An Economic and Environmental Assessment of a Glyphosate Ban for the Example of Maize Production

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Abstract:

The effects of a glyphosate ban on cultivation of silage maize are simulated using a spatially explicit bio-economic model that accounts for different pre- and post-sowing weed control strategies and production risks. We analyse the effects of a glyphosate ban on farmers' choices of field-level weed control strategies. These strategies are evaluated in two environmental dimensions. More specifically, we consider a pesticide load indicator to assess environmental toxicity, fate and human health effects as well as the energy demand of the agricultural system. We find that a glyphosate ban leads to a significant reduction of the pesticide load of silage maize production. However, a glyphosate ban also leads to somewhat higher energy consumption.

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Keywords: Herbicide, glyphosate, silage maize, output damage control, risk, pesticide load, process analysis

1. Introduction

The relicensing of glyphosate in European agriculture received massive societal and political attention in the years 2016 and 2017. Those advocating a ban used as arguments potential social costs in the form of human health risks (e.g. Guyton et al., 2015) and of environmental effects, for instance on biodiversity with regard to a decline in fodder plants for butterflies or with regard to accumulation of metabolites (e.g. Brower, 2012; Helander et al., 2012). In contrast, arguments for the continued use of glyphosate mainly relate to its private and social economic benefits and potential trade-offs for the environment and human health if glyphosate is substituted with other forms of weed control (see e.g. Duke and Powles, 2008; and Dietrich et al., 2016). Despite the fact that glyphosate was relicensed by the European Commission for five additional years in the end of 2017, the debate will continue. For example, there are on-going discussions on bans at the national, regional or even municipality level. In addition to the political debate, we observe that private actors take action and demand glyphosate-free products from suppliers.[1] These current debates on banning glyphosate or voluntary waiver solutions at private levels lack scientific information on trade-offs between different goals with respect to environmental, human health and economic implications.

[1] For example, some German and Austrian dairies decided that producers are not allowed to apply glyphosate anymore, and also in Switzerland, the integrated production organisation IP Suisse announced an internal ban of glyphosate on crops marketed under their label.

We aim to contribute to a more informed debate by focusing on key agronomic and economic aspects of a glyphosate ban in a state wide case study for a major crop based on a highly detailed bio-economic simulation model. More specifically, we test for the following potential negative consequences of a glyphosate ban: i) yield losses (Schulte et al., 2017), ii) a higher tillage intensity that leads to higher diesel consumption (Kehlenbeck et al., 2015) and iii) an increased use of post-emergence herbicides that have a higher toxicity to non-target organisms than glyphosate (Schulte et al., 2017). Our paper fills a gap in literature as so far limited scientific evidence on the consequences of a possible glyphosate ban is available (cf. Schulte and Theuvsen, 2015). More specifically, we contribute by quantifying optimal alternative weed control strategies (including mechanical and chemical pre- and post-sowing strategies) under a glyphosate ban, considering production risk and farmers' risk preferences. Those private choices are then assessed from a societal point of view with regard to adverse human health and environmental effects of pesticide applications as well as with regard to energy consumption.

As real world observations of weed control under a glyphosate ban are not available, we employ a normative modelling approach based on damage abatement functions (Karagiannis and Tzouvelekas, 2012), extending the model by Böcker et al. (2017a) that offers a highly detailed representation of weed pressure and potential weed control strategies. The model is applied to silage maize cultivation in the federal state of North-Rhine-Westphalia (NRW), Germany. In this region, silage maize is an important crop and used both for cattle feeding and for biogas production (Information und Technik Nordrhein-Westfalen, 2016). We extend the analysis by Böcker et al. (2017a) in three directions. First, we add information on adverse human health and environmental effects of the considered weed control strategies, using the Pesticide Load Indicator (PLI) developed by the Danish Environmental Ministry (*Miljøministeriet*). Second, we quantify process energy demand for these strategies accounting for all physical material flows. Thus, two dimensions for social costs are included in the model, pesticide load and energy consumption, driven by private economic decisions of farmers. Third, we implement risk and risk aversion into the model by combining spatially explicit distributions of yields and weed pressure.

2. Methodology

The model presented here is an extension of the model by Böcker *et al*. (2017a).[2] Its core consists of an output damage control approach applied to each of the close to 380 silage maize-producing regional units of NRW, $m = 1, \ldots, M$, and each year t. Thus, we differentiate weed pressure and weed control across space and time.

[2] Detailed model documentation along with its GAMS code related to the model of Böcker et al. (2017a) is provided online in Böcker et al. (2017b).

2.1. Modelling approach

The objective function of the model maximises farmers' private expected utility based on gross margins from silage maize production. Accounting for different pre- (index g) and post-sowing (index h) weed control strategies, the expected gross margin is defined as:

$$E(\pi) = [E(y) \cdot P - c(g) - c_s(b) - c(h) - c_c(y) - c_o], \tag{1}$$

where, $E(y)$ is the expected yield, P is the silage maize price, $c(g)$ and $c(h)$ the pre- and post-sowing weed control (and tillage) costs. $c_s(g)$ are costs for sowing depending on the pre-sowing weed control strategy, $c_c(y)$ are yield dependent costs for fertiliser, harvest, transport and ensiling, and c_o are other cost. The expected yield $E(y)$ depends on an output damage control approach where weed control strategies decrease damage compared to the yield distribution possible without weed pressure (Böcker et al., 2017a; Lichtenberg and Zilberman, 1986). The production function focussed on the production effects of weed control is defined as follows:

$$E(y_{m,t,\chi,g,h}) = \underbrace{\left(1 - e^{-(\alpha_0+\alpha_1\cdot v_{m,j})^2}\right)}_{\text{Pre-sowing}} \cdot \underbrace{E(y^a_{m,\chi})}_{\text{Attainable yield}} \cdot \underbrace{\left[1 - I \cdot \frac{e^{-(\beta_0+\beta_1\cdot z_{m,j})^2}}{100 \cdot \left(e^{C\cdot\Psi_{m,t}} + I \cdot \frac{e^{-(\beta_0+\beta_1\cdot z_{m,j})^2}}{A}\right)}\right]}_{\text{Post-sowing}} \tag{2}$$

The first part accounts for the pre-sowing weed control activities, $y^a_{m,\chi}$ is the expected attainable yield distribution for a regional unit and the third part accounts for the post-sowing weed control. $e^{-(\beta_0+\beta_1\cdot z_{m,j})^2}$ is the yield loss based on different control strategies (denoted further as D), I is the per cent yield loss as D approaches 0, A is the per cent yield loss as D approaches infinity, Ψ is the time of weed emergence in relation to the crop emergence (in growing degree days; this measure can be seen as an expression for the overall weed pressure in a certain year t) and C is the rate at which the yield loss I decreases as Ψ becomes larger.

