MODELLING THE EFFECTS OF A GLYPHOSATE BAN ON WEED MANAGEMENT IN MAIZE PRODUCTION

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Abstract

A bio-economic model is developed that allows a detailed representation of optimal weed management decisions. Focussing on German maize production, we apply the model to the effects of a glyphosate ban on farmers' income, other herbicide use, maize yields and labour demand. We find that a glyphosate ban has only small income effects. Our results show that selective herbicides are not used at higher levels, but glyphosate is substituted by mechanical practices leading to higher labour demand. Slight yield reduction due to less intensive pre-sowing strategies turns out as more profitable than maintaining current yield levels.

Keywords

Output damage control, herbicide, maize, glyphosate, Germany.

1 Introduction

Reducing risks caused by pesticide application is a crucial topic of current European agri-environmental policy. Different measures are proposed to control pesticide use and the connected environmental risks, for example banning specific pesticides or introducing pesticide taxes (SCHULTE and THEUVSEN, 2015; BÖCKER and FINGER, 2016). Especially the renewed licensing or banning of the broad-spectrum herbicide glyphosate provoked heated discussions after the IARC classified glyphosate as "probably carcinogenic to humans" (GUYTON et al., 2015). Ex-ante information on health and environmental risk reduction and on the impacts on farmer's income is needed to inform the debate on policy measures targeting pesticides (FALCONER, 1998). As substitution effects with other herbicides are likely if specific products are targeted, potential changes in farm management must be depicted in detail. In this paper, we develop a tool for such detailed impact assessment of environmental standards or other policy measures affecting specific pesticides and apply it to assess a potential ban of glyphosate.

In available assessments on pesticide application behaviour of farmers, mainly econometric and optimisation modelling approaches or combination of both are applied (BÖCKER and FINGER, 2017). Econometric applications are usually based on historical data, for instance of pesticide applications, and are used to explain historical developments or to make recommendations on decision making. Optimisation and simulation models presume, for example, optimal decision making based on more or less detailed production function approaches combined with an economic objective such as profit maximisation. They can hence be used for what-if-analyses even if observations are missing. Existing approaches of the latter group are, however, not detailed enough to assess measures addressing individual pesticides, such as glyphosate in our application. For example, GUAN et al. (2005) work with a monetary aggregate over fungicides, herbicides and other pesticides; but, higher total costs for pesticide applications do not necessarily lead to a better weed treatment and vice versa. KUOSMANEN et al. (2006) use the amount of active substances (AS) of insecticides as an indicator for pesticide use in cotton. KARAGIANNIS and TZOUVELEKAS (2012) measure insecticide application in olive orchards based on litres of insecticides, but ignore the diversity of different products.

In this paper, we extend the literature by making use of the output damage function approach (KARAGIANNIS and TZOUVELEKAS, 2012), differentiating in detail a larger set of pre- and post-sowing weed control options with regard to their yield impact. Specifically, we consider for each strategy both costs and efficacy of controlling individual weeds. Moreover, we develop a site-specific framework that allows investigating weed management over time and space. Our empirical analysis focuses on silage maize, one of the most relevant crops in Germany, where pest management mainly relies on herbicide application (JKI, 2016). We apply the model to North-Rhine-Westphalia (NRW) and account for spatial heterogeneity of weed pressure and yield potential at municipality level. The model identifies economically optimal herbicide strategies in silage maize in each municipality at given pesticide and crop prices and environmental standards. We apply this model to study the impact of a glyphosate ban on herbicide use and/or mechanical weed control and related costs compared to the current situation. At the moment, there are no alternative herbicides approved to replace glyphosate for pre-sowing application (KEHLENBECK et al., 2015). Thus, mechanical weed control is the only alternative, which removes potential environmental risks from herbicides before sowing. However, as claimed in some discussions on the topic, alternative herbicides could potentially be used at higher rates after sowing, even increasing the overall environmental risks.

2 Methodology

We develop a bio-economic weed control model for silage maize in *m* municipalities in NRW. A two-year cropping period is considered where maize is grown in each of the two years *t*, a standard farming practise. The expected gross margin $E(\pi)$ in year *t* for different pre- (index *b*) and post-sowing (index *h*) weed control strategies is defined as:

(1) $$E(\pi_{m,t,b,h}) = [y^*_{m,t,b,h} \cdot E(p) - c(b) - c_s(b) - c(h) - c_f(y) - c_o],$$

where $y^*_{m,t,b,h}$ is the expected yield, $E(p)$ is the expected output price for maize, $c(b)$ and $c(h)$ are the pre- and post-sowing weed management (and tillage) costs for a certain strategy and $c_s(b)$ are variable costs for sowing depending on the pre-sowing strategy (the more expensive direct precision drill is needed for some types of conservation tillage). $c_f(y)$ are costs for fertiliser depending on the yield and c_o are other costs (proportionate costs for rating and liming). Harvest costs are not included because maize is sold ex field such that the buyer performs the harvest which is reflected in lower output prices.

