 2010). Moreover, spatial and temporal interactions (e.g. rotational effects), between different activities are ignored and complementarity and substitution between different agricultural inputs and outputs are not taken into account. Availability of capital is not taken into account as a constraint. To account for variation between farms, and for temporal and spatial interactions between the outputs of agricultural activities, individual farm data and benchmarking techniques like Data Envelopment Analysis (DEA) (Cooper et al., 2007) has been used in agriculture and agricultural economics. For example, DEA was proposed by De Koeijer et al. (2002) to measure environmental and economic sustainability of Dutch sugar beet farmers. Fraser and Cordina (1999) used DEA to analyze productivity of dairy farms in Australia. Novo et al. (2013) measured productivity of family dairy farmers in Brazil. Piot-Lepetit et al. (1997) used DEA to measure the potential of reducing agricultural inputs in French agriculture while Latruffe et al. (2005) assessed technical and scale efficiency and make comparisons between crop and livestock farms in Poland.

The objective of this article is to assess the impact of climate change and associated socio-economic scenarios on arable farming systems in Flevoland (the Netherlands) and to explore different adaptation strategies at farm level. To this end we developed an integrated method in which we applied DEA (Cooper et al., 2007) using empirical data from individual farms to identify "best" current farm practices and derive the input–output relationships of current farm management. A bio-economic farm model was used to optimize the production plan of individual farmers and explore the impact of scenarios for 2050. By using DEA to quantify the input–output relationship of the bio-economic farm model we account implicitly for existing non-linearities in production and temporal and spatial interactions between crops and managements. Impacts of gradual climate change on crop yields, the effects of technological change (i.e. new crop varieties) but also expected price and policy changes were taken into account. We specifically focus on comparing the impact of different drivers, so we first demonstrate the applicability of the proposed methodology by simulating multiple integrated scenarios. Then we zoom in and discuss in detail the results from one of the evaluated scenarios that assumes strong temperature rise within a globalized economy (Riedijk et al., 2007).

2. Methods

2.1. Analysis of farm productivity with DEA

Data Envelopment Analysis (DEA) can be used to rank and benchmark farms according to their capacity to convert multiple inputs (e.g. capital, labour, land, fertilizers, agro-chemicals) into multiple outputs (e.g. potatoes, sugar beet, vegetables). Farms are technically efficient when the use of inputs cannot be decreased or production of outputs cannot be increased without decreasing outputs or increasing inputs respectively (Cooper et al., 2007, p. 3). A production frontier is developed by technical efficient farms while inefficient farms are enveloped by this frontier. The DEA frontier provides information about the maximum amount of outputs that can be achieved with different input levels.

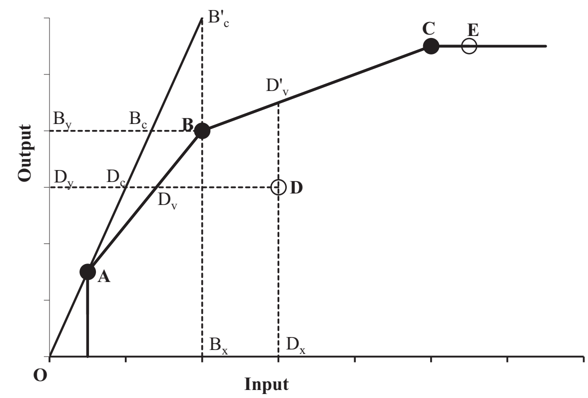

Fig. 1. Graphical representation of a simple (one input–one output) DEA problem.

A simplified DEA example that involves one input to produce one output is presented in Fig. 1. Farms A, B, C, D and E are ranked with respect to their capacity to convert one input into one output. In the case of variable returns to scale (VRS) i.e. the effect of a marginal increase in inputs results in a different increase in outputs depending on the scale of production, farms A, B, C and E are located on the frontier and they are technically efficient (i.e. it is not possible to decrease the input or increase the output without decreasing outputs or increasing inputs respectively). Farm D is enveloped by the frontier and it is technically inefficient. Point D_v is a linear combination of A and B and creates the same output as point D, but uses less input. Point D_v is the input-oriented technically efficient alternative of D. Point D can also be projected onto the frontier by expanding output and holding inputs constant (as reflected by point D'_v which is a combination of B and C). Point D'_v is the output-oriented alternative of point D. The input-oriented efficiency score of D is calculated as $\theta = D_yD_v/D_yD$ while the output-oriented efficiency score is calculated as $\varphi = D_xD_v/D_xD'_v$. The farms A, B and C are fully efficient and have input and output-oriented efficiency scores of 1. Although the output-oriented efficiency score of farm E is equal to 1, it can be seen from the figure that the same output can be produced from a smaller quantity of input. In this example, farm E is weakly efficient.

Under the assumption that productivity is constant and independent of the scale of production i.e. constant returns to scale (CRS) only farm A is technically efficient. The CRS frontier is the line that goes through points O, A and B'_c. The CRS input-oriented efficiency score of B is calculated as B_yB_c/B_yB while the output-oriented efficiency score is calculated as $B_xB/B_xB'_c$. Farm A is technically efficient under both VRS and CRS and for that reason is characterized as scale efficient. Scale efficiency can be calculated as the technical efficiency score of a farm under CRS divided by the technical efficiency score under VRS (Coelli, 2008).

In a more realistic case that involves multiple inputs and outputs a graphical presentation of DEA is not possible. Two Linear Programming (LP) models can be used to calculate the input-oriented (model 1) and output-oriented (model 2) scores of technical efficiency of each farm, respectively. Models 1 and 2 allow for the existence of variable return to scales. By omitting the constraints