We introduce risk in our model using two components, i.e. by accounting for stochastic attainable yield and weed pressure. The weed pressure Ψ in a certain year t can be observed by the farmer such that the chosen weed control is state contingent. However, the attainable yield in each year χ is assumed to be stochastic, e.g. due to stochastic weather conditions that are independent of weed pressure and weed control (e.g. Tembo et al., 2008). This yield variability is captured by an empirical yield distribution quantified for each regional unit m. The further parameters in the production function are $v_{m,j}$ and $z_{m,j}$, the pre- and post-sowing weed control effects, i.e.:

$$v_{m,j} = \sum_{i}^{I} w_{m,i} \cdot a_i \cdot g_{j,i}$$

$$z_{m,j} = \sum_{i}^{I} w_{m,i} \cdot a_i \cdot h_{j,i} \tag{3}$$

where $w_{m,i}$ is the probability that a weed i occurs in each regional unit m. a_i is the average abundance if a weed is not controlled and acts as a measure for its yield reducing effect, whereas $g = 1, \dots, G$ and $h = 1, \dots, H$ are the efficacies of the different weed control strategies j against each weed i [0,1].

The share of the pre- and post-sowing weed control strategies, i.e. $S_{g,m,t}$ and $S_{h,m,t}$ (Eq. 4), are the decisions variables. Additionally, a vector $\varphi_{g,glyphosate}$ contains either 0 or 1 reflecting scenarios whether glyphosate is licensed or not:

$$\pi_{m,t,\chi} = \sum_{g=1}^{G} \sum_{h=1}^{H} \pi_{m,t,\chi,g,h} \cdot S_{g,m,t} \cdot \varphi_{g,glyphosate} \cdot S_{h,m,t} \ , \qquad S_{g,m,t}, S_{h,m,t}, \varphi_{g,glyphosate} \in \mathbb{R} = [0,1] \tag{4}$$

Farmers face several uncertainties when deciding upon an optimal weed control strategy (e.g. Auld et al. (1987): i) the level of weed infestation, ii) the effectiveness of the weed control strategy, iii) prices, yield improvement and quality effects, and iv) reinvasion, spill-overs on own crop and time-interval effects from delays of receiving benefits. For our case study on silage maize production, the most important source of uncertainty on which we focus concerns the final yield level, because weed control usually occurs quite early in the growing season. Accordingly, the same weed control can lead to different yield outcomes. To reflect this uncertainty, the attainable yield $y^a_{m,\chi}$ is introduced, as mentioned above, as a random variable in our model. In contrast, silage maize output prices are not characterised by high volatility because the biogas boom in Germany has stimulated the widespread use of long-time supply contracts (Reise et al., 2012; Britz and Delzeit, 2013).

We use a straightforward expected utility (EU) framework to represent production risks, farmers' risk preferences and risk dependent behaviour in our programming model (see e.g. Hardaker et al., 1991; Lehmann et al., 2013), based on a power utility function:

$$U(\pi_{m,t,\chi}) = \frac{1}{1 - r_a} \cdot \pi_{m,t,\chi}^{1-r_a} \ , \tag{5}$$

where r_a symbolises the partial risk aversion coefficient (Hardaker et al., 2015: 91). This functional form allows flexible representation of risk preferences and exhibits decreasing absolute risk aversion so that downside risk aversion as a salient pattern of farmers' behaviour can be represented consistently (e.g. Chavas and Holt, 1996).

We make use of empirical distributions of attainable yield and weed pressure in our approach, i.e. we calculate for a strategy for the given and observed weed pressure Ψ in year t the resulting gross margins in each of the "yield" years χ. Expected utility is calculated as average utility over all 13 years in the analysis. Finally, expected utility is maximised over each municipality m and year t (a technical term for solving the problem in GAMS; Eq. 6):

$$\max EU(\pi) = \sum_{m=1}^{M} \sum_{t=1}^{T} \sum_{\chi=1}^{X} EU(\pi_{m,t,\chi}) \cdot \rho_{\chi} \tag{6}$$

Note that solutions for each year are not independent, as farmers cannot use certain strategies in two consecutive years (for details see Böcker et al., 2017a).[3]

To address the research questions, we compare a baseline scenario, in which glyphosate is licensed, to a counterfactual scenario, in which glyphosate is banned. We report in the main body of the paper results for slightly risk averse behaviour with r_a-=0.5, reflecting recent empirical evidence for German farmers (Maart-Noelck and Mußhoff, 2014; Meraner and Finger, 2017). We conduct additional sensitivity analyses with respect to the partial risk aversion coefficient, considering values of -2.0, 0.0, and 0.8, which reflect risk loving, risk neutral and more risk averse preferences. This is relevant as farmers are found to be on average slightly risk averse, but at the same time a large heterogeneity in the population exists (ibid.). Furthermore, we assume expected output prices for silage maize of € 4.00, 4.60 and 5.20/dt (dt denote deciton, i.e. 100 kg), reflecting the range of currently observed silage maize prices. It is assumed that harvesting and ensiling are done by the selling farmer.

2.2. Pesticide load analysis

In order to assess potential negative effects of herbicide use on the environment and human health, we employ the product specific PLI which complies with European pesticide regulations. Developed for the Danish Ministry of Environment, it serves as the basis for the Danish pesticide tax. Load values are computed individually for each active substance (AS) and are then aggregated to marketed products which can combine different AS. The PLI considers sub-indicators for Human Health Λ_{heal}, Environmental Fate and Behaviour Λ_{fate} and Environmental Toxicity Λ_{toxy} which in sum define the total load Λ_{total}:

$$\Lambda_{total} = \Lambda_{heal} + \Lambda_{fate} + \Lambda_{toxy} \tag{7}$$

[3] In order to avoid resistances of weeds against herbicides, farmers need to change the active substances of their herbicide strategies in the model. More precisely, the strategies were classified into groups according to the Herbicide Resistance Action Committee and a constraint was added to prevent that strategies from exactly the same groups are used in two consecutive years. Furthermore, strategies containing the active substance nicosulfuron are only allowed to be applied every second year.

Values for each sub-indicator are computed from a broad range of potential effects on the environment and human health. More specifically, Λ_{toxy} assesses short-term effects on eight different families of animals and plants (birds, mammals, fish, earthworms, bees, daphnia, aquatic plants and algae). Additional long-term effects are taken into account for fish, earthworms and daphnia. Λ_{fate} considers biodegradability, bioaccumulation and mobility in soil. Λ_{heal} is calculated based on Hazard- and Risk Statements with regard to human health of the specific substances as well as product formulation. For a specific pesticide product, the load per kilogram or litre is calculated based on the load of each single AS and its concentration in the product. For details, see Miljøministeriet (2012). Note that PLI values for the used products are presented in detail in the data section.