2.1 The damage control approach and specification of the damage controlling effect

An output damage function is used to determine the expected yield y^* (PANNELL, 1990). It depicts first the effect of the damage control input on the population of the damaging organism and from there the resulting yield reduction from surviving damaging organisms (KARAGIANNIS and TZOUVELEKAS, 2012:419). We follow here the more standardised notation of Guan *et al.* (2005). The concept is based on a distinction in the production function $y=G(x,D(h))$ between productive (x) and damage-controlling inputs (h) where $D(h)$ is the damage controlling effect on the interval [0,1]. h is, for example, the efficacy of a herbicide against a specific weed. If $D(h)$ is equal to unity, no losses due to pests, diseases or weeds occur. Besides chemical inputs, also mechanical inputs such as hoeing or ploughing can be considered as damage-controlling, which challenges a clear distinction between h and x. The classical form of $D(h)$ is either exponential, logistic or of the Weibull form (LICHTENBERG and ZILBERMAN, 1986). We follow GUAN et al. (2005) and use the exponential form, which represents well the underlying biological processes:

(2) $$D(h) = 1 - e^{-(\beta_0+\beta_1 \cdot z(h))^2}, \quad \beta_0, \beta_1 \geq 0.$$

The functional form implies decreasing marginal damage control in input use, a reasonable assumption as, e.g., additional weed control on an almost weed free field will not lead to much higher damage control. Parameters β_0 and β_1 quantify the effects of inputs on damage control (section 2.3). The decision variable is $z(h)$, the chosen level of damage control.

We consider the 32 most important weeds of the case study region. Each weed control strategy is characterised by its weed specific damage control effect, i.e. a column vector h with j

1 x 32 entries ranging between 0 and 1, since specific herbicides and mechanical strategies differ in their impact on individual weeds. Often, an herbicide strategy comprises several products. The resulting control success is typically not additive since the comprised herbicides may have a similar spectrum of action. More likely is the case that the maximum suppression effect of any herbicide is crucial for the success. We add a multiplier a_i to each weed $w_{m,i}$ to differentiate yield depression effects by weed, depicted by the average abundance (a_i) which measures the affected area share when that weed occurs. Finally, in order to quantify the site-specific damage controlling effect of specific herbicides, a weed-row vector w with size *i 32 x 1* depicts for each municipality m the probability that a weed occurs. The three vectors – probability of weed occurrence w, affected share a, and damage control h – define jointly the control success z for each herbicide strategy j in the different municipalities m:

$$(3) \qquad z_{m,j} = \sum_{i}^{32} w_{m,i} \cdot a_i \cdot h_{j,i}\,.$$

Eq. (3) presents the post-sowing weed controlling effects. In a similar manner, a vector $v_{m,j}$ can be constructed that accounts for pre-sowing weed management effects (denoted as b_i):

$$(4) \qquad v_{m,j} = \sum_{i}^{32} w_{m,i} \cdot a_i \cdot b_{j,i}\,.$$

2.2 Choice of functional form and implementing the damage controlling effect

Inserting the damage control expression from (3) in (2) yields the following specification:

$$(5) \qquad D_{m,j} = 1 - e^{-(\beta_0 + \beta_1 \cdot \sum_i^{32} w_{m,i} \cdot a_i \cdot h_{j,i})^2}, \qquad \beta_0, \beta_1 \geq 0.$$

One of the remaining issues is to determine the form of the production function. We follow SWINTON and KING (1994) as well as BOSNIĆ and SWANTON (1997) and use the rectangular hyperbolic approach of COUSENS (1985) which accounts for biological effects such as time of emergence. Thus, the yield function in relation to weed control is defined as follows:

$$(6) \qquad y^*_{m,t,b,h} = y^a_{m,t} \cdot \left[1 - I \cdot \frac{D_{m,j}}{100 \cdot \left(e^{C \cdot T} + I \cdot \frac{D_{m,j}}{A} \right)} \right].$$

y_a is the attainable yield when no weeds are present, I is the percent yield loss as $D_{m,j}$ approaches 0 (i.e. $D_{m,j}$ is not yet 0), A is the percent yield loss as $D_{m,j}$ approaches infinity, T is the time of crop emergence in relation to the weed emergence until the crop has a competitive advantage against weeds, measured in growing degree days, which is the sum of the average temperature of each day, and C is the rate at which the yield loss I decreases as T becomes larger. T depicts earlier or later maize emergence compared to weeds, e.g. T=0 means that maize and weeds emerge at the same time, T=-50 means that weeds have an advantage in emergence of five days with an average temperature of 10°. Fungi and insects are of limited relevance in German maize production or can be controlled by seed dressing or resistant varieties such that except for herbicides usually no other pesticides are applied (JKI, 2016). Thus, the attainable yield y^a is defined as the potential yield under given climatic and soil conditions. But, using solely the yield term (6) neglects pre-sowing weed controlling practices depicted by $v_{m,j}$. Accounting for that, the expected yield y^* for a specific strategy becomes:

$$(7) \qquad y^*_{m,t,b,h} = \underbrace{\left(1 - e^{-(\alpha_0 + \alpha_1 \cdot v_{m,j})^2}\right)}_{\text{Pre-sowing}} \cdot y^a_{m,t} \cdot \underbrace{\left[1 - I \cdot \frac{e^{-(\beta_0 + \beta_1 \cdot z_{m,j})^2}}{100 \cdot \left(e^{C \cdot T} + I \cdot \frac{e^{-(\beta_0 + \beta_1 \cdot z_{m,j})^2}}{A} \right)} \right]}_{\text{Post-sowing}}.$$

2.3 Parameterisation and pesticide application restrictions

For calibration of the model and to parameterise the production function, we conducted expert interviews with the senior herbicide consultant and three regional herbicide consultants of the chamber of agriculture from NRW who identified most frequently used strategies in different regions of NRW depending on soil types.[1] Furthermore, we collected data on the observed yield $\bar{y}$ in each municipality which should reflect the current weed control practise (IT NRW, 2016). In order to estimate the parameters of interest (α_0, α_1, β_0 and β_1), we determine the parameter values which minimise the error term between the observed yields and the yield simulated with the observed control strategies in selected municipalities where a clear assignment between expert knowledge on strategies used and weeds occurring could be made, i.e. municipalities which have homogeneous soil types but different yields:

$$(8) \qquad \min \varepsilon = \sum_{m}^{8} \left(y^{*}_{m,t^{*},b^{*},h^{*}} - \bar{y}_{m,t} \right)^2$$

Thus, we can directly account for the nonlinearity of the production function. Some further details need to be reflected during estimation and simulation. First, we assume that strategies have to be changed from year to year to avoid building up resistance of weeds against specific AS. More precisely, we classified the strategies based on the Herbicide Resistance Action Committee (HRAC, 2005) and added a constraint which prevents that strategies from the same groups are used in two consecutive years. Second, special requirements for nicosulfuron-containing strategies have to be included since this AS is only allowed to be applied every second year by law (code NG327 for the use of plant protection products) (eq. not shown).

Once the parameters are determined and inserted into the production function, optimal strategies can be determined for each *m* and *t* according to eq. (1), i.e. profits can be maximised for each municipality and year by choosing pre- and post-sowing shares for the control strategies:

$$(9) \qquad E(\pi_{m,t}) = \sum_{b=1}^{24} \sum_{h=1}^{55} E(\pi_{m,t,b,h}) \cdot S_{b,m,t} \cdot \varphi_{b,glyphosate} \cdot S_{h,m,t}\,, \quad S_{b,m,t}\ and\ S_{h,m,t} \in [0,1]$$

$$(10) \qquad \max \pi = \sum_{m=1}^{377} \sum_{t=1}^{2} E(\pi_{m,t}).$$

φ is the information matrix whether glyphosate is allowed in the analysed scenarios. $S_{b,m,t}$ and $S_{h,m,t}$ are the shares of the selected control strategies of the farmers for pre- (*b*) and post-sowing (*h*) weed management and $E(\pi_{m,t,b,h})$ is the profit for each strategy which reflects the expected yield, related fertiliser and other costs including the costs for weed control.

The model is written in GAMS code. We simulate optimal herbicide strategies under a baseline where glyphosate can be applied throughout the two periods and a counterfactual where glyphosate is banned. We conduct sensitivity analyses with regard to the attainable yield (increase by 10% in t_1 and 15% in t_2), the green maize price ex field *P* (€ 2.80, 3.30 and 3.80/dt) and the difference between weed and crop emergence *T* (40 to -90), so that effects of higher or lower prices and higher or lower weed pressure can be seen. We test the following five hypotheses: H1) average post-sowing strategies change in case of a glyphosate ban, H2) costs for weed management increase in case of a glyphosate ban, H3) working force demand increases in case of a glyphosate ban, H4) the gross margin decreases in case of a glyphosate ban, and H5) yields significantly decrease in case of a glyphosate ban. We use the average of the periods t_1 and t_2.

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[1] Regarding herbicide strategies, three major soil types can be distinguished in NRW: sandy soils where herbicides against *Panicoideae*-varieties are applied, clayey soils where strategies against *Alopecurus myosuroides* are preferred and good loamy soils where simple and cheap strategies are used. Eight municipalities were selected with known weed control strategies (4x sandy soils due their relevance in maize production, 2x loamy soils, 2x clayey soils). In municipalities with a mix of soil types, also a mix of strategies is applied.

3 Data

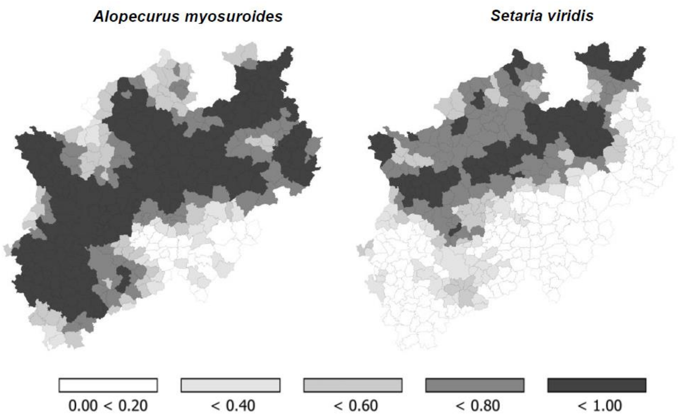
We focus on the most important weeds in maize cultivation for our case study region (defined as more than 10% degree of presence, following the samples of MEHRTENS et al. (2005) and MOL et al. (2015). Additionally, *Digitaria ischaemum* and *Mercurialis annua* were included; weeds which are of importance in specific regions of NRW as they are also listed in the agricultural recommendations (see resulting list in Table 1). Information on the occurrence of weeds is taken from the 2.88x2.75km distribution raster of Germany's pteridophytes and flowering plants (NETPHYD and BFN, 2013), and mapped via GIS operations to municipality areas. We included only the 377 municipalities which reported maize cultivation in recent years. Each municipality receives weed specific occurrence probabilities which reflect the area weighted average of raster cells where each weed was observed (see data for two weeds in Figure 1). Information on the average abundance, i.e. the share of affected area when a weed is observed and not controlled, is used from long-term field trials (Table 1).