2.3. Energy process analysis

In order to assess the energy use related to a specific weed control strategy, we use the methodology and definitions of Jones (1989) and of Hülsbergen et al. (2001) (for recent applications see e.g. Jankowski et al., 2015). The aim of the here chosen approach is to “trace all the energy inputs into an agricultural system, based on physical material flows” (Hülsbergen et al., 2001: 306f.), excluding energy flows from human labour and solar energy (Uhlin, 1999). Direct energy input (E_d) in our case study refers to the consumption of diesel whereas indirect energy inputs E_i quantifies the energy needed to produce the different inputs: seed, mineral fertilisers (we treat manure as waste from livestock production, it has therefore zero energy content), pesticides and machinery. The overall energy input E is equal to $E_d + E_i$. The energy output EO is equal to the energy content of the harvested maize minus the inherent energy in seed (which is lower than the energy needed to produce the seed). The net energy output NEO is equal to $EO – E$. All energy values are given in calorific values [MJ/ha].[4]

2.4. Hypothesis testing

With respect to the applied herbicides in case of a glyphosate ban, we test for load decreases in i) toxicity, ii) environmental fate, iii) human health, and iv) overall load (average of all load indicators, see data section). In the energy process analysis, we test the hypotheses that v) the energy output EO decreases, vi) the net energy output NEO decreases, vii) more direct energy is used (E_d increases), viii) more indirect energy is used (E_i increases), ix) more energy is used in general (E increases), and x) the energy efficiency decreases (EO/E decreases). Wilcoxon-Mann-Whitney tests are used to test our hypotheses on differences between regional unit averages of results over all years t.

[4] We opted against the focus on CO_2-equivalents due to the large uncertainties in assessing CO_2-equivalent emissions from energy production. Especially for commodity production and related demand of electricity, it depends largely on where factories are located since most countries have a mix of electricity resources and different environmental standards.

3. Data

The first part of the data section gives an overview of the most important data sources of the above presented bio-economic model. The focus lies on weed control strategies, weed spread and yield data. In the subsequent two sections, specific data for our analyses is presented, namely data for the application of the PLI and for the energy balance.

3.1. Weed data, weed control strategies and yield data

The model consists of $m = 1, \ldots, 377$ regional units, which represent the maize-producing municipalities of NRW. The complete data sources on weed spread, weed abundance, yield losses and herbicide efficacy are documented in Böcker et al. (2017a). We account spatially explicitly for $i = 1, \ldots, 32$ (grass) weeds in the model that influence the yield depending on the specific weed. Each regional unit has a certain probability that a specific weed occurs. For pre-sowing weed control, $g = 1, \ldots, 19$ strategies are considered and for post-sowing $h = 1, \ldots, 55$. This selection includes both the currently dominating strategies and strategies that are currently not yet economically viable but might become relevant under a glyphosate ban.

We introduce risk in our model using two components, i.e. by accounting for stochastic attainable yield and weed pressure. Concerning weed pressure, the stochasticity is based on uncertainty that farmers face with respect to the time of weed emergence Ψ relative to maize, which is a key indicator of weed induced potential yield losses. Herbicide strategies are typically chosen and applied early in the growing season of maize, reflecting observed weed pressure. If maize has a growth advantage over weeds in a certain year, cheaper or no herbicide strategies might be favoured. In contrast, strategies with higher efficacy that are also more complex and more expensive might be more promising if weeds have larger growth advantages over maize. Thus, we focus on the distribution of the value describing the difference between the emergence of maize and weeds in a specific year and regional unit. Ψ can be positive or negative, depending on the time of maize and weed emergence. Here, we consider the period $t = 2006$ to 2015 with yearly, changing values of Ψ depending on the regional unit m. In order to determine this distribution, we make use of the growing degree-day (GDD) concept (McMaster and Wilhelm, 1997) and use spatially and temporally specific information on weather (temperature) and phenological (starting dates of sowing and emergence) data of silage maize for our study region, provided by the German Weather Service (*Deutscher Wetterdienst*, DWD) from six weather stations in NRW in different areas. We assigned each regional unit to the closest weather station.

With regard to the attainable yield level, we make use of raster data (1 x 1 km) on water-limited potential yields of silage maize from $\chi = 1999, \ldots, 2011$ that were gratefully provided by Ganga Ram Maharjan and Thomas Gaiser from the Crop Science Group of University of Bonn. The raster data was created by a crop model that is presented and documented in Hoffmann et al. (2015) and Zhao et al. (2015). This raster data was aggregated to municipality levels. Water-limited yields are chosen as irrigation is basically irrelevant in silage maize production in the region. Modelled data are used as public once on yields are only available on county level.

The key parameters of the production function in Eq. (2), α_0, α_1, β_0 and β_1, are estimated by determining those parameter values that minimise the error term between the observed yields and the yields simulated with the control strategies used in current silage maize production (more details can be found in Böcker et al., 2017a: 184ff., 2017b). Expert knowledge from the Chamber of Agriculture of NRW was used in order to get information about the currently used practices of maize cultivation (ibid.). In addition, recent Ψ-values were included for the time period 2013 to 2015. The finally estimated parameter values are $\alpha_0 = 1.266$, $\alpha_1 = 0.683$, $\beta_0 = 0.747$ and $\beta_1 = 0.543$.

3.2. Pesticide load

Information about ASs to calculate the PLI is taken from the Pesticide Properties DataBase, which draws on publicly available sources, such as pesticide admission and regulation procedures. In addition, we obtain complementary information about ASs per product as well as their specific concentration from product specification sheets of the herbicide manufacturers and from herbicide recommendations, such as from the Chamber of Agriculture NRW (Landwirtschaftskammer Nordrhein-Westfalen, 2015) and the Bavarian State Research Centre for Agriculture (Bayerische Landesanstalt für Landwirtschaft, 2016). The overall load and the load in the three sub-categories can be found in Table 1 for all herbicide products included in our analysis. Note that the selection and weights of the indicators and the indices underlying the calculation of the load values in the PLI reflect preferences and focus in Denmark. We judge its application in here as appropriate, especially compared to developing an own approach, as it covers a broad range of environmental and health effects, is aligned with European pesticide regulations and already implemented and tested as a pesticide indicator in Denmark for several years.