Table 1: Maize weeds implemented in the output damage function approach

Name	Average abundance (%)	Name	Average abundance (%)
Grass-weeds:		*Fumaria officinalis*	2.0
Alopecurus myosuroides	21.3+	*Galinsoga parviflora*	12.0
Digitaria ischaemum	21.3+	*Galium aparine*	7.0
Echinochloa crus-galli	22.0	*Geranium pusillum*	6.0
Elymus repens/Elytrigia repens	21.3+	*Lamium spp.*	6.0
Poa annua, P. trivialis	2.0	*Matricaria spp.*	13.0
Setaria viridis	40.0	*Mercurialis annua*	6.8+
Broad-leaved weeds:		*Persicaria lapathifolia*	11.0
Amaranthus retroflexus	13.0	*Persicaria maculosa*	3.0
Atriplex patula	1.0	*Polygonum aviculare agg.*	3.0
Brassica napus	18.0	*Rumex obtusifolius*	4.0
Capsella bursa-pastoris	5.0	*Solanum nigrum*	3.0
Chenopodium spp.	20.0	*Sonchus spp.*	2.0
Cirsium arvense	4.0	*Stellaria media agg.*	6.0
Convolvulus arvensis	2.0	*Thlaspi arvense*	3.0
Equisetum arvense, E. palustre)	6.8+	*Veronica spp.*	2.0
Fallopia convolvulus	12.0	*Viola arvensis*	5.0

Note: Abundance-values marked with a + are estimates according to mean values of grass weeds or broad-leaved weeds. Data on year to year variation of the abundance were not found. Source: MEINLSCHMIDT et al. (2008)

Figure 1: Spread of *Alopecurus myosuroides* (left) and *Setaria viridis* (right)



Source: NETPHYD and BFN (2013), raster data converted to municipality borders

We consider those herbicides (combinations) that are recommended by the Chamber of Agriculture of North Rhine Westphalia (LWK NRW, 2015a) and the Bavarian State Research Centre for Agriculture (LFL, 2016). These recommendations are widely used in agricultural extension and also published in agricultural magazines. Because of lack of data on how different doses affect weed control, we use the recommended dose in each strategy instead of trying to also solve for an optimal rate (PANNELL, 1990). However, these doses may vary between strategies comprising the same AS. In total, 55 different post-sowing herbicide strategies were defined, where one reflects zero control, 6 are mechanical only and the remaining 48 apply herbicides once or twice. For each of those 55 strategies, data by the LFL (2016) and the LWK NRW (2015a) define the suppressing efficacy against each of the 32 weeds in the interval [0,1]. A value of 1 characterises total eradication, a value of zero indicates no impact on the weed, and a value between zero and one was assigned if part of the population is removed. Unfortunately, the data were not available for all 32 weeds in which case manufacturer information (obtained from product brochures) was used. Thereby, in general three categories are displayed: well or very well controllable, sufficiently controllable and not sufficiently controllable. For the first category, we assume an efficacy of 0.90, for the second category 0.33 and for the third category null efficacy.

To quantify the efficacy of the mechanical strategies, we combine information from extensive or organic farming systems with expert knowledge. Data on mechanical post-sowing techniques could be found in KEES (1984, unpub., cit. from HOFFMANN, 1990). Additionally, we consulted the organic farming expert of the Chamber of Agriculture from Lower Saxony for information on the mechanical harrowing and hoeing frequency, and their effect on specific weeds. There are 24 different pre-sowing plant protection strategies in our model, consisting of mouldboard ploughing, different chisel ploughing and harrowing combinations and of glyphosate combinations. Except for glyphosate, no other herbicides are allowed before sowing (KEHLENBECK et al., 2015). We could not find unambiguous data about the yield increasing or decreasing effect of different tillage systems. Therefore, with respect to the weed controlling capacity of conventional and conservation tillage, both strategies have almost the same yield potential. Conventional tillage has only slight advantages in weed control.

Table 2: Machinery costs and other inputs related to maize growing

Activity	Sub-activity	Work hours (h/ha) (wage: € 17.5/h)	Fix and variable machinery costs (€/ha)	Other inputs
Weed control-related activities:				
Chisel plough/Cultivator (4.5m)		0.44	24.17	
Mouldboard plough and packer		1.73	66.97	
Pesticide sprayer (24m)		0.17	6.90	
Harrow (9m)		0.17	11.09	
Hoe (6m)		0.72	30.03	
Other activities:				
Inspection (share, every 5th year)		0.04	0.26	-
Manure application (25 m³/ha)		0.74	50.23	-
	Manure cost	-	-	€ 0.00/ha
Precision drill (6m-width)		0.53	41.72	-
Direct precision drill (59% increase to normal precision drill, 20% discount on light soils)		0.53	66.31	
	Seed			€ 233.20/ha
Mounted fertiliser spreader (amount depends on *E(y)*)		0.00–0.29	0.00–6.14	
Liming (share, every 3rd year)		0.19	12.47	
	N			€ 1.10/kg
	P_2O_5			€ 0.87/kg
	K			€ 0.77/kg
	Ca			€ 0.05/kg
No harvest cost, sell ex field		-	-	-

Diesel consumption for mouldboard ploughing is assumed to be 30% higher/lower on heavy/light soils (for chisel ploughing 20% higher/lower). Sources: ACHILLES et al. (2016); fertiliser prices: LFL (2016); weight-shares: LWK NRW (2015b).

Data about actual yields are available at county-level (53 counties in NRW; IT NRW, 2016), and $\bar{y}$ is the five year average of the actually observed yield from 2011 and 2015. A 5% increase of the expected yield is assumed for the second year t_2. OERKE (2006) estimated a 5% yield loss from weeds in Western European maize production with usual weed control strategies ($y^a = 1.05\ \bar{y}$). For information about maximum losses under zero control (scalar A in eq. (7)), we draw on field trials by SÖCHTING and ZWERGER (2012). Maize yields with herbicide treatment were up to 63.8% higher compared to the untreated control group (A = 63.8%). For

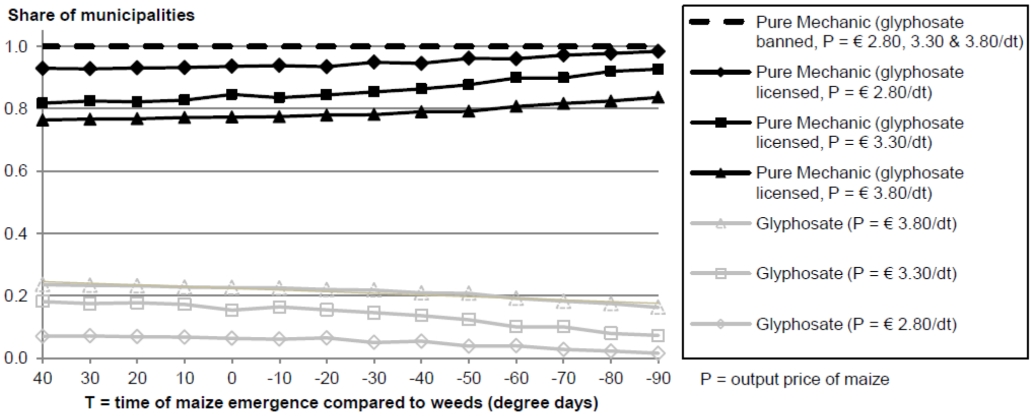
I and C in eq. (7), we rely on BOSNIĆ and SWANTON (1997), who estimated I = 0.3% and C = 0.017. Further restrictions of the estimation model are that the no-till pre-sowing strategy with no herbicide application has to achieve a yield level between 85% and 90% and that the ploughing strategy has to be larger than 95% (GEHRING et al., 2012). The zero control post-sowing strategy is fixed at 86% for normal weed emergence (in relation to the field trials of SÖCHTING and ZWERGER, 2012). Based on this data, the estimates from eq. 8 are as follows: ε has a value of 0.8–4.0% of $E(y)$ depending on the municipality in the parameterisation. The best fit parameter values are $\alpha_0=1.304$, $\alpha_1=0.770$, $\beta_0=0.724$ and $\beta_1=0.244$ (estimated at $T=0$).

Herbicide's costs are based on 2015 recommended retail prices from a German agricultural trader (ROTH AGRARHANDEL, 2015). For labour costs, € 17.5/h are assumed. In our study region, organic fertiliser is no limiting production factor (see GÖMANN et al., 2010 for details) so that we assume that slurry is for free. Table 2 above presents the relevant cost parameters.

4 Results

Figure 2 presents for three price levels the chosen pre-sowing strategies as a share of municipalities where they are applied, on average of the two years t. Applying glyphosate in a strategy is on average optimal in about 5% to 25% of the municipalities. In the other municipalities, conservation tillage with mechanical strategies consisting of one or two chisel ploughings and/or one to three harrowing passes is the most profitable. Glyphosate containing strategies are more profitable when applied closer to maize emergence, i.e. close before sowing or even close after sowing. The later maize emerges compared to weeds, the less glyphosate is applied. In case of a ban, the above mentioned mechanical strategies are used throughout, but mouldboard ploughing is not used in any year. As conservative mechanical control suppresses weeds not as efficiently as herbicides, glyphosate use is higher in t_2 since the attainable yield is assumed higher in this year. Only mechanical control is observed under a ban since no alternative herbicides are licensed for pre-sowing application.