Table 1. Values of the Pesticide Load Indicator[a] for the herbicide products included in the model

Herbicide name	Λ_{toxy}	Λ_{fate}	Λ_{heal}	Λ_{total}
Activus	0.109	1.207	0.100	1.416
Arigo	0.215	0.255	0.000	0.471
Arrat	0.064	0.585	0.267	0.916
Aspect	0.199	0.267	0.500	0.966
B 235	0.225	0.003	1.200	1.427
Buctril	0.217	0.002	1.200	1.419
Calaris	0.105	0.220	0.000	0.325
Callisto	0.035	0.041	0.000	0.076
Dash	0.073	0.058	0.675	0.807
Dual Gold	0.116	0.198	0.100	0.414
Elumis	0.048	0.053	0.000	0.101
Gardo Gold	0.086	0.179	0.100	0.366
Laudis	0.014	0.013	0.000	0.027
Lido SC	0.084	0.169	0.150	0.403
MaisTer	0.068	0.014	0.000	0.081
Motivell forte	0.040	0.039	0.000	0.079
Peak	0.707	6.067	0.033	6.808
Roundup PowerFlex	0.024	0.052	0.350	0.426[b]
Spectrum	0.162	0.183	0.000	0.346
Stomp Aqua	0.115	1.269	0.067	1.451
Successor T	0.109	0.129	0.100	0.339
Sulcogan	0.023	0.260	0.800	1.083
Tacco	0.049	0.012	0.000	0.061

[a] The unit is Load/L or Load/kg of product. The load values need to be weighted with the application rate in order to get per hectare values.

[b] The PLI is based on currently available assessments of the environmental and human health effects of pesticides. Thus, glyphosate has modest environmental and health effects among the here listed herbicides (see e.g. Gardner and Nelson, 2008).

3.3. Energy balance

Process analysis based on energy balances is a widespread method in agricultural sciences (e.g. Deike et al., 2008; Jayasundara et al., 2014), typically drawing on literature providing general information on energy use in agricultural and industrial processes (e.g. Audsley et al., 2009; Green, 1987; Hülsbergen et al., 2001). For indirect energy consumption of producing and maintaining machinery, Aguilera et al. (2017: 341) report for the year 2010 values of E_{tr} = 156 MJ/kg of machinery for tractors, E_{hr} = 102 MJ/kg for harvesters, E_{tm} = 72 MJ/kg for tillage machinery, and E_{om} = 62 MJ/kg for other machinery.

With respect to the energy requirements of herbicide production, we rely on Audsley et al. (2009) who, based on data of Green (1987), find that the energy requirements for pesticide production is related to the year of discovery. They fitted the following regression line between the energy requirement of a certain AS (E_h) (measured in [MJ/kg]) and the year of discovery as a herbicide (A_d):

$$E_h = -399 + 10.8(A_d - 1900) \quad (8)$$

Similar to Nagy (1999; cited from Jayasundara et al., 2014: 83), we add 6% to the estimated production requirements to account for formulation, packaging and delivery requirements. The assumed energy requirements used in our analysis are presented in Table 2.

Table 2. Active substances in the model and energy requirements for production[a]

Active substance	**Year of discovery (Tomlin, 2006; MacBean, 2012)**	**Estimated production energy in relation to Eq. 8 [MJ/kg]**	**Production energy plus 23 [MJ/kg] for formulation, packaging and delivery (Hülsbergen *et al.*, 2001) [MJ/kg]**
Bromoxynil	1963	281	304
Dicamba	1961	260	283
Dimethenamid-P	2000	681	704
Flufenacet	1995	627	650
Foramsulfuron	1995	627	650
Glyphosate	1971	368	391
Iodosulfuron-methyl-sodium	1999	670	693
Isodecylalcoholethoxylate (additive)	1968	335	358
Mesotrione	1998	659	682
Metosulam	1993	605	628
Nicosulfuron	1990	573	596
Pendimethalin	1974	400	423
Pethoxamid	2001	692	715
Prosulfuron	1993	605	628
Pyridate	1976	422	445
Rimsulfuron	1989	562	585
S-Metolachlor	1996	638	661
Sulcotrione	1991	584	607
Tembotrione	2005	735	758
Terbuthylazine	1966	314	337
Thiencarbazone	2007	757	780
Topramezone	2006	746	769
Tritosulfuron	2002	703	726

[a] Please notice the difference between 'herbicide product' and 'herbicide active substance' (Table 1). Herbicide products consist of one or several herbicide active substances plus solvents and adjuvants.
The energy requirements are estimates based on a regression function of Audsley et al. (2009) who use values of Green (1987). The energy requirements may differ in reality.

4. Results

Results are presented as averages over the 10-year period *t* and over the municipalities *m*. In the main text, we consider the scenario with moderate risk aversion ($r_a = 0.5$) and the three output price levels of € 4.00, 4.60 and 5.20/dt. The sensitivity analysis with respect to the partial risk aversion coefficient only lead to slightly different results and is therefore not illustrated. This section first shows some descriptive results on the weed control strategies used, before we turn to results of the herbicide load and energy process analysis.

4.1. Descriptive results

Three characteristics mainly influence the choice of pre- and post-sowing weed control strategies in our model: i) the expected revenue consisting of the output price and the attainable yield, ii) the weed pressure in a certain region and year, and iii) the soil type influencing the weed control costs and the weed occurrence. Regarding the soil type, it has to be mentioned that direct sowing with glyphosate application can be done economically on light soils, because the cost for sowing directly are cheaper. On heavy soils, direct sowing with glyphosate application is often also optimal, because alternatives that include tillage, such as two passes of chisel ploughing or mouldboard ploughing, are more expensive.

In the base scenario without policy intervention, we find that applying glyphosate is the optimal strategy in about 28.5% to 38% of the regional units, depending on the output price. A higher price of silage maize, ceteris paribus, increases glyphosate application. The major alternative to the pre-sowing weed control using glyphosate is mechanical weed control based on two passes of chisel ploughing. Other strategies, such as one pass of chisel ploughing, chisel ploughing in combination with harrowing or conventional tillage with ploughing are less frequent; ploughing is not found to be optimal in any scenario. The level of risk aversion has very limited and not significant impact on the choice of the pre-sowing strategy. Risk preferences are found to only have small effects on the choice of the post-sowing weed control strategies (not shown). The main drivers of differences in weed control expenditures and the applied AS are expected revenues (i.e. expected output price levels and the attainable yield level) (Figure 1 and 2). More specifically, average costs for weed control increase with higher expected revenues. At lower expected revenues, cheap mechanical weed control is more frequently used compared to glyphosate even in the baseline scenario without a ban. This is due to lower sowing costs after two passes of chisel ploughing compared to glyphosate application and direct sowing. We observe an increase in weed control costs in case of a glyphosate ban due to higher costs for mechanical weed control as the main substitute (note that the enforced change in weed control also impacts the yield level, it would therefore be possible that both revenues and costs increase, but clearly not their difference).