Figure 2: Shares of used pre-sowing strategies (average of t_1 and t_2 of each municipality)



Regarding selective herbicide use after sowing, we observe that with a later emergence of silage maize compared to weeds, i.e. a higher weed pressure reflected by a more negative T, more expensive herbicide strategies get more profitable. This implies that the share of mechanical strategies decreases (Figure 3). Higher silage maize prices reinforce this. Comparing the change in T from +40 to -90, for example, implies an increase in weed control costs from € 78/ha up to € 115/ha at P=€ 3.80/dt, compared to an increase from € 66/ha to € 95/ha at P=€ 2.80/dt. The composition of the chosen strategies as a function of T, i.e. maize relative to weed emergence, is summarised in Figure 4 for the glyphosate licensed-scenario and an output price of € 3.80/dt. In both scenarios, i.e. for glyphosate being licensed and banned, the most profitable AS shift from nicosulfuron, prosulfuron and S-metolachlor to terbuthylazine, mesotrione, pethoxamid, flufenacet, foramsulfuron, iodosulfuron, and thiencarbazone.

Figure 3: Shares of post-sowing strategies as average of t_1 and t_2 (glyphosate licensed)

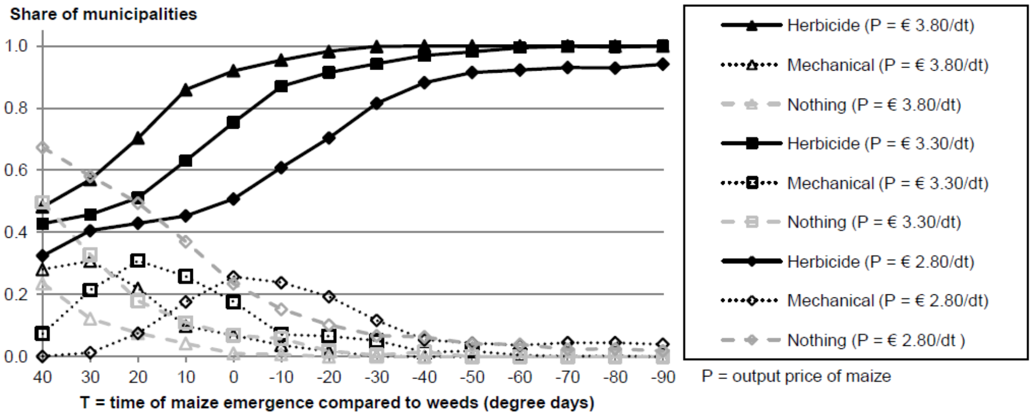


Figure 4: Shares of post-sowing strategies as average of t_1 and t_2 (glyphosate licensed)

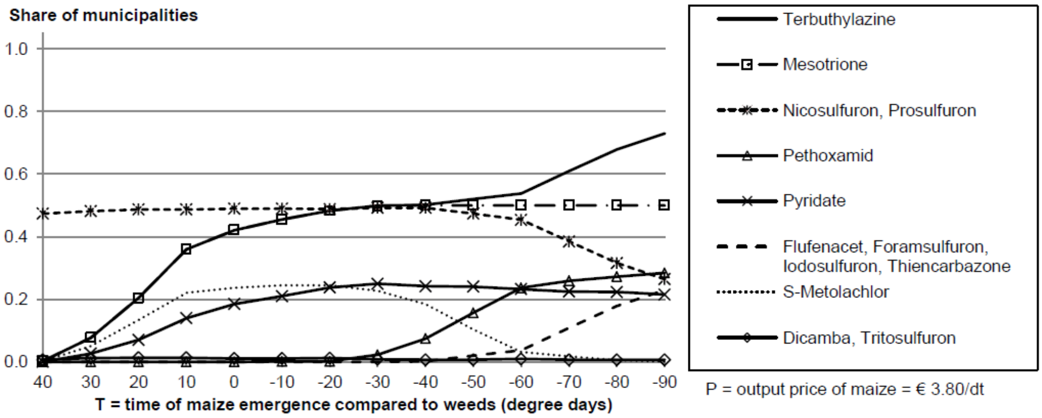


Table 3 shows the results of the hypothesis testing. Differences of mean values over all municipalities are given for different levels of *T* and for prices of € 2.80/dt and € 3.80/dt. H1 states changes in post-sowing AS use after a ban. However, the composition of the different AS changes only in few municipalities, but those changes are overall not significant.

We cannot reject H2 that weed control becomes more expensive under a ban. We find that in municipalities where glyphosate was used in the benchmark, a significant different amount is spent on weed management under a ban (plus € 4–6/ha). The effect decreases with the higher price of € 3.80/dt due to the higher intensity of pre-sowing weed management in the benchmark scenario at the higher price level. The cost increase stems from substituting glyphosate mostly with one or two passes of chisel ploughing. Note that sowing is assumed to be cheaper after two passes compared to only a single pass of chisel ploughing (and also cheaper compared to glyphosate application only). The application of mechanical strategies leads to a significant increase in labour demand (H3). That effect, however, decreases if *T* is lower, i.e. the weed pressure after sowing is high. In the latter case, more expensive post-sowing strategies with selected herbicides are used instead.