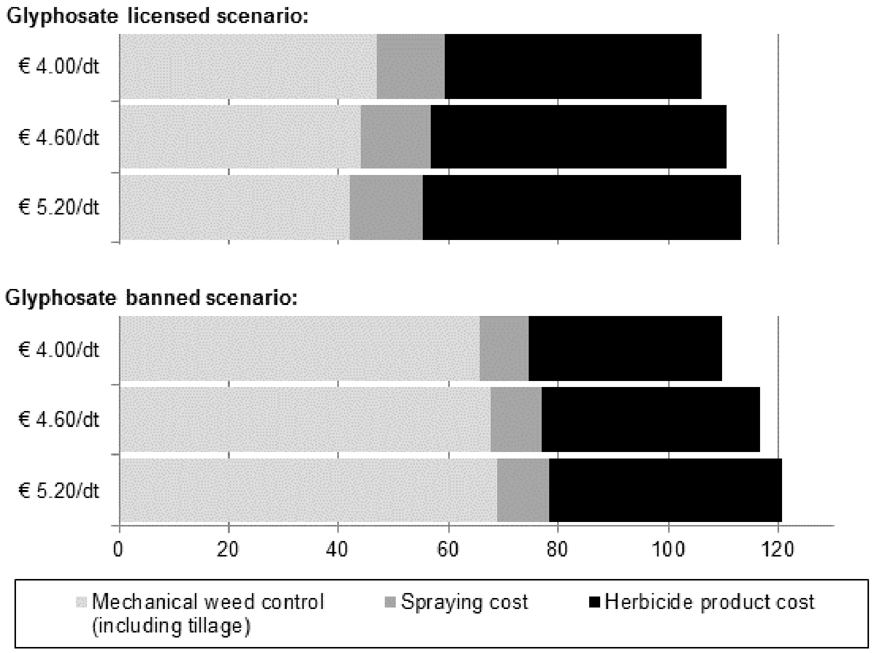

Fig. 1. Average costs for pre- and post-sowing weed control (r_a = 0.5).

The average of the applied number of AS/ha and year excluding glyphosate is presented in Figure 2. At the low price level of € 4.00/dt about 2.6 AS/ha and year are applied. At the high price level of € 5.20/dt, the number increases to about 3.0 to 3.1 AS/ha and year on average. At the low price level, nicosulfuron, profulfuron and pyridate have a relatively high share of the applied AS. Terbuthylazine, S-metolachlor, flufenacet, iodosulfuron, foramsulfuron and thiencarbazone gain in importance at higher expected revenues. The model results show that the most frequently applied AS is terbuthylazine, which is in line with observations on farm practices in the case study region (Julius Kühn-Institut, 2017). The use of different AS' is relatively constant over the four different risk aversion levels, with slightly but not significantly lower shares of AS' if a risk affine decision maker is assumed (r_a = -2.0). In case of a glyphosate ban, the composition of the AS does not change significantly (Figure 3).

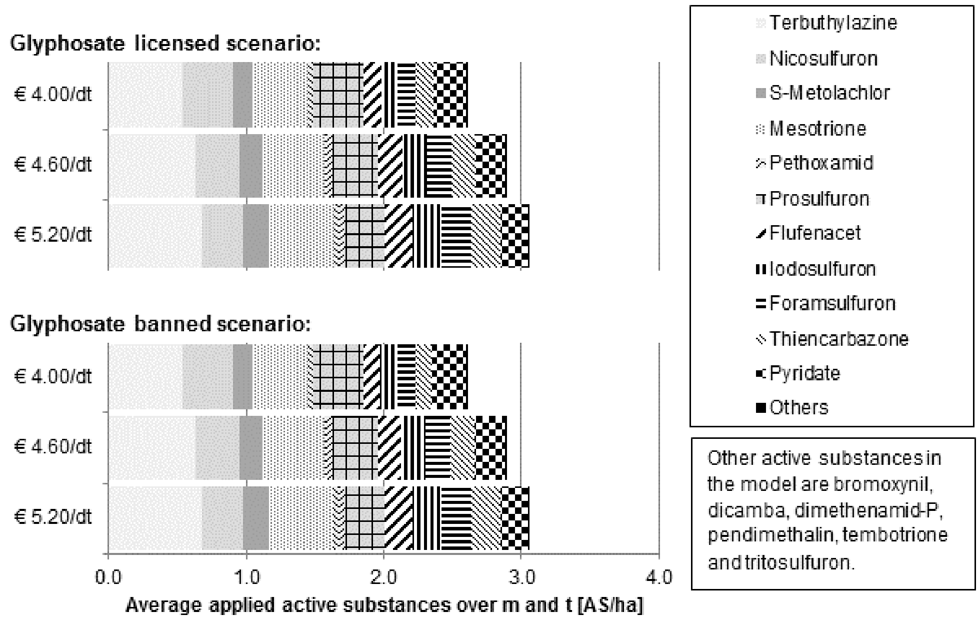

Fig. 2. Average applied active substances [AS/ha and year] post-sowing for both the glyphosate licensed and glyphosate banned scenario (r_a = 0.5).

4.2. Herbicide load analysis

The distribution of the average loads for the optimal strategies in the different municipalities are illustrated in Figure 3 under moderate risk aversion (r_a = 0.5). Load values differ strongly between the municipalities and range from about 0.2 to 1.6 Load/ha. Differences are especially large for the total and the human health load. Load values increase in output prices and attainable yield levels. The levels fit well to the average herbicide load for a hectare of maize in Denmark (where the PLI is used in policy analysis), which was 0.31 in 2014 (Ørum and Hossy, 2015: 57) and 0.38 in 2015 (Ørum and Sommer Holtze, 2017: 54) (values excluding glyphosate application).

The analysis of the four different hypotheses regarding the herbicide load is presented in Table 3 for r_a = 0.5. We find significant load reductions under a glyphosate ban in all scenarios. Furthermore, this holds for the total load indicator, as well as all sub-indicators (i.e. environmental toxicity, fate and human health). The decrease is strongest with respect to human health load followed by environmental fate. The sub-indicator for environmental toxicity has the lowest reduction reflecting the low toxicity load of glyphosate based products (Table 2).

The spatial distribution of the total load reduction across NRW is presented in Figure 4. The load reduction is highest in two types of regions. The first covers regions with heavy soils where mechanical alternatives to glyphosate require higher traction power and thus are more expensive. Glyphosate application is thus under current conditions often the optimal weed control strategy to reduce costs. The second type encompasses regions dominated by light soils such that direct tillage or strip-till practices in combination with glyphosate application are relatively cheap. On medium soils, glyphosate is applied less frequently in our model. The expected output price has a quite limited impact on the load reduction.

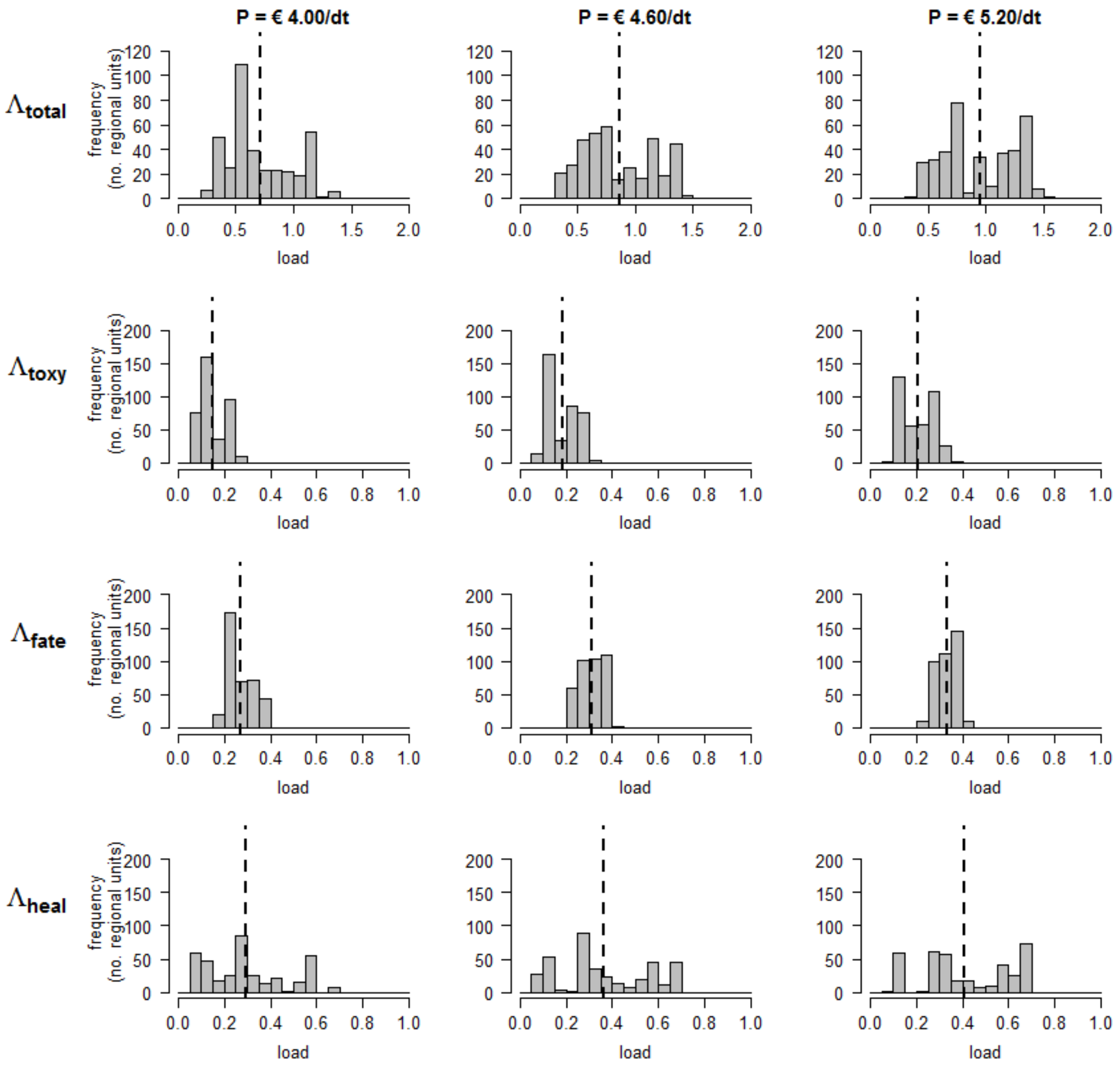

Fig. 3. Distribution of loads w.r.t. total (Λ_{total}), environmental toxicity (Λ_{toxy}) and fate (Λ_{fate}) as well as human health (Λ_{heal}) as average over the period 2006-2015 ($r_a = 0.5$; glyphosate licensed scenario).

Table 3. Change (Δ) in Load/ha by a glyphosate ban in silage maize production[a,b]

Load:	$\Delta\Lambda_{toxy}$	$\Delta\Lambda_{fate}$	$\Delta\Lambda_{heal}$	$\Delta\Lambda_{total}$
P [€/dt]:				
4.00	-0.012 ***	-0.026 ***	-0.171 ***	-0.209 ***
4.60	-0.013 ***	-0.027 ***	-0.175 ***	-0.215 ***
5.20	-0.012 ***	-0.026 ***	-0.174 ***	-0.213 ***

[a] Difference of Load/ha for the glyphosate licensed scenarios minus the glyphosate banned scenarios. Only municipalities are included in which glyphosate is used in the model under the licensed scenario ($r_a = 0.5$).

[b] *, ** and *** denote significance at the 5%, 1% and 0.1% level respectively based on Wilcoxon-Mann-Whitney-tests.

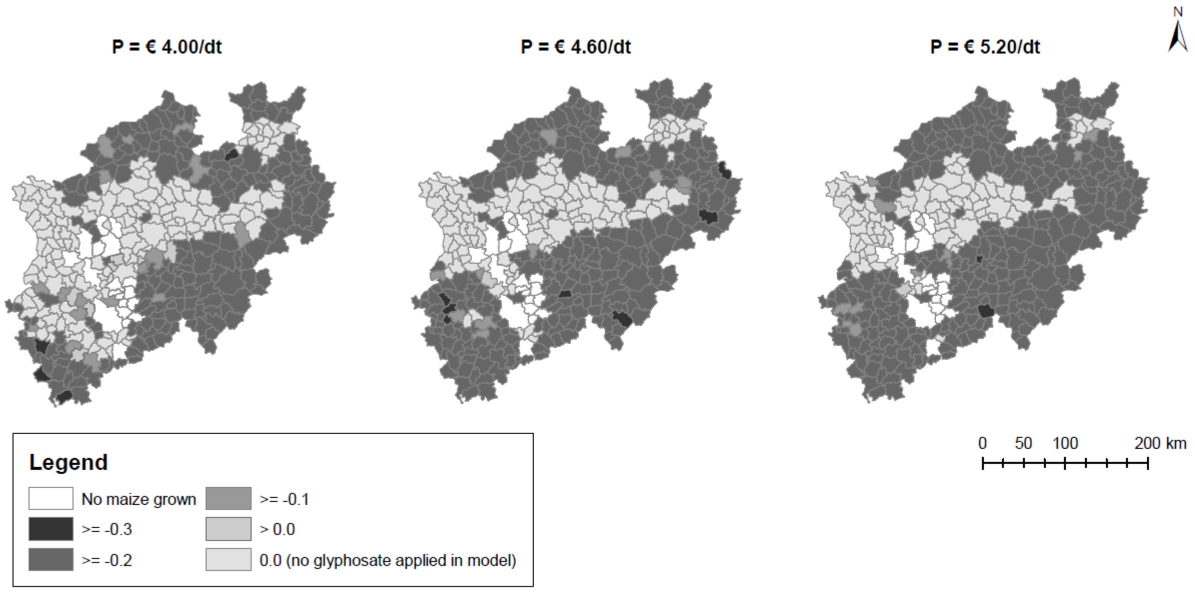

Fig. 4. Distribution of total pesticide load reduction over the state of NRW at a potential ban of glyphosate ($r_a = 0.5$).