Generally, expected gross margins vary highly across municipalities already under current legal conditions, reflecting yield differences. Furthermore, the later maize emerges compared to weeds, the lower the gross margin will be. A glyphosate ban causes in our simulation, on average over all glyphosate-using municipalities, decreases of the gross margins (already accounting for higher costs for labour) of about € 1–2/ha with maximal reductions of € 9/ha (for P=€ 2.80/dt) and € 13/ha (for € P=3.80/dt) over the two year growing period. In single years, however, costs can be higher if our assumptions on resistance management are neglected.

The reduced plant protection intensity under a ban is reflected in decreased yields by about 0.5–1%, which turns out as more profitable than maintaining the control effort with more expensive strategies (difference is significant at higher levels of *T* and the two presented prices).

Table 3: Differences between glyphosate-ban-scenario and glyphosate-licensed-scenario (mean across all municipalities) and results of hypothesis testing

	Maize emergence	T=30		T=10		T=-10		T=-30		T=-50		T=-70		T=-90	
	Price (€/dt)	**2.80**	**3.80**	**2.80**	**3.80**	**2.80**	**3.80**	**2.80**	**3.80**	**2.80**	**3.80**	**2.80**	**3.80**	**2.80**	**3.80**
H1: share of municipalities (%)	No Herbicide	1.9	4.0	2.0	1.7	6.5	2.9	7.9	-	-	-	-	-	-	-
	Mechanic	-	-	-	1.7	-	2.9	2.6	-	-	-	-	-	-	-
	Nothing	1.9	4.0	2.0	-	6.5	-	5.3	-	-	-	-	-	-	-
	Herbicide	-1.9	-4.0	-2.0	-1.7	-6.5	-2.9	-7.9	-	-	-	-	-	-	-
	Dicamba	-	-	2.0	-	-	-1.8	-	-0.6	-	-	-	0.7	-	-
	Flufenacet	-	-	-	-	-	-	-	-	-	-	-	-0.7	-	0.8
	Foramsulfuron	-	-	-	-	-	-	-	-	-	-	-	-0.7	-	0.8
	Iodosulfuron	-	-	-	-	-	-	-	-	-	-	-	-0.7	-	0.8
	Mesotrione	-	-	-	1.2		1.8	-2.6	2.4	-	-2.5	-	1.5	-	1.6
	Nicosulfuron	-1.9	-4.0	-3.9	-2.9	-6.5	-2.9	-5.3	-1.8	-	2.5	-	-1.5	-	-2.4
	Pethoxamid	-	-	-	-	-	-	-	-	-	-0.6	-	2.2	-	0.8
	Prosulfuron	-1.9	-4.0	-3.9	-2.9	-6.5	-2.9	-5.3	-1.8	-	2.5	-	-1.5	-	-2.4
	Pyridate	-	-	-	1.2	-	-1.2	-	2.4	-	-1.9	-	-0.7	-	0.8
	S-Metolachlor	-	-	-	-	-	2.9	-2.6	-	-	0.6	-	-	-	-
	Terbuthylazine	-	-	-	1.2	-	1.8	-2.6	2.4	-	-2.5	-	0.7	-	2.4
	Thiencarbazone	-	-	-	-	-	-	-	-	-	-	-	-0.7	-	0.8
	Tritosulfuron	-	-	2.0	-	-	-1.8	-	-0.6	-	-	-	0.7	-	-
H2: €/ha	Weed management costs	6.19 ***	5.48 ***	5.83 **	5.24 ***	5.88 **	4.89 ***	4.31	4.80 ***	4.02	4.38 ***	2.17	4.25 ***	8.09	3.76 **
H3: h/ha	Weed management labour demand	0.34 ***	0.34 ***	0.34 ***	0.34 ***	0.34 ***	0.33 ***	0.33 ***	0.33 ***	0.31 ***	0.33 ***	0.27 ***	0.33 ***	0.27 ***	0.31 ***
H4: €/ha	Gross margin per ha	-1.12	-1.99	-1.11	-1.87	-1.09	-1.83	-0.87	-1.68	-0.94	-1.58	-0.73	-1.51	-0.37	-1.28
H5: %	Yield difference (model yield minus real yield)	-0.7 ***	-0.4 **	-0.7 **	-0.4	-0.7 *	-0.4	-0.9 **	-0.4	-0.8	-0.4	-0.8	-0.4	-0.2	-0.4

*, ** and *** represent 5%, 1% and 0.1% significance levels using a t-test. No mark means that no significant difference occurred. Note that for tests on hypothesis H1, a Bonferroni correction was used.