4.3. Energy process analysis

The distribution and the mean values of the energy output and input are presented in Figure 5 for the risk aversion coefficient of 0.5. The expected energy output across the municipalities ranges from 141 GJ/ha to 278 GJ/ha, the energy input ranges from 2.7 to 12.2 GJ/ha. We observe a shift towards higher energy outputs with higher prices due to increased weed control and consequently higher energy inputs, but also due to the fact that higher maize price incentivise an increasing use of other inputs such as higher fertiliser. Reflecting slightly decreasing marginal returns, the energy efficiency is highest in the low price-scenario with a ratio of 26.5 compared to 25.6 in the high price-scenario. Similar trends can be observed under other risk aversion coefficients (not shown).

Table 4 presents results for the energy process analysis. Differences for the indicators between the glyphosate licensed and the glyphosate banned scenarios are depicted for the three output prices. Regarding the energy output *EO*, we observe in most scenarios a quite limited reduction by about 0.7 – 1.2 GJ due to lower harvest, which is the largest for the low output price level of € 4.00/dt (Table 5, column ΔEO). However, this difference in *EO* is overall not significant. Similar results are found for net energy output *NEO*. Direct energy use E_d increases due to a glyphosate ban significantly by about 300 MJ/ha. Indirect energy consumption E_i tends to decrease, but differences are not significant. Both types of energies rise in sum by up to 170 MJ/ha, but this increase is only significant for a high output price of P = € 5.20/dt. A glyphosate ban decreases energy efficiency, reflecting that mostly mechanical weed control is used as a substitute. This decrease is smaller for the low output price of € 4.00/dt, but larger and highly significant for the higher price levels of € 4.60/dt and € 5.20/dt. The emerging spatial distribution of the direct energy consumption (E_d) and the reduction in energy efficiency (*EO/E*) over the state of NRW resembles the one for the PLI (not shown).

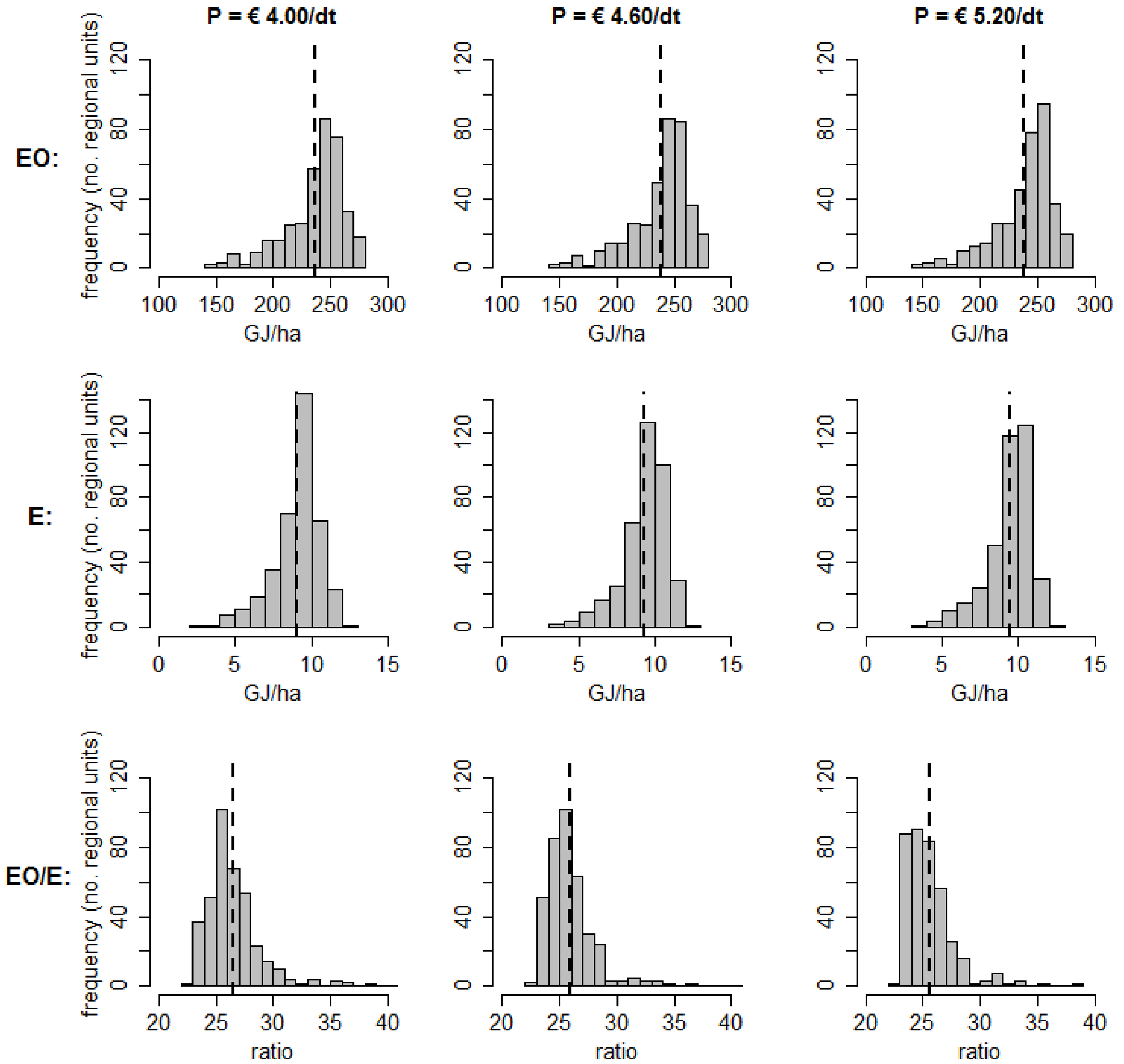

Fig. 5. Distribution of energy output, energy input and energy efficiency as average over the period 2006-2015 (r_a = 0.5). Dashed lines show mean values.

Table 4. Change (Δ) in energy output and input per hectare by a glyphosate ban in silage maize production[a,b]

Energy: P [€/dt]:	ΔEO [MJ/ha]	ΔNEO [MJ/ha]	ΔE_d [MJ/ha]	ΔE_i [MJ/ha]	ΔE [MJ/ha]	ΔEO/E
4.00	-1186	-1278	+278 ***	-187	+92	-0.444 **
4.60	-875	-1015	+302 ***	-162	+140	-0.539 ***
5.20	-671	-840	+311 ***	-141	+170 ‘	-0.586 ***

[a] Difference of process analysis for the glyphosate licensed scenarios minus the glyphosate banned scenarios: energy output (*EO*), net energy output (*NEO*), direct energy use (E_d), indirect energy use (E_i), total energy use (*E*) and energy efficiency (*EO/E*). Only municipalities are included in which glyphosate is used in the model under the licensed scenario (ra = 0.5).

[b] ‘, *, ** and *** denote significance at the 10%, 5%, 1% and 0.1% level respectively, based on Wilcoxon-Mann-Whitney-tests.

5. Discussion

Our results on potential environmental effects of a glyphosate ban clearly reveal the trade-off between reducing emissions by energy consumption on the one hand and reducing adverse effects on human health and nature on the other hand. In our case study, we find an average increase of total energy consumption of up to 170 MJ/ha and year, but the change depends strongly on expected output prices. If glyphosate is assumed to be used on 66,500 ha of silage maize in NRW (~190.000 ha silage maize according to Information und Technik Nordrhein-Westfalen, 2016, and 35% of farmers applying glyphosate; Julius Kühn-Institut, 2017), our analysis suggest an increase of energy demand of 11 TJ at state level under a ban of glyphosate for silage maize acreage only. The environmental effects of this additional energy consumption depend on energy sources. Indirect energy, i.e. for factor production, is consumed for the most part in form of electricity; direct energy relates to diesel use. The model also simulates a loss in energy efficiency if glyphosate would be banned, mostly due to somewhat lower yields. This means that more silage maize will have to be cultivated in case of a glyphosate ban to meet the demand.

Glyphosate is applied in many different arable and special crops, so that the environmental load would be reduced on a large scale. Nevertheless, the significant decrease in pesticide load of around 0.2 per hectare has to be compared to the PLI values of other crops: for example, the total load/ha of potatoes, a crop with relatively high pesticide intensity, was over all types of pesticides 2.48 in 2014 and 6.75 in 2015 (Ørum and Hossy, 2015; Ørum and Sommer Holtze, 2017). Vegetables even had higher loads/ha of 6.54 in 2014 and 8.27 in 2015 (ibid.). Regarding adverse effects of pesticides, Larsen et al. (2017) found that mainly very high exposure to pesticides lead to negative effects on human health. Reducing farmer's fungicide or insecticide dependency in cultivation of other crops leads thus probably to higher environmental benefits than reducing herbicide dependency (if glyphosate is not carcinogenic as currently assumed in the human health risk load under the PLI). Additionally, the herbicides applied post-sowing in maize have overall with 0.70 and 0.95 a larger PLI value compared to glyphosate, which also explains the modest reduction of 0.2 Load/ha (see also Figure 3).

We find that the level of risk aversion only has a small influence on the choice of the weed control strategy. This contradicts the classical view that pesticides are risk decreasing and serve as a kind of insurance, but seems reasonable because the level of weed infestation can be observed on the field and also other variables such as spray efficacy and crop prices are relatively stable (Pandey, 1989: 4). The risk lies mainly in uncertain attainable yield levels and thus the damage control effect since most of the (stochastic) growth in silage maize occurs after herbicide application. Herbicides have thus not necessarily an influence on the yield variation. Other authors found a similar influence of pesticides on economic risk (for an overview, see Möhring et al., 2017). Future models might implement alternative theories on farmers' decision making under risk. In a recent example, Carpentier (2017) applied prospect theory to pesticide application, allowing to explicitly considering farmer's reference situation to the protected or the unprotected crop.

Our results relate to short- to mid-term changes in weed control strategies in silage maize cultivation under a glyphosate ban. Furthermore, changes in crop rotations or other adjustments at farm level were not included so far. Regarding the weed control implementation into the model, additional temporal dimensions could be introduced. More specifically, temporal interdependencies of applied weed management strategies can be considered, e.g. if weed pressure spills over different periods. For example, if only conservation tillage strategies without glyphosate application are chosen, the size of the weed seed bank growths (Bàrberi et al., 1998). Furthermore, other environmental dimensions could be included in the model. For example, no till practices – possibly economically viable only if glyphosate is licensed – reduce soil erosion especially on hilly grounds (Montgomery, 2007). Moreover, we do not take into account that a change to mechanical weed control maybe has negative effects on ecological soil conditions. Along these lines, problems with nitrogen surpluses might increase due to slightly lower yield levels if glyphosate is banned and manure application is not adjusted.

6. Conclusions

We develop and employ a detailed bio-economic model focusing on weed damage control under risky conditions in order to analyse the potential effects of a glyphosate ban on both farm management and the environment. The model depicts privately optimal pre- and post-sowing weed control strategies spatially explicitly and is applied to a case study for silage maize production in North Rhine-Westphalia, Germany. We explicitly include risk preferences of farmers and treat weed pressure and attainable yields as stochastic. We assess impacts of the chosen weed control strategies on energy consumption and on human health and environmental effects. To this end, we use an energy process analysis using energy inputs and outputs and an herbicide load analysis based on the Danish Pesticide Load Indicator. Ten different hypotheses are tested with regard to a glyphosate ban.

We find under a glyphosate ban a significant reduction of adverse effects of pesticides on the ecosystem (in terms of toxicity and environmental fate) and human health (even without considering a carcinogenic effect of glyphosate), although reductions are small compared to the per hectare pesticides loads found in other crops. However, as glyphosate is mostly substituted to mechanical weed control, we find a significant, but moderate increase of direct energy consumption in the form of diesel and a reduction in energy efficiency. Even though aspects such as changes in human health effects beyond the possible carcinogenic effects of glyphosate and in energy consumption do not yet play a decisive role in the regulatory pesticide registration process, they should be considered in the on-going debates. Our results thus can contribute to shape policy debates, as well as regional and private initiatives for alternatives to glyphosate use. The main finding from our analysis is that a glyphosate ban would cause a shift towards more mechanical weed control measures, but not to more pronounced use of selective herbicides, with little impact on yields and gross margins. As a result, the chosen weed control strategy set is less toxic as expressed with the load indicator, but more energy intensive. The magnitude of these effects is found to be critically dependent on output price levels and yield expectations. As shown in our application to a glyphosate ban, our modelling approach allows quantifying impacts on profits and important externalities of weed control strategies and thus can inform debates by policy makers or private actors on measures targeting herbicide use.

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