Hypotheses: H1: average post-sowing strategies change in case of a glyphosate ban (average of t_1 and t_2),
H2: costs for weed management increase in case of a glyphosate ban (average of t_1 and t_2),
H3: working force demand increases in case of a glyphosate ban (average of t_1 and t_2),
H4: the gross margin decreases in case of a glyphosate ban (average of t_1 and t_2),
H5: yields decrease in case of a glyphosate ban (average of t_1 and t_2)

5 Discussion

Our results present potential short-term effects in herbicide demand for weed control in silage maize production and thus can be used to quantify intensive margin effects of agri-environmental policies targeting single herbicides. Our normative model simulates limited yield losses with some extra costs for farmers under a glyphosate ban, matching the relatively low yield increasing effect of glyphosate reported in literature (GEHRING et al., 2012). In our model, this leads to a relatively high efficiency and widespread use of alternative (i.e. without glyphosate) conservation tillage strategies already under the benchmark. Under a glyphosate ban and profit maximizing behaviour, overall control intensity and thus the expected maize yield would be somewhat reduced as maintaining the same level of weed suppression and the expected yield is too costly given the available alternative control strategies. Especially due to the subsidy induced boom in biogas production from silage maize in Germany (GÖMANN et al., 2011), silage maize is currently in shortage, being regionally traded at relatively high prices in years with moderate yields. Reducing yields under a glyphosate ban would most probably drive prices further up, such that more costly weed control strategies could become profitable. Farmers might anticipate these impacts and intensify weed control beyond the current profit optimal point to avoid acting as buyers in the short maize markets. If we restrict the model such that a certain yield has to be achieved (a safety threshold to avoid large maize purchases), also more intensive plant protection intensities are used (with costs > € 120/ha).

Compared to other studies being based on expert interviews (KEHLENBECK et al., 2015; SCHULTE et al., 2016), our results suggest lower costs; however, at an overall lower intensity of herbicide use. KEHLENBECK et al. (2015) estimated that a 75% increase of the glyphosate price would be necessary in order to cause a reduction of glyphosate use (in the profit equilibrium of glyphosate and plough use). The results of our normative, profit-maximising model suggest that already lower price increases would lead to use reductions. Indeed, already a 10% price increase leads to some reductions in use and at a 30% increase glyphosate was substituted by mechanical strategies in every municipality (for T=-20 and P=€ 3.80/dt). This matches estimates of more elastic demand for herbicides (BÖCKER and FINGER, 2017).

The treatment frequency, which is a measure for the average number of herbicide applications on a field, varied in German maize production between 1.31–1.47 in 2011–2015, including pre-emergence treatments with glyphosate (JKI, 2016). Our model simulated lower average treatment frequencies over the two periods, which are, for instance, between 0.57–1.15 at a level of T=0 and between 0.95–1.21 at T=-50, depending on *P*. Pesticide intensities beyond the profit maximising intensity were reported by other authors (e.g. SKEVAS et al., 2014, for the Netherlands), which could be explained by the risk-reducing effect of herbicides. This is not reflected in our profit maximising approach, but should be addressed in future research.

JKI also reports the average share of the surveyed German farms which use a specific AS in maize production (JKI, 2016). For example in 2015, 33% of all surveyed farms used an herbicide strategy containing glyphosate, 91% used a strategy containing terbuthylazine, 50% used a strategy containing bromoxynil, etc. Our simulated shares over different levels of *T* differ partly from those values. For example, bromoxynil was not selected at all, but these differences could also root in our regional focus. Still, for selected AS, and depending on *T* and *P*, quite similar shares were calculated, e.g. for nicosulfuron, mesotrione, pethoxamid and partly for glyphosate, terbuthylazine, flufenacet, foramsulfuron and iodosulfuron.

Herbicide strategies considered in our model were aggregated to some extent, e.g. by defining a two-time post-sowing herbicide application strategy as one. Future approaches could further refine the strategies such as depicting each single application according to its characteristics and time of application. That asks, however, for improved data availability such as research on weed specific impact on yields. Additional data could also allow including the control impact depending on doses of specific herbicides. So far, reduced doses are only considered in some strategies which use doses below the manufacturers' recommendation. Also, we decided to neglect potential dynamic control impacts, for instance that a conservation tillage strategy might lead to higher weed abundance in the long-term (SCHWARZ and PALLUTT, 2014) or that effective control might depress future weed infestation (SWINTON and KING, 1994), as it is hard to properly account for external weed seed import in a single plot. Here, HANZLIK and GEROWITT (2011) find that geographical position and soil conditions have a higher influence on weed species composition compared to previous weed management.

Future research could apply the presented approach to other field crops and implement it into a whole farm context. Other aspects to be covered in future extensions are effects of fertilisation, of preceding or catch crops and of weed control measures in autumn.

6 Conclusions

The raster data of NETPHYD and BFN (2013) on weed occurrence are a valuable source to analyse weed spread in Germany. Combing this data with expert information on actual weed control management allows us to develop an output damage control approach for herbicide use in silage maize production for 377 municipalities in NRW. Simulating profit maximal weed control strategies in two consecutive years of maize cultivation with and without a glyphosate ban, we find that i) economic losses of a ban are limited for farmers currently applying glyphosate, ii) costs slightly increase under a glyphosate ban as mechanical strategies for conservation tillage are used pre-sowing, while switches to more expensive selective herbicides in post-sowing strategies are simulated only in few cases. iii) Rather, somewhat lower yields reflecting decreased weed control intensity turn out as profitable, which, however, could lead to higher regional maize prices. Finally, iv) demand of labour increases due to higher shares of mechanical strategies.

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